

Comparison of the Population and Economic Variables using the Different Forecasting Models

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ABSTRACT

In this paper, the aim is to examine population and economic variables using the Exponential Smoothing, ARIMA, FTS, NNAR, and BSTS models. We have to forecast for the next ten years using these models to determine which is the best model based on the MAE, RMSE, and MAPE values, whose values are lower than the best prediction model. For population variables, the ARIMA model is best fitted as compared to other models, and the Total and Urban populations have well fitted in the ARIMA model as compared to other models and the Rural population has well fitted in the ARIMA and FTS models as compared to other models. For economic variables, the ARIMA model has the best performance as compared to other models in the Age dependency ratio variable, and the NNAR model has good performance as compared to other models in the GDP variable. Based on RMSE, MAE, and MAPE values, the ARIMA model performs better than other models like Holt's Exponential Smoothing, ANN, Fuzzy Time Series, and Bayesian Time Series Models. Except for the ARIMA model, the NNAR model has better fits than other models.

Keyword: Population, Economic, NNAR, FTS, BSTS.

Mathematics Subject Classification: 92D25, 91B55, 92B20, 03B52, 62C10

1. INTRODUCTION

Forecast accuracy is a fundamental measure that evaluates the reliability and precision of predictions made by forecasting models. In various domains such as finance, supply chain management, weather forecasting, and beyond, accurate predictions are essential for informed decision-making and planning for the future. The ability to assess and improve the accuracy of forecasts is critical for optimizing resource allocation, managing risks, and ultimately achieving organizational objectives. In a wide range of fields, several forecasting models are used to assess data, generate predictions, and direct decision-making processes. It's crucial to compare forecasting models to find the one that's the most accurate and useful for a certain dataset or problem. Each forecasting model has its own assumptions, strengths, and drawbacks. Comparing them makes it easier to choose the model that produces the most accurate forecasts and best fits the data.

The univariate forecasting or Autoregressive Integrated Moving Average (ARIMA) model was developed by Box and Jenkins (2015). Peter Pflaumer (1992) suggests that for making long-term population forecasts in the United States, the Box-Jenkins approach is equal to a simple trend model and that the Box-Jenkins approach has not performed worse than more complicated demographic models in projecting future population. Michael Funke (1992) stated that several time-series studies of the German unemployment rate have been conducted. As a result, the multiple-impact ARIMA model beats the univariate ARIMA model of both fitting and prediction for the German unemployment rate. Fuzzy set theory by Zadeh (1965) and the concept of linguistic variables to approximate reasoning development by Zadeh (1975) have been successfully applied Song and Chissom (1993) in fuzzy time series forecasting. FTS has since been studied and proven to be more efficient than traditional statistical techniques developed by Song and Chissom (1993); Tseng and Tzeng (2002). G Peter Zhang (2003) developed a hybrid technique that integrates both ARIMA models and ANNs to make use of the distinctive strengths of the ARIMA and ANN models in linear and nonlinear modeling. According to Mehdi Khashei and Mehdi Bijari (2010), ARIMA models are used in a unique hybrid model of Artificial Neural Networks to provide a more accurate forecasting model.

A comparison of several forecasting techniques such as Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Non-linear Autoregressive Network with exogenous Inputs (NARX) with Neural Networks (NN) models, the inventory database of Singapore-based Panasonic Refrigeration Devices Company is where the data for forecasting is obtained. According to the results, NN forecasting performs more effectively than conventional techniques (C. A. Mitrea, et al., 2009). Nur Haizum Abd Rahman, et al. (2015) state that three models of Fuzzy Time Series (FTS), a Seasonal Autoregressive Integrated Moving Average (SARIMA), an Artificial Neural Network (ANN), have all been used to compare the Box-Jenkins technique. Despite the fact that all of the approaches were employed as operational tools, the ANN's forecasting Air Pollution Index (API) appeared to be more precise. Since the standard ARIMA methods outpaced the performance of FTS, the results demonstrated that FTS (i.e. Chen's, Yu's, and Cheng's) performed inconsistently. However, consistent results were obtained because, when compared to FTS and ARIMA, ANNs provided the minimum forecasting error. The error value of the Fuzzy Time Series is lower than that of the ARIMA model, proving that it is a more accurate predictor of fuel price in India than other time series models (K. Senthamarai Kannan, et al. 2020).

Bishal Dey, et al. (2022) state that linear and non-linear regression models and ARIMA models are developed to make gasoline demand forecasts based on the available historical gasoline consumption data. The ARIMA (1, 1, 0) model is thought to be the best model out of all the models included, and it is used to predict the demand for gasoline in India through 2030. According to Uppala Meena Sirisha, et al. (2022), sales data is forecast using time series data and the statistical methods of Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA models (SARIMA), as well as deep learning's use of the Long Short-Term Memory (LSTM) and Neural Network Model. Results indicate that in building the best model, LSTM outperforms both statistical models.

In this paper, an attempt is made to study comparison of different forecasting models for Population and Economic variables, the first section throws light on the introduction, the second section

deals with methods and materials, third section explains the summary and discussions and last section provides conclusions.

2. METHODS AND MATERIALS

The Age Dependency Ratio data was taken from the most recent statistics information made available by Sample Registration System (SRS) published by Registrar, census of India. The economic survey of India provided the GDP statistics, while the Registrar General of India's censuses in 1971 to 2011 provided the Total population, Urban population, and Rural population.

2.1 Autoregressive Integrated Moving Average (ARIMA) model

The ARIMA model can be extended to non-stationary series by letting the differencing of the data series result in ARIMA models. The general non-seasonal model is called the ARIMA (p, d, q): in this model, p is the order of Autoregressive, d is the differencing, and q is the order Moving Average order, is given by

$$w_t = \beta_0 + \sum_{i=1}^p \beta_i w_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t$$

Where w_t denotes the d^{th} difference of y_t

While the time series literature offers several methods for evaluating models, we choose to employ Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in this paper. This technique was created by Box and Jenkins (1976) in their pioneering study on the ARIMA model. The correlation between two successive observations in a time series is known as the ACF. The method computes the linear correlation between a time series observation and a distance-measured observation, say k. In contrast to the ACF, the PACF simply assesses the correlation between the most recent and earlier observations of a time series at a distance of k (say), after removing the impact of any intervening intermediate data.

We have to check whether the time series data is stationarity or not using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). The two most prevalent model selection criteria are the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) and the Box-Ljung test (1978) is a diagnostic tool used to test the lack of fit of a time series model.

2.2 Exponential Smoothing Model

The Exponential smoothing is a simple technique for modelling time series data in which previous observations are given weights that decrease exponentially with time for the population and economic variables. Let Y_t signify time series data, S_t denotes smoothened values, and B_t denotes the best estimate of trend at time t for the Double Exponential smoothing by V. K. Sharma and U. Nigam (2020).

Then,

$$\text{If } S_1 = Y_1 \text{ and } B_1 = Y_2 - Y_1$$

$$\text{Smoothing equation: } S_t = \alpha Y_t + (1 - \alpha) * (S_{t-1} + B_{t-1})$$

$$\text{Trend equation: } B_t = \beta * (S_t - S_{t-1}) + (1 - \beta) * B_{t-1}$$

Where the data smoothing factor is $\alpha \in (0, 1)$, and the trend smoothing factor is $\beta \in (0, 1)$. For the forecast at $t = (N + h)$ years. (F_{N+h}) is determined by

$$F_{N+h} = S_t + h * B_t.$$

2.3 Fuzzy Time Series Model

2.3.1 Related Definitions and Abbasov-Mamadova Model

Definition 1: Let U be the discourse universe, with $U = u_1, u_2, \dots, u_m$. The following is the definition of a Fuzzy set A of U :

$$A = \{\mu_A(u_1)/u_1, \mu_A(u_2)/u_2, \mu_A(u_3)/u_3, \dots, \mu_A(u_m)/u_m\}$$

Where $\mu_A(u_i)$ is the membership function of A , $\mu_A(u_i): U \in [0, 1]$, $\mu_A(u_i)$ represent the degree of membership of u_i in A , $\mu_A(u_i) \in [0, 1]$ and $1 \leq i \leq m$.

The membership degree or grade of membership is the value of the membership function of a given u , $\mu_A(u)$. If the membership grade equals one, u belongs entirely to the Fuzzy set. If the membership grade is zero, u does not belong to the Fuzzy set. If the grade of membership is between 0 and 1, u is a Fuzzy set partial member.

$$\mu_A(u) = \begin{cases} = 1 & u \text{ is a full member of } A \\ \in (0, 1) & u \text{ is a partial member of } A \\ = 0 & u \text{ is not member of } A \end{cases}$$

In the above definition, a Fuzzy set A in U is defined by a membership function $\mu_A(u)$. The Membership Function A can be defined in a variety of ways $\mu_A(u)$. Some common types of membership functions include Trapezoidal Membership Functions, Triangular Membership Functions, Gaussian Membership Functions, and so on. Following that, we look at a specific situation of Definition 1 in which the universe is a time series and provide the definition proposed by Song and Chissom (1993) which is as follows.

Definition 2: Let $X(t)$, a subset of real numbers ($t = 0, 1, 2, \dots$), be the universe of discourse through which the Fuzzy sets $f_i(t)$ are defined. If $F(t)$ is a collection of $f_1(t), f_2(t), \dots$, then, $F(t)$ is called a Fuzzy Time Series (FTS) defined on $X(t)$.

