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FORECASTING AIR PASSENGERS OF CHANGI AIRPORT BASED ON SEASONAL DECOMPOSITION AND AN LSSVM MODEL

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ABSTRACT

This work aimed to determine a suitable method to provide air traffic passenger forecasts of Changi airport. A linear forecasting technique in the form of a seasonal autoregressive integrated moving average (SARIMA) model and a nonlinear technique known as the least squares support vector machine (LSSVM) were compared. A hybrid X-13 LSSVM approach was also compared. A fourth approach was proposed to leverage the outputs of the hybrid X-13 LSSVM method to conduct forecasts for longer forecasting horizons. Results showed that SARIMA, direct LSSVM and X-13 LSSVM methods were able to provide accurate 1-month-ahead forecasts. However, SARIMA and direct LSSVM methods both suffered from forecasting inaccuracy, as the forecasting horizon increased. The X-13 LSSVM outperformed both SARIMA and direct LSSVM methods, in terms of small magnitude errors and forecasting directional changes across the forecasting horizons. The proposed fourth approach was able to provide 24-months-ahead forecasts and was easy to implement.

Contribution/Originality: This study documents a suitable method to forecast air traffic passengers. A linear technique, a nonlinear technique and a hybrid X-13 LSSVM approach were compared. A fourth approach was proposed for longer forecasting horizons. Results showed that the proposed approach could provide 24-months-ahead forecasts and was easy to implement.

1. INTRODUCTION

Ever since Franklin Roosevelt signed the Chicago Convention in 1944 for the setting up of the basic framework for civil aviation, aviation has gone through significant transformations to be a key industry in today's global economy [1].

Air traffic management (ATM) [2] involves activities such as air traffic control (ATC) and aeronautical information services [3]. These enable aircraft to fly safely [4] in the airspace and allow improvements of the current status.

The aviation industry experienced a constant growth with an average of 5% annually over the past 30 years [5]. Air traffic is an important element in the flow of capital and people throughout the Asia Pacific region [6, 7]. A continual growth is expected as wealth grows, enabling airlines to serve almost every corner of the globe. A major aircraft manufacturer, Airbus, expects an average of 4.6% growth annually in air traffic from 2014 to 2034, with the Asia-Pacific region eventually becoming the largest market [8]. The International Air Transport

Association also estimates a similar figure, which would take the number of passengers to 7.3 billion by 2034, slightly more than two times the number of passengers in 2014 [9].

Despite the positive outlook for the future of the aviation industry, an expert survey by the European Organization for Safety of Air Navigation gathered as many as 16 factors that would pose some form of hindrances to the growth, if they are not well addressed [10]. Therefore, forecasts of future demands give relevant authorities knowledge on the extent of development, planning and strategic policies needed to ensure that the demands are not constrained. Forecasting also serves to provide a form of environmental assessment from carbon emissions due to aviation activities [11]. In short, plans for the future of the aviation industry cannot be made without forecasting of the air travel demand [12, 13].

Major aircraft manufacturers and aviation organizations provide long-term forecasts to give stakeholders outlooks of the future for the industry [8, 9, 11]. However, short-term forecasting is not easily available and is less commonly achieved by major organizations. That is not to say that short-term forecasts are not of importance. Short-term forecasts are used by airports and airlines for daily operation management, equipment and personnel requirements, maintenance planning and marketing campaigns [14].

Various methods have been used for short-term forecasting. A common forecasting method is a linear method in the form of an autoregressive integrated moving average (ARIMA) model, which was used to forecast the airport passenger traffic for Hong Kong [15]. Nonlinear forecasting methods in the form of artificial neural networks (ANNs) were also used to forecast the air passenger flow in Russia [16]. Researchers have also proposed hybrid methods where more than one forecasting techniques are used to compensate for the drawbacks of individual methods. Such an example was the application of the ARIMA model followed by an ANN model, which gave better forecasting accuracy compared to stand-alone methods [17]. Data pre-processing can also be carried out prior to forecasting as another form of hybrid methods [18]. Seasonal decomposition as a form of pre-processing prior to nonlinear forecasting by the least squares support vector machine (LSSVM) was used to forecast air passengers for Hong Kong International Airport for a 1-month-ahead forecasting horizon, which yielded better forecasting accuracy than various stand-alone methods [14].

Seasonal decomposition is a procedure used to remove any systematic seasonal variations [14] allowing one to observe the underlying characteristic of the time series. The trend component represents the underlying growth, fall or stagnation of the time series over a long time period [19]. The seasonal component is the pattern in the time series, which is observed in a fixed and known period [20]. Intuitive examples would be sales relating to weather seasons and weather conditions [19, 21-23]. Decomposition can be achieved by applying moving averages to smooth the time series to estimate the components that make up a time series [24].

The LSSVM is an extension of the support vector machine (SVM), which simplifies the SVM by avoiding the computation of a multi-variable quadratic optimization problem with linear constraints [19]. It is a relatively new method used for forecasting, and has also been used for wind speed prediction [25] electrical load forecasting [26] and water quality prediction [27].

The SVM was found useful in regression analyses [28]. The concept is to learn an appropriate estimator function from the training data to generate the output from the corresponding input [19]. The obtained function is used to obtain new outputs from new inputs.

This article aims to find an approach suitable for conducting short-term forecasts for Singapore Changi Airport. This work evaluated the performance of four forecasting approaches. The first approach involved the use of a linear forecasting method known as the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. For the second approach, machine learning in the form of the LSSVM was applied as a nonlinear forecasting method. The third approach similarly utilized the LSSVM but with seasonal decomposition prior to forecasting. A fourth approach was proposed to leverage the outputs of the hybrid X-13 LSSVM method by fitting a curve to the trend component and extrapolating it into the future. The seasonal component that was forecasted by the X-13

LSSVM was then superimposed onto the trend component to obtain the final forecast. This approach involved the projection of a fitted curve, not repetitive fitting of a model, into the future.

2. METHODOLOGY

2.1. Data

The total number of passengers handled by Changi Airport per month [29] was used for this work. The total number of passengers used was the summation of the numbers of passenger arrivals, departures and transits. Data of earlier years were not used, because data from too long time ago might exhibit irrelevant characteristics. Thus, the period of data used was from January 2004 to November 2015, amounting to a total of 143 observations. The plot of the data used is shown in Figure 1. The data were separated into training and testing sets. The training set was utilized to train and obtain the model parameters, whereas the testing set was used for performance evaluation to determine the forecasting accuracy of the methods.

2.2. Seasonal ARIMA (SARIMA) Approach

The seasonal ARIMA (SARIMA) method was performed in *R*, a free, open-source software environment for statistical computing [30] together with the *forecast* package by Hyndman [31]. *R* allows for packages with various other functions created by third-party users to be loaded, extending the functionality of the software. The *forecast* package is one of them and enables users to model and analyze a univariate time series [31]. It also allows users to conduct forecasts using various techniques through automatic modelling procedures.

Before model parameter selection was done, the Box-Cox transformation was first applied to stabilize the variance of the data as the data exhibited a slight increase in seasonality as the trend increased. The appropriate transformation parameter for the Box-Cox transformation was automatically identified through the relevant function call in the package. The automatic ARIMA modelling procedure was then used to fit the training data. It first conducted KPSS tests to determine if the time series was stationary and applied the appropriate differencing until stationarity was obtained [32].

Next, the non-seasonal and seasonal autoregressive orders and moving average orders were identified by minimizing the Akaike Information Criterion (AIC) and the corrected AIC (AICc) performance measures [32]. After an optimal model was identified by the automated procedure, diagnostic checks were performed to ensure the fitted model was acceptable, by conducting a Ljung-Box test on the residuals to ensure that there was no correlation present in them. *n*-months ahead forecasting was conducted by iterating 1-month ahead forecasts to *n*-months ahead by using past forecasted values as known values, otherwise known as the recursive method [33].

