Chapter 30
Inflation Rate Modelling Through a Hybrid Model of Seasonal Autoregressive Moving Average and Multilayer Perceptron Neural Network

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ABSTRACT

This study examines the performance of seasonal autoregressive integrated moving average (SARIMA), multilayer perceptron neural networks (MLPNN), and hybrid SARIMA-MLPNN model(s) in modelling and forecasting inflation rate using the monthly consumer price index (CPI) data from 2010 to 2019 obtained from the South African Reserve Bank (SARB). The forecast errors in inflation rate forecasting are analyzed and compared. The study employed root mean squared error (RMSE) and mean absolute error (MAE) as performance measures. The results indicate that significant improvements in forecasting accuracy are obtained with the hybrid model (SARIMA-MLPNN) compared to the SARIMA and MLPNN. The MLPNN model outperformed the SARIMA model. However, the hybrid SARIMA-MLPNN model outperformed both the SARIMA and MLPNN in terms of forecasting accuracy/accuracy performance.

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INTRODUCTION

Time series predicting is indeed a very powerful and essential area of interest that has grabbed the thinking of academics worldwide. Time series forecasting helps in better preparation for the future. It is widely applied in the field of econometrics, weather forecasting, finance, and engineering. Based on historical values, the ultimate goal is to establish a model where future values can best be predicted (Datta, 2011). Time series forecasting focuses primarily on collecting and analyzing past values to create models that best understands the underlying characteristics of the time series data.

Many time series models have been in use for years to improve the effectiveness and the reliability of predictions. These time series models can either be classified as univariate or multivariate models. Univariate models consist of one variable and observations of that variable are recorded consecutively over the same spaced time intervals, whereas in contrast, multivariate time series models are applicable where there is more than two variables with their respective observations (Chatfield, 2000).

There are a number of commonly applied models to modelling and forecasting time series. Amongst a few, there is Exponential smoothing where the series is decayed into a trend and seasonal element. Other approaches include Multiple Linear Regression (MLR). The disadvantage of using MLR is that it assumes that there is a linear relationship between the predictor and the dependent variables. Both Support Vector Regression (SVR) and MLR are applied in modelling multivariate time series data.

The Autoregressive Integrated Moving Average (ARIMA) model or the Box-Jenkins method is one of the most widely used and acknowledged statistical models of time series forecasting. Furthermore, The Seasonal Autoregressive Integrated Moving Average (SARIMA) model, in particular, includes a seasonal component and is used to capture seasonal trends existing in a time series. Time series modelling and forecasting have often been applied in various fields of econometrics, weather forecasting, finance and engineering (Hyndman & Athanasopoulos, 2018). However, forecasting financial time series is more complex and challenging due to nonlinear trends and random walks, that is where the application of Artificial Neural Networks (ANNs) or simply Neural Networks (NN) came into play.

ANNs are the recent and most widely used methods to forecast and resolve challenges faced by linear models in forecasting more complex and nonlinear time series data. ANNs have the ability to detect any underlying structures in the data, making them appropriate for usage in forecasting. Without human interference, ANNs can automatically learn how to implement predictions on their own (Zhang, Patuwo, & Hu, 1998). There are several kinds of feed-forward artificial neural networks, one type includes a feed-forward Multilayer Perceptron Neural Networks (MLPNNs).

Cang (2011) defines Multilayer Perceptron Neural Networks (MLPNNs) as a type of the Neural Network that is trained to approximate any function, does not make any assumptions regarding the distribution/structure of the data and can model highly nonlinear and irregular data or functions. These types of models are built on the basis of biological neural networks. There has been a lot of development in research in terms of applying hybrid models in forecasting time series data. Most scholars have applied the same logic and argued that this system can improve the forecasting performance of the model.

(Areekul, Senjyu, & Yona, 2010; Ghahnavieh, 2019; Khandelwal, Adhikari, & Verma, 2015; Prayoga, Suhartono, & Rahayu, 2017) suggest that hybrid models can be efficient means of improving the predictive reliability obtained by either of the separately used models. Essentially, the hybrid approach is a mixture of two or several model types. These kinds of models appear to increase the reliability of predictions in forecasting the time series. Motivated by these researches, this study sought to compare the forecasting performance of SARIMA, MLPNN and a hybrid SARIMA-MLPNN in terms of modelling and forecast-