

## Article

# Application of Forecasting as an Element of Effective Management in the Field of Improving Occupational Health and Safety in the Steel Industry in Poland

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**Abstract:** (1) Background: Every day, human beings fall victim to accidents. We implement solutions aimed at reducing accidents in everyday life, but we are not able to eliminate all accidents from our life. This article addresses the issue of forecasting accidents at work in the steel industry in Poland. Particular attention is paid to other accidents, given that those events are most often recorded in the sector under analysis. (2) Methods: The process of predicting quantitative data on the number of persons injured in other accidents in 2009–2018 employed Holt’s models: with an additive and multiplicative trend, with the trend smoothing effect in the multiplicative and additive formula. (3) Results: The forecasts prepared on the basis of Holt’s models and the combined model show a decreasing trend in the number of persons injured in other accidents in the steel sector, which is a positive development in the area of occupational safety and health. (4) Conclusions: The number of persons injured in other accidents at work in the steel sector shows a downward trend, which is significant and valid information for managers. The analysis of the results indicated that the combined forecast model best reflects the accidents at work in the steel industry.



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**Keywords:** occupational health and safety; accident at work; Holt’s model; combined model; steel sector in Poland

## 1. Introduction

Ensuring safety in the workplace is one of the basic duties of the organizers of the work process—employers. Employers should limit and eliminate all occupational hazards and nuisances related to the performed work that cause accidents at work and occupational diseases. The occurrence of accidental events in enterprises generates social and economic costs [1,2] to be borne by all entities, including those that cooperate with the enterprise. Anyone who performs work may potentially sustain a work-related injury [3]. It seems appropriate to clarify at the outset what events are classified as accidents at work. Under Polish law [4], an accident at work is a sudden event caused by an external factor arising from work performed that results in injury or death. All the above features of the accident must occur simultaneously for an event to be considered an accident at work. The definition of the accident varies across different countries. There is agreement as to the urgency of the event and the external cause. The differences relate to the further part of the definition regarding damage, injury, or loss [2,5].

The investigation of accidents at work is still a relevant issue examined by many researchers. It concerns, among others, safety in individual sectors of the economy important for the country, such as construction [6,7], mining [8,9], food industry [10], steel industry [11], and agriculture [12]. Researchers also show interest in the influence of external factors, such as the economic situation, e.g., recession [13], on the accident rate in enterprises. In the case of high unemployment, workers are more likely to be dismissed and, therefore, fewer accidents are reported [13]. The culture of work safety (safety climate) plays an important role in the creation of safe working conditions aimed at reducing the

number of accidents at work. Safety culture significantly affects the attitudes and behavior associated with increasing or reducing risk [14], and it has an impact on workers' attitudes and behavior related to the current safety performance of the enterprise [15,16]. It is therefore hugely important that all workers engage in activities aimed at improving safety, which may lead to a reduction in the number of accidents at work because safety culture also applies to the value system of all participants of the work process [17].

The investigation of the accident rate subject to analysis [1,11,18,19] is based on the determination of accident rates—so-called accident indices. The determined values of the indices make it possible to compare enterprises, industries, and countries in terms of the number of reported accidents at work. The so-called accident indices (frequency index and severity index) are used for the purposes of an evaluation of the accident rate. The determination of the values of accident indices under investigation is related to the analysis of historical data. The conducted investigation provides top management with valuable information to be used both for informative and motivating purposes. The provision of information to workers on the in-house accident rate and comparing it between departments (branches) may be one of the elements of developing safety awareness and building a culture of work safety [20]. However, the provided information is still of a historical nature. Given the above, this study presents the possibility of adaptation of the forecasts in the area of occupational safety and health—analysis of accident statistics. The obtained forecasts will give employers information on how their activities (carried out over a long period of time) in the area of occupational safety and health relate to the number of accidents at work. The forecast analyses will provide employers with information in the form of a numerical value on what number of accidents is forecast for the period under investigation. The information thus obtained may serve as a warning, prompting the employer to action in the event that an increase in accidents at work is indicated (numerical values of the produced forecasts), which is above all the basic function of forecasts [21–24].

