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FORECASTING OF ELECTRICITY CONSUMPTION IN ASSAM BY USING MATHEMATICAL AND TIME SERIES MODELS AND COMPARISON OF THEIR PREDICTIVE PERFORMANCES

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Abstract: Although energy exists in different forms in nature, the most important form of energy is Electricity. Considering the worldwide increasing demand for electricity with increasing population, rapid urbanization, rising incomes, changes in lifestyles and with infrastructural and industrial growth, forecasting electricity consumption becomes an important part of power sector of any country. In this paper, attempt is made to forecast the total electricity consumption in Assam with the help of two models, considering the time period from 1990-91 to 2016-17. The first one is Multiple Linear Regression model which considers the effects of Population and Per Capita Income on the electricity consumption in Assam while the second one is the Autoregressive Integrated Moving Average (ARIMA) model. By comparing the Average Relative Error of the two proposed models, the predictive performance of the ARIMA (0, 1, 2) model is found better than the Multiple Linear Regression model and ARIMA shows an annual average increasing rate of electricity consumption as 5.40% up to 2021.

Keywords: ARIMA; Assam; electricity; forecasting; multiple linear regression.

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1. INTRODUCTION

Energy, in particular electricity, plays a vital role in socio-economic development of a country. According to International Energy Agency (2011) reports, the demand for electricity has increased very rapidly over the last 25 years all over the world and in comparison to the different forms of end-user energy; its demand is expected to have the most rapidly increasing rate [10]. There are various factors influencing the usage of electricity between different areas of a country including availability of natural gas, differences in climate, the type of housing and demographics [8]. The demand for electricity of a country reflects its standard of living, economic development and geographic variations [8]. In order to meet the increasing demand in various sectors of economy viz residential, commercial, transport, service and agriculture- adequate supply of electricity is indispensable for sustainable economic growth and this is the reason behind considering consumption of electricity forecasting as national interest of any country.

A large number of studies have been made all over the world for forecasting electricity consumption. Mehmet Cakmak [10] tried to find out the relationship between electricity consumption and population, industrial enterprise and households of Turkish provinces through Panel Data Analysis and found the most accurate results through Random Effect Panel Data Analysis. Elham Pourazarm [5] again aimed to estimate the main determinants of demand for electricity in Iran for residential, industrial, agricultural and public sectors by using appropriate econometric models and also tried to focus the influence of new electricity pricing in Iran. Fintan McLoughlin [6] characterized domestic electricity patterns of use on a daily, intra-daily and seasonal basis as a function of customer characteristics in Ireland with the help of Regression, Autoregressive Markov Chain and Time Series analysis. Zaid et al. [21] investigated the influence of GDP, average price of electricity and the population of New Zealand on the annual electricity consumption through multiple linear regressions and then forecasting were also made. Zaid et al. [22] again compared the forecasting of electricity consumption in New Zealand with the help of six models viz Logistic, Harvey Logistic, Harvey, Multiple Linear regression, Variable Asymptote Logistic (VAL) and ARIMA and found the best forecasting by Harvey model for Domestic as well as for Total Electricity Consumption in New Zealand while for Non-Domestic Electricity Consumption, best forecasting result was obtained through Harvey Logistic model. Similar attempt was made by Vincenzo et al. [20] to identify the effects of economic and demographic variables on the annual electricity consumption in Italy with the intention to develop a long-term consumption forecasting model. Shuyu Li et al. [15] used the ARIMA model, Grey Model (GM) and the combination of ARIMA and GM to compare the forecasting of energy consumption in Shandong, China and found the best results by GM-ARIMA model. Three types of econometric models, viz. Growth model, ARIMA model and Artificial Neural Network were used by J.C. Paul [9] in his thesis both for untransformed and transformed series of energy consumption to get the best forecasting models of the gas and electricity consumption in Bangladesh. Gamze Ogcu et al. [7] similarly made comparison of Artificial Neural Networks (ANN) and Support Vector Regression (SVR) for forecasting electricity consumption in Turkey and found the performance of the SVR slightly better than the ANN. Pernille et al. [11] considered the variables household disposable income, population growth, electricity prices and the degree of urbanization to study the residential electricity demand in Taiwan.

