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Accidental Mortality in India: Statistical Models for Forecasting

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***ABSTRACT**: During the process of evolution, changing lifestyle introduces new elements like accidents effect mortality. The incidence of accidental deaths has shown a mixed trend with an increase of 51.8 percent in the year 2012. From National Crime Report Bureau-2012 data this paper tries to investigate the statistical model which method give best estimated value of forecasting accidental death. Time series model--Various Exponential Smoothing and Auto Regressive Integrated Moving Average (ARIMA) techniques were applied; it is found that the trend of accidental cases showing a increasing pattern. The forecast value show that 438811 numbers of deaths may be in the year 2015 with 32.5 rate of increment as compared to 2006, if the rate will be constant and there will be no change in patterns of mortality. So, on validation of Models, ARIMA performed better than the DTES. This will be help for policy maker to control such type of incidence in future.*

***KEYWORDS:** Damped trend Exponential Smoothing (DTES), Auto Regressive Integrated Moving Average (ARIMA), Mean Absolute Percentage Error (MAPE), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE)*

I. INTRODUCTION

Improved hygiene and medical discoveries reduce incidence of epidemics like cholera and small pox. Consequently, the proportion of accidental deaths due to natural causes (heart stroke, exposure to cold, starvation, epidemic, cyclone etc.) is expected to decrease significantly. Besides these, incidences of deliberate termination of life through suicide and unnatural deaths also increase. With the increasing population, accidental deaths are expected to increase in absolute terms (on the average), but a systematic increase/decrease in rates may be looked at to assess our progress towards the attainment of human well being. The incidence of accidental deaths has shown a mixed trend during the decade 2003-2012 with an increase of 51.8 percent in the year 2012 as compared to 2002, however 0.2 percent decreases was observed in 2003 over previous period 2002.

The population growth during the corresponding period was 13.6 percent whereas the increase in the rate of accidental deaths during the same period was 34.2 percent**.** A total of 394,982 accidental deaths were reported in the country during 2012 (4098 more than such deaths reported in 2011) showing an increase of 1.04 percent as compared to previous year 2011. Correspondingly, 0.3 percent increase in the population and 0.92 percent increase in the rate of accidental deaths were reported during this year as compared to previous year (National Crime Report Bureau, India). Accidents (man-made and natural) are among the most important reasons for pre-mature end to human lives. Injuries resulting from the accidents handicap many people. These unfortunate victims are important members of their families as well as of the society. As a result, the loss due to accidents is felt by family members and society at large. The deep and wide impact of accidents makes it incumbent upon society to make efforts at reducing the incidence of these phenomena.

In almost countries in Africa, Asia, and Latin America, accidental crashes have become one of the leading causes of deaths in the Older, Children and the economically active adults between ages 30 and 49 years (Murray and Lopaz 1996, Ross et al 1991). Despite this burgeoning problem, little attention has been paid to accidental injury prevention and treatment in most developing countries of which India is no exception. According to figure of 'National Crime Report Bureau (NCRB) 2012' 1082 deaths per day are happing due to accidents in India. Also, in India 358 deaths due to accidents per day in the age group 0-29 years, 352 Deaths due to accidents per day in the age group 30-44 years and 372 deaths due to accidents per day in the age group 45 years & above. 461 deaths and 1301 injuries per day due to traffic accidents 381 deaths per day and 1287 injuries per day due to road accidents.

Accidental deaths are the death caused by an accident or a natural calamity. It's not HIV/AIDS or any other disease which is the leading killer of productive youth across the globe but accidents (D. K. Dash, TNN Nov, 2012). A World Health Organization (WHO) report shows that 33, 5805 people in the 15-29 years age group succumb to road accident injuries annually and it's no different in India. At least 30 percent of road fatalities here are in this age group of 15-24 years. Mumbai, the financial capital of the country, could perhaps also be dubbed the "accident capital"(C. Tembhekar, TNN Jan, 2013). Mumbai has reported the maximum number of sudden deaths—where the cause of death is not known. Interestingly, Kolkata—the third largest city in terms of population—reported the lowest number of accidental deaths at 1.4 percent.

According to NCRB, Kerala has become a high accident-prone state on the basis of percentage share in deaths due to road accidents (Ajay, TNN Jul 2012). As road traffic crashes take the lives of nearly 1.3 million every year, and injure 20-50 million more in the world, India along with China are listed among countries with the highest number of deaths (Znews, May 2011). Mental illness is related to all sorts of accidental deaths, especially poisoning and falls (Casey Crump, sept, 2013). As countries experience the epidemiological transition with a relative decline in infectious diseases, accident rates tend to increase, particularly unnatural deaths by accidents. Countries experiencing the so-called epidemiological transition comprising a decline in mortality and morbidity from infectious diseases tend to witness an increase in the relative importance of fatal and non-fatal injuries. Unintentional injury rates in developing countries have increased to become a significant cause of premature death and morbidity (Bradley *et al*., 1992; Zwi, 1993; Murray and Lopez, 1994).

