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Forecasting of Domestic Electricity Consumption in Assam, India

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ABSTRACT

Though the power supply scenario in Assam is not comparable with other developed states of India, yet it is improving gradually. With increasing household electrification rate, increasing income and technological development, the share of Domestic electricity consumption in the state is experiencing a rapid growth in comparison to the other sectors like Industry, Commerce, Agriculture etc. and therefore the forecasting of domestic electricity consumption become very important to meet the power needs of the consumer. The aim of this study is to suggest the best forecasting model for domestic electricity consumption in Assam. For this purpose, three models viz. Multiple Linear Regression considering the effects of population and per capita income; ARIMA and Growth curves viz Linear, Quadratic, Cubic, Exponential, Logarithmic and Inverse are used considering the time period 1980-2018. When growth curves are compared in terms of diagnostic criteria- Adjusted R^2, RMSE, AME and MAPE, then it is found that exponential model fits the data better than the other growth models. After that, comparisons are made among the models Multiple Linear Regression, ARIMA and Exponential by considering their average relative error and found the efficiency of ARIMA the highest followed by Exponential and Multiple Linear Regression models. Therefore, forecasting of domestic electricity consumption in Assam has been done with ARIMA model for the next 10 years.

Keywords: Assam, ARIMA, Domestic Electricity Consumption, Forecasting, Growth Curve, Multiple Linear Regression
JEL Classifications: C01, C02, C32

1. INTRODUCTION

In developing countries like India, the domestic electricity consumption shows a rapid increasing trend and it has increased about 50 times since 1971 (Chunekar et al. [2016]). Factors like increasing household electrification rate, increasing disposable income along with rapid urbanization and development in technology which lead to the usage of more electricity enabled appliances etc. are mainly responsible for this high growth rate. Assam, which is situated in the North Eastern region of India also experiences a high growth rate in electricity consumption in recent years. Mahanta and Talukdar (2021) in their study of trend, pattern and forecasting of electricity consumption in Assam for the period 1980-2018, found that the domestic sector accounted the highest share in the total electricity consumption while the share of agricultural sector is the least and very negligible in comparison to the other sectors like Industry, Commerce etc. Though the household electrification rate in Assam is only 37% according to the census of 2011 in comparison to the national average of 67.2% but by 2016 this rate became 78.2% and 100% by 2019 through combined efforts of state and central Government. And obviously this increasing household electrification rate has influence in the total electricity consumption in Assam and leads to a great increase in demand for power both in the rural and urban areas of Assam in recent years.

Considering rapid growth of electricity consumption by this sector, it is very important to forecast the pattern of growth in future in order to provide uninterrupted supply to the consumers to enhance economic growth. The methods for predicting electricity demand can be divided into three categories viz, short-term, medium-term and long-term forecasting depending on the time zone of planning strategies (Quesada et al.) Generally Short-term load forecasting has the period from 1 h to 1 week which plays an important role for system management of daily operation and scheduling of generating units (Anwar et al. [2018]). Medium term forecasting ranging from 1 week to 1 year is mainly used for fuel allocation and maintenance scheduling and long-term forecasting ranging from a period of 5-25 years are useful to determine appropriate size and type of new generation units to be constructed to assure adequate generation capacity which will help in prediction of future needs (Mohamed [2004]). Long term forecasting plays an important role in terms of grid development, expansion planning, future investments to assist the decision-making process of any country. Considering the importance of long-term forecasting of electricity consumption for any region as well as the highest contribution of domestic sector in the total electricity consumption in Assam, we set our objectives as-

- To forecast domestic electricity consumption in Assam with Multiple Linear Regression model considering the effects of Population and Per capita income, Autoregressive integrated Moving Average (ARIMA) and with some time dependent growth models viz. Linear, Quadratic, Cubic, Exponential, Logarithmic and Inverse
- To find the best forecasting model for Domestic electricity consumption in Assam by comparing the predictive performance of the considered models in terms of their average relative error
- Forecasting of Domestic electricity consumption in Assam with the help of the best fitted model for the next 10 years.

