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Prediction of fatal accidents in Indian factories based on ARIMA

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Abstract
The inherent benefits of an accident prevention program are generally known only after an accident has occurred. The purpose of implementation of the program is to minimize the number of accidents and cost of damages. Allocation of resources to implement accident prevention program is vital because it is difficult to estimate the extent of damage caused by an accident. Accurate fatal accident predictions can provide a meaningful data that can be used to implement accident prevention program in order to minimize the cost of accidents. This paper forecast the fatal accidents of factories in India by using Auto-Regressive Integrating Moving Average Method (ARIMA) model. Accident data for the available period 1980 to 2013 was collected from the Labour bureau, Government of India to analyze the long term forecasts. Different diagnostic tests are applied in order to check the adequacy of the fitted models. The results show that ARIMA (0, 0, 1) is suitable model for prediction of fatal injuries. The number of fatal accidents is forecasted for the period 2014 to 2019. These results suggest that the policy makers and the Indian labour ministry must focus attention toward increasing fatal accidents and try to find out the reasons. It is also an opportunity for the policy makers to develop policies which may help in minimizing the number fatal accidents.

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1. Introduction

Accidents that occur in the workplace cause harm to employees, environment and damage to the equipment. Increased workplace related accidents, injuries and fatality data demonstrate that continued efforts and effective measures are necessary to reduce the number of workplace related injuries, illnesses and fatalities. Factories utilize accidents rates as a way to compare and/or benchmark their own workplace occupational injuries and illness rates against peers in their sector, as well those factories that are recognize as leaders in workplace safety. Proper resource allocation for safety programs is an integral part of effective minimizing the number of accidents that occur in the workplace. Predicting the total number of fatal accidents by utilizing statistical forecasting methods provides a common mechanism for safety professionals, managers and Government agencies to understand and communicate statistically the progress of safety intervention programs (YORK, J., GERMAND, J. 2017). Previous safety intervention decision making processes were primarily based upon instincts and experiences of safety professional and the company's historical safety record (OYEWOLE, S. 2009).

In Indian factories, the total Injuries (fatal and non-fatal) decreased from 5769 to 2445, frequency rate of injuries per day worked decreased from 0.75 to 0.37, incidence rate per thousand average daily employment declined from 0.79 to 0.67, and severity rate of man days lost due to injuries per day worked decreased from 10.33 to 6.95 from the year 2012 to 2013 respectively. Out of the total injuries (fatal and non-fatal) reported, about 98.98 per cent were men and about 1.02 per cent were women. Textile industries accounted for 21.31 per cent of the total number of injuries in 2013. Mining industry accounted highest in the frequency rate of injuries (fatal and non-fatal) per one lakh man days and the incidence rate of injuries (fatal and non-fatal) per 1000 employees was the highest in the construction sector in 2013. The Rajasthan state accounted for highest number of injuries, the state of Bihar contributed to the highest overall frequency rate of injuries and the overall severity rate of non-fatal injuries was the highest in Chhattisgarh during 2013 (GOI 2013). The Indian factories Act, 1948 serves to assist in formulating national policies in India with respect to occupational safety and health in factories and deals with various problems concerning safety, health, efficiency and well-being of the persons at work places. The few reasons of fatal accidents in

Indian factories are mainly due to lack of management commitment, failure to develop safety culture and non compliance of safety systems.

The purpose of the analysis is to predict fatal accidents in Indian factories. An accurate prediction of fatal accidents, will allow all the stakeholders to discern how safety programs would function unchanged, assess the effectiveness of new intervention program(s), and ascertain how changes in regulatory policies could affect fatal accidents. This information can then be used in a variety of situations such as; developing budgets, evaluating insurance rates, adjusting safety program resources, establishment of new policies/procedures or driving advancements in safety technology (IYER, P., HAIGHT, J., DEL CASTLLO, T. 2005, AL-MUTAIRI, A., HAIGHT, J. 2009).

