https://doi.org/10.22306/atec.v10i4.228 *Received: 06 Oct. 2024; Revised: 05 Nov. 2024; Accepted: 25 Nov. 2024*

Forecasting the number of road accidents on a weekday

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Keywords: road accident, forecasting, weekday.
Abstract: Every year, a considerable number of people lose their lives on Polish highwaysAlthough this number remains significant, it has been steadily decreasing over time. Despite a reduction in accidents since the pandemic began, the overall figures are still relatively high. To effectively minimize road accidents, it is essential to identify which days experience the highest frequency of collisions and to predict the number of accidents in the upcoming years. The objective of this article is to forecast the number of accidents occurring on Polish roads for each weekday. To achieve this, monthly accident data from the Polish Police statisticsfor 2007 was analyzed, resulting in predictions for the years 2022-2024. The findings of the study suggest that there will likely be a decrease in accidents on Polish roads compared to pre-pandemic levels; however, the ongoing impact of the pandemic complicates these results. The research employed various time series models using the Statistica program.

1 Introduction

Road accidents are incidents that not only result in injuries or fatalities to road users but also cause damage to property. According to the WHO [1], approximately 1.3 million people die in traffic accidents each year. Many countries worldwide attribute about 3% of their GDP to the consequences of these accidents. The WHO further reports that traffic accidents are the leading cause of death among children and young adults aged 5 to 29. The UN General Assembly aims to halve the number of traffic fatalities and injuries by 2030.

One crucial factor influencing the severity of a traffic accident is its magnitude. To effectively prevent accidents and reduce injuries, fatalities, and property damage, it is essential for relevant authorities to predict the severity of incidents [2,3]. Identifying the key elements that impact accident severity is vital before implementing corrective measures to mitigate and reduce the seriousness of accidents. [4] A multi-layered architecture known as DNN (Deep Neural Network) has been proposed by Yang et al. for predicting different levels of damage, fatalities, and property loss. This model facilitates a comprehensive and precise analysis of the severity of traffic incidents [5].

Accident data is sourced from various channels, primarily collected and analyzed by governmental organizations through relevant agencies. Data collection relies on police reports, insurance databases, and hospital records. Following this, incomplete data regarding traffic accidents is processed more broadly for the transportation sector [6].

Currently, intelligent transportation systems serve as the most significant source of information for analyzing and forecasting traffic accidents. This data can be analyzed in conjunction with the use of GPS devices in vehicles [7]. As noted by Khaliq et al. [8], microwave roadside vehicle detection systems can continuously record vehicle data, such as speed, traffic volume, and vehicle type. Additionally, vehicle license plate recognition systems enable the collection of substantial amounts of data on road traffic over monitored periods [9]. While social media can also serve as a data source for insights on traffic and accidents, its reliability may be limited due to the unpredictability of reports [10].

To accurately represent accident data, it is essential to collaborate with multiple data sources, all of which must be appropriately integrated. The accuracy of analysis results can be enhanced by combining various data sources and integrating heterogeneous data on traffic accidents [11].

A statistical analysis conducted by Vilaca et al. [12] examined the severity of road accidents and their correlation with other road users. The study concluded with recommendations to elevate driving safety standards and implement new transportation safety regulations.

Based on the frequency of traffic accidents and the duration taken to identify their causes, Bak et al. [13] conducted a statistical analysis of traffic safety in a specific region of Poland. This study focused on assessing the safety of individuals who cause accidents through multivariate statistical analysis.

The type of traffic issue reported influences the source of crash data utilized for the study. The accuracy of accident forecasts can be enhanced, and the number of accidents can be reduced when statistical models are combined with additional natural driving data or other information from intelligent transportation systems [14].

Numerous techniques for predicting accident numbers are documented in the literature. Among these, time series methods are the most widely used for forecasting road accidents [15,16]. However, these methods have several limitations, such as the inability to evaluate the quality of forecasts based on outdated predictions and the frequent autocorrelation of the residual values of the components [17].

Procházka et al. [18] employed a multiple seasonality model for forecasting, while Sunny et al. [19] utilized the Holt-Winters exponential smoothing method. One limitation of these approaches is that they cannot incorporate exogenous variables into the model [20,21].

Other forecasting methods include the vector autoregression model, which requires a substantial number of observations of variables to accurately estimate their parameters [22]. Additionally, Monedero et al. [23] applied autoregression models for fatality analysis, while Al-Madani [24] used curve fit regression models to predict the number of traffic accidents. These models primarily rely on simple linear relationships [25] and autoregression sequences, assuming the series are already stationary [26].

The Random Forest regression method was utilized by Biswas et al. [27] to predict the number of traffic accidents. In this context, smaller groups are favored over larger ones, but this method exhibits instability in approach and peak prediction. The data also includes groups of related features that hold similar importance to the original dataset [28,29].

For the prognostic issue discussed, Chudy-Laskowska and Pisula [30] applied an autoregressive model with a quadratic trend, a one-dimensional periodic trend model, and an exponential smoothing model. Although the moving average model can also be employed for forecasting, it has several drawbacks, including low accuracy of forecasts, data loss over time, failure to account for patterns, and neglect of seasonal impacts [31].

