Received: 21 November 2023 | Revised: 11 March 2024 | Accepted: 9 April 2024 | Published online: 10 May 2024

RESEARCH ARTICLE

Archives of Advanced Engineering Science
2024, Vol. 2(4) 206–214
DOI: 10.47852/bonviewAAES42022114

BON VIEW PUBLISHING

Optimization of Methods for Forecasting the Number of Road Accidents

Piotr Gorzelańczyk[1],* **and Henryk Tylicki[1]**

[1]*Transport Department, Stanislaw Staszic State University of Applied Sciences in Pila, Poland*

Abstract: Due to the abrupt rise in the number of vehicles on the road, there is an increasing risk of traffic accidents, which can result in fatalities and damage to economic resources. This is due to the rapid growth in the human population and the development of motorization. The biggest issue with anticipating and analyzing data on road accidents is the small quantity of the dataset that may be used for study in this area. Road accidents have a low geographical and temporal density, despite the fact that they cause millions of deaths and injuries annually. The purpose of this article is to suggest a strategy for improving methodologies for determining how frequently traffic accidents occur in Poland. Techniques for multi-criteria optimization were used in this. We can infer from the findings that the suggested method can be utilized to determine the best methods for forecasting the frequency of traffic accidents. The method can successfully be used to forecast other events not only logistics or transportation.

Keywords: traffic accidents, predicting, forecasting, multi-criteria optimization

1. Introduction

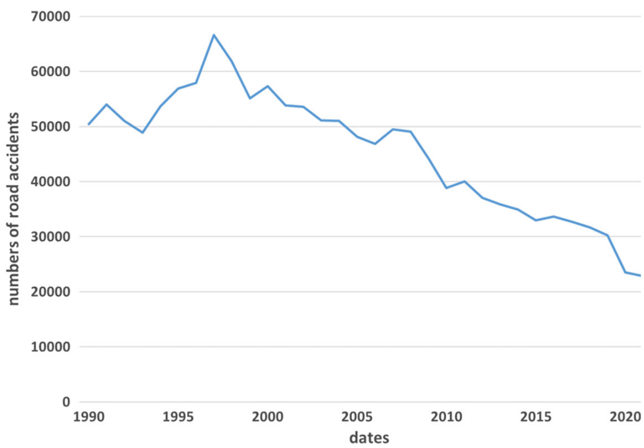
Road accidents are a major socioeconomic problem for any country. Road accidents can be brought on by a number of factors, such as poor weather, drunk driving, and excessive speeds. According to the World Health Organization (WHO) [1], more than 1.19 million people die in traffic accidents every year. Furthermore, millions more suffer catastrophic injuries and long-term negative health impacts. Traffic accidents also result in financial losses. The coronavirus disease 2019 pandemic, which has been on the rise recently, is mostly to blame for the steady drop in the frequency of road accidents.

But to what you might believe, there are a lot more accidents on the highways (Figure 1 [2]), with an average of 62 collisions daily, 6 fatalities, and 72 injuries. The aforementioned occurrences have an adverse impact on the environment (e.g., through fuel and operating fluid leaks), increase medical costs, and necessitate repairs to vehicles and road infrastructure. As a result, numerous measures are being taken to avoid and reduce traffic accidents. Two examples of such measures are the analysis of the variables influencing the number of accidents [2, 3] and the analysis of methods to estimate the number of accidents based on the variables influencing the number of accidents.

Road accidents are incidents that cause property damage as well as harm or fatality to other drivers. According to the WHO [1], 1.3 million people die in automobile accidents every year. Most countries on the planet lose money due to traffic accidents—about 3% of their gross domestic product. Traffic accidents are the leading cause of death for children and young adults between the ages of 5 and 29 years, according to the WHO [1]. The UN General Assembly hopes to see a 50% decrease in traffic-related deaths and injuries by 2030.

*Corresponding author: Piotr Gorzelańczyk, Transport Department, Stanislaw Staszic State University of Applied Sciences in Pila, Poland. Email: piotr.gorzelanczyk@ans.pila.pl

Figure 1
Accidents that occurred on Polish roads between 1990 and 2023



2. Literature Review

The scope of a traffic collision is a consideration in determining its seriousness. It is essential for relevant authorities to foresee the severity of an accident in order to prevent accidents, fatalities, and property losses and reduce injuries [4, 5]. It is crucial to determine the fundamental factors that affect accident severity before creating countermeasures to prevent and minimize it [6]. Yang et al. [7] present a multi-node Deep Neutral Network Framework for forecasting different levels of damage, fatalities, and property loss.

This enables precise and in-depth analysis of the severity of road accidents.

Accident data are gathered from a variety of sources. They are regularly gathered and assessed by government representatives by means of relevant government organizations. Data are gathered via hospital records, insurance databases, and police reports. The transportation sector is thereafter processing incomplete data on traffic accidents on a larger scale [8].

Intelligent transportation systems are currently the most important information source for the analysis and prediction of traffic incidents. This information can be processed using GPS units that are installed in vehicles [9]. Roadside microwave vehicle detection systems, according to Khaliq et al. [10], have the ability to continuously capture data on vehicles, such as speed, volume of traffic, and vehicle type. A vehicle license plate recognition system can also collect a lot of traffic data over a predefined period of time [11]. Due to the inexperience of the reporters, social media may not be as accurate as other sources of information when it comes to traffic and accidents [12].

To ensure the accuracy of accident data, it is essential to work with a variety of data sources that must be carefully handled. Combining several data sources and diverse traffic accident data can increase the accuracy of study outcomes [13].

A statistical analysis was done by Vilaça et al. [14] to ascertain the severity of accidents and the relationships between drivers and other road users. The study's conclusion suggests enacting new transportation safety rules and raising the threshold for driving safety.

Bąk et al. [15] conducted a statistical investigation of road safety in a specific Polish region in order to pinpoint the causes of accidents. The study used multivariate statistical analysis to look at the safety of those who cause accidents.

The source of accident data utilized for analysis depends on the type of traffic problem being addressed. When statistical models are integrated with extra driving data obtained naturally or via intelligent transportation systems, both the accuracy of accident forecasts and the number of accidents are increased [16].

There are numerous methods for predicting the number of accidents in the literature. The most widely used methods for forecasting the number of accidents are time series methods [17, 18], but they have the disadvantage of frequently autocorrelating the residual component and the inability to assess the forecast's accuracy based on previous predictions [19]. Procházka et al.'s [20] multiple seasonality model and Sunny et al.'s [21] Holt-Winters exponential smoothing method were both used for forecasting. Exogenous variables cannot be included in the model, which is one of its disadvantages [22, 23].

