Network and Complex Systems www.iiste.org
ISSN 2224-610X (Paper) ISSN 2225-0603 (Online)
Vol.6, No.4, 2016

A Review of Artificial Neural Networks Application to Stock Market Predictions

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Abstract
The purpose of this paper is to review artificial neural network applications used in the field of stock price forecasting. The field of stock price forecasting has increasingly grown to be an important subject matter for researchers, everyday investors and practitioners in the finance domain as it aids financial decision making. This study brings to attention some of the neural network applications used in stock price forecasting focusing on application comparisons on different stock market data and the gaps that can be worked on in the foreseeable future. This work makes an introduction of neural network applications to those novels in the field of artificial intelligence.
Keywords: Neural Networks, Forecasting Stock Price. Financial Markets, Complexity, Error Measures, Decision Making

1.0 Introduction

The field of stock market forecasting has and is still receiving substantial notice from both practitioners as well as researchers as it is an essential matter for stock fund managers, individual investors and financial analysts amongst other players in the stock markets as postulated by Hsu (2013). The ability to correctly predict future market trends according to Bagheri et al., (2014) is a prerequisite for successful financial market trading. Leung et al., (2000) believes that the success of market trading strategies depends on accurate predictions of stock price movements. Those who will win in today's business world are those with the ability into predicting the future, or at least having some future information upon which they can support their decisions as propounded by Abbassi et al., (2014). This paper is structured as follows; section 2 follows with a review of literature whilst the follow-on section 3 will touch on the different ANNs applications and a conclusion follows in section 4.

2.0 Literature Review

2.1 Stock Market Prediction a Great Challenge

The forecasting of stock price has been one of the biggest challenges to the artificial intelligence community due to complex nature of stock markets according to Naeini et al., (2010). Stock markets are described by Anish and Majhi (2015) are a complex, evolutionary and nonlinear dynamic system whose prediction is considered a challenging task. Chai et al., (2015) is of the view that predicting the stock markets is amongst the most sophisticated and challenging tasks owing its movement to being affected by a multiplicity of factors such as government policy, investor's expectations, global economic situations and correlations with other markets. Concurring with this notion is Kazem et al., (2013); Chavan and Patil (2013); Lu (2013); Hsu(2013); Wong and Versace(2012); Araujo (2012); Mohapatra and Raj (2012); Araujo (2010); Mostafa and Atiya (1996) and Hall(1994) who postulate that financial markets are characterised by high noise, non-linearity, dynamic and deterministically chaotic data, evolutionarity, non-randomness, non-stationarity and volatility. Though financial market forecasting still remains a major challenge for both academia and business according to Zhu (2010), stock markets are amongst the most rewarding and complex systems to model accurately as Salman et al., (1985) and Delnavaz (2014) put it across.

In spite of such challenges to stock price prediction, Taran et al., (2015) propose various methods that have been applied to prediction of stock markets ranging from time series forecasting, statistical analysis, fundamental analysis and technical analysis to technological analysis. Efforts to come up with prediction models has been ongoing with movements form statistical approaches such as Autoregressive Integrated Moving Averages (ARIMA) models - Box et al., (1994), to nonlinear statistical approaches such as Bilenar models(BMs) - Gabr and Rao (1984), General State Dependent models(GSDMs) - McCleland and Rumelhart (1987) and Threshold Autoregressive models (TAMs) – Ozaki(1985). ARIMA models have a limitation that most real world applications involve nonlinear problems and cannot be modelled by this approach which is highly linear assuming stationarity. In addition, Araujo (2010) believes that the nonlinear models are highly technical and mathematical, hence limiting the development of automatic prediction systems This paved way for nonlinear modelling techniques called artificial neural networks which have been successfully applied for nonlinear modelling of time series according to Ferreira et al., (2008). Dase and Pawar (2010) argue that stock index prediction using traditional time series has proven to be a challenging task and advocate for the application of artificial neural networks (ANNs). Also in support of the application of nonlinear methods is Kute and Tamhankar (2013) who believe that the use of analytical methods in time series analysis are no longer the best for predicting stock prices.

