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TREND ANALYSIS AND FORECASTING MODELS FOR UNDER-FIVE MORTALITY RATE IN MALAYSIA

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ABSTRACT

The aim of this research is to study the trend pattern, develop forecasting models and forecast future trends of under-five mortality (U5MR) in Malaysia by gender. The Box-Jenkins Model and State Space Model are used in forecasting the yearly U5MR of a 37-year period (1980 – 2016) in Malaysia. Random Walk model for Box Jenkins and Local Linear model for State Space model are identified as the best models to suit the U5MR data characteristics. The performance of these two models are evaluated based on in-sample and out-sample evaluation using lowest root mean square error (RMSE) and mean absolute percentage error (MAPE). The results show that U5MR in Malaysia fluctuated from year to year with a slowly decreasing trend pattern for both genders with male recording a higher rate compared to female. Moreover, the Local Linear Trend model is chosen as the best model for forecasting future U5MR data with the lowest value of RMSE and MAPE. Future trend slightly increased from 0.00189 from 0.001891 in 2017 to 0.001907 in 2030 for male while for female is 0.001667 in year 2017 to 0.001878 in 2030. Thus, it shows the forecast trend of Malaysia's U5MR for the male population is higher than the female. This study is significant in that it may become a reference for other countries as an indicator for human resource management and health care allocation planning.

INTRODUCTION

Mortality rate refers to the number of deaths in a population or, in a simple term, can be described as the death rate. A higher mortality rate has a direct meaning that the population is not healthy and something must be done to resolve that condition. The rate is not only important for healthiness issues but also significant to social and economic development [1]. Mortality rate, especially among young children, is the key measure of a population's health status in low to middle income countries like Malaysia. The most widely used measurement of child mortality in recent years has been the under-five mortality rate (U5MR). The U5MR is defined as the probability of dying between live birth to the age of five years old. This includes neonatal, post neonatal and childhood mortality which refer to mortality in children younger than 5 years old [2]. Reducing U5MR in a population has become the central development agenda for improving population health in most countries in the world [3]. Aligned to Sustainable Development Goals number 3 (SDG3), the global aim is to reduce the U5MR to at least 25 per 1,000 live births by 2030 [4].

Malaysia shows an outstanding performance in reducing U5MR as the goal of SDG3 has been achieved ever since 1980 with 24 per 1,000 live births and reduced to 8.6 in 2019. The result demonstrates a synergy of a wide range of policies, strategies and programs to improve the way of living. However, globally, the mortality among children under 5 years old is still high and it needs a substantial effort to achieve the SDG3's target. Even for Malaysia, U5MR could be reduced to a minimum value as it can reflect the success of new policies and strategies. It is important to forecast U5MR for the next 10 years so that new policies and strategies can be designed accordingly.

There are several forecasting tools that are designed to measure and forecast mortality rate. However, accuracy and reliability of tools are the main factors to indicate that it can be used to predict future mortality rate in specific regions. Previously, several researchers conducted studies to forecast U5MR using data of their countries [5, 6, 7, 8, 9]. In the case of Malaysia, numerous efforts were made to forecast its total mortality such as studies done by [8, 9,10]. To the researchers' knowledge, to date, there is limited literature found on forecasting Malaysia's U5MR where the attention is more on infant mortality only. However, there was a study in forecasting Malaysia's U5MR using State Space model conducted by [9]. Therefore, this study is conducted to extend the study done by previous research on Malaysia's U5MR.

Hence, the focus of this study is to develop time series models in forecasting Malaysia's U5MR until the year 2030. In the process of developing the model, this study also explores current trend and forecast future trends of U5MR. It is hoped that the results of this study may serve as a principal guideline in planning intervention for children, especially in health care and education.

RELATED WORKS

Previously, there were several studies [5, 9, 11-13] conducted on predicting and forecasting U5MR globally where most of these studies used Box-Jenkins Autoregressive Integrated Moving Averages (ARIMA) model. One of many studies is found in Iran, using monthly U5MR data from 2005 to 2012 (7 years data), a seasonal ARIMA model is used in forecasting for Iran's U5MR [5]. The model was assessed and proved to be adequate in describing variations in the data. However, unexpected presence of a stochastic increasing trend and a seasonal component with periodicity of six months in the fitted model are very likely to be a consequence of poor quality of data collection and reporting systems [5].

