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Time Horizon for Forecasting the Number of Traffic Accidents

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Abstract: On Polish roads, there are more and more automobiles each year. This results in more people using the roadways. Because of this, the threat posed by traffic accidents, which involve the loss of human life and financial resources, is quickly expanding. The rise of motorization and the quickening expansion of the human population are to blame for this. The tiny amount of the dataset that may be utilized for research in this respect is the major problem in anticipating and evaluating data on road accidents. Despite the fact that road accidents result in millions of lives and injuries worldwide each year, they are not very common. Traffic accidents are still quite common despite the pandemic's reduction. The aim of the essay is to evaluate the temporal horizon of the predicted number of traffic accidents. For this reason, an estimate of the expected number of traffic accidents in the future years was made, and its effect on the average percentage error of the projection was computed. Based on the analysis of the input data on the number of road accidents (annual and monthly), the results show that monthly and annual data can be forecast up to six years in advance.

Keywords: forecasting, traffic accident, time horizon

1. Introduction

Any nation must address the serious societal issue of road accidents. Traffic accidents can be caused by a variety of variables, including the weather, the sobriety of the drivers, the speed of the automobiles, etc. Over 1.19 million people die in car crashes each year, and millions more have serious injuries and long-term health effects, according to the World Health Organization [1]. Financial damages are another outcome of traffic accidents.

In contrast to common perception, there are a lot more accidents on the roads than you may think – an average of 62 crashes per day, 6 fatalities, and 72 injuries – as seen in Figure 1 [2]. The aforementioned incidents lead to higher medical expenses, the need to fix vehicles, and the infrastructure supporting them, as well as detrimental impacts on the environment (leaks in gasoline and operating fluid, for instance). Consequently, a lot of work is being done to reduce or avoid traffic accidents. Predicting the number of traffic accidents using well-established forecasting algorithms is one such measure. In this case, it is also important to take into account the fact that Polish roads are more congested with automobiles (Figure 2 [3]). The topic of road safety has been covered in the next articles [4–7].

There are several approaches of forecasting the frequency of accidents in the literature. Time series approaches are the most widely utilized techniques for predicting the number of traffic incidents [8]. However, these approaches have some drawbacks, including the frequent autocorrelation of the residual component and the incapacity to evaluate the prediction quality based on previous forecasts [9]. For forecasting, Sunny et al.'s Holt-Winters exponential smoothing technique [10] and Procházka et al.'s multiple seasonality model [11] were employed. Basic linear connections were considered [12].

Prochozka and Camej [13] used the GARMA technique, which imposes constraints on the parameter space, to guarantee that the process is stationary. When it comes to forecasting, stable processes are typically modeled using the ARMA model, while non-stationary processes are typically modeled using ARIMA or SARIMA [11, 13, 14]. Although the models under consideration exhibit great flexibility, this flexibility also has a disadvantage in that it requires a higher level of knowledge from researchers to develop models that work, as opposed to, for instance, regression analysis [15].

The results of the literature research show that while many scholars have studied the problem of predicting the frequency of traffic accidents, very few have examined the challenge of predicting such occurrences over the largest time horizon. As a result, this will be the main focus of the investigation that follows, as will be discussed in the paragraphs that follow. In this instance, it is important to keep in mind that the accident frequency data is seasonal, and not all forecasting techniques are appropriate for this kind of forecasting.

The problem of forecasting was also covered in the following publications [16–23].

In this case, the research question can be posed: What forecast horizon can be used when forecasting the number of road accidents in Poland?

2. Materials and Methods

The aim of the article is to determine the optimal time horizon for predicting the number of traffic accidents using different forecasting approaches, assuming annual and monthly accident

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Figure 1
The number of accidents on Polish roads from 1990 to 2021 [2]