2.2 Motivation for Use of Artificial Neural Networks

Artificial neural networks are effective to handle such nonlinear systems. Oliveira et al., (2013) advocates that there is a growing need to develop prediction models that can capture market dynamics and reduce financial markets uncertainty has been noted as evidenced by the various models to stock price predictions. Artificial Neural Networks (ANNs) have great recognition capabilities and pattern classification - Zhang et al., (1998). The strength of ANNs is that they are non-parametric and data-driven models which need no strong model assumptions and have the ability to chart whichever nonlinear function exclusive of a priori assumption as regards the properties of the data as McNelis (2004) explains. Thus, an outstanding advantage of using ANNs as elucidated by Oliveira (2011) and Miazhynskaia et al., (2006) is their ability to deal with non-linearity in the data. As a result of ANNs ability to deal with complex, nonlinear chaotic information, discovering nonlinear relationships in the data set without a priori assumption of knowledge between the input and output, they are increasingly being applied to the field of financial time series forecasting. The past decade has witnessed increased stock price prediction initiatives using artificial neural networks in varying stock markets, both developed and emerging markets.

3.0 ANNs Applications

Through a novel and interesting approach to model the nonlinear nature of stock markets, Lu et al., (2009) proposed a Nonlinear Independent Component Analysis - Support Vector Regression (NLICA-SVR) model to predict the Nikkei 225 closing price index. This model outperformed its alternate models namely the single SVR, the PCA-SVR and the LICA-SVR by having the smallest error rates namely the root mean square error (RMSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) and highest directional accuracy (DA). Kao et al., (2013) also developed a NLICA-SVR replicative study in the Nikkei 225 and Shanghai Stock Exchange Composite (SSEC) with similar comparisons and obtaining akin results. In an endeavour to optimise the model, Lu (2013) advanced the NLICA-SVR model into a NLICA-SVR-PSO model which was contrasted to a LICA-SVR-PSO, KPCA-SVR-PSO, PCA-SVR-PSO, NLICA-SVR, SVR-PSO, and single SVR model in the Taiwan Stock Exchange (TAIEX Closing Index), SSEC and Indian Stock Market (BSE) and it outperformed its alternate models.

Taking a similar approach, Dai et al., (2012) also conducted a stock market prediction exercise in the Shanghai B-Share and Nikkei 225 Closing Indices. They proposed a NLICA-BPN model which was compared to a PCA-BPN, LICA-BPN and single BPN and outweighed its alternates by having the smallest error rates (RMSE, RMSPE, MAPE, MAD, and the highest Directional Symmetry (DS)). The importance of independent analysis in stock price prediction still remains an avenue for future research with clear explanation of independent components (ICs) in stock prices a worthwhile consideration. Lu (2010) constructed an ICA-BPN forecasting model which was evaluated in comparison to a single BPN, Wavelet-BPN model and Random Walk model using data obtained from TAIEX and Nikkei 225 stock exchanges. The proposed method outperformed the alternate models.

Using a different approach, Mohapatra and Raj (2012) applied the Differential Evolutionary based Functional Link ANN (DE based FLANN) to the Indian Stock Market (BSE), INFY and NSE Nifty with the DE based FLANN proving to be a superior prediction model. In addition, Patel and Marwala (2006) also took a novel approach forecasting the JSE All Share Index, NASDAQ 100, Nikkei 225 and Dow Jones Industrial Average (DJIA) Stock exchanges where they modelled a MLP compared to RBF. The highest accuracy level was achieved in the DJIA and the lowest accuracy level recorded in the Nikkei 225 at 72% and 64% respectively with the JSE and NASDAQ having 70.4% and 69% accuracy levels. In a different study by Carpinteiro et al., (2012), the MLP was compared to the SVM and Hierarchical Models (HM) on the Brazilian Stock Market Fund and the HM was found to be better than SVM and even much better than MLP.