In 2017, [6] conducted a study in Beijing China, using an ARIMA model in forecasting U5MR and it shows a slight upward trend from 2016 to 2020 [6]. Another study on U5MR in China using data from years 2012 to 2018 utilized the ARIMA model and a simple Seasonal Exponential Smoothing model to forecast future data [7]. With the same issue of limited period of time series data as in [6], the model is not able to produce a convincing forecasting result. The ARIMA model also has been taken as the method of time series analysis to forecast the mortality rates of India [11]. There is a consistent pattern of faster decline in the U5MR compared to the neonatal mortality rate across all major states in India even though neonatal mortality rate contributes the largest share in under-five mortality [11].

Another study was by [12] on U5MR for Ghana from years 1961 to 2012. This study utilized three-time series models; Box-Jenkins (ARIMA), the Bayesian Dynamic Linear Model, and the Random walk with drift models. As a result, the Random Walk with drift model was selected the best fit model for U5MR for Ghana and it was used to make four years out-sample forecasting for 2013 to 2016.However, a variant of the Lee–Carter (LC) model with two-dimensional P-Spline approach which designed for populations with limited data was used in estimating and forecasting the U5MRs of 5 countries (Kenya, Rwanda, Senegal, Tanzania, and Uganda) by [13].

Among others, [9] used state space model in analyzing and forecasting trends of U5MR in Malaysia for 37-year period (1980 – 2016). It was found that U5MR in Malaysia had fluctuated from year to year with a slowly decreasing trend pattern for both genders with males having a higher rate compared to females. Based on Local Linear Trend model, future trend is increasing slightly and forecast trend for the male population is higher than the female.

According to [9, 14] the state space model of time series analysis has several advantages over the Box-Jenkins models. Hence, it is a worthy suggestion to look into the method of Box-Jenkins and State Space model to observe the accuracy of forecast U5MR and trend for different genders by using data from Malaysia.

METHOD

Data

Secondary data obtained from the Department of Statistics of Malaysia (DOSM) are used in this study. The data is collected from peninsular Malaysia in between 1980 to 2016 (37 years of period) and categorized based on gender.

Then, it is classified into two parts, training and testing in a ratio of 70:30 in which data from 1980 to 2009 is considered as in-sample (training) and the remaining 7 years of data is considered as out-sample (testing).

Forecasting models

Two forecasting models, Box-Jenkins and State Space model are used to forecast the trends of U5MR. Two main applications are used to analyze the data which are EViews application and R Software. The models may forecast trends and data for 14-years-ahead, from the year 2017 until 2030.

Box-Jenkins model

The general Box-Jenkins models consist of an autoregressive model of order *p* (known as AR(*p*)) model, a moving average model of order *q* (known as MA(*q*)) model and combination of AR(*p*) and MA(*q*) which is known as ARMA(*p,q)* model [15]. The classical Box-Jenkins models assume the time series is stationary, that is, the mean and variance of the series are essentially constant through time. If the time series is not stationary, the transformation, by taking the differencing of the non-stationary time series values, is needed. In this case, the integrated ARMA(*p,q)* model needs to be considered. The general term for integrated ARMA(*p,q)* model was ARIMA (*p,d,q*) where '*d*' was the number of time the variable needs to be differenced in order to achieve the stationarity. The non-seasonal ARIMA (*p,d,q*) model was suitable for this research as the data set used is not influenced by seasonal component. The AR(*p*) model can be written as:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \qquad (1)$$

where $\phi_1, \phi_2, \dots, \phi_p$ are unknown parameters relating y_t to $y_{t-1}, y_{t-2}, \dots, y_{t-p}$. While, the MA(*q*) model is:

$$y_t = \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (2)$$

where $\theta_1, \theta_2, \dots, \theta_p$ are unknown parameters relating y_t to $\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$. The ARMA(*p,q*) models was written as:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (3)$$

where ϕ and θ are unknown parameters and ε are independent identically distributed error terms with zero mean. While the non-seasonal ARIMA (*p,d,q)* model can be written as

