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Arkadiusz JÓŹWIAK
Paulina OWCZAREK
Leon PROCHOWSKI
Andrzej ŚWIDERSKI

ANALYSIS OF THE IMPACT OF THE USE TIME OF N1 MOTOR VEHICLES ON THE ECONOMIC EFFICIENCY OF THEIR MAINTENANCE

BADANIE WPŁYWU CZASU WYKORZYSTANIA SAMOCHODÓW KATEGORII N1 NA EFEKTYWNOŚĆ EKONOMICZNĄ ICH EKSPLOATACJI*

The efficiency of operation of motor vehicles with a DMC (Permissible Laden Mass) <3.5 tonnes is considered. These are vehicles belonging motor vehicles of category N1, usually referred to as delivery vehicles. The results of observations on the implementation of transport orders in 7 transport companies from the MŚP (Small and Middle-size Companies) sector were used to conduct the effectiveness analysis. The research group covered 24 vehicles that implementation transport orders in the urban zone and in the immediate vicinity of the city. Information was collected on a monthly basis.During the analysis of economic efficiency the income measures (absolute and relative) were used. The calculations were carried out using the model of the vehicle operation process in the form of a neural network, in which a set of 12 input variables and 3 output variables were taken into account. Using the Statistica 13.3 computer program and defining the group and factors describing the process of implementation of individual transport tasks, the developed neural network model enabled searching for the impact of selected operational factors on the economic efficiency of N1 category cars.The calculations showed a significant impact of the number of vehicle days in a month, the weight of the load, as well as the time of year. The obtained calculation results showed the specific features of the impact of the number of working days on revenue in a transport company. The increase in the number of working days favors the increase in income in a limited way, and this restriction depends, among others since the time of year.

Keywords: *operation of vehicles, motor vehicles of category N1, economic efficiency, neural networks.*

Rozważa się efektywność eksploatacji samochodów ciężarowych o DMC < 3,5 tony. Są to pojazdy należące do kategorii N1 (według Dyrektywy 2007/46/WE) zwykle nazywane samochodami dostawczymi. Do prowadzonej analizy efektywności wykorzystano wyniki obserwacji z realizacji zleceń przewozowych w 7 firmach transportowych z sektora MŚP. Grupa badawcza objęła 24 pojazdy, które wykonywały zadania transportowe w strefie miejskiej i w najbliższym otoczeniu miasta. Informacje gromadzono w cyklach miesięcznych. Podczas analizy efektywności ekonomicznej zastosowano kilka miar przychodu (bezwzględny i względny). Obliczenia prowadzono przy wykorzystaniu modelu procesu eksploatacji pojazdów w postaci sieci neuronowej, w której brano pod uwagę zbiór 12 zmiennych wejściowych i 3 zmienne wyjściowe. Stosując program komputerowy Statistica 13.3 oraz zdefiniowanie grupy i czynniki opisujące proces realizacji poszczególnych zadań transportowych, opracowany model sieci neuronowej umożliwił poszukiwanie wpływu wybranych czynników eksploatacyjnych na efektywność ekonomiczną samochodów kategorii N1. Przeprowadzone obliczenia pokazały istotny wpływ liczby dni pracy pojazdów w miesiącu, masę ładunku, a także porę roku. Uzyskane wyniki obliczeń pokazały specyficzne cechy wpływu liczby dni pracy na przychód w firmie transportowej. Wzrost liczby dni pracy sprzyja wzrostowi przychodu w sposób ograniczony, a to ograniczenie zależy m.in. od pory roku.

Słowa kluczowe: *eksploatacja samochodów, pojazdy samochodowe kategorii N1, efektywność ekonomiczna, sieci neuronowe.*

1. Introduction

The specificity of the use of N1 motor vehicles constantly raises a lot of controversy, and in the area of legal conditions there are still a number of ambiguities, which affects the existence of rather negligible amount of literature on this subject. Every month there is new information regarding the statistics of the Main Road Transport Inspectorate about the results of N1 category motor vehicles inspections. For several years, the percentage of vehicles with a load exceeding their permissible capacity in relation to the category N1 vehicles inspected has remained on average at the 93% level (table 1) [19]. It is a fact that the Road Transport Inspectorate usually checks heavy goods vehicles over 3.5 tons, while N1 category vehicles only when it considers that there is a clear suspicion of committing a specific offense. The number of vehicles inspected is negligible, but the percentage ratio of vehicles with a load exceeding their permissible load capacity of up to 3.5 tons may indicate the existence of a complex problem that should be subject to detailed analysis.

Therefore, it becomes justified to be interested in the subject of increasing the profits from operation of the N1 category motor vehicles. Reproducing and simplifying real phenomena in the form of a model becomes an important element in the search for effective methods to

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

Table 1. Percentage share of vehicles with a load exceeding their permissible capacity in relation to the N1 category vehicles tested [19]

	2014	2015	2016	2017
Number of all vehicles with GVW up to 3.5 t	2 399 323	2 447 764	2 515 751	2 574 312
Number of vehicles checked with GVW up to 3.5 t	6 685	6 507	7 594	10 048
Number of tickets issued for vehicles with a load exceeding their maximum capacity	6 135	6 172	6 172	9 396
Percentage share	92%	95%	92%	94%

describe problems and disturbances in the process of operating and servicing motor vehicles. As a result, it makes it easier to find ways to increase the economic efficiency of transport companies.