2. LITERATURE REVIEW

Large numbers of literature are available for forecasting of electricity consumption all over the world with the help of various traditional models like Multiple Regression, ARIMA etc. to recent machine learning models. Mohamed and Bodger (2005) and Bianco et al. (2009) investigated the effects of economic and demographic variables on the electricity consumption for New Zealand and Italy respectively using Multiple Linear Regression model. Ozturk and Ozturk (2018) and Miao (2015) used ARIMA model for forecasting of energy consumption in Turkey and China respectively. Various types of growth curves are employed for forecasting of electricity consumption for various countries. Mohamed (2004) made comparison of three growth models viz. Logistic, Harvey Logistic and Harvey model for forecasting electricity consumption for selected countries and world regions. Skiadas and Giovanis (1997) used a stochastic Bass Innovation Diffusion model for studying the growth of electricity consumption in Greece while for Morocco; Gutierrez et al. (2006) employed two models of univariate stochastic diffusion viz. the time-homogeneous Gompertz Diffusion process and the time-non-homogeneous Gompertz Diffusion Process and obtained the better result through the second model. Again, Bodger and Tay (1987) made comparison of Logistic and Energy Substitution Models for forecasting electricity consumption in New Zealand.

Ozoh et al. (2014) employed modified Newton's model for modeling of electricity consumption while Hussain et al. (2016) applied Holt-Winter and ARIMA for forecasting electricity consumption in Pakistan and found the Holt-Winter more appropriate than ARIMA for the considering period. Cakmak (2014) again made the comparison of fixed effects, random effects and dynamic panel data analysis to obtain the best forecasting model of electricity consumption for the provinces of Turkey and found the random effect panel data analysis the best forecasting model.

Artificial Neural Network was extensively used by the researchers Nizami and Ahmed (1995), Adhiswara et al. (2019), Escriva-Escriva et al. (2011), Widodo and Fitriatien (2016), Hsu and Chen (2003), Paul (1998), Moon et al. (2019) etc. for forecasting of electricity consumption both for long and short term for various countries of the world. Hong (2009) and Oğcu et al. (2012) found the performance of support vector machines (SVMs) better than Artificial Neural Network for forecasting electricity consumption of Taiwan and Turkey respectively.

In our country, Saravanan et al. (2012) tried to forecast future projection of electricity demand in India with the help of Regression Analysis, Artificial Neural Networks (ANNs), combining Regression Analysis with Principal Components (PC) and combining ANNs with PC while for prediction of electricity demand in New Delhi, Goel and Goel (2014) used Multiple Regression, Trend Seasonality and ARIMA modeling considering the significance of climatic and seasonal factors on electricity demand. Rajkumari and Gayithri (2017) used ARIMA model for forecasting of electricity consumption in Karnataka and while studying the pattern of electricity consumption, they found the share of agricultural category the highest than the other categories like Industry, Domestic etc. for Karnataka. In Assam, Mahanta and Talukdar (2021) employed Multiple Linear Regression (MLR) and ARIMA for long term forecasting of total electricity consumption in Assam where ARIMA fitted better than MLR and Borgohain and Goswami (2015) made short term load forecasting by using Regression based time series method with temperature and fuzzy ideology for minimizing the actual and predicted load error.

To our knowledge, work on the forecasting of domestic electricity consumption- the highest contributing category in the total electricity consumption in Assam has not been done so far and therefore, attempt is made through this paper to fill up the gap in literature and it is expected that the analysis would be useful to the Government and other related agency for proper policy implication in this respect.

3. DATA AND METHODOLOGY

Domestic electricity consumption data is 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). Since per capita income data is available at different base year, different series are spliced at 2004-2005 base year in order to get a comparable series.

3.1. Multiple Linear Regression Model

The multiple linear regression model is given by

$$Y=a+a_1X_1+a_2X_2+u \quad (1)$$

Where
Y is the domestic annual electricity consumption (MU) in Assam
X_1 is population
X_2 is per capita income (in Rs.)
u is the error term.

The quantity R^2 known as coefficient of determination gives the proportion of the total variation in the Domestic Electricity Consumption explained by the predictor variables, namely, Population and Per Capita Income in Assam. Here we use adjusted coefficient of determination i.e., Adjusted R^2 instead of R^2 which is the modified version of R^2 that has been adjusted for the number of predictors in the regression model. Again, to test the overall and individual significance of the coefficients of the model, F-test and t-test are used respectively.

3.2. ARIMA Model

The generalized univariate ARIMA model with p, d, and q process has the form:

$$Y_t=\mu+\phi_1Y_{t-1}+\phi_2Y_{t-2}+\ldots+\phi_pY_{t-p}-\theta_1e_{t-1}-\theta_2e_{t-2}-\ldots-\theta_qe_{t-q} \quad (2)$$

Where Y_t is the differenced domestic 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.

