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Risk prediction based on a time series case study: Tazareh coal mine

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Abstract

In this work, the time series modeling was used to predict the Tazareh coal mine risks. For this purpose, initially, a monthly analysis of the risk constituents including frequency index and incidence severity index was performed. Next, a monthly time series diagram related to each one of these indices was for a nine year period of time from 2005 to 2013. After extrusion of the trend, seasonality, and remainder constituents of the time series modeling, the final time series model of the indices was determined with high precision. The precision level of the resulting model was evaluated using the root mean square error (RMSE) method. The values obtained for the severity index and accident frequency index were 0.001 and 6.400, respectively. Evaluation of the seasonal time series constituent of the frequency index showed that, yearly, most number of accidents occurred in April, and the least one took place in January. Additionally, evaluation of the seasonal time series constituent of the severity index showed that, every year, the severest accidents occurred in October, and the least ones happened in January. Using the final model, a monthly prediction of indices was performed for a four year period of time from 2014 to 2017. Subsequently, using the known mean work hours in the mine, predictions of the number of accidents and the number of work days lost within a similar time period were made. The prediction results showed that in the future, the number of accidents and the number of work days lost would have a down-going trend such that for similar months, annually, an average 22% decrease in the number of accidents and an average 24% decrease in the number of work days lost are expected.

Keywords: *Prediction, Risk, Time Series, Accident Frequency Rate, Accident Severity Rate.*

1. Introduction

In the recent years, severe and catastrophic accidents have happened in coal mines globally. Accidents in coal mines not only have led to severe economic damages for countries and people but also have had negative effects on the society and policies. Therefore, safety management and risk management need to be seriously thought of in coal mines [1]. A risk is considered to be an unknown reason for harm, which exists objectively in the nature, society or economy [2]. Risk prediction can provide a very important basis for risk management. It prediction includes predicting the kinds of dangers, their levels, and their frequencies [3]. Overall, up to the present time, seven main risk prediction methods have been used. They include the scenario analysis, regression, time series, mark-off chain, grey model, neural network, and Bayesian network methods. Each one of these methods has its own special applications [4]. In the cases where there is a regular continuity in the observations made in equal time intervals, the time series method has applications. Time series, which is a branch of statistics and probability, has numerous applications in various sciences such as geophysics, economy, communications engineering, and meteorology. So far, few studies have been conducted in mining engineering based on the time series modeling (see Table 1). In this work, the time series modeling was used to perform risk prediction in the Tazareh coal mine, considering the monthly reports of the observed accidents.

Table 1. Studies based on time series modeling in mining engineering.

Author	Year	Subject of study
Xia-Ting Feng et al. [5]	2004	Displacement of geomaterials
Mehmet Sari et al. [6]	2009	Prediction of accident risks
Qiao Meiying et al. [7]	2011	Prediction of gas outbursts
Li Peixian et al. [8]	2011	Prediction of mining subsidence
Reza Memarya et al. [9]	2012	Environmental impacts
Kirti Soni et al. [10]	2014	Prediction of aerosol optical depth

2. Quantitative risk assessment

The quantitative analysis of the accident and injury data for measuring the safety performance and identifying the safety problems is usually carried out through two basic indices, accident frequency rate (*AFR*) and accident severity rate (*ASR*), as follows [11]:

$$\text{AFR} = \frac{\text{Total number of accidents} \times 1000000}{\text{Total number of man} \times \text{hours worked}} \quad (1)$$

$$\text{ASR} = \frac{\text{Total number of days lost} \times 1000}{\text{Total number of man} \times \text{hours worked}} \quad (2)$$

