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Exponential Smoothing State Space Innovation Model for Forecasting Road Accident Deaths in India

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Abstract
Now-a-days, road traffic accident increases day by day and becomes burning problem in India. With the use of statistical methods and models it is possible to predict the future occurrence of road accident or deaths with the available data. The present study talk about the development of a exponential smoothing state space innovation model for the annual deaths due to road accident in India considering the period from 1967 to 2015 and to forecast the number of annual deaths expected to occur in forthcoming days**.** The researchers' collected data from National Crime Record Bureau, Ministry of Home Affairs, India. After examining all the probable models, it is observed that exponential smoothing state space model (A, A, N) is suitable for the given data set. Further, study also shows that forecasted number of deaths for the upcoming 10 years from the proposed model also reveals an upward trend.

Keywords: Akaike information criteria, Kolmogorov-Smirnov test, mean absolute percentage error, mean absolute scaled error.

1. Introduction

Technology has significant impact on transportation system. Ancient time's people are moving from one place to another on foot or by sea which is time consuming. But, due to enormous development of technology, people can easily move from one place to another by bus, train or airplane. Transportation through road is easily accessible to the common people. Further, Afere et al. (2015) also suggested that the development of all forms of trade and industry and community activities is incorporated with road transport. Due to the expansion of economic and financial condition of the people number of motor vehicles also increases which leads to overcrowding on road. Moreover, Sivakumar and Krishnaraj (2015) also state that overcrowding on road leads to traffic accident. Finally, accident creates in injury, deaths, damage to property of the victims. Sometimes, injuries causes from the accident make many people physical or mental disability. Finally, the lost due to accident adversely affect the family and the nation.

Road Traffic Accident (RTA) which is identified as the third most important causes of overall mortality and the main cause of death among the age group 15-44 years and it represents 12% of global burden of disease. The study carried out by Sivakumar and Krishnaraj (2015) shows that about 25% of all deaths gathered from road accident injury. National Crime Records Bureau, Ministry of home affairs, India (2018) announced the number of vehicles increased by 28.6% (from 141,866 in 2011 to 182,445 in 2013) and the no. of road accidents have also increased by 5.6% for that period. In view of the significance of the condition, it is necessary to acquire proper actions for reducing the deaths and injuries from road accident. Further, forecasting of number of road accidents or number of deaths or injuries may be extremely significant information for the government to take different protection events.

Usually, time series observations are occurs in identical interval and the prime objective is to prepare and fit a suitable mathematical model for the observed data. After fitting the appropriate model, the next intension is to predict the future outcomes of the events. Moreover, Dutta et al. (2020) discussed the importance forecasting technique which is usually applied to controlling past and present operations which may assist with any long-term planning or decision making. Exponential smoothing technique is generally used for forecasting purposes. The term “exponential smoothing” replicates the information that the weights are decreases exponentially as the observations become older. However, a limitation of exponential smoothing is that prediction intervals cannot be obtained from this technique and only point forecasts are available. On the other hand, Hyndman et al. (2008) in his study discussed the ETS model which provides maximum likelihood estimation, procedures for model selection and prediction intervals. Here, the triplet (E,T,S) represents to three components: error, trend and seasonality respectively. This technique is first developed by Pegels (1969). This was later extended by Gardner (1985) who used damped trend to the classification of the models. This extension is again modified by Hyndman et al. (2002) and extended again by Taylor (2003) for multiplicative damped trend. Details of ETS models are clearly discussed in Section 2.