For evaluating the number of fatalities [24], a vector autoregression model has also been employed to forecast the frequency of traffic accidents, in addition to the curve-fitting regression models of Al-Madahi [25] and Monedero et al. [24]. The drawback of this model is that it necessitates a substantial amount of observations of variables in order to precisely estimate their parameters [26]. These, in turn, only require simple linear relationships [27] and an order of autoregression (assumed the series is stationary already) [28].

Biswas et al. [29] used Random Forest regression to predict the frequency of traffic accidents. Smaller groups are preferable in this situation over larger ones [30], and the method and spike prediction are unstable [31]. Additionally, the data include collections of linked attributes that are just as significant as the original data. Chudy-Laskowska and Pisula [32] used an autoregressive quadratic trend model, a univariate periodic trend model, and an exponential equalization model for the presented forecasting task. A moving average model can also be used to anticipate the number of accidents; however, this approach suffers from poor prediction accuracy, data loss over time, disregard for trends, and seasonal effects.

Procházka et al. [20] used the GARMA technique, which limits the parameter space, to guarantee that the process remains stationary. For forecasting, stationary processes are often represented by the ARMA model, whereas non-stationary processes are typically represented by the ARIMA or SARIMA model [20, 21, 33, 34]. Although the models under consideration are highly versatile, this flexibility also has a disadvantage in that it requires more experience on the part of researchers to discover successful models than, for example, in regression analysis [35]. Another flaw in the ARIMA model is its linearity [22].

Chudy-Laskowska and Pisula [32] used an analysis of variance in their 2015 study to predict the incidence of traffic collisions. This method involves additional assumptions, particularly the assumption of sphericity, which might lead to inaccurate conclusions [8].

The use of artificial neural network (ANN) models for traffic crash prediction has disadvantages, according to Chudy-Laskowska and Pisula [32], including the need for prior expertise in the subject and the dependence of the solution on the network's initial conditions. According to StatSoft Data Mining Techniques [36], the ANN model is referred to as a "black box" because the user provides the input and the model produces it without knowing how to analyze it. There are no restrictions on interpretability as a result.

Another prediction method is the Hadoop model by Kumar et al. [37]. This method has the limitation that small data files cannot be employed [38].

Karlaftis and Vlahogianni [34] used the Garch model to generate predictions. The complex model and form of this method are its weaknesses [39, 40]. Contrarily, Mcilroy and his associates employed the Augmented Dickey–Fuller test, which has the disadvantage of having low power for the autocorrelation of the random component [41].

The drawback of utilizing data mining to predict the frequency of accidents is the frequently enormous size of general description sets [42]. These methods have also been employed by authors of publications [43, 44]. The combination of models proposed by Sebego et al. [45] can alternatively be seen as a combination of numerous models. The idea of parametric models was previously presented in Bloomfield's work [46].

According to the current literature analysis, even though many academics have considered the problem of predicting the frequency of traffic accidents, none of them have optimized the forecasting methodologies listed above. Therefore, this will be the main subject of the inquiry, which is discussed in the following sections.

3. A Model of Multi-criteria Optimization

It is difficult to construct a single scalar quality function F when defining an optimization assignment because the acceptable solutions X may include a large range of characteristics whose values indicate the quality of the solution. This calls for the development of an optimization task (ZO) with multiple (e.g., N) quality indicators in the form of a criterion function F [47–50]:

$$F : X \rightarrow RN \tag{1}$$

This function returns the numerical evaluation of each valid response $x \in X$ as a vector:

$$F(x) = (F_1(x), \ldots, F_n(x), \ldots, F_N(x)) \in R^N \tag{2}$$

where

$N = \{1, \ldots, i, \ldots, n\}$ – collecting data for quality indicators,

$Fn\ (x)$ – the n-th quality indicator's value or the n-th criterion function for the $x \in X$ solution.

The following is the formulation of the problem's solution in finding the best course of action, denoting

A – the range of possibilities
B – the range of solution assessments

F: A ⇒ B: a particular subset ***X*** (the set of acceptable solutions) can be chosen using a criterion function, which assigns to each answer **X** ⊂ ***A*** its grade ***Z*** ∈ ***B*** and assumes that the set of possible solutions ***A*** is not empty, in order to

$$Z = F(X) = \{F(x) \in B \,|\, x \in X\} \tag{3}$$

Following the determination of the set ***X***, the mapping function ***F***, and the dominance relation ***Φ***, the optimization task (***ZO***) is formulated as follows:

$$ZO = (X, F, \Phi) \tag{4}$$

where

X = *{ x1, . . . ,xn }* – a list of possible fixes
F – criteria function for choosing potential answers $\boldsymbol{F: X \Rightarrow R^N}$

$$F(X) = (f_1(X), f_2(X),), \ldots, f_n(x), \ldots, f_N(x)) \tag{5}$$

where MAX has a preference in the dominating relationship ***Φ***:

$$\Phi = \{ (c_1, c_2, \ldots, c_n, \ldots, c_N) \in C\,x\,C : c_1^1 \geq c_2^1 \wedge c_1^2 \geq c_2^2 \} \tag{6}$$

where:

C – image of the set X when mapped F,
c_1, c_2 – points of space C:

$$C = F(X) = \{(f_1(x), f_{1,2}(x)) \in R^2 : x \in X\} \tag{7}$$

With the aforementioned information in mind, a method for finishing a multi-criteria optimization task is provided. Consider the optimization problem of locating potential solutions, for instance:

$$(X_1, F_1, \Phi_1) \tag{8}$$

where

X_1 – a collection of suitable responses that could be described as

$$X_1 = \{x_{1,1}, x_{1,2}, x_{1,3}, x_{1,4}\} \tag{9}$$

F_1 – a certain quality indication, such as $F_{1:}\ X_1 \Rightarrow R^2$

$$F_1(X_1) = (f_{1,1}(x), f_{1,2}(x)) \tag{10}$$

Φ1 – connection of preference dominance, for example, MAX, MAX.

Two tasks must be accomplished as a result:

1) Maximize the function

$$f_{1,1}(x) = e_j(x),\ x \in X_1;\ j = 1, \ldots, n \tag{11}$$

2) Maximize the function

$$f_{1,2}(x) = r_j(x),\ x \in X_1;\ j = 1, \ldots, n \tag{12}$$

Decide on the sets of X_1^1 and X_1^2 after that

$$X_1^1 = \{x^* \in X_1 : e_j(x^*) = max\, e_j(x)\}\ for\ x \in X_1 \tag{13}$$

$$X_1^2 = \{x^* \in X_1 : r_j(x^*) = max\, r_j(x)\}\ for\ x \in X_1 \tag{14}$$

According to the aforementioned comments, the maximum values of the Equations (13) and (14) determine the coordinates of the ideal point $c^* = (c_1^*, c_2^*)$:

$$c_1^* = max\, e_j(x);\ c_2^* = max\, r_j(x) \tag{15}$$

From the adopted form of the criterion function $F1 = \{f_{1,1}, f_{1,2}\}$, it follows that for c^*, the maximum value of e_j is demanded and the maximum value of k_j is demanded.