Using the Abbasov-Mamedova (AM) model and also the algorithm for determining the optimal constant (DOC) using the Modified Abbasov and Mamedova (MAM) approach model by Ha Che-Ngoc et al. (2018).

2.4 Artificial Neural Network

The Artificial Neural Network (ANN) is a technique designed to mimic human neural networks. This approach is used to assist humans in a variety of sectors, including image processing, sensor instruments in homes, workplaces, hospitals quantitative forecasting methods and others. ANN is made up of inputs, processes, and outputs developed by Hyndman. R. J. and G. Athanasopoulos (2018). The

multi-hidden layer ANN model is distinguished by the fact that it hides more than one hidden layer between the input and output layers. We have used a hidden layer model in this work, one hidden layer with three neurons and one output, as illustrated in Fig. 1.

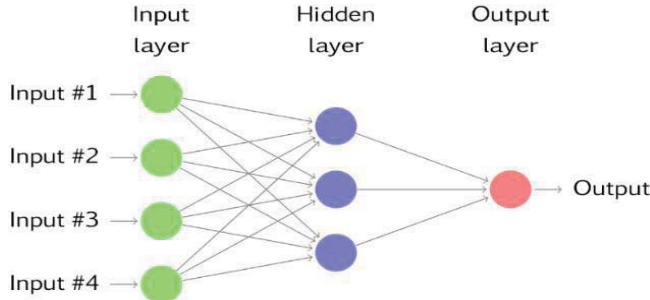


Figure 1. A Neural Network with four inputs and one hidden layer with three hidden neurons

2.4.1 Backpropagation Model

The Backpropagation Model is an algorithmic model in supervised learning Artificial Neural Networks. This technique is widely employed in predicting models using the ANN algorithm. Backpropagation training or learning comprises three stages: feedforward (forward feed) from the input pattern, counting errors from the learning process, and modifying the weights. In this Backpropagation Model, each node's input is a weighted linear combination. The outputs of the weighted linear combination are changed using a nonlinear function to form the output of this ANN. This linear combination function is denoted by

$$z_j = b_j + \sum_{i=1}^4 w_{i,j} x_i$$

Where

z_j is the sum function of the unit bias to j on the hidden layer

b_j is a weight in the bias unit to j

$w_{i,j}$ is weight of the layer i bias to j

x_i is the network input to i

It has a binary sigmoid activation function, which is a nonlinear function, as shown in Equation (6).

$$s(z) = \frac{1}{1 + e^{-z}}$$

In the equation, the nonlinear binary sigmoid function is a component of the linear combination function (5). In a single-layer network model, this binary sigmoid function is one of the functions for the Backpropagation Method.

2.4.2 Neural Network Auto-regression (NNAR)

The NNAR model is an ANN with one variable input and lag 1, lag 2, and so on models till the lag- p , thus the name Neural Network Auto-regressive (NNAR). This approach is only applicable to feed-

forward networks in a single hidden layer, and is represented as NNAR (p, k), where p represents lag-p as input and k as hidden layer nodes by Hyndman, R. J and G. Athanasopoulos, (2018). The NNAR approach utilizes a unique hidden layer, as shown in Fig.1, and a nonlinear function, as shown in Equation (5), to provide weight and provide ANN output. We have only studied feed-forward networks with one hidden layer, and used the notation NNAR (p, k) to signify that the hidden layer has p-lagged inputs and k nodes. An NNAR (9, 5) model, for example, is a neural network with the past nine observations used as inputs for forecasting the output y_t and five neurons in the hidden layer.

2.5 Bayesian Structural Time Series (BSTS) model

A combination of time series models applying the state-space representation and Bayesian statistics is known as a Bayesian structural time series. Defining the prior distribution for each model parameter, such as the error variances, is the first step in applying the Bayesian framework to the structural time series model. In every equation, the error variances are used as model parameters and follows inverse Gamma priors. For getting posterior distributions, which are calculated numerically utilizing a software-based simulation approach that is MCMC algorithm using R programming. The predictions in BSTS are derived from the posterior predictive distribution, although MCMC technique and Kalman filtering are employed to fit the model.

The BSTS model is defined by a pair of equations as given by

$$Y_t = Z_t^T \alpha_t + \varepsilon_t,$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t,$$

The above equation is the observation equation and the state equation ; it ties the observed data (Y_t) to the state vector (α_t). Where $\varepsilon_t \sim N(0, \sigma^2_{\varepsilon})$ and $\eta_t \sim N(0, Q_t)$, both error terms are independent of all other unknowns and ε_t and η_t are observation error and system error respectively. Z_t , T_t , R_t and Q_t denotes output vector, transition matrix, control matrix, and state-diffusion matrix respectively. In our study, we have applied linear trend model (a BSTS model without regression components) that assumes level and slope as random walk components by Muhammed Navas T, Shazia Farhin, and Athar Ali Khan (2022).

2.5.1 Local Level Model

The local Level model is the simplest structural time series model. This model assumes the trend is a random walk:

$$Y_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2_{\varepsilon})$$

$$\mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma^2_{\eta})$$

In the local level matrices Z_t , T_t , and R_t in equation have collapsed to the scalar value '1'. Parameters of the model are variances of the error term (σ^2_{ε} , σ^2_{η}).

2.5.2 Local linear trend model

The local linear trend model is an appreciated alternative for trend modeling because it replies immediately to local variation, which is crucial when creating short-term projections. The following equation:

$$Y_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

The equation of the level component is given by

$$\mu_t = \mu_{t-1} + \delta_t + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

And the equation of the slope is given as;

$$\delta_t = \delta_{t-1} + \nu_t, \quad \nu_t \sim N(0, \sigma_\nu^2)$$

Where μ_t denotes the local level at time t and δ_t denotes the slope trend at time t .

The assumption underlying the local linear trend is that the slope and mean components both indicate random walks. Here, we have ε_t, η_t and ν_t are independent Gaussian random noise with variances $\sigma_\varepsilon^2, \sigma_\eta^2, \sigma_\nu^2$.

To forecast the population, Bayesian analysis was used in R programming. The analysis started with the formulation of a probability model, the selection of a prior distribution, and the development of a likelihood based on the data and the model. The prior distribution was mixed with the likelihood. The posterior probability density function (pdf) was obtained. On the basis on it, future estimates were determined.

2.5.3 Performance Evaluation

Forecasting accuracy may be calculated to determine how accurate forecasting is performed. To choose the optimal model with the minimum error, it is crucial to assess predicting performance. The model validation can be measured using a number of statistical methods. The Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are typically used to quantify predicting accuracy. Then:

$$MAPE = \frac{1}{n} \left(\sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \right) * 100$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (A_t - F_t)^2}{n}}$$

$$MAE = \frac{\sum_{t=1}^n |A_t - F_t|}{n}$$

Where A_t denotes the actual value, F_t denotes the estimated value, and n denotes the number of values.

3. RESULTS AND DISCUSSION

In this article, we have made an attempt to study the selected variables - Population and Economic variables such as the Total population, Urban population and Rural population are population variables, GDP and Age dependency ratio are Economic variables that have been chosen for analysis and forecasting for the next ten years by using the different forecasting models and compared these different forecasting models.

3.1 Estimation of Population and Economic variables with the ARIMA model

3.1.1 Stationarity of the series

A series is said to be stationary if its statistical characteristics, such as mean, variance, and covariance, are not dependent on time and do not alter with time. The GDP, Total, Urban and Rural populations show growing trends in their time series movement, but the Age dependence ratio is declining. This suggests that non-stationarity is present in trends where the mean, variance, and covariance fluctuate with time. Specifically, the series displays unique mean values and fluctuations across several sample sub-periods.

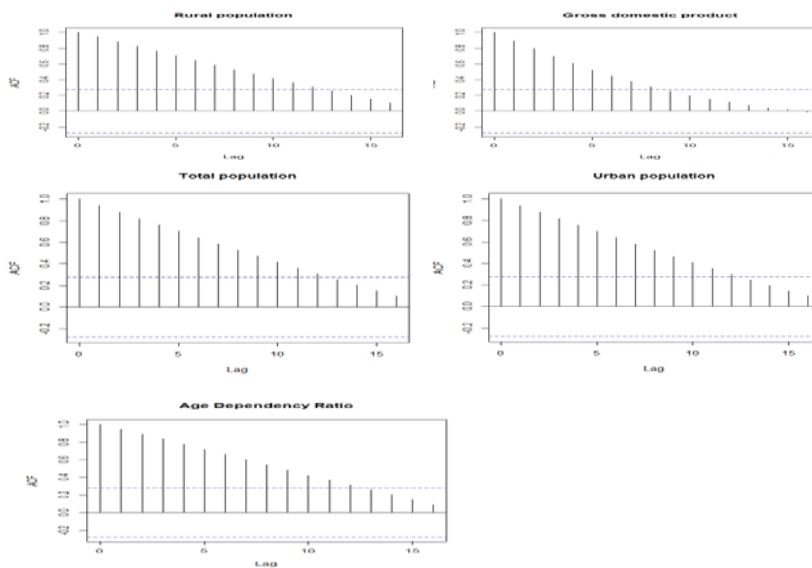


Figure 2. Autocorrelation Function for Population and Economic variables

Further stationarity of the various series is examined through Autocorrelation Function. The analysis of the result shows, a correlogram of the series, displaying the Autocorrelation Function (ACF) for 16 lags for the Population and Economic variables. Because the correlogram starts with a very high correlation coefficient of 0.99, the ACF plot progressively decays and the series has a highly expressed autocorrelation even for many lags, the series is non-stationary. Furthermore, the study checks the statistical significance of the sample autocorrelation coefficients to see if they really represent the population's true ACF plot (see Fig.2). If dealing with a random process, the ACF is roughly described by the normal distribution, with a zero mean and variance of $(1/n)$, where n is the sample size, as stated in statistical theory (Gujarati, D.N, 1995).