There are extensive literatures available for using exponential smoothing and innovations state space models in different fields. Hyndman et al. (2002) developed automatic forecasting of exponential smoothing technique which allows calculating (i) likelihood function (ii) model selection criteria based on Akaike information criteria (AIC), corrected Akaike information criteria (AIC_C) and Bayesian information criteria (BIC). (iii) Computation of prediction intervals (iv) random simulation from the underlying state space model. Further, Taylor (2003) used damped multiplicative exponential smoothing trend to make an experiential study using time series data from M3-competetion. This technique is the extension of the original multiplicative trend which was developed by Pegels (1969). Moreover, Hyndman et al. (2008) discussed the admissible parameter space for exponential smoothing. In this study, the researchers come to the conclusion that usual boundaries on smoothing parameters (i.e. lie between 0 and 1) do not always lead to stable models. Similarly, Paul (2011) discussed the procedure for selection of optimal value of exponential smoothing constant. In this study, the researcher used trial and error method to determine the optimal value of smoothing constant so that Mean Square Error (MSE) and Mean Absolute Deviation (MAD) would be minimized. Moreover, Makatjane and Moroke (2016) made a comparative study of Holt-Winters triple exponential smoothing method and SARIMA model to predict the monthly car sales in South Africa. The researcher used Power test to make the comparison between SARIMA and Holt-Winters Model. The study shows that Holt-Winters model have 0.3% more predictive power as compared to SARIMA model.

From the above discussion, the researchers come to know that exponential smoothing state space model widely used in modeling and forecasting time series observations. With this background, the researchers proposed exponential smoothing state space model to determine the trend and identify the suitable model for the annual deaths due to road accident in India. Finally, the fitted model is used to forecast the number of annual deaths expected to occur in future. The paper is dived into four sections. Section 2 talks about sources of the data and complete methodology assumed in the study. In Section 3, results of the study are discussed. Finally, conclusion of the study is given in Section 4.

2. Data and Methodology

The data of the present study are completely secondary and collected from National Crime Record Bureau, Ministry of Home Affairs, India. Researchers collected information about yearly deaths due to road accident in India covering the period from 1967 to 2015. In this study, the methodology propounded by Hyndman et al. (2008) called the exponential smoothing state space (ETS) method is used. The ETS (error, trend, seasonal) model provides an automatic technique of choosing the best model for forecasting and also provides the prediction intervals. There are two models for each method: one with additive error and one with multiplicative errors, i.e. in total 30 models are given in the following table.

Table 1 Classification of ETS model

Trend Component	Seasonal Component		
	N(None)	A(Additive)	M(Multiplicative)
N(None)	ANN/MNN	ANA/MNA	ANM/MNM
A(Additive)	AAN/MAN	AAA/MAA	AAM/MAM
A_d(Additive damped)	AA_dN/MA_dN	AA_dA/MA_dA	AA_dM/MA_dM
M(Multiplicative)	AMN/MMN	AMA/MMA	AMM/MMM
M_d(Multiplicative damped)	AM_dN/MM_dN	AM_dA/MM_dA	AM_dM/MM_dM

Table 1 shows the classification of ETS models. The first letter in each model represents type of error (additive or multiplicative), the second letter represents type of trend (none, additive, additive damped, multiplicative or multiplicative damped) and the third letter denotes the type of seasonality (none, additive or multiplicative). Some of the combination of ETS model can lead to numerical difficulties. These models are: ETS(A,N,M), ETS(A,A,M), ETS(A,A_d,M), ETS(A,M,N), ETS(A,M,A), ETS(M,M,A), ETS(A,M,M), ETS(A,M_d,N), ETS(A,M_d,A), ETS(M,M_d,A), ETS(A,M_d,M). Models with multiplicative errors are useful for strictly positive data- but are not numerically stable with data containing zeros or negative values. In that case only the six fully additive models will be applied please see details of Hyndman et al. (2008).

The state space models for all 30 exponential smoothing methods suggested by Hyndman et al. (2008) are given below.

The general model framework involves a state vector x_t and state space equations of the form

$$Y_t = h(x_{t-1}) + k(x_{t-1})\varepsilon_t, \tag{1}$$

$$X_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t, \tag{2}$$

where $\{\varepsilon_t\}$ is a Gaussian white noise process with mean zero and variance σ^2. Here, $x_t = \left(l_t, b_t, s_t, s_{t-1}, \ldots, s_{t-(m-1)}\right)$, $e_t = k(x_{t-1})\varepsilon_t$ and $\mu_t = h(x_{t-1})$. Then $y_t = \mu_t + e_t$.

