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EXPLORING ARIMA, ANN, SVM AND REGRESSION WITH ARIMA ERRORS FORECASTING METHODS WITH APPLICATION TO AIR PASSENGER DATA

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Abstract. *The emergence of machine learning methods which found applicability in time series forecasting, motivated more recent researches and a challenge for choosing appropriate forecasting methods. This study explored the performance of four forecasting methods: autoregressive integrated moving averages (ARIMA), artificial neural networks (ANN), support vector machines (SVM) and regression models with ARIMA errors. To improve their performance, bootstrap aggregating (bagging) was applied. The performance of the different methods was illustrated using South African air passenger data collected for planning purposes by the Airports Company South Africa (ACSA). The results of the accuracy measures illustrated that the regression model with ARIMA errors outperformed all the other methods, followed by the ARIMA model. The results of the training and the test data sets show that the ANN method is prone to overfitting. The bagged models showed mixed results with marginal improvement on some of the methods for some performance measures. It can be concluded that the traditional statistical forecasting methods (ARIMA and the regression model with ARIMA errors) performed better than the machine learning methods (ANN and SVM) on this data set.*
Keywords: Time series forecasting, Autoregressive integrated moving averages (ARIMA), Artificial neural networks (ANN), Support vector machines (SVM), Regression model with ARIMA errors, Bootstrap aggregating (bagging), Air passengers

1. **Introduction.** Forecasting is an essential planning tool for organizations, enabling them to better understand the future. One of the most critical steps in the forecasting process is choosing and fitting suitable models.

In recent years there has been an increase in the number of time series forecasting methods available to the forecaster. This is mainly due to the emergence of the machine learning methods, which also found applicability in time series forecasting. These methods include the artificial neural networks (ANN) and support vector machines (SVM). The increase in the number of time series methods has also presented some challenges when deciding on the forecasting methods to consider for evaluation. The motivation for this research is to explore traditional statistical and machine learning forecasting methods, and compare their performance on forecasts using air passenger data. Trend and seasonal components are usually identified in air passenger data and the behaviour of the forecasting methods under these conditions is of interest. The forecasting methods identified were the autoregressive integrated moving average (ARIMA), ANN, SVM and regression with ARIMA errors. Bootstrap aggregating (bagging), which is popular in machine learning and is used to improve the accuracy of the predictors, was applied to all the methods

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to investigate improvement. The results indicated that the ARIMA and regression with ARIMA errors performed best for this data.

The literature shows wide applicability for these forecasting methods. These include [1, 2, 3] for ARIMA, [4, 5, 6] for ANN, [7, 8] for SVM and [9] for regression models with ARIMA errors. A comparison of some of these forecasting methods can be found in [10, 11].

Time series forecasting is widely used in aviation to forecast air passenger demand. The application of time series methods to forecast this demand in the literature includes studies by [12, 13, 14, 15]. An ensemble empirical mode decomposition (EEMD)-Slope-SVMs was proposed by [12]; this modelling approach is based on the SVM modelling framework. They used air passenger data from selected airlines in the United Kingdom and the United States for comparing the use of the SVM, Holt-Winters and ARIMA methods. Single moving average and simple exponential smoothing methods were used by [13] to forecast demand for air passengers in Nigeria. Bagging and Holt-Winters methods were combined to forecast demand for air passengers using data from 14 different countries [14]. An application of neural network forecasting in an airline can be found in [15]. They compared the method with traditional forecasting methods and the results showed promising performance. The performances of the traditional statistical forecasting methods were compared with the machine learning methods by [11]. The results showed that the traditional statistical methods outperformed machine learning methods and the authors concluded that there is still a lot of work required to improve machine learning methods for forecasting. The most recent algorithms of machine learning methods were applied in this research.

The forecasting methods investigated in Section 2 are ARIMA, ANN, SVM, regression models with ARIMA errors and bagging. Accuracy measures to compare the performance of different methods are summarized in Section 3. An application to South African air passenger data is illustrated in Section 4, with conclusions in Section 5.

2. Forecasting Methods.

A compact description of the methods follows.

2.1. ARIMA.

An ARIMA model assumes that all the information needed to predict the future is contained in the history of the time series. The model can be represented by the notation ARIMA(p, d, q). The variables p and q represent the order of the AR and the MA part of the model, respectively. The d represents the order of differencing and corresponds to the I in ARIMA. If the time series is not stationary in the mean, one needs to take the first difference of the series. If, after differencing, the series still shows signs of non-stationarity, then further differencing can be done until the series becomes stationary. For a seasonal time series, a seasonal difference is recommended. If the time series remains non-stationary after seasonal differencing of the data, first differencing can be applied to the resulting data.