3.3. Definition of Growth Curves

To study the behaviour of some variables as they vary with respect to time, the growth curves are used. These are graphical representation of how a particular quantity increases over time. To determine the type of growth pattern of the domestic electricity consumption in Assam whether it is linear, quadratic, cubic, exponential etc. six types of time-dependent models considered are:

1. Linear: $Y_t=b_o+b_1t+e_t$
2. Quadratic: $Y_t=b_o+b_1t+b_2t^2+e_t$
3. Logarithmic: $Y_t=b_0+b_1\ln t+e_t$
4. 4. Cubic: $Y_t=b_o+b_1t+b_2t^2+b_3t^3+e_t$
5. Exponential: $Y_t=b_0\exp(b_1t)e_t$
6. Inverse: $Y_t=b_0+b_1/t+e_t$

Where Y_t represents the annual domestic electricity consumption in Assam in Million Unit (M.U) and e_t is the error term assumed to be distributed as normal with mean zero and constant variance.

The considered models are compared in terms of the following criteria in order to select the best model:

1. Adjusted $R^2=1-\dfrac{\left(1-R^2\right)\times\left(N-1\right)}{\left(N-k-1\right)}$

Where N is the number of observations used in model and k is the number of independent regressors, i.e., the number of variables in the model, excluding the constant.

2. Absolute mean error (AME) = $\dfrac{\sum_{t=1}^{N}\left|Y_t-\hat{Y}_t\right|}{N}$
3. Root mean square error (RMSE) = $\sqrt{\dfrac{\sum_{t=1}^{N}\left(Y_t-\hat{Y}_t\right)^2}{N}}$
4. Mean absolute percentage error (MAPE)=

$$\frac{1}{N}\sum_{t=1}^{N}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right|\times 100$$

Where Y_t represents the observed and $\hat{Y}_t$ represents the predicted values and N is the number of observations used in the model.

The greater value of Adjusted R^2 and the minimum values of the last three criteria are desirable for the adequacy of a model.

4. STATISTICAL ANALYSIS

The domestic electricity consumption in Assam increased from 65 M.U in 1980-3476.59 M.U in 2018. From Figure 1, it is clear that there is almost a continuous increasing trend in domestic electricity consumption except for some intermediate years like 1982, 1997 and 2018.

4.1. Findings of Multiple Linear Regression

From Table 1, it is found that the correlation between Domestic Electricity Consumption and population is 0.831 and that of between Per Capita Income is 0.987 implying that the two explanatory variables are highly correlated to the dependent variable though the correlation between per capita income is much higher than the population to the Domestic Electricity Consumption. The correlation between Population and Per Capita Income is 0.865 showing that the problem of multicollinearity may exist here. Therefore, when we consider the Variance Inflation

Figure 1: Growth of domestic electricity consumption in Assam

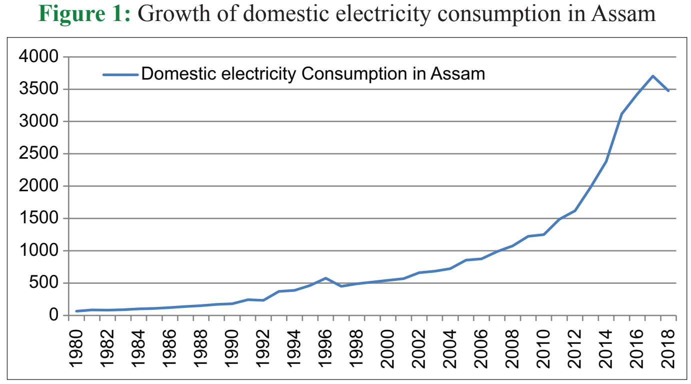


Table 1: Correlation matrix for variables used in the multiple linear regression model

Variables	Domestic electricity consumption	Population	Per capita income
Domestic electricity consumption	1	0.831	0.987
Population	0.831	1	0.865
Per capita income	0.987	0.865	1

Factor (VIF) for population and per capita income, it is found as 3.97. VIF which is recommended as a "rule of thumb" statistic for determining when correlations among the predictor variables may be a problem should be <5 to get rid of the problem of multicollinearity (Snee [1973]). Since we get this value as 3.97 (<5) therefore we assume that multicollinearity is not present between the two explanatory variables.