The model with additive errors is written as $y_t = \mu_t + \varepsilon_t$ where $\mu_t = F_{(t-1)+1}$ denotes the one-step forecast made at time $t-1$. So, in this case $k(x_{t-1}) = 1$. The model with multiplicative errors is written as $y_t = \mu_t(1+\varepsilon_t)$. Thus, $k(x_{t-1}) = \mu_t$ for this model and $\varepsilon_t = \frac{e_t}{\mu_t} = \frac{(y_t - \mu_t)}{\mu_t}$ and hence ε_t is a relative error for the multiplicative model. The underlying equations are given in Table 2.

The only difference between the additive error and multiplicative error models is in the observation (1). The state (2) can be put in exactly the same form by substituting $\varepsilon_t = \frac{e_t}{k(x_{t-1})}$ into each state equation.

Table2 State space equations for each additive error model in the classification (multiplicative error models are obtained by replacing ε_t by $\mu_t \varepsilon_t$ in the equations)

Trend	Seasonal		
	N	A	M
N	$\mu_t = l_{t-1}$ $l_t = l_{t-1} + \alpha\varepsilon_t$	$\mu_t = l_{t-1} + s_{t-m}$ $l_t = l_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = l_{t-1} + s_{t-m}$ $l_t = l_{t-1} + \frac{\alpha\varepsilon_t}{s_{t-m}}$ $s_t = s_{t-m} + \frac{\gamma\varepsilon_t}{l_{t-1}}$ $l_t = l_{t-1} + \frac{\alpha\varepsilon_t}{s_{t-m}}$ $s_t = s_{t-m} + \frac{\gamma\varepsilon_t}{l_{t-1}}$
A	$\mu_t = l_{t-1} + b_{t-1}$ $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	$\mu_t = l_{t-1} + b_{t-1} + s_{t-m}$ $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = (l_{t-1} + b_{t-1})s_{t-m}$ $l_t = l_{t-1} + b_{t-1} + \frac{\alpha\varepsilon_t}{s_{t-m}}$ $b_t = b_{t-1} + \frac{\beta\varepsilon_t}{s_{t-m}}$ $s_t = s_{t-m} + \frac{\gamma\varepsilon_t}{l_{t-1} + b_{t-1}}$

Table 2 (Continued)