There are measures which can be taken, however, to reduce accidents and their effects, and people's beliefs should not be taken to mean that they are satisfied with the status quo. Discussion of preventative actions need to incorporate a wider range of factors, such as cultural beliefs and understanding, and accidents need to be placed within a social, economic and political context. There needs to be an increase in resources given both to research to understand the problem, and to tackling it.

II. STATEMENT OF THE PROBLEM

India is the second largest country in the world which has 1210.6 millions populations (census 2011) and more than 64 percent of population is in age group 15-64 years. Where death rate is 7.0 n India (SRS, 2012) and in total deaths 78.9 percent share of age group 15 to 60 years & above. There has been no respite from accidental deaths for the state, which has moved up from the low accident-prone state category to high in the National Crime Records Bureau's (NCRB) Report 2012. The magnitude of 'accidental deaths' by causes attributable to nature has declined by 3.1% and that of deaths by un-natural causes have increased by 1.0% during 2012 over the year 2011.Under causes attributable to nature, the share of deaths due to cold and exposure, Starvation/thirst, torrential rains and heatstroke has increased whereas the share of causes such as avalanche cyclone/tornado, earthquake epidemic, flood, landslide and lighting has decreased in 2012 over 2011.

The share of causes not attributable to nature has increased for causes such as falls sudden deaths ,poisoning ,suffocation and traffic accidents whereas the share of causes such as ,air crash ,collapse of structure, drowning, ,electrocution, explosion ,factory /machine accidents, fire arms, killed by animals, mine or quarry disaster and stampede has decreased to the previous year. The average rate of accidental deaths has marginally increased from 32.3 in 2011 to 32.6 in 2012.

III. OBJECTIVE

[1] To investigate the statistical model which method give best estimate for forecasting accidental mortality in India.

[2] To estimate accidental deaths for next three years according to current rate of increment of accidental death in India.

[3] To comparison between observed values which has been used for analysis with forecast value estimated by different model.

IV. DATA SOURCE

Every year Ministry of Home Affairs, Government of India publishes data on accidental deaths and suicides in India. The data for present study has been drawn from National Crime Report Bureau annually report on accidental deaths and suicides in India. The annual publication of 'National Crime Record Bureau 'Accidental Deaths and Suicides in India – 2012**'** is publish in the third week of June 2013.This annual publication is the 46th in series which started in the year 1967 and contains valuable information on accidents and suicides and pattern in the society. So for this study we select to given data from year 1991 to 2012 i.e., total accidental deaths, midyear population, accidental rate in India.

V. METHODOLOGY

Damped-Trend Exponential Smoothing

This is a modification of Holts Double exponential smoothing. Damped-Trend Exponential Smoothing assumes level and damped trend parameters. This model is appropriate for series with a linear trend that is dying out with no seasonality (Gardner and Mckenzie 1985). Its smoothing parameters are level, trend and damping trend. It describes how a damping parameter ϕ can be used within the Holt's method to give more control over trend extrapolation. The damped trend is given by:

$$L_t = \alpha(1-\alpha)(L_{t-1+}\ \phi\ T_{t-1})$$
$$T_t = \gamma\ (L_{t-}\ L_{t-1)+(1-}\ \gamma)\ \phi\ T_{t-1}$$

Where,

$L_{t=}$ smoothing level at time t of the series, computed after y_t is observed

α =smoothing parameter for the level of the series

T_t= smoothed trend at the end of the period t and γ= smoothing parameter for trend.

ϕ= trend modification or damping parameter if 0< ϕ<1, trend is damped and the forecasts approach an asymptotic given the horizontal straight line or plateau:

$L_t + T_t\ \phi\ (1-\phi)$ if the ϕ=1 the model is identical to the standard Holt (1957) model and the trend is linear. If ϕ=0, the model is identical to standard simple exponential smoothing and if ϕ>1 , the forecast function has an exponential trend.