In the article, the subject of research is the effectiveness of operation of the N1 category cars, which according to [27] are defined as vehicles designed and constructed for transporting loads and having a maximum total weight not exceeding 3.5 tons (GVW up to 3.5 t). In practice, this type of vehicle is referred to as delivery vehicles, which is why this term will be used interchangeably later in the article.

Planning and implementing the process of using motor vehicles in a complex transport system is associated with solving multi-criteria decision problems, which focus on, among the others minimizing costs and achieving maximum profit. This issue concerns the issues of two basic elements of the operation process, i.e. the use and maintenance of motor vehicles. Effective use of transport means in every enterprise is one of the main ways to achieve competitive advantage.

Extensive analyzes of the motor vehicles operation process most often relate to minimizing the costs associated with their use and ensuring maximum reliability of the transport system, as well as the impact of operating the vehicles on the natural environment [21], or safety aspect [20]. Whereas the assessment of the intensity of motor vehicle operation is carried out taking into account, inter alia, mileage values, engine capacity, vehicle's age [18], repair costs, revenues [16], technical availability, intensity of motor vehicle use [6]. Due to the random nature of vehicle failures, the knowledge of stochastic processes is necessary to maintain their efficient and safe operation [2].

Modelling and assessment of such complex processes based on classic mathematical models and techniques of reliability theory may be difficult to carry out and not bring the expected results due to the large amount of quantitative and qualitative data and due to the dynamically changing conditions of the vehicle operation system. In such a case, other computational methods are proposed, e.g. models using Markov processes or reliable phase diagrams, a Petri network model or Monte Carlo simulation processes [13], an algorithm of resistance clonal selection [5].

Considering the degree of complexity of the studied problem and the increasing use of artificial intelligence methods to solve this type of task, the goal of this study is to assess the economic efficiency of transport companies using a neural network. The evaluation is focused on transport companies operating for package cargo transport in urban and suburban areas. The work uses several measures of revenue in transport activities described later in this work.

Wherever there are no grounds for linear approximation of occurring phenomena and processes, usually when solving difficult and troublesome evaluation issues, including efficiency of car operation, it may be rational to refer to neural networks or other artificial intelligence algorithms (i.e. models that map non-linear relationships) [7], [9], [10], [24]. Artificial neural networks are one of the techniques used by artificial intelligence. There are also other uses of artificial intelligence in transport. For example: for assessing the quality of transport means, for optimizing travel routes [11], or for evaluating the configuration of transport service management [23].

2. Cost analysis of a transport enterprise with a fleet of N1 category motor vehicles

The transport service provider is still selected by the minimum price criterion as the first choice. High competition and constantly growing requirements of the transport market force carriers to constantly search for methods to minimize the costs of a transport company. Generating revenues at the transport companies is primarily based on the intensity of the vehicle operation. As a rule, they are proportional to the number of kilometers traveled, load weight or hours worked. The intensive operation of vehicles generates not only an increase in revenues, but also costs, which is why it is extremely important to carry out their detailed analysis.

In enterprises, including transport ones, one of the most commonly used cost sharing methods is their generic system, containing 7 groups, which are also the names of synthetic accounts: depreciation, consumption of materials and energy, external services, taxes and fees, salaries, social insurance and other benefits, other costs (generic ones).

According to many publications, the costs of external services represent the largest percentage in relation to all costs of the transport company [15]. In this study, the research subjects are micro, small and medium enterprises (micro and SMEs), therefore the cost structure will be slightly different from the general classification of generic type of costs of the enterprises. The reason for this could be, for example, the fact that micro and SMEs only have their own, not leased rolling stock, which provides transport services directly without the participation of outsourcing companies. Issues related in detail to the costs of road freight transport enterprises are of interest to many authors [1], [4], [8], [12], [15], [26] who most often reduce them to four basic generic groups and determine their percentage values in relation to other costs:

- depreciation of 6% - 12%,
- operation 20% - 68%,
- drivers' remuneration 14% - 45%,
- remaining costs 12% - 30%.

Based on the cited analysis of the literature, the fig. 1 presents the shares of the three basic cost groups of automotive freight transport enterprises from the perspective of several authors.

For the purpose of achieving the research goal, the data was collected, which was classified into four groups of factors: utility, season, service, economic.

3. Research method and object

Tasks carried out at the transport companies that provide services in Poland have been examined. The operation of rolling stock, belonging to 7 different transport companies from the SME sector, involves the implementation of transport tasks in accordance with the needs of customers. The research group includes 24 N1 category motor vehicles, 5 models: Renault Master, Renault Mascott, Citroen Jumper and Fiat Ducato. The study only took into account technical data that had an impact on the aforementioned factors.