In India, S. Saravanan et al. [17] aimed to forecast future projection of electricity demand with the help of Regression Analysis, Artificial Neural Networks (ANNs), combining Regression Analysis with Principal Components (PC) and combining ANNs with PC. Aayush Goel et al. [1] used Multiple Regression, Trend Seasonality and ARIMA modeling for prediction of electricity demand of New Delhi by considering the significance of climatic and seasonal factors on electricity demand. In Assam, R.R Borgohain and B Goswami [13] tried to forecast short-term load for Assam with the help of Regression based time series method with temperature and used fuzzy ideology to minimize the error between actual and predicted load.

Assam is one of the eight states in the North Eastern Region (NER) of India and shares international boundaries with Bhutan and Bangladesh. The scenario of increasing demand for electricity in Assam is not exceptional from the global one. Though the status of power generation in the state is not satisfactory as compared to its demand, yet to achieve the

Sustainable Development Goals (SDG) 7, Assam energy vision 2018 is developed to ensure access to affordable, reliable, sustainable and modern energy for all by 2030 [2]. Considering its ever increasing demand, various new schemes have been undertaken by the Government to provide uninterrupted and quality power to the consumers and reduce the gap between demand and supply.

The paper is organized as follows: After the first section that gives a brief introduction of the importance of present work along with existing literature, section 2 presents the objectives of our study and section 3 provides the sources of data and methodology used. Section 4 discusses the statistical analysis of the findings while section 5 gives the forecasted results of the better model after comparison of the two proposed models and the last section presents the conclusion part of the study.

2. OBJECTIVES

In order to build the foundation for developing an energy roadmap to provide affordable and reliable energy access for all as well as for short and long term power planning activities, forecasting electricity consumption plays a crucial role. Hence we set our objectives in the present study as:

- To forecast electricity consumption in Assam by using Multiple Linear Regression model considering the effects of Population and Per Capita Income on electricity consumption and by Autoregressive Integrated Moving Average model.
- To analyze the predictive performance of the proposed models in terms of their Average Relative Error.
- To suggest the better model for forecasting electricity consumption in Assam.

Since data on electricity consumption in Assam beyond the period 2016 have not been made public yet, we have considered the period of forecasting from 2017 onwards. Also, from the extensive review of literature, we understand that work on long-term forecasting of electricity consumption in Assam has not been done so far. From that perspective, this study will be considered as an original study and will help the stakeholders in better understanding of the trend and forecasting of electricity consumption of our state.

3. METHODOLOGY

Here we have used secondary data for the period from 1990-91 to 2016-17. Data on total electricity consumption in Assam has been collected from Economic Survey of Assam and Statistical Handbook Assam (Source: Assam State Electricity Board). Population data is collected from Economic Survey of Assam (Source: Population Projection, Registrar General of India) and data on per capita income is collected from the Publications of Reserve Bank of India on Indian States (Source: Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India). Income data is available at different base year and in order to get a comparable series, different series are spliced at 2004-05 base year.

3.1 Multiple Linear Regression Model

The multiple linear regression model is given by

$$Y = \alpha + \alpha_1 X_1 + \alpha_2 X_2 + u \quad \ldots \quad (1)$$

Where

Y is the total annual electricity consumption (MU) in Assam

X_1 is population

X_2 is per capita income (in Rs.)

u is the error term.

To validate the given model, different statistical tests are done with the help of SPSS. The quantity R^2 known as coefficient of determination gives the proportion of the total variation in the Electricity Consumption explained by the predictor variables, namely, Population and Per Capita Income in Assam. Again F-test and t-test are used respectively to test the overall as well as individual significance of the coefficients of the given regression model [14].