Trend	Seasonal		
	N	A	M
A_d	$\mu_t = l_{t-1} + \phi b_{t-1}$ $l_t = l_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t$ $b_t = \phi b_{t-1} + \beta \varepsilon_t$	$\mu_t = l_{t-1} + \phi b_{t-1} + s_{t-m}$ $l_t = l_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t$ $b_t = \phi b_{t-1} + \beta \varepsilon_t$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$\mu_t = (l_{t-1} + \phi b_{t-1}) s_{t-m}$ $l_t = l_{t-1} + \phi b_{t-1} + \frac{\alpha \varepsilon_t}{s_{t-m}}$ $b_t = \phi b_{t-1} + \frac{\beta \varepsilon_t}{s_{t-m}}$ $s_t = s_{t-m} + \frac{\gamma \varepsilon_t}{(l_{t-1} + \phi b_{t-1})}$
M	$\mu_t = l_{t-1} b_{t-1}$ $l_t = l_{t-1} b_{t-1} + \alpha \varepsilon_t$ $b_t = b_{t-1} + \frac{\beta \varepsilon_t}{l_{t-1}}$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$\mu_t = l_{t-1} b_{t-1} + s_{t-m}$ $l_t = l_{t-1} b_{t-1} + \alpha \varepsilon_t$ $b_t = b_{t-1} + \frac{\beta \varepsilon_t}{l_{t-1}}$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$\mu_t = l_{t-1} b_{t-1} s_{t-m}$ $l_t = l_{t-1} b_{t-1} + \frac{\alpha \varepsilon_t}{s_{t-m}}$ $b_t = b_{t-1} + \frac{\beta \varepsilon_t}{(s_{t-m} l_{t-1})}$ $s_t = s_{t-m} + \frac{\gamma \varepsilon_t}{(l_{t-1} b_{t-1})}$
M_d	$\mu_t = l_{t-1} b_{t-1}{}^{\phi}$ $l_t = l_{t-1} b_{t-1}{}^{\phi} + \alpha \varepsilon_t$ $b_t = b_{t-1}{}^{\phi} + \frac{\beta \varepsilon_t}{l_{t-1}}$	$\mu_t = l_{t-1} b_{t-1}^{\phi} + s_{t-m}$ $l_t = l_{t-1} b_{t-1}^{\phi} + \alpha \varepsilon_t$ $b_t = b_{t-1}^{\phi} + \frac{\beta \varepsilon_t}{l_{t-1}}$ $s_t = s_{t-m} + \gamma \varepsilon_t$	$\mu_t = l_{t-1} b_{t-1}^{\phi} s_{t-m}$ $l_t = l_{t-1} b_{t-1}^{\phi} + \frac{\alpha \varepsilon_t}{s_{t-m}}$ $b_t = b_{t-1}^{\phi} + \frac{\beta \varepsilon_t}{(s_{t-m} l_{t-1})}$ $s_t = s_{t-m} + \frac{\gamma \varepsilon_t}{(l_{t-1} b_{t-1}^{\phi})}$

The different steps for forecasting of ETS models are discussed below:

Step 1. First applies the method to all the models that are appropriate for the data and optimize the parameters of the model using any optimization criterion. Details of parameter estimation procedure are discussed below:

It is easy to compute the likelihood of the innovation state space models and so parameters are obtained using the maximum likelihood approach.

Suppose, the Likelihood is $L^*(\theta, X_0) = n \log\left(\sum_{t=1}^{n} e_i^2 \Big/ k^2(x_{t-1}) \right) + 2\sum_{t=1}^{n} \log\left| k(x_{t-1}) \right|$. Then L^* is equal to twice the negative logarithm of the conditional likelihood function (with constant terms eliminated). Further, the parameters $\Omega = (\alpha, \beta, \gamma, \phi)$ and the initial states of the model i.e. $x_0 = (l_0, b_0, s_0, s_{-1}, \ldots, s_{-m+1})$ can be estimated by minimizing L^*. On the other hand, parameters of the model can be estimated by minimizing the one step Mean Square Error (MSE), minimizing the one step Mean Absolute Percentage Error (MAPE), minimizing the residual variance σ^2.

Step 2. In this step, identify the best of the models using −AIC, corrected AIC, Bayesian information criterion (BIC). It is necessary to select that model which has minimum value of AIC, BIC or AIC_C

Step 3. Next, the appropriate model is used for forecasting. Forecast performances of the model are examined by Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE).

RMSE = $\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2}$, where n is the number of time periods, Y_t is the actual number of observations at time period *t* and F_t is the forecasted number of observations at time period *t*.

MAPE = $\frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{Y_t}\right| \times 100$ where n is the number of time periods, Y_t is the actual number of observation at time period t and e_t is the forecast error in time period t.

MASE = mean ($|q_t|$), where $q_t = \frac{e_t}{\frac{1}{n}\sum_{t=2}^{n}|y_t - y_{t-1}|}$, e_t is the forecast error in time period t, and Y_t is the observations at time period t.

Step 4. This is the final step where the prediction intervals of the fitted model are obtained. Exact formula for prediction intervals is available for some models. In general, simulate future sample paths conditional on the last estimate of the states and to obtain prediction intervals from the percentiles of these simulated future paths.