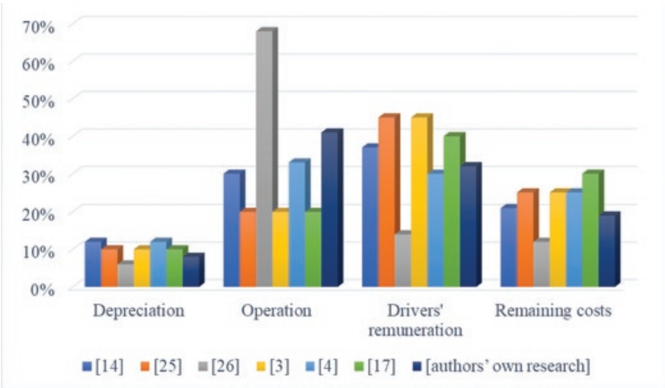

Fig. 1. Comparison of the share of selected cost groups of road freight transport enterprises

Table 2. Set of factors used to modelling maintenance process

	Designation of groups and factors		Units of measurement
	Y^U	**Group: factors of the motor vehicles operation**	
1	Y_D^U	number of days of the vehicle use in a month	number
2	Y_R^U	monthly vehicle's mileage	kilometres
3	Y_J^U	monthly vehicle's driving time	minutes
4	Y_C^U	monthly vehicle's working time	minutes
5	Y_P^U	average fuel consumption	litres/100 km
6	Y_M^U	average daily load weight	kilograms
7	Y_E^U	percentage value of the capacity utilization	%
	Y^K	**Group: time of year**	
8	Y_W^K	time of year	season 1, season 2, season 3
	Y^O	**Group: servicing activities of motor vehicles**	
9	Y_P^O	service fluid refilling	performed, not performed
10	Y_K^O	tire service	performed, not performed
11	Y_H^O	brakes service	performed, not performed
	Y^E	**Group: economic factors**	
12	Y_Z^E	monthly value of orders	PLN
13	Y_K^E	monthly operating cost	PLN
14	Y_M^E	month revenue from the implementation of transport services	PLN
15	Y_L^E	relative unit revenue	PLN/ km
16	Y_W^E	relative unit profit	PLN/ km

The following measures of economic efficiency have been defined:

- revenue $[Y_M^E]$ - expressed as the difference between the monthly value and the monthly operating costs,
- relative revenue $[Y_L^E]$ - expressed as the ratio of the monthly value of orders to the monthly mileage,
- relative profit $[Y_W^E]$ - expressed as the ratio of the revenue to the monthly mileage. There are 4 main groups of factors taken into account in the research:
- Y^U - a group of quantities describing the factors of operating motor vehicles: characterizing the manner and intensity of the work performed,
- Y^K - a group of quantities describing the seasons: defining the external conditions in which the vehicle is used,
- Y^O - a group of quantities describing the maintenance of motor vehicles: concerning the maintenance strategy and its effects,
- Y^E - a group of quantities describing economic factors: related to the costs and profitability of carrying out transport tasks.

A set of factors describing the above groups are shown in table 2.

For such defined groups, a real data from one year of vehicles operation (2017) was collected in monthly cycles. These vehicles droved mainly in urban traffic with a few routes outside the city, within this country. The data was obtained from transport orders in the period under review, analyses of the service expertises and interviews with experts (dispatchers, drivers, service technicians, mechanics). The 156 observations of the above factors were made for each vehicle. This way, 3744 data was collected, which was used to model the operation process using a neural network.

4. Neural modelling

When creating the neural network, some of the signals from the table 2 were used, these are:

- quantitative input ones: Y_D^U, Y_R^U, Y_J^U, Y_C^U, Y_P^U, Y_M^U, Y_E^U, Y_K^E,
- quantitative output: Y_M^E, Y_L^E, Y_W^E.

Use the results, among the others [22] of the scientific work, a Multilayer Perceptron and teaching algorithms were used: conjugate gradients; the fastest fall and BFGS (Broyden - Fletcher - Goldfarb - Shanno). The division of the data set into parts in neural modelling was adopted:

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

After determining the input signals, output signals and network parameters, the neural network teaching process was carried out using the Statistica 13.3 computer program. Examples of its results are presented in table 3.

Table 3. Sample results of the neural network teaching process

ID	Network name	Teaching quality	Testing quality	Validation quality	Teaching algo-rithm	Hidden activation	Output activation
1	MLP 17-11-3	0,796875	0,746498	0,874968	BFGS 28	Exponential	Exponential
2	MLP 17-16-3	0,785931	0,764052	0,874283	BFGS 50	Sinus	Logistic
3	MLP 17-36-3	0,775433	0,804533	0,828288	BFGS 17	Sinus	Exponential
4	MLP 17-30-3	0,762021	0,760954	0,861609	BFGS 23	Sinus	Linear
5	MLP 17-9-3	0,649014	0,612412	0,770544	BFGS 12	Sinus	Tanh
6	MLP 17-6-3	0,755626	0,766049	0,867752	BFGS 51	Linear	Tanh
7	MLP 17-8-3	0,767523	0,742646	0,876113	BFGS 66	Sinus	Tanh
8	MLP 17-31-3	0,776866	0,784677	0,872670	BFGS 36	Linear	Logistic
9	MLP 17-26-3	0,730811	0,783034	0,825576	BFGS 10	Exponential	Sinus
10	MLP 17-9-3	0,807437	0,754784	0,865342	BFGS 38	Logistic	Linear
11	MLP 17-26-3	0,794570	0,754735	0,874439	BFGS 24	Tanh	Logistic
12	MLP 17-3-3	0,796772	0,816948	0,850614	BFGS 52	Logistic	Sinus
13	MLP 17-29-3	0,776284	0,783517	0,874145	BFGS 31	Linear	Logistic
14	MLP 17-19-3	0,813487	0,752890	0,844996	BFGS 45	Logistic	Sinus
15	MLP 17-23-3	0,776775	0,783067	0,873542	BFGS 32	Linear	Logistic
16	MLP 17-17-3	0,838238	0,761414	0,700263	BFGS 64	Tanh	Tanh
17	MLP 17-7-3	0,768890	0,799204	0,819687	BFGS 17	Linear	Exponential
18	MLP 17-6-3	0,780286	0,768095	0,886923	BFGS 28	Logistic	Linear

5. Validation of the neural network model and calculations results

The structure of the best neural network took the form of MLP 17-19-3, which means 17 neurons in the input layer, 19 neurons in the hidden layer and 3 neurons in the output layer (fig. 2).