3.2 ARIMA model

ARIMA models generally written as ARIMA (p,d,q) where p represents the order of the Autoregressive part, d denotes the order of difference to obtain stationary series if the series are non-stationary and q denotes the order of the Moving Average part are commonly used to forecast future values of time series data [22]. The generalized univariate ARIMA model with p, d, and q process has the following form:

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots\ldots\ldots + \phi_p Y_{t-p} - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots\ldots\ldots\ldots - \theta_q e_{t-q} \ldots \quad (2)$$

Where Y_t is the differenced electricity consumption time series value, ϕ and θ are unknown parameters and p is the number of autoregressive terms and q is the number of lagged forecast errors in the prediction equation. The Box-Jenkins method applies ARIMA tofind the best fit of a time series model to past values of a time series which consists of model identification and model selection, parameter estimation, statistical model checking by testing and forecasting [3].

In order to compare the model performances and their reliability, Average Relative Error is used. The formula for Relative Error (RE) is

$$RE_{accuracy} = (\text{Absolute error} / \text{“True value”}) * 100\%$$

4. STATISTICAL ANALYSIS

4.1 Findings of Multiple Linear Regression

Table 1: Correlation matrix for variables used in the linear regression model

	Total E.C	Population	P.C.I
Total E.C	1	0.835	0.981
Population	0.835	1	0.913
P.C.I	0.981	0.913	1

Table 1 gives the correlation matrix for the variables: Total Electricity Consumption, Population and Per Capita Income used in the analysis of our data for Assam. It is found from the above table that the correlation between Total Electricity Consumption and Population is .835 and that of Per Capita Income is .981 i.e. we can infer that two explanatory variables are highly correlated to the dependent variable. Again the correlation coefficient for Population vs. Per Capita Income is 0.913 which shows that the problem of multicollinearity may exist here. But to get rid of the problem of multicollinearity, some authors suggest that the Variance Inflation Factor (VIF) should be less than 10 and according to some others, this value should be less than 5 [20]. Here the corresponding VIF for Population and Per Capita Income is 6 which are close to 5 and much less than 10. So we can assume that multicollinearity is not present between the two explanatory variables.

Table 2:

Adjusted R^2	**Constant (α)**	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$
0.985	4982.172	-0.180	0.127

Table 2 shows that the adjusted coefficient of determination is .985 which implies that 98.5% of the variance in dependent variable is explained by the combination of independent variables. The values of the constant and the coefficients of Population and Per Capita Income of equation (1) are also represented in Table 2. Thus, our proposed multiple linear regression equation becomes

$$Y = 4982.172 - 0.180X_1 + 0.127X_2 \qquad (3)$$

The calculated values of F and t along with their 99% critical values are given in Table 3.

Table 3:

Model	**99% critical F**	**calculated F**	**99% critical t**	**t_1(cal)**	**t_2(cal)**
Total Electricity Consumption	5.61	834.813	2.492	-6.203	22.121

The calculated value of F along with the critical value for (2, 24) d.f. is shown in the above table and found that the critical value is much smaller than the calculated F. Therefore, it can be concluded that at 99% confidence level, linear regression equation is significant, rejecting the null hypothesis that all of the regression coefficients are equal to zero. Similarly, by taking the absolute values of t-test results t_1, t_2 for the coefficients of X_1 and X_2 representing Population and Per Capita Income respectively along with 99% critical value of t reveal that the coefficients $\alpha_1$and α_2 are significant in the model.

4.1.1 Error Analysis

To compare the performance of the individual model, Average Relative Error is calculated with the help of table 1.1 which is given in the appendix.

Average Relative Error of Multiple Linear Regression Model = 6.02 %

4.2 The Construction of ARIMA model

To examine whether the series is stationary or not, Augmented Dickey-Fuller (ADF) test is carried out with the null hypothesis that data are non-stationary [16]. Many authors suggested the usefulness of log-transformation before differencing the series to obtain improved result of Box-Jenkins ARIMA model. With this intent, Log-transformation of the original series is done here.