3. Findings

Figure 1 shows the time plot of total number of deaths due to road accident in India from 1967-2015. Figure1 reveals a significant upward trend. The researchers also investigated some descriptive statistics like mean and variance of the data set. It is observed that an average death due to road accident for the period is 58,621 with standard deviation 44,568. After that, the entire data set is separated into two sections i.e. testing part (1967-2005) and validation part (2006-2015). First, the researchers develop the ETS model for testing part and compare the forecasted values from the model with validation part. In the second step, if the model adequately fitted to the testing data and satisfies all the assumptions, then model is refit for the whole data set i.e. 1967-2015.Finally, the potential model is applied to forecast the number of deaths due to road accidents for the upcoming 10 years.

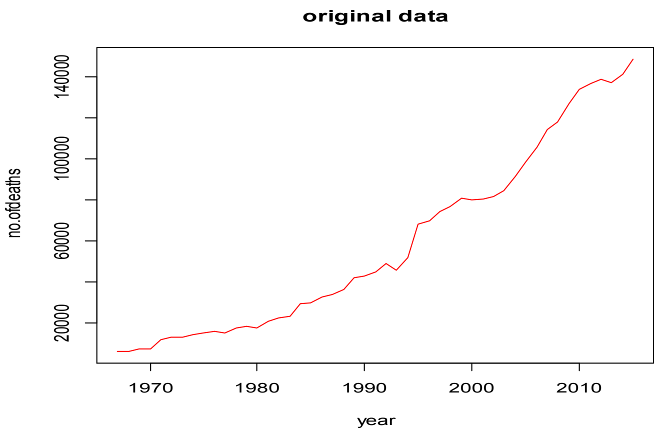

Figure 1 Plotting of original data

The researchers first apply all the models that are appropriate for the data and optimize the parameters of the model using likelihood criterion. In this stage, the researcher found that out of thirty models only six models are appropriate for the data. This is due to the fact that data set contains only trend component, therefore the researchers ignored all the seasonal component models. Secondly, ETS(A,M,N) and ETS(A,M_d,N) model lead to numerical difficulties and they are not appropriate for the data. The suitable models for the data are namely ETS(A,A,N), ETS(M,A,N), ETS(A,Ad,N), ETS(M,Ad,N), ETS(M,Md,N), ETS(M,M,N). Next for choosing the best model, the researchers calculated information criteria value for each of the model which are mentioned in Table 3.

Table 3 Information criterion value for the ETS model

Models	AIC	AIC_C	BIC
ETS(A,A,N)	783.47	785.29	791.79
ETS(M,A,N)	777.04	778.86	785.36
ETS(A,A_d,N)	786.73	789.35	796.71
ETS(M,A_d,N)	780.85	783.47	790.83
ETS(M,M_d,N)	777.90	780.52	787.88
ETS(M,M,N)	783.65	785.46	791.96

Table 3 shows the information criteria value against each of the ETS model. Comparing all the models it is observed that ETS(M,A,N) model has the minimum of AIC, AIC_C, BIC values. From this result, the researchers may conclude that ETS(M,A,N) model is suitable for the data set. Next, to check the forecasting precision of the models point forecast are estimated along with RMSE, MAPE and MASE value for each of the model. Forecast accuracy of the models are presented in the following table.

Table 4 Accuracy measures of ETS model

Models	RMSE	MAPE	MASE
ETS(A,A,N)	3,243.89	6.70	0.75
ETS(M,A,N)	3,498.10	6.99	0.83
ETS(A,A_d,N)	3,296.59	6.72	0.76
ETS(M,A_d,N)	3,564.58	7.07	0.85
ETS(M,M_d,N)	3,291.39	6.55	0.78
ETS(M,M,N)	3,709.01	7.68	0.94

Now, comparing the accuracy measures of the models it is observed that RMSE and MASE is minimum for the ETS(A,A,N) model whereas MAPE is lowest for ETS(M,M_d,N) followed by ETS(A,A,N). The MASE was proposed by Hyndman and Koehler (2006) is used to determine the suitable model for the given data. From the above result, it is observed that ETS(A,A,N) Model is accurate for forecasting as compared to the other models.