$$y'_t = \mu + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \cdots + \phi_p y'_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (4)$$

where y'_t is the differenced series. One of the special cases of the ARIMA (*p,d,q)* model is ARIMA (0,1,0) with and without constant (μ) value which is known as random walk model if without constant and random walk with drift model if with constant value. The random walk model was written as:

$$y_t = y_{t-1} + \varepsilon_t \quad (4)$$

Random walk with drift can be written as:

$$y_t = y_{t-1} + \mu + \varepsilon_t \quad (5)$$

The Box-Jenkins methodology adopted in this study consists of five iterative steps. The first step is simple data investigation by constructing a simple time plot in identifying the level of trend differencing (d). The second step is where the time series was transformed in order to achieve time series stationarity. Subsequently, historical data were used to identify the appropriate Box-Jenkins model that is the order of AR (p) and order of MA (q) using Autocorrelation function (ACF) and Partial Autocorrelation function (PACF). Then, in the third step, the data were used to estimate model parameters that have been identified in the previous step. Next, adequacy of each of the model was verified by Ljung-Box statistics that is useful for testing the randomness of residuals by testing that the null hypothesis of the residuals is white noise. Finally, based on their adequate predictions, the most appropriate models have been chosen. Akaike Information Criterion (AIC) and Bayesian information criteria (BIC) have been used to compare the goodness-of-fit of different ARIMA (p,d,q) models.

State space model

Univariate state space model for time series is also known as structural time series model. The model is in state space form which state of the system represents the various unobserved components such as trend and seasonal [16]. The types of univariate state space models include local level model and local linear trend model where the trend in the local level model is just a random walk model [17]. The local level model is a basic univariate state space [17] which consists of level component. Level component in this model can be conceived equivalent to intercept in the regression equation. The difference between intercept in the regression and the level component in the intercept is treated as a deterministic process, while the level component is treated as a stochastic process which allows the level components to vary over time. The local level model can be written as:

$$y_t = \mu_t + \varepsilon_t, \ \varepsilon_t \sim \text{NID}(0, \sigma^2{}_{\varepsilon}),$$
$$\mu_t = \mu_{t-1} + \eta_t, \ \ \eta_t \sim \text{NID}(0, \sigma^2{}_{\eta}) \quad (6)$$

where $t = 1, \ldots, T$, y_t is observation at time t, μ_t is level component at time t, ε_t is an irregular component or also known as the observation disturbance, η_t is level disturbance. Parameter ε_t and η_t are normally and identically distributed with mean zero and variance constant. The first equation in Eq. (6) represents measurement or observation equation while the second equation represents a state equation.

The local linear trend model is the model in which the slope component is added to the local level model. Slope in this model is equivalent to the slope in the regression equation. The only difference is the slope in this model is allowed to vary over time, while the slope in the regression equation is fixed through time. There are two state equations in the local linear trend model, one represents the level component and another one represents the trend component. The local linear trend model is progressively broad in the trend component that had a stochastic slope, β_t, which adheres to a random walk. The local linear trend model can be written as follows:

$$y_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim \text{NID}(0, \sigma^2{}_\varepsilon),$$
$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}(0, \sigma^2{}_\eta), \quad (7)$$
$$\beta_t = \beta_{t-1} + \zeta_t, \quad \zeta_t \sim \text{N}(0, \sigma^2{}_\zeta),$$

where $t = 1, \ldots, T$, β_t denotes a trend component or slope and ζ_t denotes slope disturbance. The unpredictable, level and slope disturbance, ε_t, η_t and ζ_t, separately, are commonly independent. If both variances $\sigma^2{}_\eta$ and $\sigma^2{}_\zeta$ are zero, the pattern is deterministic, that is

$$\mu_t = \mu_0 + \beta_t, \quad (8)$$

At that point, when just $\sigma^2{}_\zeta$ is zero, the slope is constant, and the trend diminished to a random walk with drift

$$\mu_t = \mu_{t-1} + \beta + \eta_t. \quad (9)$$

The parameters of a state space model are fundamentally assessed by the maximum likelihood that is maximized by utilizing the Kalman filters (KF) and Kalman smoothers (KS) [18]. The KF utilized the observed data to find out the unobservable state factors which portray the state of the model. The KF is, for the most part, distribution-free and gives the most excellent straight indicators within the sense of minimizing the mean squared error [19] while KS solves the anticipated esteem of the covered up state condition on all the data [18]. The KF is a recursive method that includes steps such as initialization, expectation, adjustment and probability development.