2.2. ANN.

There are two main network designs for the ANN method, namely feed-forward networks and recurrent networks. The feed-forward network (FFN) design has all the arcs of the network pointing forward, while the recurrent network allows for information to be fed back to the previous nodes in the network. The FFN model is called a multi-layer perceptron (MLP) and uses a network consisting of three layers, namely the input, hidden and output layers, which are connected by acyclic links. As input, each node gets a weighted sum of the nodes in the previous layer. Then a transfer function is applied to the input nodes and the relevant output is weighed to produce the final output. Some variants of the ANN model use the feed-forward network. The time-lagged neural networks and seasonal artificial networks are also suitable for time series forecasting.

2.3. **SVM.** The SVM model uses the structural risk minimization principle which aims to minimize the upper bound of the generalization error. This may be compared to the traditional neural networks, which use an empirical risk minimization principle. The advantage of using SVM is that it is able to generalize to unseen data. The solution found by SVM is always unique and optimal and this therefore guarantees that the solution found is not a local minimum. To use the SVM for time series analysis, the concept of support vector regression (SVR) needs to be understood. The method is discussed by [16] and uses an ϵ-intensive loss function. The idea is to penalize errors that lie outside the ϵ-tube created. This tube is formed symmetrically around the estimated function with a minimal radius. Small values are desirable as they minimize the error of misclassification. The least square version of the SVM was formulated by [17] and uses the equality constraint instead of the inequality constraint. It employs a sum-squared error (SSE) cost function, instead of the quadratic program used in traditional SVM. The dynamic least squares support vector machine (DLS-SVM) is derived from the LSSVM. According to [18], the method works well on time series data and real-time systems. The goal of the DLS-SVM procedure is to ensure that the model adjusts to the nonlinear dynamics in the data over time. This is achieved by removing older observations from the training data and replacing them with the latest observations when they become available and the model is refined accordingly.

2.4. **Regression with ARIMA errors.** An ARIMA$(p, 0, 0)$ or AR(p) model is defined as

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \tag{1}$$

where c is a constant term, ϕ_i is the ith autoregressive parameter and e_t is the error term at time t.

If Y_{t-i} for $i = 1, 2, \ldots, p$ are replaced by $X_{i,t}$ where $X_{i,t}$ are independent variables, then Y_t becomes a multiple regression model. Equation (1) can now be rewritten as

$$Y_t = c + \phi_1 X_{1,t} + \phi_2 X_{2,t} + \cdots + \phi_p X_{p,t} + e_t. \tag{2}$$

In multiple regression analysis the error term e_t is assumed to be an uncorrelated series. If this assumption is relaxed and correlated errors are allowed for, then Equation (2) becomes a regression model with ARIMA errors. The error term is modelled as an ARIMA process and represented by N_t.

The method of ordinary least squares estimation cannot be used for this type of regression where the errors are correlated as this leads to incorrect estimates of the parameters. This problem is caused by the autocorrelated errors from the model, while the other problem is that autocorrelated errors may lead to spurious regression. Instead, a generalized least squares estimation or method of maximum likelihood estimation is recommended. A procedure to fit a regression model with ARIMA errors is found in [19].

2.5. **Bootstrap aggregating.** Bootstrap aggregating, also known as bagging, was first suggested by [20]. In time series analysis, bagging is achieved by randomly generating new time series that are similar to the original time series with the aid of a bootstrap method. With this approach, the inputs to the model are bootstrapped and copies of possible predictors are estimated from the bootstrapped inputs. An aggregate of the output of these predictors is then used as the final output of the model. Variations are the moving block bootstrap (MBB), the dependent wild bootstrap (DWB) and the tapered block bootstrap (TBB) bagging procedures.

3. **Accuracy Measures.** The error of a forecast, $e_t = Y_t - F_t$, is defined as the difference between the actual value Y_t and the forecast value F_t of the series. Some well-known accuracy measures from the literature used in this study are summarized in Table 1.

