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THE USE OF NEURAL NETWORKS TO FORECAST THE NUMBER OF ROAD ACCIDENTS IN POLAND

Summary. Every year, a large number of traffic accidents occur on Polish roads. However, the pandemic of recent years has reduced the number of these accidents, although the number is still very high. For this reason, all measures should be taken to reduce this number. This article aims to forecast the number of road accidents in Poland. Thus, using Statistica software, the annual data on the number of road accidents in Poland were analyzed. Based on actual past data, a forecast was made for the future, for the period 2022-2040. Forecasting the number of accidents in Poland was conducted using selected neural network models. The results show that a reduction in the number of traffic accidents is likely. The choice of the number of random samples (learning, testing and validation) affects the results obtained.
Keywords: road accident, pandemic, forecasting, neural networks

1. INTRODUCTION

A large number of people die in traffic accidents every year. According to the WHO, about 1.3 million people die each year as a result of traffic accidents. Road accidents are the leading cause of death for minors and young people between the ages of 5 and 29 [1]. The UN General Assembly has set a goal of halving road deaths and injuries by 2030.

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Data on road accidents can be obtained from various sources. These include data collected by government bodies through relevant government agencies. Data collection is done through police reports, insurance databases or hospital records. Partial information on traffic accidents is then processed for the transportation sector on a larger scale.

In the literature, one can find various methods used to forecast the number of accidents. Among the most popular of these are the time series methods [2, 3], which have the disadvantages of not being able to assess the quality of the forecast based on outdated forecasts and frequent autocorrelation of the residual component [4]. In contrast, Procházka et al. [5, 6] used the multiple seasonality model for forecasting, and Sunny et al. [7,8] used the Holt-Winters exponential smoothing method. The disadvantage of these methods is that exogenous variables cannot be introduced into the models [9-11].

We can also use the vector autoregressive models for forecasting, the disadvantage of which is the need to have a large number of observations of variables to correctly estimate their parameters [12], which is not always achievable, as well as autoregressive models [13] and regression models with curve fitting [14]. These, in turn, require only simple linear [15, 16].

Chudy-Laskowska and Pisula, in their work [17, 18], used the ANOVA method to forecast the issue at hand. The disadvantage of this method is that it makes additional assumptions, the violation of which can lead to erroneous conclusions [19]. Neural network models are also used to forecast the number of traffic accidents. The disadvantage of this method is not having working knowledge in this area [17, 18, 20]. In addition, the prediction result depends on the adoption of the initial conditions of the network, as well as the inability to interpret traditionally, since SNF is usually referred to as a black box in which input data is given, and the model gives the results without knowledge of the analysis [21]. The latter is addressed in this article.

2. MATERIALS AND METHODS

Every year, a large number of traffic accidents occur on Polish roads. However, the pandemic of recent years has reduced the number of road accidents, although the number is still very high (Figure 1). Thus, efforts should be made to reduce this number. Comparing the data on the number of accidents in Poland with that of the European Union shows that the value is still very high.

Selected neural network models, which mimic the behavior of the human brain, were used to predict the number of road accidents. In this way, they enable computer programs to recognize patterns and solve typical problems in the fields of artificial intelligence, among others. The network in question consists of nodes that have inputs, weights, deviations and outputs. In this study, the optimal weights were selected using Statistica. The result of the prediction using this method depends on the choice of the model and its parameters.

The following errors of expired forecasts determined from equations (1-5) were used to calculate measures of analytical forecast excellence:

- ME - average error:

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right) \tag{1}$$

- MAE - mean error

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}\left|\mathrm{Y_i}\text{-}\mathrm{Y_p}\right| \tag{2}$$