At present, the information concerning accidents in Indian factories was updated up to 2013, lagging by four years, while an accurate prediction of the number of fatal accidents is useful to the Government as well as managements of the factories to initiate the new safety management systems and practices to minimize them. Available data collected from the Labour Bureau, Ministry of Labour &Employment, Government of India for the period 1980 to 2013 will be used to predict fatal accidents for the period 2014 to 2019 by autoregressive integrating moving average method (ARIMA). Accurate prediction of fatal accidents can provide factories with meaningful data that can be used to optimize resource allocation within a safety program in order to maximize their return on investment.

2. Literature Review

Forecasting is an effective tool to enhance understanding how something may behave based upon studying and analyzing applicable data. As a part of a safety intervention models, forecasting has been used to predict incident rates. These predictions are used to assist in adjusting the allocation of resources to obtain the desired allocation that produces the lowest incident rates and optimization of other resources such as time and money. The incident rates obtained from the artificial neural network model indicated that the predictions of the model were not close to the actual results due to low residual result and average forecast error (AL-MUTAIRI, A., HAIGHT, J. 2009). The double exponential smoothing method was applied with 71.58% incident rate prediction accuracy and a mean square error of 4.76 (OYEWOLE, S. 2009). The industrial accident data-series of Portugal for the period 1903 to 2012 was analyzed and the statistical distributions of the number of fatalities caused by industrial accidents reveal power law behaviour, which allows to understand better the complexity of modern industrial accidents (ANTONIO, M., TENREIRO, J. 2015). The auto regressive moving average (ARMA), has been used as an incident rate prediction model for mining operations USA and compared the results with different forecasting methods; the double exponential smoothing and ARIMA statistical forecasting methods provided the most accurate incident rate predictions compared to other methods (YORK, J., GERNAND, J. 2017). The characteristics of construction accidents in Korea were analyzed from 2011 to 2015 by means of analysis of variance to examine the relationship between incidence and mortality rates. It was observed that these rates were significantly higher in case of male workers than female workers. (BYUNG, W., YUN SUNG, L., JUNG HOON, K., RANA MUHAMMAD, A. 2017). The characteristics of occupational injuries for construction employees in Turkey, suggests that small companies should be checked more systematically and should be encouraged to properly train their workers in terms of safety (COLAK, B., ETILER, N., BICER, U. 2004). Developing countries do not have reliable occupational data due to a lack of proper safety reporting and notifying culture, but this unreliable data is used as a basis for creating prevention policies in these countries (HAMALAINEN, P., SAARELA, K., TAKALA, J. 2009). The trends of industrial accidents in Pakistani factories between 1993 and 2009 were analyzed by means of an index value calculation method. The results indicate that there is an increase of fatal accidents which can be the major concern for safety stakeholders (ABBAS, A., BALKHYOUR, A. 2015). This study analyzes the determinants of industrial accidents in 44 Malaysian manufacturing industries during the period from 1993 to 2008 with pooled ordinary least square method. It was discovered that industrial accidents were negatively influenced by the size of a company (SAAD MOHD, S., FATIMAH, S., ZAIRIHAN, A. 2012). A study was conducted in India to predict the correlation between the causes of accident with severity of the accident and the loss of people by formulating artificial neural network and the model was developed by considering 173 accidents (GAJBHIYE, P., WAGHMARE, A. 2016).

The incident rates obtained from the ANN prediction model had a residual result of -0.63 and average percent error of 55% which indicated that the ANN model produced predictions that were not close to the actual results. Park performed a comparison of the regression models used in resource allocation models, which utilized the moving average method to predict the future incident rates based upon changes to resource allocation input which demonstrated the expected results of the other studies employing the Moving Average method, yet when the entire resource model was applied to other work groups less than desirable results were achieved (AL-MUTAIRI, A., HAIGHT, J. 2009). In view of the reviewed literature, it could be stated that the majority of the forecasting models which have been developed in the context of accidents are less reliable due to consideration of small data sets. In the present study, the ARIMA model has been developed on the basis number of accidents in Indian factories data over 34years.