Table 2 represents the values of adjusted coefficient of determination, constant and coefficients of the population and per capita income of the considered regression model. The adjusted R^2 value implies that 97.4% of the variance in Domestic electricity consumption is explained by the combination of Population and Per Capita Income. Our proposed multiple linear regression equation becomes

$$Y=314.913-0.019X_1+0.056\ X_2 \quad (3)$$

From Table 3, observing the calculated F along with tabulated F for (2, 36) d.f. it is clear that at 99% confidence level, the linear regression equation is highly significant rejecting the null hypothesis that all of the coefficients are equal to zero. Again, by considering the absolute values of t, it is found that though the coefficient of X_2 representing the per capita income in the regression model is significant at 99% confidence level, but the coefficient of population is found insignificant in the model at 99% confidence level and for 95% confidence level also which tabulated value is 1.69, it is found slightly insignificant.

4.2. The Construction of ARIMA Model

To test the stationarity of the series, Augmented Dickey-Fuller (ADF) test is performed with the null hypothesis that data are non-stationary (Prabhakaran). Following the suggestion of log-transformation for obtaining better result of Box-Jenkins ARIMA model from various researchers, Log-transformation of the original series is done.

ADF test is carried out with the help of EViews 11 software and observing the values of p from Table 4, it is found that the series become stationary at first order difference.

Then the next step is to determine the order p and q of AR and MA process and model selection criteria of best fitted ARIMA namely Akaike Information Criterion (AIC) is used for this purpose.

Table 2: Statistical results of multiple linear regression model

Adjusted R^2	Constant (a)	a_1	a_2
0.974	314.913	−0.019	0.056

Table 3: Statistical results of multiple linear regression model

Model	99% critical F	Calculated F	99% critical t	t_1 (cal)	t_2 (cal)
Domestic electricity consumption	5.25	711.245	2.43	−1.670	20.355

Considering the values of AIC from Table 5, ARIMA (1, 1, 3) is selected for forecasting of Domestic electricity consumption in Assam. In Tables 6 and 7, the values of model statistics and parameters are represented to test whether the selected model could be accepted or not.

The autocorrelation and partial autocorrelation plots of the residuals of ARIMA (1, 1, 3) model are represented in Figure 2.

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	−0.5275	−3.6156	−2.9411	−2.6091	0.8746
Q*	−8.3481	−3.6210	−2.9434	−2.6103	0.0000

ADF: Augmented Dickey-Fuller

Table 5: Values of model diagnostic criteria

Model	AIC
(1, 1, 3)	−1.5973
(0, 1, 2)	−1.5620
(1, 1, 4)	−1.5482
(2, 1, 3)	−1.5477
(0, 1, 3)	−1.5306
(0, 1, 4)	−1.5282
(1, 1, 2)	−1.5203
(2, 1, 4)	−1.5041
(2, 1, 2)	−1.5007
(3, 1, 3)	−1.4953
(4, 1, 3)	−1.4762
(4, 1, 4)	−1.4690
(4, 1, 1)	−1.4681
(3, 1, 2)	−1.4532
(3, 1, 4)	−1.4530
(1, 1, 0)	−1.4413
(4, 1, 0)	−1.4210
(2, 1, 0)	−1.4194
(4, 1, 2)	−1.4192
(0, 1, 1)	−1.4039
(1, 1, 1)	−1.4020
(3, 1, 0)	−1.3937
(0, 1, 0)	−1.3772
(2, 1, 1)	−1.3728
(3, 1, 1)	−1.3621

AIC: Akaike information criterion

Table 6: Model statistics

Model	Stationary R Squared	Ljung-BoxQ (18)	df	Significant
Domestic electricity consumption	0.250	14.237	14	0.432

Table 7: Autoregressive integrated moving average model parameters

Model (Domestic electricity consumption)	Estimate	SE
Constant	0.100	0.024
AR (Lag 1)	−1.00	0.033
Difference	1	
MA (Lag1)	−0.781	0.210
MA (Lag2)	−0.423	0.210
MA (Lag3)	−0.635	0.192