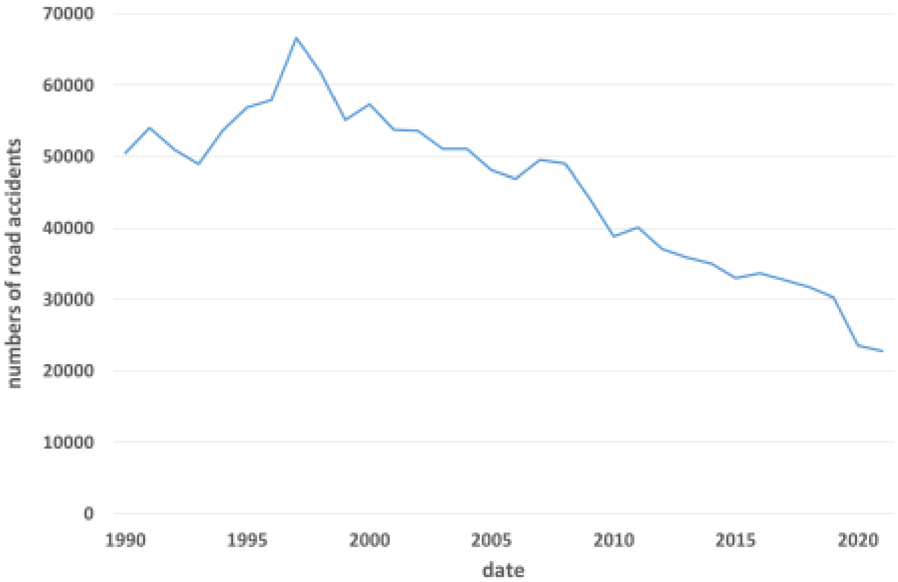

Fig. 1. Number of road accidents in Poland from 2009 to 2021 [23]

- MPE - mean percentage error

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i - Y_p}{Y_i} \tag{3}$$

- MAPE - mean absolute percentage error

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - Y_p|}{Y_i} \tag{4}$$

- SSE - mean square error

$$SSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2} \tag{5}$$

where:
n – length of forecast horizon,
Y – observed value of traffic accidents,
Y_p – projected value of traffic accidents.

A neural network model for which the average percentage error was the smallest was used to predict the number of traffic accidents. The error values (especially the average absolute percentage error), 6-9%, indicate a fairly good fit of the models to historical data. It is therefore to be trusted that forecasts for future months of future years will also be successful. In the case under analysis, ideally, the ME error should be close to zero. The same is true for the errors of the other analyzed errors, MAE, RMSE, and MAPE, which should be positive and close to zero. In addition, MPE informs what percentage of the actual realizations of the forecast variable is forecast errors in the period m of prediction. MAE informs how much, on average - during the prediction period - the actual realizations of the forecast variable will deviate - in absolute value - from the forecasts. MAPE reports the average size of forecast errors for the period = 1, 2, ..., m, expressed as a percentage of the actual values of the forecast variable. MAPE values allow comparison of the accuracy of forecasts obtained by different models [22].

3. RESULTS

The value of the statistic for the analyzed non-parametric Kruskall-Wallis test is 31, with a test probability of p=0.4662. Based on the test performed, we can reject the hypothesis of equality of the average level of traffic accidents during the analyzed period. This leads to a systematic decrease in the average level of accidents from year to year. This is particularly evident in recent years during the pandemic period for the analyzed period (Figure 2).

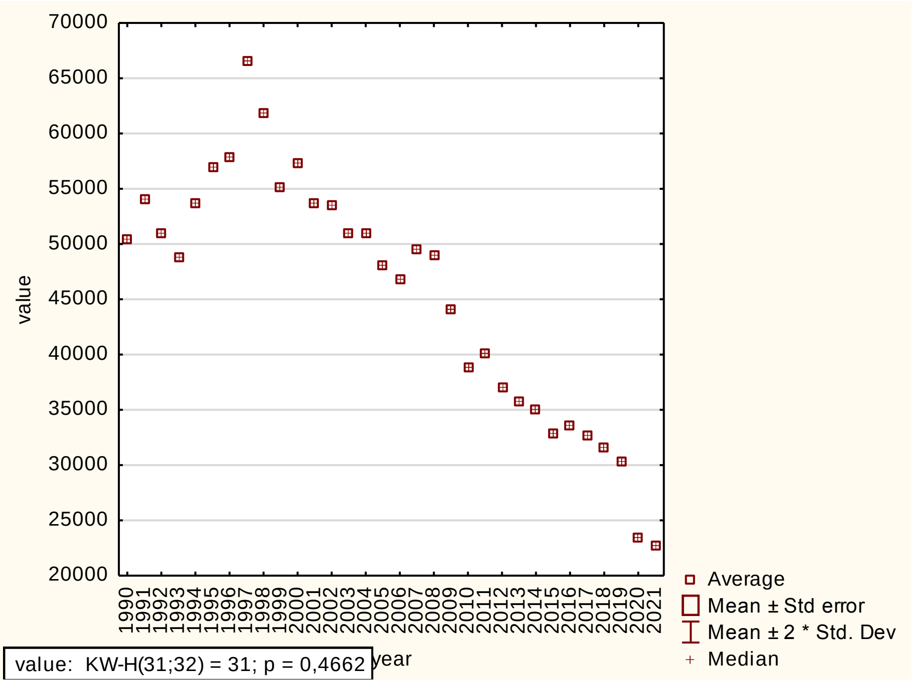

Fig. 2. Average number of traffic accidents by month from 2000 to 2021 [23]