3. Methodology

Time series forecasting models help in interpreting the relationship of the past observations of a variable and its future values (SHUMWAY, R., STOFFER, D. 2011). The application of a time series model becomes more vital in the absence of an explanatory model, which relates the prediction variable to other explanatory variables. In addition, the surge in the applications of forecasting models has also been highlighted by various researchers in their studies (CHANG W. 2014, ZHANG G. 2003).

Time series models include the modeling with ARIMA, neural network and support vector machines. However, the applications of such models are based on the dominant patterns that exist in the data sets, i.e. linear or non-linear pattern. The ARIMA modeling is most suitable for linear pattern data sets, whereas NN and SVMs are fit for non-linear data (ZHANG, G., PATUWO, B., HU, M. 1998). The data of the present study follow linear pattern; therefore, it has been modeled with the help of an ARIMA model.

3.1. ARIMA model

The ARIMA model has the statistical properties that make it suitable for the forecasting of linear data patterns. It is assumed in an ARIMA model that linear function of numerous past observations and random errors are the future values of a variable. Therefore, the fundamental process of generating a time series can be given in the form of equation 1.

$$y_t = \alpha_0+\alpha_1 y_{t-1}+..+\alpha_p y_{t-p}+\varepsilon-\beta_1\varepsilon_{t-1}-..-\beta_q\varepsilon_{t-q} \qquad (1)$$

where y_t and ε_t represents the actual value and random error at time period t, respectively; α_i (i= 1,2,3,....,p) and β_j (j = 0,1,2,3......, q) are model parameters; p and q are integers that are usually referred as the order of the model.

In addition, random errors, ε_t are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2. The model converges into an autoregressive (AR) model of order p, if q = 0 in Eq. (1), and the model converges into a moving average (MA) model of order q, if p = 0 in Eq. (1). Likewise, it can be concluded that the main task of an ARIMA model formulation is to decide an appropriate model of order (p, q). Box and Jenkins (1976) developed the methodology of formulating ARIMA model. Box and Jenkins' three steps methodology of ARIMA model building include identification, parameter estimation and diagnostic checking (BOX G., JENKINS G. 1976).

- Step 1: To check the time series is stationary or not; if, the time series is not stationary and it shows some trend and heteroscedecity, then the difference and power transformation are applied on it. With this, the time series converts into a stationary time series with uniform variance for fitting the ARIMA model.
- Step 2: In view of the target of minimization of overall errors, the model parameters are estimated out-rightly after the formulation of a tentative model.
- Step 3: To check and validate, the model assumptions about error terms, ε_t, are accomplished. The goodness–of-fit tests have been performed using statistical information such as the value of Akaike Information criteria (AIC). The importance of AIC and SC, in terms of more the better; therefore, the values of these criteria help in choosing this model (BOX G., JENKINS G. 1976). Therefore, the diagnostic information helps in achieving the appropriate ARIMA model. Finally, the above-mentioned three steps of the model formulation process are repeated to achieve a desired objective in the form of an ARIMA model.

3.2. Evaluation criteria for forecasting

Mean absolute percentage error (MAPE) or mean absolute error (MAE) has been coined as a term for the measurement of variation of dependent series data from its model predicted (forecasted) level. Because this measure is independent of the units of a series, therefore, it can be used to compare the series with different units.