A state space model has a direct interpretation and is formulated straightforwardly as far as various imperceptibly or inactive components such as trend, cycle or seasonal [20]. Professionals chose the structures and the models for parts that are pertinent in clarifying the elements watched within the information. An advantage of using state space model is that this technique considers time dependency of the underlying parameters [21].

Model evaluation

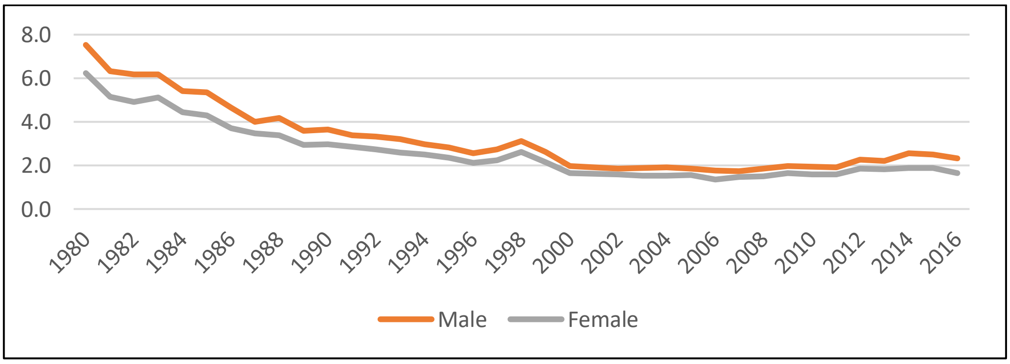
At the initial stage of analysis, the data of U5MR were separated into two parts which were training data (in-sample); 1980 - 2009 and testing data set; 2010 - 2016 (out-sample). The evaluation procedure involved fitting the models using in-sample data and the models were then evaluated using out-sample. The evaluation was conducted with the objective of minimizing root mean square error (RMSE) and mean absolute percentage error (MAPE) for all models. The best performance model is based on minimum error. The equation of these error measures are as follows [22]:

$$RMSE = \sqrt{mean(\boldsymbol{e}_t^2)} \qquad (10)$$

$$MAPE = mean\left|\frac{\boldsymbol{e}_t}{\boldsymbol{m}_t}\right| \times 100 \qquad (11)$$

RESULTS AND DISCUSSION

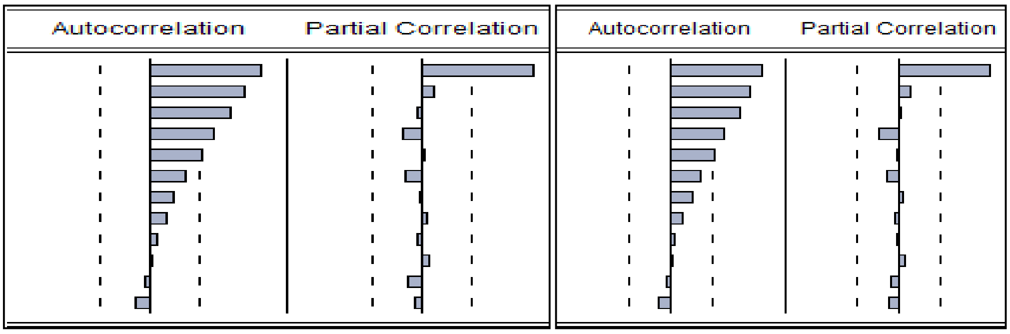
The results of this study were based on the secondary data obtained from the Department of Statistics (DOSM) which includes 37 observations of U5MR for males and females in Peninsular Malaysia from year 1980 to the year 2016. By analyzing the changes of U5MR year by year, Malaysia's U5MR has shown a gradual decline over time. As shown in Figure 1, the trend of U5MR is decreasing for both male and female population with U5MR for male population is higher than female population. There exists random shock of irregular components in U5MR data where the rates drastically increased in 1997 and 1998. This is because Malaysia was having an economic crisis during those years. During the economic crisis, food cost increased and had a widespread impact on nutritional and health status of the population, particularly among children [23]. This situation has prompted to increase U5MR in the years 1997 and 1998. However, starting from year 2000 until 2011, the figure shows that the trend of U5MR is a uniformed pattern. In years 2012 to 2015, U5MR slightly increased and dropped back in 2016.