2.3. Hybrid X-13 LSSVM Forecasting Approach

The hybrid X-13 LSSVM forecasting approach was proposed by Xie, et al. [14] who used seasonal decomposition to decompose a time series into its irregular, seasonal and trend components. The LSSVM was then utilized to forecast all individual components before aggregating the outputs to obtain the final forecasted time series. The process flow diagram from Xie, et al. [14] was redrawn to depict a clearer view for the methodology, as shown in Figure 2.

2.3.1. Seasonal Decomposition

For a time series, under the assumption that the components are dependent on and affect one another, the observation y_t, can be represented as Adhikari and Agrawal [19]; Hyndman and Athanasopoulos [24]:

$$y_t = I_t \times S_t \times T_t \tag{1}$$

Where I_t is the irregular component, S_t is the seasonal component, and T_t is the trend component.

The seasonal decomposition was achieved using the X-13ARIMA-SEATS (or X-13 for short) technique. X-13 is the software developed by the United States Census Bureau in collaboration with the Bank of Spain, which can be used to decompose a given time series into its individual components [34]. X-13 uses simple and more complex moving averages together with other extra features for the seasonal adjustment, and addresses the shortfall of classical moving averages [24]. X-13 facilitates the implementation of seasonal adjustments to a time series by including various automatic statistical tests to aid in the selection of appropriate model parameters [35].

X-13 was performed in *R* [30] together with the *forecast* package [31] and the *seasonal* package. The *seasonal* package provides a user-friendly interface for X-13 seasonal adjustments [36] and allows for the modelling and analysis of time series data in *R* [31]. The seasonal decomposition was carried out using the guide from the United Kingdom Office for National Statistics (ONS) [35].

2.3.2. LSSVM

The LSSVM forecasting was performed in MATLAB with the LS-SVMlab v1.8 toolbox [37] and its user's guide [38]. The procedure for the LSSVM forecasting, as outlined in this section, also applies to the direct LSSVM forecasting method. The mathematical formulation for the LSSVM is presented here. Given a set of data in the form below [19]:

$$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\} \quad (2)$$

where N is the number of samples in the data, and $x_i \in \Re^n$ and $y_i \in \Re$ are the input vector and the corresponding output respectively, the following function is formulated for a regression problem [19]:

$$y(x) = w^T \varphi(x) + b \quad (3)$$

Where $\varphi(x)$ is a mapping function, w^T are weight vectors, and b is a bias term. The mapping function maps the input data into a space such that a linear hyperplane can be constructed, hence allowing for the solving of nonlinear problems [39].

Before applying Eq. (3) to the time series of nonlinear characteristics, the forecasting problem can be first modelled as a nonlinear autoregressive model, where the forecasted value is a nonlinear function of its own lagged variables [28]. The approach for 1-month-ahead forecasting is shown as follows [40]:

$$\hat{y}_{(k+1)} = f\left(y_k, \ldots, y_{(k-p)}\right) \quad (4)$$

Where $\hat{y}_{(k+1)}$ is the forecasted value at one month ahead, k is the number of available data, and p is the order of the lag variable.

However, 1-month-ahead forecasts might be of limited use. Multi-steps-ahead forecasts can be made by a recursive method where past forecasted values are used to relate the present forecasted value with its lagged variables, shown as follows [40]:

$$\begin{aligned} \hat{y}_{(k+2)} &= f\left(\hat{y}_{(k+1)}, \ldots, y_{(k-p+1)}\right) \\ \hat{y}_{(k+m)} &= f\left(\hat{y}_{(k+m-1)}, \ldots, y_{(k-p+m)}\right) \end{aligned} \quad (5)$$

Where, $\hat{y}_{(k+m)}$ is the forecasted value at *m*-months ahead. The regression function of Eq. (3) can hence be represented as Langone, et al. [40]:

$$\hat{y}_{(k+1)} = w^T \varphi\left(y_k, y_{(k-1)}, \ldots, y_{(k-p+1)}\right) + b \quad (6)$$

The problem can then be considered a constrained optimization function given below [14, 19]:

$$Min\, J(w,\mathrm{e}) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{N} \mathrm{e}_i^2 \tag{7}$$

subject to: $y(x_i) = w^T\varphi(x_i) + b + \mathrm{e}_i$

Where e_i is an error variable, and γ is the regularization parameter, which decides the trade-off between the function smoothness and minimization of the estimation error [14]. The Lagrange function is applied as follows [14, 19] to resolve the constrained optimization problem:

$$L(w,b,\mathrm{e},\alpha) = J(w,\mathrm{b},\mathrm{e}) - \sum_{i=1}^{N} \alpha_i\{w^T\varphi(x_i) + b + \mathrm{e}_i - y_i\} \tag{8}$$

Where $\alpha_i(i = 1, \ldots, N)$ are Lagrange multipliers. Based on optimality conditions, L is partially differentiated with respect to w, b, e and α to obtain the following [14]:

$$\begin{aligned}
&\frac{\partial L}{\partial w} = 0 \rightarrow w = \textstyle\sum_{i=1}^{N} \alpha_i\, \varphi(x_i),\\
&\frac{\partial L}{\partial b} = 0 \rightarrow \textstyle\sum_{i=1}^{N} \alpha_i = 0\,,\\
&\frac{\partial L}{\partial \mathrm{e}_i} = 0 \rightarrow \alpha_i = \gamma \mathrm{e}_i\,, i = 1, \ldots, N\\
&\frac{\partial L}{\partial \alpha_i} = 0 \rightarrow w^T\varphi(x_i) + b + \mathrm{e}_i - y_i = 0\,, i = 1, \ldots, N
\end{aligned} \tag{9}$$

From Eq. (9), w and e are then eliminated to obtain a linear system where values of α_i and b can be estimated [41]. Recalling Eq. (3), the terms w and $\varphi(x)$ can now be written as Xie, et al. [14]; Adhikari and Agrawal [19]:

$$y(x) = \sum_{i=1}^{N} \alpha_i k(x_i, x_j) + b \tag{10}$$

Where $k(x_i, x_j)$ is the kernel function, and $\alpha_i = \gamma \mathrm{e}_i\,, i = 1, \ldots, N$.

The kernel function allows for the nonlinear mapping into high dimensional feature space to obtain a linear hyperplane without calculating the explicit computation in this high dimensional feature space [39]. The use of a suitable kernel function would allow for the solving of the problem without needing to know $\varphi(x)$ [19].

The radial basis function (RBF) kernel was used in this work, because the literature on LSSVM time series forecasts used the RBF kernel, which gave desirable results [42]. The RBF kernel allows for a nonlinear model and it takes the form of Xie, et al. [14]:

$$k(x_i, x_j) = e^{\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)} \tag{11}$$

Where σ^2 is the width of the kernel, which accounts for how much the model smooths the function [43]. The model parameters to be tuned are γ, σ^2 and p [40].

The number of lag variables to be included was determined by plotting the autocorrelation function for the trend, seasonal and irregular components. Significant correlations between lag variables would determine the order of the lag variables to be used. The method used to tune γ and σ^2 was based on those in the LS-SVMlab v1.8 toolbox [43].

