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by Piotr Gorzelanczyk and Henryk Tylicki

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Article

Optimization of Traffic Accident Quantity Estimation Method Synergy of Factors Affecting Traffic Accident Quantity with Raw Values

Piotr Gorzelanczyk * and **Henryk Tylicki**

Stanislaw Staszic State University of Applied Sciences in Pila, ul. Podchorazych 10, 64-920 Pila, Poland
* For correspondence: piotr.gorzelanczyk@ans.pila.pl

Abstract As the number of vehicles on the road increases, traffic accidents are becoming more destructive, causing loss of life and work. This is due to rapid population growth and the development of motorization. The most important challenge in estimating and studying information about street twists of fate is the small amount of facts available for this analysis. Although car accidents kill and injure millions of people around the world each year, they are rare in time and space. The motive of this article is to advise an effective approach to estimating the number of accidents on Poland's roads, based primarily on a combination of factors affecting such layered situations. The methodology presented in this paper for the use of multi-criteria optimization procedures using a multi-criteria optimization model (a set of forecasting methods, sub-criteria of the criterion function, and elements of the dominance relationship) allows us to conclude that the above methodology can be used to optimize methods for forecasting road accidents in Poland.

Keywords traffic accidents; the synergy of factors affecting the variety of traffic accidents; forecasting methods; multi-criteria optimization

1. Introduction

Road accidents are a social problem for all nations. The cause of avenue injuries depends on a number of elements, which include weather, state of intoxication, speed, and other factors. According to the World Health Corporation [1], more than 1.35 million people die annually in traffic accidents, and hundreds of thousands are critically injured and become disabled. Commuter injuries further motivate economic losses.

Road conditions have worsened over the years, and this is largely due to the COVID 2019 pandemic in recent years. However, traffic accidents are very serious (Figure 1), causing an average of 62 accidents, 6 fatalities, and 72 injuries per day. The aforementioned elements result in multiplied learning expenses, the need for vehicle and infrastructure maintenance, as well as negative environmental impacts (including oil and water runoff).

For this reason, a number of measures have been taken to prevent traffic injuries and reduce the incidence of traffic accidents. Such measures are the assessment of factors affecting the occurrence of injuries [2,3] and the technique of estimating the number of injuries on the road, taking into account the layer of conditions affecting incidents.

For most countries in the world, traffic accidents result in injury or loss of life, and road traffic injuries account for about three per cent of their GDP (gross domestic product). Road traffic injuries are the leading cause of death for adolescents and young adults aged 5–29 [1]. This makes it a problem that cannot be clearly solved.

The severity of a visitor's accident is a function that determines its severity. Estimating the severity of accidents is crucial for authorities to increase traffic safety regulations to postpone injuries and reduce loss of life and property [4,5].

Knowing the essential elements affecting severe injuries is a prerequisite for efforts to get rid of and reduce critical injuries [6]. According to Yang et al. [7], some of the DNN (deep neutral network) frameworks are designed to estimate the severity of accidents, fatalities, and property damage in different ranges. This allows for an in-depth and correct assessment of the severity of traffic accidents.

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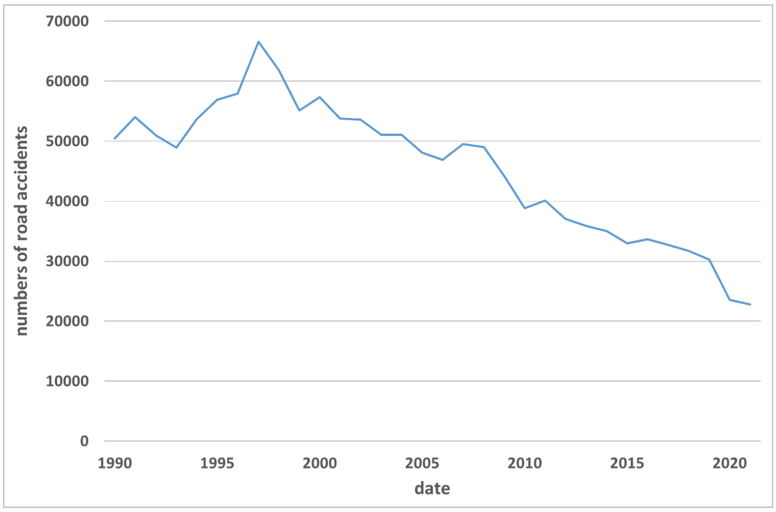

Figure 1. Variability of road accidents in Poland between 1990 and 2021 [3].