Note: Rate per 1000 live birth

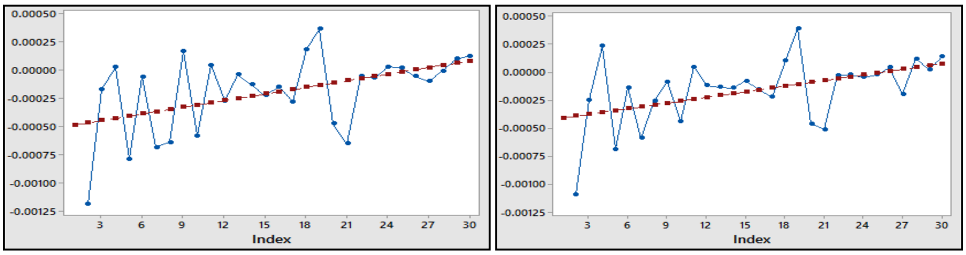
Figure1 Trend of Peninsular Malaysia's U5MR for male and female population

The first step of model development consists of fitting the Box-Jenkins model to the data under consideration. Based on the U5MR series in Figure 1, it was shown that the series contains trends and irregular components. The series seems to show an upward pattern towards the on-going data; hence, the data series was not stationary. Further analysis utilized autocorrelation function (ACF) and partial autocorrelation function (PACF) to confirm the stationarity of the data as shown in Figure 2 and it was confirmed that the U5MR for both populations were not stationary. Therefore, the non-seasonal differencing was performed in order to remove the trend component in the data series. The difference series in Figure 3 seems to show an upward pattern toward the on-going data. Therefore, further analysis of ACF and PACF on difference series is conducted to confirm the stationarity of the series as shown in Figure 4.



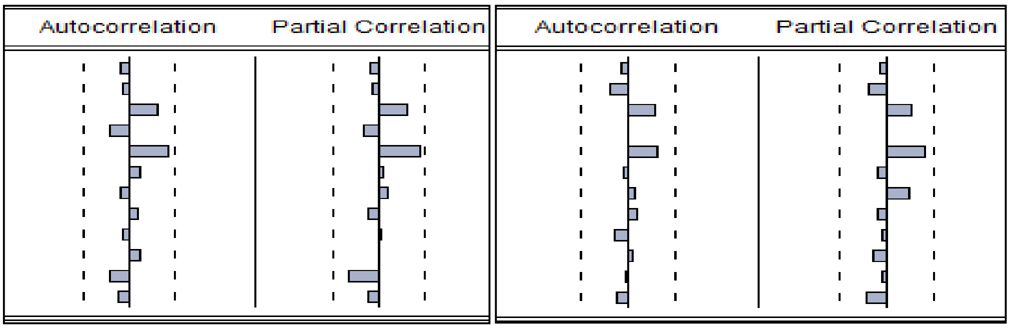
(a) Male Population (b) Female Population

Figure 2 Autocorrelation function and partial autocorrelation function for U5MR



(a) Male Population (b) Female Population

Figure 3 Trend of first differencing for U5MR



(a) Male Population (b) Female Population

Figure 4 Autocorrelation function and partial autocorrelation function of first differencing for U5MR

Figure 4 show that the difference series of U5MR has no pattern and no significant spike at any lag since they do not surpass the limit in ACF and PACF for both populations. From this outcome, the suitable model for both male and female populations' U5MR is ARIMA (0,1,0) which is known as a random walk model. Therefore, this study turns out with only one possible model which is a random walk with drift since the nature trend of the data after differencing is increasing. Because of this, the necessary validation test on the model as a way out is performed.