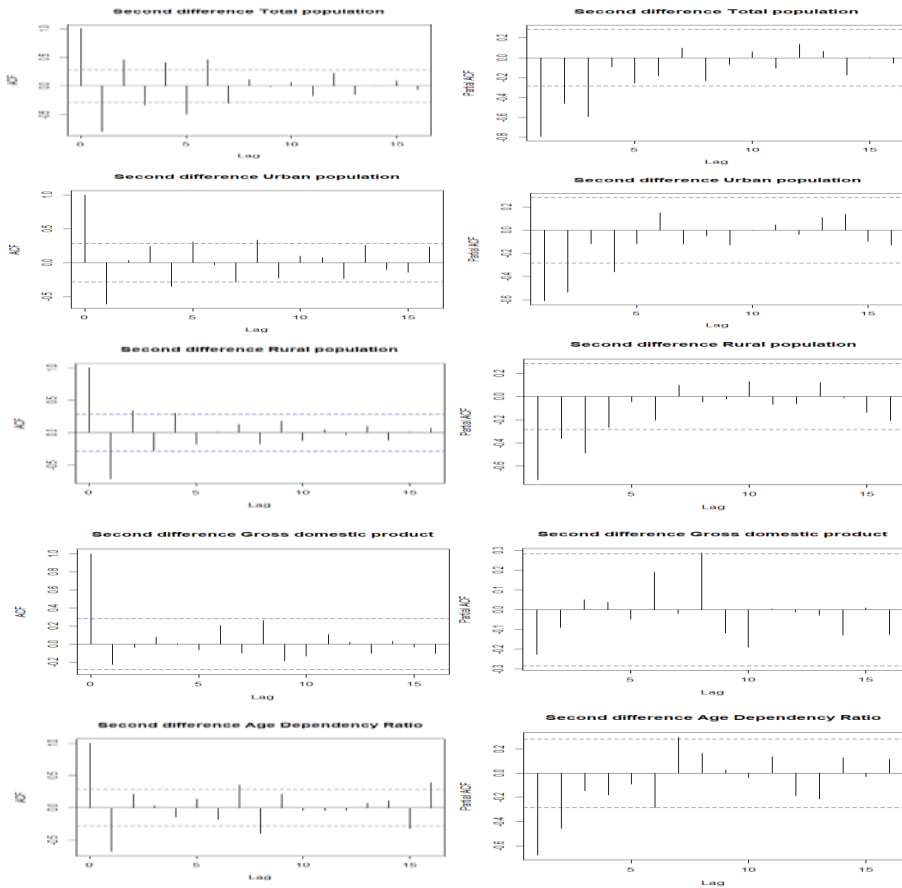


Figure 3. Autocorrelation Function and Partial Autocorrelation Function for Population and Economic variables (Second difference)

As a result, $\sqrt{1/50} = 0.1414$ can be used to calculate the standard error of the ACF. The 95 per cent confidence interval for the ACF is $(0 \pm 1.96 \times 0.1414) = \pm 0.277$. The null hypothesis that the true ACF of the population is zero ($H_0: \rho = 0$) cannot be rejected, if the computed ACF falls within the confidence

interval. The first twelve lags for Total population, Urban population, Rural population and Age dependency, as well as the first eight lags for GDP, ACF are statistically significant (i.e., different from zero), the coefficients from lag 13 to lag 16 and lag 9 to lag 16 respectively lie within the confidence interval and then these coefficients are once again different from zero, as shown in Fig.2. The non-stationarity nature of the series is again confirmed by the large number of statistically significant coefficients.

The time series X_t 's variables are all stationary by a second difference, lack a trend, and move in a wave-like manner. When the series is second differenced, the autocorrelation coefficients exhibit a wave-like pattern of movement, starting at low values and rapidly declining to zero and lag 16. The results above show that second-differencing the initial time series can lead to stationarity. The emergence of the ACF and PACF in the differenced series was next investigated, and the values of the ARIMA model parameters, p and q , were ascertained by comparing the two plots in Fig. 3.

Table 1: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for stationarity (second difference)

Variables	ADF	p-value	PP	p value
Total population	-6.4424	0.01	-77.399	0.01
Urban population	-7.6739	0.01	-66.082	0.01
Rural population	-7.5304	0.01	-77.089	0.01
GDP	-5.9729	0.01	-56.976	0.01
Age Dependency Ratio	-3.5894	0.04368	-72.097	0.01

The ADF test and the PP test are used to determine stationarity. Table 1 shows that the p values are less than the significance level of 0.05, which suggests that the null hypothesis of a unit root, which can be rejected, implying that the second-differenced series is achieved stationarity. $d = 2$ in the ARIMA model. To determine the Box–Jenkins methodology can be used.

3.1.2 Model selection

The study employs the AIC and BIC tests for model selection; the model that best fits all of the specified variables is determined by the test's minimal values.

The optimal ARIMA (p, d, q) model is then determined by combining the AIC and BIC. The AIC and BIC were calculated in the study using different combinations (p, d, q). Next, select the best-fitting ARIMA model with the lowest AIC and BIC from all the models that were analyzed. The AIC and BIC (see Table 2) indicate that the ARIMA (0, 2, 5), (0, 2, 5), (0, 2, 4), (1, 2, 2), and (0, 2, 2) models are the best-fitted for the Total population, Urban population, Rural population, GDP, and Age Dependency Ratio, respectively.

Table 2: Evaluation of various ARIMA models (without a constant)

Variables	Models	AIC	BIC
Total population	(0, 2, 3)	1113.38	1120
	(0, 2, 4)	1065.96	1075.32
	(0, 2, 5)	1034.81	1046.04
Urban population	(0, 2, 1)	1231.23	1234.97
	(0, 2, 2)	1179.42	1180.03
	(0, 2, 3)	1120.09	1127.57
	(0, 2, 4)	1068.44	1077.79
	(0, 2, 5)	1021.37	1032.59
Rural population	(0, 2, 1)	986.4	989.86
	(0, 2, 2)	928	933.67
	(0, 2, 3)	876.8	884.33
	(0, 2, 4)	856.6	865.96
GDP	(0, 2, 2)	1276.55	1282.4
	(0, 2, 3)	1277.68	1285.16
	(1, 2, 2)	1271.58	1279.06
	(1, 2, 3)	1275.3	1284.65
Age Dependency ratio	(0, 2, 1)	73.36	77.1
	(0, 2, 2)	64.3	69.51
	(0, 2, 3)	66.3	73.78
	(0, 2, 4)	67.11	76.46

3.1.3 Estimation of Coefficient for Selected Model

The Maximum Likelihood Estimator for Population and Economic Variables is used to estimate the coefficients. The modeling results of an ARIMA (0, 2, 5), (0, 2, 5), (0, 2, 4), (1, 2, 2), and (0, 2, 2) models with Total, Urban and Rural population, GDP, and Age dependency ratio, respectively, are reported in Table 3 and are used to estimate the Maximum Likelihood Estimators. At the 1% level of significance, every computed coefficient for the population and Economic variables is statistically significant.

Table 3: Estimation of parameters of the model by Maximum likelihood Estimator for Population and Economic variables

Variables	Model		Coefficients	Standard error	z values	Pr(> z)
Total population	(0, 2, 5)	MA(1)	4.0922	0.2133	19.1840	2.2e-16 ***
		MA(2)	7.2809	0.5878	12.3863	2.2e-10 ***
		MA(3)	7.0389	0.6593	10.6758	2.2e-16 ***
		MA(4)	3.6969	0.3843	9.6178	2.2e-16 ***
		MA(5)	0.84378	0.1136	7.4233	1.143e-13***
Urban population	(0, 2, 5)	MA(1)	4.459562	0.225708	19.758	2.2e-16 ***
		MA(2)	8.405965	0.679595	12.369	2.2e-16 ***
		MA(3)	8.365046	0.780988	10.711	2.2e-16 ***
		MA(4)	4.394968	0.409693	10.727	2.2e-16 ***
		MA(5)	0.976139	0.091874	10.625	2.2e-16 ***
Rural population	(0, 2, 4)	MA(1)	2.66308	0.22392	11.893	2.2e-16 ***
		MA(2)	3.32458	0.34536	9.6264	2.2e-16 ***
		MA(3)	2.30072	0.2509	9.1699	2.2e-16 ***
		MA(4)	0.74497	0.1525	4.8851	1.034e-06 ***

GDP	(1, 2, 2)	AR(1)	0.906252	0.073181	12.3837	2.2e-16 ***
		MA(1)	-1.493693	0.120032	-12.4441	2.2e-16 ***
		MA(2)	0.683387	0.118488	5.7676	8.043e-09 ***
Age Dependency Ratio	(0, 2, 2)	MA(1)	-1.3315	0.14072	-9.4618	2.2e-16 ***
		MA(2)	0.53167	0.14494	3.6683	0.0002442 ***

