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Development of short-term prediction with regard to a number of accidents at work using the scoring method

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Abstract
The mining industry is an industry branch with one of the highest rates of accidents at work in Poland and the presented analysis develops the knowledge about the safety in the mining sector. The work below presents a short-term prediction of the overall work accident number in a selected industrial facility, developed on the basis of statistical accident rate data and using 25 selected econometric models. In the summary assessment of a specific prediction, the scoring method was applied, taking the following weights into consideration: *C1* and *C2* criteria (*C*) – 10 % each, *C3* and *C4* criteria – 20% each, and *C5* criterion – 40 %, where: *C1* was the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2007 and 2016; *C2* was the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2007 and 2018; *C3* was the value of coefficient of random variation *Ve* for the *ex post* predictions from the period between 2007 and 2016 (for all predictions except the linear and linearized models, the *RMSE** value was applied to estimate their value); *C4* was the value of coefficient of random variation *Ve* for the *ex post* predictions from the period between 2007 and 2018 (for all predictions except the linear and linearized models, the *RMSE** value was applied to estimate their value); *C5* was the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2017 and 2018. Statistical work accident rate data covering the period between 2007 and 2018 were used in the analysis.

Keywords
Industry, accidents at work, statistical analysisList the keywords covered in your paper.

Introduction

Currently, the Polish coal mining industry remains an important economy sector with over 75,000 employees. Over the last 3 decades, the mining industry in Poland has faced deep (radical) changes. In addition to increasingly innovative technology, these changes also related to work organisation and management.

Despite large-scale preventive and control actions, the work accident rate in Poland remains at a high level. In 2019, the Central Statistical Office recorded an overall number of 83,205 accidents at work, including 184 fatal cases and 390 serious accidents (Accidents at work, 2020). Work safety is a key factor that determines proper development of each economic activity as there is a close relationship between human activity and the need of safety.

Predictions of accident numbers can be modelled based on quantitative prognostic methods which enable determination of the event course over specific time period, and the prediction results let us recognise possible future scenarios and select the optimal one (Strategor, 2001; Pelon and Gil, 2020).

While developing predictions, there are a couple of methods applied: elementary, exponential smoothing, autoregressive, linear and linearized prognostic regressive models (Brown, 1963; Chatfield, 1986; Gajdzik and Szymszal, 2016; Gajdzik and Szymszal, 2017; Gardner, 1985; Holt, 2004; Mianowana et al., 2016; Szeja, 1992). Optimisation of the predictive value is based on a search for a minimum value of the selected error which is assumed to be its criterion (Czyżycki and Klóska, 2011; Welfe, 2009; Witkowska, 2005; Zheng and Liu, 2009). On the basis of statistical accident rate data from selected coal mines and using selected econometric models, a short-term prediction of the expected accident number in a selected industrial facility can be developed.

The aim of this paper is to develop a short-term prediction of the overall work accident number in a selected industrial facility (a coal mine). Presented methodology can be used to develop the safety management.

Materials and methods

The own research was conducted based on a coal mine in Poland. The analysed mine employs about 4 thousand people. The accident rate data for the selected hard coal mine for own staff regarding the period between 2007 and 2018 were chosen for prediction development. Due to a small share of the analysed mine in the structure of overall accidents concerning the Polish mining industry, the research object should be considered as a case study (Statistical data, 2019).

Based on the absolute analysis of the statistical data, it can be demonstrated for the overall accident number: the total number was 1128 cases; the mean number: 94 accidents per year; the range: 85-112; a lack of trend can be claimed. Moreover, the medium-term percent rate of decline in the overall number of accidents was 1.5% over the entire analysed period. The fatal cases – the total number: 15 accidents; the mean number: 1.5 cases; the range: 0-7; 1.33 % of the overall accident number; every 75th accident on average; the fatal cases were observed over the years: 2007-2009, 2012 and 2014; a lack of trend can be claimed. The serious cases – the total number: 18 accidents; the mean number: 1.5 cases; the range: 0-15; 1.60 % of the overall accident number; every 63rd accident on average; the serious cases were observed over the years: 2009, 2010, 2014 and 2018; a lack of trend can be claimed.