From Table 2, the equations of the model are:

Observation equation: $\mu_t = l_{t-1} + b_{t-1},$

State equations: $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t,\ b_t = b_{t-1} + \beta\varepsilon_t,$

where l_t denotes the series level at time t, b_t denotes the slope at time t, ε_t denotes the error component, α and β are smoothing parameters.

The parameters of the accurate model are estimated and optimized the value of the parameters based on likelihood function. The values of the smoothing parameters are: α = 0.99, β = 0.08 with initial states l = 4,128.17 and **b** = 1,371.34.

The following fig shows the plot of the residuals from the fitted model, Autocorrelation Function (ACF) of the residuals and histogram of the residuals.

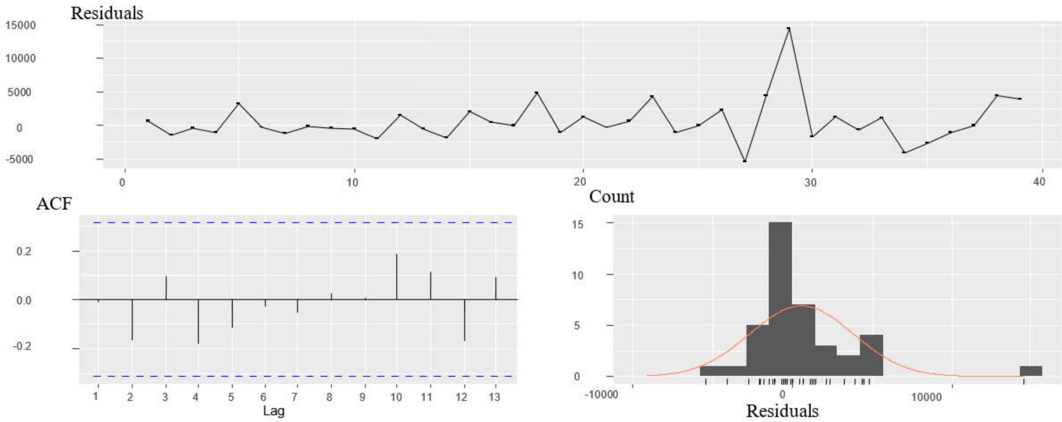

Figure 2 Residuals, ACF of the residuals and histogram of the residuals of ETS(A,A,N) Model

From Figure 2, it is observed that autocorrelation coefficient of the residuals is inside the confidence limits and histogram of the residuals plot indicates that the residuals are not normally distributed. Further, white noise of the residuals are test from a univariate test (from the normwhn.test package in R). The p-value of the test is found to be0.1856 which indicates that the residuals follow white noise. Moreover, the normality of the residuals are checked using Kolmogorov- Smirnov test. The test reveals that residuals are not normally distributed. Therefore, the researchers applied bootstrap simulation to determine the prediction intervals. This result reflects that ETS(A,N,N) model is adequate for the data.

Now, the precision of the fitted model is checked plotting the actual observations with the predicted values along with 95% prediction interval.

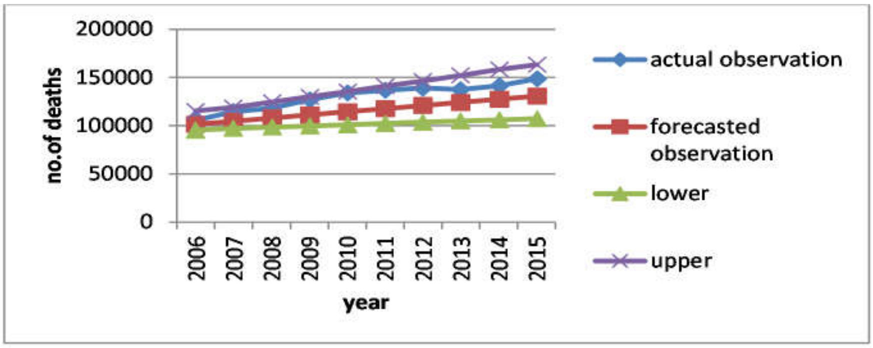

Figure 3 Plot of actual observations versus forecasted observations along with 95% confidence interval