The term prognosis is derived from the Greek prognosis and means making a prediction based on specific data [23]. Prognoses are built on the basis of experts' opinions or models that best describe, according to a "specific criterion", the issue under analysis. The prognostic model provides a more or less accurate reflection of the real subject to analysis. Depending on the type of prognosis, its purpose, and the nature of the forecast phenomenon, various forecasting methods are used in practice. Given the above, in order to analyze the use of forecasting methods, a review of bibliometric databases was made, namely: Web of Science, Scopus, Google Scholar. Keywords "forecasting models", "adaptation models", "Holt's model", "Winters' model", "ARIMA model", were entered in those databases. Prognostic models were applied to, *inter alia*, forecasting the processes of: steel production volume [25], Euro selling rate [26], exchange rates [27], economic cycles [28], revenue [29], sales of motorcycles [30], livestock and wheat prices [31], consumption of materials [32], forecasting of load in the electric industry [33], emission of organic water pollutants [34], telecommunication data [35], network anomaly detection [36], electric load [37], customer-credit evaluation [38], predicting lung cancer cases [39]. The bibliometric analysis, the type of the model, and its practical application are presented in Table 1. It does not list exhaustively all the possible applications of forecasting to the investigation of various phenomena.

The occurrence of accidents at work has a significant impact on the day-to-day operations of the enterprise, and consequently on its functioning. Understanding why accidents happen at work is the first step in preventing them. A favorable and competitive working environment may help the company in its day-to-day operations, as well as in achieving strategic goals [40]. This study, therefore, presents the possibility of adaptation of prognostic models in the area of accident rates as an option for planning and assessing the effectiveness of implemented preventive solutions aimed at improving work safety. The nationwide effectiveness of the implemented preventive solutions (technical, organizational) is assessed in the number of people injured in accidents at work, e.g., in the years for which forecasts have been made. Therefore, the designated forecasts may constitute important

information enabling the assessment of the activities already implemented by employers in the field of improving working conditions. This study presents the possibilities of using prognostic models in terms of the number of people injured in accidents. However, the prediction can also be used in the scope of forecasting: the number of days of incapacity for work, causes of accidents, or accident rates.

**Table 1.** Selected applications of prognostic models—literature review.

Authors, Year of Publication	Type of Model	Application
Gajdzik et al., 2016 [25]	Holt's model	forecasting the volume of steel production
Halicka et al., 2013 [26]		forecasting the Euro sales rate
Agapie et al., 1997 [28]	Holt–Winters model/ Winters model	forecasting economic cycles
Rachman et al., 2016 [29]		revenue forecasting
Yang et al., 2017 [32]		forecasting for air material consumption
Putharn et al., 2014 [30]		forecasting motorcycle sales
Ramos et al., 2013 [33]		forecasting of load in the electric industry
Paraschiv et al., 2015 [34]		forecasting emission of organic water pollutants
Ortiz 2016 [27]		forecasting exchange rates
Madden et al., 2007 [35]	linear model	telecommunications data forecasting
Wah et al., 2021 [39]	Bayesian spatio-temporal models	predicting lung cancer cases
Pena et al., 2013 [36]	ARIMA neutral networks	forecasting the detection of network anomalies
Kohzadi et al., 1996 [31]		forecasting of livestock and wheat prices
Wang et al., 2010 [37]	combined model	electric load forecasting
Zhu et al., 2016 [38]		forecasting customer-credit evaluation

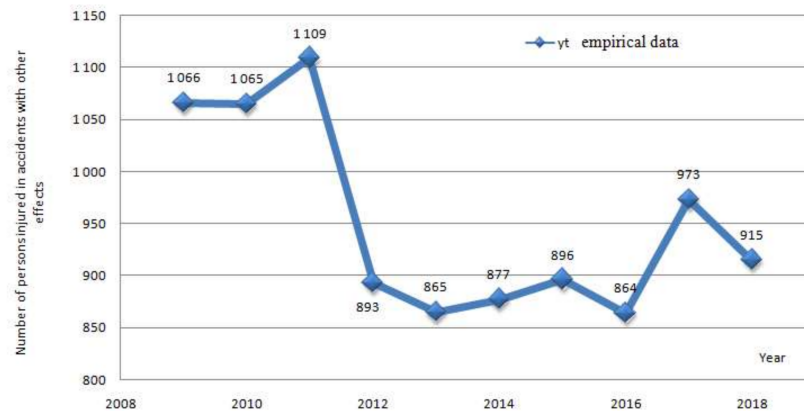
The most common causes of accidents in the steel industry in Poland (including other accidents) include incorrect behavior of an employee, ignorance of health and safety hazards and regulations, disregard for hazards in the workplace, lack of experience, lack of concentration of employees [41]. Therefore, an important element is the implementation of preventive measures aimed at reducing the causes of accidents at work in the form of a combination of technical and organizational solutions. The assessment of the effectiveness of the implemented solutions is possible to observe thanks to the possibility of using the forecasted number of people injured in accidents, where the designated forecasts (number of injured persons) will indicate a probable trend (decreasing, increasing) or fluctuations (increasing, decreasing).

