# MODELING AGEING POPULATION (60+ YEARS) IN SRI LANKA

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**Abstract**

*Population ageing is an universal phenomenon and it is expected to be among the most prominent global demographic trends of the 21st century. In Sri Lanka there was a rising trend of ageing population throughout the past years and has recorded the highest number of agers within South Asia. However, no sound statistical or mathematical models were developed to project ageing population in Sri Lanka. Using the population aged 60 years and above in Sri Lanka during 1950-2016, three types of statistical models: (i) ARIMA (0, 2, 1), (ii) exponential trend model, and (iii) double exponential smoothing model were developed. The models were compared using various statistical indicators and some statistical diagnostics tests. The comparison was done for both training set as well as validation set. Among these models the double exponential smoothing model was found as the best fitted model. According to the forecast derived from the best fitted model, it was found that the increasing trend of ageing population in the country will continue in the future and there will be approximately 2,936,000 ageing population in Sri Lanka in 2020. The information obtained this study is beneficial for planners and decision makers in the government sector and other relevant organizations to cater the needs of the increasing agers in the future of Sri Lanka.*

**Keywords:** Ageing Population, ARIMA, Demographic, Exponential Smoothing

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## Introduction

Ageing population ageing (60+ years) is a shift in the distribution of a country's population towards older ages. This is usually reflected in an increase in the population's mean and median ages, a decline in the proportion of the population composed of children and a rise in the proportion of the population that is elder (Gavrilov and Heuveline, 2003). Ageing population has become a universal phenomenon which gives more attention throughout the world. United Nations has mentioned that Sri Lanka has the fastest aging population among South Asia and consequently various authors. Abeyratne et, al, (2014) have highlighted the importance of forecasting of aging population in spite of lack of consistence annual data. De Silva (1994) mentioned that with rapid decrease of fertility which occurred early in time and the increasing trend of international migration within the working age group influenced to accelerate the onset of ageing process. Aberathna et al. (2014) mentioned that the factors such as fertility control policies, vast education of reproductive practices, increases in the marital age limit of females has contributed to the decline in fertility.

Since ageing population forecasting is also a part of population projection, no doubts these projections will be helpful for government to plan necessary actions for better care of elderly population. Li, Reuser, Kraus, and Alho (2009) also claimed that it is necessary to predict the level of population ageing, to inform policy debates about the likely effect of different intervention strategies. The two common methods used to project national population are: (i) mathematical model and (ii) cohort component method. Even though population ageing related topics has been discussed by many authors in different countries (Manike, 2014a; Manike, 2014b; Siddhisena, 2005; Prasannath, 2014) in Sri Lankan only a single study (De Silva, 2007) has been carried out for the projection of future ageing population using cohort component method. It was found that this method has various drawbacks from both mathematical and statistical point of view. In view of the above, this study was initiated to develop a statistical model for ageing population for short-term prediction.

## Data and Methodology

The study uses the secondary data on annual ageing population data from 1950 to 2016. Data from 1950 to 1991 were acquired from statistical abstracts published by the Department of Census and Statistics (DCS) Sri Lanka (2015) and the corresponding data for the period of 1992 to 2016 were acquired from Registrar General's Department (RGD) in Sri Lanka (2016). Data consisted of both the censured and estimated ageing population data as the DCS has carried out only six housing and population census in 1953, 1963, 1971, 1981, 2001 and 2012 during the entire period from 1950-2016.

The statistical models techniques used are ARIMA models, growth model and double exponential smoothing models. All models were trained using data from 1950 to 2012 (63 years) and validated for the period of 2013-2016. EViews and Minitab statistics softwares were used for data analysis.

## Results and Discussion

### ARIMA Model

The annual aging population can be considered as a time series at equal intervals and thus ARIMA models were developed. Augmented Dickey-Fuller (ADF) test confirmed (Table 1) that second differenced series is not significantly deviated from stationary.