AFR is an expression relating the number of specific accidents to the number of man-hours worked. The objective of a severity rate is to give some indication of the loss in terms of incapacity resulting from the occupational accidents. AFR is calculated by dividing the number of accidents (multiplied by 1,000,000) occurring during the period covered by the statistics by the number of man-hours worked by all persons exposed to the accident risk during the same period. The severity rate is calculated by dividing the number of working days lost (multiplied by 1000) by the number of hours of working time hours of all the persons included. The US Mine Safety and Health Administration [12] was adopted the same approach with changes in the constants. The incidence rate is defined as the number of injuries per 200,000 employee-hours, and the severity measure is the number of lost work days per 200,000 employee-hours. The number 200,000 is used to standardize 100 full-time employees working 40 h/week-50 weeks/year. It is possible to make sound comparisons using these indices over a number of years for a sector or between different sectors in a specific year to obtain an overview of the safety level [13-15]. In fact, these numbers cannot include the uncertainty and variability inherent in the frequency of accidents. Mining can never have zero risk to the occupational safety and health. There is always a degree of uncertainty with regard to the type and extent of the adverse impacts that could arise. On the other hand, [16-20] have applied appropriate statistical distributions on the accident data in different industries. The results obtained have shown that it is possible to measure the frequency and severity of the consequences in quantitative terms including the uncertainty and variability revealed by the available data.

3. Method

The time series is a sequence of n observations Y_1, Y_2, …, Y_t, …, Y_n of a process in equal time intervals. The time series method itself is classified into the two classic and non-classic groups. In the classic (or analytic) method, the time series is divided into the four constituents of trend, seasonal, cyclic, and irregular. The final prediction model is identified after extrusion of the equations for each constituent [6]. In the non-classic method, where the series lacks seasonal and cyclic constituents, autoregressive, moving mean, and ARIMA are used for modeling. In the classic kind, the series is decomposed into its four constituents. In the multiplicative model, the four constituents are multiplied to each other, and in the summation model the four constituents are summed to each other. The multiplicative model can be shown by Eq. 3 [21].

$$Y_t = TR_t \times SN_t \times CL_t \times IR_t \quad (3)$$

where

Y: value of variable at time t;

TR_t: trend constituent;

SN_t: seasonal constituent;

CL_t: cyclic constituent;

IR_t: remaining constituent.

3.1. Trend constituent

This constituent describes the overall long-term movement of the series. The trend function can have a linear, exponential or growth curve. The fitness of the series is performed by the method of smallest sum of squares.

3.2. Seasonal constituent

This constituent describes the model of repetitive changes in yearly periods. It is a sequence of relatively repetitive periods. Calculation of the seasonal constituent is performed using the method of moving average. The moving average of a time series is obtained by placing the means of the consecutive overlapping sequences resulting from K observations in the series instead of those sequences. K is the number of expressions whose average is calculated. If the number of expressions whose moving average needs to be obtained is even, the focused moving average is used. For example, if the purpose of the moving average is the number of months in a year, which is 12, the focused moving average is used. Calculation of the seasonal constituent using the moving average method is according to the following steps:

a. First, the main series is smoothed with calculation of the moving average.

b. By dividing the main series by the smoothed values, the special seasonal ratio is obtained.

c. The median of the special seasonal ratio is identified.

d. Since the seasonal model needs to be scaled to a period of one year, the multiplicative model requires the median of the special seasonal ratios to be 100%. As a result, a final modification occurs to obtain the seasonal index or seasonal constituent.

3.3. Cyclic constituent

This constituent describes the periods of alternating relative expansion and contraction with the above time period (more than ten years). It includes the periods that change regarding the domain and time.

3.4. Remainder constituent (irregular)

This constituent describes the effects of all the other factors other than the trend, seasonal, and cyclic ones.

Now, after familiarity with the time series, we can consider the monthly observations relevant to the parameters forming the risk as a time series. After formation of the time series diagrams for those parameters, they can be analyzed, and the prediction model can be extruded. Therefore, having the monthly statistics on the number of accidents, number of lost work days, and total number of work hours, we can calculate the monthly indices of the frequency and severity of the incidence, and, therefore, create a time series for each one of the mentioned indices.