ARIMA Model

In light of the problem associated with ordinary methods, several researchers have turned to the ARIMA model as a means to better predict accident variables. The ARIMA model is a useful statistical method for analyzing longitudinal data with a correlation among neighboring observations. This method has proven to be very useful in the analysis of multivariate time series. (Sales etal, 1980)

In ARIMA analysis, there are two simple components for representing the behavior of observed time series processes, namely the autoregressive (AR) and moving average (MA) models (Pankratz, A.1988). The AR model is used to describe a time series in which the current observation depends on its preceding values, whereas the moving average (MA) model is used to describe a time series process as a linear function of current and previous random errors (Shumway, 1988) It is possible that a time series model will consist of a mixture of AR and MA components. In this case the series is said to be computed by an autoregressive moving average process of order (p, q), where p and q are the orders of the AR and MA components respectively. The selection strategy for such models was developed and selected by the Box and Jenkins method (Box and Jenkins 1976). A general ARIMA model can be written as the following

The model such as:

$$B^d\ N_t = \frac{\theta(B)et}{\phi(B)}$$

Where e_t is assumed to have white noise is the backshift operator, N representing the stochastic part and d is the order of regular differencing needed to achieve time series stationary. Other parameters in the model are defined as follows :

$$\theta_q(B) = 1-\theta_1-\theta_2B^2-\ \ldots\ldots\ldots\ldots..\theta_qB^q$$
$$\phi_p(B) = 1-\phi_1-\phi_2B^2-\ldots\ldots\ldots\ldots\ldots.\ \phi_pB^p$$

Where $\phi_{1\ldots\ldots\ldots}\phi_p$ are autoregressive (AR) parameters,θ_1..............θ_q are moving average (MA) parameter.

ARIMA model development consist of a three-stage iterative process, which comprises of identification of the model, model parameter estimation and diagnostic checking of residuals of the fitted model(Brock well and Davis 1991).

This forecasting model was proposed by Box and Jenkins in 1976. An ARIMA process is a mathematical model used for forecasting. Box-Jenkins modeling involves identifying an appropriate ARIMA process, fitting it to the data, and then using the fitted model for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (e.g., Makridakis, Wheelwright and Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application (or forecasting).

Data preparation

This involves transformations and differencing. Transformations of the data (such as square roots or logarithms) can help stabilize the variance in a series where the variation changes with the level. This often happens with business and economic data. Then the data are differenced until there are no obvious patterns such as trend or seasonality left in the data. Differencing means is taking the difference between consecutive observations or between observations a year apart. The differenced data are often easier to model than the original data.

Model selection (Identification)

Here the Box-Jenkins framework uses various graphs based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data. In the identification stage of model building, we determine the possible models based on the data pattern. But before we can begin to search for the best model for the data, the first condition is to check whether the series is stationary or not. The ARIMA model is appropriate for stationary time series data (i.e. the mean, variance, and autocorrelation are constant through time). If a time series is stationary then the mean of any major subset of the series does not differ significantly from the mean of any other major subset of the series.

Also if a data series is stationary then the variance of any major subset of the series will differ from the variance of any other major subset only by chance (see Pankratz, 1983). The stationary condition ensures that the autoregressive parameters invertible. If this condition is assured then, the estimated model can be forecasted (see Hamilton, 1994). To check for stationarity, we usually test for the existence or nonexistence of what we called unit root or observed the trend of the graph of the data. Unit root test is performed to determine whether a stochastic or a deterministic trend is present in the series. The ACF and the PACF are also so used to determine the stationary of the data and the order of the model. Though the ACF and PACF assist in determine the order of the model but this is just a suggestion on where the model can be build from. It becomes necessary to build the model around the suggested order. In this case several models with different order can be considered.

The final model can be selected using a penalty function statistics such as the Bayessian Information Criterion (BIC). The BIC which are measure of goodness of fit with others like the MAPE, MAE are used to select the best model. Given a data set, several competing models may be ranked according to their BIC with the one having the lowest information criterion value being the best. In the general case, the AIC and BIC take the form as shown below:

AIC= 2K-Log(L) or 2k+nlog(RSS/n)
BIC= - 2log(L)+ K log(n) or
$\mathrm{Log}(\sigma^2)+\frac{k}{n}\ \log(k)$

Model estimation

Model estimation means finding the values of the model coefficients which provide the best fit to the data. At the identification state one or more models are tentatively chosen that seen to provide statistically adequate representations of the available data. At this stage we get precise estimates of the coefficients of the model chosen at the identification stage. That is we fit the chosen model to our time series data to get estimates of the coefficients. This stage provides some warning signals about the adequacy of our model. In particular, if the estimated coefficients do not satisfy certain mathematical inequality conditions, that model is rejected. . There are sophisticated computational algorithms designed to do this.