The GARMA technique, used by Procházka and Camej [32], imposes restrictions on the parameter space to ensure the stationarity of the process. Several studies highlight the frequent use of the ARMA model for forecasting stationary processes [19, 32-34] and the ARIMA or SARIMA model for non-stationary processes. While these models offer significant flexibility, this can also be a disadvantage, as effective model identification requires more in-depth research knowledge compared to methods like regression analysis [35]. Additionally, the linearity of the ARIMA model is another limitation [36].

In their 2015 study, Chudy-Laskowska and Pisula [37] employed the ANOVA approach to predict traffic accident numbers. However, this method has the drawback of necessitating additional assumptions, particularly regarding sphericity, the violation of which may lead to incorrect conclusions [38].

Neural network models are also utilized for predicting traffic accident frequency [37,39]. However, Artificial Neural Networks (ANN) come with several drawbacks, including the need for prior knowledge in the field, the final outcome's reliance on the network's initial conditions, a lack of traditional interpretability, and the "black box" nature of ANN, where input data is provided, and results are outputted without insight into the analysis proces [40].

Kumar et al. [41] introduced the Hadoop model as a novel prediction technique. A limitation of this technology is its inability to process small data files [42]. The GARCH model was used by Karlaftis and Vlahogianni [34] for predictions, but its complexity in both form and model poses a challenge [43,44]. On the other hand, the ADF test was employed by McIlroy [45] and colleagues, although this method suffers from low power when dealing with autocorrelation of random components [46].

The authors of the articles [47,48] also explored data-mining approaches for forecasting, which typically face the challenge of handling large datasets with general descriptions [49]. Additionally, a model combination was proposed by Sebe [50], suggesting a blend of various models. Bloomfield [51] also recommended parametric models for predicting the number of traffic accidents in Poland.

2 A study of the seasonality of accidents on the roads

When on Polish highways, a large number of individuals pass away. Despite the value declining year over year, the total is still very substantial. Although there have been fewer accidents on the roads since the pandemic, the number is still relatively high. When the data is examined on a monthly basis, it can be concluded that there are definite variations and a persistent downward tendency. In Poland, there are still a lot more accidents than in the rest of the European Union. On Sundays, there are fewer car accidents than on Fridays, when there are more. Due to this, it is imperative to lower this number and determine the days that will see the greatest number of incidents on the roads (Figure 1).

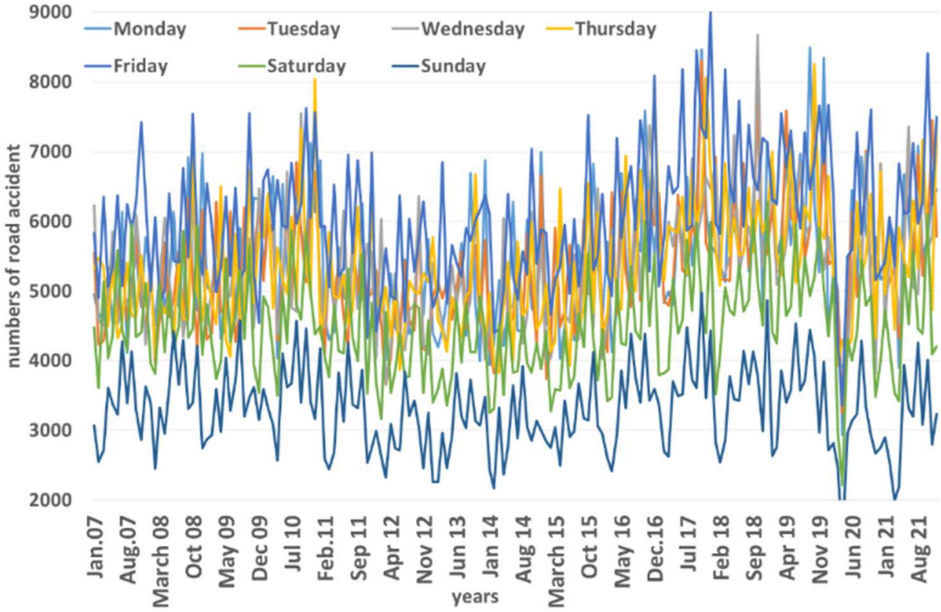

Figure 1 Accidents in Poland between 2007 and 2021

The average number of traffic accidents throughout the studied period was tested after that to determine whether there had been a substantial difference. Poland's non-parametric Kruskall-Wallis test statistic value is 587, with a test probability of p=0.000. In this situation, it is necessary to reject the premise that the average number of traffic accidents during the studied time was equal. This indicates that the average number of incidents in the current situation are consistently declining from year to year (Figure 2). According to the data acquired, Fridays have the highest number of traffic accidents, while Sundays see the lowest number [52].