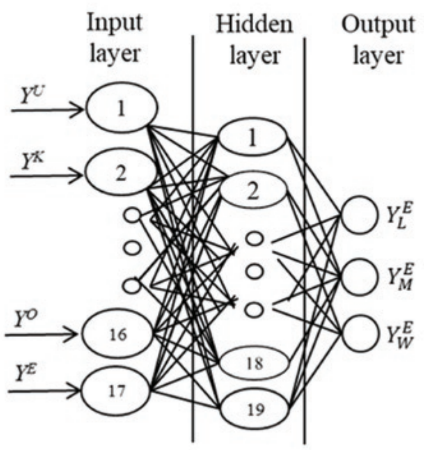

Fig. 2. Structure of the created MLP 17-19-3 network

Since among the input signals, the qualitative input signals have appeared, the total number of neurons at the input represent the sum of all quantitative and qualitative signals, broken down into their individual values. table 4 shows the input signals of the selected neural network.

In the table 3, the MLP 17-19-3 network teaching quality was estimated at around 81% probability of indicating the correct answer, i.e. the adopted measure of economic efficiency. Testing quality - at 75% level and validation quality - at 85%. The BFGS 45 algorithm turned

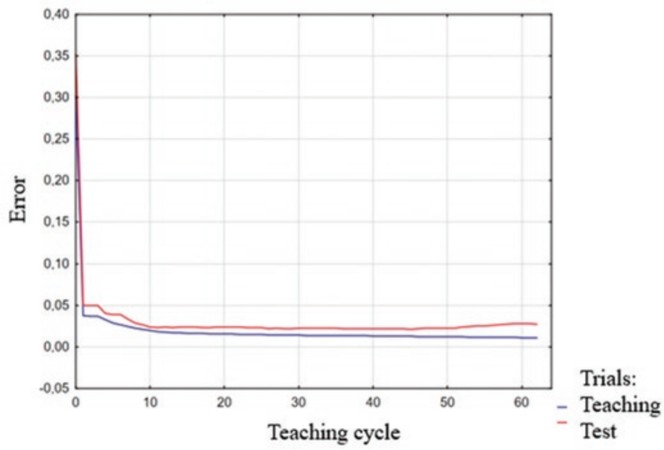

Fig. 3. Results of MLP 17-19-3 neural network teaching

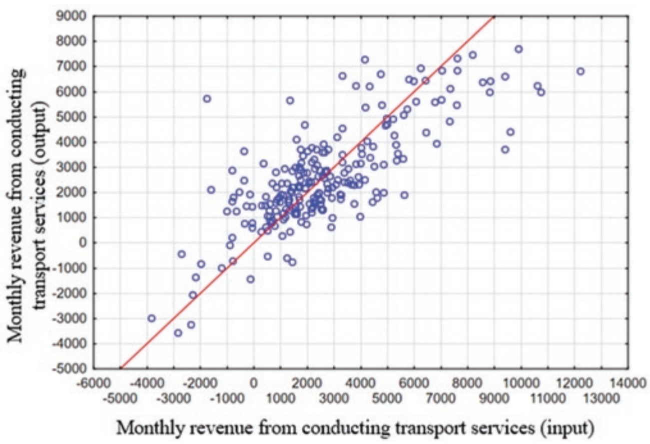

Fig. 4. Dispersion of the dependent variable of the MLP 17-19-3 neural network

Table 4. MLP 17-19-3 neural network individual input signals

	Designation of groups and factors	Units of measurement	ID of the neuron	Value of the neuron
1	Y_D^U	number	1	Y_D^U
2	Y_R^U	kilometers	2	Y_R^U
3	Y_J^U	minutes	3	Y_J^U
4	Y_C^U	minutes	4	Y_C^U
5	Y_P^U	litres/100 km	5	Y_P^U
6	Y_M^U	kilograms	6	Y_M^U
7	Y_E^U	%	7	Y_E^U
8	Y_W^K	season 1, season 2, season 3	8	Y_W^K *seazon*1
			9	Y_W^K *seazon*2
			10	Y_W^K *sezaon*3
9	Y_P^O	completed, not completed	11	Y_P^O *completed*
			12	Y_P^O *not completed*
10	Y_K^O	completed, not completed	13	Y_K^O *completed*
			14	Y_K^O *not completed*
11	Y_H^O	completed, not completed	15	Y_H^O *completed*
			16	Y_H^O *not completed*
12	Y_K^E	PLN	17	Y_K^E