Model checking (Diagnosis)

This involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to Step 2 and try to identify a better model. Ideally, a model should extract all systematic information from the data. The part of the data unexplained by the model (i.e., the residuals) should be small. These checks are usually based on the residuals of the model. One assumption of the ARIMA model is that, the residuals of the model should be white noise. . For a white noise series the all the ACF are zero. In practice if the residuals of the model is white noise, then the ACF of the residuals are approximately zero. If the assumption of are not fulfilled then different model for the series must be search for. A statistical tool such as Lung-Box Q statistic can be used to determine whether the series is independent or not.
The test statistics Q is

$$Q_m = n(n+2)\sum_{n=1}^{m}\left(.\frac{r2(e)}{n-k}\right) \sim \chi^2_{m-r}$$

Where,

$r^2(e)$ = the residual correlation at lag k.

m = the number of times lags includes in the test, n = the number of residuals

The p-value associated with the Q- statistics is small (p-value <α) the model is considered inadequate. Moreover we can check the properties of the residual with the following graph. The normality of the residual can be check by considering the normal probability plot or the p-value from the One- Sample Kolmogorov-Smirrno test. Also we can check the randomness of the residual by considering the graph of the ACF and PACF of the residual. The individual residual autocorrelation should be small and generally within $\pm\ 2/\sqrt{n}$of zero.

Error Magnitude Measurement

The error magnitude measures allow forecasters to evaluate and compare the performance of various models across different time periods. It relates to forecast error and is defined by

$\mathcal{E}_t = A_t - F_t$

Where $\mathcal{E}_t$ =the forecast error, A_t= actual number of period t, F_t= forecast value. In a summary of visitation trend forecasts, Witt and Witt (1995) found that accuracy is the most important evaluation criterion. Because of their clear definitions, the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) was selected for this project. The MAPE is written as

$$\text{MAPE} = \frac{1}{n}\sum_{t}^{n}\frac{\mathcal{E}t}{At} \text{ X } 100\%$$

Where n= number of time periods, $\mathcal{E}t =$ forecast error in time period t ,At =actual number of inflation at time period t,

Lower MAPE values are better because they indicate that smaller percentages errors are produced by the forecasting model. The following interpretation of MAPE values was suggested by Lewis (1982) as follows: Less than 10% is highly accurate forecasting, 10% to 20% is good forecasting, 21% to 50% is reasonable forecasting and 51% and above is inaccurate forecasting. The Root Mean Square Error (RMSE) is also an accuracy measure which was considered. This approach is capable of comparing actual rates of changes in time series data and computes the averages forecast errors. It is given by

$$\text{RMSE} = \sqrt{\frac{1}{n}}(At - Ft)2$$

VI. RESULTS AND DISSCUSSION

Forecasting: It is the process of making statements about events whose actual outcomes have not yet been observed. It is an important application of time series. If a suitable model for the data generation process of a given time series has been found, it can be used for forecasting the future development of the variable under consideration. To choose a final model for forecasting the accuracy of the model must be higher than that of all the competing models. The accuracy for each model can be checked to determine how the model performed in terms of in-sample forecast. Usually in time series forecasting, some of the observations are left out during model building in other to access models in terms of out of sample forecasting also.

The accuracy of the models can be compared using some statistic such as mean error (ME), root mean square error. (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE) etc. A model with a minimum of these statistics is considered to be the best for forecasting.

Sl. No.	Year	Total Number of Accidental Deaths	Estimated Mid-Year Population* (In Lakh^{+})	Rate of Accidental Deaths
1	2	3	4	5
1	1991	188003	8496	22.13
2	1992	194910	8677	22.46
3	1993	192357	8838	21.76
4	1994	190435	8999	21.16
5	1995	222487	9160	24.29
6	1996	220094	9319	23.62
7	1997	233903	9552	24.49
8	1998	258409	9709	26.62
9	1999	271918	9866	27.56
10	2000	255883	10021	25.53
11	2001	271019	10270	26.39
12	2002	260122	10506	24.8
13	2003	259625	10682	24.3
14	2004	277263	10856	25.5
15	2005	294175	11028	26.7
16	2006	314704	11197.8	28.1
17	2007	340794	11365.5	30
18	2008	342309	11531.3	29.7
19	2009	357021	11694.4	30.5
20	2010	384649	11857.6	32.4
21	2011	390884	12101.9	32.3
22	2012	394982	12133.7	32.6

Table 1: Data on yearly accident deaths in India for the period 1991 to 2012
Fig 1: Distribution of total number of accidental deaths in different state of India during year 2012

Table 2: Exponential Smoothing Model Parameters

	Model		Estimate	SE	t	Sig.
Accident-Model_1	No Transformation	Alpha (Level)	1.0	.268	3.736	.001
		Gamma (Trend)	.000	.208	.001	.999
		Phi(Trend damping factor)	.999	.017	57.60	.000