Tab. 1. Statistical data (Statistical data, 2019)

No	Year	Accidents		
		Overall	Fatal	Serious
	T	*A*	A_f	A_s
1	2007	100	2	0
2	2008	92	3	0
3	2009	91	2	1
4	2010	90	0	1
5	2011	99	0	0
6	2012	96	1	0
7	2013	93	0	0
8	2014	112	7	15
9	2015	92	0	0
10	2016	89	0	0
11	2017	89	0	0
12	2018	85	0	1

The calculations (building forecast) were based on 25 models (Table 2); their specifications as follow: 1 to 9 - adaptive models, 10 to 22 - exponential smoothing models, 23 - prediction based on the linear model; 24 - prediction based on the nonlinear model – linearization; 25 - autoregressive (AR) models. Predictions for the 25 models were performed with the use of the Excel sheet with built-in functions, data analysis tools and the Solver program as the optimisation tool (Fylstra et al., 1998; Gajdzik and Szymszal, 2016).

Tab. 2. Specifications of the models tested

Model no	Name	Starting point
1	Model of a naive method with the additive aspect for the time series with a development trend	
2	Model of a naive method with the multiplicative aspect for the time series with a development trend	
3	Model of a simple moving average	
4	Model of a simple moving average for the time series shaping around a constant value (average) (k=2)	
5	Model of a simple moving average for the time series shaping around a constant value (average) (k=3)	
6	Model of a weighted moving average for the time series shaping around a constant value (average) (k=3)	
7	Model of a simple moving average for the time series shaping around a development trend (k=2)	
8	Model of a simple moving average for the time series shaping around a development trend (k=3)	
9	Model of a weighted moving average for the time series shaping around a development trend (k=3)	
10A	Model of simple exponential smoothing	$y_1^* = y_1$
10B		$y_1^* = \frac{y_1 + y_2 + y_3 + y_4 + y_5 + y_6}{6}$
11	Model of single exponential smoothing (Brown's model)	
12	Model of exponential autoregression (k=3)	
13	Model of exponential autoregression (k=2)	
14A	Holt's linear model with the additive trend (for various starting	$S_1 = y_2 - y_1$
14B	mechanisms)	$S_1 = 0$
15A	Holt's linear model with the multiplicative trend (for various	$S_1 = y_2 / y_1$
15B	starting mechanisms)	$S_1 = 1$
16A	Holt's linear model with the effect of additive trend damping	$S_1 = y_2 - y_1$
16B	(for various starting mechanisms)	$S_1 = 0$
17A	Holt's linear model with the effect of multiplicative trend damping (for various starting mechanisms)	$S_1 = y_2 / y_1$
17B		$S_1 = 1$
18A	Holt's quadratic model in the additive formula (for various	$S_1 = y_2 - y_1$
18B	starting mechanisms)	$S_1 = 0$
19	Method of Brown's double exponential smoothing for the linear model	
20	Method of Brown's triple exponential smoothing for the quadratic model	
21	Advanced model of exponential autoregression	
22	Model of a creeping trend – prediction using the method of harmonic weights	
23	Prediction based on the linear model	
24	Prediction based on the nonlinear model – linearization	
25	Autoregressive (AR) models	