4. Case study

In this work, by having the regular monthly statistics of the number of severe and very severe accidents, number of lost work days, and number of work hours in the Tazareh coal mine [22], the monthly frequency rates and accident severities were calculated for the years 2005-2013. Next, the time series diagrams for these two variables were prepared. After formation of the time series diagrams, their trend, seasonal, cyclic, and remainder constituents were analyzed. The trend component with consideration of Figures 1 and 2, for the severity rate and frequency rate of the incidence was obtained, in the forms of Eqs. 4 and 5, respectively.

$$TR_t = 0.047 \times 0.97286^t \tag{4}$$

$$TR_t = 2.714 \times 0.9712^t \tag{5}$$

The values for the seasonal constituent of the time series for the severity index and frequency index were calculated using the method of scaled moving average. The results obtained from these calculations were tabulated in Table 2.

As shown in this table, the highest severity index belong to October, and the least one to January, and this means that, yearly, the most sever accidents have occurred in October and the least sever ones have taken place in January. Highest frequency index belongs to April, and the least one is in January, and this means that, annually, most accidents have occurred in April, and the least ones have been in January.

Yet, evaluation of the cyclic constituent was not performed in this study. The reason for this is that, as mentioned earlier, this constituent was present in the time series with periods higher than ten years. After analysis of the trend and seasonal constituents, the remainder constituent evaluated for each one of the indices. Their scatter plots are shown in Figure 3. These plots showed that the indices had high amounts of the remainder constituent, and in addition, they showed particular trends. Therefore, it was necessary to prepare the time series

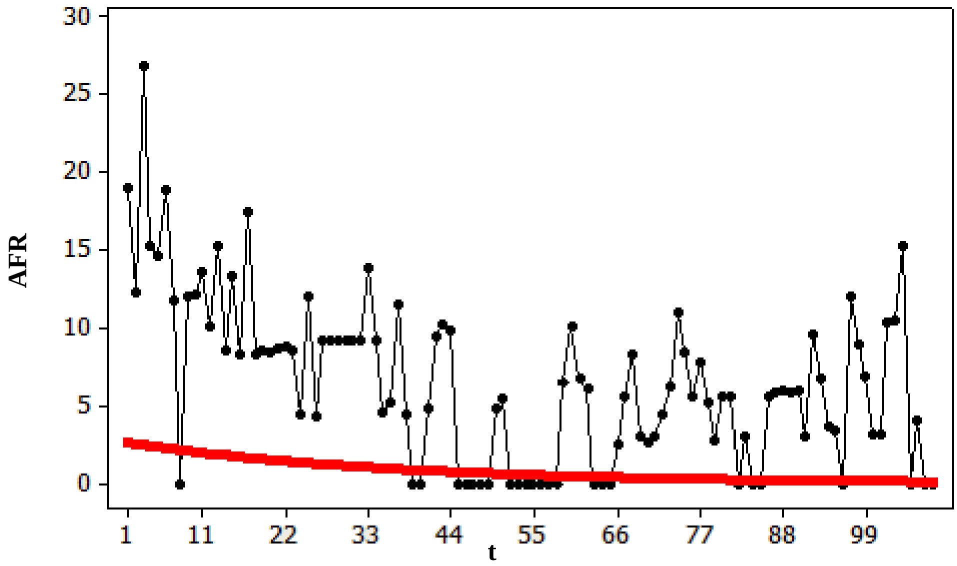


Figure 1. Trend component plot for AFR.