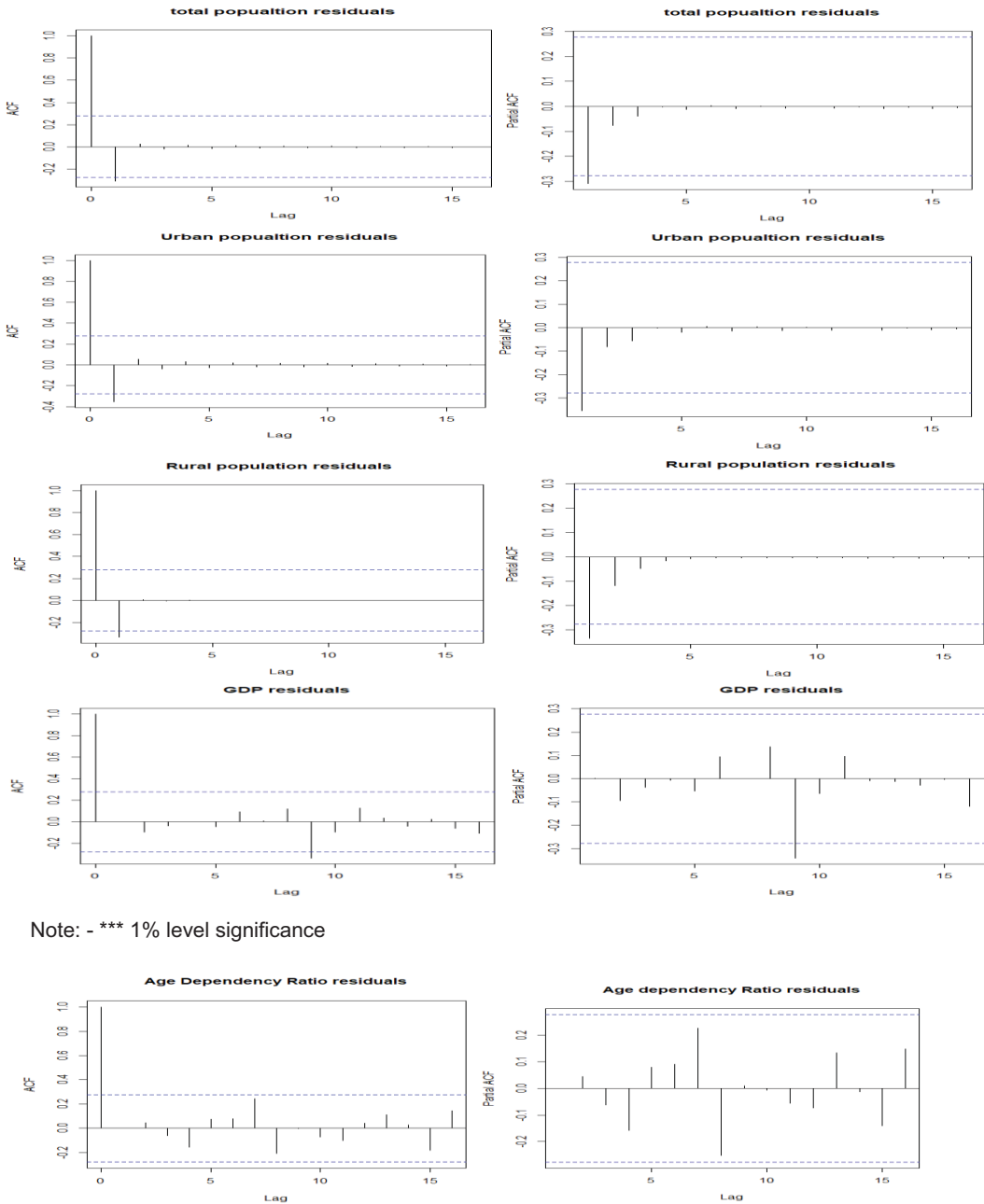


Figure 4. Autocorrelation Function and Partial Autocorrelation Function for Population and Economic variables (White noise)

3.1.4 Diagnostic check

After the models are constructed, diagnostic testing is necessary to make sure they are statistically significant and relatively acceptable for prediction. One of the easy diagnostic methods is to obtain the residual models' ACF and PACF correlograms. The estimated ACF and PACF are displayed in Fig. 4. These correlograms give the impression that all coefficient lags, with the exception of the first lag for the Total population, Urban population, and Rural population, are within the confidence interval, indicating that the time series data are independently distributed (white noise). Fig.4 displays the estimated ACF and PACF, which demonstrate that the ACF and PACF correlograms give the impression that all coefficient lags for GDP are within the confidence interval excluding ninth lag, that value is ignored indicating that our time series data are independently distributed. All coefficient lags for the Age dependency ratio appear to be inside the confidence interval in the computed ACF and PACF correlograms, indicating that our time series data are independently distributed (white noise) (see Fig.4).

Table 4: The Box-Ljung test for Population and Economic variables

Variables	Statistic test (Q)	DF	p-value	Chi-square Table Value
Total population	17.1050	11	0.1048	19.6751
Urban population	7.1264	11	0.7888	19.6751
Rural population	5.9266	12	0.9197	21.0260
GDP	12.2780	13	0.505	22.36203
Age Dependency Ratio	14.8330	14	0.3897	23.6848

Box-Ljung test statistic for all the variables and the corresponding p values, which is much larger than 0.05 and the Box-Ljung test is less than the Chi-square critical values, Then, we fail to reject the null hypothesis of the test and conclude that our residuals are independent, which indicates that our fitted model is adequate.

3.2 Estimation of Population and Economic variables with the Exponential Smoothing model

The estimates for the parameters (α and β) and initial values (S1 and B1) for Exponential Smoothing model was applied to various variables, such as Total population, Urban population, Rural population, GDP and Age dependency ratio.

Table 5: Estimates for parameters of the Exponential Smoothing model

Variables	Estimated			
	α	β	S1	B1
Total population	0.1	0.1	529059855	15157090
Urban population	0.1	0.1	110599658	4949269.37
Rural population	0.1	0.1	419767995	10280892.3
GDP	0.1	0.1	33790.4097	8954.2745
Age Dependency Ratio	0.1	0.1	79.4182	-0.5846

Exponential Smoothing model is used for time series forecasting and involves Exponential Smoothing of both the level (S) and the trend (B) components. Considering the historical data and the

specified smoothing and trend parameters, these parameters and initial values will be used to forecast future values for each respective variable using the Exponential Smoothing model

3.3 Fuzzy Time Series Model

According to the Abbasov and Mamedova Model (2003) the detailed technique is broken down steps may written as

The universal set U is used to define Fuzzy sets. "The variation in Total population" in this example is a linguistic variable with the following linguistic values: A_1 = (Very Low Level (VLL)); A_2 = (Low Level (LL)); A_3 = (Changeless (CL)); A_4 = (Moderate (M)); A_5 = (Normal Level (NL)); A_6 = (High Level (HL)); A_7 = (Very High Level (VHL)); Every linguistic value correlates to a fuzzy variable, which is allocated against a corresponding Fuzzy set determining the meaning of this variable according to a set of rules. The fuzzy variable [VLLPG, [13690146, 14726361], A_1], for example, gives the linguistic value "Very Low-Level Population Growth," where A_1 is a Fuzzy set defined on the domain [13690146, 14726361] of the universal set U .

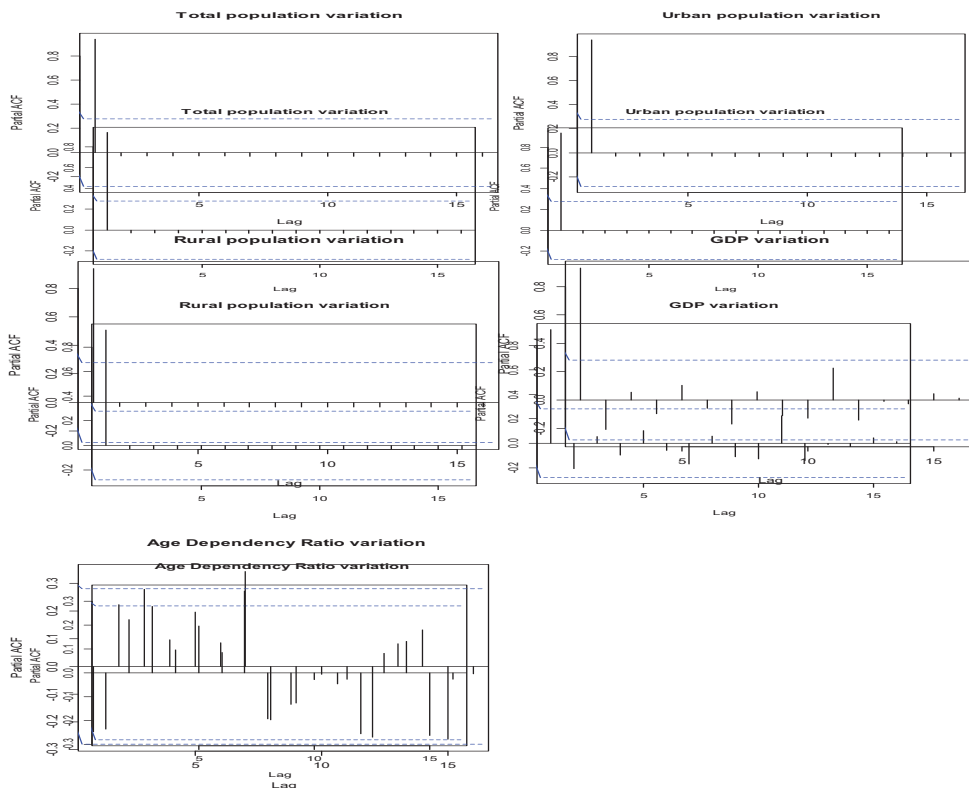


Figure 5. Graph of Partial Autocorrelation Function (PACF)

The PACF computed and presented in Fig.5 is used as the criterion to determine the appropriate w . According to Fig.5, for 'w', PACF reaches its maximum value at lag 1 and then the 'w' is chosen as 2.