Information on incidents comes from many sources. They are usually recorded and analyzed according to the professional policies of major government groups. Later, a number of visitor accident statistics are processed to the site visitor center on a larger scale [8]. As such, this is currently the most relevant source of statistics for case evaluation and forecasting.

These facts can be obtained using a GPS device in the car [9]. Roadside microwave detection structures can continuously collect information about cars (speed, number of cars, car type, etc.) [10]. License plate recognition structures can also collect various facts about a car during inspections [11]. Social media can be any other source of traffic and accident data, but its accuracy may be insufficient due to the lack of newshound capabilities [12].

In order to ensure the accuracy of accident records, it is necessary to carry out the procedure of a huge variety of statistics that must be properly implemented. Integrating specific information by integrating the accident data of site visitors will increase the accuracy of analysis results [13].

Vilaca et al. [14] conducted an observation in which they analyzed violence and observed a high-quality relationship between accidents and street customers. This observation resulted in guidelines for improving safety standards in alleys and implementing other regulations related to transportation safety.

Bąk et al. [15] made an observation on the use of protection in decided regions of Poland based on the extent of automobile injuries, which is a proxy for determining the cause of the twist of fate layer. In this study, a series of statistical analyses were used to have insight into the protection of unprotected people from accidents.

The idea of the convergent information selected for evaluation comes from the form of the guest problem being solved. Combining the computational version with other driving force records or different facts from clever engines can increase the accuracy of accident prediction and aid injury removal [16].

Various methods for estimating the number of chances can be found in the literature. Vector autoregression models are used in [17], where their advantages and disadvantages are presented.

Biswas et al. [18] used random forest regression to estimate the number of vehicle crashes. In such cases, records contain ability clusters related to the validity of the original statistic, small agencies outperform huge companies [19], and there are inconsistencies in methods and standard estimates [20].

Chudy-Laskowska & Pisula [21] used an autoregressive version of the quadratic mod, a univariate version of the periodic trend, and an exponential equilibrium version to solve estimation problems. The moving average version can also be used to estimate the size of guest injuries, but the negative aspects are lower estimation accuracy, lack of a set of facts, and surprising distinctions and hazards. Procházka et al. [22] used the GARMA (generalized autoregressive moving average) approach, in which certain parameters are inside the parameter domain to guarantee the stability of the method. A version of ARMA (autoregressive moving average) for a stationary method or a version of ARIMA (autoregressive integrated moving average) or SARIMA (seasonal autoregressive integrated moving average) for a non-decibel system is commonly used for estimation [22–26]. The model in question has many variables, but this is also a disadvantage because analyzing a good version requires more knowledge from the researcher than regression analysis and various things [26].

Some other downside is the nature of the ARIMA version [27]. Chudy-Laskowska & Pisula used ANOVA (analysis of variance) in their observation to estimate the number of injuries to site visitors [21]. The disadvantage of this approach is that it results in additional assumptions that limit its applicability [8]. A neural network model for predicting the number of traffic accidents is covered in [21], while how to manipulate the data when there are no restrictions on interpretation is covered in [28].

Every other approach is a version of Hadoop by Kumar et al. [29]. The disadvantage of this method is that it cannot systematize small facts [30].

Karlaftis & Vlahogianni [25] used a version of Garch for prediction. The disadvantage of this technique is its complex form and complicated structure [31].

McIlroy and his group, on the other hand, used the Accimap checker [32], which suffers from the bias of non-uniform gadgets [33]. Course authors [34,35] have made extensive use of statistics mining strategies to estimate a wide range of car accidents, but the drawback is that the size of the overall description is regularly large [36]. The combination formula proposed by Sebego et al. [37] has also been discovered. It is based entirely on a mixture of different models. Parametric models were also advised in [38].

Based entirely on the evaluation of statistical data, it can be concluded that the problem of estimating a wide range of visitor injuries has been considered by many researchers, but currently, no one has paid attention to developing a way to optimize the estimation of the range of visitor accidents. Therefore, the above question may be the difficulty of this view, the content of which will be proposed in the next stage. The methodology presented below for the use of multi-criteria optimization procedures using a multi-criteria optimization model allows us to conclude that the above methodology can be used to optimize methods for forecasting road accidents in Poland.