Table 4: The stationary test of the series of total electricity consumption in Assam

Sequence	**ADF Statistic**	**Critical Value**			**Value of p**
		1%	5%	10%	
Q	-0.7592	-4.356068	-3.595026	-3.233456	0.9569
Q*	-4.3321	-4.374307	-3.603202	-3.238054	0.0110

Using the Eviews 11 software we carry out ADF test and observing the values of p and critical values for Q, Q*(the first order difference of Q), found that the series become stationary in first order differences.

After determining the order of difference, the next step is to determine the order p and q of AR and MA process. For this purpose, model selection criteria of best fitted ARIMA namely Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used.

Considering the values of AIC and BIC of various ARIMA models of first difference from Table No. 1.2 given in the appendix, the best fitted ARIMA model for forecasting total electricity consumption in Assam is found as ARIMA (0, 1, 2). After determining the ARIMA model, SPSS software is used to fit the model. The values of model statistics and parameters are given in table 5 and 6.

Table 5:

Model Statistics

Model	**Stationary R Squared**	**Ljung-BoxQ (18)**	**d.f.**	**Sig**
Total Electricity Consumption	.197	14.08916	16	0.592

Table 6: **ARIMA Model Parameters**

Model		**Estimate**	**SE**
Total Electricity Consumption	Constant	0.050	0.23
	Difference	1	
	MA (lag1)	-0.324	0.198
	MA (lag2)	-0.407	0.203

The autocorrelation and partial autocorrelation plots of the residuals of ARIMA (0, 1, 2) model are shown in figure 1.1.