In summary, the Abbasov-Mamedova Model employs $n = 7$ for all the variables and $w = 2, 2, 2, 2, 8$ based on PACF for Total population, Urban population, Rural population, GDP and Age Dependency ratio respectively. With $n = 7$ and $w = 2$, performing the DOC algorithm, the optimal value of C is 0.00002563264 for Total population. As similarly $w = 2, 2, 2, 8$ performing the DOC algorithm, the optimal value of C is 0.000005924608, 0.000302948864, 0.007756070912, 0.999996037632 and 0.000000208256 for Urban population, Rural population, GDP and Age Dependency ratio respectively.

Table 6: Seven different values of Universal set U with respect to range for Population and Economic variables

Variables		u_1	u_2	u_3	u_4	u_5	u_6	u_7
Total Population	L	13690146	14726361	15762576	16798791	17835007	18871222	19907437
	U	14726361	15762576	16798791	17835007	18871222	19907437	20943652
	M	14208254	15244469	16280684	17316899	18353114	19389329	20425544
Urban population	L	3358042	4482048	5606053	6730059	7854065	8978071	10102076
	U	4482048	5606053	6730059	7854065	8978071	10102076	11226082
	M	3920045	5044051	6168056	7292062	8416068	9540073	10664079
Rural population	L	9717570	9805360	9893151	9980941	10068732	10156522	10244313
	U	9805360	9893151	9980941	10068732	10156522	10244313	10332103
	M	9761465	9849256	9937046	10024837	10112627	10200417	10288208
GDP	L	3361.00	270442.70	537524.40	804606.10	1071687.90	1338769.60	1605851.30
	U	270442.70	537524.40	804606.10	1071687.90	1338769.60	1605851.30	1872933.00
	M	136901.90	403983.60	671065.30	938147.00	1205228.70	1472310.40	1739392.10
Age Dependency Ratio	L	-1.00	-0.86	-0.71	-0.57	-0.43	-0.29	-0.14
	U	-0.86	-0.71	-0.57	-0.43	-0.29	-0.14	0.00
	M	-0.93	-0.79	-0.64	-0.50	-0.36	-0.21	-0.07

Note: U is Upper value, L is Lower value, M is middle value

3.4 Autoregressive Neural Network model

3.4.1 Training of data samples

To make the NNAR model work properly, the data training must be completed. First, 40 data points from 50-years Population and Economic variables are used to create training data samples. The training model with the lowest RMSE value should be selected as the best. Following that, models with the second and third lowest RMSE training values will be chosen. The selection of the best NNAR model among the three NNAR models is based on RMSE in forecasting the year's population. Table 7 displays the results of the calculations.

3.4.2 Testing of data samples

Testing data was drawn from the last ten years of selected all of the Population and Economic variables, as the training and testing data should be balanced in number because it is a sample taken to create and validate the model. The criteria used to select the model tested are the same as those used in the training model, which are the smallest error, which is RMSE, with the results of model selection in the training model and testing model, which are shown in Table 7.

Table 7: Model selection for Population and Economic variables

Variables	Models	RMSE	
		Training	Testing
Total population	NNAR (2, 4)	199225.5	27730066.1
	NNAR (3, 4)	205843.8	28524711.5
	NNAR (4, 4)	191675.1	20910852.3
Urban population	NNAR (2, 4)	94564.92	18360369.4
	NNAR (3, 4)	72141.08	15582940.5
	NNAR (4, 4)	67929.6	14990193.2
Rural population	NNAR (2, 4)	147010.2	15346464
	NNAR (3, 4)	133805.3	11177977.1
	NNAR (4, 4)	108203.2	9379160
GDP	NNAR (2, 1)	42463.43	6518081.12
	NNAR (3, 1)	42771.5	6940832
	NNAR (4, 1)	42365.5	6485030.3
Age dependency ratio	NNAR (2, 1)	0.3802	3.3752
	NNAR (3, 1)	0.3710	3.3863
	NNAR (4, 1)	0.3723	3.4656

The optimal forecasting model and the NNAR model (4, 4) for the Total population may be selected based on the lowest RMSE training and testing values. Because the RMSE training values for the NNAR (4, 4), (4, 4) and (4, 4) models are the smallest, 191675.1, 67929.6 and 108203.2, respectively, Table 7 shows that these models are the best at forecasting population variables like Total population, Urban population, and Rural population. The best forecasting models for economic variables, such as GDP and Age dependency ratio, are the NNAR (4, 1) and (3, 1) models, given their respective least RMSE training values are 42365.5 and 0.3710. NNAR (4, 4) introduces a neural network for the Total population that uses four neurons in one hidden layer and the four preceding observations as inputs to anticipate the output. Furthermore, the remaining variables that were chosen the same. Out of the three NNAR models, we selected one to be used for model prediction since it has the lowest RMSE.

3.5 Bayesian Structural Time Series Model

In order to analyse and forecast these factors, which can be taken into consideration for the next ten years, this study uses the Local Linear Trend in the BSTS model. We also provided the state specification, set the number of MCMC iterations to 10,000, and provided burn-in samples of 4,000 in order to build the posterior distribution and fit the model to our time series data.

3.5.1 Estimation of parameters

In accordance with the model's predictions, the posterior estimates for the BSTS model are statistically significant.

Table 8: Estimation of parameters for posterior mean and median for Population and Economic variables

Variables	Parameters	Mean	Median	Lower	Upper
Total population	σ_{obs}	3974816.2	3932382	3218238	4947336
	σ_{level}	441362.1	357117.2	127513.8	1239875
	σ_{slope}	492489.9	462326.7	274685.3	891580.6
Urban population	σ_{obs}	1744706.6	1725569	1405079	2188964
	σ_{level}	207133.9	163287	55112.01	609755.7
	σ_{slope}	420524.6	402547.2	262965.5	679502.1
Rural population	σ_{obs}	2234210.7	2209443	1822373	2764946
	σ_{level}	225975.3	186943.8	71544.6	612426
	σ_{slope}	120278.2	108572.4	55671.38	258934.1
Gross Domestic Product	σ_{obs}	117002.59	115357.5	91398.39	151221.3
	σ_{level}	16464.91	11271.91	2994.731	59870.3
	σ_{slope}	101840.95	99512.98	73166.53	143303.7
Age Dependency Ratio	σ_{obs}	0.3449	0.3415	0.275	0.4342
	σ_{level}	0.0475	0.031	0.0055	0.1865
	σ_{slope}	0.0832	0.079	0.0464	0.1429

A posterior parameter estimate for σ_{obs} for the whole population, ranging from 3218238 to 4947336, indicates that zero falls outside of a credible 95% CI, demonstrating the parameter's statistical significance. In the same way, the parameters σ_{level} and σ_{slope} have statistical relevance for the Total population. The values of σ_{level} and σ_{slope} for the whole population are 441362.1 and 492489.9, respectively. For Urban population, Rural population, GDP and Age dependency ratio zero excluded in all the interval for all the three parameters indicating all selected variables are statistically significant (Devi Azarina Manzilir Rohmah, Ani Budi Astuti, Achmad Efendi, 2023) (see Table 8).

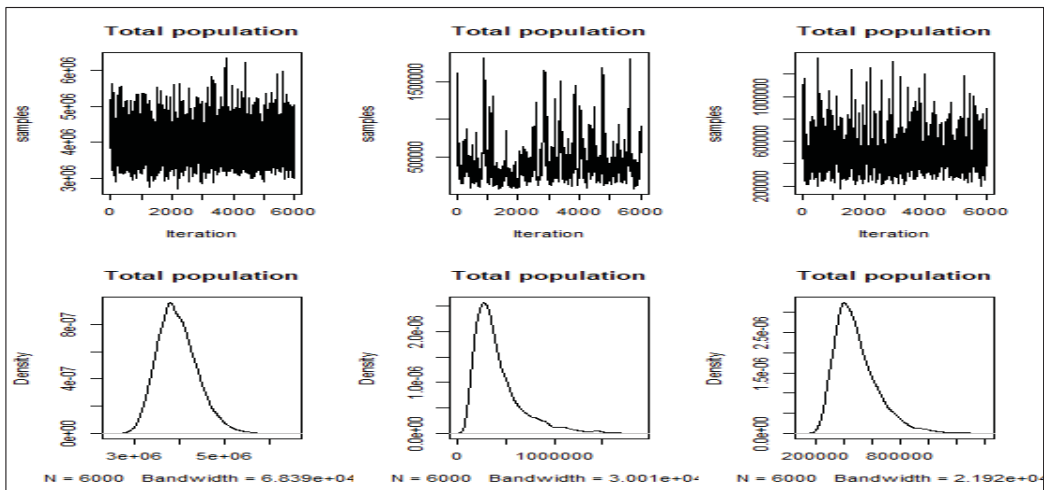


Figure 6. BSTS model for Total population (σ_{obs} , σ_{level} , σ_{slope}), trace plot and posterior density plot
 Note: Fig.6 first and second row σ_{obs} , σ_{level} , σ_{slope} are trace plot and density plot respectively