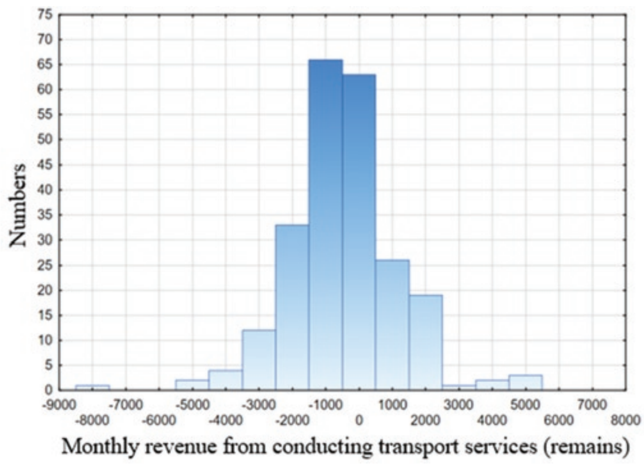

Fig. 5. Distribution of the residues of MLP 17-19-3 neural network

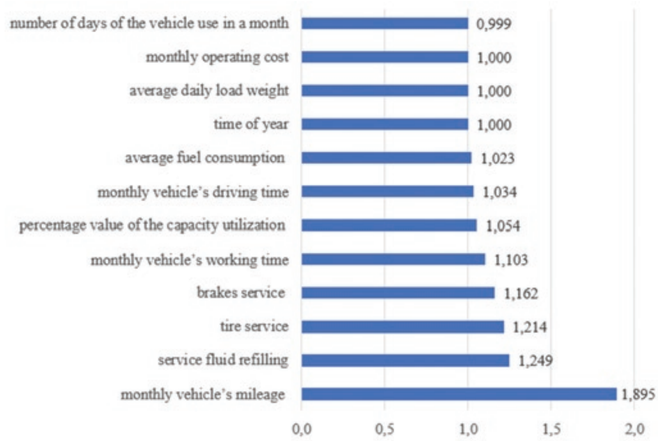

Fig. 6. Global sensitivity analysis for the MLP 17-19-3 neural network

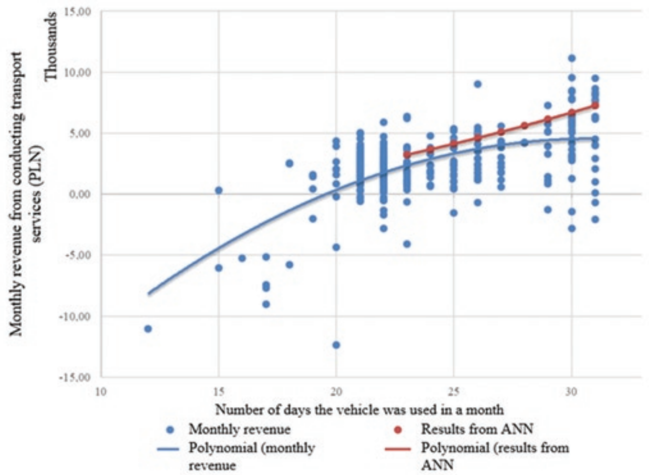

Fig. 7. Monthly revenue in relation to the number of days of the vehicle's operation

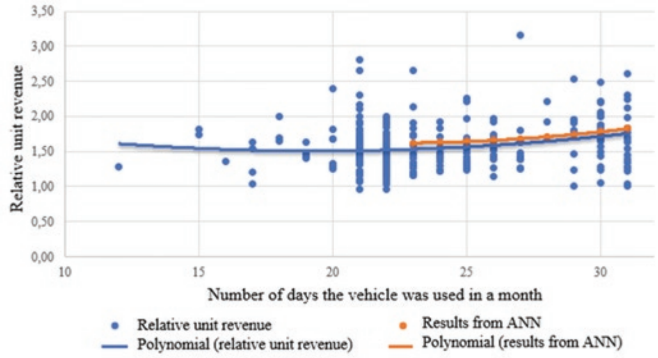

Fig. 8. Relative unit revenue in relation to the number of days of the vehicle's operation

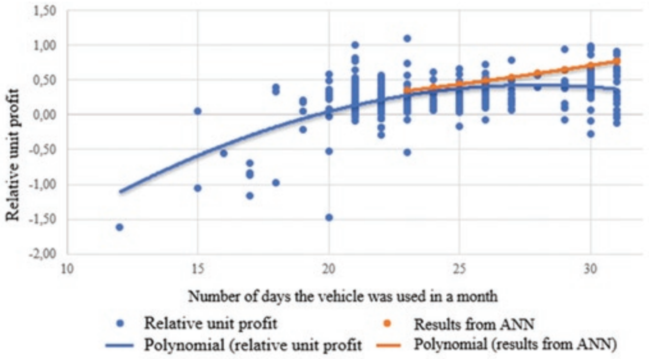

Fig. 9. Relative unit profit in respect to the number of days of operation of the vehicle

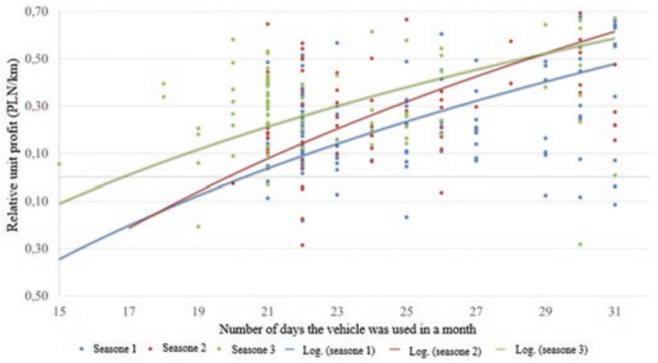

Fig. 10. Relative unit profit in relation to the number of days of operation of the vehicle in respect to Y^K