For machine learning applications, normalization of input data may improve forecasting performance by preventing values of large magnitude to dominate over those of smaller values. Normalization may also lead to better forecasting accuracy compared to non-normalized data [41]. Therefore, the trend, seasonal and irregular components were normalized to obtain unit variance and zero mean using Eq. (12) [44]; [45]:

$$y_t' = \frac{y_t - \bar{y}_{tr}}{\sigma_{tr}} \tag{12}$$

Where y_t' is the normalized output, y_t is the variable to be normalized, $\bar{y}_{tr}$ is the mean of the training set of variable y, and σ_{tr} is the standard deviation of the training set of variable y. The mean and standard deviation in Eq. (12) were calculated based on the training data. The testing data were also normalized but based on the standard deviation and mean of the training data. This was to ensure that the model was not given any information on the testing values that were to be forecasted. The forecasts for the trend, seasonal and irregular components were denormalized before aggregating to form the final air traffic passenger forecasts. The LS-SVMlab v1.8 toolbox would use the recursive technique to compute *n*-months-ahead forecasting.

2.4. Fitted Trend Curve Superimposed on LSSVM Seasonal Forecasts

This approach involved fitting a curve to the trend component which was obtained from seasonal decomposition. Next, the seasonal component forecasted by the LSSVM was superimposed on the trend component to give the final forecasts. The irregular component was not forecasted due to the inherent difficulty in forecasting such an unpredictable component. The process flow diagram for the fitted trend curve superimposed on the LSSVM seasonal forecasts is shown in Figure 3.

A linear curve was first fitted to the trend component that was obtained from the seasonal decomposition in the X-13 LSSVM approach. Curve fitting was performed in MATLAB with the use of the Curve Fitting Tool™. With the obtained curve equation, the trend component was then projected into the future. The seasonal component forecasts from the X-13 LSSVM approach were then superimposed onto the linear curve to obtain the final forecasts. In other words, superimposing of the seasonal and trend components was performed by multiplying both of the components to obtain the final forecasts.

To compare this approach with the other three approaches, the 24-months-ahead seasonal forecasts from the LSSVM were superimposed on the projected trend component. As this approach involved the projection of a linear curve into the future and not a repetitive fitting of any model, comparison between multi-steps-ahead forecasting horizons would not be appropriate. Hence, only the 24-months-ahead forecasting horizon was evaluated for this approach, to allow it to be compared with the other approaches.

2.5. Performance Measures

All the methods conducted were evaluated using performance measures computed based on the accuracy of forecasts of the testing data set. The performance measures used in this research are MAE (mean absolute error), RMSE (root mean squared error), MAPE (mean absolute percentage error) and D_{stat} (directional change), which are commonly used in the literature on forecasting. MAE, MAPE and RMSE were computed using Eqs. (13), (14) and (15) [19] respectively:

$$MAE = \sum_{t=1}^{N} \frac{|y_t - \hat{y}_t|}{N} \tag{13}$$

$$RMSE = \sqrt{\frac{[\sum_{t=1}^{N}(y_t - \hat{y}_t)^2]}{N}} \tag{14}$$

$$MAPE = \left(\frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right|\right) \times 100\% \tag{15}$$

Where, y_t is the actual value of a particular month, $\hat{y}_t$ is the forecasted value of the particular month, and N is the number of data in the testing set.

In forecasting, it is important to not only achieve small magnitudes of forecasting errors, but also accurately forecast turning points within the forecasting period. D_{stat} is a performance measure computed to indicate the directional accuracy, and was computed as follows [14]:

$$D_{stat} = \sum_{t=1}^{N} \frac{d_t}{N} \tag{16}$$

where $$d_t = \begin{cases} 1, & (y_t - y_{t-1})(\hat{y}_t - y_{t-1}) \geq 0 \\ 0, & otherwise \end{cases}$$

D_{stat} has a range from 0 to 1, with 1 indicating that the rise and fall for every observation in the testing set are correctly forecasted. Therefore, a higher value is desired [14].

3. RESULTS AND DISCUSSIONS

3.1. Comparison of the Forecasting Approaches

In this section, the 24-months-ahead forecasts obtained using the four approaches studied would first be examined. Next, a comparison of the performance measures for the four approaches with three forecasting horizons is presented.

The hybrid X-13 LSSVM 24-months-ahead forecasts for the trend, seasonal and irregular components are shown in Figures 4 to 6. These three components were multiplied to give the 24-months-ahead air traffic passenger forecasts, as shown in Figure 7. As shown in Figure 4, a flat trend was forecasted instead of a gradual increase. This might be due to the recursive method for *n*-months ahead forecasts because previous forecasted values were used as known values to project multiple months ahead, causing deterioration of forecasting performance due to the accumulation of forecasting errors [33]. The 24-months ahead seasonal forecast (Figure 5) had great accuracy. The seasonal pattern was captured by the model as the magnitudes of the forecasted values did not deviate much from the actual values. The regular patterns could be forecasted with great accuracy using LSSVM. The poor forecasting accuracy from July 2015 (Figure 7) was due to the flat trend forecasts obtained, which did not forecast the gradual rise in the actual trend. Hence, the passenger forecasts starting from July 2015 were under-forecasted. However, directional changes were forecasted accurately where the rise and fall of passengers were depicted in the forecasts because of the accurate seasonal forecasts.

Figure 8 and 9 show the graphs related to the proposed approach for 24-months-ahead forecasts. In Figure 8, the fitted trend curve for the trend component is shown. The fitted trend curve was superimposed onto the 24-months-ahead seasonal forecasts (Figure 5) to obtain the final forecasts shown in Figure 9. The 24-months-ahead forecasts obtained from the proposed approach of superimposing the fitted trend curve on the LSSVM seasonal forecasts had relatively good accuracy.

The 24-months-ahead forecasts using the direct LSSVM approach are shown in Figure 10. The forecasts had poorer performance, compared to the above-discussed two approaches. The 24-months-ahead forecasts using the SARIMA approach are shown in Figure 11. Forecasting with the SARIMA approach yielded the poorest performance among the four approaches evaluated. The automatic ARIMA modelling procedure from the *forecast* package chose the ARIMA (0, 1, 1) (0, 1, 1) model for the dataset used. The residuals from the fitted model passed the diagnostic check as a p-value higher than the predefined significance level was obtained for the Ljung-Box test and hence the null hypothesis that the residuals are uncorrelated was not rejected.

Based on the actual values and the forecasted values obtained using the SARIMA, direct LSSVM and X-13 LSSVM approaches, the performance measures were computed and are shown in Table 1, for the comparison of the forecasting performance. The proposed approach of superimposing the fitted trend curve on the LSSVM seasonal forecasts was also compared with the other approaches for the 24-months-ahead forecasting horizon.

From Table 1, it can be seen that the 1-month-ahead forecasts obtained using the SARIMA, direct LSSVM and X-13 LSSVM methods had good forecasting accuracy with low magnitude errors. The poorest MAPE for 1-month-ahead forecasts came from the direct LSSVM method, which was only 2.32%. However, only the hybrid X-13 LSSVM had a high D_{stat} value of 0.917. The SARIMA and direct LSSVM methods had a much lower D_{stat} value of 0.792.

This shows that seasonal decomposition was able to improve the accuracy of forecasting directional changes. This is because seasonal decomposition allows for the accurate forecast of the seasonal component, which is the component that determines the directional changes in the data. The poor D_{stat} performance from the SARIMA model is due to its 'backward looking' modelling technique [46].

As the forecasting horizon increased, there was an increase in MAE, MAPE and RMSE across the SARIMA, direct LSSVM and X-13 LSSVM approaches. This was due to the recursive technique used to forecast *n*-months ahead, since multi-steps-ahead forecasting was performed by iterating 1-month-ahead forecasts to *n*-months ahead by using past forecasted values as known values. Hence, there was an accumulation of forecasting errors as the forecasting horizon increased [33]. The SARIMA method had the poorest performance as the forecasting horizon increased, with constant gradual increments in MAE, MAPE and RMSE. The MAE, MAPE and RMSE for the direct LSSVM method were only slightly better than that of the SARIMA method as the forecasting horizon increased. This suggests that the nonlinear forecasting method in the form of the direct LSSVM outperformed the SARIMA linear forecasting method by only a slight margin for MAE, MAPE and RMSE performance measures. The poor ability of the SARIMA method to forecast directional changes was due to its 'backward looking' modelling technique [46].