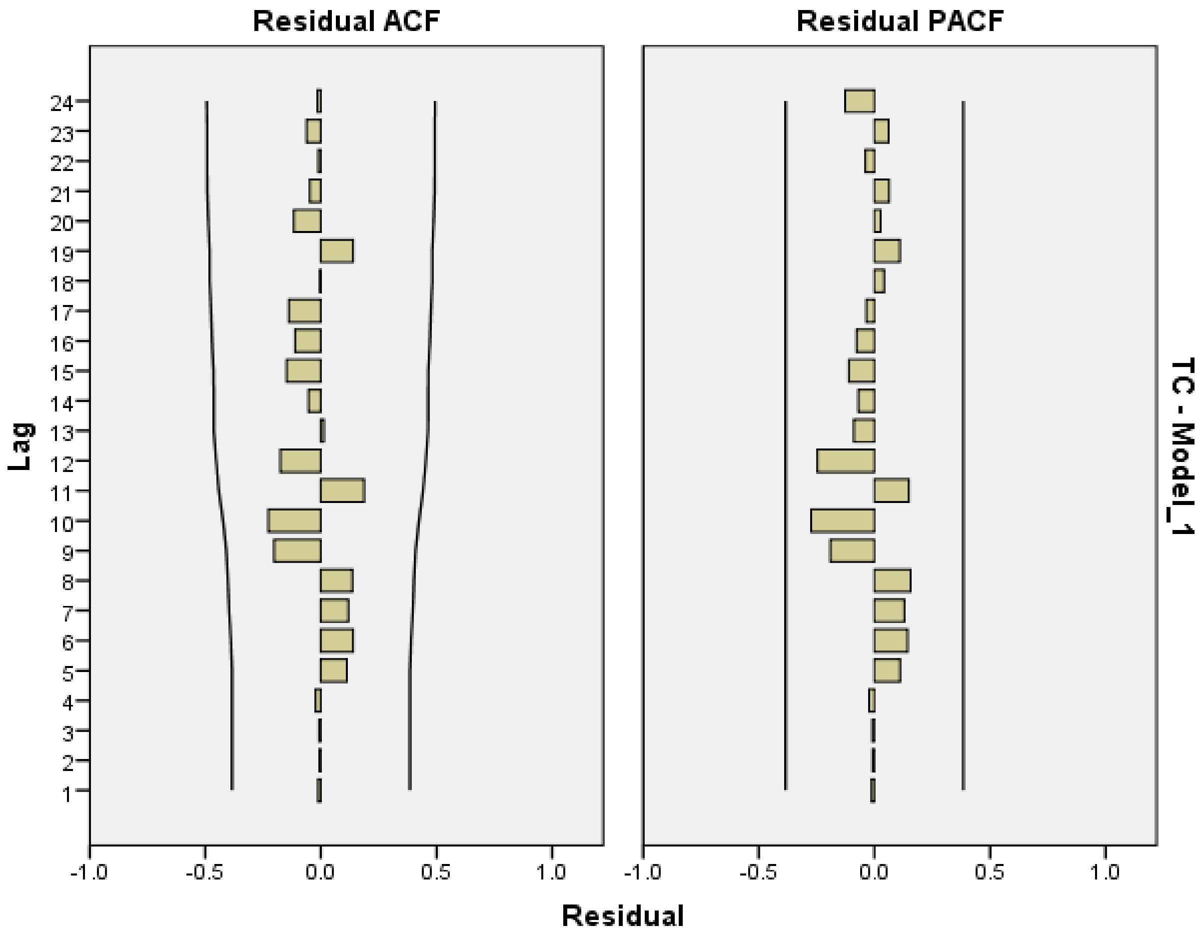

Figure 1.1: ACF and PACF of the residuals of ARIMA (0, 1, 2) model

Figure 1.1 shows that the residuals are white noise since almost all the autocorrelation and partial autocorrelation coefficients are small and within the required bounds. Further, by comparing the value of the Ljung-Box statistic which is 14.089 for 16 d.f. with the corresponding chi-square (χ^2) value 26.296, we infer that the correlations are not significant and hence the residuals are white noise.

The prediction results and residual values of ARIMA (0, 1, 2) model are given in the table 1.3 of appendix and found the values of Average Relative Error is as follows.

Average Relative Error of ARIMA (0, 1, 2) Model= 5.21%

By comparing the average relative error of the above two models, we have found the ARIMA (0, 1, 2) model fits the data better than multiple linear regression model.

The fit of the Total Electricity Consumption given by the ARIMA (0, 1, 2) model is shown in Figure 1.2.