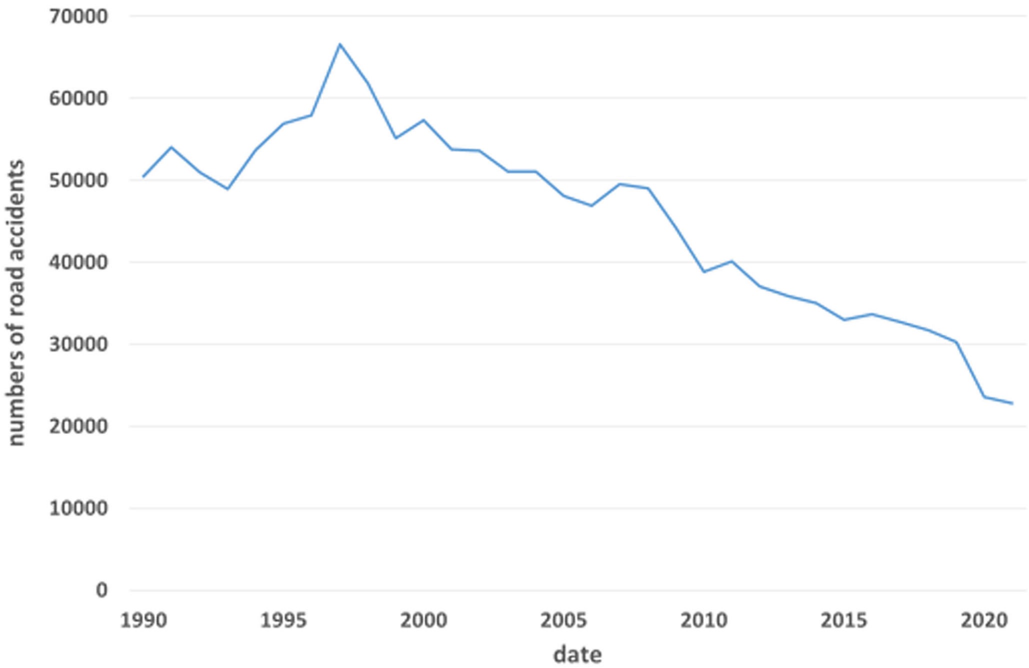
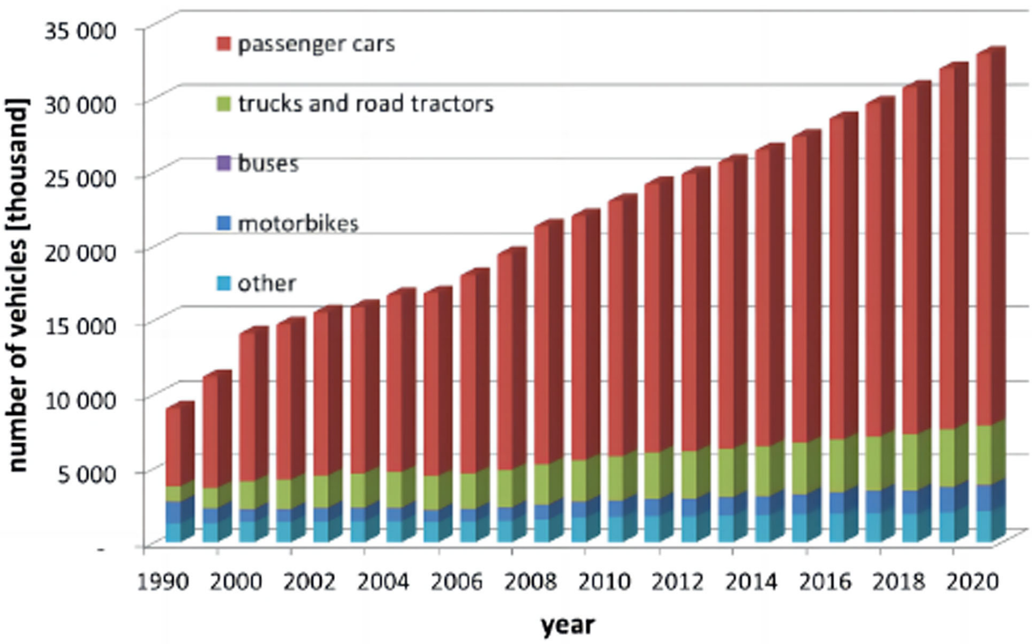


Figure 2
The number of automobiles registered in Poland from 1999 to 2020 [3]



data from police statistics for the following factors affecting the number of traffic accidents. The workday, the climate, and the province were among them. The total number of accidents in Poland was also taken into consideration, without taking into account other factors that could have an impact on this figure. Considering the previous method evaluation, the author selected the following forecasting methodologies in his study to determine the forecast horizon for the number of traffic accidents:

- Neural network techniques, presuming the following:
  - random sample size of 10% for testing, 10% for validation, and 80% for teaching;