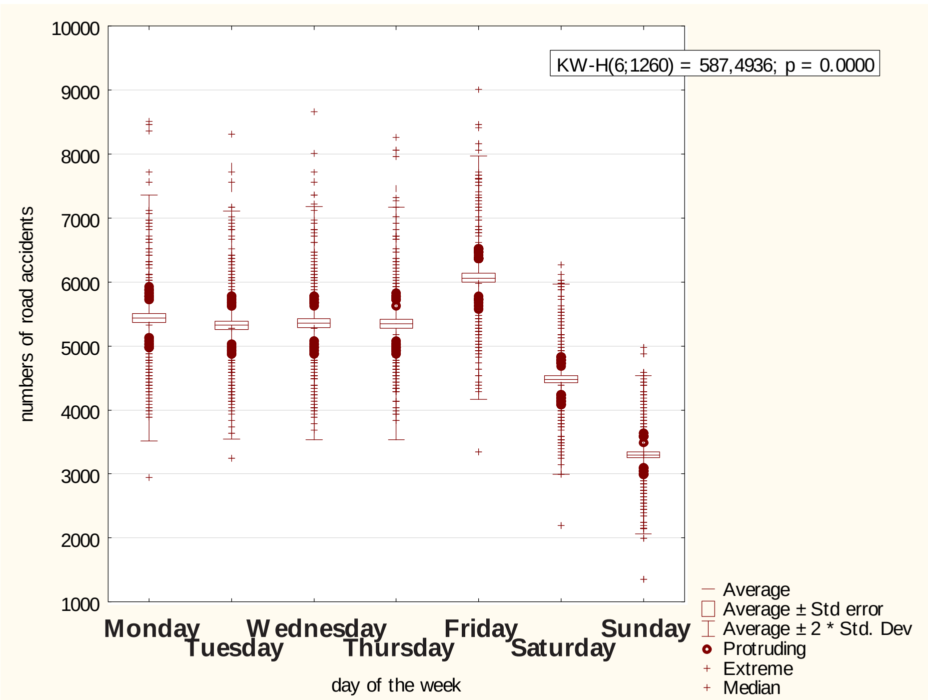

Figure 2 Road accident averages in Poland from 2007 to 2021, broken down by day of the week

The research of the number of accidents on Polish roads leads to the conclusion that they are seasonal in character and on the decline. Therefore, for additional analysis, the expected number of traffic accidents in the investigated period based on the day of the week was determined using a few time series models.

3 Forecasting the number of road accidents

Selected exponential equalization models were used to predict the number of traffic accidents. The fundamental idea behind this approach is that the predicted variable's time series is represented by a weighted moving average, with the weights chosen in accordance with an exponential function. The study's software, Statistica, selected the weights in the most effective way possible.

In this instance, the forecast is based on a weighted average of the series' recent and historical values. The model and its parameters that are selected will determine the forecast's outcome. Selected time series models with a linear trend were used to predict the number of accidents. Specifically, the exponential model and the linear trend model (Holt and Winters technique).

Measures of analytical forecasting perfection were calculated using the errors of forecasts that had expired, which were calculated using equations (1-5):

- ME – mean error
$$ME = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_p) \tag{1}$$
- MAE –mean everage error
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - Y_p| \tag{2}$$
- 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
$$SSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_p)^2} \tag{5}$$

where:
n – the projected horizon's length,
Y – observed value of traffic collisions,
Y_p – forecasted value of road accidents.

The mean percentage error was minimized in order to compare the number of accidents that occurred during a pandemic and those that did not.

Forecasting the number of road accidents in Poland

Forecasts for the number of accidents by day of the week were made using information from the Polish Police from 2007 to 2021. Figure 3 - Figure 9 displays the predicted results for each day of the week. The various forecasting techniques utilized in the study are denoted by the letters M1, M2,... and Mn. The following are the forecasting methods applied in the study:

M1 - moving average method 2-points,
M2 - moving average method 3-points,
M3 - moving average method 4-points,
M4 - exponential smoothing no trend seasonal component: none,
M5 - exponential smoothing no trend seasonal component: additive,
M6 - exponential smoothing no trend seasonal component: multiplicative,
M7 - exponential smoothing linear trend seasonal component: none HOLTA,
M8 - exponential smoothing linear trend seasonal component: additive,
M9 - exponential smoothing linear trend seasonal component: multiplicative WINTERSA,
M10 - exponential smoothing exponential seasonal component: none,
M11 - exponential smoothing exponential seasonal component: additive,
M12 - exponential smoothing exponential seasonal component: multiplicative,
M13 - exponential smoothing fading trend seasonal component: none,
M14 - exponential smoothing fading trend seasonal component: additive,
M15 - exponential smoothing fading trend seasonal component: multiplicative).

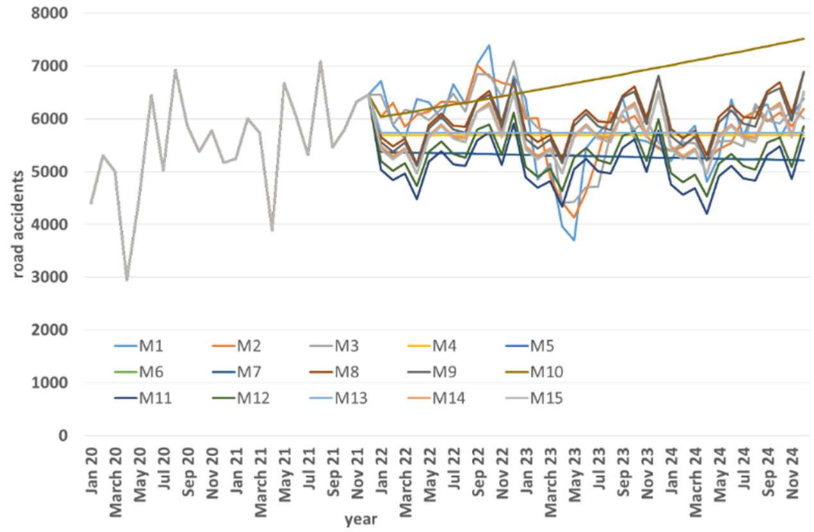

Figure 3 Forecasting the number of traffic accidents on Monday between 2022 and 2024