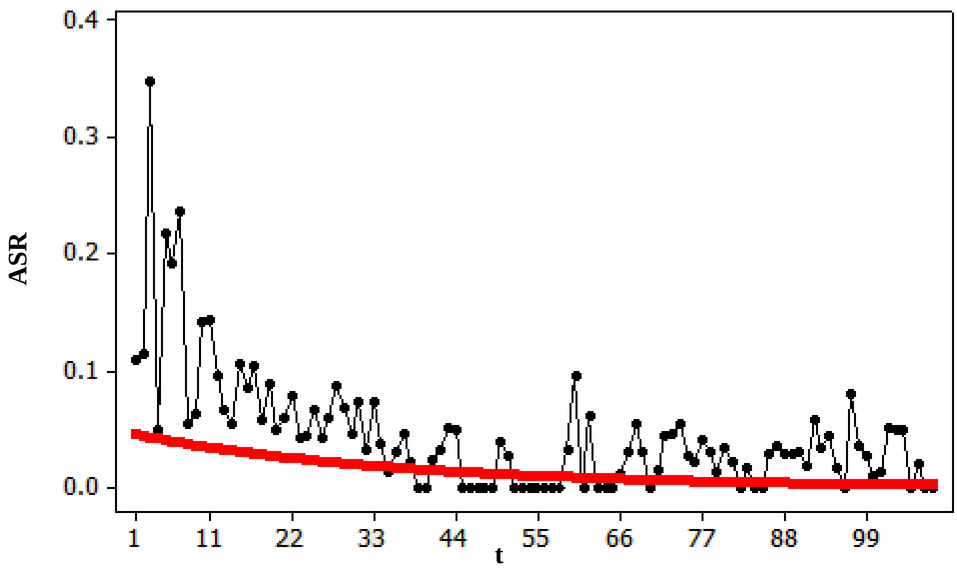
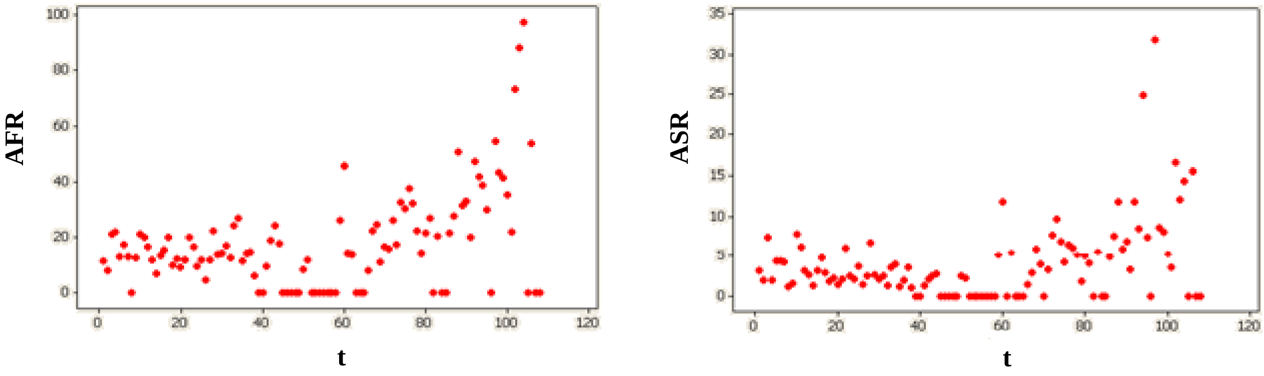


Figure 2. Trend component plot for ASR.

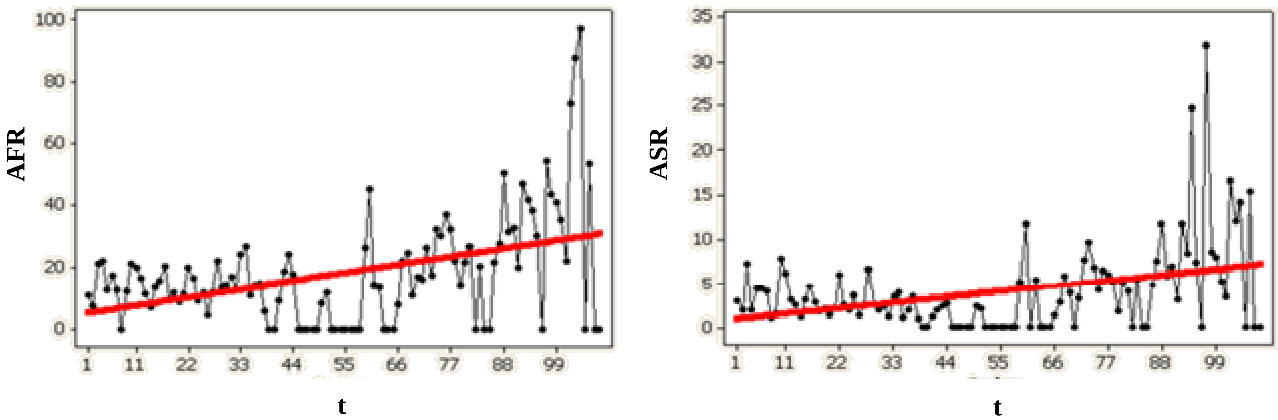
Table 2. Seasonal constituent (SN_t) for ASR and AFR.