Table 1
Optimal forecasting methods for annual data

Group of methods	Factors influencing the frequency of accidents on the road		The optimal method
Adaptive methods	None	Poland	exponential smoothing exponential seasonal component: additive
Regression methods	Weather conditions	good conditions	linear trend model
		fog, smoke	exponential trend model
		rainfall	exponential trend model
		snowfall, hail	exponential trend model
		dazzling sun	power trend model
		cloudy	exponential trend model
		strong wind	exponential trend model
Neural networks – random sample size teaching 70%, testing 15% and validation 15%	Days of the week	Monday	MLP 10-5-1
		Tuesday	MLP 10-2-1
		Wednesday	MLP 10-3-1
		Thursday	MLP 10-5-1
		Friday	MLP 10-3-1
		Saturday	MLP 10-3-1
		Sunday	MLP 10-7-1

Table 2
Optimal forecasting methods for monthly data

Group of methods	Factors influencing the frequency of accidents on the road		The optimal method
Adaptive methods	None	Poland	exponential smoothing of linear trend seasonal component: additive
Regression methods	Weather conditions	good conditions	exponential trend model
		fog, smoke	exponential trend model
		rainfall	exponential trend model
		snowfall, hail	exponential trend model
		dazzling sun	linear trend model
		cloudy	linear trend model
		strong wind	exponential trend model
Neural networks – random sample size teaching 70%, testing 15% and validation 15%	Province	lower Silesia	MLP 12-7-1
		kujawsko-pomorskie	MLP 12-2-1
		lubelskie	MLP 12-8-1
		lubuskie	MLP 12-5-1
		łódzkie	MLP 12-4-1
		małopolskie	MLP 12-5-1
		Mazowieckie	MLP 12-7-1
		Opole	MLP 12-5-1
		podkarpackie	MLP 12-6-1
		Podlaskie	MLP 12-5-1
		Pomeranian	MLP 12-7-1
		śląskie	MLP 12-5-1
		świętokrzyskie	MLP 12-8-1
		warmińsko-mazurskie	MLP 12-2-1
		wielkopolskie	MLP 12-4-1
		zachodniopomorskie	MLP 12-4-1

  - random sample size of 15% for testing, 15% for validation, and 70% for teaching;
- Adaptive methods:
  - no trend seasonal component in exponential smoothing;
  - additive exponential smoothing with no trend seasonal component;
  - multiplicative exponential smoothing with no trend seasonal component;
  - the two-point, three-point, and four-point moving average methods;
  - there is no exponential smoothing of the linear trend's seasonal component – HOLTA;
  - additive exponential smoothing of the seasonal component of the linear trend;
  - multiplicative exponential smoothing of the seasonal component of the linear trend – Winters;

Table 3
MAPE error value for annual data

Group of methods	Factors affecting lwd	Forecast time [years] 1	2	3	4	5	6
Adaptive methods	Poland	**3,93%**	**3,76%**	**3,57%**	**3,47%**	**4,57%**	**4,67%**
Neural networks	Monday	1,44%	1,45%	1,55%	1,60%	3,75%	5,02%
	Tuesday	1,67%	1,59%	1,43%	1,79%	3,43%	3,76%
	Wednesday	3,71%	3,90%	4,19%	4,11%	5,58%	6,71%
	Thursday	0,26%	0,24%	0,74%	0,67%	2,76%	3,23%
	Friday	3,02%	2,83%	2,87%	2,77%	3,70%	3,37%
	Saturday	2,68%	2,40%	2,55%	2,88%	5,06%	7,26%
	Sunday	3,89%	3,87%	3,89%	3,87%	5,91%	7,33%
	Average	**2,38%**	**2,33%**	**2,46%**	**2,53%**	**4,31%**	**5,24%**
Linear regression	good conditions	3,59%	3,50%	3,96%	4,47%	4,63%	4,59%
	fog, smoke	15,48%	15,70%	15,16%	15,05%	14,96%	14,31%
	rainfall	10,51%	11,23%	11,27%	10,86%	10,61%	11,34%
	snowfall	36,64%	35,41%	34,42%	33,18%	42,81%	43,11%
	sun glare	7,27%	6,89%	7,37%	7,16%	8,57%	9,90%
	cloudy	12,98%	13,28%	12,76%	12,54%	13,48%	14,61%
	strong wind	19,64%	19,62%	18,92%	18,60%	19,65%	19,45%
	Average	**15,16%**	**15,09%**	**14,84%**	**14,55%**	**16,39%**	**16,76%**

- No seasonal component of the trend fading by exponential smoothing;
- Seasonal trend decay component: exponential smoothing of seasonal trend component: multiplicative;
- Seasonal trend fading trend seasonal component: additive;
- no exponential smoothing of the seasonal component that is exponential:
- additive exponential smoothing of the exponential seasonal component;
- multiplicative exponential smoothing of the exponential seasonal component.