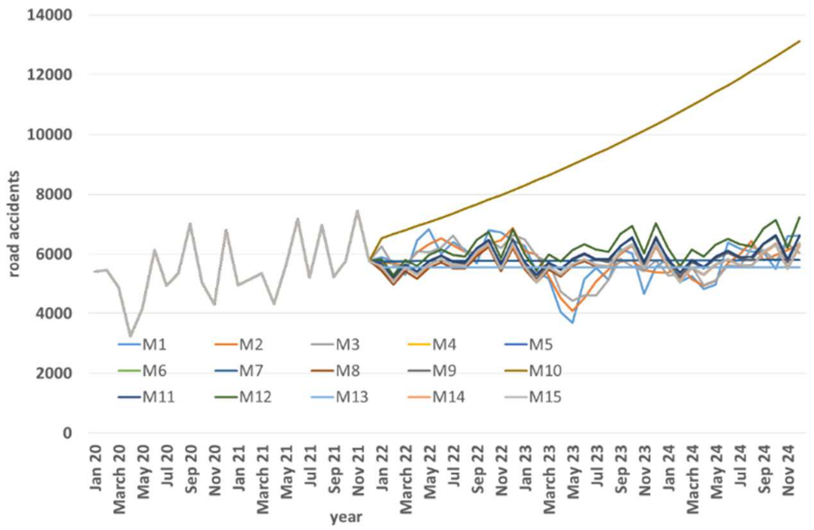

Figure 4 Forecasting the number of traffic accidents on Tuesday from 2022 to 2024

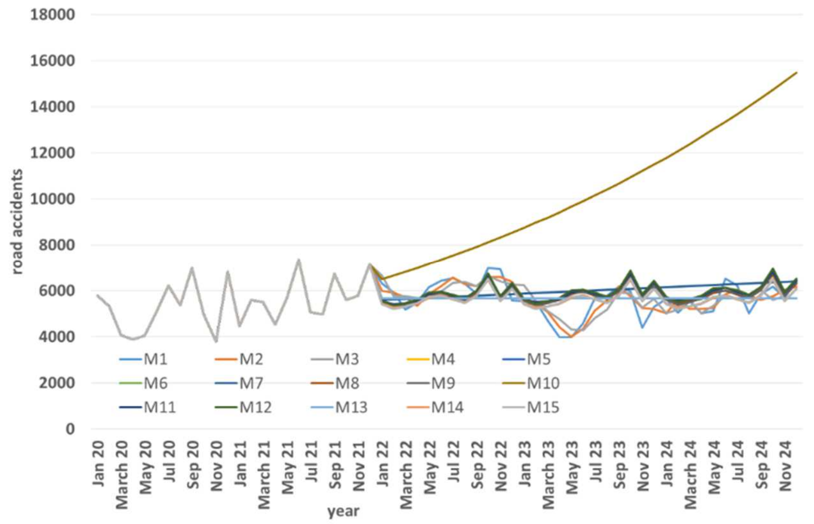

Figure 5 Forecasting the number of road accidents on Wednesday from 2022 to 2024

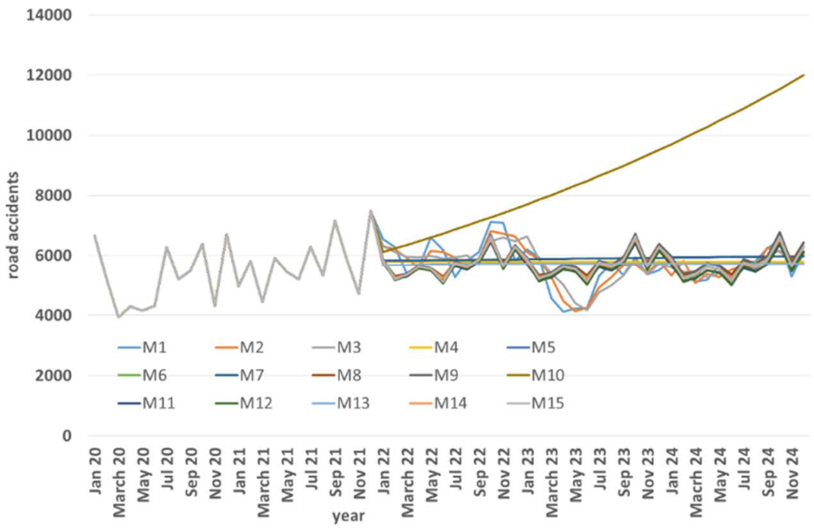

Figure 6 Forecasting the number of traffic accidents on Thursday from 2022 to 2024