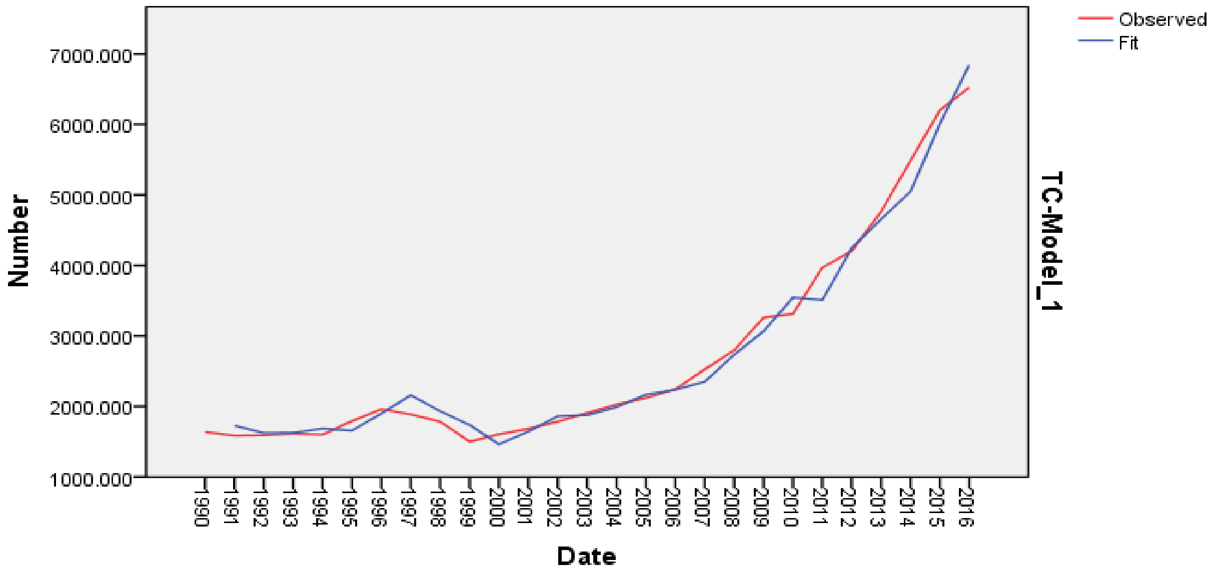

Figure 1.2: ARIMA (0, 1, 2) model fit for the Total Electricity Consumption

From the above analysis, it can be suggested that the ARIMA (0, 1, 2) model fits the data better than Multiple Linear Regression model and therefore more accurate forecast data can be obtained through this model.

5. FORECASTED FIGURES OF THE ARIMA (0,1,2) MODEL

Table 7: Forecasted total electricity consumption (in million units) in Assam

Year	ARIMA
2017	6875.819
2018	7131.241
2019	7555.907
2020	8005.862
2021	8482.612

The forecasted results of the ARIMA (0,1,2) model shows an upward trend of electricity consumption. The annual average increasing rate of total electricity consumption in Assam for the years 2017-2021 as forecasted by the ARIMA model is found as 5.40%.

6. CONCLUSIONS

The total electricity consumption of Assam has been forecasted for the year 2017-2021 with the help of Multiple Linear Regression and ARIMA models. From the multiple linear regression analysis, carried out in the present study, it has been found that the two explanatory variables viz. Population and Per Capita Income are highly correlated with the dependent variable –Total Electricity Consumption in Assam. Also the higher adjusted R^2, one important measure of model accuracy, as well as the significant F and t statistics indicate the effectiveness of Population and Per Capita Income in forecasting electricity consumption in Assam.

Again by analyzing the model statistics, residual ACF and PACF plots and Figure 1.2 of ARIMA, it can be recommended that ARIMA (0, 1, 2) model can be used for getting even better forecasting results in regards of electricity consumption in Assam.

When we compare the performance of these two in terms of their average relative error, ARIMA fits the data better than multiple linearregression and therefore forecasting for the next five years has been with the help of ARIMA model. As mentioned earlier due to the non-availability of official publication of data on electricity consumption beyond 2016 in Assam, it is not possible for us to compare the forecast results of electricity consumption from 2017-2021 of ARIMAmodel. But by analyzing the error part of the proposed models, we may suggest that ARIMA model provides a better way to forecast the electricity consumption in Assam than Multiple Linear Regression Model.

Since the current supply scenario of electricity is not satisfactory with respect to its demand in Assam, adequate steps should be taken by the Government to meet the increasing future needs of electricity to ensure sustainable economic growth. In future, attempts will be made to obtain the forecast results of electricity consumption in Assam with the help of some other models considering the factors like rapid urbanization, changing lifestyles etc. and some more recent data in order to have a more comprehensible picture about the accuracy of various models.

APPENDIX

Table 1.1: The prediction results and residual values of Multiple Linear Regression Model