TABLE 1. Accuracy measures for forecasting

Accuracy measure	Acronym	Formula
Mean error	ME	$\frac{1}{n}\sum_{t=1}^{n} e_t$
Root mean squared error	RMSE	$\sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$
Mean absolute error	MAE	$\frac{1}{n}\sum_{t=1}^{n} \mid e_t \mid$
Mean percentage error	MPE	$\frac{1}{n}\sum_{t=1}^{n}\left(\frac{Y_t-F_t}{Y_t}\right) \times 100$
Mean absolute percentage error	MAPE	$\frac{1}{n}\sum_{t=1}^{n}\left\lvert\left(\frac{Y_t-F_t}{Y_t}\right)\right\rvert \times 100$

A smaller value of the accuracy measure indicates a closer forecast to the true value. The method with the smallest value can be regarded as performing best.

4. **Application.** In this section, the selected methods are applied to air passenger data.

4.1. **The time series.** The time series consists of 94 observations, the total number of air passengers passing through major South African airports per month and pertains to the period between April 2012 and January 2020 obtained from the Airports Company South Africa website [21].

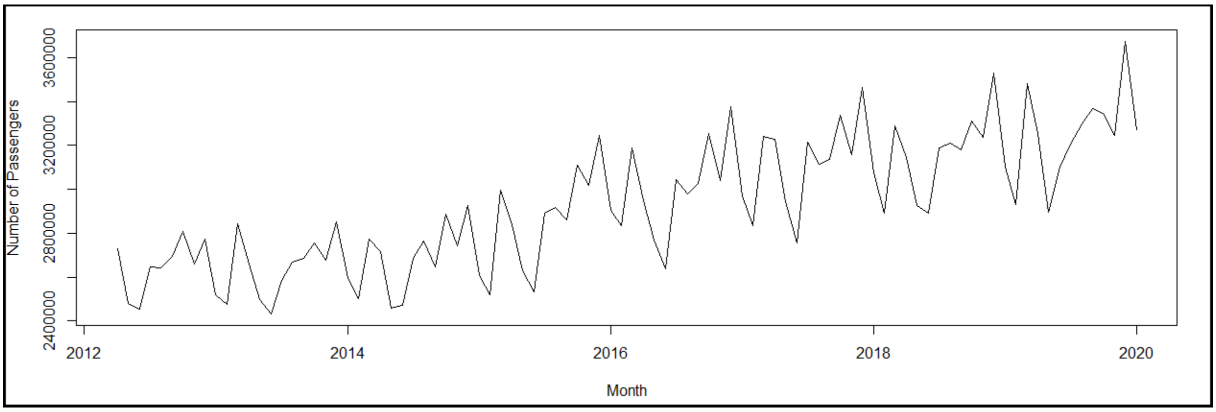

FIGURE 1. Passengers passing through South African airports from April 2012 to January 2020

Figure 1 shows an upward trend and signs of seasonality, where passenger numbers are at their highest for the year in December and March, and lowest in June. The peaks correspond to the summer holiday season in the southern hemisphere, while the lows correspond to the winter season. The visibility of trend and seasonality means that the series is not stationary in the mean. The slight variation in the level of seasonality over time was left as it is.

For the purpose of fitting the different forecasting methods, the last 12 months of the data were reserved as a test set. The data used for fitting the models will be referred to as the training set and the remaining observations will be referred to as the test set.

4.2. **ARIMA model.** The R function `auto.arima()` from the forecast package was used to fit a suitable ARIMA model for the time series. An ARIMA$(0,1,1)(0,1,1)_{12}$ model with MA parameter -0.6038 and seasonal MA parameter -0.4723 was chosen to fit the air passenger data best. There is a normal differencing of order one, together with a 12-month seasonal differencing of order one.

4.3. **ANN model.** The `nnetar()` function in the R forecast package implements a feed-forward neural network with a single hidden layer and lagged inputs for forecasting univariate time series [22]. This function allows for an automatic model selection of an ANN model and was used in this section to fit ANN models for the time series data under investigation. An ANN model can be written as $\mathrm{NNAR}(p, P, k)_m$, where k is the number of hidden nodes, the parameter p is the number of lagged inputs and P is the number of seasonal lags. The parameters P and p are equivalent to the order of the seasonal AR and the order of non-seasonal AR in the ARIMA model respectively and m is the length of the season. An $\mathrm{NNAR}(5, 1, 4)_{12}$ model was identified for the passenger data. This model contains a network with five input nodes, four hidden nodes and one lagged seasonal input.

4.4. **SVM model.** In fitting the SVM model, the e1071 package in R written by [23] was used to fit the time series for the passengers. The function `tune.svm()` allows for the fitting of an SVM model and automatically tunes the model based on the intervals provided for the different parameters of the SVM model. The automatically tuned model parameters for the series are 1, 0.08 and 0.1 for the Cost, Gamma and Epsilon, respectively.