It follows that for c^*, the maximum value of e_j and the maximum value of k_j are demanded from the accepted form of the criteria function $F1 = \{f_{1,1}, f_{1,2}\}$.

The following definition of the normalized index of the quality of the task's solution is utilized in further considerations [51]:

$$F_1^*(x) = \{f_{1,1}^*(x), f_{1,2}^*(x)\} \tag{16}$$

where

$$f_{1,1}^*(x) = \frac{f_{1,1}(x)}{c_1^{max}},\ f_{1,2}^*(x) = \frac{f_{1,2}(x)}{c_2^{max}} \tag{17}$$

whereby

$$c_1^{max} = max\, f_{1,1}(x),\ c_2^{max} = max\, f_{1,2}(x) \tag{18}$$

This normalization method has the advantage of maintaining the ratio after normalization. The greatest value of the ratio is 1, and its minimum value is greater than or equal to 0. The normalized ideal point then assumes the form:

$$c^{**} = (c_1^{**}, c_2^{**}) \tag{19}$$

The approximate outcome of the compromise for the norm |•| is then determined using a method that is then proposed, which is a measure of the distance of the results $c^* \in C^*$ from the ideal point c^{**} [52]. The ideal point identified by Equation (19) is then denoted by c^{**} and the known set of normalized outcomes is denoted by C^*:

$$C^* = \{c^{*i}\},\ i = 1, \ldots, n \tag{20}$$

where $c^{*i} = (c_1^{*i}, c_2^{*i})$, whereby

$$c_1^{*i} = \frac{c_1^i}{c_1^{max}};\ c_2^{*i} = \frac{c_2^i}{c_2^{max}} \tag{21}$$

Next, using the relationship as a guide, calculate the standard |•| error using the parameter $p = 2$.

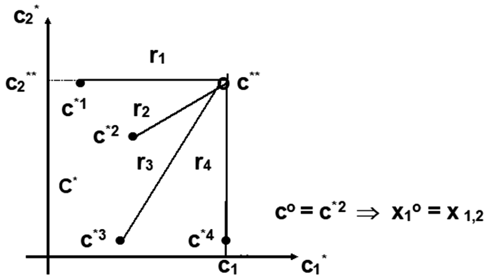
$$r_i = |c^{**} - c^{*i}|^2 = \sqrt{(c_1^{**} - c_1^{*i})^2 + (c_2^{**} - c_2^{*i})^2} \qquad (22)$$

and choosing a c^o result that would minimize the calculated r_i norm values, for example, $x_1^o = x_{1,2}$:

$$x_1^o = c^o = min\ r_i \qquad (23)$$

An explanation of the above technique is shown in Figure 2.

Figure 2
The conclusion of the optimization task



4. Improving Methods for Estimating How Many Accidents There Will Be on the Road

In the case of multi-criteria methodology for optimizing methods of estimating the frequency of traffic accidents based on the model presented above, numerous solutions to this problem are possible. Figure 3 shows one method for addressing the optimization problem of selecting the most effective methodology for forecasting the number of traffic accidents in Poland.

The following options are chosen as an acceptable set $\boldsymbol{X}$ based on research [51–53]:

$$\mathrm{X} = \{\mathrm{X}_2\} \qquad (24)$$

where

$X_2 = \{x2,1, \ldots, x2,n\}$ – is a collection of methods that have been tested for estimating the number of accidents on the road, l_{wd}:

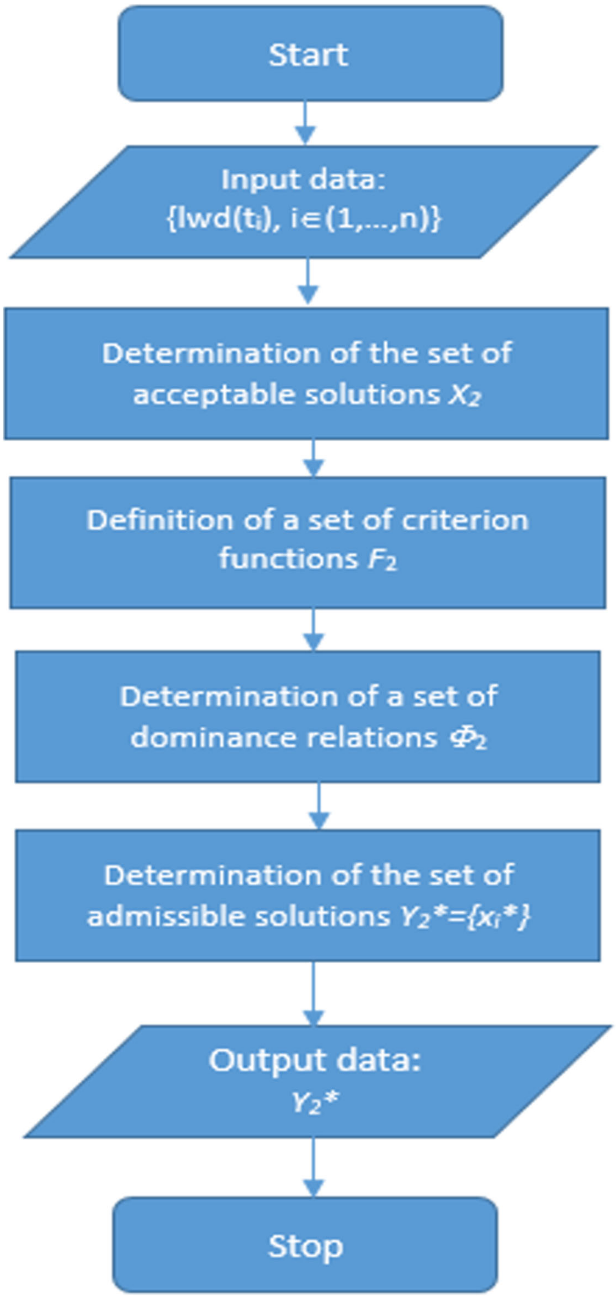
$$X_2 = \left(x_{2,1},\ x_{2,2},\ \ldots,\ x_{2,35}\right) \qquad (25)$$

where

• Adaptive methods:

1) $x_{2,1}$ – 2-point moving average method
2) $x_{2,2}$ – 3-point moving average method
3) $x_{2,3}$ – 4-point moving average method
4) $x_{2,4}$ – exponential smoothing no trend seasonal component: none
5) $x_{2,5}$ – exponential smoothing without trend seasonal component: additive
6) $x_{2,6}$ – exponential smoothing without trend seasonal component: multiplicative
7) $x_{2,7}$ – exponential smoothing of the seasonal component of the linear trend: none – HOLTA