• Regression methods:

- There are several different types of trend models: exponential, linear, logarithmic, trend model polynomial of second degree, third degree, fourth degree, fifth degree, sixth degree, and trend model of power.

It is evident that there are numerous forecasting methods and a wide range of results when it comes to accident frequency projections. Because of this, the author used the following forecasting approaches (Tables 1 and 2) for additional analysis. For the factors impacting the number of traffic accidents, the forecast of the number of accidents with the shortest average absolute percentage error of MAPE (1) was used. The study looked at data from the Police Department's Road Accident Statistics, 2022, which included the years 2001 through 2021 for yearly data and the years 2007 through 2021 for monthly data, about the number of traffic accidents. Up to 2015, estimates of the number of accidents were produced using the methods that were evaluated. The number of traffic accidents over the ideal forecast horizon was calculated using police data from 2016 to 2021. The study's time horizon periods were determined to be as follows:

• for annual data:1, 2, 3, 4, 5, 6 years.
• for monthly data:

- 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12 monthly,
- 6, 12, 18, 24, 30, 36, 42, 48, 54, 60, 66, 72 monthly.

$$\mathrm{MAPE} = \frac{1}{\mathrm{K}}\sum_{i=1}^{\mathrm{K}} \frac{|\mathrm{lwd}(t_i) - \mathrm{lwd}(t_p)|}{\mathrm{lwd}(t_i)} \tag{1}$$

where

k – number of observances,
$l_{wd}(t_i)$ – number of traffic accidents over time t_i,
$l_{wd}(t_p)$ – expired forecasts.

3. Results

The study was used to determine the time horizon for the chosen forecasting approaches, variables influencing the number of traffic accidents, and the adopted periods, while also taking into account monthly and annual data on the number of traffic accidents (lwd) (Tables 3–5). The author's prior research [6, 7] has shown that the extremely high MAPE error value is the reason why forecast results for monthly data using linear regression networks were excluded from additional study. As is evident, trend models are not very good at predicting the number of traffic accidents that occur each month with seasonality.

For monthly data, MAPE's assumed forecasting error increased as the forecasting time increased. It was the largest with the linear regression method and amounted to more than 15%. The situation was also similar for monthly data. There, in the case of regression, the error was very high.

For the data shown in Tables 3–5, the average MAPE error was determined for each forecasting method and the factors affecting this value, except for linear regression for monthly data (Figures 3–5).