Table 3: Exponential model Parameters

Model	Model Fit Statistics				Ljung-Box Q(18)		
	R-squared	RMSE	MAPE	BIC	Statistics	DF	Sig.
Accident-Model_1	.967	12103.961	3.687	19.224	20.451	15	.155

For the smoothing of the data the damped trend exponential smoothing technique was found to be the most appropriate. Several of combination of, and values were tried. The various smoothing techniques were applied to smooth the data it was found that the Damped Trend gives accurate forecast based on the set criterion of least values of their RMSE and MAPE.Table3 above shows the exponential smoothing model parameters. It has an α value of 1.0, γ value of zero and value of ϕ 0.999. It can be seen that they are all significant. Thus their p-values are all less 5%.

Model Identification

At the identification stage, the appropriate AR and MA parameters are found by examining Autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series. Autocorrelation and partial autocorrelation analyses were conducted on the stationary time series. Autocorrelation measures the unconditional relationship of values between time lags, while partial autocorrelation measures the conditional relationship.

The stationary check of the series showed that it was non stationary. Merely by using the first differencing technique it was made stationary as in Fig.3 By implication the mean value is zero and all the variances are constant. Fig 4 and 5 shows the correlogram of the both the PACF and the ACF of the first difference of the data. It can be seen that the ACF has one significant cut off at the first lag showing the presence of white noise and the PACF also shows two major spikes.The graphs of the sample ACF and PACF were plotted (Fig.4 and Fig .5)

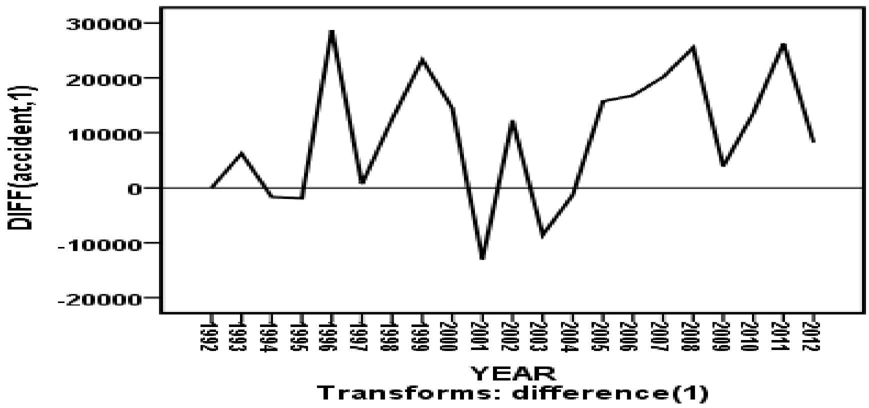


Fig.3: Graph of first difference

From figures 4 and 5 two models were selected based on their ability of reliable prediction. Four criterions namely the Normilsed Bayesian Information Criteria (BIC), the R-square, Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) were used. Lower values of the BIC, MAPE, RMSE and high value of R-square were preferable. This is

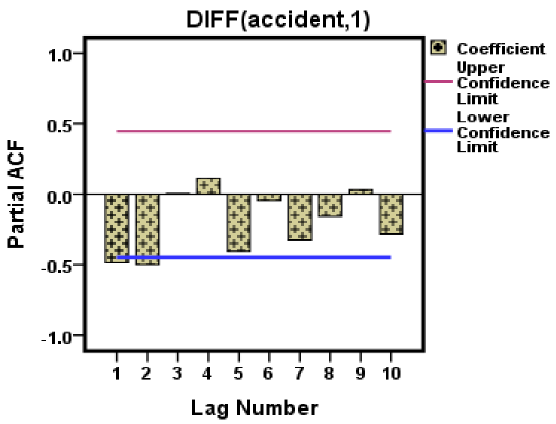


Fig.4 Graph of PACF of first difference

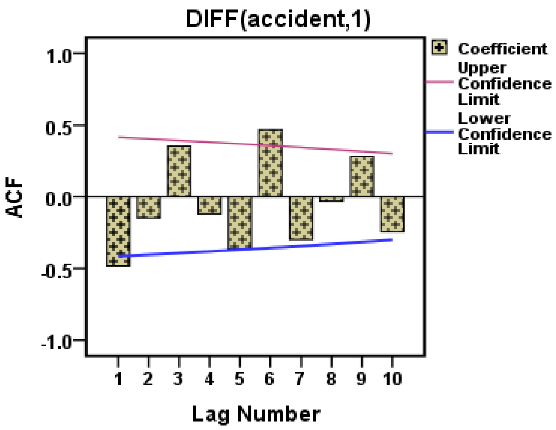


Fig. 5 Graph of ACF of first difference

Table 4: Suggested Models of ARIMA by criteria of different parameters

MODEL	MAPE	BIC	RMSE	R^2
ARIMA (1,1,1)	3.190	19.232	11228.8	.973
ARIMA (2,1,1)	3.471	19.398	12197.02	.968

From the above table and the set criterion it was found that ARIMA (1, 1, 1) was the best fitted model.