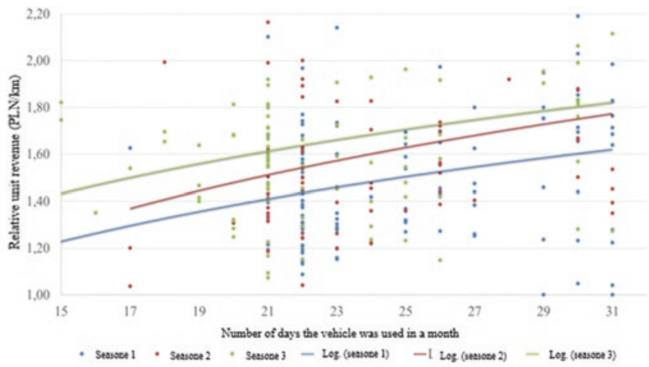

Fig. 11. Relative unit revenue in relation to the number of days of operation of the vehicle in respect to Y^K

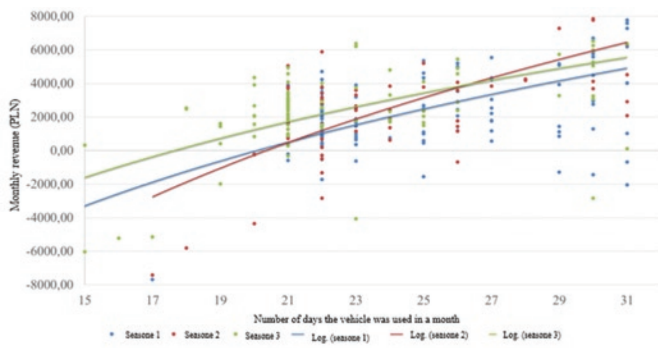

Fig. 12. Monthly revenue in relation to the number of days of operation of the vehicle in respect to Y^K

out to be the best teaching algorithm. The positive result of teaching the neural network is demonstrated, by the teaching graph (fig. 3). It shows that the best network structure was found in the 43-rd cycle; the share of incorrect answers was 19% and the error was estimated at 0.002. Also the course of the dispersion changes, shown in fig. 4, indicates a positive outcome of teaching the network.

The results of the calculations presented in fig. 4 show the dispersion between the forecasted revenue value (the result of the calculation in the network during teaching) and its actual value. The visible gathering of the dispersion value around zero is a good result of the model calculations.

The histogram presented in fig. 5 (distribution of residues, i.e. differences between the output variable and its prediction) shows the number of results of the scatter calculation near zero, which also means a high level of reproducing of the output signals.

In the next stage, a sensitivity analysis was carried out, which involved checking how the network error behaves when input signals are modified. In this calculation, the input signal values are replaced by the average of this signal from the teaching set. After inputting such modified data, the network error was checked. If the error has increased significantly, it means that the network is very sensitive to the signal.

The global sensitivity analysis reflects the impact of individual network input variables on the output signals (fig. 6). These calculations have shown that the greatest impact on the output signals of the neural network have: the monthly number of days of the vehicle's operation, the cost of operation, load weight and time of year.

Based on the selected neural network and the data collected for the neural network teaching process, the trends of changes in the value of efficiency measures are shown, namely: monthly revenue,

Table 5. Example results of the calculations of revenue, unit relative income and unit relative profit for a data set not used in the teaching process