The hybrid X-13 LSSVM method was superior for longer forecasting horizons for all performance measures considered, compared to the SARIMA model and the direct LSSVM. It was able to provide forecasts of up to the 24-months-ahead forecasting horizon with forecasting accuracy comparable to its 1-month-ahead forecasts. Seasonal decomposition was able to improve the forecasting accuracy for longer forecasting horizons. Seasonal decomposition allowed for a distinct seasonal pattern to be obtained from Changi Airport's air traffic passenger data. Since the data were highly seasonal, accurate seasonal forecasts could improve the overall forecasting accuracy.

The proposed approach of superimposing the fitted trend curve on the LSSVM seasonal forecasts was able to provide 24-months-ahead forecasts with accuracy comparable to that of the X-13 LSSVM approach. A linear curve fitted onto the trend component was found to be an accurate fit. By superimposing the linear curve with the accurately forecasted seasonal component obtained from the LSSVM, it was no surprise that this approach was able to obtain accurate forecasts. Furthermore, the lower RMSE obtained using this approach compared to the X-13 LSSVM method showed that there were fewer instances of high magnitude errors, since RMSE penalized the errors of high magnitude. In other words, the approach of superimposing the linear trend on the seasonal component provided more consistent forecasts over time. This approach could also result in a higher D_{stat} value compared to the X-13 LSSVM, suggesting that a linear forecasted trend curve was able to provide better forecasted directional change performance.

Table 2 shows the overall advantages and disadvantages of the X-13 LSSVM and the proposed approach. Although the X-13 LSSVM approach has good forecasting performance, it requires more efforts to implement, compared to the traditional forecasting methods that are widely accepted due to their simplicity. This is especially so when there is a change in the characteristic of the trend component. This is because new model parameters for the trend component must be identified, which may be time consuming. This is where the proposed approach of superimposing the fitted trend curve on the LSSVM seasonal forecasts addresses this problem, by taking the advantage of the obtained trend component from seasonal decomposition and the forecasted seasonal components from the X-13 LSSVM. Firstly, the fitted trend curve equation can be used to project the trend component into the future without the need to redefine the equation, as long as it gives reasonable accuracy. If there is a change in the characteristic of the trend, it would only require a new curve to be fitted. The new curve would most likely not be complex, since the trend component does not exhibit erratic characteristics. Next, since the seasonal component forecasted by the LSSVM does not suffer from significant errors for longer forecasting horizons, it can also be projected to further forecasting horizons. In other words, the overall process to carry out the proposed approach is easier than the X-13 LSSVM, given that the trend component may exhibit changes after a long period of time.

3.2. Forecasting of Future Air Traffic Passengers

Using the proposed approach of superimposing a linear trend curve on the LSSVM seasonal forecasts, an outlook for the years ahead could be obtained. The 24-months-ahead forecasting for future air traffic passengers starting from the last testing data used is shown in Figure 12.

During the course of this work, the air traffic passengers handled by Changi Airport in December 2015 and January 2016 that were not yet available previously, were released. A comparison of the values obtained from the 24-months-ahead forecasting and the released actual values shows promising results (Table 3).

Based on the forecasts, Changi Airport will operate below its maximum handling capacity of 66 million passengers per annum [47] for the coming two years. In fact, the total number of passengers handled for the year 2017 based on the forecasts is expected to be approximately 61 million, 92% of the maximum handling capacity of Changi Airport. With the expected completion of Terminal 4 by 2017, the total handling capacity would be increased to 82 million passengers [47]. In other words, the construction of Terminal 4 is timely, as it increases the handling capacity before the maximum handling capacity is reached, relieving the operating strain on the existing three terminals.

With the expected completion of Terminal 5 by 2025 which would increase the handling capacity of Changi Airport by another 50 million passengers per annum [48] it is ideal that the number of passengers handled prior to 2025 to be below the maximum handling capacity of 82 million passengers before the operation of Terminal 5. An estimation of the number of passengers handled for the year 2025 was obtained by taking the sum of the forecasted passengers from the linear trend for the months in 2025, without superimposing the seasonal component onto the trend component. The estimated annual passengers handled for the year 2025 was found to be 80 million, which is just under the maximum handling capacity that Changi Airport would have with the four terminals. Hence, this suggests that the opening of Terminal 5 in 2025 is an ideal period to begin operations.

4. CONCLUSIONS

To determine an appropriate method to forecast the air traffic passenger numbers of an important Asian hub airport, four methods were considered. Results showed that the SARIMA, direct LSSVM and X-13 LSSVM approaches could provide accurate 1-month-ahead forecasts. As forecasting horizon increased, there was a decrease in forecasting accuracy due to the recursive techniques in multi-step-ahead forecasting. This phenomenon was more apparent for the SARIMA and direct LSSVM methods, but was less so for the hybrid X-13 LSSVM approach. The X-13 LSSVM approach could provide accurate forecasts for longer forecasting horizons with the performance comparable to that of its 1-month-ahead forecast. This was due to the ability of the X-13 LSSVM method to accurately forecast the seasonal component, which heavily influenced the time series and had little changes over time.

Besides the magnitudes of forecasting errors, accurate forecasting of directional changes is also important. The hybrid X-13 LSSVM methods outperformed the SARIMA method in terms of forecasting directional changes, suggesting that a nonlinear forecasting method provided better directional accuracy compared to a linear forecasting method in the form of the SARIMA.

Although the X-13 LSSVM approach has good forecasting performance, it requires more efforts to implement, compared to the traditional forecasting methods that are widely accepted due to their simplicity. New model parameters for the trend component must be identified, which may be time consuming. This is where the proposed approach addresses this problem. The fitted trend curve equation can be used to project the trend component into the future without the need to redefine the equation, as long as it gives reasonable accuracy. The overall process to carry out the proposed approach is easier than the X-13 LSSVM.

By simplifying the forecasting of the trend component and subsequently taking the advantage of the accurately forecasted seasonal component from LSSVM, the proposed approach of superimposing a linear trend curve on the LSSVM seasonal forecasts could provide 24-months-ahead forecasts with accuracy close to that of the hybrid X-13 LSSVM approach. Lower RMSE and higher D_{stat} were obtained, showing that there were fewer instances of high magnitude errors and that a linear forecasted trend curve could provide better forecasted directional change performance. This approach is different from the X-13 LSSVM, and it is easier to implement.

Overall, the hybrid X-13 LSSVM method outperformed the SARIMA and direct LSSVM methods in terms of the performance measures across all forecasting horizons. The proposed approach was easier to implement compared to the X-13 LSSVM, and could provide comparable forecasting accuracy for the 24-months-ahead forecasting horizon.

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Appendix

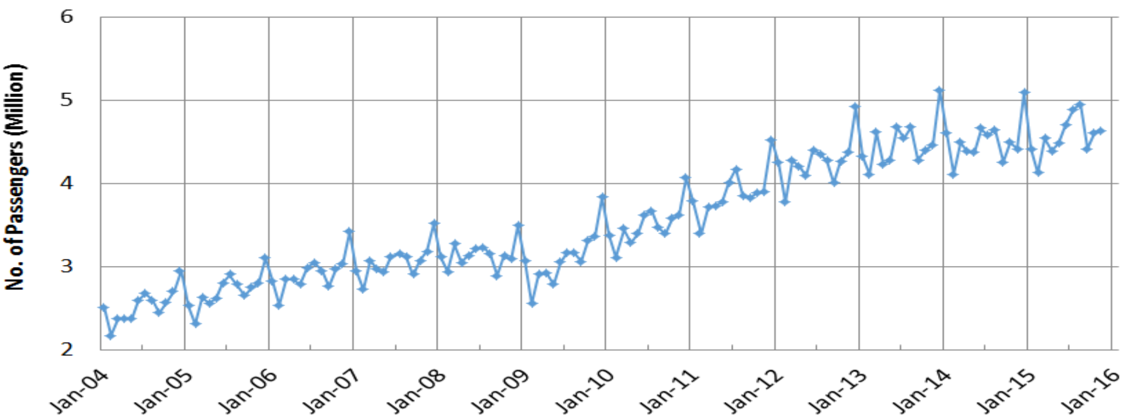

Figure-1. Monthly passengers handled by Changi Airport from Jan 2004 to Nov 2015.