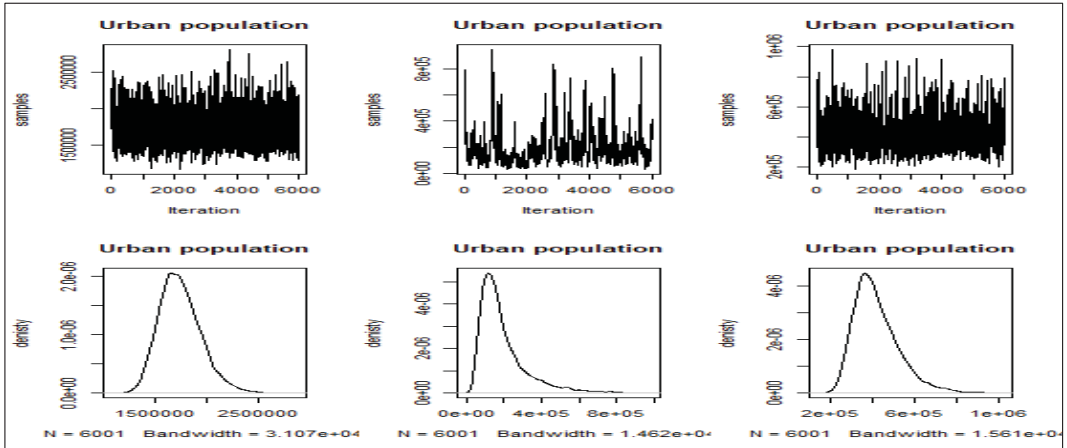


Figure 7. BSTS model for Urban population (σ_{obs} , σ_{level} , σ_{slope}), trace plot and posterior density plot
Note: Fig.7 first and second row σ_{obs} , σ_{level} , σ_{slope} are trace plot and density plot respectively

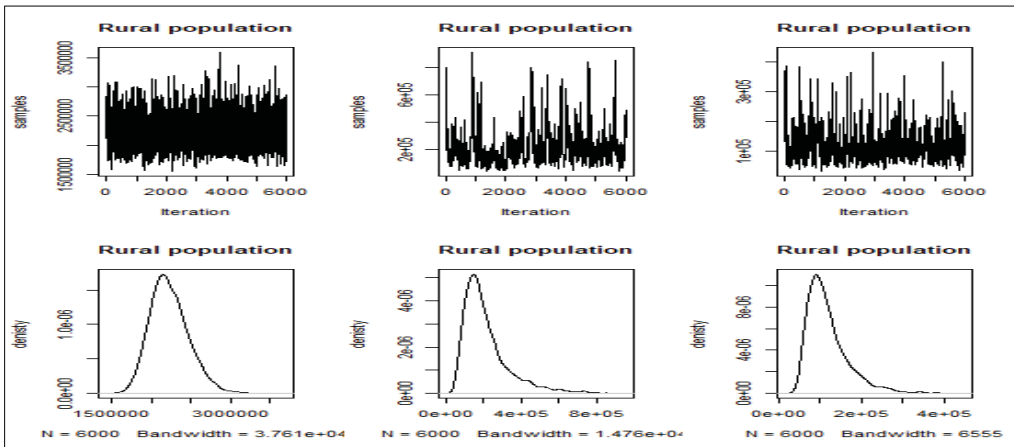


Figure 8. BSTS model for Rural population (σ_{obs} , σ_{level} , σ_{slope}), trace plot and posterior density plot
Note: Fig.8 first and second row σ_{obs} , σ_{level} , σ_{slope} are trace plot and density plot respectively

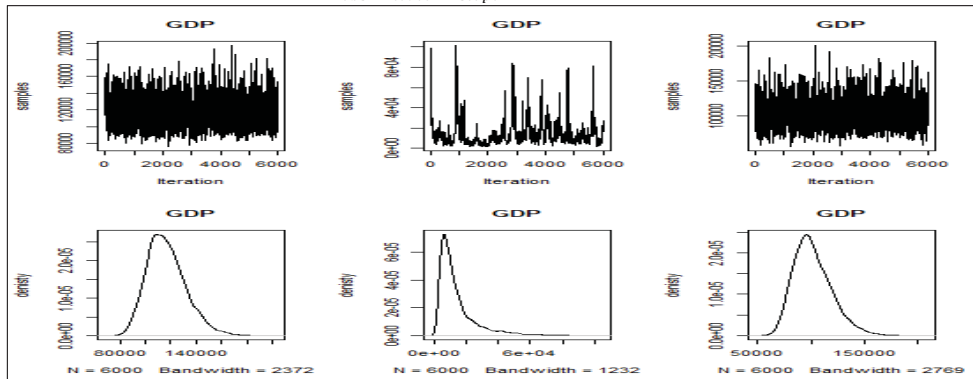


Figure 9. BSTS model for GDP (σ_{obs} , σ_{level} , σ_{slope}), trace plot and posterior density plot
Note: Fig.9 first and second row σ_{obs} , σ_{level} , σ_{slope} are trace plot and density plot respectively

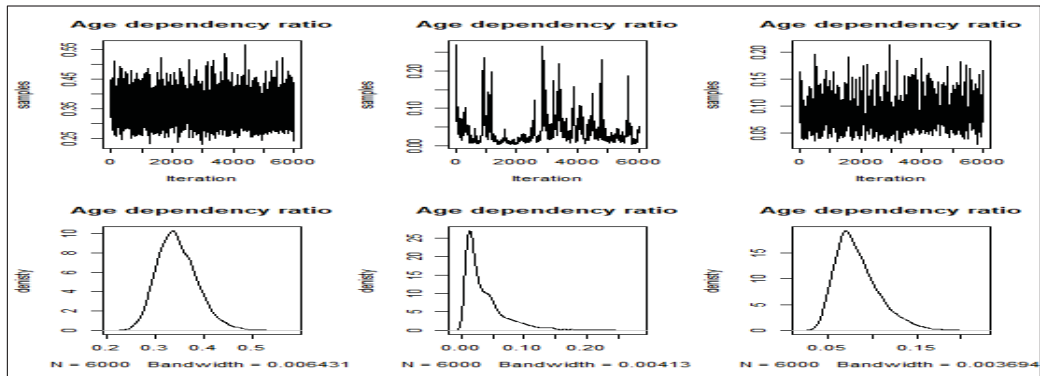


Figure 10. BSTS model for Age dependency ratio (σ_{obs} , σ_{level} , σ_{slope}), trace plot and posterior density plot

Note: Fig.10 first and second row σ_{obs} , σ_{level} , σ_{slope} are trace plot and density plot respectively

Fig.6 - 10 show that a trace plot is a graphical representation used in Bayesian analysis to assess the convergence and mixing of a Markov Chain Monte Carlo (MCMC) sampler used in Bayesian modelling. The trace plot helps visualize the sampled values of a parameter or set of parameters over iterations of the MCMC simulation. If the trace plot shows any patterns, trends, or cycles, that plot might indicate issues with convergence. This plot can suggest that the MCMC has not converged or that the sampler is not mixing well. For all the selected variables viz: Total population, Urban population, Rural population, GDP and Age dependency ratio, we have used 10,000 iterations and burn-in period 4000 and then we got a stable trace, indicating that the MCMC has reached a relatively stationarity state for σ_{obs} , σ_{level} , and σ_{slope} . Interpreting a trace plot is crucial to ensure that the MCMC process has converged and is providing reliable estimates.

3.6 Forecasting of the Population and Economic variables

Forecasting population and economic variables involves using statistical models to project future values based on historical data and relevant factors

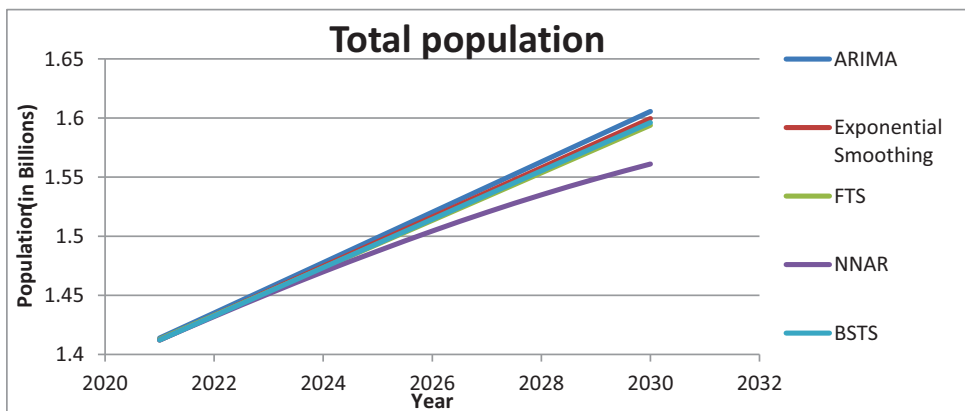


Figure 11. Forecasts of the Total population using different forecasting models from 2021 to 2030

In 2020, there will be 1.39 billion people living in India. Over the five years of the projected period, the Total population expanded by around 0.11 billion, and between 2021 and 2030, its value climbed by 0.22 billion. It will have shifted from 7.62% in 2025 to 15.27% by 2030. Based on the ARIMA model, this forecast indicates a growth rate of 15.27%, or 1.52 per year, between 2021 and 2030. The forecasting period for the Exponential Smoothing model will be less than 0.01 billion, as we described in the ARIMA model. Furthermore, the population grew by 7.91% in 2025 and 15.10% by the end of the predicted period.