Month	ASR	AFR
January	0.51	0.61
February	0.68	0.74
March	0.90	0.68
April	0.77	1.48
May	1.31	1.41
June	1.10	1.17
July	0.60	0.65
August	1.23	1.07
September	1.10	1.06
October	1.47	0.91
November	1.30	1.23
December	1.10	1.00



(a) **(b)**

Figure 3. Scatter plots of residuals. a) AFR, b) ASR.



(a) **(b)**

Figure 4. Trend plots of residuals. a) AFR, b) ASR.

Diagram related to the remainder constituent according to Figure 4, and to determine the relations between their trends according to Eqs. 6 and 7 for the severity index and frequency index, respectively.

$$TR_{IRT} = 0.930 + 0.0579t \qquad (6)$$

$$TR_{IRT} = 5.09 + 0.238t \qquad (7)$$

With identification of the relations relevant to the trend, seasonal, and remainder constituents of the time series for the severity index and frequency index of the accidents, their final time series model was summarized in the form of Eqs. 8 and 9, respectively.

According to Figure 5, the remainder values resulting from these equations were much less compared to the remaining values in the first stage, and these equations were accepted as the final equations of the time series of the indices.

$$Y_t = 0.047 \times 0.97286^t \times SN_t \times (0.930 + 0.0579t) \qquad (8)$$

$$Y_t = 2.714 \times 0.9712^t \times SN_t \times (5.09 + 0.238t) \qquad (9)$$

Additionally, accuracy of the prediction model was evaluated by the RMSE method (equation 10). Its values for the severity index and frequency index of the accidents were 0.001 and 6.400, respectively. These values show very high precisions for the severity index and frequency index of the models.

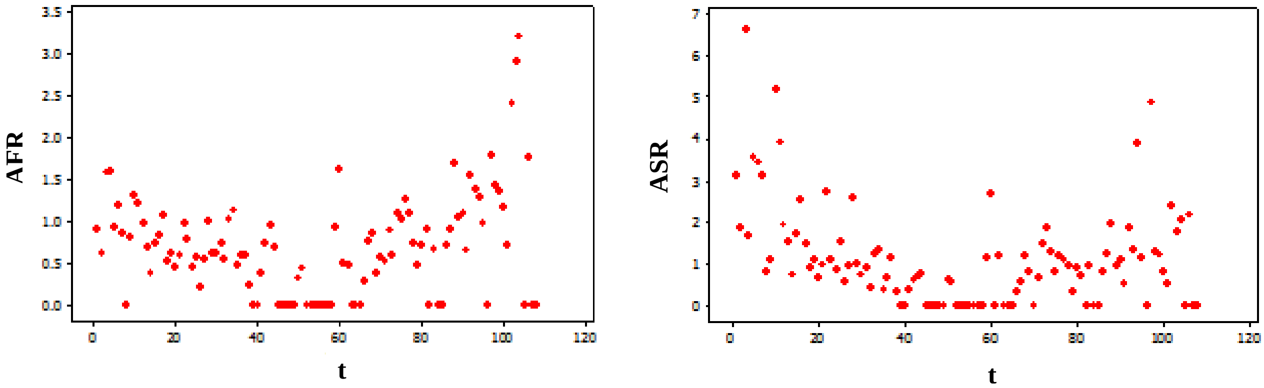
$$RMSE = \sqrt{\frac{1}{n}\sum (d_t - Y_t)^2} \qquad (10)$$

where

d_t: predicted amounts;

Y_t: observed amounts.

After obtaining the final models for the time series, the task of monthly prediction of the indices for a four year period of time from 2014 to 2017 was performed. Next, having the mean work hours of the mine and using Eqs. 3 and 4, monthly predictions of the number of accidents and number of lost work days were performed for the years 2014-2017. The values resulting from these predictions showed that the number of accidents and number of lost work days in the mine for similar months in the mentioned years would have a decreasing trend. This fall in the accidents is shown in Figures 6 and 7. Table 3 shows the yearly total values.