## 2. Materials and Methods

### 2.1. Research Subject

Other accidents (accidents resulting in short-term absenteeism) are events that were most often recorded in the steel sector in Poland in the years 2009–2018 under analysis. Those events are marked by fluctuations, i.e., an increase and decrease in the number of persons injured, which may not be viewed as positive information for managerial staff. The recorded fluctuations were due to the changes that occurred in the employment structure in the steel sector in Poland in the analyzed period. The largest number of persons injured in other accidents was reported in 2011 (1109 injured persons). Since that year, a decrease in the total number of persons injured in accidents was observed. In the years 2012–2016,

the number of persons injured in other accidents did not exceed 900 cases. The year 2017 saw an increase in injuries—973 persons, followed by a decrease in 2018—i.e., 915 persons injured in other accidents. The number of persons injured in other accidents in the steel sector is presented graphically in Figure 1. Given the fact that those events prevail in the accident statistics of the steel sector in Poland, they were subjected to analysis in terms of forecasting the number of such events for the years 2019–2022.



**Figure 1.** Number of people injured in accidents remaining the steel sector in Poland in 2009–2018 (own elaboration based on Statistic Poland [41]).

The choice of the time period (ten years) was conditioned by the availability and consistency of data on accidents in the remaining steel sector in Poland. Since 2009, there have been changes in the classification of economic activities in Poland, and so, in 2008 the production of metals and metal products was mentioned, while from 2009, the area was related to the production of metals, which made it possible to compare the number of people injured in other accidents with each other.

## 2.2. Purpose and Methodology of Research

The aim of this study is to present the possibility of adapting Holt's models in the process of forecasting the number of persons injured in other accidents (so-called minor accidents) in the steel sector in Poland. In connection with the above, a research methodology was developed, allowing the achievement of the objective pursued in this study. The research process was divided into steps (four-step process). The first step involved the development of prognostic models based on empirical data on the number of persons injured in other accidents (so-called minor accidents) in the steel sector in Poland—data obtained from Statistics Poland for the years 2009–2018 [41]. For the purposes of this study, the following models were developed [22–24,42,43]: Holt's square model (M1), Holt's model with a multiplicative trend (M2), Holt's model with an additive trend (M3), Holt's model for the trend smoothed in the additive formula (M4) Holt's model for the trend smoothed in the multiplicative formula (M5).

In the second step, the accuracy of forecasts was assessed by means of ex post forecast errors used in the relevant literature on forecasting [21–24,26,43–49]:

- adjusted average relative ex post error  $\Theta$  (1):

$$\Theta = \frac{1}{n-m} \cdot \sum_{t=m+1}^n \left| \frac{y_t - y_t^*}{(y_t + y_t^*)/2} \right| \quad (1)$$

- mean error  $\psi$  (2):

$$\psi = \frac{1}{n-m} \sum_{t=m+1}^n \frac{|y_t - y_t^*|}{y_t} \quad (2)$$

- mean absolute error  $MAE$  (3):

$$MAE = \frac{1}{n} \cdot \sum_{t=1}^n |y_t - y_t^*| \quad (3)$$

- Rot Mean Square Error  $RMSE$  (4):

$$RMSE = \sqrt{\frac{1}{n-m} \cdot \sum_{t=m+1}^n (y_t - y_t^*)^2} \quad (4)$$

where:  $y_t$ , empirical data;  $y_t^*$ , forecasts value;  $n$ , number of elements of the time series;  $m$ , number of initial time moments  $t$ . For the listed errors, the following limiting assumptions were made [21,23,42,49]:

