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MODELING AND FORECASTING OF IMPORTS IN SRI LANKA. ARIMA Model Approach

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Abstract

This study attempts to make a forecast by using the ARIMA model based on time series data on imports for Sri Lanka. This paper tries to predict time series data using ARIMA models on total annual imports of Sri Lanka from the year 1980 to 2020 with the help of statistical software EViews. The Box-Jenkins approach was used to identifying, estimating, diagnostic and forecasting a univariate time series model in this study. It is found that the ARIMA (9, 1, 1) model is suitable for predicting the total annual imports of Sri Lanka. The model ARIMA (9,1,1) has the lowest AIC and SIC criteria. Therefore, this model is chosen. The ARIMA (9,1,1) model seem to be an adequate predictive model for the import of Sri Lanka from 1980 to 2020. This finding can be an important tool in forecasting future imports of the country and helps future researchers in economic forecasting.

Keywords: Sri Lanka, Imports, ARIMA Models, Forecasting, Time Series

Introduction

For a developing country like Sri Lanka, international trade is essential. Sri Lanka is a nation of lower-middle-income countries, with a GNI of USD 4020 (2020). Sri Lanka, for example, needs certain imports that she cannot produce domestically. Sri Lanka imports petroleum, textile fabrics, foodstuffs, and machinery and transportation equipment for domestic production and consumption. Sri Lanka is one of the world's most import-intensive countries. Imports of Sri Lanka play a significant role in all economic sub-sectors and are a source of development in the country. Importing goods provides the local market with fresh and high-quality products and the ability to manufacture new products domestically. Further, developing countries will improve their economies by producing high-quality goods and increasing revenue by supplying new products to domestic markets. Imports from other countries broaden the market's diversity. Academics say imports are a cost to the economy. on the other hand, the import of capital goods plays a vital role in economic growth. Import is a growth facilitator in many developing countries. Autoregressive Integrated Moving Average (ARIMA) models are widely applied in various sectors of economic forecasting. This study attempts to make a forecast by using the ARIMA model based on time series data on imports for Sri Lanka.

Problem Statement of the Study

This study attempts to make a forecast by using the ARIMA model based on time series data of Sri Lankan Total Import volumes. The forecast accuracy has an important bearing on the policy discussions of import of Sri Lanka. The study attempts to show the accuracy level of the ARIMA forecasting model. Economic development and structural change in Sri Lanka develop the need to study models of forecasting in the area of trade and commerce.

Objectives of the Study

The broad objectives of the study are as follows:

1. To check whether the series of Sri Lankan import volumes are stationary or not.
2. To identify and select the best ARIMA model following the principle of parsimony and selection criteria.
3. To select the best ARIMA model for Sri Lankan Imports.
4. To forecast the Sri Lankan import volumes for the next five points efficiently.

Theoretical Background of the ARIMA model

Time series analysis and its applications have become increasingly crucial in Economics. Many scholars conducted various modelling approaches to forecast economic time series data. A model that explains the pattern or variation in actual time series data is known as a time series model. ARIMA model is used to forecast a time series using the past values. It aims to describe the autocorrelations in the data (Hyndman & Athanasopoulos, 2018). ARIMA model is a generalization of an autoregressive moving average (ARMA) model. ARIMA (p,d,q) is a linear model originating from the autoregressive model AR (p), the moving average model MA (q) and thus the combination of the two AR (p) and MA (q) is the ARIMA (p,d,q). The order of the AR model and MA model can be expressed through p and q respectively. The number of time series differences is expressed by d to produce stationary. A pure Auto-Regressive (AR only) model is one where Yt depends only on its lags. That is, Yt is a function of the 'lags of Yt'.