From Figure 3, it is observed that the total number of predicted deaths due to road accidents in

India from 2006-2015 is nearly equal and same pattern with the actual observation. From the figure, it is also observed that actual observations are also within the prediction limit (95%). As a result, it may be accomplished that proposed model would be good fitted to the given data.

After examining the accuracy of the model, the reserchers again fit the model for the whole data set. The value of the smoothing parameters are $\alpha = 0.99$, $\beta = 0.11$ with initial states $l = 4,128.35$ and $\mathbf{b} = 1,327.15$.

Now, the forecasted number of deaths due to road accident in India from the final model is shown in the following table.

Table 5 Forecasted number of deaths from ETS(A,A,N) model for upcoming 10 years

Year	Point forecast	95% Confidence Interval	
		lower	upper
2016	152,963.4	146,760.9	163,558.5
2017	157,220.2	148,846.8	170,945.5
2018	161,476.9	150,478.5	177,788.1
2019	165,733.7	152,431.1	183,905.2
2020	169,990.5	154,332.1	190,894.2
2021	174,247.2	156,125.3	198,095.4
2022	178,504.0	158,167.5	204,901.5
2023	182,760.7	159,912.8	211,237.0
2024	187,017.5	161,947.3	218,208.0
2025	191,274.3	164,165.3	225,267.2

Table 5 shows the number of deaths due to road accidents for the period 2016-2017 along with 95% confidence interval. Form the table it is observed that number of deaths due to road accidents will be increase for the upcoming days.

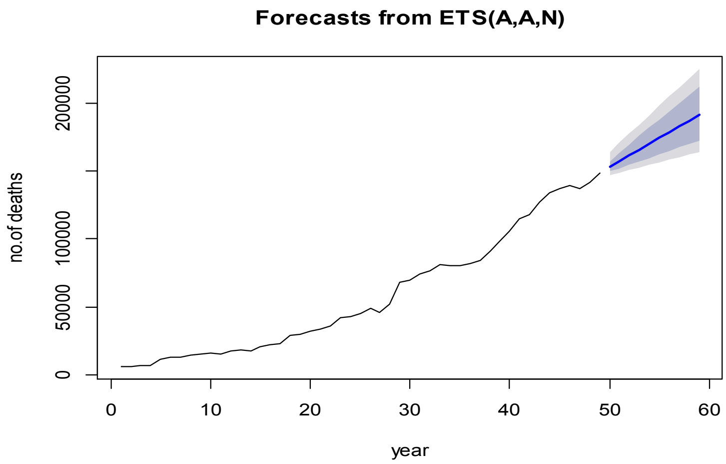

Figure 4 Plot of the forecasted values from the ETS(A,A,N) model

The above figure shows the forecasted number of deaths due to road accident cases possibly to take place in India for the upcoming 10 years. The mean absolute percentage error of the fitted model is found to be 5.84 and MASE of the fitted model is 0.69.

4. Conclusions

In this paper, ETS methodology is used examine the trend of number of yearly deaths due to road accident in India. The estimation and diagnostic study of the proposed model shows that the model is effectively fitted to the given data. The residual analysis of the fitted model, established that there is no contravention of the postulates in relation to model adequacy apart from normality of residuals is not satisfied. Finally, the results of the present study reveals that forecasted number of deaths due to road accidents in India for the upcoming 10 years also shows an upward trend.

From this study it may be concluded that although ETS models are not widely applied in forecasting purposes, but the empirical results assert the importance of their application.

Acknowledgements

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