P_Y^X	Y_D^U	Y_R^U	Y_J^U	Y_C^U	Y_P^U	Y_M^U	Y_E^U	Y_K^E	Y_W^K	Y_P^O	Y_K^O	Y_H^O	Y_M^E	Y_L^E	Y_W^E
1	30	11360	425	480	15	1661	1,33	12873,13	season 2	yes	yes	yes	5976,87	1,66	0,53
2	31	13331	516	553	15	1771	1,61	15669,06	season 2	yes	yes	yes	2920,94	1,39	0,22
3	24	10127	422	454	15	1408	1,14	13172,67	season 2	yes	yes	yes	1787,33	1,48	0,18
4	30	13750	516	581	15	1887	1,45	16232,06	season 2	yes	yes	yes	9537,95	1,87	0,69
5	30	9470	350	427	15	1697	1,31	14113,56	season 2	yes	yes	yes	3686,44	1,88	0,39
6	28	10527	376	442	15	1556	1,64	16041,24	season 2	yes	yes	yes	4178,76	1,92	0,40
7	17	10700	684	784	15	1588	1,22	20263,87	season 2	yes	yes	yes	-7413,87	1,20	-0,69
8	31	16362	528	602	15	1765	1,36	19235,94	season 2	yes	yes	yes	4514,06	1,45	0,28
9	17	10700	684	784	15	1349	1,23	20120,94	season 2	yes	yes	yes	-9020,94	1,04	-0,84
10	21	7824	447	484	13	743	0,99	9727,43	season 2	yes	yes	yes	722,57	1,34	0,09
11	21	9632	459	491	14	1114	1,11	11636,10	season 2	yes	yes	yes	1593,90	1,37	0,17
12	23	10560	515	635	14	1190	1,04	11430,36	season 2	yes	yes	yes	3319,64	1,40	0,31
13	22	6990	350	430	14	1162	1,01	9105,71	season 2	yes	yes	yes	3794,29	1,85	0,54
14	21	8297	395	459	14	1263	1,05	10928,23	season 2	yes	yes	yes	1541,78	1,50	0,19
15	21	9090	433	497	14	1036	1,04	10968,52	season 2	yes	yes	yes	1881,48	1,41	0,21
16	21	8000	419	520	14	771	1,03	9847,90	season 2	yes	yes	yes	952,10	1,35	0,12
17	31	11760	380	445	15	1454	1,32	15814,58	season 1	yes	yes	yes	4005,42	1,69	0,34
18	26	8600	331	378	15	1561	1,25	11779,84	season 1	yes	yes	no	5200,16	1,97	0,60
19	24	10570	441	538	15	1621	1,32	14242,71	season 1	yes	yes	yes	757,29	1,42	0,07
20	25	10980	440	503	15	1686	1,37	13236,73	season 1	yes	yes	no	5363,27	1,69	0,49
21	31	13230	471	552	15	1802	1,39	15843,46	season 1	yes	yes	yes	8356,54	1,83	0,63
22	30	11520	384	472	15	1620	1,25	16784,69	season 1	yes	yes	yes	2965,31	1,71	0,26
23	31	14500	468	493	15	1642	1,26	16733,81	season 1	yes	yes	yes	1016,19	1,22	0,07
24	31	14400	465	502	15	1513	1,16	15500,69	season 1	yes	yes	yes	8099,31	1,64	0,56
25	22	11290	514	571	15	1563	1,20	12614,45	season 1	yes	yes	yes	865,55	1,19	0,08
26	30	14930	498	603	15	1645	1,73	16990,02	season 1	yes	yes	yes	4509,98	1,44	0,30
27	31	17810	575	613	15	1558	1,64	19222,32	season 1	yes	yes	yes	-672,32	1,04	-0,04
28	30	12860	429	530	15	1645	1,73	17773,67	season 1	yes	yes	yes	5766,33	1,83	0,45
29	30	17040	569	674	15	1807	1,39	19713,65	season 1	yes	yes	yes	1286,35	1,23	0,08
30	12	6850	571	663	15	1779	1,37	19805,28	season 1	yes	yes	yes	-11055,28	1,28	-1,61
31	31	17980	580	618	15	1584	1,22	20049,37	season 1	yes	yes	yes	-2049,37	1,00	-0,11
32	25	14400	576	680	15	1596	1,45	14674,60	season 1	yes	yes	yes	4325,40	1,32	0,30
33	31	10936	423	488	15	1597	1,42	15795,00	season 3	yes	yes	yes	5475,83	2,05	0,50
34	30	10304	405	466	15	1588	1,38	14079,57	season 3	yes	yes	yes	4563,86	1,77	0,44
35	29	8372	358	413	15	1679	1,41	12553,19	season 3	no	no	no	3348,62	1,94	0,40
36	26	11752	503	598	15	1536	1,34	13012,55	season 3	yes	yes	yes	2188,21	1,33	0,19
37	26	10224	430	531	15	1430	1,30	13012,55	season 3	yes	yes	yes	3282,31	1,53	0,32
38	25	11422	472	548	15	1609	1,39	15104,38	season 3	yes	yes	yes	2220,28	1,56	0,19
39	25	8985	389	486	15	1473	1,34	12577,23	season 3	yes	yes	yes	1037,22	1,54	0,12
40	24	9015	391	488	15	1476	1,34	12564,77	season 3	no	no	no	1176,01	1,54	0,13
41	23	10850	435	500	15	1614	1,39	14725,20	season 3	no	no	no	3184,18	1,68	0,29
42	22	8902	441	524	14	1101	1,08	10680,49	season 3	no	no	no	1885,16	1,45	0,21
43	21	8784	435	523	14	1112	1,09	10635,87	season 3	no	no	no	2458,52	1,46	0,28
44	20	8761	434	523	14	1112	1,09	10628,81	season 3	no	no	no	1839,10	1,47	0,21
45	23	11580	475	547	15	1646	1,40	15622,78	season 3	no	no	no	2371,98	1,57	0,20
46	21	9126	434	518	14	1158	1,15	11411,48	season 3	no	no	no	1562,54	1,46	0,17
47	22	8903	437	530	14	1066	1,10	10670,73	season 3	no	no	no	1702,55	1,43	0,19
48	24	9126	409	502	15	1461	1,24	12763,30	season 3	yes	yes	yes	801,64	1,47	0,09

relative unit revenue and relative unit profit in respect to the number of days of vehicle operation (fig. 7, fig. 8, fig. 9).

The analysis conducted also shows that the selected network correctly reproduces the selected measures of economic efficiency. In order to carry out a detailed analysis of the impact of this factor on the output signal, the impact of the time of year on the values of efficiency measures in relation to the number of days of the vehicle operation was extracted (fig. 10, fig. 11, fig. 12).