Source: This figure was plotted based on the data in Government of Singapore [29].

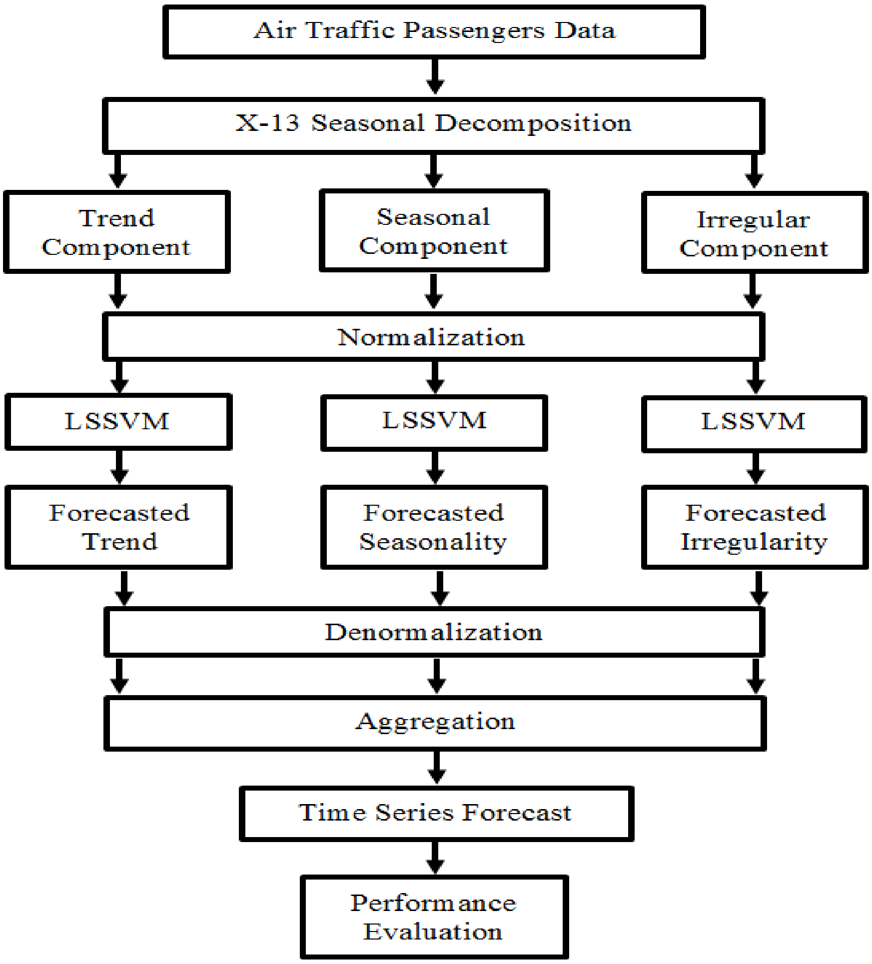

Figure-2. The process diagram of the hybrid X-13 LSSVM forecasting approach [14] with normalization that is not required in Xie, et al. [14].

Source: The process flow diagram in Xie, et al. [14] was redrawn [45] with normalization that is not required in Xie, et al. [14].

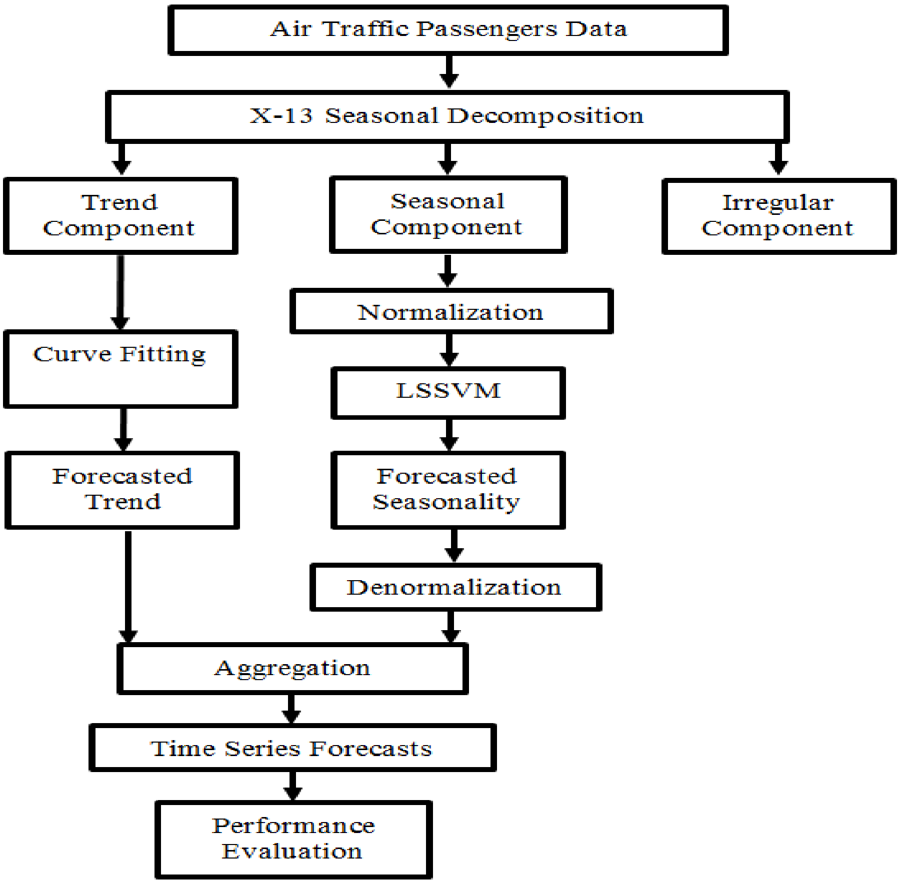

Figure-3. The process flow diagram of the proposed approach (fitted trend curve superimposed on the LSSVM seasonal forecasts).
Source: Vu [45]