SE: Standard error

Figure 2: ACF and PACF of the residuals of ARIMA (1, 1, 3) model

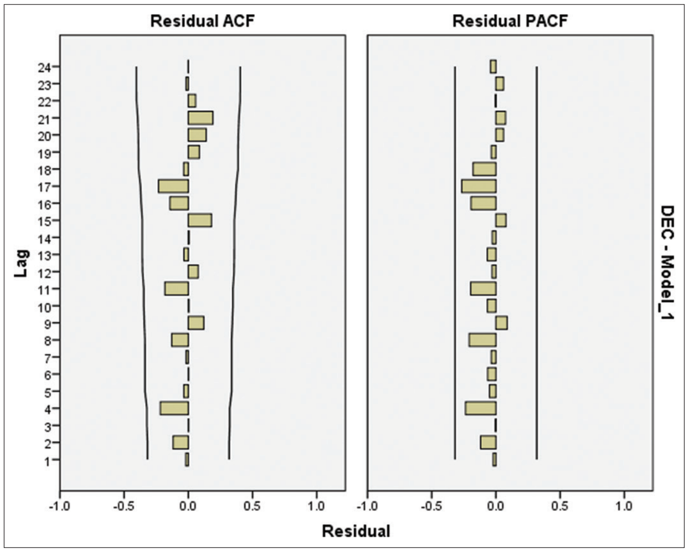
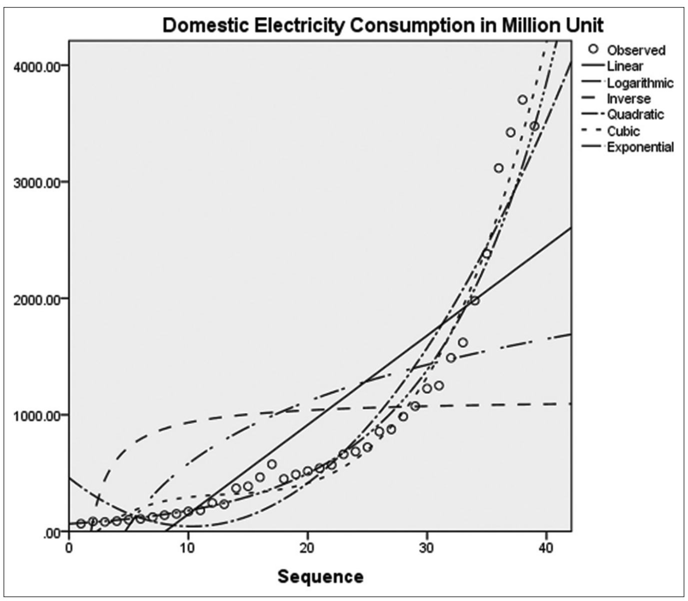


Figure 3: Observed and various types of fitted growth model for domestic electricity consumption



From Figure 2, it is clear that all the autocorrelation and partial autocorrelation of the residuals are small and within the required bounds and also by comparing the value of Ljung-Box statistic which is 14.237 with the corresponding critical Chi-square value at 14 d.f. (23.685) represented in Table 6, we can conclude that the residuals of ARIMA (1, 1, 3) model are white noise.

4.3. The Growth Model of Domestic Electricity Consumption in Assam

When we consider the model diagnostic criteria i.e., the values of Adj R^2, AME, RMSE and MAPE for our considered growth models from Table 8 and also from Figure 3, it is found that the best fitted growth model for domestic electricity consumption in Assam is exponential followed by cubic and quadratic.

The estimated equation of the exponential growth model for domestic electricity consumption in Assam is $Y_t = 64.110 \exp(0.102t)$.

Table 8: Values of diagnostic criteria for selecting best growth model for domestic electricity consumption in Assam

Model	Adjusted R_2	AME	RMSE	MAPE
Linear	0.725	415.147	522.117	125.566
Quadratic	0.924	221.650	271.165	59.541
Cubic	0.972	129.960	160.634	37.003
Exponential	0.983	111.246	188.688	11.687
Logarithmic	0.419	586.546	758.279	179.986
Inverse	0.106	711.512	940.667	224.847

AME: Absolute mean error, RMSE: Root mean square error, MAPE: Mean absolute percentage error

Table 9: Comparison of multiple linear regression, autoregressive integrated moving average (1, 1, 3) and exponential model

Model	Average relative error (%)
Multiple linear regression	16.04
ARIMA (1, 1, 3)	7.66
Exponential	11.69

ARIMA: Autoregressive integrated moving average

Table 10: Forecasted domestic electricity consumption (in million units) in Assam

Year	Domestic electricity consumption (MU)
2019	3776.53
2020	3714.53
2021	4237.83
2022	4639.84
2023	5293.44
2024	5795.71
2025	6612.02
2026	7239.56
2027	8259.12
2028	9043.16

4.4. Comparison of the Models

In Table 9, the Average Relative Errors of the considered models are represented which are calculated with the predicted values of these three models along with the actual values given in Appendix Table 1. By comparing the values of the Relative Error of our proposed model, it is found that the efficiency of the ARIMA model is the highest followed by Exponential and Multiple Linear Regression for domestic electricity consumption in Assam. Therefore, the forecasting of domestic electricity consumption in Assam for the next 10 years i.e. from 2019 to 2028 has been done with the help of ARIMA (1, 1, 3) model which are shown in Table 10.