This prediction indicates that there will be yearly gains of 1.51 per cent and 15.10 per cent between 2021 and 2030 (see fig.11). The population of India is expected to increase by 1.59 billion over the next ten years, from 1.39 billion in 2020 to 1.59 billion in 2030, with nearly 0.2 billion added around 2030. Based on the Fuzzy Time Series Model, this represents a 14.4% increase over ten years at a rate of 1.4% annually. NNAR projects that during the next five years, India's overall population is expected to grow by 1.49 billion, from 1.39 billion in 2020 to 1.56 billion in 2030, with about 0.2 billion in 2030. This represents a 12.2% increase over ten years at a pace of 1.2% per year. The BSTS model projected that there would be 1.39 billion people in 2020. India's population is expected to grow to 1.49 billion in 2025 and 1.59 billion in 2030, respectively. The population will rise by 1.4% per year, or 14.38%, over ten years. The percentage differences for 2025 and 2030 will be 7.19% and 14.38%, respectively.

In 2020, there were 0.47 billion people in India who lived in Urban areas; that number increased by around 0.06 billion between 2021 and 2025 and by approximately 0.12 billion between 2021 and 2030. Over the ten years from 2021 to 2030, the population of cities will increase by 0.12 billion, with percentage changes of 12.21% in 2025 and 24.51% after the forecast timeframe. This forecasts 24.51 per cent growth between 2021 and 2030 based on the ARIMA model. The Exponential Smoothing model will have a forecasting period of more than 0.01 billion, as we have stated in the ARIMA model. In addition, the Urban population is expected to grow by 23.73% by the end of the projected period and by 11.86% in 2025.

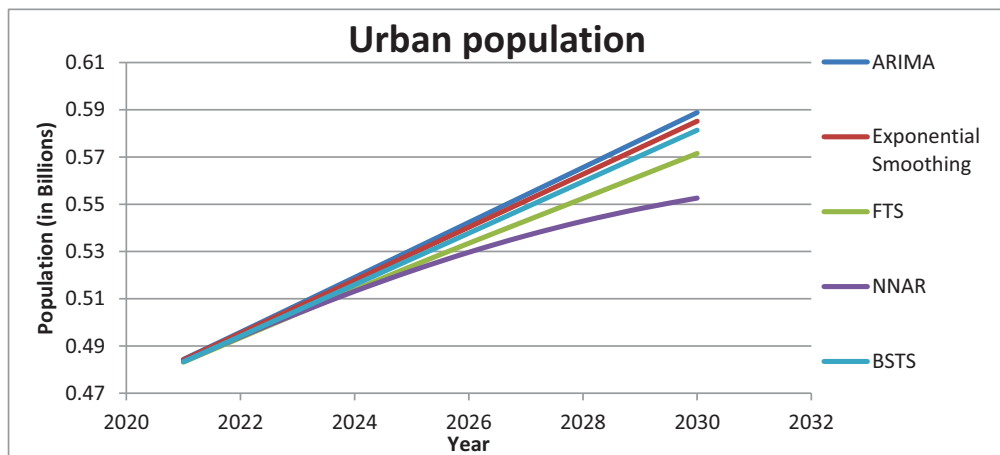


Figure 12. Forecasts of the Urban population using different forecasting models from 2021 to 2030

With the use of the Fuzzy Time Series model, the Urban population, which was recorded at 0.47 billion in 2020, is predicted to rise to 0.52 billion in the following five years and 0.57 billion by 2030, representing a 20.8 per cent growth from the original period of forecasting at a pace of almost 2 per cent per year (see fig. 12). Using the NNAR model, the Urban population, which was 0.47 billion in 2020, is expected to expand to 10.6% in the following five years and 0.55 billion by 2030, a 17% increase from the initial forecast period at a pace of almost 1.7% per year. The Urban population of India is good fit for the BSTS model. Forecasts indicate that by 2025 and 2030, there may be between 0.53 and 0.58 billion people, respectively, living in Urban areas. The Urban population will increase by 2.3% per year, for a Total increase of 23.2 per cent over ten years. The gaps will be 10.63% and 23.2% for the years 2025 and 2030, respectively. As more people move to metropolitan regions, cities and towns grow for the betterment of their lives, necessitating more housing, transportation, utilities, and other infrastructure. To support the expanding Urban population, governments and private organizations may need to make investments in creating and modernizing Urban infrastructure. People seeking jobs and better economic prospects are frequently drawn to Urban regions since they typically provide a wide variety of employment options in many sectors.

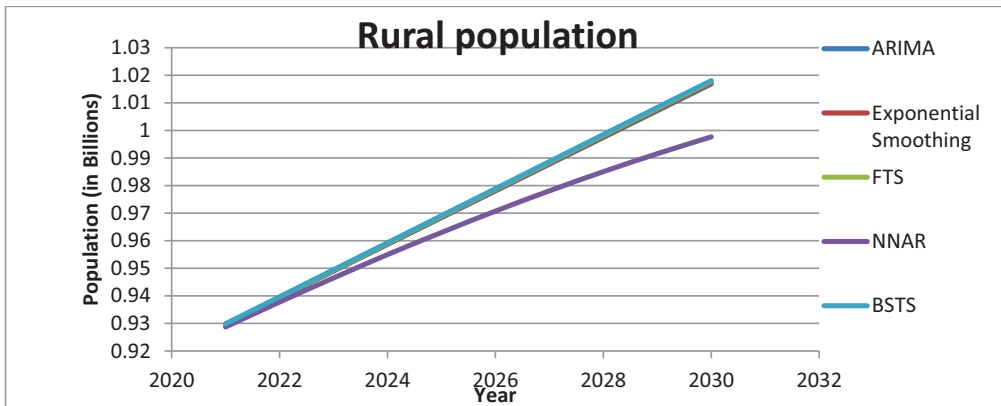


Figure 13. Forecasts of the Rural population using different forecasting models from 2021 to 2030

India had 0.92 billion people living in Rural areas as of 2020. The Rural population increased by around 0.05 billion throughout the half-decade of the predicted period, and between 2021 and 2030, its value changed by 0.10 billion. During the period from 2021 to 2030, the population of Rural areas grew by 0.10 billion, with per cent changes of 5.27 per cent in 2025 and 10.53 per cent after the projected period. A 10.53 per cent increase is anticipated by the ARIMA model between 2021 and 2030. The forecasting period given by the ARIMA model will closely match that of the Exponential Smoothing model. The Rural population was estimated by the Fuzzy Time Series model to be 0.91 billion in 2020 and is projected to grow to 0.96 billion by 2025, representing a 5.3% increase in the last five years. By the next ten years, the forecasted number will rise to 1.02 billion, indicating a 10.6% increase over 2020 at a rate of one per cent per year. The Urban population is predicted to expand at a rate almost twice as high as the Rural population, accounting for almost half of the overall population. Consequently, the rate of Urban population increase is higher than that of Rural and overall population growth. Based on the

NNAR model, the Rural population, which was 0.91 billion in 2020, is expected to climb to 0.96 billion by 2025, a 5.4% increase over the previous five years, and then to 0.99 billion by the end of the current decade, an 8.7% increase over the next ten years (see fig. 13). India's Rural populace conforms to the BSTS paradigm. In 2020, there will be 0.91 billion Rural residents in India. In Rural regions, there may be 0.97 billion people living there in 2025 and 1.02 billion in 2030. The population of Rural areas will increase by 1.2% a year, or 12.08 per cent, during the next ten years. The differences were 12.08% and 6.59% for the years 2025 and 2030, respectively.

India's GDP was projected by the ARIMA model to reach 203 trillion in 2020. Throughout the projection period, the GDP grew by around 297.74 trillion, and between 2021 and 2030, its value changed by 386.38 trillion. The Exponential Smoothing model predicts that GDP will rise by 350.42 trillion in 2030 and 277.26 trillion in 2025.