To estimate the level of acceptability for the assumed prognostic models as well as to select the best methods, evaluation of two most common *ex-post* prediction errors was performed: a mean value of the relative *ex-post* prediction error Ψ and the square root calculated based on the root mean square error (*RMSE**) for the *ex-post* predictions. Optimisation of the point predictive value was based on a search for a minimum value of the above errors assumed to be its criterion. The mean value of relative *ex-post* error Ψ is determined as follows: after the value of y_t^* prediction is defined, for each period *t* – where $t \in (\overline{1,T})$,, a quotient is calculated being a value of the relative difference $\frac{|y_t - y_t^*|}{y_t}$ where y_t is an empirical value, i.e. a variable *Y* over a specific period *t*. Next, the calculated sum of relative values is divided by their number $n - m$, according to the following equation (Czyżycki and Klóska, 2011; Statistical data, 2019; Welfe, 2009; Zheng and Liu, 2009):

$$\Psi = \frac{1}{n-m} \sum_{t=m+1}^{n} \frac{|y_t - y_t^*|}{y_t}, \tag{1}$$

where: m – a number of initial periods or moments of the time t for which no *ex-post* prediction was developed or the prediction is a result of the starting mechanism.

The $RMSE^*$ value is determined as follows: after the value of y_t^* prediction is defined, for each assumed period t where $t \in (\overline{1,T})$, values of squared differences $(y_t - y_t^*)^2$ are estimated; next, all the values of squared differences are added together, their sum is divided by their number (i.e. $n - m$), and the square root is calculated. Ultimately, this error is defined according to the following equation (Czyżycki and Klóska, 2011; Statistical data, 2019; Welfe, 2009; Zheng and Liu, 2009):

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

Statistical assessment results of the obtained models are also described by the coefficient of random variation V_e which is calculated as the standard error S_e (the residual standard deviation), being a square root of the estimated variation of a random component, divided by the arithmetic mean of dependent variable $\overline{y}$:

$$V_e = \frac{S_e}{\overline{y}} = \frac{\sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(y_t - y_t^*\right)^2}}{\frac{1}{n}\sum_{t=1}^{n} y_t} \tag{3}$$

The coefficient V_e informs about the percent value of the arithmetic mean of dependent variable $\overline{y}$ that is the residual standard deviation S_e. When the coefficient V_e is not higher than the pre-defined limit value, which is commonly set at the maximum limit of 15%, this allows to conclude that the model and the empirical data are well matched (Statistical data, 2019).

Implementation of algorithms for the 25 models and related calculations were performed with the use of the Excel sheet with built-in functions, data analysis tools and the Solver program as the optimisation tool (Fylstra et al., 1998; Gajdzik and Szymszal, 2016; Middleton, 2004). To achieve the maximum neutral level of assessment of the predictions quality, it was based on the following criteria (*C*): *C1* – the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2007 and 2016; *C2* – the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2007 and 2018; *C3* – the value of coefficient of random variation V_e for the *ex post* predictions from the period between 2007 and 2016 (for all predictions except the linear and linearized models, the $RMSE^*$ value was applied to estimate their value); *C4* – the value of coefficient of random variation V_e for the *ex post* predictions from the period between 2007 and 2018 (for all predictions except the linear and linearized models, the $RMSE^*$ value was applied to estimate their value); *C5* – the value of *ex post* prediction error Ψ for the series including the empirical data covering the period between 2017 and 2018. Each of the above error and coefficient values was standardised through dividing the difference between the specific value and the mean value of all applied predictions by the standard deviation value for each criterion. In the summary assessment of a specific prediction, the scoring method was applied, taking the following weights into consideration: *C1* and *C2* criteria – 10 % each (for *C1* was used wage: w_1=0.1, for *C2* was used wage: w_2=0.1), *C3* and *C4* criteria – 20 % each (for *C3* was used wage: w_3=0.2, for *C4* was used wage: w_5=0.2),, and *C5* criterion – 40 % (for *C5* was used wage: w_5=0.4), and Σwi=1.

Prediction of the overall work accident number

The next step was the prediction verification for all the obtained predictions based on 25 models. The values obtained were 2.0911 to -1.4726. Based on the above results, it can be concluded that the best goodness of fit (green shades) to the empirical points being the overall number of accidents is demonstrated by the following prognostic models with the standardised and weighted summary assessment score less than -0.5000 (< -0.5000): 16B – the Holt's linear model with the effect of additive trend damping, 17B – the Holt's linear model with the effect of multiplicative trend damping, and 22 – the model of creeping trend (predictions developed using the method of harmonic weights). The investigations were preceded by the analysis of the situation in the Polish mining industry and of the literature concerning statistical methods used for the accident rate analysis in coal mines by other authors.