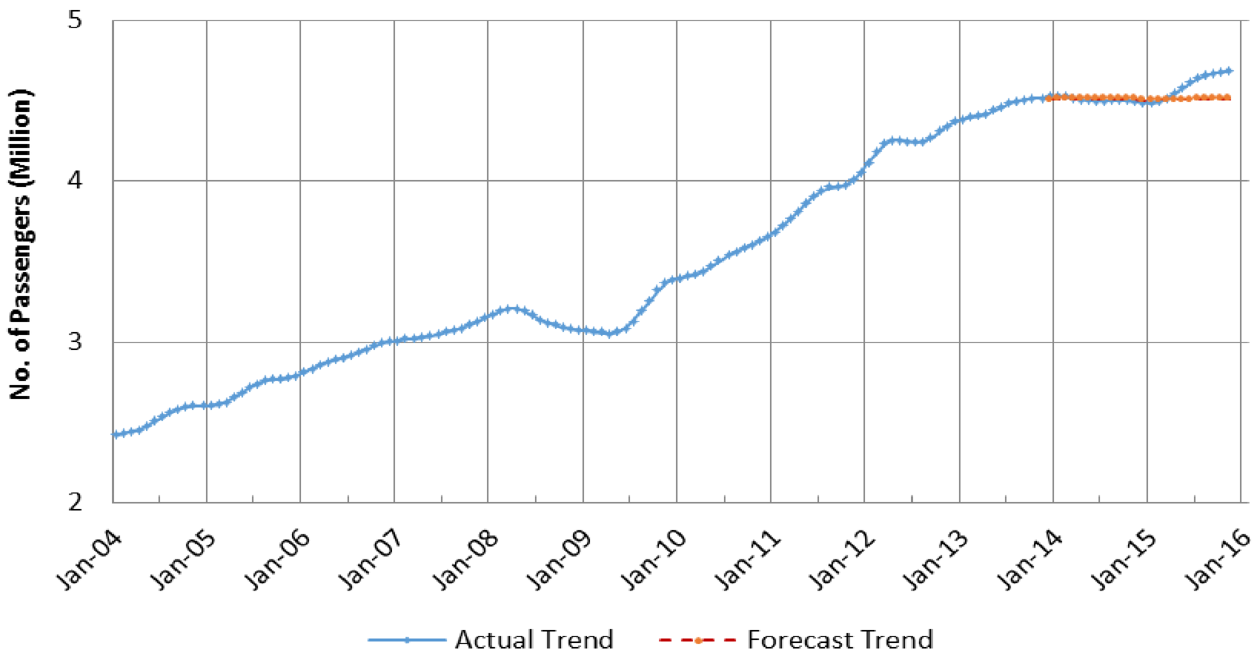

Figure-4. Comparison of the 24-months-ahead trend forecasted using the LSSVM and the actual trend
Source: The actual trend was obtained based on the analysis of the data in Government of Singapore [29].

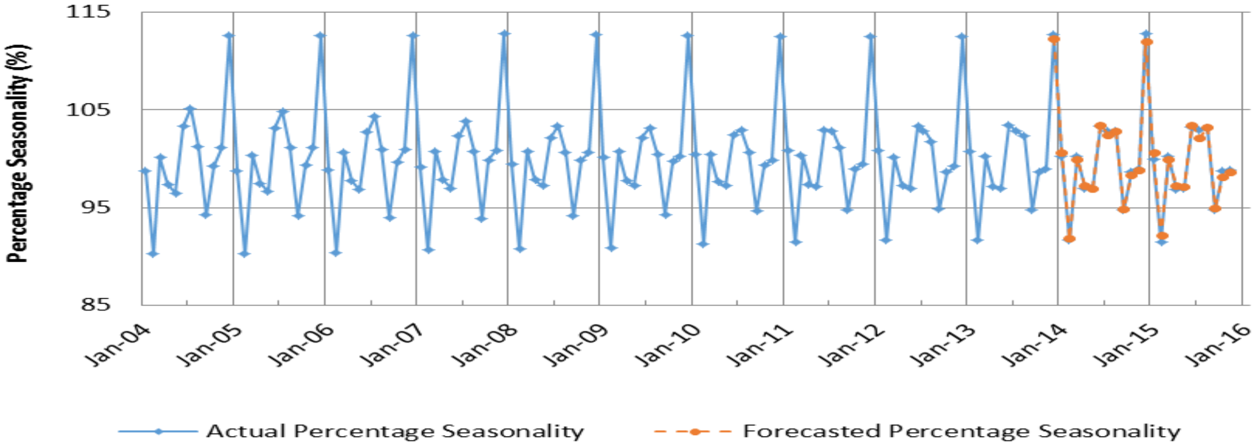

Figure-5. Comparison of the 24-months-ahead percentage seasonality forecasted using the LSSVM and the actual percentage seasonality.
Source: The actual percentage seasonality was obtained based on the analysis of the data in **Government of Singapore [29]**.

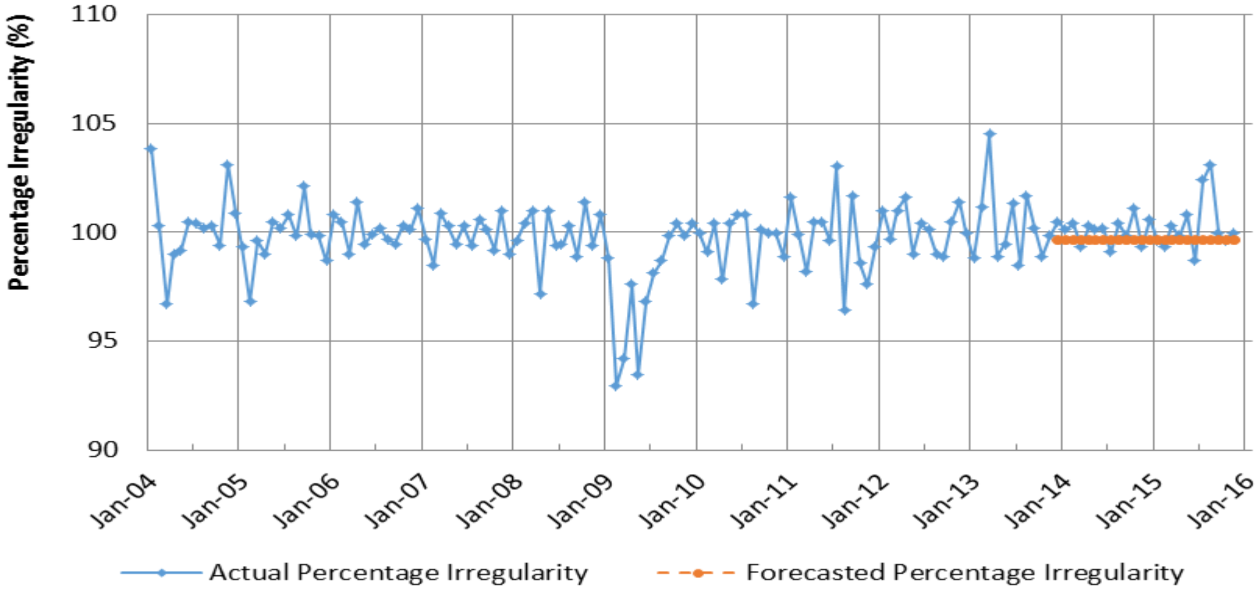

Figure-6. Comparison of the 24-months-ahead percentage irregularity forecasted using the LSSVM and the actual percentage irregularity.
Source: The actual percentage irregularity was obtained based on the analysis of the data in **Government of Singapore [29]**.