- adjusted average relative ex post error  $\Theta$ —the error value should be in the range from  $<0-200\%>$ ;
- mean error  $\psi$ , the error value should not exceed 10%;
- mean absolute error  $MAE$ , the error value should satisfy the relationship that occurs between the measures— $MAE \leq RMSE$ ;
- root mean square error ( $RMSE$ ) takes values less than or equal to the standard deviation of the  $S_e$  model residuals. The standard deviation of the model residuals is determined from the relationship (5):

$$S_e = \sqrt{\frac{1}{n-2} \cdot \sum_{i=1}^n (y_t - y_t^*)^2} \quad (5)$$

The third step consisted in a qualitative analysis of ex post forecasts and assessment of the validity of the developed forecasting models. The validity of the model was assessed using the Janus coefficient ( $J^2$ ), which determines the matching ratio of the forecasts and the model to the actual data. The econometric model is considered valid when the value  $J^2 \leq 1$ . Only a model for which the Janus coefficient is estimated at  $J^2 \leq 1$  may be used for ex ante forecasts. Otherwise, it must be changed [22]. The Janus coefficient was determined on the basis of mathematical dependency (6):

$$J^2 = \frac{\frac{1}{T-n} \sum_{t=n+1}^T (y_t - y_t^*)^2}{\frac{1}{n} \sum_{t=1}^n (y_t - y_t^*)^2} \quad (6)$$

where  $T$  is the number of the least period.

The fourth step involved the production of ex ante forecasts of the number of persons injured in other accidents for the models that fulfill the assumptions made in the second stage concerning the acceptability of expired forecast errors and the third stage dedicated to the assessment of the validity of the developed models. A combined forecast model defined by dependency (7) was constructed on the basis of the developed models. The combined model built on the basis of the developed Holt's models contained "W" weights that were assigned to the ex ante forecasts. The sum of the weights was 1. The values of the weights depended on the value of ex post forecast errors for the developed models (Table 2). The lower the ex post error values, the higher the value for the "W" weight.

$$y_t^* = \sum_{i=1}^m \lambda_i \cdot y_t^{*(i)} \quad (7)$$

where:  $y_t^*$ , combined forecast per period  $t$ ;  $\lambda_i$ , weight assigned to the forecast made by  $i$ -th method;  $y_t^{*(i)}$ , forecast per period  $t$  made by  $i$ -th method;  $m$ , number of methods used to produce the forecast [22].

**Table 2.** Values of ex post forecast errors and Janus coefficient  $J^2$  (own elaboration).

Forecasting Model (Model Designation)	Designated ex Post Forecast Errors				$S_e$	Coefficient Values $J^2$			
	$\Psi$ , %	$\Theta$ , %	RMSE	MAE		2015	2016	2017	2018
1	2	3	4	5	6	7	8	9	10
Holt's square model (M1)	6.3	1.5	92.9	58.4	105.4	0.000	0.082	0.471	0.438
Holt's model with a multiplicative trend (M2)	6.1	1.5	86.2	56.5	97.7	0.128	0.065	0.529	0.400
Holt's model with an additive trend (M3)	6.1	1.5	87.1	56.2	98.7	0.155	0.077	0.577	0.433
Holt's model for the trend smoothed in the additive formula (M4)	6.2	1.5	84.1	57.9	95.3	0.171	0.097	0.689	0.569
Holt's model for the trend smoothed in the multiplicative formula (M5)	5.8	1.4	83.1	53.9	94.2	0.117	0.061	0.604	0.453

### 3. Results

#### 3.1. Error Analysis and Evaluation of the Validity of the Developed Models

In compliance with research methodology (Section 2.2—Purpose and methodology of research), prognostic models were constructed (Table 2) for which ex post forecast errors were determined (Table 2, column 2–4). The analysis of Holt's models, i.e., quadratic model (M1), model with a multiplicative trend (M2), additive trend (M3), and models with the trend expiration effect (M4 and M5) showed that the values of ex post forecast errors (Table 1) make it possible to consider the forecasts as acceptable. The values of the estimated errors were as follows:

- the mean error  $\psi$  was in a range between 5.8% for model (M5) and 6.3% for model (M1);
- the adjusted average relative ex post error  $\Theta$  was in a range between 1.4% for model (M5) and 1.5% for the other Holt's models (M1–M4);
- Root Mean Square Error RMSE values of ex post forecast errors were in a range between 83.1 and 92.9 and did not exceed the values set for the standard deviation of the residuals of model  $S_e$  (Table 2, column 6);
- the values of mean absolute error MAE were lower than the values of RMSE errors.