Figure 3
Diagram for selecting the most accurate method of estimating the number of accidents on Polish roads



8) $x_{2,8}$ – exponential smoothing of the linear trend seasonal component: additive
9) $x_{2,9}$ – exponential smoothing of the linear trend seasonal component: multiplicative, WINTERSA
10) $x_{2,10}$ – exponential smoothing of the exponential seasonal component: none
11) $x_{2,11}$ – exponential smoothing exponential seasonal component: additive
12) $x_{2,12}$ – exponential smoothing exponential seasonal component: multiplicative
13) $x_{2,13}$ – exponential smoothing seasonal component of trend decay: none

14) $x_{2,14}$ – exponential smoothing of trend decay seasonal component: additive
15) $x_{2,15}$ – exponential smoothing component of seasonal trend decay: multiplicative

- Neural network methods:

1) $x_{2,16}$ – teaching sample size 70%, test 15%, and validation sample size 15%
2) $x_{2,17}$ – teaching sample size 80%, test 10%, and validation sample size 10%

- Regression methods:

1) $x_{2,18}$ – exponential trend model
2) $x_{2,19}$ – linear trend model
3) $x_{2,20}$ – logarithmic trend model
4) $x_{2,21}$ – trend model 2nd degree polynomial
5) $x_{2,22}$ – trend model 3rd degree polynomial
6) $x_{2,23}$ – trend model 4th degree polynomial
7) $x_{2,24}$ – trend model 5th degree polynomial
8) $x_{2,25}$ – trend model 6th degree polynomial
9) $x_{2,26}$ – trend model power

Based on the research by Bhandari et al. [52], it was agreed that the following would be the vector solution quality index $F2$ for the optimization of methods for forecasting the frequency of road accidents in Poland.

$$F_2 = \left(f_{2,1}, f_{2,2}\right) \tag{26}$$

where

$f_{2,1}$ – mean absolute percentage error – MAPE
$f_{2,2}$ – Theil's error

whereby

$$f_{2,1} = \frac{1}{K}\sum_{i=1}^{K}\frac{|lwd(t_i) - lwd(t_p)|}{lwd(t_i)} \tag{27}$$

$$f_{2,2} = \frac{\sum_{i=1}^{K}\left(lwd(t_i) - lwd(t_p)\right)^2}{\sum_{i=1}^{K} lwd(t_i)^2} \tag{28}$$

where

k – number of data
$l_{wd}(t_i)$ – number of accidents on the road throughout time t_i
$l_{wd}(t_p)$ – expired predictions

Based on the research by Gorzelanczyk et al. [53], a set of dominance relations Φ_2 for the F_2 function was also established.

$$\Phi_2 = \left\{\Phi_{2,1}, \Phi_{2,2}\right\} \tag{29}$$

where

$\Phi_{2,1}$ – connection of dominance at $f_{2,1}$ with preference for MIN
$\Phi_{2,2}$ – connection of dominance at $f_{2,2}$ with preference for MIN

Therefore, according to the optimization task ZO, the following method is the most effective for forecasting the quantity of traffic accidents in Poland:

$$ZO = \langle X_2, F_2, \phi_2 \rangle \tag{30}$$

The following algorithm is then used to implement the optimization task's (30) solution:

1) Normalize the criterion space D*, and then the collection of normalized outcomes D*

$$D^* = \{d^{*i}\},\ i = 1,\ldots,n \tag{31}$$

2) Calculating the ideal point's coordinates – d**:

$$d^{*i} = (d_1^{*i},\ d_2^{*i},\ d_3^{*i}),$$

$$d_1^{**} = min\, f_{1,1}^*(x),\ d_2^{**} = min\, f_{1,2}^*(x) \tag{32}$$

3) Calculating the standard |•| value using the parameter $p = 2 - ri$ (D*)

Table 1
$f_i \in F_2$ sub-criteria values and dominance relations $\Phi_i \in \Phi_j$ for one factor (good weather conditions)

	x1	*x2*	*x3*	*x4*	*x5*	*x6*	*x7*	*x8*	*x9*
f1	56.02	53.88	50.60	4.57	4.30	4.35	2.03	0.25	0.02
f2	0.30	0.34	0.38	0.01	0.01	0.01	0.00	0.00	0.00
	x10	***x11***	***x12***	***x13***	***x14***	***x15***	***x16***	***x17***	***x18***
f1	2.33	1.71	2.43	4.40	0.51	1.13	0.07	0.08	0.68
f2	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00
	x19	***x20***	***x21***	***x22***	***x23***	***x24***	***x25***	***x26***	***Φ***
f1	0.33	1.57	0.38	0.39	0.27	0.43	3.60	0.93	**MIN**
f2	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	**MIN**

Table 2
Visualization of the solution to the optimization task (values: *f1*, min *(f1)*, *d1, *d1***, *f2*, min *(f2)*, *d2**, *d2***) for one factor (good weather conditions)**

F/X	*f1*	*Min (f1)*	*d1**	*d1***	*f2*	*Min (f2)*	*d2**	*d2***
x1	56.02	0.02	0.00	0.00	0.30	0.00	0.01	56.02
x2	53.88		0.00		0.34		0.01	53.88
x3	50.60		0.00		0.38		0.00	50.60
x4	4.57		0.01		0.01		0.28	4.57
x5	4.30		0.01		0.01		0.33	4.30
x6	4.35		0.01		0.01		0.29	4.35
x7	2.03		0.01		0.00		0.42	2.03
x8	0.25		0.09		0.00		0.52	0.25
x9	0.02		1.00		0.00		0.50	0.02
x10	2.33		0.01		0.01		0.33	2.33
x11	1.71		0.01		0.00		0.42	1.71
x12	2.43		0.01		0.00		0.42	2.43
x13	4.40		0.01		0.01		0.28	4.40
x14	0.51		0.05		0.00		0.49	0.51
x15	1.13		0.02		0.00		0.37	1.13
x16	0.07		0.32		0.01		0.24	0.07
x17	0.08		0.30		0.01		0.22	0.08
x18	0.68		0.04		0.00		0.52	0.68
x19	0.33		0.07		0.00		0.72	0.33
x20	1.57		0.02		0.01		0.14	1.57
x21	0.38		0.06		0.00		0.66	0.38
x22	0.39		0.06		0.00		0.67	0.39
x23	0.27		0.09		0.00		0.90	0.27
x24	0.43		0.06		0.00		1.00	0.43
x25	3.60		0.01		0.00		0.50	3.60
x26	0.93		0.03		0.02		0.10	0.93

The distance $d^* \in D^*$ that results from the ideal point d^{**} is measured by norm |•|:

$$r_i(D^*) = |d^{**} - d^{*i}|^2$$

$$= \sqrt{(d_1^{**} - d_1^{*i})^2 + (d_2^{**} - d_2^{*i})^2 + (d_3^{**} - d_3^{*i})^2} \quad (33)$$

4) Find the x2o result that is best in an optimization task, for example, x2o = x2,2, if

$$x_2{}^o = x_{2,2} \; if \, d^o = min \, r_i \, ; because \, d^o = min \, r_3 \quad (34)$$

The best course of action would thus be to identify the technique for predicting the volume of traffic accidents in Poland for $xi \in X_2$ (in this instance, the $x_{2,2}$ method). In order to predict the frequency of traffic accidents in Poland, one approach, such as the 3-point moving average method $x_{2,2}$, must be chosen from the best set of one-element solutions.