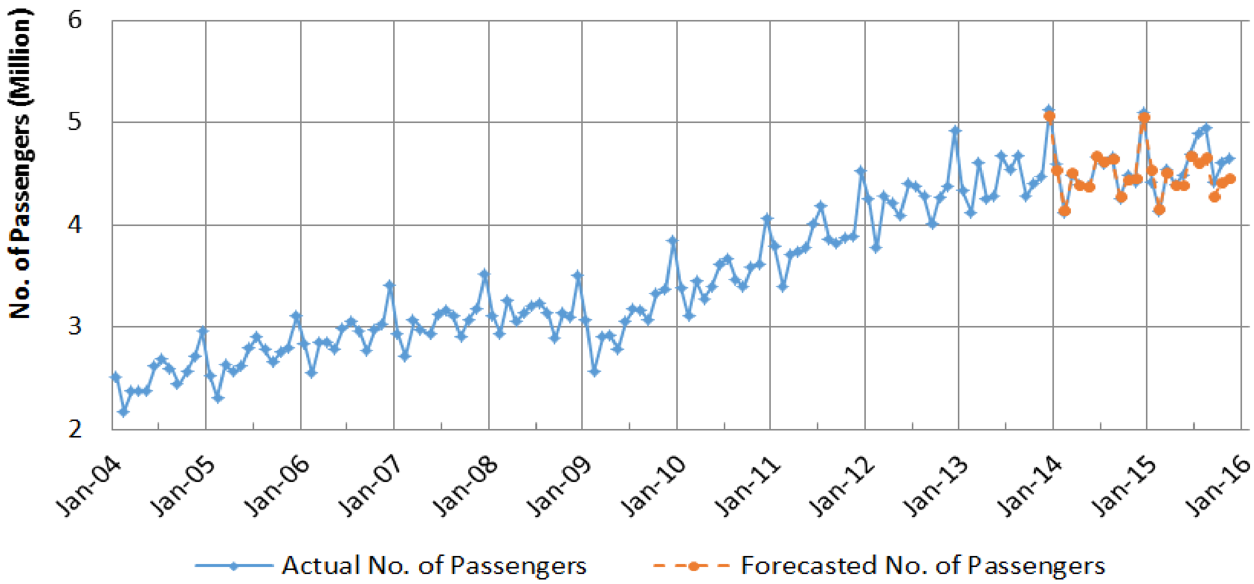

Figure-7. Comparison of the 24-months-ahead passenger numbers forecasted using the hybrid X-13 LSSVM and the actual passenger numbers.
Source: The actual No. of passengers was plotted based on the data in **Government of Singapore [29]**.

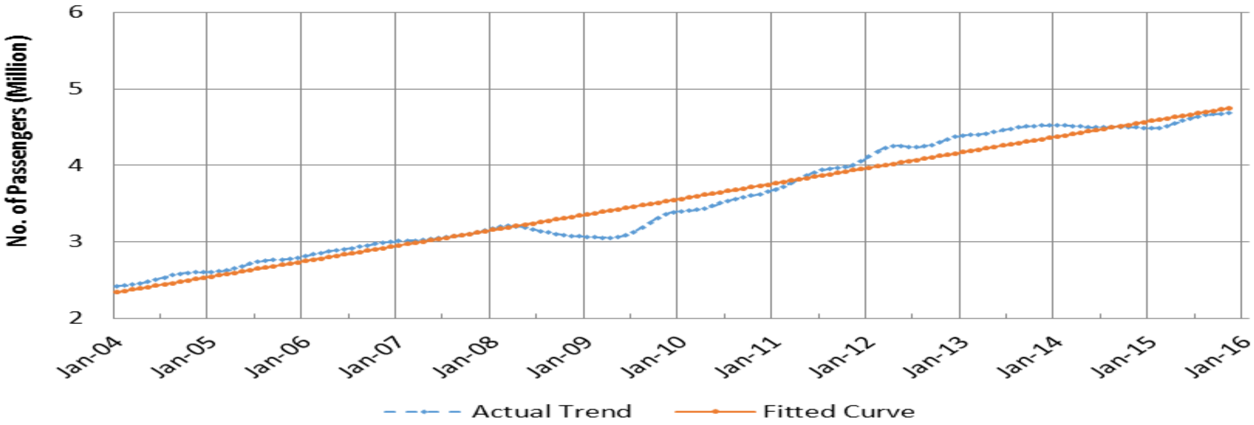

Figure-8. Comparison between the fitted linear trend curve and the actual trend

Source: The actual trend was obtained based on the analysis of the data in **Government of Singapore [29]**

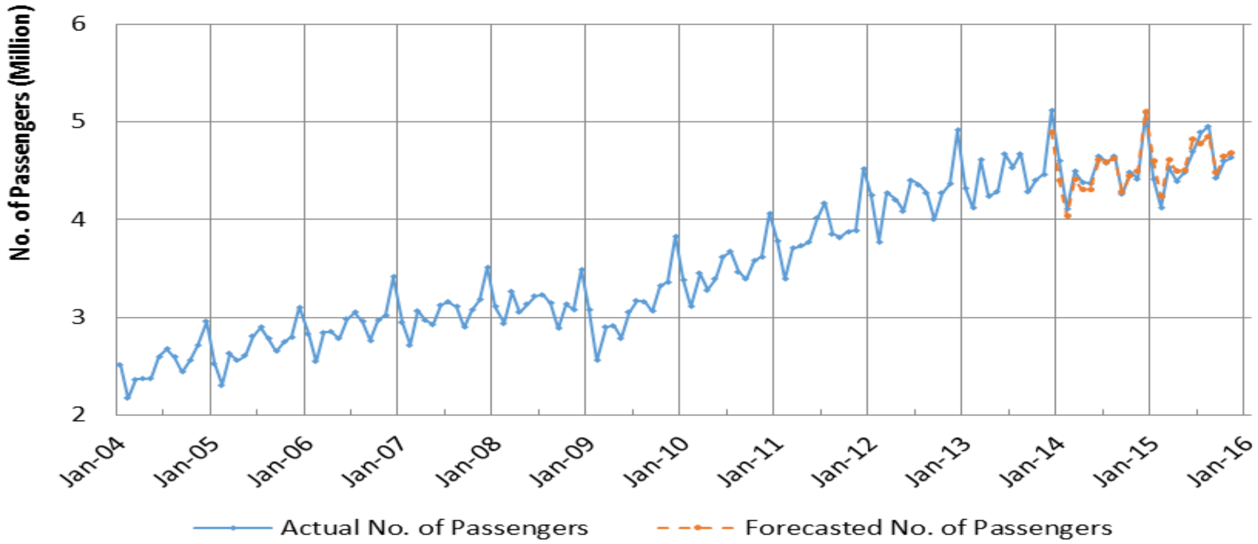

Figure-9. Comparison of the 24-months-ahead passenger numbers forecasted from the superimposing of the fitted trend curve on the LSSVM seasonal forecasts and the actual passenger numbers.

Source: The actual No. of passengers was plotted based on the data in Government of Singapore [29].

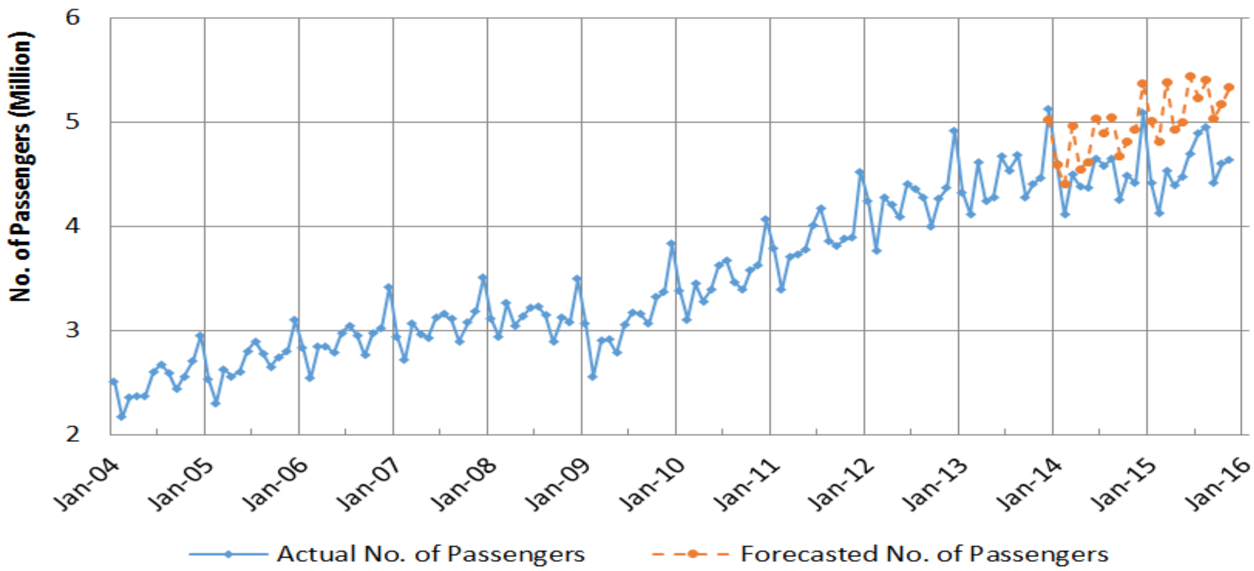

Figure-10. Comparison of the 24-months-ahead passenger numbers forecasted using the direct LSSVM and the actual passenger numbers.