A method, seasonal support vector regression, for forecasting time series data with a seasonal component was suggested by [24]. The modelling procedure begins by splitting the time series into its basic components. The time series is then deseasonalized and an SVM model is fitted to the deseasonalized time series. In order to select optimal values for the parameters, a hybrid genetic algorithm and tabu search called GA/TS are used. Finally, the forecasts are produced by combining the forecasts from the SVM with the seasonal estimates from the decomposition method.

In order to account for seasonality in the SVM model fitted to air passengers, a similar methodology is followed, but instead of using the GA/TS method for fitting the SVM, the e1071 package was used to fit the deseasonalized time series. The air passengers time series was decomposed by means of seasonal and trend decomposition using Loess (STL). The R function `mstl()` was used to decompose the time series. Using the `tune.svm()`, the values of the parameters were calculated as 1, 10 and 0.1 for Cost, Gamma and Epsilon, respectively.

4.5. **Regression model with ARIMA errors.** To fit a regression model with ARIMA errors, the same function used for fitting a normal ARIMA model was used. In addition, an argument `xreg` was used to allow for the fitting of the regression part of the model. The argument takes on a vector of inputs equal in size to the time series under investigation. A vector of length 94 was generated, which should be of the same size as the time series under investigation. This new time series was used in the argument `xreg` of the function for the time series under investigation.

A regression model with $\mathrm{ARIMA}(0, 0, 1)(1, 0, 0)_{12}$ errors was identified with an intercept of 2 589 233.25, a slope of 7 366.131, an MA coefficient of 0.4125 and a seasonal AR coefficient of 0.8687 as parameters. This model indicates that the error series is seasonal and there is no differencing.

4.6. **Performance of the methods.** Table 2 shows the performance of the different models on both the training set and test set.

Based on the value of RMSE, the selected ANN model produced the minimum of 33 035 for the training set and performs best on the data series. This model is followed by the seasonal SVM model with an RMSE value of 46 472. The $\mathrm{ARIMA}(0, 1, 1)(0, 1, 1)_{12}$ model followed, with an RMSE value nearly twice the minimum value at 59 604. The original SVM model came in last with an RMSE value of 157 773. This is more than four times the RMSE value of the best performing model. The ordering of the models based on the

TABLE 2. Performance measures of the fitted models

Method	Data set	ME	RMSE	MAE	MPE	MAPE
ARIMA	Training set	5 957.163	59 604.470	46 273.640	0.184	1.585
	Test set	21 071.795	91 643.330	81 043.460	0.566	2.503
ANN	Training set	−37.640	33 034.940	27 062.850	−0.029	0.936
	Test set	59 915.340	96 902.880	76 799.790	1.757	2.299
SVM	Training set	40 732.090	157 772.900	122 457.300	1.167	4.312
	Test set	98 522.520	126 370.700	103 313.600	2.958	3.124
Seasonal SVM	Training set	333.694	46 472.390	38 307.370	−0.014	1.338
	Test set	78 768.870	130 327.000	104 566.900	2.294	3.174
Regression with ARIMA errors	Training set	−1 457.905	79 724.410	65 069.170	−0.168	2.280
	Test set	13 201.449	83 800.700	73 454.360	0.296	2.266

best RMSE is the ANN, seasonal SVM, ARIMA$(0,1,1)(0,1,1)_{12}$, regression model with ARIMA$(0,0,1)(1,0,0)_{12}$ errors and SVM.

The same performance and ordering can also be observed for MAE. The absolute errors remained high for SVM and low for the ANN model. Looking at MAPE, the chosen ANN model achieved a value below a percentage point on the training set, followed by the seasonal SVM model with MAPE of 1.34%. All the models produced values of MAPE that are below 5%.

For the test set, the RMSE for the regression model with ARIMA$(0,0,1)(1,0,0)_{12}$ errors produced the minimum value of 83 801 and performs best compared to the other models. This was followed by the ARIMA$(0,1,1)(0,1,1)_{12}$ model with an RMSE value of 91 643. Similar to the training set, the original SVM produced the worst results on the test set compared to the other methods with an RMSE value of 126 371 for the model fitted to the test set of the original data and 130 327 on the seasonal SVM model.