5. An Illustration of Approach Optimization for Traffic Accident Frequency Forecasting in Poland

The multi-criteria optimization job was solved using a computer program called "multi-criteria optimization task" [53]:

1) Presentation of the group X_j and choice of the elements $x_i \in X_j$
2) Presentation of the set F_j and selection of the members $f_i \in F_j$ and the dominance relation $\Phi_i \in \Phi_j$ by the computer program's user in accordance with two possibilities:
   Option 1: manually enter data ($f_i \in F_j$ values)
   Option 2: calculate $f_i \in F_j$ values using information gathered from experimental or simulated studies
3) Visualization of the optimization task's resolution (calculation and presentation of calculation results – Tables 1–4)

Table 1 shows the values of criteria $f_i \in F_2$ and dominance relations $\Phi_i \in \Phi_j$ for one factor affecting the number of traffic accidents in good weather conditions. Table 2 shows the calculated values of $f_{2,1}$, min ($f_{2,1}$), $d1^*$, $d1^{**}$ and the values of ($f_{2,2}$), min ($f_{2,2}$), $d2^*$, $d2^{**}$ for one factor affecting the number of traffic accidents in good weather conditions. Tables 3 and 4 show the values of distance r_i for

Table 3
Visualization of the solution to the optimization task: Distance values r_i for forecasting methods $x_i \in X_j$, with different factors affecting the number of traffic accidents – Part 1

	x1	*x2*	*x3*	*x4*	*x5*	*x6*	*x7*	*x8*	*x9*	*x10*	*x11*	*x12*	*x13*
Good weather conditions	0.00	0.00	0.00	0.28	0.32	0.29	0.42	0.53	1.12	0.32	0.42	0.42	0.27
Fog. smoke	0.06	0.05	0.05	0.15	0.17	0.16	0.17	0.19	0.16	0.09	0.17	0.18	0.14
Rainfall	0.00	0.00	0.00	0.22	0.24	0.24	0.28	0.34	0.34	0.19	0.29	0.28	0.24
Snowfall. hail	0.01	0.01	0.00	0.19	0.34	0.34	0.25	0.38	0.39	0.09	0.37	0.37	0.13
Dazzling sunshine	0.01	0.00	0.00	0.27	0.36	0.35	0.27	0.35	0.32	0.21	0.35	0.34	0.27
Cloudy	0.00	0.00	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.08	0.09	0.08	0.10
Strong wind	0.01	0.01	0.01	0.02	0.02	0.02	0.05	0.02	0.03	0.02	0.02	0.02	0.02
Monday	0.00	0.00	0.00	0.07	0.08	0.08	0.11	0.11	0.11	0.09	0.09	0.10	0.07
Tuesday	0.00	0.00	0.00	0.37	0.36	0.38	0.52	0.52	0.54	0.37	0.46	0.47	0.46
Wednesday	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.01	0.01	0.00	0.00	0.00
Thursday	0.00	0.00	0.00	0.26	0.28	0.28	0.43	0.43	0.44	0.36	0.40	0.39	0.28
Friday	0.00	0.00	0.00	0.35	0.39	0.40	0.57	0.57	0.58	0.43	0.49	0.55	0.34
Saturday	0.00	0.00	0.00	0.31	0.33	0.33	0.45	0.53	0.52	0.30	0.41	0.41	0.31
Sunday	0.00	0.00	0.00	0.32	0.31	0.31	0.45	0.01	0.45	0.33	0.37	0.38	0.31
Lower Silesia	0.02	0.01	0.00	0.40	0.43	0.43	0.49	0.53	0.54	0.34	0.45	0.45	0.38
Kuyavian-Pomeranian	0.00	0.00	0.00	0.17	0.18	0.17	0.35	0.09	0.33	0.32	1.07	0.38	0.30
Lublin	0.00	0.00	0.00	0.34	0.31	0.28	0.50	0.49	0.47	0.26	0.44	0.42	0.34
Lubuskie	0.00	0.00	0.00	0.07	0.08	0.09	0.09	0.09	0.09	0.08	0.08	0.09	0.07
Łódź	0.00	0.00	0.00	0.37	0.39	0.39	0.41	0.44	0.44	0.39	0.42	0.42	0.34
Małopolskie	0.00	0.00	0.00	0.33	0.37	0.35	0.43	0.48	0.45	0.36	0.46	0.43	0.33
Mazowieckie	0.00	0.00	0.00	0.26	0.26	0.26	0.45	0.45	0.47	0.15	0.31	0.33	0.26
Opolskie	0.00	0.00	0.00	0.26	0.30	0.30	0.34	0.46	0.45	0.14	0.38	0.39	0.33
Podkarpackie	0.00	0.00	0.00	0.36	0.41	0.38	0.49	0.54	0.54	0.44	0.35	0.51	0.44
Podlaskie	0.00	0.00	0.00	0.46	0.46	0.45	0.51	0.52	0.52	0.50	0.73	0.71	0.42
Pomeranian	0.00	0.00	0.00	0.32	0.32	0.30	0.41	0.35	0.35	0.30	0.41	0.38	0.33
Silesia	0.00	0.00	0.00	0.06	0.06	0.06	0.09	0.10	0.10	0.07	0.08	0.07	0.06
Świętokrzyskie	0.00	0.00	0.00	0.16	0.17	0.18	0.25	0.26	0.30	0.21	0.26	0.27	0.18
Warminsko-Mazurskie	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Greater Poland	0.00	0.00	0.00	0.23	0.25	0.23	0.25	0.26	0.25	0.23	0.26	0.24	0.23
Zachodniopomorskie	0.00	0.00	0.00	0.23	0.25	0.23	0.39	0.46	0.43	0.28	0.36	0.35	0.22
Freeway	0.00	0.00	0.00	0.13	0.14	0.15	0.20	0.19	0.19	0.17	0.17	0.17	0.30
Expressway	0.00	0.00	0.00	0.07	0.07	0.07	0.12	0.18	0.18	0.14	0.18	0.20	0.09
With two one-way carriageways	0.00	0.02	0.80	0.15	0.21	0.20	0.16	0.24	0.24	0.14	0.16	0.14	0.16
Road – one-way	0.00	0.00	0.01	0.18	0.18	0.17	0.22	0.25	0.23	0.15	0.26	0.25	0.17
Road – two-way. single carriageway	0.03	0.01	0.02	0.02	0.08	0.06	0.02	0.03	0.10	0.02	0.06	0.06	0.02

forecasting methods $x_i \in X_j$, with different factors affecting the number of traffic accidents.