3.1 Road accident forecasting

Polish Police data from 1990-2021 [23] was used to forecast the monthly number of accidents. The study was conducted using Statistica software, assuming two random sample sizes:

- teaching 70%, testing 15% and validation 15%
- teaching 80%, testing 10% and validation 10%

with the following number of teaching networks: 20, 40, 60, 80, 100, 200, where the minimum MPE error is marked in yellow (Tables 1 and 2).

Tab. 1

Summary of neural network learning for the case of random sample sizes: teaching 70%, testing 15% and validation 15%

Number of learning	Network name	Quality (learning)	Quality (learning)	Quality (validation)	Learning algorithm	Activation (hidden)	Activation (output)	Errors				
								ME	MAE	MPE %	MAPE %	SSE
20	MLP 10-3-1	8,52E-01	6,79E-01	9,80E-01	BFGS 13	Logistics	Linear	2,21E+02	1,98E+03	0,21	5,40	2,47E+03
20	MLP 10-6-1	8,50E-01	6,79E-01	9,75E-01	BFGS 5	Tanh	Linear	1,46E+02	2,13E+03	0,39	5,63	2,62E+03
20	MLP 10-7-1	8,52E-01	6,79E-01	9,81E-01	BFGS 8	Tanh	Tanh	1,24E+04	1,29E+04	39,31	40,08	1,59E+04
20	MLP 10-6-1	8,51E-01	6,79E-01	9,72E-01	BFGS 7	Exponential	Exponential	1,29E+04	1,32E+04	40,46	41,04	1,62E+04
20	MLP 10-2-1	8,48E-01	6,79E-01	9,72E-01	BFGS 3	Exponential	Exponential	6,90E+02	2,10E+03	0,73	5,77	2,79E+03
40	MLP 10-3-1	8,48E-01	6,79E-01	9,90E-01	BFGS 9	Logistics	Logistics	6,65E+02	2,17E+03	0,63	5,82	2,75E+03
40	MLP 10-8-1	8,45E-01	6,79E-01	9,87E-01	BFGS 11	Logistics	Tanh	4,16E+02	2,32E+03	0,11	6,09	2,77E+03
40	MLP 10-4-1	8,42E-01	6,79E-01	9,87E-01	BFGS 8	Tanh	Tanh	6,18E+02	2,47E+03	0,64	6,35	2,89E+03
40	MLP 10-2-1	8,37E-01	6,79E-01	9,89E-01	BFGS 8	Exponential	Logistics	1,00E+03	2,65E+03	1,52	6,70	3,16E+03
40	MLP 10-4-1	8,46E-01	6,79E-01	9,85E-01	BFGS 6	Linear	Tanh	2,53E+02	2,18E+03	0,13	5,81	2,59E+03
60	MLP 10-5-1	8,46E-01	6,79E-01	9,87E-01	BFGS 5	Tanh	Tanh	2,33E+01	2,22E+03	0,38	5,90	2,60E+03
60	MLP 10-2-1	8,36E-01	6,79E-01	9,88E-01	BFGS 7	Tanh	Tanh	1,26E+03	2,71E+03	2,27	6,67	3,26E+03
60	MLP 10-4-1	8,44E-01	6,79E-01	9,90E-01	BFGS 11	Exponential	Logistics	6,67E+02	2,28E+03	0,89	6,05	2,77E+03
60	MLP 10-2-1	8,33E-01	6,79E-01	9,90E-01	BFGS 8	Exponential	Logistics	9,31E+02	2,67E+03	1,42	6,79	3,17E+03
60	MLP 10-8-1	8,46E-01	6,79E-01	9,88E-01	BFGS 5	Linear	Tanh	9,41E+01	2,21E+03	0,12	5,82	2,57E+03
80	MLP 10-6-1	8,41E-01	6,79E-01	9,89E-01	BFGS 8	Exponential	Logistics	6,57E+02	2,36E+03	0,89	6,22	2,84E+03
80	MLP 10-4-1	8,45E-01	6,79E-01	9,89E-01	BFGS 5	Linear	Tanh	1,75E+02	2,25E+03	0,54	5,90	2,67E+03
80	MLP 10-4-1	8,47E-01	6,79E-01	9,89E-01	BFGS 9	Logistics	Logistics	6,40E+02	2,14E+03	0,72	5,79	2,68E+03
80	MLP 10-3-1	8,44E-01	6,79E-01	9,88E-01	BFGS 10	Exponential	Logistics	6,14E+02	2,33E+03	0,59	6,14	2,84E+03
80	MLP 10-3-1	8,30E-01	6,79E-01	9,88E-01	BFGS 9	Exponential	Logistics	1,29E+03	2,78E+03	2,36	6,94	3,37E+03
100	MLP 10-6-1	8,36E-01	6,79E-01	9,91E-01	BFGS 6	Logistics	Logistics	1,19E+03	2,61E+03	1,98	6,62	3,23E+03
100	MLP 10-3-1	8,41E-01	6,79E-01	9,93E-01	BFGS 9	Logistics	Logistics	8,70E+02	2,44E+03	1,08	6,33	3,02E+03
100	MLP 10-5-1	8,45E-01	6,79E-01	9,90E-01	BFGS 12	Exponential	Logistics	6,08E+02	2,28E+03	0,64	6,01	2,76E+03