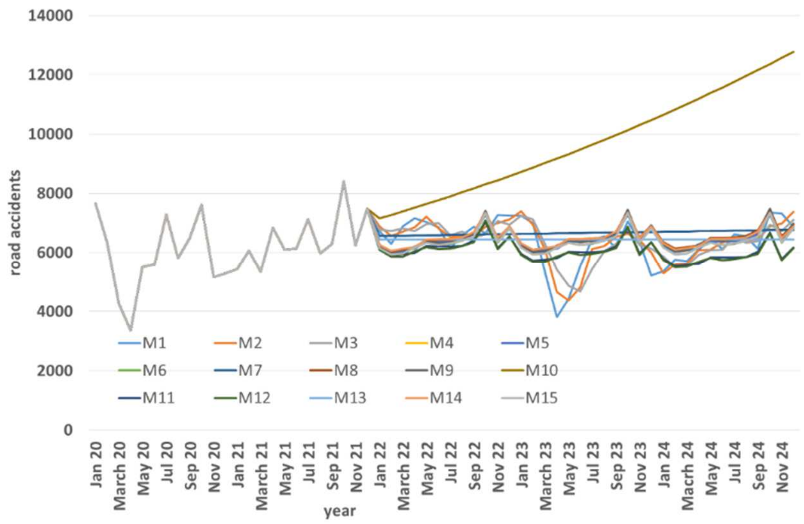

Figure 7 Forecasting the number of road accidents on Friday from 2022 to 2024

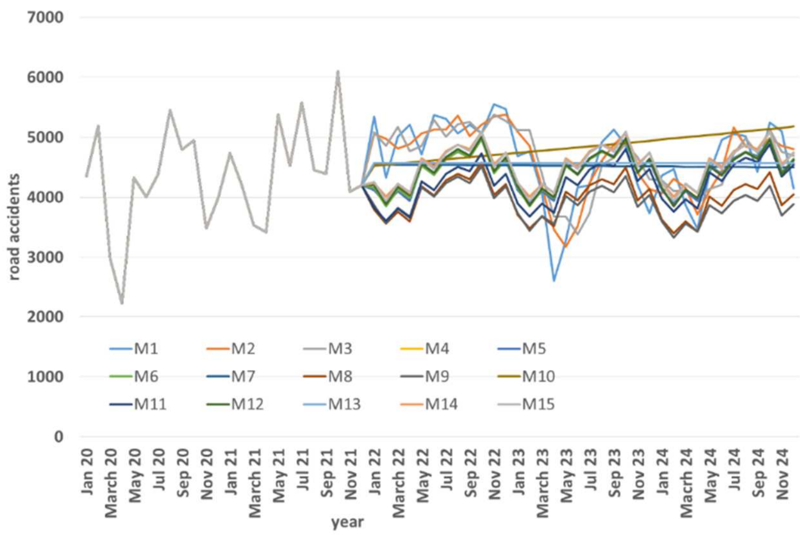

Figure 8 Forecasting the number of traffic accidents on Saturday from 2022 to 2024

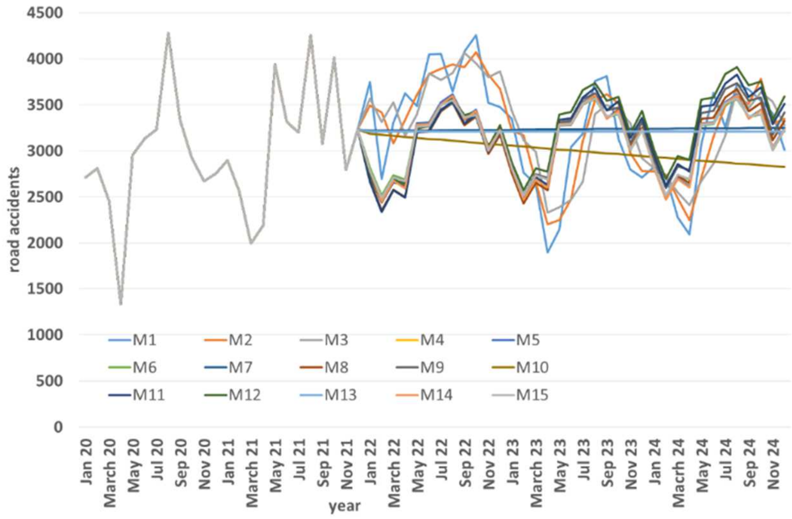

Figure 9 Forecasting the number of traffic accidents on Sunday from 2022 to 2024

Forecasts for the number of accidents by day of the week were made using information from the Polish Police from 2007 to 2021. Figure 3-9 displays the predicted results for each day of the week. The various forecasting techniques utilized in the study are denoted by the letters M1, M2,... and Mn. The following are the forecasting methods applied in the study:

- Monday - M2,
- Tuesday - M3,
- Wednesday - M2,
- Thursday - M3,
- Friday - M2,
- Saturday - M2,
- Sunday - M1.

The moving average approaches provided the minimum MPE error, according to the data received. This served as the foundation for the forecast of the quantity of traffic accidents according to the day of the week depicted in Figure 10, and the resulting forecast errors are displayed in Table 1. The findings indicate that, with a slight drop, we may still anticipate a level of traffic accidents similar to those that existed prior to the epidemic. The pandemic, it should be mentioned, distorted the outcomes. The selection of an efficient forecasting technique is shown by an error value of no more than 5%.