Based on the interview with vehicles' drivers, the time of year was determined as the general conditions for meeting the orders, as well as driving comfort and safety:

- season 1 is assigned to months: May, June, July, August,
- season 2: March, April, September, October,

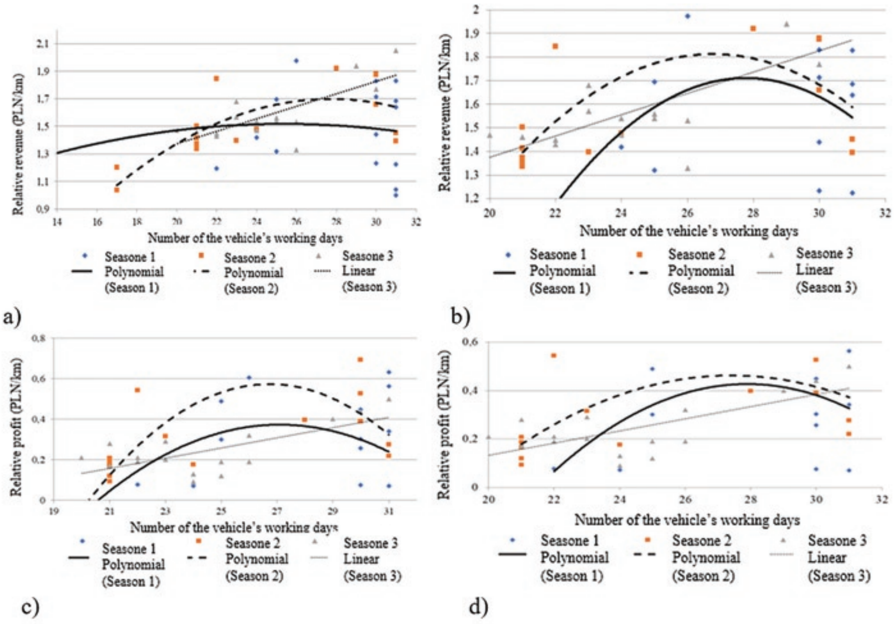

Fig. 13. Results of calculations the revenue and relative profit as a function of the number of days of the vehicle's work

• season 3: January, February, November, December.

The research showed that the highest values of efficiency measures are achieved during the operation of vans and fulfilling orders during season 3, and the lowest during season 1. This is confirmed by the fact of seasonality in providing transport services. Bad weather conditions determining the winter season is the time of increased use of vehicles due to the growing demand for services (season 3), with reduced supply of them. Good weather conditions are observed in the summer season, but then the demand for transport services decreases (season 1). The supply of services in the analyzed sector in this period is higher than the demand for services.

The verification of the proposed method was carried out based on the results of subsequent calculations made after inputting in the neural network a data not used in the teaching process. Examples of final results are presented in table 5.

Based on the global sensitivity analysis and the results obtained (table 5), it can be concluded that revenue increases with the increase in the number of days the vehicle works. Relative revenue and relative profit are calculated below in two ways: taking into account all variants of orders together with those generating a loss and taking into account only variants generating profit from order execution.

The studies have also shown that the season is also an important factor influencing the relationship between the number of working days and revenue or profit. The season determines the rate of increase in relative income and relative profit. This rate is high in the range of 10-22 days of vehicle work and becomes moderate in the range of 23-25 days of work per month. However, increasing the number of working days above 26-27 no longer results in an increase in benefits. The results presented in fig. 13c) confirm that in order to achieve relative profit vehicles should be used not less than 20 days a month, while the analysis of predictions without taking into account orders bringing losses (fig. 13d) confirms that it is over 21 days of work for season 2 and 22 days for season 1.

6. Summary

The results obtained and presented in the article allowed the statements that the adopted measures of economic efficiency have illustrated the impact of the number of vehicles' working days on the revenue and profit from transport services, and that the developed model is useful for predicting monthly revenue from transport services.

The results of the calculations provide the basis for the statement that increasing the number of days of the vehicle's work has a limited impact on the revenue growth process in the company. It is observed that positive income values are achieved with the number of working days over 19-20.

Both the number and type of data used in the neural network allowed to achieve high analysis results at the level of 80-90% efficiency.

The calculations results obtained results showed the specific features of the impact of the number of working days on the revenue in a transport company. The increase in the number of working days is conducive to increased revenue in a limited way, and this restriction depends on the season of the year.

The neural network model developed supports decision making in the implementation of transport processes, taking into account the economic efficiency of the motor vehicle operation process. Thus, the obtained results showed the usefulness of the adopted measures of economic efficiency and the model built to predict the economic results of the company's transport activities.

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Arkadiusz JÓŹWIAK
Paulina OWCZAREK
Faculty of the Security, Logistics and Management
Military University of Technology
ul. gen. Sylwestra Kaliskiego 2, 00-908 Warsaw 46, Poland

Leon PROCHOWSKI
Faculty of Mechanical Engineering
Military University of Technology
ul. gen. Sylwestra Kaliskiego 2, 00-908 Warsaw 46, Poland

Andrzej ŚWIDERSKI
Motor Transport Institute
ul. Jagiellońska 80, 03-301 Warsaw, Poland

E-mails: arkadiusz.jozwiak@wat.edu.pl, paulina.owczarek@wat.edu.pl, leon.prochowski@wat.edu.pl, andrzej.swiderski@its.waw.pl