**Table 1: Results of ADF test of ageing series**

| Series | Augmented Dickey-Fuller test statistic | |
|---|---|---|
| | t- statistics | Probability |
| Original series | -0.797412 | 0.9601 |
| First differenced series | -5.76380 | 0.6701 |
| Second differenced series | -9.99196 | 0.0000 |

In order to decide possible ARIMA models to the stationary series the observed patterns of ACF and PACF of stationary series were compared with the theoretical ACF and PACF of AR(1), MA(1) and ARMA(1,1). Three models: ARIMA (1, 2, 0), ARIMA(0,2,1) and ARIMA(1,2,1) were considered as possible parsimonious models and tested for the significance of the parameters of the models (Table 2).

**Table 2: Validation of the parameters of three parsimonious models**

| Model | Variable | Coefficient | t-Statistic | Prob. |
|---|---|---|---|---|
| ARIMA (1,2,0) | C | 6.531 | 0.656 | 0.5141 |
| | AR(1) | -0.493 | -3.303 | 0.0016 |
| ARIMA (0,2,1) | C | 1.575 | 1.389 | 0.1698 |
| | MA(1) | -0.945 | -30.690 | 0.000 |
| ARIMA (1,2,1) | C | 1.550 | 1.396 | 0.167 |
| | AR(1) | -0.068 | -0.365 | 0.716 |
| | MA(1) | -0.944 | -29.538 | 0.000 |

According to the results in Table 2, the model ARIMA (1, 2, 1) was rejected as the AR parameter is not significant. It was then confirmed that errors of both models: ARIMA (1,2,0) and ARIMA(0,2,1) are random using Box-Pierce statistics at different lags. Furthermore, it was found that there is no serial correlation in ARIMA (0,2,1) since the Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) test statistic was not significant at 5% level . Also it has the lowest Akaike Information Criteria (AIC). Thus, ARIMA (0, 2, 1) model was identified as the best fitted ARIMA model for ageing data. The percentage errors for the validation data was also found to be below 10%.

### Growth Model

Growth model in the form of : $y^t = a*b_t$ was fitted and found both the model and parameters are significant. The fitted model is $Y = 350.833*(1.029)^t$ ($R^2$ = 91.7%, Adj$R^2$ = 91.5%). The residuals of the fitted growth model were found to be white noise. The percentage errors through the developed growth model for the validation dataset were also found to be below 10% for all four years. Thus this model can also be used to predict future ageing population.

## Double Exponential Smoothing Model

According to Siregar (2016), double exponential smoothing method smoothed trend component separately using the two parameters namely α and β. He further mentioned that double exponential smoothing uses a dynamic trend component that works well for the series having shift in the trend. Smoothing constants are the key to success of exponential smoothing. Therefore prior to applying double exponential smoothing it is necessary to decide those two smoothing constants. Thus in order to select the most appropriate constants a simulation study through trail and error method was carried out by changing α starting from 0.063613 to 0.963613 with an increment of 0.1 and that of β starting from 0.944218 to 0.044218 with an increment of 0.1. The best combination of α and β selected based on the minimum mean absolute percentage error (MAPE).

Having decided the two smoothing constants, the initial starting point values and the initial forecast are very important. However, in this case the default option in Minitab software was used. According to calculations it was found that the initial value of level is 409.03 and initial value of trend is 19.24. Therefore the initial forecast for the first observation of the series was taken as 409.03 + 19.24 = 417.27. The double exponential smoothing plot obtained from Minitab is shown in Fig. 1.