(a) **(b)**

Figure 5. Scatter plots for residuals of final models. a) AFR, b) ASR.

Table 3. Predicted number of accidents and days-lost.

Year	Number of accidents	days-lost
2014	32	845
2015	25	659
2016	19	514
2017	15	401

5. Conclusions

In this work, by studying the statistics of the monthly accidents in the Tazareh coal mine during the years 2005-2013, and creation of the time series from the risk parameters, the accidents were analyzed using the classic time series. By analyzing the time series constituents, frequency indices and accident severities, the final model for these indices was determined. The RMSE values for evaluating the precision of the model for the severity index and frequency index were 0.001 and 6.400, respectively, which shows the very high precision for the models obtained. Evaluation of the seasonal constituent of the time series showed that, yearly, the most number of accidents occurred in April and the least ones in January. Additionally, the severest yearly accidents occurred in October, and the least ones in January. Prediction of the risk indices was performed using the final models obtained for the years 2014-2017. Finally, with the help of the predicted indices, the number of accidents and number of work days lost for the mentioned years were predicted. The values predicted showed that the accidents in the future would have down-going trends in the number and severity such that in similar months, yearly, there would be 22% decrease in the number of accidents and 24% decrease in the number of work days lost.

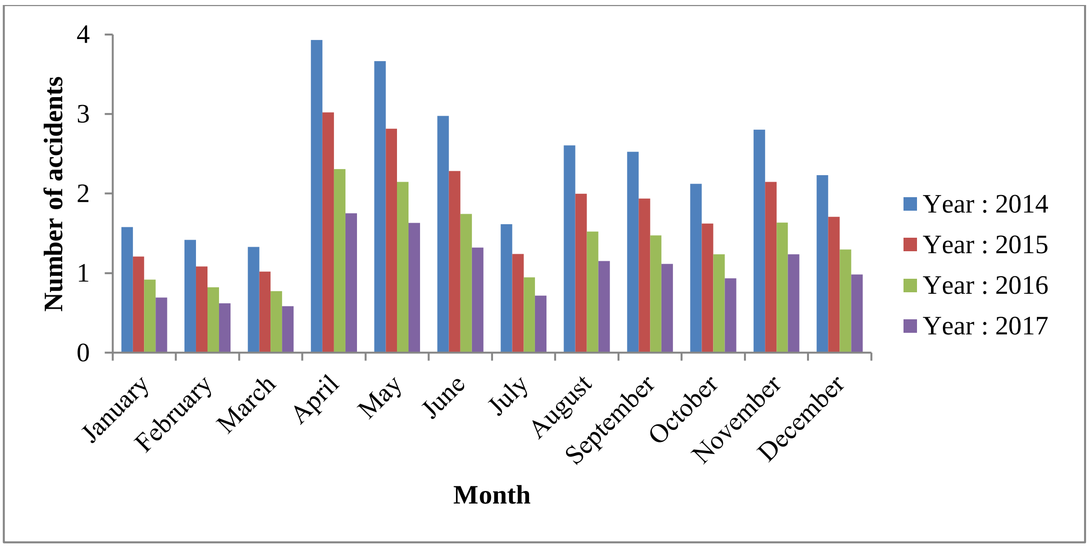


Figure 6. Diagram of comparison of number of accidents predicted for similar months in years 2014-017.