Table 4
MAPE error value for monthly data part 1

Group of methods	Factors affecting lwd	Forecast time [month] 1	2	3	4	5	6	7	8	9	10	11	12
Adaptive methods	Poland	**6,25%**	**6,34%**	**6,37%**	**6,34%**	**6,31%**	**6,29%**	**6,24%**	**6,20%**	**6,18%**	**6,17%**	**6,13%**	**6,16%**
Neural networks	Lower Silesia	7,16%	7,12%	7,06%	7,02%	6,97%	6,98%	6,92%	6,86%	6,85%	6,90%	6,88%	6,95%
	kujawsko-pomorskie	6,50%	6,49%	6,49%	6,48%	6,55%	6,57%	6,51%	6,48%	6,42%	6,53%	6,56%	6,64%
	lubelskie	5,89%	5,89%	5,93%	5,93%	5,96%	5,97%	5,95%	5,92%	5,93%	5,98%	5,99%	6,06%
	lubuskie	7,17%	7,14%	7,10%	7,08%	7,07%	7,18%	7,15%	7,09%	7,03%	7,16%	7,15%	7,23%
	łódzkie	6,11%	6,09%	6,10%	6,11%	6,12%	6,21%	6,18%	6,17%	6,16%	6,16%	6,11%	6,19%
	małopolskie	5,88%	5,85%	5,80%	5,83%	5,89%	5,85%	5,85%	5,90%	5,84%	5,88%	5,85%	5,86%
	Mazowieckie	8,01%	7,93%	7,88%	7,81%	7,84%	7,86%	7,86%	7,85%	7,85%	7,92%	7,86%	7,90%
	Opole	7,57%	7,61%	7,63%	7,62%	7,64%	7,71%	7,65%	7,69%	7,64%	7,68%	7,66%	7,77%
	podkarpackie	6,66%	6,71%	6,74%	6,79%	6,82%	6,87%	6,81%	6,80%	6,79%	6,80%	6,77%	6,87%
	Podlaskie	8,55%	8,71%	8,78%	8,73%	8,70%	8,62%	8,57%	8,53%	8,49%	8,48%	8,42%	8,42%
	Pomeranian	7,29%	7,26%	7,21%	7,25%	7,35%	7,38%	7,47%	7,49%	7,48%	7,46%	7,51%	7,58%
	śląskie	5,82%	5,82%	5,80%	5,77%	5,74%	5,74%	5,68%	5,71%	5,72%	5,76%	5,76%	5,81%
	świętokrzyskie	5,75%	5,69%	5,74%	5,70%	5,73%	5,77%	5,79%	5,86%	5,88%	5,89%	5,93%	5,91%
	warmińsko-mazurskie	6,56%	6,54%	6,52%	6,53%	6,60%	6,62%	6,56%	6,57%	6,56%	6,58%	6,60%	6,67%
	wielkopolskie	5,97%	6,03%	6,01%	6,06%	6,05%	6,11%	6,09%	6,17%	6,17%	6,27%	6,26%	6,31%
	zachodniopomorskie	7,16%	7,15%	7,17%	7,14%	7,19%	7,28%	7,35%	7,38%	7,34%	7,37%	7,40%	7,47%
	Average	**6,75%**	**6,75%**	**6,75%**	**6,74%**	**6,76%**	**6,80%**	**6,77%**	**6,78%**	**6,76%**	**6,80%**	**6,79%**	**6,85%**
Linear regression	good conditions	81,54%	81,48%	81,48%	81,51%	81,57%	81,63%	81,67%	81,72%	81,78%	81,75%	81,74%	81,74%
	fog smoke	444,35%	440,42%	441,56%	440,73%	445,21%	441,48%	439,81%	473,07%	481,60%	477,54%	473,85%	470,16%
	rainfall	78,77%	78,87%	78,93%	78,98%	78,99%	79,02%	79,09%	79,14%	79,09%	79,23%	79,32%	79,41%
	snowfall	96,99%	97,01%	97,03%	97,05%	97,07%	97,09%	97,12%	97,14%	97,16%	97,17%	97,19%	97,21%
	sunshine	24090,07%	23871,55%	23657,53%	23491,86%	23547,82%	23573,65%	23627,92%	23767,22%	23904,13%	23770,64%	23570,93%	23374,54%
	cloudy	25449,43%	25345,52%	25237,28%	25310,86%	25391,38%	25674,63%	25990,63%	26116,84%	25980,87%	25817,69%	25617,50%	25424,84%
	strong wind	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%
	Average	**7191,59%**	**7144,98%**	**7099,11%**	**7085,86%**	**7106,01%**	**7149,64%**	**7202,32%**	**7245,02%**	**7246,37%**	**7203,43%**	**7145,79%**	**7089,70%**