100	MLP 10-2-1	8,40E-01	6,79E-01	9,88E-01	BFGS 11	Logistics	Tanh	5,33E+02	2,37E+03	0,75	6,02	2,81E+03
100	MLP 10-6-1	8,49E-01	6,79E-01	9,91E-01	BFGS 5	Exponential	Logistics	5,14E+02	2,10E+03	0,60	5,71	2,53E+03
200	MLP 10-4-1	8,43E-01	6,79E-01	9,92E-01	BFGS 5	Tanh	Logistics	3,26E+02	2,22E+03	0,36	5,93	2,63E+03
200	MLP 10-7-1	8,37E-01	6,79E-01	9,92E-01	BFGS 8	Logistics	Logistics	1,29E+03	2,62E+03	2,27	6,67	3,23E+03
200	MLP 10-7-1	8,40E-01	6,79E-01	9,89E-01	BFGS 7	Logistics	Tanh	1,22E+03	2,38E+03	2,62	5,97	2,99E+03
200	MLP 10-2-1	8,45E-01	6,79E-01	9,91E-01	BFGS 11	Logistics	Logistics	8,32E+02	2,27E+03	1,29	6,04	2,77E+03
200	MLP 10-8-1	8,43E-01	6,79E-01	9,91E-01	BFGS 9	Logistics	Logistics	8,55E+02	2,34E+03	1,16	6,12	2,91E+03

Tab. 2

Summary of neural network learning for the case of random sample sizes: teaching 80%, testing 10% and validation 10%