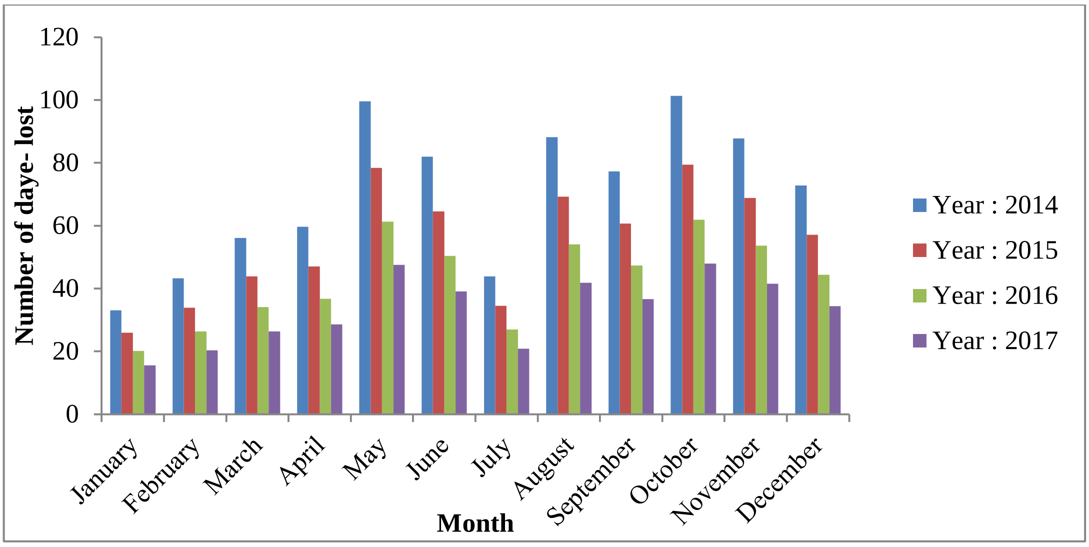


Figure 7. Diagram of comparison of number of lost work days predicted for similar months in years 2014-2017.

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پیش‌بینی ریسک بر اساس سری زمانی، مطالعه موردی: معدن زغال‌سنگ طزره

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چکیده:

در این تحقیق، برای پیش‌بینی ریسک معدن زغال‌سنگ طزره از مدل سری زمانی و از نوع کلاسیک ضربی آن استفاده شد. به این منظور، ابتدا آنالیز ماهیانه مؤلفه‌های ریسک شامل، شاخص‌های تکرار و شدت حادثه انجام شد و پس از آن نمودار سری زمانی ماهیانه مربوط به هرکدام از این شاخص‌ها برای یک دوره نه‌ساله، از سال ۱۳۸۴ تا ۱۳۹۲، ایجاد شد. در ادامه پس از استخراج مؤلفه‌های روند، فصلی و باقیمانده، مدل نهایی سری زمانی شاخص‌ها با دقت بالایی معین شد. میزان دقت مدل‌های حاصله با استفاده از روش «ریشه میانگین مربعات خطا» (RMSE) سنجیده شد که مقادیر آن برای شاخص‌های شدت و تکرار حادثه به ترتیب ۰/۰۰۱ و ۶/۴۰۰ به دست آمد. بررسی مؤلفه فصلی سری زمانی شاخص تکرار نشان داد که سالیانه، بیشترین تعداد حوادث در فروردین‌ماه و کمترین تعداد حوادث در دی‌ماه صورت می‌گیرد. همچنین بررسی مؤلفه فصلی سری زمانی شاخص شدت نشان داد که سالیانه شدیدترین حوادث در مهرماه و خفیف‌ترین آن‌ها در دی‌ماه واقع می‌شود. با استفاده از مدل نهایی، پیش‌بینی ماهیانه شاخص‌ها برای یک دوره چهار ساله از سال ۱۳۹۳ تا ۱۳۹۶ انجام شد. در ادامه با معلوم بودن میانگین ساعات کاری معدن، پیش‌بینی ماهیانه تعداد حوادث و تعداد روزهای کاری از دست رفته برای مدت مشابه صورت گرفت. نتایج حاصل از پیش‌بینی نشان داد که در آینده تعداد حوادث و تعداد روزهای کاری از دست رفته، دارای سیر نزولی خواهند بود؛ به‌طوری‌که برای ماه‌های مشابه، سالیانه به‌طور متوسط مقدار ۲۲ درصد کاهش در تعداد حوادث و مقدار ۲۴ درصد کاهش در تعداد روزهای کاری از دست رفته وجود خواهد داشت.

کلمات کلیدی: پیش‌بینی، ریسک، سری زمانی، شاخص تکرار حادثه، شاخص شدت حادثه.