The formula for the calculation of MAPE is shown in equation 2,

$$M = \frac{100\%}{n}\left|\frac{A_i-F_i}{A_i}\right| \qquad (2)$$

where A_i and F_i denote the actual and forecasted values, respectively. If the value of MAPE (M) is zero, then it would be considered as a perfect fit for an ARIMA model. However, there is no specification about the upper limit of MAPE values (BOX, G., JENKINS, G., REINSEL, G. 2008)

4. Results and discussion

This section is related to the statistical analysis of data. In this chapter analysis of data and graphical study has been carried out. It is necessasary to forecast the fatal accidents for the purpose of planning to minimize them. It can be done by means of time series and ARIMA model. The data has been collected from the ministry of labour, Government of India. Data comprises the number of fatal accidents in Indian factories from 1980 to 2013.

Figure 1 depicts the trend in fatal accidents from the year 1980 to 2013. This graph shows that the fatal accidents data are stationary; therefore, a forecasting technique applies to them.

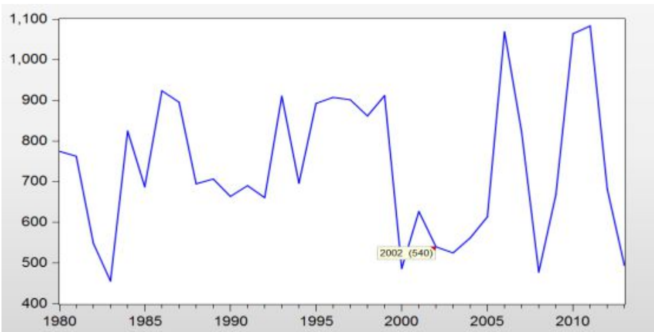

Fig. 1. Fatal accidents (in numbers)

Figure 2 is histogram about the actual number of fatal accidents. Its probability is 0.498521 which is more than the value of α = 0.05, which shows that the fatal accidents data are normal.

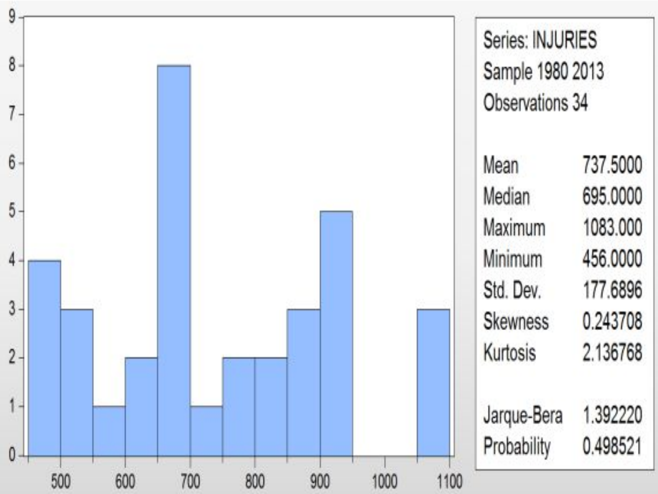

Fig. 2. Histogram of fatal accidents

The Figure 3, augmented dickey fuller test has been applied on fatal accidents data at zero level. Here the p-value is 0.0020 which is less than the value $\alpha = 0.05$, it shows that the fatal accidents are stationary at zero level.

Null Hypothesis: INJURIES has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.293949	0.0020
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

Fig. 3. Augmented Dicky Fuller Test at Zero Level

4.1. Model Identification

In BOX-Jenkins ARIMA methodology (BOX, G., JENKINS, G., REINSEL, G., LJUNG, G. 2015) the selection of good MA (moving average) and AR (auto regression) depend upon the result of correlogram of partial auto correlation and auto correlation. The work of correlogram is to describe the order of MA and AR. In this the order of MA term is described by auto-correlation function and the order of AR term is described by partial auto-correlation. Correlogram table is also used for checking the stationary of the data. If the lags are absent from the intervals it means the data are not stationary. In order to assess the stationarity and to find the orders of MA and AR terms, a correlogram of the steel production data at level is to be constructed.

Figure 4 shows that AR (1) and MA (1) are approximate to the intervals and the remaining lags are inside the intervals, which mean the data are stationary at zero level. It also shows the order of AR term and MA term. In this case AR (1) term and MA (1) term are the correlogram model and are also known as orders. They are used as an experimental model to check which model model is the best. Subsequently, parameters need to be estimated to define the best model.