So, on the validation the ARIMA (1,1,1) model has minimum RMSE and MAPE and highest R^2 value as compared to the ARIMA(2,1,1) model

Table 5: Suggested Models Parameters of ARIMA

ARIMA Model Parameters

					Estimate	SE	T	Sig.
Accident-Model_1	Accident	No Transformation	Constant		2960.128	3079.251	.961	.350
			AR	Lag 1	.649	.454	1.430	.171
			Difference		1			
			MA	Lag 1	.996	12.131	.082	.935
	Year	No Transformation	Numerator	Lag 0	595.749	275.799	2.160	.045

Model Estimation

Table 6: ARIMA Model Parameter which has been used from above selection of model

Model	Model Fit statistics				Ljung-Box Q(18)		
	R-squared	**RMSE**	**MAPE**	**Normalized BIC**	**Statistics**	**DF**	**Sig.**
Accident-Model_1	.973	11228.8	3.19	19.232	21.390	16	.164

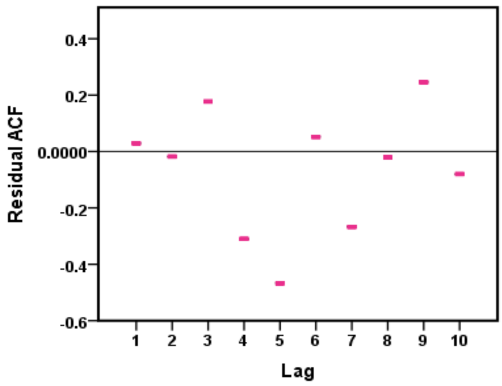


Fig6. Graph of residual PACF

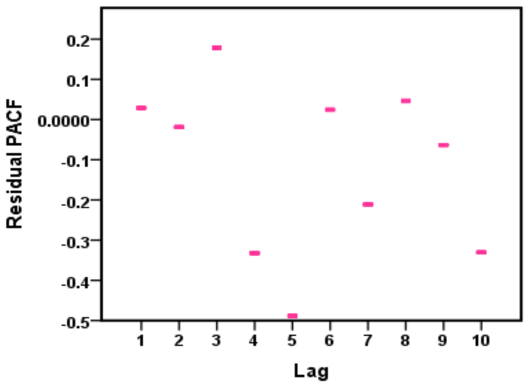


Fig 7. Graph of residual ACF

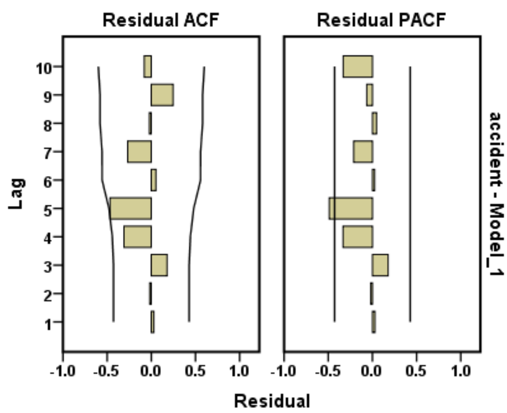


Fig 8: Graph of ARIMA model

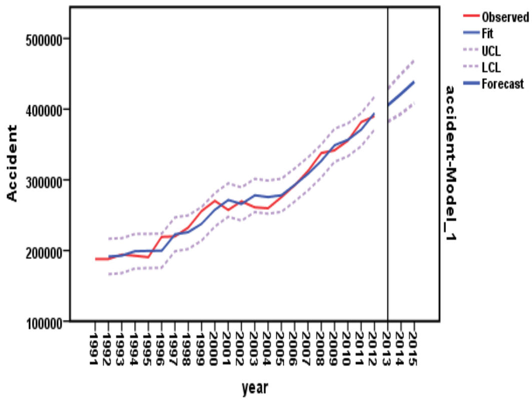


Fig 9: Graph of ARIMA model

The Ljung-Box statistic of the model is not significantly different from 0, with a value of 21.39 for 16 DF and associated p- value of 0.164, thus failing to reject the null hypothesis of no remaining significant autocorrelation in the residuals of the model. This indicates that the model adequately captured the correlation in the time series. Moreover the low RMSE indicates a good fit for the model and the high value of the R-squared shows a perfect prediction over the mean. The coefficient of both the AR and MA are all less than 1.