2. Multi-criteria Optimization Model

When constructing an optimization design, it is difficult to define a scalar nice F characteristic due to the fact that the answer X will have many unique properties, the cost of which varies with the quality of the solution. Therefore, in this example, it is important to assemble an optimization challenge (ZO) with several (N) fine metrics inside the form of F-version characteristics [39–43]:

$$F: X \to R^N \tag{1}$$

This feature assigns each acceptable response $x \in X$ its numerical rating inside the form of an equation:

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

where:

$N = \{1, \dots, i, \dots, n\}$—collection of quality indicator numbers,

$F_n(x)$—the value of the n-th quality indicator (n-th criterion function for the solution $x \in X$).

After determining the set X, the mapping function F, and the dominance relation Φ, the optimization undertaking (ZO) is formulated in the form:

$$ZO = (X, F, \Phi) \tag{3}$$

where:

$X = \{x_1, \dots, x_n\}$—set of possible solutions;

F—criterion function for selecting feasible answers $F: X \Rightarrow R^N$.

$$F(X) = \big(f_1(X), f_2(X) \dots, f_n(X), \dots, f_N(X)\big) \tag{4}$$

Φ—Dominance relationship having a MAX or MIN preference.

Based entirely on the above, a technique for solving a multi-criteria optimization task is provided, for example, allowing to solve the optimization task of determining feasible answers:

$$(X_1, F_1, \Phi_1) \tag{5}$$

where:

X_1—the set of acceptable answers specified, for example, as:

$$X_1 = (x_{1,1}, x_{1,2}, x_{1,3}, x_{1,4}) \tag{6}$$

F_1—a quality indicator defined, for example, as $F_1 \colon X_1 \Rightarrow R^2$

$$F_1(X_1) = \left(f_{1,1}(x), f_{1,2}(x)\right) \tag{7}$$

Φ_1—dominance relationship of choice, e.g., MAX, MAX.

Therefore, two tasks must be solved:

a) maximize function:

$$f_{1,1}(x) = e_j(x), x \in X_1, j = 1, \dots, n \tag{8}$$

b) maximize function:

$$f_{1,2}(x) = r_j(x), x \in X_1, j = 1, \dots, n \tag{9}$$

According to the above remarks, the largest value of the feature (8) and the maximum value of the feature (9) determine the coordinates of the corresponding coefficient $c^* = (c_1^*, c_2^*)$:

$$c_1^* = \max e_j(x); c_2^* = \max r_j(x) \tag{10}$$

From the followed form of the criterion function $F_1 = \{f_{1,1}, f_{1,2}\}$ it follows that for c^* the maximum value of e_j is demanded and the maximum value of r_j is demanded.

In further consideration, the normalized tremor index of the venture solution (3,4) is used, which is proposed as:

$$F_1^*(x) = \{f_{1,1}^*(x), f_{1,2}^*(x)\} \tag{11}$$

where:

$$f_{1,1}^*(x) = \frac{f_{1,1}(x)}{c_1^{\max}}, f_{1,2}^*(x) = \frac{f_{1,2}(x)}{c_2^{\max}} \tag{12}$$

whereby:

$$c_1^{\max} = \max f_{1,1}(x), f_{1,1}(x) = \max f_{1,2}(x) \tag{13}$$

The advantage of this normalization technique is that the ratio is preserved after normalization. The highest price of the ratio is 1, and the lowest is additional than or equal to zero. The normalized best point then has the form:

$$c^{**} = (c_1^{**}, c_2^{**}) \tag{14}$$

In the next step, a way is proposed to determine the approximate end result (and therefore the solution) of the trade-off for the norms $|\cdot|$, which is a measure of the distance of the results $c^* \in C^*$ from the ideal point c^{**} [5,44]. Then c^{**} denotes the ideal point determined by relation (14) and C^* an established set of standard effects:

$$C^* = \{c^{*i}\} \text{ for } i = 1, \dots, n \tag{15}$$

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

$$c_1^{*i} = \frac{c_1^i}{c_1^{\max}}, c_2^{*i} = \frac{c_2^i}{c_2^{\max}} \tag{16}$$

Then calculating the value of the norms $|\cdot|$ with the parameter $p = 2$ according to the relationship:

$$r_i = |c^{**} - c^{*i}|^2 = \sqrt{(c_1^{**} - c_1^{*i})^2 + (c_2^{**} - c_2^{*i})^2} \tag{17}$$

and deciding this type of result c^o, which can reduce the calculated values of r_i norms, e.g., ${x_1}^o = x_{1,2}$:

$${x_1}^o = c^o = \min r_i \tag{18}$$

The interpretation of the above method is shown in Discernment 2.