The developed models were also subject to a validity assessment. The values of the Janus coefficient ( $J^2$ ) were established for that purpose. In order to establish the value of the coefficient, the ex post period was divided into the trial period (the numerical value of the trial period was 5) and the testing period (the numerical value of the testing period was 4). The determined values of the Janus coefficient (Table 2, column 7–10) were lower than one (the highest value of the coefficient was  $J^2 = 0.689$  – model M4). Given the above, the models must be considered as valid and may be used for the determination of the value of ex ante forecasts.

#### 3.2. Forecasts of the Number of Persons Injured in Other Accidents in the Years 2019–2022

Ex ante forecasts of the number of persons injured in other accidents in the steel sector in Poland were prepared (Table 3, column 2–5) on the basis of the developed prognostic models. The forecasting of the number of persons injured in other accidents with the use of Holt's model involved the minimization of the mean error of expired forecasts  $\psi$  (Table 2, column 2). The optimal values for the smoothing parameters  $\alpha$ ,  $\beta$  as well as the trend expiration parameter  $\Phi$  were selected on an individual basis for each model using Solver software (Table 3, column 6–8).

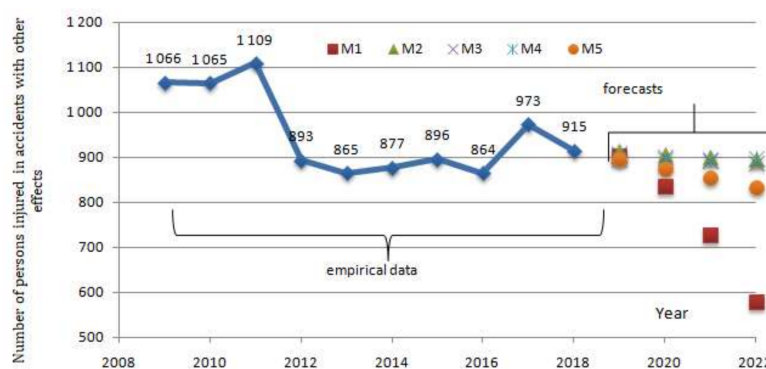
**Table 3.** Forecasts of the number of persons injured in other accidents (minor accidents), smoothing parameters  $\alpha$ ,  $\beta$ , and trend expiration parameter  $\Phi$  (own elaboration).

Forecasting Model (Model Designation)	Forecasts				Model Parameters		
	2019	2020	2021	2022	$\alpha$	$\beta$	$\Phi$
1	2	3	3	5	6	7	8
Holt's square model (M1)	903	836	728	579	0.85	0.05	0.60
Holt's model with a multiplicative trend (M2)	913	907	901	895	0.65	0.12	-
Holt's model with an additive trend (M3)	909	901	893	886	0.63	0.12	-
Holt's model for the trend smoothed in the additive formula (M4)	896	896	896	897	0.96	0.16	0.39
Holt's model for the trend smoothed in the multiplicative formula (M5)	894	873	853	833	0.69	0.01	0.99

The determined values of ex ante forecasts of the number of persons injured in other accidents show a decreasing trend in relation to empirical data (Figure 1):

- model (M1) shows a decline in the number of persons injured in other accidents throughout the whole period considered. A drop of 1.3% is indicated in 2019 in relation to 2018, but in 2022, a significant drop of 36.7% is revealed in relation to 2018, which must be viewed as a very unlikely event;
- model (M2) shows a decreasing trend. A decline of 0.21% is indicated in 2019 in relation to 2018, whereas the year 2022 brings a drop of 2.2% in relation to 2018;
- model (M3) shows a decreasing trend in 2019–2022. A decline of 0.65% is indicated in 2019 in relation to 2018, whereas the year 2022 brings a decline of 3.2% in relation to 2018;
- model (M4) shows a decreasing trend in 2019–2021 (a drop of 2.1% in relation to 2018), but an increase in the number of persons injured in other accidents is indicated in 2022, i.e., 897 injured persons are recorded;
- model (M5) shows a decline throughout the whole period considered, in 2019, a drop of 2.3% in relation to 2018, whereas in 2022, a drop of 8.9% is revealed in relation to 2018.