The performance of the models when compared using the value of the MAE shows that the regression model with ARIMA$(0,0,1)(1,0,0)_{12}$ errors remained the best method, with an MAE of 73 454. This regression model was followed closely by the ANN method, with an MAE of 76 800. The chosen SVM model and seasonal SVM model were placed last with the highest MAE values.

The regression model with ARIMA$(0,0,1)(1,0,0)_{12}$ errors remained the best model on all the measures considered, producing an MAPE of 2.266, a minimum compared to the other models. This model was closely followed by the ANN model, with an MAPE of 2.299. The SVM performed the worst on all the measures considered here, even though the model performance improved on the test set compared to the training set.

Although the worst performing model, the selected SVM model is the only model that showed improved results on the test set when compared to the training set. All other models showed degrading performance on the test set. For example, the selected ANN model performed better on the test set but could not replicate this performance on the test set.

4.7. **Bagging the models.** The models were bagged to see if their performances can be improved on the test set. Ten different time series were created by using a bootstrap method on the training set. Thereafter a forecasting model was fitted to each time series for a given forecasting method and grouped by forecasting method. Forecasts were then produced for each time series using the fitted model. Finally, the mean of the forecasts for each month was taken as the forecast for the month. This new time series, consisting of mean forecasts, was compared with the test set. Table 3 shows the performance of the bagged models on the test set.

A comparison of the bagged models with regard to the MAPE shows that the bagged ANN model performed better than the other bagged models, with an MAPE of 2.384. This

TABLE 3. Performance measures of the fitted bagged model on test data

Model	ME	RMSE	MAE	MPE	MAPE
Bagged ARIMA	92.573	89 638.360	81 783.800	−0.096	2.537
Bagged ANN	44 257.040	94 523.970	78 785.180	1.262	2.384
Bagged SVM	50 870.190	212 405.000	165 450.700	1.164	5.060
Bagged seasonal SVM	86 413.900	134 573.000	108 178.400	2.527	3.272
Bagged regression model with ARIMA errors	2 664.602	89 255.480	80 148.470	−0.036	2.476

was followed by the bagged regression model with ARIMA errors, which had an MAPE of 2.476. The bagged model that performed the worst on the value of the MAPE was the SVM model. This model produced an MAPE of 5.06. Interestingly, all the models still performed worse than their original counterparts on this measure of performance. The same order of performance was also observed for the MAE. The bagged ANN model produced the lowest MAE of 78 785.

On the values of the RMSE, the bagged regression model with ARIMA errors performed better than the other bagged models with an RMSE value of 89 255. This was closely followed by the bagged ARIMA model which produced an RMSE value of 89 638. The bagged regression model with ARIMA errors also produced the best MPE absolute value of 0.036 followed again by the bagged ARIMA model with an MPE absolute value of 0.096.

5. Conclusions.

The fitted models were explored and compared using forecast accuracy measures such as the ME, RMSE, MPE, MAE and MAPE. The artificial neural network NNAR$(5, 1, 4)_{12}$ model outperformed the other models on the training data, performing better than the other models on most of the accuracy measures used. This model was followed by ARIMA$(0, 1, 1)(0, 1, 1)_{12}$. The regression model with ARIMA$(0, 0, 1)(1, 0, 0)_{12}$ errors came out third overall. Based on the performance of the models on the test set, the regression model with ARIMA$(0, 0, 1)(1, 0, 0)_{12}$ errors performed better than the other methods on the air passenger data. The ARIMA$(0, 1, 1)(0, 1, 1)_{12}$ model again came second, which shows the consistency of the ARIMA method in general. The SVM models performed worst on this data set according to the accuracy measures despite being the only models that showed an improved performance on the test set. Although the selected ANN model was the best on the training data, it failed to emulate that performance on the test set. Consequently, the SVM and ANN models failed to perform better than the regression with ARIMA errors and the ARIMA models.

A bagging procedure using a moving block bootstrap was also applied to the time series in order to improve the performance of the different forecasting methods. There was an improvement in the performance of the bagged ANN and ARIMA models when the values of the RMSE and MPE were compared, but these results did not influence the order of performance of the original models. It is therefore evident that bagging helps to reduce bias in a forecasting model.

For this study, it can be concluded that the traditional statistical forecasting methods (ARIMA and regression model with ARIMA errors) performed better than the machine learning methods (ANN and SVM) on this data set. This is in line with a study conducted by [11]. The application of the forecasting methods to data sets in other sectors might result in other methods performing better.

Future studies on the development of a comprehensive framework that guides the identification of methods to be considered for evaluation will enhance the field of forecasting.

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