Using the results of calculating the values of distance ri, for forecasting methods $x_i \in X_j$, with various factors affecting the number of traffic accidents (Tables 3 and 4), we can formulate an answer to the question of which method of forecasting the number of traffic accidents $x_i \in X_j$ is the best according to the adopted criteria for the corresponding factor affecting the number of traffic accidents? Table 5 provides the answer to this question for the variables analyzed that affect the frequency of traffic accidents and the group of forecasting methods examined, X_j.

Table 4
Visualization of the solution to the optimization task: Distance values r_i for forecasting methods $x_i \in X_j$, with different factors affecting the number of traffic accidents – Part 2

	x14	*x15*	*x16*	*x17*	*x18*	*x19*	*x20*	*x21*	*x22*	*x23*	*x24*	*x25*	*x26*
Good weather conditions	0.49	0.37	0.40	0.37	0.52	0.72	0.14	0.66	0.66	0.90	1.00	0.49	0.10
Fog. smoke	0.17	0.21	1.12	1.30	0.56	0.60	0.38	0.50	0.51	0.52	0.52	0.00	0.29
Rainfall	0.19	0.21	1.14	1.27	0.58	0.59	0.35	0.39	0.40	0.41	0.45	0.41	0.25
Snowfall. hail	0.37	0.13	1.34	1.32	0.34	0.39	0.29	0.32	0.33	0.34	0.33	0.07	0.20
Dazzling sunshine	0.35	0.30	0.88	1.03	0.09	0.06	0.08	0.48	0.85	0.96	0.44	0.19	0.25
Cloudy	0.09	0.08	1.04	1.17	0.05	0.05	0.03	0.16	0.16	0.16	0.22	0.05	0.05
Strong wind	0.02	0.02	1.02	1.15	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.00	0.02
Monday	0.09	0.08	1.00	1.03	0.12	0.17	0.03	0.14	0.15	0.16	0.21	0.01	0.03
Tuesday	0.32	0.33	0.90	1.01	0.60	0.80	0.13	0.81	0.81	0.98	1.00	0.65	0.12
Wednesday	0.00	0.00	1.00	1.00	0.02	0.01	0.00	0.01	0.01	0.02	0.01	0.00	0.00
Thursday	0.28	0.28	1.00	1.13	0.25	0.53	0.07	0.57	0.59	0.71	1.22	0.16	0.07
Friday	0.45	0.45	1.08	1.16	0.57	1.00	0.09	0.72	0.72	0.87	0.93	0.14	0.08
Saturday	0.32	0.32	1.05	1.07	0.55	0.84	0.13	0.69	0.71	0.84	1.01	0.82	0.10
Sunday	0.30	0.31	1.04	0.99	0.27	0.67	0.09	0.55	0.59	0.78	0.94	1.00	0.08
Lower Silesia	0.41	0.39	1.19	1.09	0.80	0.98	0.34	0.76	0.82	0.88	0.84	0.14	0.28
Kuyavian-Pomeranian	0.34	0.30	0.61	0.83	0.59	0.83	0.07	0.44	0.65	1.01	0.36	0.09	0.02
Lublin	0.32	0.28	1.17	1.27	0.55	0.91	0.15	0.78	0.90	0.96	1.00	0.00	0.07
Lubuskie	0.09	0.09	1.01	1.06	0.05	0.05	0.03	0.10	0.13	0.13	0.11	0.00	0.03
Łódź	0.35	0.36	1.07	1.06	0.14	0.17	0.07	0.51	0.59	0.86	0.99	0.00	0.11
Małopolskie	0.35	0.33	0.46	1.00	0.44	0.29	0.09	0.51	0.90	1.01	0.90	0.02	0.12
Mazowieckie	0.23	0.24	1.36	1.34	0.41	0.33	0.24	0.42	0.41	0.41	0.24	0.13	0.13
Opolskie	0.31	0.36	0.55	1.02	1.04	0.30	0.12	0.49	0.49	0.64	0.73	0.00	0.12
Podkarpackie	0.40	0.49	0.75	1.03	0.54	0.35	0.09	0.91	0.96	1.02	0.99	0.54	0.12
Podlaskie	0.62	0.61	1.14	1.13	0.82	0.93	0.18	0.76	0.76	1.00	0.54	0.00	0.09
Pomeranian	0.32	0.29	1.08	1.28	0.45	0.39	0.17	0.42	0.93	0.99	0.92	1.03	0.23
Silesia	0.06	0.05	1.02	1.11	0.03	0.05	0.01	0.29	0.23	0.29	0.27	0.03	0.01
Świętokrzyskie	0.17	0.19	1.04	1.11	0.13	0.31	0.04	0.30	0.31	0.79	0.47	0.00	0.03
Warminsko-Mazurskie	0.01	0.00	1.00	1.02	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00
Greater Poland	0.25	0.21	1.01	1.05	0.16	0.14	0.15	0.21	0.23	0.29	0.62	0.07	0.13
Zachodniopomorskie	0.35	0.23	0.82	1.01	0.68	1.01	0.13	0.62	0.63	0.67	0.57	0.00	0.11
Freeway	0.13	0.15	0.82	1.01	0.21	0.20	0.07	0.20	0.47	0.48	0.88	1.00	0.10
Expressway	0.08	0.09	1.01	1.01	0.29	0.12	0.02	0.50	0.59	0.62	0.77	1.02	0.03
With two one-way carriageways	0.20	0.19	1.14	1.12	0.24	0.22	0.25	0.27	0.31	0.40	0.43	1.38	0.28
Road – one-way	0.17	0.15	0.46	0.65	0.38	0.34	0.18	0.37	0.39	0.52	0.60	1.40	0.22
Road – two-way. single carriageway	0.57	0.15	1.03	1.03	0.08	0.04	0.04	0.05	0.06	0.17	0.20	0.75	0.10

Table 5
Optimal forecasting methods

The 4-point moving average method:	Weather conditions: good weather conditions, fog, smoke, blinding sun, cloudy
	Days of the week: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
	Voivodeship: Lower Silesian, Kuyavian-Pomeranian, Lublin, Lodz, Lesser Poland, Mazovian, Subcarpathian, Podlasie, Pomeranian, Silesian, Warmian-Masurian, West Pomeranian
6-degree polynomial trend model	Weather conditions: rainfall, strong wind Province: Lubuskie, Opolskie, Swietokrzyskie
2-point moving average method	Province: Greater Poland Road type: highway, expressway, two one-way roadways
3-point moving average method	Weather conditions: snowfall, hail Type of road: road – one-way, two-way, single carriageway

6. Conclusion

Based on the study, it can be concluded that for forecasting the number of traffic accidents for the analyzed conditions under which a traffic accident may occur, the most optimal method becomes the 4-point moving average method. For accident forecasting, good results are also obtained by using the following methods: 6-degree polynomial trend model, 2-point moving average method, and 3-point moving average method.