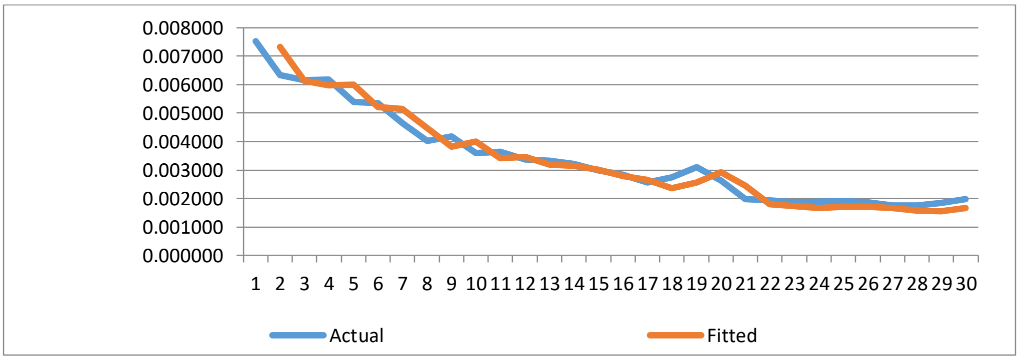
The modelling process was then proceeded with State Space model. In this study, the analysis of state space model chose the local linear trend as the suitable model since the data displayed inconsistent trend as shown in Figure 1. The parameters of a state space model and fitting a structural model for a time series are fundamentally estimated by maximum likelihood. Firstly, the parameters of the model were estimated by constructing a fit of the local linear trend model for U5MR of the male and female populations and the result is shown in Table 1.

Table 1 Estimation parameter by local linear trend model

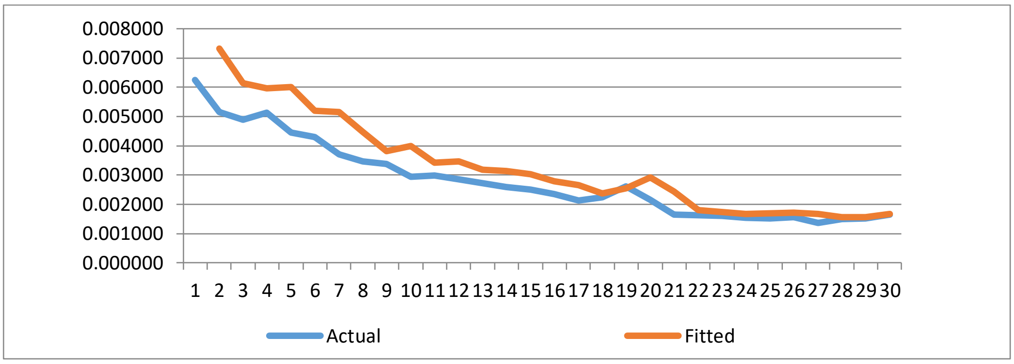
	Level	Slope	Observational
Male	1.681e-08	2.446e-09	4.628e-08
Female	2.878e-09	1.967e-09	4.086e-08

The maximum likelihood estimates (MLEs) for the variance of level disturbance of male population is 1.681e-08 while 4.628e-08 for the variance of the observation disturbances and the variance of the slope disturbances is 2.446e-09. Furthermore, 2.878e-09, 1.967e-09, and 4.086e-08 were MLEs for variance of level disturbance, the variance of the slope disturbance and variance of the observation disturbance, respectively for the female population. It shows, the state variance of both genders for the slope component is almost equal to zero, meaning that the value of the slope hardly changes over time. The estimation of all parameters within the model were calculated employing a KF and KS rule. The KF provides an ideal state such as the lowest mean square error that estimates the unobserved data up to time, whereas the KS tackles the expected value of the covered up state conditioned on all the data.

The historical series of U5MR from the year 1980 to the year 2009 is used in estimating the model to produce the predicted (fitted) values. Then, the goodness of fit of the models is examined using the time series plot of predicted and actual values. The predicted values from for random walk with drift model and local linear trend model together with the actual U5MR are shown in Figure 5 and Figure 6, respectively.