5. CONCLUSION

Through this work, attempts have been made to find out the best model for forecasting of Domestic Electricity Consumption in Assam by comparing the performances of Multiple Linear Regression, ARIMA and growth models. In case of Multiple Linear Regression model, it is observed that the correlation of the explanatory variable- per capita income is much higher than the population to the dependent variable – Domestic Electricity Consumption. The adjusted coefficient of determination is very high and also, though the significance of F indicates the overall effectiveness of the model along with t statistic for per capita income yet the slightly insignificant t statistic for population implies that by considering some other explanatory variables influencing the domestic electricity consumption along with these two variables i.e., population and per capita income we might get better regression model. Similarly, the analysis of the model statistics and residual ACF and PACF plots of selected ARIMA (1, 1, 3) support the application of the model for forecasting Domestic Electricity Consumption. Again, by comparing the values of diagnostic criteria of six types of growth model, it is found that the exponential model fits the data better than the other five growth models. Therefore, the comparison is made among the Multiple Linear regression, ARIMA (1,1,3) and Exponential model by comparing the average relative error and it is found that the relative error of ARIMA model is the smallest implying the efficiency of the ARIMA model is the highest followed by Exponential and Multiple Linear Regression model and forecasting for the period 2019-2028 has been done with the ARIMA (1, 1, 3) model accordingly. Due to non-availability of any official forecasting figures of domestic electricity consumption in Assam for our considering period, it is not possible for us to compare our predicted figures. In future, attempts will be made to obtain some better forecasting model, if possible, for Domestic Electricity Consumption in Assam with reduced relative error than ARIMA.

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APPENDIX

Appendix Table 1: Observed and predicted values of domestic electricity consumption in Assam

Year	Observed	Predicted (MLR)	Predicted (ARIMA)	Predicted (exponential)
1980	65	78.22		71.02
1981	84	98.10	72.46	78.68
1982	80.04	105.04	89.49	87.17
1983	87.49	122.09	97.49	96.57
1984	99	139.44	93.91	106.98
1985	106.31	145.95	103.87	118.52
1986	121.66	150.00	120.37	131.30
1987	138.30	164.45	138.37	145.45
1988	150	166.82	153.72	161.14
1989	170.83	198.01	169.53	178.52
1990	180	231.67	185.30	197.77
1991	243.20	253.34	204.92	219.09
1992	232	266.49	252.81	242.72
1993	369	256.87	298.51	268.89
1994	385.62	300.24	363.41	297.89
1995	464.32	325.34	497.24	330.01
1996	575.5	342.70	531.63	365.60
1997	449.57	372.40	617.29	405.02
1998	488.57	421.84	554.88	448.70
1999	516.59	498.15	464.53	497.08
2000	540.80	518.25	511	550.68
2001	569.31	537.99	646.99	610.07
2002	661.25	605.67	666.09	675.85
2003	684.44	657.66	689.42	748.73
2004	721.72	729.12	750.89	829.47
2005	855.91	812.46	817.66	918.92
2006	875.11	880.53	908.15	1018.01
2007	984.75	960.61	1026.82	1127.79
2008	1073.97	1111.47	1065.33	1249.40
2009	1224.61	1345.32	1180.3	1384.13
2010	1250.18	1602.81	1340.35	1533.39
2011	1488	1777.52	1470.62	1698.74
2012	1620	1942.04	1555.59	1881.93
2013	1979.46	2189.96	1832.99	2084.86
2014	2382	2339.89	2186.62	2309.68
2015	3117	2726.10	2781.62	2558.75
2016	3423	3040.90	3513.13	2834.67
2017	3703.25	3423.98	4199.69	3140.35
2018	3476.59	3798.92	4095.60	3478.99

MLR: Multiple linear regression, ARIMA: Autoregressive integrated moving average