Figure 2 shows the corresponding designations:
$c^{**} = ({c_1}^{**}, {c_2}^{**})$—The ideal point of the solution of the optimization task with coordinates,
$C^* = \{c^{*i}\}, i = 1, \dots, n$—The set of normalized results of an optimization task,
$r_i = |c^{**} - c^{*i}|^2 = \sqrt{({c_1}^{**} - {c_1}^{*i})^2 + ({c_2}^{**} - {c_2}^{*i})^2}$—values of the standard,
${x_1}^o = c^o = min r_i$—optimal solution ${x_1}^o = {x_{1,2}}^o$.

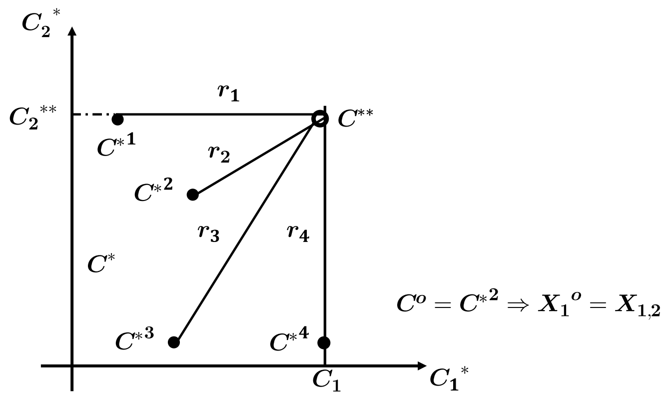

Figure 2. Graphic interpretation of the response to the optimization task.

3. Optimization of Methods for Forecasting the Number of Traffic Accidents Depending on the Factors Affecting the Number of Accidents

Adopting the definition of the synergy of factors affecting the range of visitor injuries, as the interaction of various factors whose impact (the variety of visitor injuries) is greater or less than the sum of the nature of the separate movements of these elements, it is pleasantly accessible to believe that the unique combinations of these elements and their synergy will affect the choice of the best forecasting technique.

Based totally on the multi-criteria optimization version supplied above, a method is proposed for forecasting the number of visitor injuries in terms of the synergy of things affecting the variety of injuries. One of the ways to resolve this problem is the set of rules proven within the diagram below (Figure 3), wherein both the technique for solving the optimization task [42] and the attention to the effect of the synergy of things affecting the quantity of traffic injuries are taken under consideration.

A set of admissible solutions X, based on research [44,45], is taken:

$$X = \{X_2\} \tag{19}$$

where $X_2 = \{x_{2,1}, \dots, x_{2,n}\}$ is the set of forecasting methods analyzed l_{wd}.
In this case, we consider 26 forecasting methods.

$$X_2 = \{x_{2,1}, x_{2,2}, \dots, x_{2,26}\} \tag{20}$$

where:
1. Adaptive methods:
   a) $x_{2,1}$—2-point moving average method;
   b) $x_{2,2}$—3-point moving average method;
   c) $x_{2,3}$—4-point moving average method;
   d) $x_{2,4}$—Exponential smoothing no trend seasonal component: none;
   e) $x_{2,5}$—Exponential smoothing without trend seasonal component: additive;
   f) $x_{2,6}$—Exponential smoothing without trend seasonal component: multiplicative;
   g) $x_{2,7}$—Exponential smoothing of the seasonal component of the linear trend: none—HOLTA;
   h) $x_{2,8}$—Exponential smoothing of the linear trend seasonal component: additive;
   i) $x_{2,9}$—Exponential smoothing of the linear trend seasonal component: multiplicative—WINTERSA;
   j) $x_{2,10}$—Exponential smoothing of the exponential seasonal component: none;
   k) $x_{2,11}$—Exponential smoothing exponential seasonal component: additive;

l) $x_{2,12}$—Exponential smoothing exponential seasonal component: multiplicative;
m) $x_{2,13}$—Exponential smoothing seasonal component of trend decay: none;
n) $x_{2,14}$—Exponential smoothing of trend decay seasonal component: additive;
o) $x_{2,15}$—Exponential smoothing component of seasonal trend decay: multiplicative.

2. Neural network methods:
   a) $x_{2,16}$—teaching sample size 70%, test 15%, and validation sample size 15%;
   b) $x_{2,17}$—teaching sample size 80%, test 10% and validation sample size 10%.