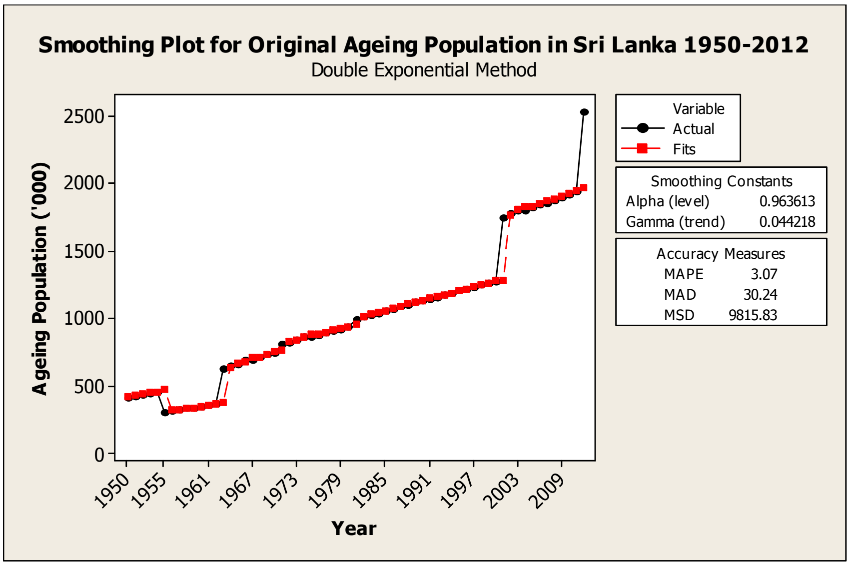


**Fig 1**: Double exponential smoothing curve for the ageing population in Sri Lanka

It was found that the percentage errors through the developed double exponential smoothing model for the validation dataset is very low (<4%) compared with other two models and the output is given in the Table 3.

**Table 3: Percentage errors for the validation dataset**

| Year | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|
| Estimated ageing population (in '000) | 2555 | 2609 | 2664 | 2718 |
| Actual ageing population (in '000) | 2548 | 2571 | 2593 | 2623 |
| % Error | -0.3% | -1.5% | -2.7% | -3.6% |

To confirm the suitability of the double exponential smoothing technique to forecast the future ageing population in Sri Lanka, validation measurement such as MAPE was considered for both the training set and the validation set separately and found that those statistics are low compared with other two models.

## Comparison of Three Models

The percentage errors for the validation dataset obtained using the three models were compared simultaneously (Table 4).

**Table 4: Comparison of the percentage errors of three models for the validation set**

| Model | Ageing Population ('000) | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|
| ARIMA(0,2,1) | Estimated | 2599 | 2678 | 2758 | 2840 |
| | Actual | 2548 | 2571 | 2593 | 2623 |
| | % Error | -2.0% | -4.2% | -6.7% | -8.8% |
| Growth Model | Estimated | 2249 | 2315 | 2383 | 2454 |
| | Actual | 2548 | 2571 | 2593 | 2623 |
| | % Error | 11.7% | 9.9% | 8.1% | 6.5% |
| Double Exponential Smoothing | Estimated | 2555 | 2609 | 2664 | 2718 |
| | Actual | 2548 | 2571 | 2593 | 2623 |
| | % Error | -0.3% | -1.5% | -2.7% | -3.6% |

As per results in Table 4, it is clear that the percentage errors of the ARIMA (0,2,1) and double exponential smoothing models are increasing with respect to time except the growth model. It can be seen that the percentage errors for all years are the highest for growth model and that are lowest for double exponential smoothing method. Thus in respect to the percentage errors it can be concluded that double exponential smoothing model is better than the other two. Similar results were obtained for the training sets of the three models. Siregar et al. (2016) mentioned that smaller the accuracy of measures the better the forecast. The three accuracy measures namely MAPE, MAD and MSD obtained for were compared simultaneously for the training set as well as for the validation set (Table 5).

**Table 5: Comparison of the accuracy of the models through training set and validation set**

| Type of the dataset | Accuracy measurement | ARIMA(0,2,1) model | Exponential trend model | Double exponential smoothing model |
|---|---|---|---|---|
| Training dataset | MAPE | 4.5% | 13.6% | 3.1% |
| | MAD | 43.49 | 104.66 | 30.94 |
| | MSD | 9624 | 14677 | 10135 |
| Validation dataset | MAPE | 5.2% | 9.1% | 2% |
| | MAD | 135 | 234 | 53 |
| | MSD | 22091 | 57049 | 3855 |

According to the Table 5, the two measurements MAPE and the MAD derived from the training set of the double exponential smoothing model are smaller, comparing with the same measurements derived from the two other models. Simultaneously the smaller MSD value of the training set belongs to the ARIMA (0, 2, 1) model. When considered about the validation set, all the three accuracy measurements (MAPE, MAD, and MSD) derived from double exponential smoothing model are comparatively small. Based on these reasons it can be mentioned that the double exponential smoothing model is the best fitted model compared with the other two models. It should be highlighted that MAPE are less than 4% for the double exponential model. In fact, Siregar (2016) mentioned that if MAPE is less than 10% the fitted model is said to be excellent. Therefore double exponential model is also recommended as the most suitable model.