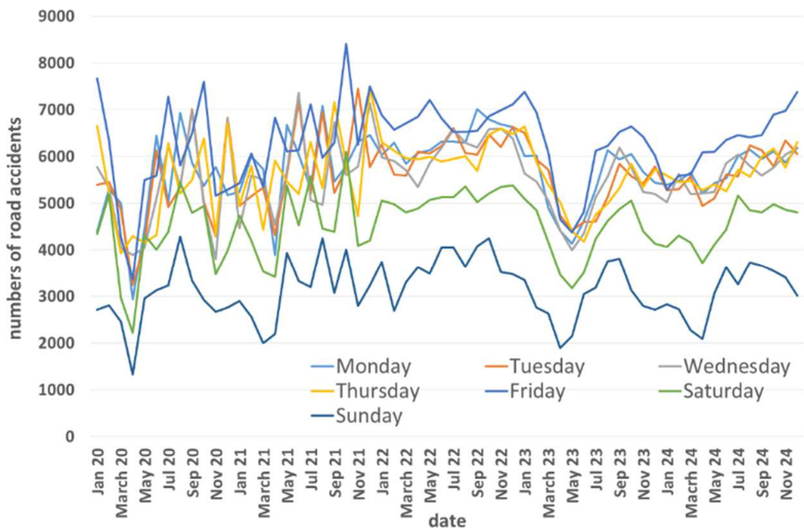

Figure 10 Projected number of traffic accidents by day of the week in 2022-2024

Table 1 Forecast error

Forecast error/day of the week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ME	141.28	164.40	124.80	172.14	141.07	9.72	58.93
MPE	0.50%	0.23%	0.66%	0.26%	0.24%	2.55%	5.30%
SSE	1099.78	1043.67	1091.87	1126.39	1129.20	816.72	687.25
MAPE	16.04%	15.29%	16.20%	16.06%	14.85%	15.32%	17.96%
MAE	875.66	825.96	871.29	877.93	897.84	664.13	552.28

4 Conclusion

Using the Statistica application, exponential equalization methods were used to predict the number of accidents in Poland. The computer calculated the weights in use to reduce the mean absolute error and mean absolute percentage error.

The findings indicate that, with a slight drop, we may still anticipate a level of traffic accidents similar to those that existed prior to the epidemic. The results were biased by the pandemic, it should be highlighted. The selection of an efficient forecasting technique is demonstrated by the error value of a maximum of 5%.

The article's forecasted traffic accident data can be utilized in the future to develop new policies aimed at reducing accidents in the countries under study. These changes might include, for instance, increasing the fines for moving violations on Polish roads starting in 2022.

The authors intend to include more elements affecting Poland's accident rates in their future research. The amount of traffic, the weather, or the age of the accident's perpetrator are just a few examples extensions.

References

[1] World Health Organization, WHO, The Global status on road safety 2018, [Online], Available: https://www.who.int/publications/i/item/9789241565684 [15 Sep 2024], 2018.

[2] TAMBOURATZIS, T., SOULIOU, D., CHALIKIAS, M., GREGORIADES, A.: Maximising accuracy and efficiency of traffic accident prediction combining information mining with computational intelligence approaches and decision trees, *Journal of Artificial Intelligence and Soft Computing Research*, Vol. 4, No. 1, pp. 31-42, 2014. http://dx.doi.org/10.2478/jaiscr-2014-0023

[3] ZHU, L., LU, L., ZHANG, W., ZHAO, Y., SONG, M.: Analysis of accident severity for curved roadways based on bayesian networks, *Sustainability*, Vol. 11, No. 8, 2223, pp. 1-17, 2019. https://doi.org/10.3390/su11082223

[4] ARTEAGA, C., PAZ, A., PARK, J.: Injury severity on traffic crashes: A text mining with an interpretable machine-learning approach, *Safety Science*, Vol. 132, No. December, 104988, 2020. https://doi.org/10.1016/j.ssci.2020.104988

[5] YANG, Z., ZHANG, W., FENG, J.: Predicting multiple types of traffic accident severity with explanations: A multi-task deep learning framework, *Safety Science*, Vol. 146, No. February, 105522, 2022. https://doi.org/10.1016/j.ssci.2021.105522

[6] GORZELANCZYK, P., PYSZEWSKA, D., KALINA, T., JURKOVIC, M.: Analysis of road traffic safety in the Pila poviat, *Scientific Journal of Silesian University of Technology. Series Transport*, Vol. 107, pp. 33-52, 2020. https://doi.org/10.20858/sjsutst.2020.107.3

[7] CHEN, C.: Analysis and forecast of traffic accident big data, *ITM Web of Conferences*, Vol. 12, 04029, pp. 1-6, 2017. https://doi.org/10.1051/itmconf/20171204029

[8] KHALIQ, K.A., CHUGHTAI, O., SHAHWANI, A., QAYYUM, A., PANNEK, J.: Road accidents detection, data collection and data analysis using V2X communication and edge/cloud computing, *Electronics*, Vol. 8, No. 8, 896, pp. 1-28, 2019. https://doi.org/10.3390/electronics8080896

[9] RAJPUT, H., SOM, T., KAR, S.: An automated vehicle license plate recognition system, *Computer*, Vol. 48, No. 8, pp. 56-61, 2015. https://doi.org/10.1109/MC.2015.244

[10] ZHENG, Z., WANG, C., WANG, P., XIONG, Y., ZHANG, F., LV, Y.: Framework for fusing traffic information from social and physical transportation data, *PLoS ONE*, Vol. 13, No. 8, e0201531, pp. 1-19, 2018. https://doi.org/10.1371/journal.pone.0201531