Number of learning	Network name	Quality (learning)	Quality (learning)	Quality (validation)	Learning algorithm	Activation (hidden)	Activation (output)	Errors				
								ME	MAE	MPE %	MAPE %	SSE
20	MLP 10-8-1	8,27E-01	8,75E-01	9,72E-01	BFGS 8	Logistics	Logistics	9,39E+02	2,65E+03	1,99	6,87	3,13E+03
20	MLP 10-6-1	8,34E-01	8,75E-01	9,66E-01	BFGS 6	Logistics	Logistics	6,50E+02	2,47E+03	1,24	6,67	2,88E+03
20	MLP 10-6-1	8,29E-01	8,75E-01	9,73E-01	BFGS 5	Logistics	Logistics	1,49E+03	2,71E+03	3,05	6,93	3,30E+03
20	MLP 10-3-1	7,49E-01	8,75E-01	9,93E-01	BFGS 4	Logistics	Tanh	1,37E+03	4,21E+03	1,84	9,93	5,04E+03
20	MLP 10-8-1	8,33E-01	8,75E-01	9,71E-01	BFGS 8	Logistics	Logistics	3,74E+02	2,36E+03	0,46	6,22	2,79E+03
40	MLP 10-5-1	8,09E-01	8,75E-01	9,87E-01	BFGS 5	Logistics	Logistics	8,25E+02	3,04E+03	1,56	7,70	3,58E+03
40	MLP 10-5-1	7,94E-01	8,75E-01	9,86E-01	BFGS 7	Exponential	Logistics	1,01E+03	3,38E+03	1,75	8,31	3,96E+03
40	MLP 10-3-1	7,81E-01	8,75E-01	9,85E-01	BFGS 6	Logistics	Linear	9,84E+02	3,63E+03	1,70	8,95	4,25E+03
40	MLP 10-3-1	8,02E-01	8,75E-01	9,80E-01	BFGS 6	Logistics	Linear	5,43E+02	3,16E+03	1,02	8,00	3,66E+03
40	MLP 10-2-1	7,81E-01	8,75E-01	9,99E-01	BFGS 5	Tanh	Logistics	2,04E+03	3,95E+03	4,47	9,72	4,71E+03
60	MLP 10-3-1	7,92E-01	8,75E-01	9,83E-01	BFGS 6	Exponential	Logistics	1,05E+03	3,47E+03	1,80	8,54	4,05E+03
60	MLP 10-8-1	8,05E-01	8,75E-01	9,81E-01	BFGS 5	Logistics	Tanh	7,69E+02	3,26E+03	2,02	8,53	3,73E+03
60	MLP 10-7-1	8,27E-01	8,75E-01	9,68E-01	BFGS 6	Logistics	Linear	5,66E+02	2,64E+03	0,49	6,59	3,10E+03
60	MLP 10-5-1	7,94E-01	8,75E-01	9,93E-01	BFGS 5	Logistics	Logistics	1,29E+03	3,47E+03	2,46	8,60	4,10E+03
60	MLP 10-3-1	8,12E-01	8,75E-01	9,55E-01	BFGS 5	Logistics	Tanh	2,81E+03	3,69E+03	6,65	9,01	4,40E+03

80	MLP 10-3-1	7,94E-01	8,75E-01	9,80E-01	BFGS 6	Logistics	Tanh	1,28E+03	3,46E+03	2,66	8,57	4,04E+03
80	MLP 10-8-1	8,16E-01	8,75E-01	9,83E-01	BFGS 6	Logistics	Logistics	1,10E+03	2,94E+03	2,28	7,48	3,50E+03
80	MLP 10-2-1	7,87E-01	8,75E-01	9,82E-01	BFGS 6	Logistics	Tanh	1,19E+03	3,63E+03	2,77	9,33	4,18E+03
80	MLP 10-2-1	8,17E-01	8,75E-01	9,85E-01	BFGS 7	Logistics	Logistics	2,13E+03	3,15E+03	5,10	7,93	3,92E+03
80	MLP 10-2-1	8,01E-01	8,75E-01	9,89E-01	BFGS 5	Tanh	Logistics	1,13E+03	3,28E+03	2,22	8,24	3,88E+03
100	MLP 10-7-1	7,86E-01	8,75E-01	9,89E-01	BFGS 4	Tanh	Logistics	2,08E+03	3,99E+03	3,92	9,53	4,68E+03
100	MLP 10-2-1	7,92E-01	8,75E-01	9,88E-01	BFGS 6	Exponential	Logistics	1,85E+03	3,57E+03	4,04	8,67	4,33E+03
100	MLP 10-3-1	7,79E-01	8,75E-01	9,85E-01	BFGS 5	Logistics	Tanh	6,69E+02	3,60E+03	0,69	8,84	4,23E+03
100	MLP 10-2-1	7,93E-01	8,75E-01	9,82E-01	BFGS 6	Logistics	Linear	9,69E+02	3,44E+03	2,13	8,74	3,99E+03
100	MLP 10-5-1	7,96E-01	8,75E-01	9,86E-01	BFGS 5	Exponential	Logistics	2,16E+03	3,25E+03	4,69	7,71	4,01E+03
200	MLP 10-4-1	8,11E-01	8,75E-01	9,85E-01	BFGS 7	Exponential	Logistics	8,47E+02	2,97E+03	1,78	7,50	3,53E+03
200	MLP 10-3-1	7,87E-01	8,75E-01	9,83E-01	BFGS 6	Logistics	Linear	8,81E+02	3,44E+03	1,43	8,48	4,07E+03
200	MLP 10-4-1	8,04E-01	8,75E-01	9,80E-01	BFGS 5	Exponential	Logistics	1,14E+03	3,20E+03	2,24	7,95	3,79E+03
200	MLP 10-2-1	7,78E-01	8,75E-01	9,99E-01	BFGS 5	Logistics	Logistics	1,36E+03	3,81E+03	2,50	9,35	4,46E+03
200	MLP 10-3-1	7,79E-01	8,75E-01	9,94E-01	BFGS 6	Logistics	Tanh	2,54E+03	4,12E+03	5,41	9,73	4,92E+03