3. Regression methods:
   a) $x_{2,18}$—exponential trend model;
   b) $x_{2,19}$—linear trend model;
   c) $x_{2,20}$—logarithmic trend model;
   d) $x_{2,21}$—trend model 2nd degree polynomial;
   e) $x_{2,22}$—trend model 3rd degree polynomial;
   f) $x_{2,23}$—trend model 4th degree polynomial;
   g) $x_{2,24}$—trend model 5th degree polynomial;
   h) $x_{2,25}$—trend model 6th degree polynomial;
   i) $x_{2,26}$—trend model power.

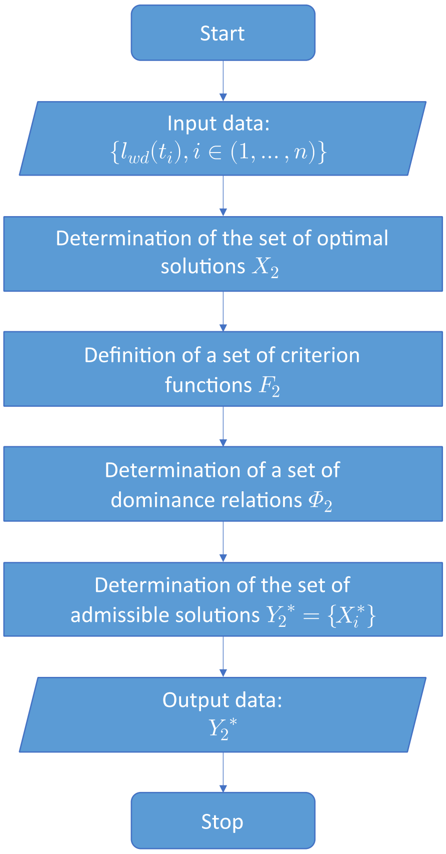

Figure 3. Multi-criteria optimization scheme for determining the most compliant method for predicting the variety of road accidents in Poland for different combinations of factors affecting the extent of road injuries.

Based on [45], a set of factors affecting the number of traffic accidents Y is taken as a set of factors:

$$Y = \{Y_1\} \tag{21}$$

where $Y_1 = \{y_{1,1}, \ldots, y_{1,n}\}$ is a set of components affecting the number of traffic accidents l_{wd},

$$Y_2 = (y_{1,1}, y_{1,2}, \ldots, x_{1,n}) \tag{22}$$

whereby:

1. Factors—weather conditions:
   a. $y_{1,1}$—good weather conditions;
   b. $y_{1,2}$—fog, smoke;
   c. $x_{1,3}$—rainfall;
   d. $y_{1,4}$—snowfall, hail;
   e. $y_{1,5}$—blinding sun;
   f. $y_{1,6}$—cloudy;
   g. $y_{1,7}$—strong wind.

2. Factors—day of the week:
   h. $y_{1,8}$—Monday;
   i. $y_{1,9}$—Tuesday;
   j. $y_{1,10}$—Wednesday;
   k. $y_{1,11}$—Thursday;
   l. $y_{1,12}$—Friday;
   m. $y_{1,13}$—Saturday;
   n. $y_{1,14}$—Sunday.

3. Factors—province:
   o. $y_{1,15}$—Lower Silesia;
   p. $x_{1,16}$—Kuyavian-Pomeranian;
   q. $x_{1,17}$—Lublin;
   r. $x_{1,18}$—Lubuskie;
   s. $x_{1,19}$—Lodzkie;
   t. $x_{1,20}$—Małopolskie;
   u. $x_{1,21}$—Mazowieckie;
   v. $x_{1,22}$—Opolskie;
   w. $x_{1,23}$—Subcarpathian;
   x. $x_{1,24}$—Podlaskie;
   y. $x_{1,25}$—Pomeranian;
   z. $x_{1,26}$—Silesian;
   aa. $x_{1,27}$—Swietokrzyskie;
   bb. $x_{1,28}$—Warmian-Masurian;
   cc. $x_{1,29}$—Greater Poland;
   dd. $x_{1,30}$—West Pomeranian.

4. Factors—type of road:
   ee. $x_{1,31}$—highway;
   ff. $x_{1,32}$—expressway;
   gg. $x_{1,33}$—with two one-way carriageways;
   hh. $x_{1,34}$—road—one-way;
   ii. $x_{1,35}$—road—two-way, single carriageway.