Additionally, we can draw the conclusion that the above methodology can be used to optimize methods for forecasting road accidents in Poland based on the methodology presented above for the use of multi-criteria optimization procedures using a multi-criteria optimization model (a set of forecasting methods X_j, sub-criteria of the criterion function F_2, and elements of the dominance relation Φ_2).

The primary benefit of the proposed methodology is its universality, which results from the possibility of applying its procedures in the following scenarios:

1) When the criterion function's elements are both quantitative and qualitative;
2) When a multi-element or single-element optimal set of solutions is required;
3) When a one-element optimal set of solutions is required for the synergy.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available 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; **Henryk Tylicki:** Conceptualization, Methodology, Formal analysis, Project administration.

References

[1] WHO. (2020). *Global status report on road safety 2020*. Retrieved from: https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023

[2] Eurostat Statistics. (n.d.). Retrieved from: https://ec.europa.eu/eurostat

[3] STATYSTYKA. (n.d.). *Police statistics*. Retrieved from: https://statystyka.policja.pl/

[4] Tambouratzis, T., Souliou, D., Chalikias, M., & Gregoriades, A. (2014). 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*, *4*(1), 31–42.

[5] Zhu, L., Lu, L., Zhang, W., Zhao, Y., & Song, M. (2019). Analysis of accident severity for curved roadways based on Bayesian networks. *Sustainability*, *11*(8), 2223.

[6] Arteaga, C., Paz, A., & Park, J. (2020). Injury severity on traffic crashes: A text mining with an interpretable machine-learning approach. *Safety Science*, *132*, 104988.

[7] Yang, Z., Zhang, W., & Feng, J. (2022). Predicting multiple types of traffic accident severity with explanations: A multi-task deep learning framework. *Safety Science*, *146*, 105522. https://doi.org/10.1016/j.ssci.2021.105522

[8] Gorzelańczyk, P., Pyszewska, D., Kalina, T., & Jurkovic, M. (2020). Analysis of road traffic safety in the Pila poviat. *Scientific Journal of Silesian University of Technology. Series Transport*, *107*, 33–52. https://doi.org/10.20858/sjsutst.2020.107.3

[9] Chen, C. (2017). Analysis and forecast of traffic accident big data. In *4th Annual International Conference on Information Technology and Applications*, *12*, 04029. https://doi.org/10.1051/itmconf/20171204029

[10] Khaliq, K. A., Chughtai, O., Shahwani, A., Qayyum, A., & Pannek, J. (2019). Road accidents detection, data collection and data analysis using V2X communication and edge/cloud computing. *Electronics*, *8*(8), 896. https://doi.org/10.3390/electronics8080896

[11] Rajput, H., Som, T., & Kar, S. (2015). An automated vehicle license plate recognition system. *Computer*, *48*(8), 56–61. https://doi.org/10.1109/MC.2015.244

[12] Zheng, Z., Wang, C., Wang, P., Xiong, Y., Zhang, F., & Lv, Y. (2018). Framework for fusing traffic information from social and physical transportation data. *PLoS ONE*, *13*(8), e0201531. https://doi.org/10.1371/journal.pone.0201531

[13] Abdullah, E., & Emam, A. (2015). Traffic accidents analyzer using big data. In *International Conference on Computational Science and Computational Intelligence*, 392–397. https://doi.org/10.1109/CSCI.2015.187

[14] Vilaça, M., Silva, N., & Coelho, M. C. (2017). Statistical analysis of the occurrence and severity of crashes involving vulnerable road users. *Transportation Research Procedia*, *27*, 1113–1120. https://doi.org/10.1016/j.trpro.2017.12.113

[15] Bąk, I., Cheba, K., & Szczecińska, B. (2019). The statistical analysis of road traffic in cities of Poland. *Transportation Research Procedia*, *39*, 14–23. https://doi.org/10.1016/j.trpro.2019.06.003

[16] Chand, A., Jayesh, S., & Bhasi, A. B. (2021). Road traffic accidents: An overview of data sources, analysis techniques and contributing factors. *Materials Today: Proceedings*, *47*, 5135–5141. https://doi.org/10.1016/j.matpr.2021.05.415

[17] Helgason, A. (2016). Fractional integration methods and short time series: Evidence from a simulation study. *Political Analysis*, *24*(1), 59–68.

[18] Lavrenz, S., Vlahogianni, E., Gkritza, K., & Ke, Y. (2018). Time series modeling in traffic safety research. *Accident Analysis & Prevention*, *117*, 368–380.

[19] Prognozowanie i Symulacje. (2022). *Prognozowanie na podstawie szeregów czasowych* [Forecasting based on time series]. Retrieved from: http://pis.rezolwenta.eu.org/Materialy/PiS-W-5.pdf

[20] Procházka, J., Flimmel, S., Čamaj, M., & Bašta, M. (2017). Modelling the number of road accidents. In *20th International Conference on Applications of Mathematics and Statistics in Economics*. https://doi.org/10.15611/amse.2017.20.29

[21] Sunny, C. M., Nthya, S., Sinshi, K. S., Vinodini, V. M. D., Lakshmi, A. K. G., Anjana, S., & Manojkumar, T. K. (2018). Forecasting of road accident in Kerala: A case study. In

International Conference on Data Science and Engineering, 1–5. https://doi.org/10.1109/ICDSE.2018.8527825

[22] Dudek, G. (2013). Forecasting time series with multiple seasonal cycles using neural networks with local learning. In *Artificial Intelligence and Soft Computing: 12th International Conference*, 52–63. https://doi.org/10.1007/978-3-642-38658-9_5

[23] Szmuksta-Zawadzka, M., & Zawadzki, J. (2009). Forecasting on the basis of Holt-Winters models for complete and incomplete data. *Research Papers of the Wrocław University of Economics, 38*.