Sample: 1980 2013
Included observations: 34

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.276	0.276	2.8352	0.092
		2	-0.200	-0.299	4.3619	0.113
		3	-0.197	-0.051	5.8957	0.117
		4	0.004	0.036	5.8964	0.207
		5	-0.027	-0.124	5.9261	0.313
		6	-0.240	-0.241	8.4445	0.207
		7	-0.250	-0.153	11.285	0.127
		8	-0.046	-0.070	11.383	0.181
		9	0.010	-0.167	11.388	0.250
		10	-0.043	-0.136	11.482	0.321
		11	0.075	0.048	11.778	0.381
		12	0.134	-0.064	12.771	0.386
		13	0.118	-0.024	13.589	0.403
		14	-0.050	-0.140	13.741	0.469
		15	-0.048	-0.036	13.891	0.534
		16	-0.160	-0.334	15.641	0.478

Fig. 4. Correlogram of Fatal Accidents (Zero level)

4.1.1. Model 1

In Figure 5, the coefficient of AR (1) is -0.070257 and its probability is 0.8845 which is greater than the value of $\alpha = 0.05$, which means the effect of AR (1) term is insignificant. Then, the coefficient of the MA (1) term is 0.445862 and its probability is 0.2889 which is greater than the value of $\alpha = 0.05$. It means the effect of MA (1) term is insignificant. From the above result it is concluded that model-1 is not best fit. The value of Durbin- Watson test is 1.951965, which is in the range of acceptance region (1.5 to 2.5), so according to Durbin-Watson model-1 is best fit. However, due to the insignificant effect of AR term and MA term it is concluded that the model 1 is not suitable to forecast fatal accidents of Indian factories.

Dependent Variable: INJURIES
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/08/18 Time: 11:59
Sample: 1980 2013
Included observations: 34
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	735.8759	39.63563	18.56602	0.0000
AR(1)	-0.070257	0.479384	-0.146557	0.8845
MA(1)	0.445862	0.412938	1.079730	0.2889
SIGMASQ	26760.89	8575.047	3.120786	0.0040

R-squared	0.126744	Mean dependent var	737.5000
Adjusted R-squared	0.039419	S.D. dependent var	177.6896
S.E. of regression	174.1523	Akaike info criterion	13.27266
Sum squared resid	909870.2	Schwarz criterion	13.45223
Log likelihood	-221.6352	Hannan-Quinn criter.	13.33390
F-statistic	1.451397	Durbin-Watson stat	1.951965
Prob(F-statistic)	0.247572		

Inverted AR Roots	-.07
Inverted MA Roots	-.45

Fig. 5. Parameter Estimation AR (1), MA (1)

4.1.2. Model 2

In the Figure 6, the coefficient of MA (1) is 0.393358 and its probability is 0.0373 which is less than the value of $\alpha = 0.05$. It means the effect of MA (1) term is significant. From the above result it can be seen that model-2 is the most suitable, because of its sufficiency. What is more, the value of Durbin- Watson test is 1.973418, which lies in the range of acceptance region (1.5 to 2.5), so according to the Durbin-Watson test, model 2 is the best. Therefore, it can be concluded that model 2 is sufficient to forecast the fatal accidents.