[11] ABDULLAH, E., EMAM, A.: *Traffic accidents analyzer using big data*, In: 2015 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, pp. 392-397, 2015. https://doi.org/10.1109/CSCI.2015.187

[12] VILAÇA, M., SILVA, N., COELHO, M.C.: Statistical analysis of the occurrence and severity of crashes involving vulnerable road users, *Transportation Research Procedia*, Vol. 27, pp. 1113-1120, 2017. https://doi.org/10.1016/j.trpro.2017.12.113

[13] BĄK, I., CHEBA, K., SZCZECIŃSKA, B.: The statistical analysis of road traffic in cities of Poland, *Transportation Research Procedia*, Vol. 39, pp. 14-23, 2019. https://doi.org/10.1016/j.trpro.2019.06.003

[14] CHAND, A., JAYESH, S., BHASI, A.B.: Road traffic accidents: An overview of data sources, analysis techniques and contributing factors, *materialstoday: Proceedings*, Vol. 47, Part 15, pp. 5135-5141, 2021. https://doi.org/10.1016/j.matpr.2021.05.415

[15] HELGASON, A.: Fractional integration methods and short Time series: evidence from a simulation study, *Political Analysis*, Vol. 24, No. 1, pp. 59-68, 2016. http://www.jstor.org/stable/24573204

[16] LAVRENZ, S., VLAHOGIANNI, E., GKRITZA, K., KE, Y.: Time series modeling in traffic safetyresearch, *Accident Analysis & Prevention*, Vol. 117, No. August, pp. 368-380, 2018. https://doi.org/10.1016/j.aap.2017.11.030

[17] Forecasting based on time series, Prognozowanie na podstawie szeregów czasowych, [Online], Available: http://pis.rezolwenta.eu.org/Materialy/PiS-W-5.pdf [15 Sep 2024], 2022. (Original in Polish)

[18] PROCHÁZKA, J., FLIMMEL, S., ČAMAJ, M., BAŠTA, M.: *Modelling the Number of Road Accidents*, 20th AMSE, Applications of Mathematics and Statistics in Economics, International Scientific Conference: Szklarska Poręba, 30 August - 3 September, 2017, Publishing house of the University of Economics in Wrocław, Wrocław, pp. 355-364, 2017. https://doi.org/10.15611/amse.2017.20.29

[19] SUNNY, C.M., NITHYA, S., SINSHI, K.S., VINODINI, V.M.D., LAKSHMI, A.K.G., ANJANA, S., MANOJKUMAR, T.K.: *Forecasting of Road Accident in Kerala: A Case Study*, 2018 International Conference on Data Science and Engineering (ICDSE), Kochi, India, pp. 1-5, 2018. https://doi.org/10.1109/ICDSE.2018.8527825

[20] DUDEK, G.: *Forecasting Time Series with Multiple Seasonal Cycles Using Neural Networks with Local Learning.* In: Rutkowski, L., Korytkowski, M., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M. (eds) Artificial Intelligence and Soft Computing, ICAISC 2013, Lecture Notes in Computer Science, Vol. 7894, Springer, Berlin, Heidelberg, pp. 52-63, 2013. https://doi.org/10.1007/978-3-642-38658-9_5

[21] SZMUKSTA-ZAWADZKA, M., ZAWADZKI, J.: *Forecasting on the basis of Holt-Winters models for complete and incomplete data*, Research papers of the Wrocław University of Economics, Vol. 2009, No. 38, pp. 85-99, 2009.

[22] WÓJCIK, A.: *Autoregressive vector models as a response to the critique of multi-equation structural econometric models*, Publishing house of the University of Economics in Katowice, Vol. 193, 2014.

[23] MONEDEROA, B.D., GIL-ALANAA, L.A., MARTÍNEZAA, M.C.V.: Road accidents in Spain: Are they persistent?, *IATSS Research*, Vol. 45, No. 3, pp. 317-325, 2021. https://doi.org/10.1016/j.iatssr.2021.01.002

[24] AL-MADANI, H.: Global road fatality trends'estimations based on country-wise microlevel data, *Accident Analysis & Prevention*, Vol. 111, No. February, pp. 297-310, 2018. https://doi.org/10.1016/j.aap.2017.11.035

[25] MAMCZUR, M.: Machine learning How does linear regression work? And is it worth using?, [Online], Available: https://miroslawmamczur.pl/jak-dziala-regresja-liniowa-i-czy-warto-ja-stosowac/ [16 Sep 2024], 2020. (Original in Polish)

[26] PIŁATOWSKA, M.: The choice of the order of autoregression depending on the parameters of the generating model, *Econometrics*, Vol. 4, No. 38, 2012.

[27] BISWAS, A.A., MIA, J., MAJUMDER, A.: *Forecasting the Number of Road Accidents and Casualties using Random Forest Regression in the Context of Bangladesh*, 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, pp. 1-5, 2019.

[28] Random Forest, [Online], Available: https://pl.wikipedia.org/wiki/Las_losowy [16 Sep 2024], 2008. (Original in Polish)

[29] FIJOREK, K., MRÓZ, K., NIEDZIELA, K., FIJOREK, D.: Forecasting electricity prices on the day-ahead market using data mining methods, *Rynek Energii*, Vol. 91, No. 3, 2010.