The developed forecasting models allow for the conclusion that the number of persons injured in other accidents shows a downward trend, which is a positive forecast for the steel industry in Poland (Figure 2). In connection with the above, measures should be taken to improve occupational safety, ensuring that the forecast trend for the number of persons injured in other accidents (so-called minor accidents) is maintained.

**Figure 2.** The number of persons injured in other accidents in the steel sector in Poland, with regard to forecasts produced on the basis of Holt's models, M1–M5 (own elaboration).

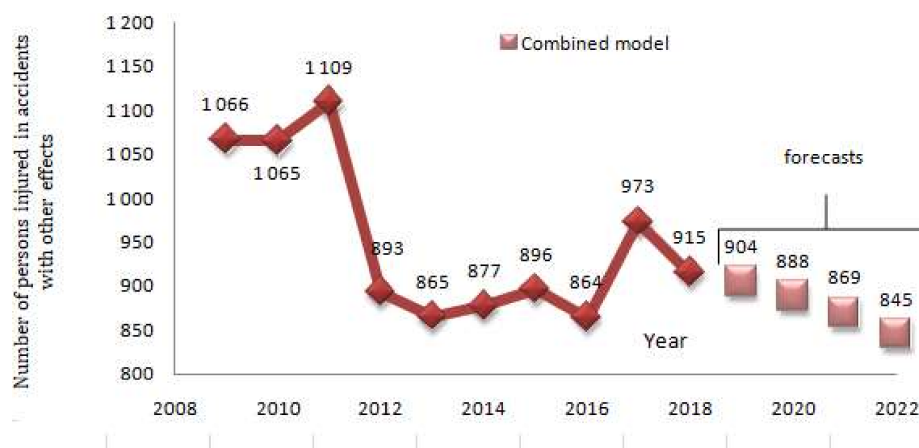
### 3.3. Combination of Forecasts

A combination of forecasts of the number of persons injured in other (minor) accidents in the steel industry in Poland was carried out using mathematical dependency (7), which prescribes that the value of a combined forecast for a given year (Table 4, column 2–5) is the sum of the values of ex ante forecasts (Table 3), taking into account the assigned values of weights “ $\lambda$ ”. The values of weights “ $\lambda$ ” depend on the value of determined ex post errors (Table 2, column 2–5) calculated for models M1–M5. The adopted values of the weights were as follows:  $\lambda_1 = 0.3$  (model M5);  $\lambda_2 = 0.25$  (model M2);  $\lambda_3 = 0.20$  (model M3);  $\lambda_4 = 0.15$  (model M4);  $\lambda_5 = 0.10$  (model M1). Table 4 shows combined forecasts prepared for the number of persons injured in other accidents in the steel sector in Poland in 2019–2022.

**Table 4.** Combined forecast values(own elaboration).

Forecasting Model (Model Designation)	Forecasts			
	2019	2020	2021	2022
1	2	3	3	5
Combined model ( $M_c$ )	904	888	869	845

The analysis of the combined forecasts for the number of persons injured in other accidents shows a downward trend (Figure 3), as is the case with the developed Holt models (M1–M5). As regards the combined model, the differences in individual years between the number of persons injured in other accidents may be considered acceptable due to the lack of significant declines. The forecast values provide guidance for the managerial staff and confirm the forecast trend of changes disclosed due to the analyses of models M1–M5. The combined forecasts show a decline in the number of persons injured in other accidents in relation to 2018 of, respectively, 1.2% in 2019, 2.9% in 2020, 5.0% in 2021, and 7.7% in 2022.



**Figure 3.** The number of persons injured in other accidents in the steel sector in Poland with regard to forecasts prepared on the basis of the combined model ( $M_c$ ).