Likewise, a pure Moving Average (MA. only) model where Yt depends only on the lagged forecast errors.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \epsilon_1$$

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

An ARIMA model is one where the time series was differenced at least once to make it stationary, and you combine the AR. and MA. terms. So, the equation becomes:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

(Prabhakaran, 2021)

Box-Jenkins Method

Box-Jenkins methodology consists of four consecutive steps that should be followed when building an ARIMA model. The first step is called identification, and the purpose of this step is to determine appropriate values for p, d, and q. The ACF and the partial autocorrelation function (PACF) with their respective correlograms are used for pattern detection of p, d, and q in the first step. The PACF measures the autocorrelation between observations in a time series separated by the number of lags and the intermediate autocorrelation between the lags is held constant. Estimation of the parameters in the model is the second step. Step three is diagnostic checking, which tests the chosen ARIMA model's goodness of fit, usually done by testing if the residuals are white noise. In the case of residuals that are not white noise, step one, two, and three should be repeated using new values for p, d, and q. However, if the residuals are white noise, the model should be accepted, and it is possible to proceed to step four. Forecasting is the fourth step where the model may be used to predict desired periods for the time series (Gujarati & Porter 2008)

Literature Review

There are several studies which uses ARIMA models on different time series data in order to forecast future values of the variable. A review of such literature is given as follows. Ghosh (2017) used the ARIMA model to forecast Tea exports and resulted in better prediction accuracy. Farooq (2014) used ARIMA Model to Build and Forecast the Imports and Exports of Pakistan. Farooq tried to build a time series model called the ARIMA (Auto-Regressive Integrated Moving Average) model with particular reference to the Box and Jenkins approach on annual total Imports and Exports of Pakistan. The fitted model is then used to forecast some future values of Imports and export of Pakistan. Alim (2019) recently predicted exports and imports through an artificial neural network and autoregressive integrated moving average model in Saudi Arabia. In this study, total annual exports and imports of Saudi Arabia are forecasted using Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) models. This paper tries to predict time series data using ANN and ARIMA models on total annual exports and imports of Saudi Arabia. The applied models are used to predict some future values of total annual exports and imports of Saudi Arabia. Gulshan Kumar and Sanjeev Gupta, built a mathematical model to forecast the exports of industrial goods from Punjab in 2010. Upadhyay, (2013) attempted to find out appropriate ARIMA model by using Box-Jenkins methodology to forecast the export/import of wood-based panel in India on time series data. In a paper Tyagi & Shah, (2021) aimed to evaluate the implications of COVID-19 on the trade economy of New Zealand by exploratory data analysis and ARIMA modeling. An ARIMA model was implemented to assess and determine the total imports and exports value of New Zealand. In one another paper, identified an Appropriate Forecasting Model for Forecasting Total Import of Bangladesh (Tanvir Khan, 2011). Seasonal autoregressive integrated moving average (SARIMA) model was used in this paper. An attempt was made to derive a unique and suitable forecasting model of total import of Bangladesh in this research. In addition, many scholars, Dave et al. (2021), Ghauri, et al. (2020). Hyndman, R.J., & Athanasopoulos, G. (2018), Newbold, P. (1983), Manoj & Anand (2014), Narayan, et al. (2008), and Major, (1967) used the ARIMA model to predict the various microeconomics variables for the policy formulation in many countries.

Methodology

The present study is based on secondary data. The data on Imports of Sri Lanka were collected from the annual reports of the Central Bank of Sri Lanka. The data comprised were in a million Sri Lankan rupees from the years 1980 to 2020. Based on the data, an appropriate ARIMA model was used to estimate the model. Estimating the proper model has a series of steps, including appropriate transformation and differencing, detection of ARIMA pattern, estimation of the parameters, and diagnostic checking of the residuals (Fildes, 1976). The present study focuses on the Box-Jenkins (1976) approach to identifying, estimating, diagnostic and forecasting a univariate time series model. Firstly, the time-series data is plotted using standard plots and summary statistics to see the behaviour of the data.

Empirical Analysis and Results.