## Short-Term Forecasting

Using the developed double exponential smoothing model forecasting was carried out for the ageing population in Sri Lanka for the years 2017, 2018, 2019 and 2020 and the results are shows in Table 6.

**Table 6: Forecasted Aging Population in Sri Lanka from 2017-2020**

| Year | Forecasted Ageing Population (in '000) |
|---|---|
| 2017 | 2,772 |
| 2018 | 2,827 |
| 2019 | 2,881 |
| 2020 | 2,936 |

As per the Table 6 the forecasted ageing population in Sri Lanka will be increasing from 2017 to 2020 and the expected aging population in 2020 will be approximately 2,936,000 ageing population in Sri Lanka in 2020 according to the estimations.

## Conclusions and Recommendations

The Double Exponential Smoothing model gave better forecast values for ageing population in Sri Lanka during 1950 to 2016. The forecasted ageing populations for 2017 to 2020 are 2.772, 2.827, 2.881 and 2.936 million respectively. Until a further model is developed DES model can be used to forecast ageing population in Sri Lanka. The forecasted ageing populations up to

2020 would be very useful for policy makers to implement various projects to care elderly persons in Sri Lanka.

The government or the relevant authorities should cater the needs of the elderly population by rethinking and developing necessary welfare facilities. A better method need to be developed to estimate ageing population for non-census years due to the drawbacks found with related to those estimations. Furthermore, it is suggested to find the possibility of neural network models and multivariate time series techniques (Vector Autoregression or Bayesian Autoregression models) by incorporating the factors such as mortality, fertility, births, deaths and migrations.

## References

Aberathna, W., Alles, L., Wickremasinghe, W. N., & Hewapathirana, I. (2014). Modeling and forecasting mortality in Sri Lanka. *Sri Lanka Journal of Applied Statistics,* Vol. 15, No. 3, pp 141-170.

Department of Census and Statistics Sri Lanka (2015). *Census of Population and Housing 2012*, ISBN:978-955-577-940-1.

De Silva, W. I. (1994). How serious is ageing in Sri Lanka and what can be done about it?. *Asia-Pacific Population Journal,* Vol. *9, No. 1*, pp 19-36.

De Silva, W. I. (2007). A population projection of Sri Lanka for the new millennium 2001-2101 trends and implications. Institute for health policy, Colombo.

Gavrilov, L. A., & Heuveline, P. (2003). The aging of population. *Manuscript of article in the encyclopedia of population*, Retrieved from

Li, O., Reuser, M., Kraus, C., & Alho, J. (2009). Aging of a giant: a stochastic population forecast for China 2006-2060. *Journal of Population Research, Vol.* 26, pp 21-50.

Menike, H. R. A. (2014a). Age structure transition and demographic bonus in Sri Lanka. *International Journal of Social Sciences and Entrepreneurship,* Vol 1, No. 12,, pp 421-431.

Menike, H. R. A. (2014b). Important features of the elderly population in Sri Lanka*. Research Process,* Vol 2, No. 2, pp 29-38.

Prasannath, V. (2014). Trends in aging population and its consequences in Sri Lanka. *Proceedings of second Annual Research Conference, Faculty of Commerce and Management, South Eastern University of Sri Lanka*, 100-104.

Registrar's General Department of Sri Lanka (2016). Age and sex specific midyear population sizes of Sri Lanka - 1992-2016.

Siddhisena, K. A. P. (2005). Social- economic implications of aging in Sri Lanka: an overview, *Oxford Institute of Aging Working Papers*, 105. Retrieved from *http://www.ageing.ox.ac.uk/download/98*

Siregar, B., Butar, I. A. B., Rahmat, R. F., Andayani, U., & Fahmi, F. (2016). Comparison of exponential smoothing methods in forecasting palm oil real production. *Journal of Physics*, 801, pp 20-28.