Based on [42,43], the vector solution quality index F_2 for optimization of methods for forecasting the number of traffic accidents in Poland for different combinations of factors affecting the number of accidents was determined as:

$$F_2 = F_2(X_2) = \big(f_{2,1}(X_2), f_{2,2}(X_2)\big) \tag{23}$$

and determine F_2 criterion functions, for optimizing the synergy of factors affecting the number of traffic accidents in Poland, for example, as [45]:

$$F_2 = (f_{2,1}, f_{2,2}) \tag{24}$$

where:

$f_{2,1}$—average absolute percentage error (MAPE), Equation (25),

$f_{2,2}$—Theil's error, Equation (26).

$$f_{2,1} = \frac{1}{K}\sum_{i=1}^{K}\frac{|l_{wd}(t_i) - l_{wd}(t_p)|}{l_{wd}(t_i)} \tag{25}$$

$$f_{2,2} = \frac{\sum_{i=1}^{K}(l_{wd}(t_i) - l_{wd}(t_p))^2}{\sum_{i=1}^{K} l_{wd}(t_i)^2} \tag{26}$$

where:

k—testing period,

$l_{wd}(t_i)$—number of traffic accidents over time t_i,

$l_{wd}(t_p)$—expired forecasts.

A set of dominance relations Φ_2 for the F_2 function was also determined based on [42,45].

Φ_2—relation of the dominance of possible forecasting methods:

$$\Phi_2 = \{\Phi_{2,1}, \Phi_{2,2}\} \tag{27}$$

where:

$\Phi_{2,1}$—dominance relationship at $f_{2,1}$ with preference MIN,

$\Phi_{2,2}$—dominance relationship at $f_{2,2}$ with preference MIN.

Then the solution to the optimization task of determining the optimal synergy of factors affecting the number of road accidents in Poland ZO takes the form:

$$ZO = \langle X_2, F_2, \Phi_2 \rangle \tag{28}$$

It is then implemented according to the following algorithm:

1. Normalization of the criterion space—space D^*.

The set of normalized results D^*:

$$D^* = \{d^{*i}\}, i = 1, \dots, n; d^{*i} = \left(d_1{}^{*i}, d_2{}^{*i}\right) \tag{29}$$

2. Determination of the coordinates of the ideal point—d^{**}

$$d_1{}^{**} = \min f_{1,1}{}^*(x); d_2{}^{**} = \min f_{1,2}{}^*(x) \text{ for } x \in X_1 \tag{30}$$

3. Calculation of the value of the norm $|\cdot|$ with parameter $p = 2 - r_i(D^*)$

Norm $|\cdot|$ is a measure of the distance of $d^* \in D^*$ results from the ideal point d^{**}:

$$r_j(D^*) = |d^{**} - d^{*i}| = \sqrt{\left(d_1{}^{**} - d_1{}^{*i}\right)^2 + \left(d_2{}^{**} - d_2{}^{*i}\right)^2} \tag{31}$$

4. Determination of the optimal result $x_2{}^o$ in an optimization task, for example, if $x_2{}^o = x_{2,2}$:

$$x_2{}^o = x_{2,2} \text{ if } d^o = \min r_i; \text{ because } d^o = \min r_1 \tag{32}$$

Then the solution to the optimization task, i.e., to determine the method of forecasting the number of road accidents in Poland for a selected combination of factors affecting the number of accidents, for $x_i \in X_2$ is the $x_{2,2}$ method, which means that the optimal set of one-element solutions is obtained (the choice of one method of forecasting the number of road accidents in Poland, such as the moving average 4-point $x_{2,2}$ method).

4. Example of Optimization of Methods for Forecasting the Number of Traffic Accidents Depending on the Factors Affecting the Number of Accidents

In order to solve the task of multi-criteria optimization, a computer program "Multi-Criteria Optimization Task 2017" was developed [42], which allows:

a) presentation of a set X_j and selection of elements $x_i \in X_j$;
b) presentation of the set F_j and selection, by the computer program operator, of the elements $f_i \in F_j$ and the dominance relation $\Phi_i \in \Phi_j$;
c) data entry according to two options: option 1—manual data entry $f_i \in F_j$ values), option 2—calculation of $f_i \in F_j$ values) based on data obtained during experimental or simulation studies.
d) visualization of the solution of the optimization project (calculation and reporting of the effects of the calculations—Tables 1 and 2).

Table 1 shows the values of the number of road accidents in Poland for some combinations of factors affecting the number of accidents in 2007–2121 [3].

Table 2 shows the values of the distance r_i for forecasting methods $x_i \in X_j$ for different combinations of factors affecting the number of traffic accidents.

Table 1. Number of road accidents in Poland for some combinations of factors affecting the number of accidents.