Based on the applied methods of accident rate prediction for the investigated coal mine in Poland, the best models were selected according to the analysis of prediction errors. The obtained results (models: 16B, 17B and 22) were presented in Table 3. The table contains a set of values for each criterion regarding the prognostic methods applied as well as the standardised and weighted summary assessment score for the criteria.

Tab. 3. Estimation criteria in the best prognostic models

Model no	Prediction errors 2007-2016		Prediction errors 2007-2018		Coefficient Ve, %		2017-2018	Prediction verification	Range
	Ψ, % $w_1 = 0.1$	$RMSE$*	Ψ, % $w_2 = 0.1$	$RMSE$*	2007-2016 $w_3 = 0.2$	2007-2018 $w_4 = 0.2$	Ψ, % $w_5 = 0.4$		
16 B	5.43	7.89	5.19	7.10	8.30	7.60	1.78	-0.8820	3
17 B	5.61	8.20	4.69	7.13	8.60	7.60	1.54	-0.9085	2
22	3.04	3.52	2.47	3.13	3.80	3.30	4.15	-1.4726	1

Based on the results presented as well as the standardised and weighted summary assessment of the criteria, it can be concluded that the best goodness of fit (green shades) to the empirical points of the overall number of accidents among the employees is demonstrated by the following models:

- 16B – the Holt's linear model with the effect of additive trend damping (starting mechanism: $S_1 = 0$),
- 17B – the Holt's linear model with the effect of multiplicative trend damping (starting mechanism: $S_1 = 1$),
- 22 – the model of creeping trend ($k = 3$) - predictions developed using the method of harmonic weights).

For the predictions regarding the overall accidents considered, there is no universal prognostic method. The best option is the prognostic method (22) of harmonic weights with the prediction quality assessment score of (minus) -1.4726.

Due to the character of the time series regarding the overall number of accidents, the prognostic models with the standardised and weighted summary assessment score above 1.0000, i.e. 2 – the model of naive method with the multiplicative aspect, 7 – the model of simple moving average, and 9 – the model of weighted moving average, seem to be completely useless.

Implementation of algorithms for the presented models and related calculations were performed with the use of the Excel sheet with built-in functions, data analysis tools and the Solver program as the optimisation tool.

In the Holt's linear model (16B) with the effect of additive trend damping (for various starting mechanisms), version B (Gajdzik and Szymszal, 2016; Yar and Chatfield, 1990; Żarowska-Mazur and Węglarz, 2012), the starting point is $S_1 = 0$. The *ex-post* prediction model is defined by the following system of equations:

$$\begin{cases} F_1 = y_1 \\ S_1 = 0 \\ F_t = \propto y_t + (1-\propto)(F_{t-1} + S_{t-1})\Phi, \ for \ t = 2, \dots, n \\ S_t = \beta(F_t - F_{t-1}) + (1-\beta)S_{t-1}\Phi, \ for \ t = 2, \dots, n \\ y_t^* = F_{t-1} + S_{t-1}\Phi, \ for \ t = 2, \dots, n \end{cases}, \tag{4}$$

while for the *ex-ante* predictions:

$$\begin{cases} F_n = \propto y_n + (1-\propto)(F_{n-1} + S_{n-1})\Phi \\ S_n = \beta(F_n - F_{n-1}) + (1-\beta)S_{n-1}\Phi \\ y_T^* = F_n + (T-n)S_n\Phi^{(T-n)}, \ for \ T = n+1, \dots, \tau \end{cases}. \tag{5}$$

where: F_t – smoothed assessment of the level (the mean value) for the moment or the time t; S_t – smoothed assessment of the development trend in the time series for the moment or the time t; y_t* – the value of *ex-post* prediction ($l < t < n$); y_T* – the prediction of the variable y_t for the time $n < T < \tau$; α – the smoothing parameter for the level of dependent variable within the values (0,1]; β – the smoothing parameter for the increase due to the development trend within the values (0,1]; Φ – the parameter of trend damping within the values (0,1]. The values of α, β and Φ parameters were determined for the minimum *ex-post* prediction error Ψ.

