

# Chapter 69

## Modelling and Forecasting Portfolio Inflows: A Comparative Study of Support Vector Regression, Artificial Neural Networks, and Structural VAR Models

**Mogari I. Rapoo**

 <https://orcid.org/0000-0002-3602-7016>

*North-West University, South Africa*

**Elias Munapo**

*North-West University, South Africa*

**Martin M. Chanza**

*North-West University, South Africa*

**Olusegun Sunday Ewemooje**

 <https://orcid.org/0000-0003-3236-6018>

*Federal University of Technology, Akure, Nigeria*

### ABSTRACT

*This chapter analyses efficiency of support vector regression (SVR), artificial neural networks (ANNs), and structural vector autoregressive (SVAR) models in terms of in-sample forecasting of portfolio inflows (PIs). Time series daily data sourced from Rand Merchant Bank (RMB) covering the period of 1st March 2004 to 1st February 2016 were used. Mean squared error, root mean squared error, mean absolute error, mean absolute squared error, and root mean scaled log error were used to evaluate model performance. The results showed that SVR has the best modelling performance when compared to others. In determining factors that affect allocation of PIs into South Africa based on SVAR, 69% of the variation was explained by pull factors while 9% was explained by push factor. Hence, SVR model is more accurate than ANNs. This chapter therefore recommends that banking sector particularly RMB should use machine learning technique in modelling PIs for a better financial solution.*

DOI: 10.4018/978-1-6684-2408-7.ch069

## INTRODUCTION

Conventional econometric models have been used in modelling portfolio inflows for decades. These econometric models are significant in analysing the data since they are linear in nature while time series data are not as they are nonlinear in nature. This is because the dynamics and patterns of the series are nonlinear whereas the linear models assume a linear structure of the series. The discovery of the financial data being nonlinear has led its centre stage taken in analysing financial data. Nonlinear models have utmost accuracy in analysis series for their best modelling properties, thus, making them the most reliable models in predicting financial time series. Recent development in nonlinear models analyses has proved machine learning models to be better and powerful approximates. These machine learning models have been utilized in analysing time series data in different disciplines. In instances where linear models cannot address the fundamentals of time series data, nonlinear models are used as they capture those fundamentals. Therefore, this chapter investigates whether machine-learning models are effective in modelling portfolio inflows or not using econometric model of Structural VAR to identify the key drivers of portfolio inflows into South Africa and furthermore assess the efficiency and performance of machine learning models namely support vector regression (SVR) and artificial neural networks (ANNs) models in modelling and forecasting portfolio inflows, respectively.

## BACKGROUND

In the literature, the effect(s) of strong wave of portfolio inflows are highlighted; under ordinary conditions capital flows have valuable impacts for developing economies. In a few events, floods of strong portfolio flows have gone before scenes of money related instability, for instance, the Mexican emergency of 1994 and the Asian emergency 1997 (Lo Duca, 2012). As this is the case, the negative effect of portfolio inflows to receiving economies calls for appropriate policies to be put in place, in which case the drivers of these flows may be used in developing these policies.

There are several applications of Support Vector Regression in solving forecasting problems in many fields where the model was successfully applied such as atmospheric science forecasting (Hong, 2009) and financial time series (stock index and exchange rate) forecasting (Cao, 2003). Chen and Wang (2007) employed Support Vector Regression, back-propagation neural networks (BPNN) and Autoregressive Integrated Moving Average (ARIMA) to forecast tourism demand and genetic algorithm was employed to select the optimal parameters of the Support Vector Regression model and show that Support Vector Regression outperforms other selected models. Hong (2009) also employed chaotic particle swarm optimization (CPSO) for choosing parameters for the Support Vector Regression model and showed that CPSO outperforms both the genetic algorithm (GA) and simulated annealing algorithm. Kazem et al. (2013) forecasted stock market prices employing a model based on Support Vector Regression, chaotic mapping and firefly algorithm using a time series data of stock prices, bank shares and intel. They compared their proposed model with Genetic Algorithm based Support Vector Regression (SVR-GA), Chaotic Genetic Algorithm based Support Vector Regression (SVR-CGA), Firefly based Support Vector Regression (SVR-FA), Artificial Neural Networks (ANNs) and Adaptive-Network-based Fuzzy Inference Systems (ANFIS), and revealed that the proposed model outperformed other models. Also, Adebisi et al., (2014) compared artificial neural networks (ANNs) and Autoregressive Integrated Moving Average (ARIMA) models as far as anticipating precision of the stock market data sourced from New York Stock

20 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

[www.igi-global.com/chapter/modelling-and-forecasting-portfolio-inflows/289020](http://www.igi-global.com/chapter/modelling-and-forecasting-portfolio-inflows/289020)

## Related Content

---

### Study and Analysis of Visual Saliency Applications Using Graph Neural Networks

Gayathri Dharaand Ravi Kant Kumar (2023). *Concepts and Techniques of Graph Neural Networks* (pp. 108-131).

[www.irma-international.org/chapter/study-and-analysis-of-visual-saliency-applications-using-graph-neural-networks/323825](http://www.irma-international.org/chapter/study-and-analysis-of-visual-saliency-applications-using-graph-neural-networks/323825)

### Artificial Neural Network for PWM Rectifier Direct Power Control and DC Voltage Control

Arezki Fekik, Hakim Denoun, Ahmad Taher Azar, Mustapha Zaouia, Nabil Benyahia, Mohamed Lamine Hamida, Nacereddine Benamroucheand Sundarapandian Vaidyanathan (2022). *Research Anthology on Artificial Neural Network Applications* (pp. 440-470).

[www.irma-international.org/chapter/artificial-neural-network-for-pwm-rectifier-direct-power-control-and-dc-voltage-control/288970](http://www.irma-international.org/chapter/artificial-neural-network-for-pwm-rectifier-direct-power-control-and-dc-voltage-control/288970)

### VLSI Implementation of Neural Systems

Ashok Kumar Nagarajan, Kavitha Thandapani, Neelima K., Bharathi M., Dhamodharan Srinivasanand SathishKumar Selvaperumal (2023). *Neuromorphic Computing Systems for Industry 4.0* (pp. 94-116).

[www.irma-international.org/chapter/vlsi-implementation-of-neural-systems/326835](http://www.irma-international.org/chapter/vlsi-implementation-of-neural-systems/326835)

### Neural Networks in ECG Classification: What is Next for Adaptive Systems?

G. Camps-Vallsand J. F. Guerrero-Martinez (2006). *Neural Networks in Healthcare: Potential and Challenges* (pp. 81-104).

[www.irma-international.org/chapter/neural-networks-ecg-classification/27274](http://www.irma-international.org/chapter/neural-networks-ecg-classification/27274)

### Artificial Higher Order Neural Networks for Modeling Combinatorial Optimization Problems

Yuxin Ding (2013). *Artificial Higher Order Neural Networks for Modeling and Simulation* (pp. 44-57).

[www.irma-international.org/chapter/artificial-higher-order-neural-networks/71794](http://www.irma-international.org/chapter/artificial-higher-order-neural-networks/71794)