MLP models though one of the earliest model architectures is still in very important prediction model architecture. Using a MLP with varying hidden nodes trained with either a gradient descent (GD) or Broyden-Fletcher-Goldfarb-Shanno (BFGS) activation function on the Romanian Stock Market, Ruxanda and Badea (2014) showed that the lowest error is achieved by the model MLP 3-4-1 BFGS 7 T which uses a BFGS training algorithm, 4 hidden nodes and hyperbolic tangent function in the hidden layer. A replicative study was also conducted on the Croatian Stock Market by the same authors and it was still found that a BFGS learning algorithm is a much better option to modelling volatile stock market data. In another study by Olatunji et al., (2013), it was found out that MLP achieves a correlation coefficient in the Saudi Arabia Stock Market. For all of the afore-mentioned applications, technical indicators were used inclusive of the opening price, high, low and closing prices as well as volumes traded amongst some other technical variables.

Comparing ANNs to statistical methods, Ghezelbash and Keynia (2014) performed an analysis between a MLP and statistical and parametric models such as multiple regressions on the Tehran Stock Exchange and the ANN model outperformed statistical methods. Adebiyi et al., (2014) performed a comparative study between ANNs and ARIMA models on the New York Stock Exchange and found out that ANNs had superior performance compared to ARIMA. In addition, Isenah and Olubasoye (2014) also made a comparison between ANN and ARIMA but on the Nigerian Stock Exchange and obtained similar results as found by Adebiyi et al., (2014). The uses of analytical methods in time series analysis are no longer the best for predicting stock price according to Kute and Tamhankar (2013)and ANNs are effective to handle such nonlinear systems In comparison to an ARIMA-GARCH model, Luna and Ballini (2012) applied an Adaptive Fuzzy Inference System (AdaFIS) to forecast the Petrobras Stock Exchange (PETR4) , Sao Paulo Stock Exchange Index (Ibovespa) and the Commercial Exchange rate of Brazillian Real (R$) per USD (BRL/USD).

With the use of another novel approach of Increasing Decreasing Linear Neuron (IDLN), Araujo et al., (2015) performed stock price prediction exercise with the model being compared to ARIMA (statistical model), MLP (ANN model), IMP(morphological NN model) and a SHIF (hybrid model). Data for this experiment was obtained from Banco do Brasil SA (BBAS3), Brasil Foods SA (BRFS3) and BR Malls Participacoes SA (BRML3) counters on the Brazilian Stock Exchange. Findings from this experiment revealed a reliable better performance of the proposed model to its alternates.

Though single ANN architectures have been useful in stock price prediction as compared to statistical approaches, it has been noted that use of hybrid ANNs gives even much better forecasting accuracy. For instance, Kao et al., (2013) used a hybrid approach that integrated wavelet-based feature extraction with MARS and SVR using data from the SSEC, BOVESPI, Nikkei 225 and Dow Jones Indices. In comparison to a single ARIMA, single SVR, single ANFIS, Integrated wavelet-SVR model and integrated wavelet-MARS model, the proposed hybrid model outperformed the other five models proving that hybrid models are better prediction models. Using data obtain on the Dow Jones Index, Araujo (2010) developed a Quantum-Inspired Evolutionary Hybrid Intelligent model (QIEHI) with results approving that hybrid models outperform single models. In this experiment, the QIEHI was compared to a MLP and TAEF (time delay added evolutionary forecasting) model. Pan (2010) proposed a hybrid model of PCR and GAGRNN which was compared to single PCR and single GRNN. The same observation that hybrid models are better predictors than single models was also noted in this experiment which used data from the TAIEX and China Stock Exchange. Delnavaz (2014) implemented a Fuzzy-Neural Network and GA hybrid model which was compared to individual neural networks models obtaining the same results that a combination of models is much better. The experiment was conducted in the Tehran Stock exchange. Similar results were noted in the Wavelet-ANFIS-QPSO-DWT model of Bagheri et al., (2014).

4.0 Conclusion

Although use of single ANNs proved to be a better forecasting technique as compared to statistical techniques, use of hybrid models has even proved to be a much better approach. In addition, more focus has been on Asian markets and a run of such experiments in other markets all over the world is very important to ascertain if the different ANN models are universal or not. A bias on the use of technical input variables in the above mentioned experiments leaves room for future research that also incorporates fundamental and behavioural input variables. With advances in such dimensions, neural network applications will better financial decision making for everyday investors and traders.

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