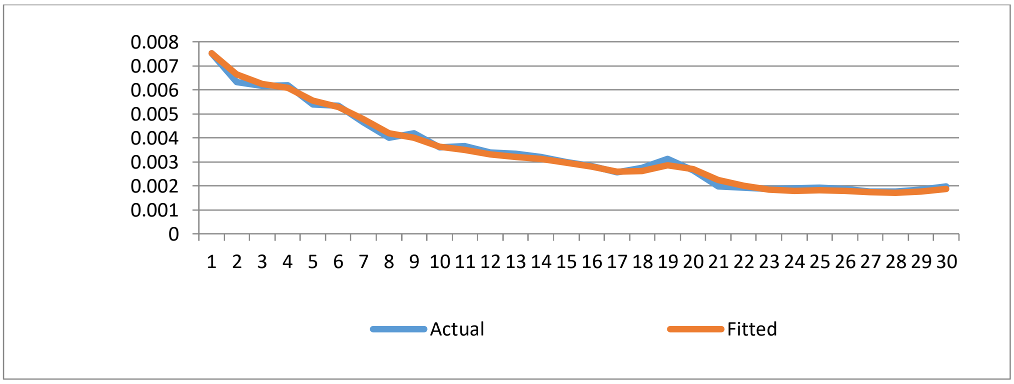


(a) Male Population

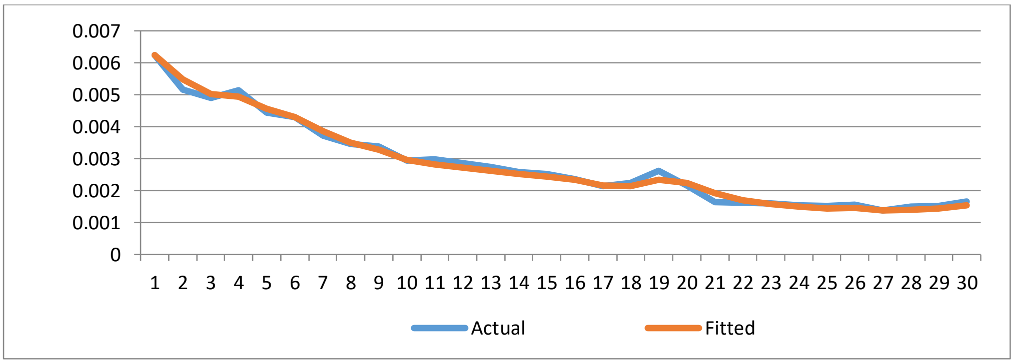


(b) Female Population

Figure 5 Predicted U5MR of random walk with drift model



(a) Male Population



(b) Female Population

Figure 6 Predicted U5MR of local linear trend model

As shown in Figure 5, the predicted values for a random walk with drift for male is close to the actual value, while the predicted value of the female population for a random walk with drift is a little bit far from the actual value compared to the male population. Based on Figure 6, the predicted values for local linear model for both populations are very close and almost overlapping to the actual value compared to a random walk with the drift model. This means that the error prediction for local linear trend model is smaller than random walk with drift model and able to fit the data very well. Therefore, it can be concluded that the local linear model is perform better than random walk with drift model.

To further evaluate the performance of the random walk with drift model and local linear trend model to the Malaysia U5MR, in-sample and out-sample evaluation is conducted by examining the two error measures which are RMSE and MAPE. In-sample evaluation is based on the ability of the models to fit the historical data, while out-sample evaluation is based on the ability of the models in producing good forecasts for the future U5MR. As shown in Table 2, the results prove that the local linear trend model produces a smaller value of RMSE and MAPE for male and female population of U5MR for both in-sample and out-sample evaluations compared to a random walk with a drift model. Overall, it shows that the local linear trend model is the best model when compared to random walk with drift model because it is more consistent in producing in-sample fit and out-sample forecasts. In this respect it is noted that a good model should provide accurate fits to the historical data as well as produce plausible forecasts [24]. Hence Malaysia's, future U5MR are forecasted using linear trend model.