Source: The actual No. of passengers was plotted based on the data in Government of Singapore [29].

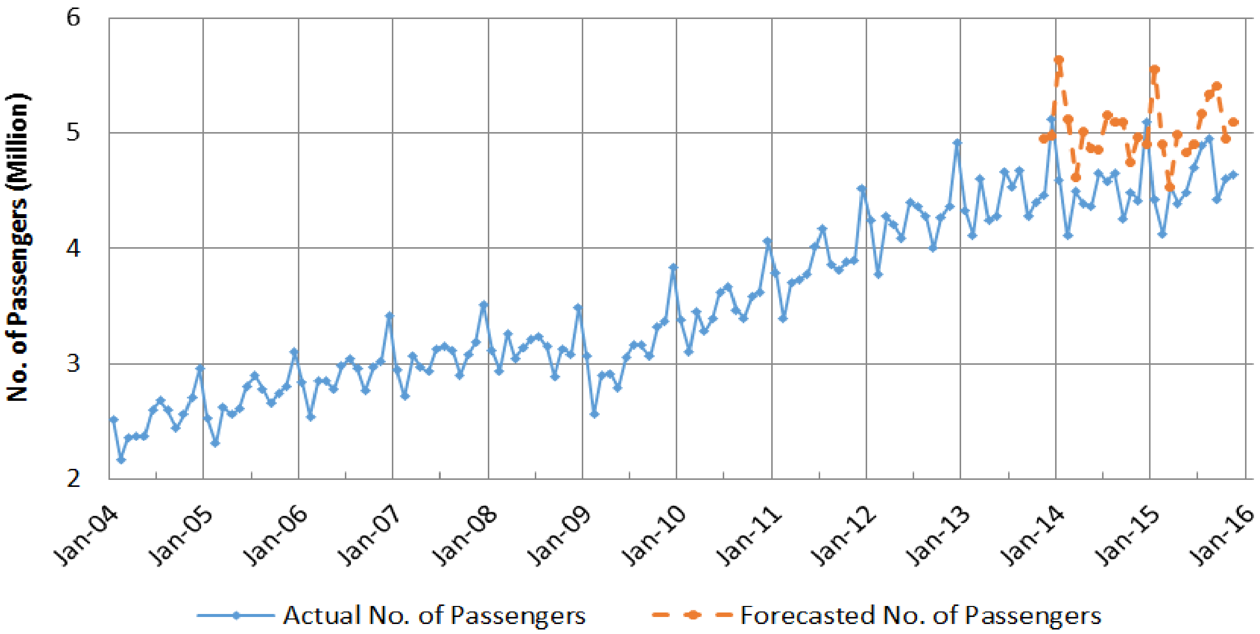

Figure-11. Comparison of the 24-months-ahead passenger numbers forecasted using the SARIMA model and the actual passenger numbers.
Source: The actual No. of passengers was plotted based on the data in Government of Singapore [29].

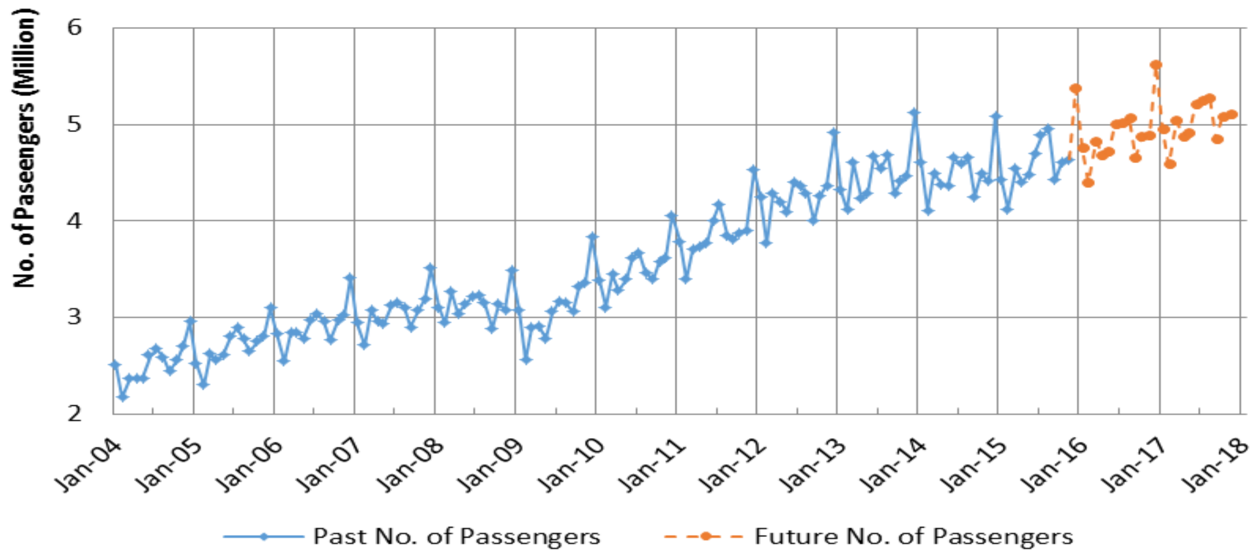

Figure-12. 24-months-ahead future passenger forecasting.
Source: The past No. of passengers was plotted based on the data in **Government of Singapore [29]**.

Table-1. Comparison of performance measures of the approaches (the number of predictions =24; the forecasting period = Dec 2013 to Nov 2015)

n-months ahead	Method	MAE (10^4)	RMSE (10^4)	MAPE (%)	D_{stat}
1	**SARIMA**	8.44	10.23	1.84	0.792
	Direct LSSVM	10.47	14.19	2.32	0.792
	X-13 LSSVM	6.04	9.71	1.30	0.917
12	**SARIMA**	24.29	34.01	5.32	0.708
	Direct LSSVM	19.98	25.13	4.45	0.708
	X-13 LSSVM	7.08	10.79	1.52	0.833
24	**SARIMA**	50.20	59.28	11.28	0.542
	Direct LSSVM	43.61	48.07	9.65	0.667
	X-13 LSSVM	7.55	11.22	1.62	0.833
	Linear Trend + Seasonal Forecasts	8.17	9.92	1.79	0.917

Source: The values in this table were computed using the actual data in **Government of Singapore [29]** forecasted values and Equations (13)-(16).

Table-2. Advantages and disadvantages of the X-13 LSSVM and linear trend seasonal LSSVM.

Method	Advantages	Disadvantages
X-13 LSSVM	• Better MAE and MAPE performance	• Trend component forecasts are not accurate for long forecasting horizons • Re-identifying trend model parameters may be time consuming
Linear Trend + Seasonal Forecasts	• Better RMSE and D_{stat} performance • Allows for forecasts of long forecasting horizons	• Fitted curve may be difficult to identify for complex trend characteristics

Source: This table is presented based on this study [45].

Table-3. Comparison between forecasted values and previously unavailable actual data

	Forecasted Value	Actual Value	Percentage Error (%)
December 2015	5379403	5293165	1.63
January 2016	4766519	4860156	1.93

Source: The actual values were from **Government of Singapore [29].**