The study covers the period of 1980 -2020. Table -1 present the summary of the Import volume (I.M.) in million Sri Lankan rupees.

Table-1 Summary of the Sri Lankan Import 1980-2020

Mean	1011966.
Median	532964.0
Maximum	3606644.
Minimum	33942.00
Std. Dev.	1127202.
Skewness	0.989628
Kurtosis	2.568961

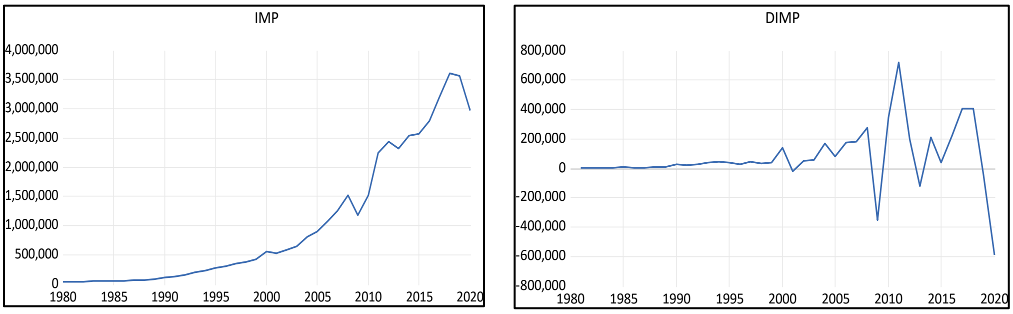


Figure-1 Sri Lankan Import 1980-2020

Figure 1 shows that the Imports of Sri Lanka are slowly increasing and decreasing over time up till the year 2020. It can be seen that the import of Sri Lanka has an increasing trend with a seasonal pattern over time. Then it can be recommended ARIMA model for the forecasting model for the import of Sri Lanka.

Stationary Test

This section of the paper reveals the time-series properties of the import data from 1980 to 2020. It is usual to test the stationary of variables in time series analysis. If a data series is found to be stationary, it implies that the mean, variance, and autocovariance of the series are independent of time. Augmented Dickey-Fuller (ADF) and Philips Perron (P.P.) unit root tests were conducted to check the stationarity of original time series data of Sri Lankan import volume. Table 2 shows the output of the stationery test of original time series data.

Table 2: Unit Root Tests of import volume (I.M.)

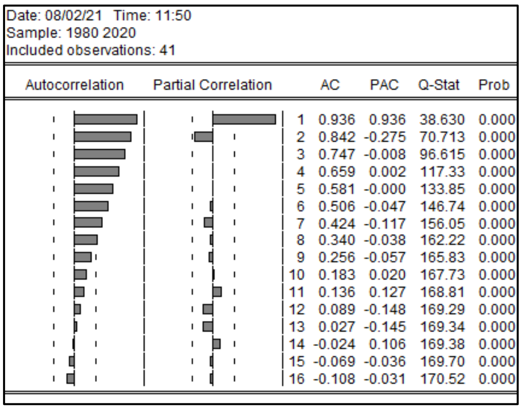
Variable	ADF		PP	
	Level I (0)	**1st Diff. I (1)**	**Level I (0)**	**1st Diff. I (1)**
Import	1.532790 (0.9991)	-4.756546 (0.0004)	0.704985 (0.9908)	-3.787120 (0.0063)

The unit-root tests were performed on both levels and first differences of the variable. The ADF and P.P. tests reveal that volume of imports is not stationary at level I (0). This implies that the null hypothesis of unit root at the level I (0) cannot be rejected for the variable. As per the ADF and P.P. Test, imports have been stationary at 1st difference. Since the P-value of tests was less than 0.05. It confirms that the import time series data of Sri Lanka has a long-term mean. The Autoregressive Integrated Moving Average model is appropriate only after converting the series considered for forecasting into a stationary series. Therefore, time series of imports is recommended for the model building.