Table 2 Results of in-sample and out-sample evaluation

		In-sample		Out-sample	
		Random Walk with Drift Model	Local Linear Trend Model	Random Walk with Drift Model	Local Linear Trend Model
Male	RMSE	0.000286	**0.000128**	0.001186	**0.000429**
	MAPE	8.182573	**3.351198**	43.837422	**15.174329**
Female	RMSE	0.000672	**0.000130**	0.000837	**0.000194**
	MAPE	18.067574	**4.098678**	41.085707	**8.341987**

Since this study also interested in forecasting the U5MR for both populations from 2017 until 2030, therefore, the fourteen-step ahead forecast were also generated using local linear trend model. The forecast values for U5MR of Malaysian male and female populations from 2017 until 2030 are shown in Table 3. There is a slightly increasing trend from 0.001891 in 2017 to 0.001907 in 2030 for male while for female it is 0.001667 in 2017 to 0.001878 in 2030. The trend of the forecast U5MR can be clearly seen in Figure 7 which shows the trend of the actual U5MR data from 1980 to 2016 for both male and female populations and the future trend of U5MR from year 2017 until year 2030. The future trends indicate an increased pattern in male and female population and the rate is significantly higher for the male population than for the female population. This consequence happens is due to the unstable pattern in historical U5MR series. These results are similar to the previous study done by [9].

Table 3 Forecast values for U5MR of male and female populations

Year	Male	Female
2017	0.001891	0.001667
2018	0.001892	0.001684
2019	0.001893	0.001700
2020	0.001894	0.001716
2021	0.001896	0.001732
2022	0.001897	0.001748
2023	0.001898	0.001765
2024	0.001900	0.001781
2025	0.001901	0.001797
2026	0.001902	0.001813
2027	0.001904	0.001829
2028	0.001905	0.001846
2029	0.001906	0.001862
2030	0.001907	0.001878

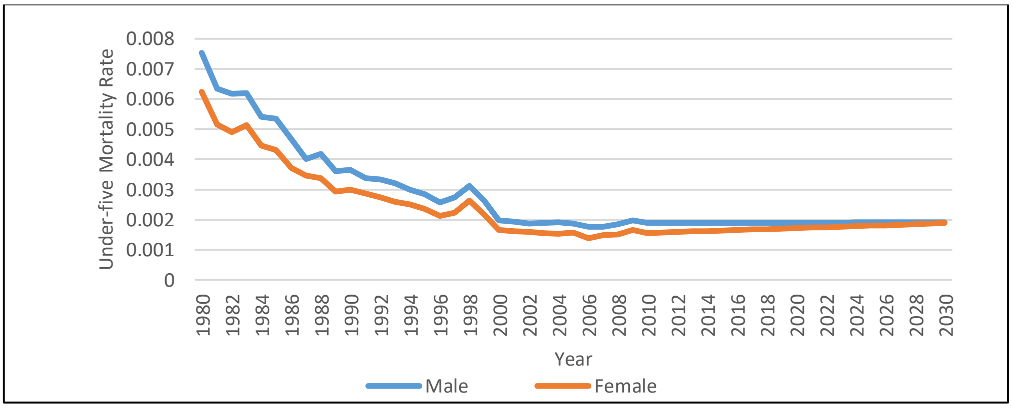


Figure 7 Trend of actual and forecast values for U5MR of male and female populations

CONCLUSION

This paper studied the trend pattern of U5MR in Malaysia by gender. The trend analysis over the data of U5MR by gender from year 1980 to 2016 found that the series of U5MR for male and female populations was impacted by trend and irregular component. This situation shows that the U5MR series is an unstable pattern. In developing the forecasting model for U5MR, random walk model for Box Jenkins and local linear model for State Space model were utilized. These two models are identified suited the characteristic of U5MR data. The performance of developed models was evaluated based on smallest value of RMSE and MAPE. Local linear trend of the State Space model is the best model to forecast future U5MR for both male and female populations. This model also does not require complicated assumptions needed as traditional time series models.

Malaysia has made considerable progress in reducing U5MR from 1980 to 2016. However, based on forecast values produced by local linear trend model, U5MR shows a slight upward trend from 2017 to 2030 for both male and female populations. This maybe because of the distribution of U5MR data is not equal across the country. Thus, future researchers may consider spatio-temporal forecasting model because this model is able to produce spatially out-of-sample forecasts. In addition, it is possible, if any, to consider other models, which are able to forecast U5MR more accurately and capture its patterns more specifically.

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