Table 5
MAPE error value for monthly data part 2

Group of methods	Factors affecting lwd	Forecast time [month]											
		6	12	18	24	30	36	42	48	54	60	66	72
Adaptive methods	Poland	**6,29%**	**6,16%**	**6,13%**	**6,02%**	**6,02%**	**6,04%**	**6,13%**	**6,04%**	**6,84%**	**6,98%**	**7,20%**	**7,18%**
Neural networks	Lower Silesia	6,98%	6,95%	6,96%	6,96%	6,94%	6,91%	6,86%	6,78%	7,42%	7,46%	7,48%	7,38%
	kujawsko-pomorskie	6,57%	6,64%	6,66%	6,64%	6,58%	6,65%	6,58%	6,53%	7,16%	7,17%	7,21%	7,14%
	lubelskie	5,97%	6,06%	6,12%	6,08%	6,05%	6,02%	6,17%	6,04%	6,66%	6,72%	6,81%	6,87%
	lubuskie	7,18%	7,23%	7,36%	7,42%	7,53%	7,50%	7,44%	7,37%	7,79%	7,80%	7,72%	7,76%
	łódzkie	6,21%	6,19%	6,17%	6,14%	6,11%	6,03%	5,94%	5,81%	6,21%	6,24%	6,33%	6,24%
	małopolskie	5,85%	5,86%	5,83%	5,80%	5,66%	5,58%	5,69%	5,61%	5,67%	5,64%	5,63%	5,70%
	Mazowieckie	7,86%	7,90%	7,72%	7,73%	7,57%	7,65%	7,55%	7,49%	7,84%	7,88%	7,90%	7,84%
	Opole	7,71%	7,77%	7,97%	7,75%	7,87%	7,90%	7,83%	7,76%	8,24%	8,15%	8,25%	8,18%
	podkarpackie	6,87%	6,87%	6,60%	6,59%	6,55%	6,38%	6,40%	6,30%	6,77%	6,86%	6,93%	6,97%
	Podlaskie	8,62%	8,42%	8,25%	8,25%	8,24%	8,39%	8,50%	8,48%	9,22%	9,27%	9,50%	9,36%
	Pomeranian	7,38%	7,58%	7,43%	7,37%	7,16%	7,23%	7,17%	7,01%	7,75%	7,94%	7,99%	7,94%
	śląskie	5,74%	5,81%	5,67%	5,74%	5,73%	5,68%	5,71%	5,60%	5,89%	5,92%	6,07%	6,16%
	świętokrzyskie	5,77%	5,91%	5,79%	5,74%	5,76%	5,72%	5,84%	5,80%	6,16%	6,19%	6,17%	6,18%
	warmińsko-mazurskie	6,62%	6,67%	6,54%	6,60%	6,59%	6,56%	6,57%	6,43%	6,90%	7,04%	7,02%	7,04%
	wielkopolskie	6,11%	6,31%	6,30%	6,29%	6,42%	6,35%	6,23%	6,21%	6,64%	6,59%	6,58%	6,59%
	zachodniopomorskie	7,28%	7,47%	7,42%	7,39%	7,23%	7,25%	7,21%	7,08%	7,76%	7,82%	7,87%	7,80%
	Average:	**6,80%**	**6,85%**	**6,80%**	**6,78%**	**6,75%**	**6,74%**	**6,73%**	**6,64%**	**7,13%**	**7,17%**	**7,22%**	**7,20%**
Linear regression	good conditions	81,63%	81,74%	81,83%	81,95%	82,10%	82,24%	82,36%	82,55%	82,54%	82,61%	82,59%	82,66%
	fog smoke	441,48%	470,16%	454,02%	451,37%	449,67%	455,74%	452,23%	463,17%	463,41%	467,57%	464,25%	469,42%
	rainfall	79,02%	79,41%	79,45%	79,92%	79,53%	79,71%	79,49%	79,71%	79,74%	79,97%	79,85%	80,08%
	snowfall	97,09%	97,21%	97,31%	97,40%	97,49%	97,57%	97,64%	97,70%	97,76%	97,80%	97,86%	97,90%
	sunshine	23573,65%	23374,54%	22479,09%	21925,28%	21425,99%	21479,94%	21169,34%	22697,49%	22191,07%	23286,90%	22623,32%	22295,39%
	cloudy	25674,63%	25424,84%	27362,27%	26912,89%	27331,71%	27202,00%	27502,58%	27478,98%	29255,22%	29064,97%	29209,26%	28794,07%
	strong wind	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%	99,99%
	Average:	**7149,64%**	**7089,70%**	**7236,28%**	**7092,69%**	**7080,93%**	**7071,03%**	**7069,09%**	**7285,66%**	**7467,11%**	**7597,12%**	**7522,45%**	**7417,07%**