Calculations related to the *ex-post* and *ex-ante* predictions based on the Holt's model (16B) with the effect of additive trend damping (for various starting mechanisms), version B, were performed according to the systems of equations 4 and 5. For the empirical data covering the periods between 2007 and 2016 as well as 2007 and 2018, the prediction results are presented in Figure 1. The summary assessment value of this prediction using the scoring method is -0.8719, being the third in the model assessment ranking.

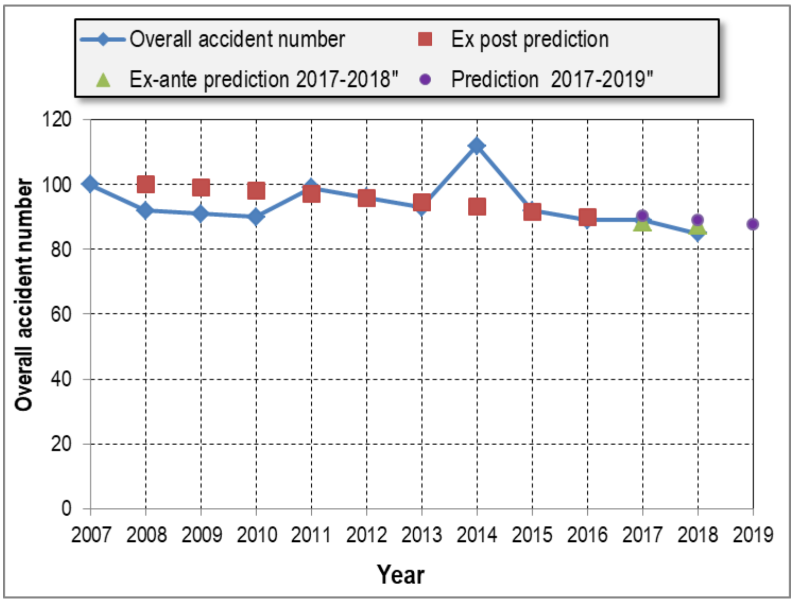

Fig. 1. Prediction based on the Holt's model (16B) with the effect of additive trend damping for the empirical data covering the periods between 2007 and 2016 as well as 2007 and 2018

In the Holt's linear model (17B) with the effect of multiplicative trend damping (for various starting mechanisms), version B (Krawiec, 2014; Radzikowska, 2004; Yar and Chatfield, 1990; Żarowska-Mazur and Węglarz, 2012), the starting point is $S_1 = 1$. The *ex-post* predictions are defined by the following system of equations:

$$\begin{cases} F_1 = y_1 \\ S_1 = 1 \\ F_t = \propto y_t + (1-\propto)F_{t-1}S_{t-1}\Phi, \;\; for \;\; t = 2, \dots, n \\ S_t = \beta \frac{F_t}{F_{t-1}} + (1-\beta)S_{t-1}\Phi, \;\; for \;\; t = 2, \dots, n \\ y_t^* = F_{t-1}S_{t-1}\Phi, \;\; for \;\; t = 2, \dots, n \end{cases} , \tag{6}$$

while for the *ex-ante* predictions:

$$\begin{cases} F_n = \propto y_n + (1-\propto)(F_{n-1}S_{n-1})\Phi \\ S_n = \beta \frac{F_n}{F_{n-1}} + (1-\beta)S_{n-1}\Phi \\ y_T^* = F_n S_n^{(T-n)} \Phi^{(T-n)}, \;\; for \;\; T = n+1, \dots, \tau \end{cases} . \tag{7}$$

The values of α, β and Φ parameters were determined for the minimum *ex-post* prediction error Ψ.