Model Diagnostics

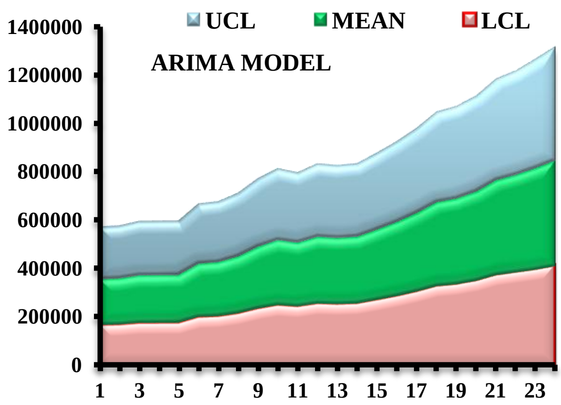
From the graphs of the residual ACF and PACF below it can be seen that all points are randomly distributed and it can be conclude that there is an irregular pattern which means the model is adequate. Also the individual residual autocorrelation are very small and are generally within ± 2/n of zero. The model is adequate in the sense that the graphs of the residual ACF and PACF shows a random variation, thus from the origin zero (0) the points below and above the mean are all uneven, hence the model fitted. Once our model has been found and its parameters has been estimated and checked, we can therefore do our forecasting with 95% confidence interval. Now the forecast of these models were compared by validating. On comparison of the results revealed that among the models fitted ARIMA (1, 1, 1) model came out to be performing better when the forecast was validated.

Table 7: Data on yearly accident deaths in India for the period 1991 to 201

				Forecast (Number of accidental Deaths) by model					
Year	Number of Accident deaths	Midyear population	Smoothing (Deaths)	ARIMA(Deaths Population)	Exponential (Deaths Population)	Rate of accident	Smoothing rate	Rate (EXP.)	Rate (ARIMA)
1991	188003	8496	N/A	N/A	187995	22.13	N/A	22.1	N/A
1992	194910	8677	188003	191559	197293	22.46	22.1	22.7	22.1
1993	192357	8838	194219	192778	197284	21.76	22.4	22.3	21.8
1994	190435	8999	192543	199081	203492	21.16	21.8	22.6	22.1
1995	222487	9160	190646	199404	201807	24.29	21.2	22.0	21.8
1996	220094	9319	219303	199635	199900	23.62	24.0	21.5	21.4
1997	233903	9552	220015	222949	228551	24.49	23.7	23.9	23.3
1998	258409	9709	232514	226025	229255	26.62	24.4	23.6	23.3
1999	271918	9866	255820	237792	241747	27.56	26.4	24.5	24.1
2000	255883	10021	270308	257650	265046	25.53	27.4	26.4	25.7
2001	271019	10270	257326	271497	279528	26.39	25.7	27.2	26.4
2002	260122	10506	269650	265824	266536	24.8	26.3	25.4	25.3
2003	259625	10682	261075	278002	278852	24.3	25.0	26.1	26.0
2004	277263	10856	259770	275560	270267	25.5	24.4	24.9	25.4
2005	294175	11028	275514	278169	268953	26.7	25.4	24.4	25.2
2006	314704	11197.8	292309	292808	284689	28.1	26.6	25.4	26.1
2007	340794	11365.5	312464	308456	301478	30	27.9	26.5	27.1
2008	342309	11531.3	337961	326714	321628	29.7	29.8	27.9	28.3
2009	357021	11694.4	341874	348975	347119	30.5	29.7	29.7	29.8
2010	384649	11857.6	355506	356596	351024	32.4	30.4	29.6	30.1
2011	390884	12101.9	381735	371005	364649	32.3	32.2	30.1	30.7
2012	394982	12133.7	389969	394284	390872	32.6	32.3	32.2	32.5

Table 8: Forecast table of accidental mortality during period 2009 to 2015 of India

			Forecast of accidental deaths	
Year	**Observed accidents**	**Observed (Smoothing)**	**ARIMA (1,1,1)**	**Damped trend**
2009	357021	341874	348975	347119
2010	384649	355506	356596	351024
2011	390884	381735	371005	364649
2012	394982	389969	394284	390872
2013			405483	399099
2014			421786	408222
2015			438811	417336
MAPE			**3.19**	**3.69**
RMSE			**11228.8**	**12104.0**