Model Identification

Model building depends on the pattern of Sample ACF and Sample PACF. The Correlogram test was carried to meet the condition mentioned above. Autocorrelation and partial correlation approach were performed to identify the model. Autocorrelation and partial autocorrelation plots are heavily used in time series analysis and forecasting. These graphically summarize the strength of a relationship with observation in a time series with observations at prior time steps

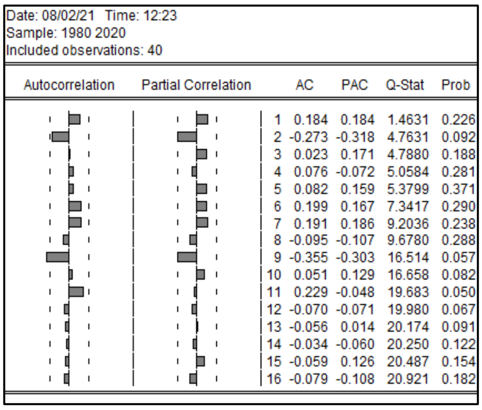
Original Time Series



Date: 08/02/21 Time: 11:50
Sample: 1980 2020
Included observations: 41

	AC	PAC	Q-Stat	Prob
1	0.936	0.936	38.630	0.000
2	0.842	-0.275	70.713	0.000
3	0.747	-0.008	96.615	0.000
4	0.659	0.002	117.33	0.000
5	0.581	-0.000	133.85	0.000
6	0.506	-0.047	146.74	0.000
7	0.424	-0.117	156.05	0.000
8	0.340	-0.038	162.22	0.000
9	0.256	-0.057	165.83	0.000
10	0.183	0.020	167.73	0.000
11	0.136	0.127	168.81	0.000
12	0.089	-0.148	169.29	0.000
13	0.027	-0.145	169.34	0.000
14	-0.024	0.106	169.38	0.000
15	-0.069	-0.036	169.70	0.000
16	-0.108	-0.031	170.52	0.000

1st Differencing



Date: 08/02/21 Time: 12:23
Sample: 1980 2020
Included observations: 40

	AC	PAC	Q-Stat	Prob
1	0.184	0.184	1.4631	0.226
2	-0.273	-0.318	4.7631	0.092
3	0.023	0.171	4.7880	0.188
4	0.076	-0.072	5.0584	0.281
5	0.082	0.159	5.3799	0.371
6	0.199	0.167	7.3417	0.290
7	0.191	0.186	9.2036	0.238
8	-0.095	-0.107	9.6780	0.288
9	-0.355	-0.303	16.514	0.057
10	0.051	0.129	16.658	0.082
11	0.229	-0.048	19.683	0.050
12	-0.070	-0.071	19.980	0.067
13	-0.056	0.014	20.174	0.091
14	-0.034	-0.060	20.250	0.122
15	-0.059	0.126	20.487	0.154
16	-0.079	-0.108	20.921	0.182

Figure 2 Correlogram of ACF and PACF

Figure 2 shows the Correlogram of ACF and PACF graphs for both the original series and the first difference series of Sri Lankan imports from 1980 to 2020. The left side figure shows the ACF and PACF for the actual time series. So, it is found that the Auto Correlation Function is tailing off and Partial Auto Correlation Function cutoff with the order 2. It concludes that the auto-correlation of the original time series exceeds the significant limits at leg one and auto-correlations tail off to zero after lag 8.

On the other hand, the correlogram of ACF and PACF of the 1st Differencing series does not exceed the significant level from the leg order 1. It has one outlier at lag 2 and 9. The coefficient at lag 2 and 9 are almost touching the significant limits. According to the partial autocorrelation functions (PACs), for the first difference of import series. The partial autocorrelation for lag 2 is significantly different from zero. Also, there is a significant negative point at lag two, and other partial autocorrelations are within the 95 per cent confidence limit. So, the autoregressive process's tentative order can also be 2 (that is, p = 2). Therefore, multiple ARIMA (p, d, q) models are tested for a range of values of p and q to establish a more accurate model.