[24] Monedero, B. D., Gil-Alana, L. A., & Martínez, M. C. V. (2021). Road accidents in Spain: Are they persistent? *IATSS Research*, *45*(3), 317–325. https://doi.org/10.1016/j.iatssr.2021.01.002

[25] Al-Madahi, H. (2018). Global road fatality trends' estimations based on country-wise microlevel data. *Accident Analysis & Prevention*, *111*, 297–310. https://doi.org/10.1016/j.aap.2017.11.035

[26] Wójcik, A. (2014). Autoregressive vector models as a response to the critique of multi-equation structural econometric models. *Studia Ekonomiczne*, *193*, 112–128.

[27] Mamczur, M. (2020). *Jak działa regresja liniowa? I czy warto ją stosować* [How does linear regression work? And is it worth using?]. Retrieved from: https://miroslawmamczur.pl/jak-dziala-regresja-liniowa-i-czy-warto-ja-stosowac/

[28] Piłatowska, M. (2012). The choice of the order of autoregression depending on the parameters of the generating model. *Econometrics*, *4*(38), 16–35.

[29] Biswas, A. A., Mia, J., & Majumder, A. (2019). Forecasting the number of road accidents and casualties using random forest regression in the context of Bangladesh. In *10th International Conference on Computing, Communication and Networking Technologies*, 1–5. https://doi.org/10.1109/ICCCNT45670.2019.8944500

[30] IBM. (n.d.). *What is random forest?* Retrieved from: https://www.ibm.com/topics/random-forest

[31] Fijorek, K., Mróz, K., Niedziela, K., & Fijorek, D. (2010). Forecasting electricity prices on the day-ahead market using data mining methods. *Energy Market*.

[32] Chudy-Laskowska, K., & Pisula, T. (2015). Forecasting the number of road accidents in Podkarpacie. *Logistics*, *4*, 2782–2796.

[33] Dutta, B., Barman, M. P., & Patowary, A. N. (2020). Application of Arima model for forecasting road accident deaths in India. *International Journal of Agricultural and Statistical Sciences, 16*(2), 607–615.

[34] Karlaftis, M., & Vlahogianni, E. (2009). Memory properties and fractional integration in trans-portation time-series. *Transportation Research Part C: Emerging Technologies*, *17*(4), 444–453.

[35] Łobejko, S. (2015). *Time series analysis and forecasting with SAS*. Poland: Main Business School in Warsaw.

[36] StatSoft. (n.d.). *Data mining techniques*. Retrieved from: https://www.statsoft.pl/textbook/stathome_stat.html?https%3A%2F%2Fwww.statsoft.pl%2Ftextbook%2Fstdatmin.html

[37] Kumar, S., Viswanadham, V., & Bharathi, B. (2019). Analysis of road accident. *IOP Conference Series: Materials Science and Engineering*, *590*, 012029. https://doi.org/10.1088/1757-899X/590/1/012029

[38] DataFlair. (n.d.). *Top advantages and disadvantages of Hadoop 3*. Retrieved from: https://data-flair.training/blogs/advantages-and-disadvantages-of-hadoop/

[39] Perczak, G., & Fiszeder, P. (2014). GARCH model – Using additional information on minimum and maximum prices. *Bank and Credit, 45*(2), 105–132.

[40] Fiszeder, P. (2009). *GARCH class models in empirical financial research*. Poland: Scientific Publishers of the Nicolaus Copernicus University.

[41] Mcilroy, R. C., Plant, K. A., Hoque, M. S., Wu, J., Kokwaro, G. O., Nam, V. H., & Stanton, N. A. (2019). Who is responsible for global road safety? A cross-cultural comparison of actor maps. *Accident Analysis & Prevention*, *122*, 8–18. https://doi.org/10.1016/j.aap.2018.09.011

[42] Marcinkowska, J. (2015). *Metody statystyczne i eksploracji danych (data mining) w ocenie występowania omdleń w grupie częstoskurczu z wąskim zespołem QRS (AVNRT i AVRT)* [Statistical methods and data mining in assessing the occurrence of syncope in the group of narrow QRS tachycardia (AVNRT and AVRT)]. Retrieved from: http://www.wbc.poznan.pl/Content/373785/index.pdf

[43] Shetty, P., Sachin, P. C., Kashyap, V. K., & Madi, V. (2017). Analysis of road accidents using data mining techniques. *International Research Journal of Engineering and Technology, 4*(4), 1494–1496.

[44] Li, L., Shrestha, S., & Hu, G. (2017). Analysis of road traffic fatal accidents using data mining techniques. In *IEEE 15th International Conference on Software Engineering Research, Management and Applications*, 363–370. https://doi.org/10.1109/SERA.2017.7965753

[45] Sebego, M., Naumann, R. B., Rudd, R. A., Voetsch, K., Dellinger, A. M., & Ndlovu, C. (2014). The impact of alcohol and road traffic policies on crash rates in Botswana, 2004–2011: A time-series analysis. *Accident Analysis & Prevention*, *70*, 33–39. https://doi.org/10.1016/j.aap.2014.02.017

[46] Bloomfield, P. (1973). An exponential model in the spectrum of a scalar time series. *Biometrika*, *60*(2), 217–226.

[47] Ameljańczyk, A. (1986). *Multi-criteria optimization*. Poland: Military University of Technology Publishing.

[48] Tylicki, H. (2009). Optimization of the anthropotechnical system. In *Proceedings of the Materials of the XXXVII Winter School of Reliability*, 22–23.

[49] Tylicki, H., & Gorzelańczyk, P. (2013). The use of condition forecasting methods in the logistics of means of transport. *Logistics*, *1*, 2–6.

[50] Tylicki, H., & Gorzelańczyk, P. (2014). Automation of the process of monitoring the condition of means of transport. *Logistics*, *6*, 10766–10775.

[51] Jurasz, J. (2016). *Optimization of installed power in the solar-wind-pump system of energy sources*. Dissertation, AGH, Krakow. https://winntbg.bg.agh.edu.pl/rozprawy2/11091/full11091.pdf

[52] Bhandari, B., Kyung, T. L., Gil, Y. L., Young, M. C., & Sung, H. A. (2015). Optimization of hybrid renewable energy power systems: A review. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *2*(1), 99–112.

[53] Gorzelanczyk, P., Tylicki, H., Kalina, T., & Jurkovič, M. (2021). Optimizing the choice of means of transport using operational research. *Communications – Scientific Letters of the University of Zilina*, *23*(3), A193–A207. https://doi.org/10.26552/com.C.2021.3.A193-A207

How to Cite: Gorzelańczyk, P., & Tylicki, H. (2024). Optimization of Methods for Forecasting the Number of Road Accidents. *Archives of Advanced Engineering Science*, *2*(4), 206–214. https://doi.org/10.47852/bonviewAAES42022114