## 4. Discussion

The issue of work safety plays an important role in the functioning of every enterprise. This study presents the adaptation of Holt’s models to forecast the number of persons injured in other accidents in the steel sector in Poland. The developed prognostic models M1–M5 made it possible to prepare ex ante forecasts which may be subjected to an assessment once the data concerning the number of persons injured in other accidents in 2019–2022 is published. The obtained forecast values provide significant information for the managerial staff. The developed models show the continuation of the downward trend in 2019–2022, although significant decreases in the number of persons injured in other



accidents are also revealed—model (M1) in 2022. Notably, the other models (M2–M5) do not indicate such a case. The knowledge on the accident rate suggests that this situation is unlikely to occur. In order to avoid the selection of the best model, a model of combined forecasts was developed. Its forecasts are more probable and may thus predict the number of persons injured in other accidents in the steel sector in Poland.

Analyzing the numerical values of the forecasts of the number of persons injured in other accidents in 2020, a scenario of models showing a visible decline in the number of injured persons in 2020 may be likely (Holt's square model, Holt's model with the trend expiration effect in the additive and multiplicative formula, combined model). These models show, respectively,  $M1 = 836$ ,  $M4 = 873$ ,  $M5 = 873$ ,  $M_c = 888$  persons injured in other accidents. That situation is probably due to the occurrence of infections caused by SARS-CoV-2 all over the world and in Poland, which led to production limitations and work stoppages. For example, steel production from January to June 2020 decreased by about 16% compared to 2019 [50]. The downward trend is also recorded in the years 2021–2022, in respect of which we do not have the necessary knowledge at present on what the situation related to infections, restrictions, and thus the implementation of production tasks will look like. The registered downward trend indicates the effectiveness of the implemented protective prophylaxis in relation to the most common causes of accidents at work (e.g., OHS training, shaping the health and safety culture, occupational risk assessment, technological improvements). It may also be useful to apply the other solutions provided, for example, in the lean manufacturing concept (e.g., 6S, TPM, OPL, VM, Kaizen) [51].

## 5. Conclusions

Analyzing the numerical values of the forecasts of the number of persons injured in other accidents in 2020, a scenario of models showing a visible decline in the number of injured persons in 2020 may be likely (Holt's square model, Holt's model with the trend expiration effect in the additive, and multiplicative formula, combined model). These models show, respectively,  $M1 = 836$ ,  $M4 = 873$ ,  $M5 = 873$ , and  $M_c = 888$  persons injured in other accidents. That situation is probably due to the occurrence of infections caused by SARS-CoV-2 all over the world and in Poland, which led to production limitations and work stoppages. For example, steel production from January to June 2020 decreased by about 16% compared to 2019 [50]. The downward trend is also recorded in the years 2021–2022, in respect of which we do not have the necessary knowledge at present on what the situation related to infections, restrictions, and thus the implementation of production tasks will look like.

The issue of work safety plays an important role in the functioning of any enterprise. The relative risk of accidents in the industrial sector (including steel) in Poland is estimated at the level of  $RR = 0.33$ . However, in other countries it is significantly lower: Latvia ( $RR = 0.15$ ), Lithuania ( $RR = 0.12$ ), and Bulgaria ( $RR = 0.052$ ) [52]. Therefore, the risk of an accident at work is higher in Poland, and therefore all measures should be taken to reduce the number of accidents at work.

This study presents the adaptation of Holt's models to forecast the number of persons injured in other accidents in the steel sector in Poland. The developed prognostic models M1–M5 made it possible to prepare ex ante forecasts that may be subjected to an assessment once the number of persons injured in other accidents in 2019–2022 is published. The obtained forecast values provide significant information for the managerial staff. The developed models show the continuation of the downward trend in 2019–2022, although significant decreases in the number of persons injured in other accidents are also revealed—model (M1) in 2022. Notably, the other models (M2–M5) do not indicate such a case. The knowledge on the accident rate suggests that this situation is unlikely to occur. In order to avoid the selection of the best model, a model of combined forecasts was developed. Its forecasts are more probable and may thus predict the number of persons injured in other accidents in the steel sector in Poland.

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