Dependent Variable: INJURIES
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/08/18 Time: 12:44
Sample: 1980 2013
Included observations: 34
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	735.5687	40.66395	18.08896	0.0000
MA(1)	0.393358	0.180788	2.175792	0.0373
SIGMASQ	26789.34	8264.351	3.241554	0.0028

R-squared	0.125816	Mean dependent var	737.5000
Adjusted R-squared	0.069417	S.D. dependent var	177.6896
S.E. of regression	171.4114	Akaike info criterion	13.21505
Sum squared resid	910837.5	Schwarz criterion	13.34973
Log likelihood	-221.6559	Hannan-Quinn criter.	13.26098
F-statistic	2.230816	Durbin-Watson stat	1.973418
Prob(F-statistic)	0.124407		

Inverted MA Roots	-.39

Fig. 6. Parameter Estimation AR (0), MA (1)

In addition to Model 1 and 2, other combinations were also considered that is (i)AR(1), MA(1) and MA(2), (ii) AR(1), MA(1),MA(2) and MA(3)and (iii) AR(1), MA(1),MA(2), MA(3) and MA(4). In all the three cases, the probability is more than 0.05. The value of akaike and Schwarz criterion is minimum in MODEL 2 that is AR(0) MA(1).

4.2. Diagnostic Checks (Model 2)

ARMA structure showing that the inverted MA Root is -0.39. The MA root lies in the range (-1 to +1), so it is concluded that all the MA processes are invertible and all the AR processes are stationary. In Figure 7, as per the correlogram of residual (q-statistic) of model-2, all the lags are within the intervals and the probability of each lag is greater than 10%. It means according to the correlogram of residual, that model 2 is sufficient, and the most suitable to forecast the fatal accidents.

Sample: 1980 2013
Included observations: 34
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0015	
		2	-0.127	-0.127	0.6183	0.432
		3	-0.188	-0.193	2.0162	0.365
		4	0.038	0.016	2.0763	0.557
		5	0.021	-0.028	2.0944	0.718
		6	-0.161	-0.201	3.2291	0.665
		7	-0.192	-0.213	4.8998	0.557
		8	-0.021	-0.104	4.9213	0.670
		9	0.052	-0.100	5.0539	0.752
		10	-0.079	-0.223	5.3756	0.800
		11	0.092	0.015	5.8260	0.830
		12	0.071	-0.027	6.1087	0.866
		13	0.131	0.007	7.1127	0.850
		14	-0.087	-0.132	7.5745	0.870
		15	0.035	0.028	7.6552	0.907
		16	-0.190	-0.289	10.115	0.812

Fig. 7. Residual Q Statistic Probabilities of AR(0), MA (1)

Figure 8 is of correlogram of squared residual of model 2. In this table all the lags are within the interval, so it can be concluded that according to the table of correlogram of squared residual the model 2 is sufficient.

Date: 03/09/18 Time: 15:01
Sample: 1980 2013
Included observations: 34

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.210	-0.210	1.6330	0.201
		2	0.177	0.139	2.8264	0.243
		3	-0.145	-0.089	3.6554	0.301
		4	0.253	0.203	6.2721	0.180
		5	-0.075	0.033	6.5089	0.260
		6	0.140	0.073	7.3699	0.288
		7	0.045	0.140	7.4611	0.382
		8	0.018	-0.032	7.4757	0.486
		9	-0.070	-0.077	7.7142	0.563
		10	0.066	0.020	7.9349	0.635
		11	0.126	0.128	8.7849	0.642
		12	-0.159	-0.167	10.198	0.599
		13	0.051	-0.012	10.347	0.665
		14	-0.061	-0.024	10.572	0.719
		15	-0.068	-0.184	10.866	0.762
		16	-0.026	0.030	10.914	0.815

Fig. 8. Squared Residual Probabilities of AR (0), MA (1)

Figure 9 depicts the histogram is of model 2. Its probability is 0.544976 which is greater than the value of $\alpha = 0.05$, it shows that the model 2 is normal. So it can be stated that, according to the histogram, the model 2 is sufficient.

The graph in Figure 10 shows actual and forecasted values of model 2 (which is best model), shows that when the actual values of fatal accidents move upwards, the forecasted values also move upwards and when actual values of fatal accidents move downward, the forecasted values of the production of steel in also moves downwards. It means the actual and forecasted values of the fatal accidents move in same manner and close to each other. It means that the model 2 is best to forecast fatal accidents.