Calculations related to the *ex-post* and *ex-ante* predictions based on the Holt's linear model (17B) with the effect of multiplicative trend damping (for various starting mechanisms), version B, were performed according to the systems of equations 6 and 7. For the empirical data covering the periods between 2007 and 2016 as well as 2007 and 2018, the prediction results are presented in Figure 2. The summary assessment value of this prediction using the scoring method is -0.8986, being the second in the model assessment ranking.

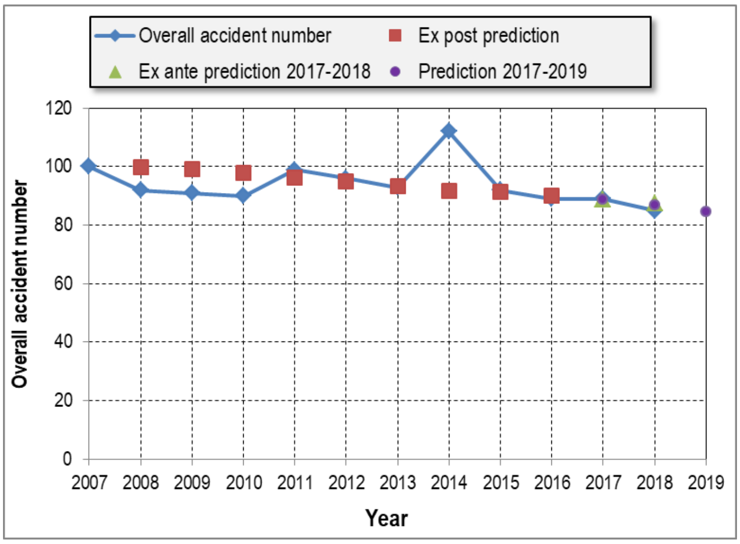

Fig. 2. Prediction based on the Holt's linear model (17B) with the effect of multiplicative trend damping for the empirical data covering the periods between 2007 and 2016 as well as 2007 and 2018

In the method of creeping trend with harmonic weights (22), which demonstrates the best goodness of fit, development trends of the dependent variable are distinguished (Czyżycki and Klóska, 2011; Zheng and Liu, 2009). The method of harmonic weights is a tool that enables development of predictions when there has been no cause-and-effect or development trend model of adequate quality for the dependent variable. The basic assumptions of this prognostic method included:

- determination of the smoothing constant $k < n$ (e.g. selection of segments $k = 3$ observations each)
- estimation of linear trend functions based on the further series fragments of the length k
- calculation of theoretical values resulting from the individual trend functions
- calculation of the creeping trend value for each period (the arithmetical mean of theoretical values of the adequate trend functions for the specific period)
- calculation of the trend function w_{t+1} increases according to the following equation:

$$w_{t+1} = y^*_{t+1} + y^*_t, \; for\; t = 1, \dots, n-1\,, \tag{8}$$

- assignment of weights to the individual increases C that are described by the following equation:

$$C^n_{t+1} = \frac{1}{n-1}\sum_{i=1}^{t}\frac{1}{n-i}, \; for\; t = 1, \dots, n-1; \tag{9}$$

- the *ex-ante* prediction for the period T, calculated according to the following formula:

$$y^*_T = y_n + (T-n)\left(\sum_{t=1}^{n-1} w_{t+1}\right), \; for\;\; T = n+1, \dots, \tau. \tag{10}$$

Calculations related to the *ex-post* and *ex-ante* predictions based on the creeping trend model ($k = 3$) using the method of harmonic weights were performed according to the formulas 8 to 10. For the empirical data covering the periods between 2007 and 2016 as well as 2007 and 2018, the prediction results are presented in Figures 3 and 4, respectively. The summary assessment value of this prediction using the scoring method is -1.4610, being the best in the model assessment ranking.