This study estimates the best ARIMA model based on volatility, standard error of the regression, adjusted R- square, Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). An ARIMA model can be selected as the best model if it has the least volatility, higher adjusted R-square (Adj. R2), and lower standard error of the regression (SER), AIC and SIC values.

Table 3 Test Results of ARIMA (p, d, q) Model Fitting

No	Model	No of Sig Variables	SIGMASQ	Adj. R2	SER	AIC	SIC
1	ARIMA (1,1,1)	02	2.98E+10	0.1055	182026.9	27.166	27.335
2	ARIMA (2,1,1)	03	2.86E+10	0.1410	178380.4	27.129	27.298
4	ARIMA (1,1,2)	04	2.94E+10	0.1194	180601.1	27.151	27.319
5	ARIMA (2,1,2)	02	3.54E+10	0.0452	197426.5	27.327	27.495
6	**ARIMA (9,1,1)**	**04**	**2.69E+10**	**0.2677**	**172905.0**	**27.120**	**27.289**

Table 3 indicates that the best model among all fitted models is ARIMA (9,1,1), with the highest adjusted R-square and the lowest SER, AIC and SIC values. Hence this model can be the best predictive model for forecasting future values of our time series data on Sri Lankan Imports.

Table 4 Estimation Results of ARIMA (9,1,1) Model (Dependent Variable: d(import)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	75490.42	29196.22	2.585623	0.0139
AR(9)	-0.494511	0.188503	-2.623356	0.0127
MA(1)	0.398650	0.078020	5.109569	0.0000
SIGMASQ	2.69E+10	5.01E+09	5.371186	0.0000

R-squared	0.324032	Mean dependent var	73524.33
Adjusted R-squared	0.267701	S.D. dependent var	202052.1
S.E. of regression	172905.0	Akaike info criterion	27.12093
Sum squared resid	1.08E+12	Schwarz criterion	27.28982
Log likelihood	-538.4186	Hannan-Quinn criter.	27.18199
F-statistic	5.752317	Durbin-Watson stat	1.972063
Prob(F-statistic)	0.002542		

Diagnostic Check

In the process of diagnostic checking, the nature of the systematic pattern of the residuals is examined.

Figure 3 Correlogram of ACF and PACF for Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.106	-0.106	0.4851	
		2	-0.172	-0.186	1.7964	
		3	0.177	0.142	3.2164	0.073
		4	0.003	0.007	3.2168	0.200
		5	0.015	0.075	3.2275	0.358
		6	0.256	0.260	6.4742	0.166
		7	0.016	0.096	6.4868	0.262
		8	-0.053	0.038	6.6327	0.356
		9	-0.109	-0.197	7.2736	0.401
		10	-0.054	-0.160	7.4357	0.490
		11	0.200	0.107	9.7621	0.370
		12	-0.088	-0.122	10.232	0.420
		13	-0.008	0.055	10.235	0.509
		14	-0.035	-0.086	10.315	0.588
		15	-0.042	0.077	10.430	0.658
		16	-0.074	-0.057	10.810	0.701

As reported in Figure 3, the correlogram of the residuals and correlogram of squared residuals are both flat. The result indicates that model residual autocorrelations and partial autocorrelations of all lags are not significantly different from zero. This shows that all the points are within the 95 per cent confidence limit. This means that residuals are random, and the model is an excellent fit for data.

Forecasting

Figure 4 show the plot for 5 years' forecast of the imports by fitting ARIMA (9, 1, 1) model to the time series data. The model is used to analyze the fitting effect with the import value in 2020. The forecast value in 2021is 2,833,885 million Sri Lankan Rupees. The ARIMA (9,1,1) model predicted an increase in the Sri Lankan import from 2020-2025. There are some researches indicate that imports have a significant positive effect on productivity growth in the economy (Kim et al, 2007).