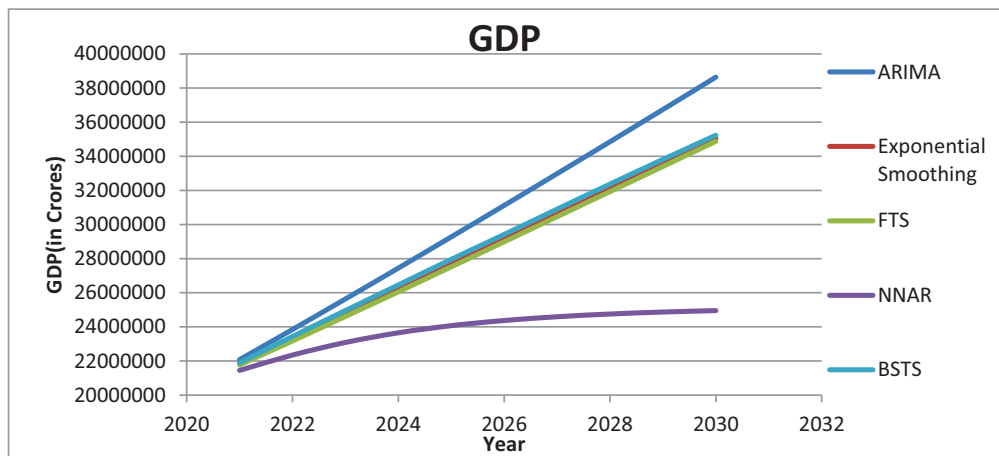


Figure 14. Forecasts of the GDP using different forecasting models from 2020 to 2030

India's GDP was estimated by FTS to be 203 trillion in 2020, and it is expected to expand by 275 trillion over the next five years and 348 trillion over the last ten years. India's GDP was estimated by the NNAR model to be 203 trillion in 2020, and it is expected to expand to 240 trillion in the following five years, more than it was in 2020. Over the preceding 10 years, the GDP increased by 249 trillion. The BSTS model is compatible with India's GDP. The GDP may reach 279 and 352 trillion by 2025 and 2030, respectively. Over the next 10 years, the GDP will increase (see fig. 14). Economic development will result in a sharp increase in GDP. Numerous factors, such as increased consumer spending, business investment, and exports, might be to blame for this. Technological developments may increase efficiency and productivity across a wide range of sectors, leading to increased output and economic expansion, which eventually helps to increase GDP.

India's Age dependency ratio was 49% in 2020. The Age Dependency Ratio reduces by 2% throughout the half-decade of the projected time, and by 5% between 2021 and 2030. The per cent declines are 5.79% in 2025, 11.02% at the conclusion of the projection period, and 1.1% annually. An 11.02 per cent decline is anticipated between 2021 and 2030 based on the ARIMA model. Throughout the forecasting period, the Exponential Smoothing model's value will be quite close to that of the ARIMA

model. Furthermore, by 2030, the Age dependence ratio would have decreased by 5.91 per cent in 2025 and 10.81 per cent in 2030 at the end of the forecast period, with a decline of 1.08 per cent per year. According to FTS, India's Age dependence ratio was 49% in 2020 and was expected to drop to 46.5% by 2025, a 5.1% decline in the next 5 years and 44% by 2030, a 10.2% decrease in the next ten years.

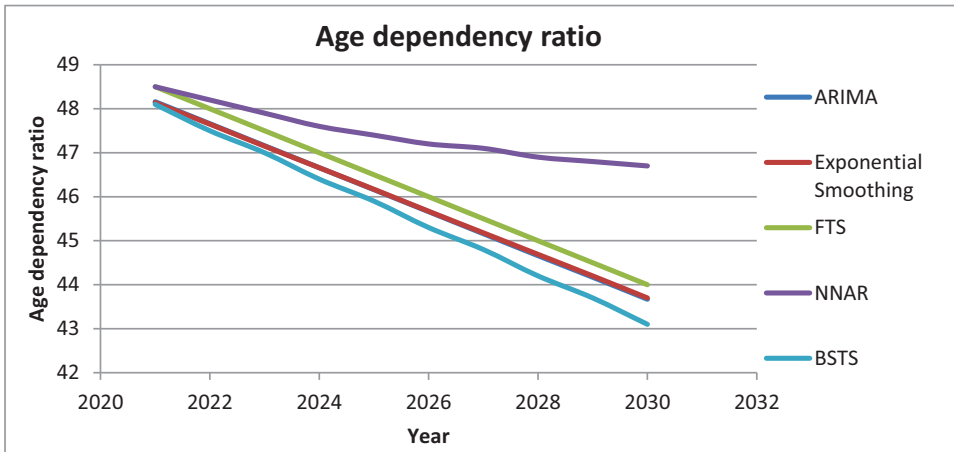


Figure 15. Forecasts of the Age dependency ratio using different forecasting models from 2021 to 2030

The GDP will rise in tandem with the growth of the working-Age population and the declining Age dependence ratio. The projection shows an inverse connection between the two variables. India's Age Dependency Ratio was 49% in 2020 and was expected to drop to 47.4% in 2025, a 3.2% decline in the next half decade and 46.7% by 2030, a 4.6% decrease in the following ten years (see fig. 15). The Neural Network Auto-regression model predicts that throughout the next ten years, the Age dependence ratio will gradually decline. The Age dependence ratio might reach 45.9 and 43.1% in 2025 and 2030, respectively, according to the BSTS model. This suggests that over the anticipated period from 2021 to 2030, the Age dependence ratio is declining. Reduced birth rates may result in a drop in the population's proportion of children, which would reduce the Age dependence ratio. Longer life spans and advancements in healthcare might contribute to an increase in the proportion of elderly people in the population.

3.7 Comparison of different forecasting models and performance of accuracy for Population and Economic variables

To study comparison of the forecasting of the Population and Economic variables using different forecasting models such as ARIMA, Holt Exponential Smoothing, Fuzzy Time Series, NNAR, and BSTS for the next ten years. These models are based on the MAPE, RMSE, and MAE for performance accuracy tests. An attempt is also made to compare the accuracy of several forecasting models across various variables. These indicators give an idea of the accuracy of each forecasting model's performance. Better model performance is often indicated by lower values of RMSE, MAE, and MAPE.

Table 9: Comparison of different models forecasting and performance of accuracy for Population variables

Models		Total population	Urban population	Rural population
ARIMA	RMSE	105008	23001	82644
	MAE	25576	9904	16196
	MAPE	0.00419	0.00604	0.00361
Exponential Smoothing	RMSE	2071176	2246651	444865
	MAE	1744660	1892472	332404
	MAPE	0.2097	0.92106	0.05905
Fuzzy time series	RMSE	2020467	324025	24801
	MAE	1711929	275233	21175
	MAPE	0.025	0.1043	0.0037
NNAR	RMSE	221587	89728	132547
	MAE	165087	67951	107439
	MAPE	0.0180	0.0357	0.0179
BSTS	RMSE	9781412	5876111	1694921
	MAE	1514517	982534	260008
	MAPE	0.1648	0.4392	0.0372

For the ARIMA model, all population variables, the RMSE, MAE and MAPE values are relatively small, showing accuracy in absolute terms. The ARIMA model's potential to estimate Urban population using the given data is demonstrated by the fact that RMSE, MAE, and MAPE are quite low as compared to other variables.

Table 10: Compared different models forecasting and performance of accuracy for Economic variables

Variables/Models		GDP	Age dependency ratio
ARIMA	RMSE	121599	0.4261
	MAE	66570	0.3627
	MAPE	2.5214	0.5631
Exponential smoothing	RMSE	649696	0.5386
	MAE	379986	0.4566
	MAPE	11.1247	0.7175
Fuzzy Time Series	RMSE	179385	0.499
	MAE	144338	0.498
	MAPE	49.83	0.783
NNAR	RMSE	103797	0.4313
	MAE	59650	0.3772
	MAPE	5.52780	0.4945
BSTS	RMSE	470861	0.4538
	MAE	98458	0.3896
	MAPE	19.1	0.5980

Among the models evaluated, ARIMA is the most accurate for population forecasting, followed by BSTS, Fuzzy Time Series, NNAR, and Holt's Exponential Smoothing Models. For the ARIMA and Fuzzy Time

Series Models, the Rural population is well-fitted within this variable based on the smallest value by using RMSE, MAE, and MAPE. ARIMA and NNAR, which appear to consistently outperform other methods with regard to RMSE, MAE, and MAPE across a variety of variables. According to the RMSE, MAE, and MAPE values, the ARIMA model has a greater performance than other models. Except for the ARIMA model, the NNAR model has outperformance compared to other models. The Holt exponential smoothing model has worse performance than other models.

Generally speaking, NNAR shows moderate to low errors for GDP. For the Age dependency ratio variable, ARIMA has the lowest RMSE, MAE and MAPE among the models, indicating that its predictions are the most accurate. The Holt's Exponential Smoothing Model has a greater RMSE, MAE and MAPE values, which has worse prediction; whereas ARIMA, NNAR and BSTS also function pretty well. For economic variables, the ARIMA model has a more satisfactory performance than other models, indicating prediction values close to the actual values. The Exponential Smoothing Model has a poorer performance than the other models. Except for the ARIMA model, the NNAR model has a better performance than other models.

4. CONCLUSION

In this paper, an attempt is made to study the population and economic variables by using different forecasting models such as ARIMA, Exponential Smoothing, Fuzzy Time Series, NNAR, and BSTS. The population and economic variables have good performance by using the different forecasting models except the GDP variable by using the fuzzy time series model. For population variables, the ARIMA model is best fitted as compared to other models, and the Total and Urban populations have well fitted in the ARIMA model as compared to other models as well, and the Rural population has well fitted in the ARIMA and FTS models as compared to other models. For economic variables, the ARIMA model has the best performance as compared to other models in the Age dependency ratio variable, and the NNAR model has good performance as compared to other models in the GDP variable. Based on RMSE, MAE, and MAPE values, the ARIMA model performs better than other models like Holt's Exponential Smoothing, ANN, Fuzzy Time Series, and Bayesian Time Series Models. Thus, we have determined that the data is very straightforward and that short-term projections are enough. Because of its simplicity, the ARIMA model may be an appropriate choice. The NNAR model performs better than the other models, except the ARIMA model. Hence, since the simplest neural network autoregressive (NNAR) is effective at predicting series that contain trends, like data on population and economic variables, we could conclude that it can be utilized for population and economic variable forecasting in the future.

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