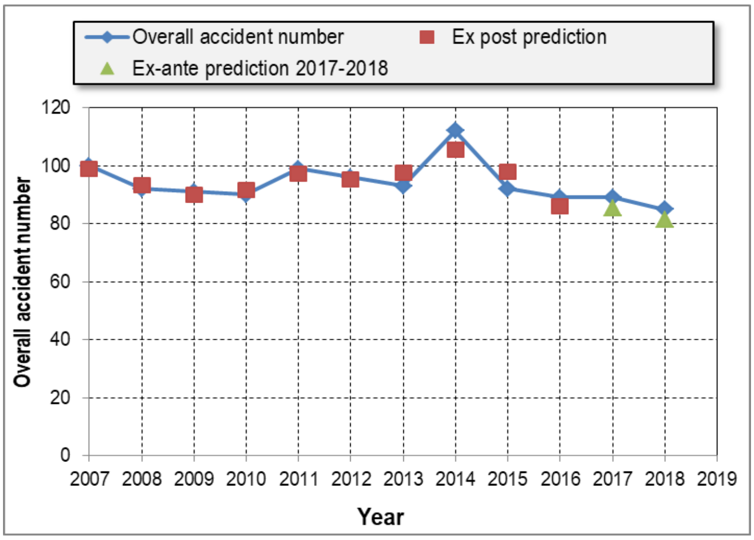

Fig. 3. Prediction based on the creeping trend model (k = 3) using the method of harmonic weights for the empirical data covering the period between 2007 and 2016

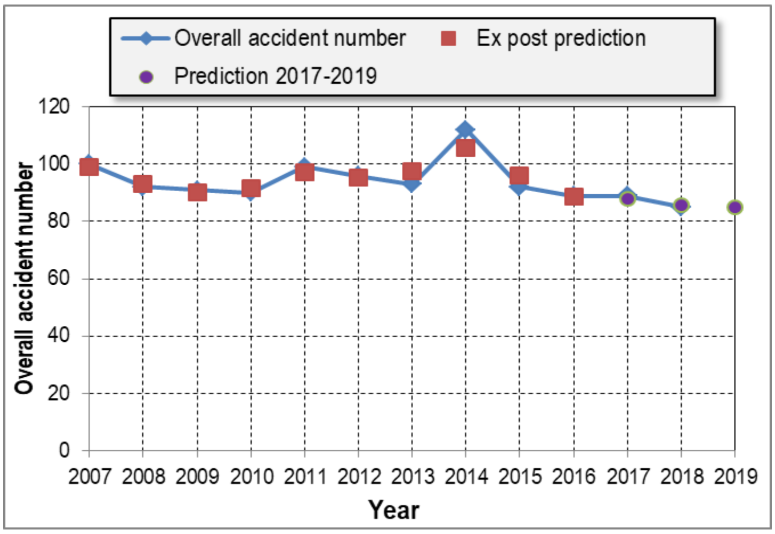

Fig. 4. Prediction based on the creeping trend model (k = 3) using the method of harmonic weights for the empirical data covering the period between 2007 and 2018

Conclusions

Based on the results presented as well as the standardised and weighted summary assessment of the criteria, it can be concluded that the best goodness of fit (green shades) to the empirical points of the overall number of accidents among the employees is demonstrated by the following models: the model of a creeping trend ($k = 3$) – predictions using the method of harmonic weights; the Holt's linear model with the effect of multiplicative trend damping (starting mechanism: $S_1 = 1$); the Holt's linear model with the effect of additive trend damping (starting mechanism: $S_1 = 0$).

For the predictions regarding the overall accidents considered, there is no universal prognostic method. The best option is the prognostic method of harmonic weights with the prediction quality assessment score of -1.4610.

The proposed prediction methodology with the use of assessments (i.e. weights) for individual predictions adds to the knowledge of prediction methods and facilitates selection of the best one.

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