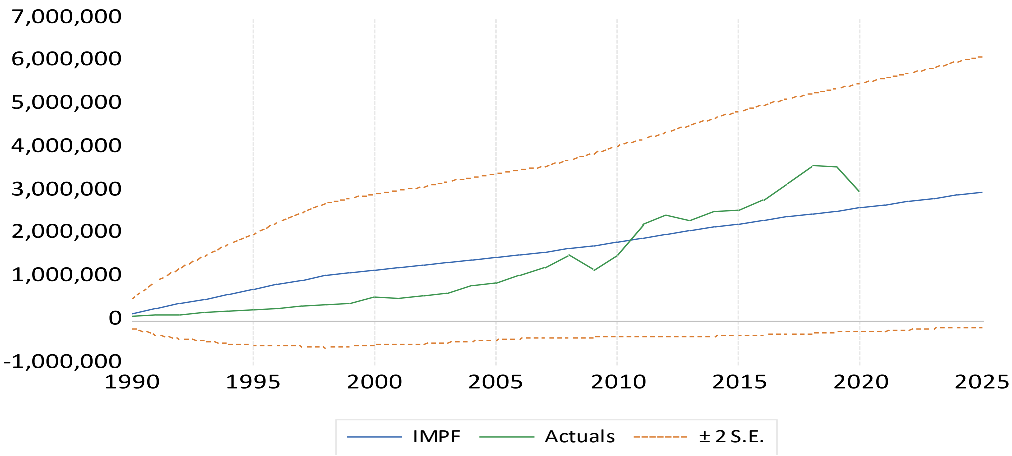


Figure 4 Forecast of Imports 1980-2025

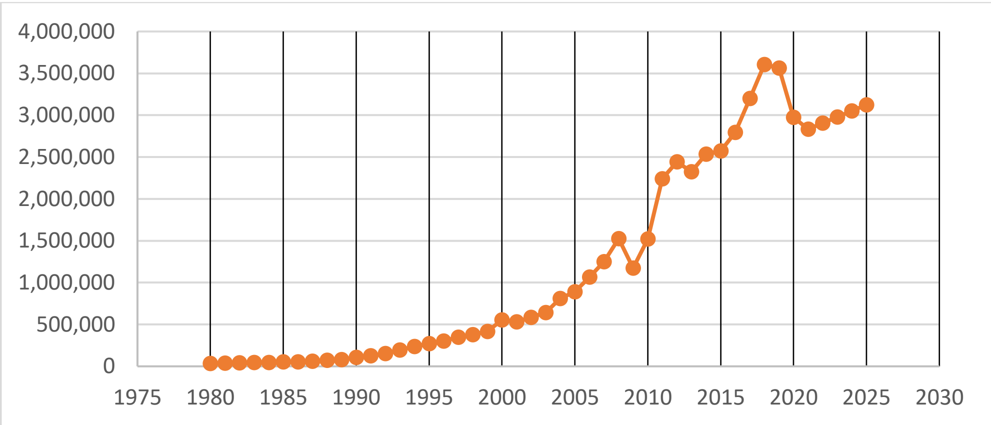


Figure 5 Forecast of Imports 2020-2025

Conclusions

In the present study on Modeling and Forecasting of Imports of Sri Lanka, the ARIMA (9,1,1) was the best model selected for predicting Sri Lankan imports time series data. ARIMA was used to make predictions using time series data with any pattern and with autocorrelations between the successive values in the time series. The study also statistically tested and validated that the forecast errors in the fitted ARIMA time series were not correlated. The residuals seem to be normally distributed with mean zero and constant variance. Therefore, it can conclude that the ARIMA (9, 1, 1) model seem to be an adequate predictive model for the import of Sri Lanka from 1980 to 2020. Therefore, this finding can be an important tool in forecasting future imports of the country and helps future researchers in economic forecasting.

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