Year	Province: Lubuskie, Road type: with two one-way carriageways		Province: Wielkopolskie, Road type: autostrada		Province: Warmińsko-Mazurskie, Road type: Expressway	
	Weather conditions: good	Day of the week: Wednesday	Weather conditions: fog, smoke	Day of the week: Monday	Weather conditions: strong wind	Day of the week: Thursday
2007	843	205	16	94	0	2
2008	647	178	17	114	0	2
2009	628	197	17	85	0	3
2010	668	170	17	114	1	5
2011	648	158	25	84	1	7
2012	572	148	21	90	2	12
2013	645	143	14	93	2	28
2014	683	152	10	106	2	14
2015	742	187	11	94	2	19
2016	744	194	14	107	0	22
2017	686	196	12	148	1	27
2018	863	216	8	142	1	54
2019	1036	238	4	135	4	68
2020	817	214	7	81	4	61
2021	680	176	16	134	2	78

The presented results of calculating the values of distance r_i, for the methods of forecasting $x_i \in X_j$; are summarized with different combinations of factors affecting the number of traffic accidents (Table 2), these are:

a) Province: Lubuskie; Road type: with two one-way carriageways; Weather conditions: good; Day of the week: Wednesday.
b) Province: Wielkopolskie; Type of road: highway; Weather conditions: smoke fog; Day of the week: Monday.
c) Province: Warmian-Masurian; Road type: expressway; Weather conditions: strong wind; Weekday: Thursday.

The analysis of the calculation results allows to determine the optimal method of forecasting the number of traffic accidents for any combination of factors affecting the number of accidents, these are respectively:

a) for the combination of factors: Province: Lubuskie; Type of road: with two one-way carriageways, Weather conditions: good—$x_{2,1}$ (2-point moving average method),
b) for a combination of factors: Province: Lubuskie; Type of road: with two one-way carriageways; Day of the week: Wednesday—$x_{2,26}$ (power trend model),

c) for the combination of factors: Province: Greater Poland; Road type: highway; Weather conditions: smoke fog—$x_{2,1}$ (2-point moving average method),
d) for the combination of factors: Province: Wielkopolskie; Type of road: highway—$x_{2,25}$ (trend model polynomial of 6th degree),
e) for the combination of factors: Province: Warmińsko-Mazurskie; Type of road: expressway, Weather conditions: strong wind—$x_{2,1}$–$x_{2,26}$,
f) for the combination of factors: Province: Warmian-Masurian; Type of road: expressway, Day of the week: Thursday—$x_{2,11}$ (exponential smoothing exponential seasonal component: additive).

Table 2. Visualization of the solution to the optimization task: r_i distance values for $x_i \in X_2$ forecasting methods with different combinations of factors affecting the number of traffic accidents (minimum values are marked).