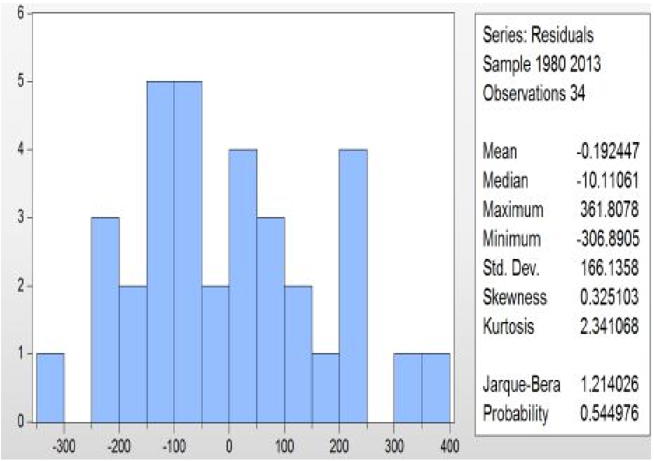

Fig. 9. Histogram (Model 2)

The graph in Figure 11 gives information about static forecast and depicts forecasted fatal accidents. It lies between the intervals. It shows that the model 2 is the most appropriate. Nevertheless, further tests will be undertaken to authenticate the applicability of Model 2 of ARIMA through performing comparative analysis and forecasting for the period of 10 years.

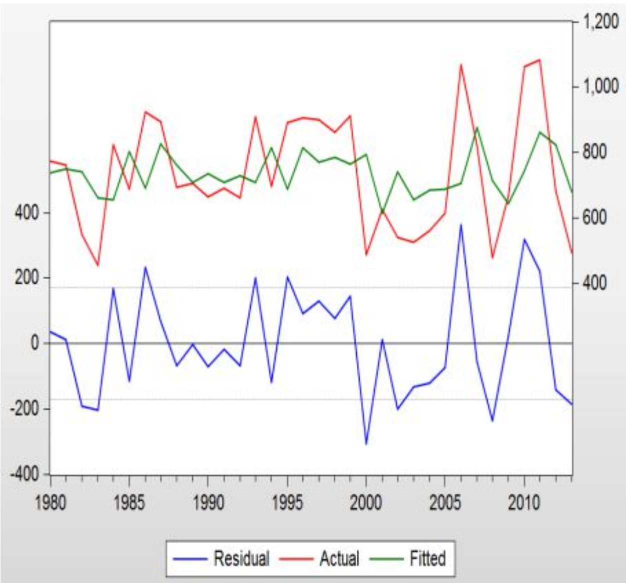

Fig. 10. Graph of Actual, Forecasted and Residual data

Durbin Watson test shows that the two models are the most appropriate to forecast the accidents, but the value of model 2 is greater (1.973418), so it shows that model 2 is best to forecast fatal accidents. The model 2 has minimum standard error of regression as compared to model 1.

It means model 2 is the most appropriate to forecast the fatal accidents. The q-stat correlogram shows that model 2 is suitable to forecast fatal accidents. The standard correlogram shows model 2 as sufficient to forecast fatal accidents. Finally, model 2 is best fitted for forecasting fatal accidents of Indian factories. Model 2 was used for conducting forecast analysis