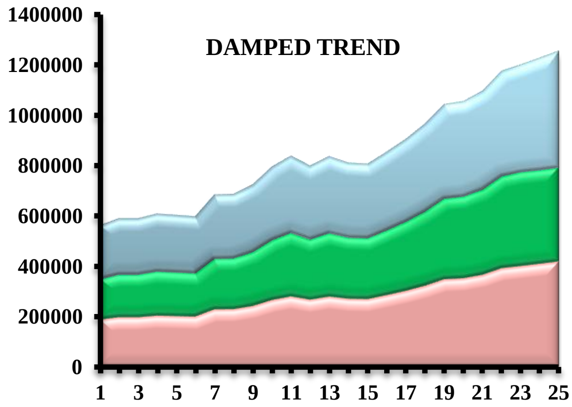
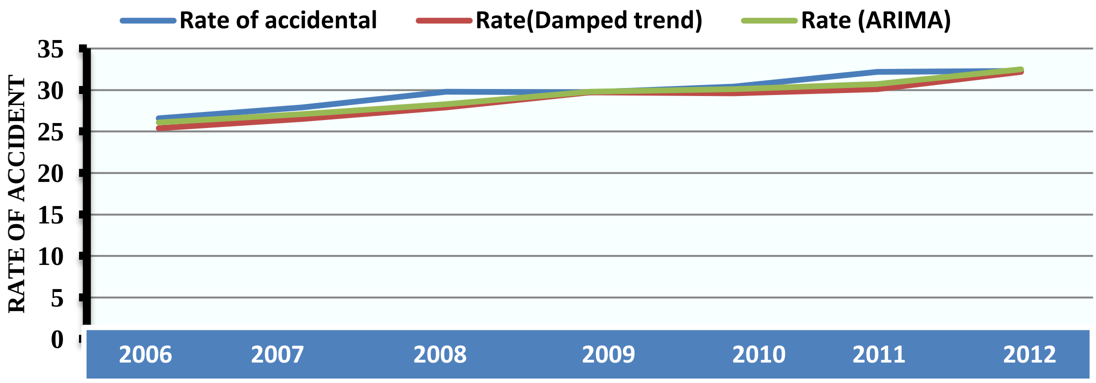


Table 9: Rate of accidental deaths in India 2006 to 2012 by actual, ARIMA and Damped trend

Year	Rate of accidental	Rate(Damped trend)	Rate (ARIMA)
2006	26.6	25.4	26.1
2007	27.9	26.5	27.1
2008	29.8	27.9	28.3
2009	29.7	29.7	29.8
2010	30.4	29.6	30.1
2011	32.2	30.1	30.7
2012	32.3	32.2	32.5



MAJOR FINDINGS OF THE STUDY

The following are the major findings of this study:

[1] Both the model ARIMA and exponential damped trend has been used to forecast the value, where mean absolute percentage error (MAPE) and root mean square error (RMSE) of ARIMA (1, 1, 1) model is less as compared to Damped trend exponential model. So, minimum value of both errors MAPE and RMSE of ARIMA (1, 1, 1) model indicates that this model performed best as compared to damped trend exponential model in forecast.

[2] The finding of this study also suggest that the ARIMA (1,1,1) model will always give the best forecast value as compared to other model at this type of time series data.

[3] The forecast value of the both model are showing that there will be an increment trend in accidental death during present to in future. It is showing the death due accident will be increase in future even also from the year 2015, if the rate of increment of accidental death will follows same pattern.

[4] The results of the model predict that there will be total 438811 deaths during the year 2015 with 34.3 percent rate of accidental death follow by 394982 deaths during year 2006. If the models are follows same pattern of death due to accident and if there should be some improvement of pattern than even also there will be more than five lakh deaths annually due to accident in India.

VII. CONCLUSION

The accident has a serious impact on mental health and also the pattern of accidental deaths is a reflection of the prevailing social set up and mental health status, loss of economic stability, and long-term threats to health in current and possibly future generations of the region. Many cultural and socio-economic factors of a country are responsible for the causation of such type of deaths. Accidental deaths happen almost everywhere in the world said 'Dr Margaret China, WHO's director general, suggesting that it is important to have an action plan for an intensified response. So, forecasting of accidental mortality enables stakeholder and policy makers to take various prevention measures to control different type of accident in India.

VIII. LIMITATION OF STUDY

The limitations of this study are that the rate of increment of accident should be same with some fluctuation in future also as compared to current level. The social setup should be following the same status like present scenario. The distribution of deaths came from cohered of same age group, which have already mentioned in national crime report that most of the deaths distributed from below 29 to 45 years and above age group.

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