X_2	Province: Lubuskie Road type: with two one-way carriageways		Province: Wielkopolskie Road type: highway		Province: Warmińsko-Mazurskie Road type: Expressway	
	Weather conditions: good	Day of the week: Wednesday	Weather conditions: fog, smoke	Day of the week: Monday	Weather conditions: strong wind	Day of the week: Thursday
$x_{2,1}$	0.00×10^{0}	2.67×10^{-2}	2.7×10^{-10}	3.70×10^{-3}	0.00×10^{0}	3.47×10^{-6}
$x_{2,2}$	1.10×10^{-3}	2.76×10^{-2}	4.47×10^{-5}	8.88×10^{-3}	0.00×10^{0}	7.26×10^{-5}
$x_{2,3}$	1.89×10^{-2}	7.01×10^{-2}	4.97×10^{-4}	9.43×10^{-1}	0.00×10^{0}	2.13×10^{-4}
$x_{2,4}$	8.28×10^{-2}	4.94×10^{-2}	3.31×10^{-3}	1.12×10^{-2}	0.00×10^{0}	6.97×10^{-4}
$x_{2,5}$	5.28×10^{-2}	8.03×10^{-2}	3.28×10^{-3}	2.97×10^{-1}	0.00×10^{0}	4.04×10^{-4}
$x_{2,6}$	7.23×10^{-2}	7.41×10^{-2}	2.49×10^{-3}	9.15×10^{-2}	0.00×10^{0}	8.94×10^{-4}
$x_{2,7}$	4.86×10^{-2}	2.38×10^{-2}	3.51×10^{-3}	9.76×10^{-3}	0.00×10^{0}	5.52×10^{-4}
$x_{2,8}$	2.32×10^{-2}	4.80×10^{-2}	5.97×10^{-3}	2.37×10^{-2}	0.00×10^{0}	2.62×10^{-4}
$x_{2,9}$	2.26×10^{-2}	5.17×10^{-2}	4.00×10^{-3}	2.89×10^{-2}	0.00×10^{0}	8.40×10^{-4}
$x_{2,10}$	4.05×10^{-1}	4.14×10^{-2}	3.82×10^{-4}	4.20×10^{-3}	0.00×10^{0}	6.81×10^{-4}
$x_{2,11}$	1.09×10^{-2}	9.13×10^{-2}	3.68×10^{-4}	7.08×10^{-2}	0.00×10^{0}	3.46×10^{-7}
$x_{2,12}$	2.50×10^{-2}	1.00×10^{0}	2.03×10^{-3}	4.98×10^{-2}	0.00×10^{0}	4.95×10^{-4}
$x_{2,13}$	2.38×10^{-2}	6.88×10^{-2}	3.31×10^{-3}	5.86×10^{-2}	0.00×10^{0}	2.18×10^{-3}
$x_{2,14}$	5.24×10^{-2}	5.91×10^{-2}	9.01×10^{-3}	1.31×10^{-1}	0.00×10^{0}	6.71×10^{-4}
$x_{2,15}$	5.37×10^{-2}	5.68×10^{-2}	5.53×10^{-2}	3.41×10^{-1}	0.00×10^{0}	2.65×10^{-3}
$x_{2,16}$	8.58×10^{-1}	6.84×10^{-1}	3.76×10^{-1}	8.12×10^{-1}	0.00×10^{0}	7.44×10^{-2}
$x_{2,17}$	1.41×10^{0}	1.29×10^{0}	1.41×10^{0}	9.98×10^{-1}	0.00×10^{0}	1.41×10^{0}
$x_{2,18}$	6.96×10^{-2}	5.45×10^{-2}	3.86×10^{-3}	4.59×10^{-2}	0.00×10^{0}	4.65×10^{-3}
$x_{2,19}$	3.28×10^{-2}	4.70×10^{-2}	1.86×10^{-3}	2.27×10^{-2}	0.00×10^{0}	2.06×10^{-4}
$x_{2,20}$	2.77×10^{-2}	5.39×10^{-2}	1.49×10^{-3}	2.08×10^{-2}	0.00×10^{0}	3.80×10^{-4}
$x_{2,21}$	3.73×10^{-2}	5.17×10^{-2}	1.87×10^{-3}	2.29×10^{-2}	0.00×10^{0}	1.48×10^{-3}
$x_{2,22}$	8.16×10^{-2}	1.09×10^{-1}	3.22×10^{-3}	2.60×10^{-2}	0.00×10^{0}	2.33×10^{-3}
$x_{2,23}$	1.01×10^{-1}	3.72×10^{-1}	1.86×10^{-3}	2.29×10^{-2}	0.00×10^{0}	2.39×10^{-3}
$x_{2,24}$	7.73×10^{-1}	2.81×10^{-1}	3.38×10^{-4}	9.62×10^{-3}	0.00×10^{0}	4.22×10^{-2}
$x_{2,25}$	1.02×10^{-2}	1.94×10^{-3}	4.03×10^{-5}	0.00×10^{0}	0.00×10^{0}	8.39×10^{-4}
$x_{2,26}$	5.85×10^{-2}	0.00×10^{0}	3.09×10^{-3}	4.35×10^{-2}	0.00×10^{0}	2.51×10^{-3}

5. Conclusions

The methodology presented above for the use of multi-criteria optimization procedures using a multi-criteria optimization model and some elements of the ZO optimization task (sub-criteria of the F_2 criterion function and elements of the dominance relation Φ_2) for some combinations of factors affecting the number of traffic accidents allows us to conclude that the above methodology can be used to optimize methods of forecasting traffic accidents in Poland.

The main advantage of the presented methodology is its universality, which is due to the fact that it will probably be possible to apply the procedures of the presented methodology in the situation:

- when the elements of the criterion function will be quantitative and qualitative;
- when there will be a need to obtain a multi-element or single-element set of optimal solutions;
- when there will be a need to take into account different combinations of factors affecting the number of traffic accidents.

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Author Contributions

Methodology: P.G., & H.T.; Project administration: P.G., & H.T.; Resources: P.G.; Software: P.G.; Supervision: P.G.; Validation: P.G.; Visualization: P.G.; Writing – original draft: P.G.; Writing – review & editing: P.G.

Conflicts of Interest

The authors have no conflict of interest to declare.

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