Figure 3
Average MAPE error depending on the method used for annual data

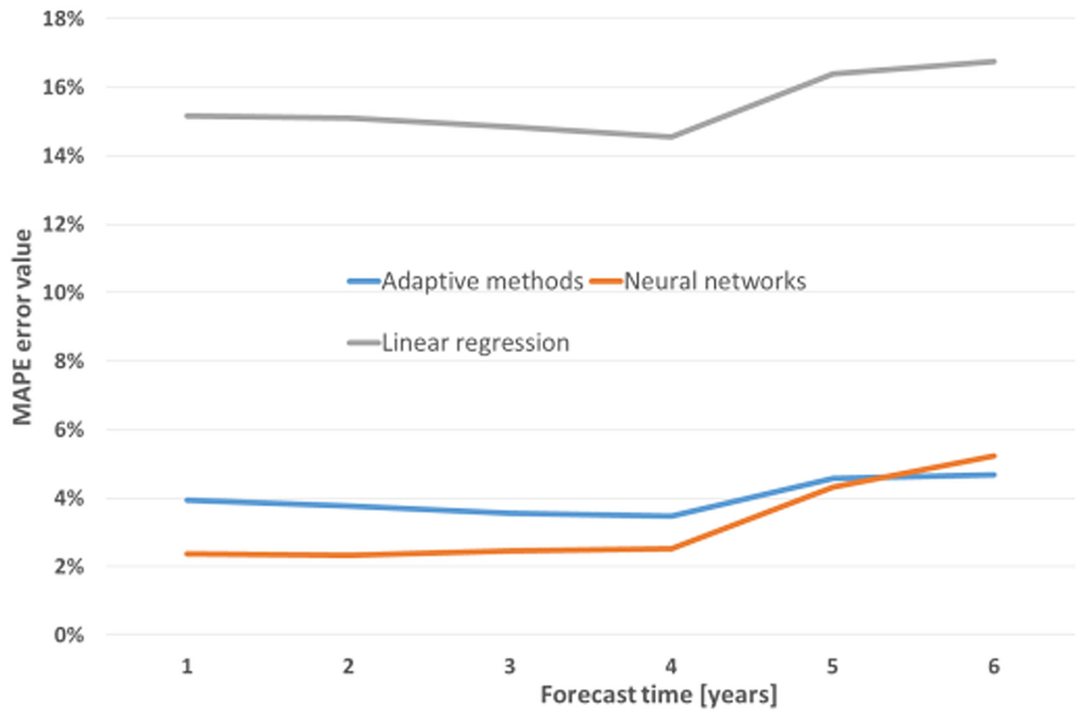


Figure 4
Average MAPE error depending on the method used for monthly part 1 data

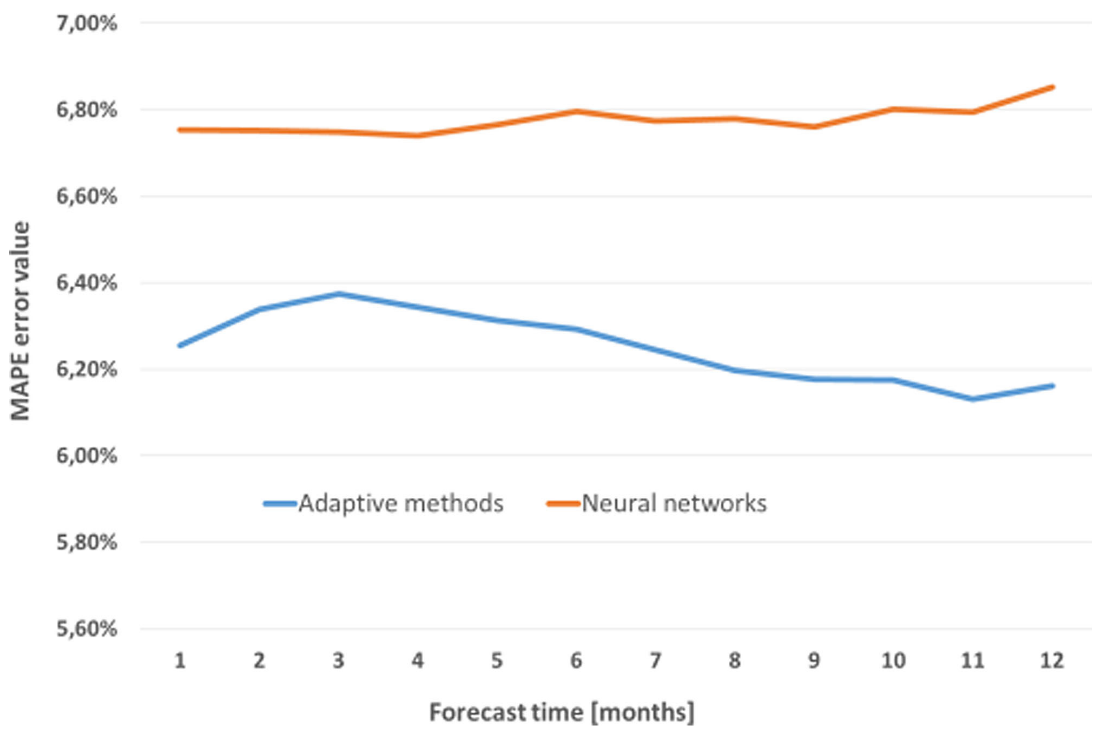
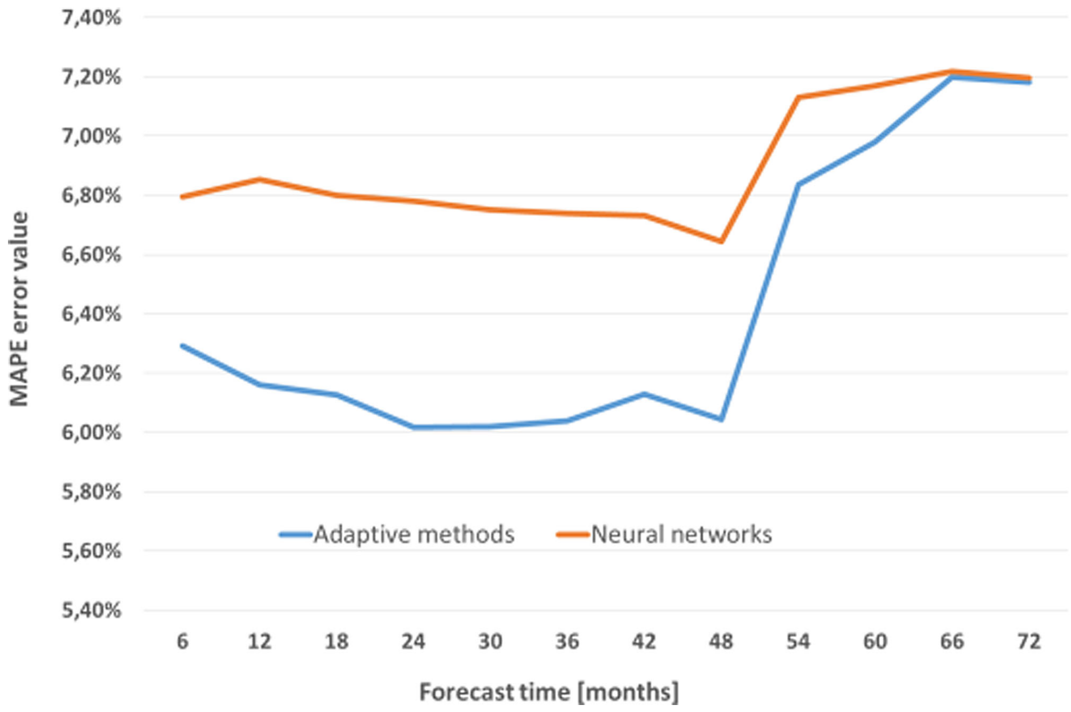


Figure 5
Average MAPE error depending on the method used for monthly part 2 data



4. Summary and Conclusions

The article looks at the effects of the forecasting approach, the variables influencing this value, the statistical data (annual and monthly) utilized, and, most crucially, the forecasting horizon on the MAPE error value when predicting the number of accidents in Poland. Based on the research, it can be said that using adaptive methods and neural networks, we can successfully predict the number of traffic accidents up to 6 years in the future (MAPE error value of 6% maximum) using annual statistical data on the number of accidents. However, since linear regression requires a value of close to 15% even for forecasting over a single year, we should not use it for yearly data. It represents a very high value.

Based on the analysis of monthly data, we can conclude that adaptive approaches and neural networks can be used to accurately predict the frequency of accidents for up to 6 years. In this instance, the predicted error number is not more than 7.2%. We should not use linear regression methods to predict the frequency of traffic accidents using monthly data and taking into account how the weather would effect the prediction since the average inaccuracy in this situation reaches 7000%. However, it should be kept in mind that the pandemic not only led to major changes in projections but also decreased the number of accidents on the roadways [5–7].

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Piotr Gorzelańczyk: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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