Based on the results presented, it can be concluded that the number of traffic accidents in Poland will decrease from year to year. The results are influenced by the selection of the random sample size. Increasing the percentage of the learning group relative to the test and validation group minimizes the average percentage error. For a learning group of 70%, a test group of 15% and a validation group of 15% in proportions (70-15-15), the error was 0,36%, while for the second sample (80-10-10), the error was 0,46%. In addition, the number of learning networks affected the results obtained. A higher number of learning networks results in a decrease in the analyzed error. In both analyzed cases, the quality of teaching, testing and validation is above 83%. For the case of 70-15-15, it is 85%, while for 80-10-10, it is 83%.

In the next step, the projected number of traffic accidents for the following years was determined (Figure 3). The following models, for which the minimum error was the smallest, were adopted for the study:

- 70-15-15 (MPE = 0,36%) - number of networks: 20, network name: MLP 10-3-1
- 80-10-10 (MPE = 0,46%) - number of networks: 20, network name: MLP 10-8-1.

Based on the received data on the projected number of traffic accidents, it can be concluded that in the coming years, a reduction in the number of traffic accidents is likely, especially seen in the assumed 70-15-15 group. However, the presented results may be influenced by the pandemic.

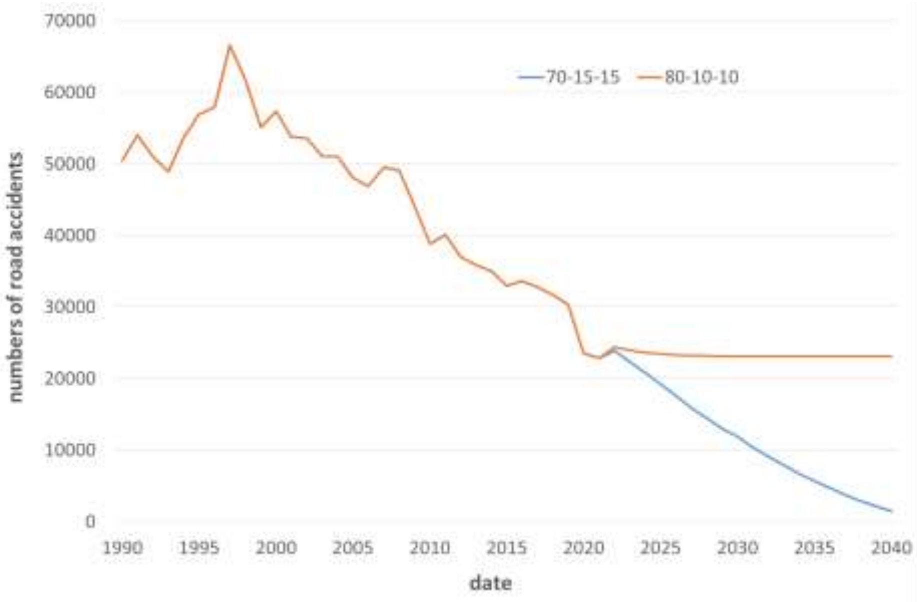

Fig. 3. Projected number of road accidents for 2022-2040

4. CONCLUSION

Neural networks were used to forecast the number of accidents in Poland, and a study was conducted in the Statistica environment. The weights used in the study were estimated by the program in such a way as to minimize the average absolute error and the average absolute percentage error.

Based on the data obtained, it can be concluded that the pandemic has resulted in a reduction in traffic accidents, and a further decrease in traffic accidents can be expected in the coming years. However, a further pandemic may change the value of the obtained results. The calculated forecast errors prove the accuracy of the models used.

The forecasts of the number of traffic accidents obtained in this article can be used in future formulations for further measures to minimize the number of accidents. These measures may include, for example, the introduction of higher fines for traffic offenses on Polish roads from January 1, 2022. The pandemic, which drastically altered the number of traffic accidents, certainly had an impact on disturbing the obtained results of the study.

In further studies, the authors plan to consider more factors affecting accident rates and use various statistical methods to determine the number of traffic accidents. These may include traffic volume, weather conditions or the age of the accident perpetrator, as well as exponential methods for determining the number of traffic accidents.

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