Year	Observed Value	Predicted Value	Residual	Relative Error
1990	1636.000	1746.953	-110.953	6.782%
1991	1584.280	1724.481	-140.201	8.850%
1992	1590.000	1684.660	-94.660	5.953%
1993	1611.000	1592.856	18.144	1.126%
1994	1599.095	1620.340	-21.240	1.328%
1995	1790.190	1607.597	182.593	10.200%
1996	1960.490	1578.469	382.021	19.486%
1997	1886.200	1578.040	308.160	16.338%
1998	1782.390	1622.870	159.520	8.950%
1999	1499.690	1728.795	-229.105	15.277%
2000	1602.870	1708.630	-105.760	6.598%
2001	1682.980	1792.364	-109.384	6.499%
2002	1783.912	1883.630	-99.720	5.590%
2003	1906.770	1945.370	-38.599	2.024%
2004	2026.736	2051.898	-25.158	1.241%
2005	2118.990	2185.538	-66.548	3.141%
2006	2243.990	2285.119	-41.129	1.833%
2007	2525.527	2412.245	113.285	4.486%
2008	2797.601	2699.743	97.857	3.498%
2009	3258.786	3174.065	84.725	2.600%
2010	3312.350	3701.713	-389.363	11.755%
2011	3969.890	4042.863	-72.973	1.838%
2012	4205.000	4361.342	-156.342	3.718%
2013	4763.210	4867.891	-104.681	2.198%
2014	5485.000	5153.830	331.170	6.038%
2015	6200.000	5970.946	229.054	3.694%
2016	6526.000	6626.712	-100.712	1.543%

Table 1.2: Values of diagnostic criteria for selecting best ARIMA model

Model	AIC	BIC
(0,1,2)	**-2.268553**	**-2.075000**
(1,1,0)	-2.251521	-2.106356
(2,10)	-2.224206	-2.030652
(0,1,1)	-2.206311	-2.061146
(1,1,1)	-2.204912	-2.011359
(0,1,0)	-2.204536	-2.107759
(0,1,3)	-2.193695	-1.951753
(1,1,2)	-2.193252	-1.951310
(3,1,0)	-2.168360	-1.926418
(2,1,2)	-2.167203	-1.876873
(2,1,1)	-2.161830	-1.919888
(0,1,4)	-2.116839	-1.826509
(1,1,3)	-2.116440	-1.826110
(1,1,4)	-2.098445	-1.759726
(4,1,0)	-2.093465	-1.803135
(4,1,2)	-2.076949	-1.689842
(2,1,4)	-2.075559	-1.688452
(3,1,1)	-2.070648	-1.780318
(2,1,3)	-2.050911	-1.712192
(4,1,1)	-2.027440	-1.688721
(3,1,2)	-2.024612	-1.685893
(3,1,3)	-2.020979	-1.633873
(4,1,3)	-2.010410	-1.574915
(3,1,4)	-2.000688	-1.565193
(4,1,4)	-1.936888	-1.453005

Table 1.3: The prediction results and residual values of ARIMA (0, 1, 2) model

Year	Observed	Estimated	Residual	Relative Error
1990	1636			
1991	1584.28	1726.032	141.752	8.95%
1992	1590	1622.029	32.029	2.01%
1993	1611	1625.024	14.024	0.87%
1994	1599.095	1684.541	85.446	5.34%
1995	1790.19	1655.556	-134.634	7.52%
1996	1960.49	1898.906	-61.584	3.14%
1997	1886.2	2159.242	273.042	14.48%
1998	1782.39	1931.880	149.49	8.39%
1999	1499.69	1736.112	236.422	15.76%
2000	1602.87	1461.992	-140.878	8.79%
2001	1682.98	1643.420	-39.56	2.35%
2002	1783.912	1859.673	75.761	4.25%
2003	1906.77	1877.081	-29.689	1.56%
2004	2026.736	1990.308	-36.428	1.80%
2005	2118.99	2167.118	48.128	2.27%
2006	2243.99	2238.377	-5.613	0.25%
2007	2525.527	2350.536	-174.991	6.93%
2008	2797.601	2733.130	-64.471	2.30%
2009	3258.786	3065.578	-193.208	5.93%
2010	3312.35	3544.347	231.997	7.04%
2011	3969.89	3508.869	-461.021	11.61%
2012	4205	4245.731	40.731	0.97%
2013	4763.21	4655.614	-107.596	2.26%
2014	5485	5048.623	-436.377	7.96%
2015	6200	6006.755	-193.245	3.12%
2016	6526	6843.105	317.105	4.86%

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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