[30] CHUDY-LASKOWSKA, K., PISULA, T.: Forecast of the number of road accidents in Poland, *Logistics*, Vol. 2014, No. 6, 2014.

[31] KASHPRUK, N.: *Comparative research of statistical models and soft computing for identification of time series and forecasting*, Opole University of Technology, 2010.

[32] PROCHAZKA, J., CAMAJ, M.: *Modelling the number of road accidents of uninsured drivers and their severity*, Proceedings of International Academic Conferences 5408040, International Institute of Social and Economic Sciences, 2017.

[33] DUTTA, B., BARMAN, M.P., PATOWARY, A.N.: Application of Arima model for forecasting road accident deaths in India, *International Journal of Agricultural and Statistical Sciences*, Vol. 16, No. 2, pp. 607-615, 2020.

[34] KARLAFTIS, M., VLAHOGIANNI, E.: Memory properties and fractional integration in trans-portation time-series, *Transportation Research Part C: Emerging Technologies*, Vol. 17, No. 4, pp. 444-453, 2009. https://doi.org/10.1016/j.trc.2009.03.001

[35] ŁOBEJKO, S.: *Time series analysis and forecasting with SAS*, Main business school in Warsaw, Warsaw, 2015.

[36] DUDEK, G.: Exponential smoothing models for short-term power system load forecasting, *Rynek Energii*, Vol. 106, No. 3, pp. 14-19, 2013. (Original in Polish)

[37] CHUDY-LASKOWSKA, K., PISULA, T.: Prognozowanie liczby wypadków drogowych na Podkarpaciu, *Logistics*, Vol. 2015, No. 4, pp. 2782-2796, 2015. (Original in Polish)

[38] Road safety assessment handbook, [Online], Available: https://etsc.eu/network-wide-road-safety-assessment-methodology-published/ [16 Sep 2024], 2024.

[39] WROBEL, M.S.: *Application of neural fuzzy systems in chemistry*, PhD thesis, Katowice, University of Silesia, 2017.

[40] Data mining techniques StatSoft, [Online], Available: https://www.statsoft.pl/textbook/stathome_stat.html?https%3A%2F%2Fwww.statsoft.pl%2Ftextbook%2Fstdatmin.html [17 Sep 2024], 2024. (Original in Poland)

[41] KUMAR, S., VISWANADHAM, V., BHARATHI, B.: Analysis of road accident, *IOP Conference Series: Materials Science and Engineering*, Vol. 590, No. 1, 012029, pp. 1-6, 2019. https://doi.org/10.1088/1757-899X/590/1/012029

[42] Dataflair Team, Top Advantages and Disadvantages of Hadoop 3, [Online], Available: https://data-flair.training/blogs/advantages-and-disadvantages-of-hadoop/ [17 Sep 2024], 2022.

[43] PERCZAK, G., FISZEDER, P.: *GARCH model - using additional information on minimum and maximum prices*. Bank and Credit. Number 2. 2014

[44] FISZEDER, P.: *GARCH class models in empirical financial research*, Scientific Publishers of the Nicolaus Copernicus University, Torun, 2009.

[45] MCILROY, R.C., PLANT, K.A., HOQUE, M.S., WU, J., KOKWARO, G.O., NAM, V.H., STANTON, N.A.: Who is responsible for global road safety? A cross-cultural comparison of factor maps, *Accident Analysis & Prevention*, Vol. 122, No. January, pp. 8-18, 2019. https://doi.org/10.1016/j.aap.2018.09.011

[46] MUCK, J.: Econometrics, Modeling of time series, Stationary, Unit root tests, ARDL models, Co-integration, [Online], Available: http://web.sgh.waw.pl/~jmuck/Ekonometria/EkonometriaPrezentacja5.pdf [17 Sep 2024], 2022.

[47] SHETTY, P., SACHIN, P.C., KASHYAP, V.K., MADI, V.: Analysis of road accidents using data mining techniques, *International Research Journal of Engineering and Technology*, Vol. 2017, No. 4, 2017.

[48] LI, L., SHRESTHA, S., HU, G.: *Analysis of road traffic fatal accidents using data mining techniques*, 2017 IEEE 15th International Conference on Software Engineering Research, Management and Applications (SERA), pp. 363-370, 2017. https://doi.org/10.1109/SERA.2017.7965753

[49] MARCINKOWSKA, J.: *Statistical methods and data mining in assessing the occurrence of syncope in the group of narrow-QRS tachycardia (AVNRT and AVRT)*, Medical University of Karol Marcinkowski in Poznań, Poznań, 2015. (Original in Poland)

[50] SEBEGO, M., NAUMANN, R.B., RUDD, R.A., VOETSCH, K., DELLINGER, A.M., NDLOVU, C.: The impact of alcohol and road traffic policies on crash rates in Botswana, 2004–2011: A time-series analysis, *Accident Analysis & Prevention*, Vol. 70, No. September, pp. 33-39, 2014. https://doi.org/10.1016/j.aap.2014.02.017

[51] BLOOMFIELD, P.: An exponential model in the spectrum of a scalar time series, *Biometrika*, Vol. 60, No. 2, pp. 217-226, 1973.

[52] Statistic Road Accident, [Online], Available: https://statystyka.policja.pl/ [17 Sep 2024], 2024.

Review process

Single-blind peer review process.