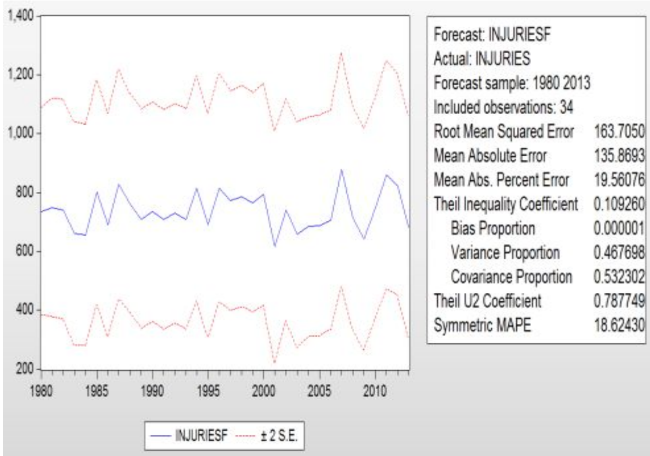

Fig. 11. Forecasting Graph

4.3. Forecasting

The purpose of the study was to develop and evaluate ARIMA model for fatal accident prediction. Thus it is imperative to exhibit its applicability. Table 1 shows the comparison of actual and forecasted values for the 15 year period (2005-2019), and depicts that the actual values and the forecasted values are closer to each other. All in all, it is concluded that model 2 is perhaps the best model to forecast fatal accidents of Indian factories.

Table 1. Actual and Forecasted Accidents

Year	Actual	Forecasted
2005	613	688
2006	1068	996
2007	821	878
2008	478	513
2009	668	643
2010	1064	1045
2011	1083	1061
2012	682	722
2013	494	518
2014		662
2015		725
2016		738
2017		749
2018		746
2019		741

5. Conclusion

This analysis presents extensive process of building ARIMA model for fatal accident prediction. The experimental results obtained with best ARIMA model demonstrated the potential of ARIMA models to predict fatal accidents on short-term basis. It is concluded that model 2 is best model to forecast the production of fatal accidents. After checking all the tests, it is evident that the data is stationary zero level and AR (0) and MA(1), with zero order is suitable for forecasting the fatal accidents. The forecasted values obtained from model 2 are closer to the actual values. The forecasted number of fatal accidents from 2014 and 2019 is based on the past 34 years. Therefore, from the forecasting technique, it is known that the number of fatal accidents from 2014 to 2019 is smaller than in 2010 and 2011. The results are useful to analyze how the number of fatal accidents is affected by the implementation of various strategies and what would happen without any intervention. The implementation of accident prevention program, are generally realized after an accident has occurred and resource allocation has the imperative task of balancing costs and often unrealized benefits. Factories management can allocate additional resources to an accident prevention program because it is difficult to estimate the return on investment, especially since the returns are a set of negative outcomes not manifested.

Accurate accident forecasts, will allow users to discern how safety programs would function in an unchanged form, assess the effectiveness of new intervention program(s), and ascertain how changes in regulatory policies could affect accidents. This information can then be used in a variety of situations such as; developing budgets, evaluating insurance rates, adjusting safety program resources, establishment of new policies/procedures or driving advancements in safety technology. In this study, the forecasting models are evaluated neither control for workplace intervention nor other regulatory interventions. The limitations of the study are number of fatal accidents depends on various factors such as human related, policy decisions of factory management and regulatory aspects that are difficult to predict or even unpredictable.

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基于 ARIMA 预测印度工厂的致命事故

關鍵詞
致命事故
预测
平稳
相关图
自回归综合移动平均法

摘要
事故预防计划的固有好处通常只有在事故发生后才会知道。该方案的实施目的是尽量减少事故的数量和损失的成本。分配资源实施事故预防计划至关重要，因为很难估计事故造成的损害程度。准确的致命事故预测可以提供有意义的数据，可用于实施事故预防计划，以最大限度地降低事故成本。本文采用自回归积分移动平均法（ARIMA）模型预测印度工厂的致命事故。从印度政府劳动局收集 1980 年至 2013 年期间的事故数据以分析长期预测。应用不同的诊断测试来检查拟合模型的适当性。结果表明，ARIMA（0,0,1）是预测致命伤害的合适模型。预测 2014-2019 年间发生致命事故的数量。这些结果表明决策者和印度劳工部必须将注意力集中在致命事故增加并试图找出原因。这也是决策者制定可能有助于减少致命事故数量的政策的一个机会。