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Research paper

A survey on net asset value prediction using artificial neural network and its variants

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Abstract

Net Asset Value (NAV) prediction is one of the important financial time series forecasting task as various investors are interested to invest their money in mutual funds. NAV specifies the price at which investors can buy or sell units of a fund. It is calculated on a daily basis. Since the financial market is dynamic and chaotic in nature, it becomes very difficult to predict the NAV. From the literatures, it is found that different nonlinear models using computational intelligence methods have been proposed to predict the financial time series data i.e. stock market index, exchange rate, NAV. The basic objective of different time series prediction models using computational intelligence methods is to improve the prediction accuracy and to reduce the model complexity. This survey is primarily focused on the usage of Artificial Neural Network model and their variants on NAV prediction. The ability to map the nonlinear relationship and the self-adaptive nature of ANN makes it useful in predicting different financial time series data. It is concluded that the performance of different neural network models is superior to other linear models in NAV prediction.

Keywords: *Functional Link Artificial Neural Network; Multilayer Perceptron; Nonlinear; Recursive Least Square; Soft Computing.*

1. Introduction

Financial market has an important role in the economical development of the society [1-2]. In the current financial market, mutual funds are considered as the most common investment tool, where people want to put their money. Mutual funds provide good returns and at the same time involve minimum risks [3-4]. It is not possible to predict the changes occurring in the mutual fund for the common investors and financial advisors, particularly prediction of Net asset value (NAV) of the mutual funds [5]. The mutual fund investors should know the NAV of the trade date of different funds and it helps in evaluating the future performance of those funds before putting their money. NAV plays an important role in the investment strategies. NAV can be calculated as the price per share value of a mutual fund. The asset value of a fund is the total value of all the securities in the fund's portfolio. To determine the per-share value of the fund, the liabilities is subtracted from the asset value of the fund and the result is divided by the numbers of shares. In case of mutual fund, NAV is computed on a daily basis depending on the closing market prices of the securities in the fund's portfolio. Therefore, the NAV prediction of mutual funds is very essential for investors and fund managers.

The NAV forecasting problem can be classified with respect to its linearity behaviour i.e. it can be linear or nonlinear. The linear time series forecasting models can be developed using econometric models such as simple Autoregressive (AR) models, simple moving average (MA) models, and mixed autoregressive moving average (ARMA) models [6-7]. As the historical NAV data is nonlinear, the NAV prediction task is categorized as nonlinear forecasting problem. Soft Computing models such as Artificial Neural Network (ANN), Support Vector Machine (SVM) etc. are efficient in reflecting the nonlinear relationship among the historical financial time series data as compared to traditional statistical forecasting models [8-10]. Various researchers have used ANN and its variants i.e. Multilayer Perceptron (MLP), Functional Link Artificial Neural Network (FLANN) as prediction tools to forecast the different financial time series data. The purpose of our survey is based on the prediction of NAV of different mutual funds along with other financial time series data using ANN and its variants. Our paper is organized as follows. Section 2 describes the general prediction model. Section 3 and 4 describes the use of ANN and FLANN model for NAV prediction. Section 5 includes the conclusion along with the performance measures of different models.

2. General prediction model

From the literatures, it is found that the basic nonlinear financial time series prediction model includes the following steps [1], [11], and [12].

i) Dataset preparation
ii) Procedural definition
iii) Model Training
iv) Model testing and evaluation

These operational steps can be shown in figure 1.The steps are described as follows. The dataset preparation step consists of collecting financial time series data from various sources. Then the statistical indicators are added with these historical data and then the values are normalized. From the dataset, some values are considered for training purpose and some are used for testing purpose. In the procedural definition phase, the prediction model using the soft computing methods is determined and designed. In the model training phase, the designed model is trained using the training dataset and the model parameters are finalized. In the model testing and evaluation phase, the model is validated using the test dataset and different performance measures are evaluated

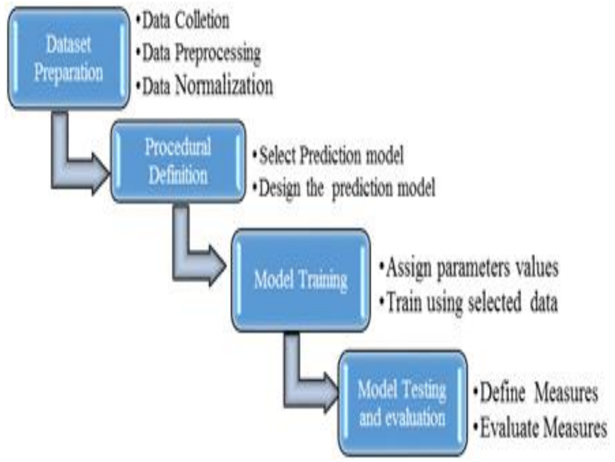

Fig. 1: General Processing Steps of a Prediction Model.

3. ANN model

The literature survey suggest that ANN has become popular in financial time series data prediction due to its data driven and self-adaptive nature. ANN can simulate the nonlinear characteristics of the time series data. Gooijer and Hyndman conducted a survey on time series forecasting from 1982 to 2005[13]. This survey suggested that the use of statistical and simulation methods in time series forecasting. It was found that the ANN was superior to other linear methods and ANN architecture can also be improvised G. Zhang proposed a hybrid model involving both Autoregressive integrated moving average (ARIMA) and Artificial Neural Network (ANN) model to improve the forecasting accuracy of time series data[14]. This work combined the linear nature of ARIMA model and nonlinear nature of ANN model. The performance of the combined model was superior to the individual model. Gurusen, Kayakutlu and Daim used the Multilayer perceptron (MLP), dynamic ANN and hybrid ANN models and compared the performances in predicting the market values [15]. The results obtained using hybrid ANN model was better as compared to other two models. In [16], the authors proposed a novel hybridization of ANN and ARIMA model for the financial time series forecasting and obtained better performance than the traditional hybrid model. A. Moghaddam et al. performed stock market index prediction using different structures of MLP. The authors found the optimized ANN with 3 hidden layers and 20-40-20 hidden neurons [17]. Various researchers have used ANN model for the NAV prediction and shown that the results obtained are superior to the other statistical methods [18-21]. The findings and limitations of their work have been shown in Table-1.

Table 1: NAV Prediction Using ANN Model

Sl No	Authors	Methodology	Findings	Limitations / Future Scope
1	W.C. Chiang, T.L. Urban, G.W. Baldridge [18]	Back Propagation Neural Network Model	The result is superior to traditional economic techniques (Linear and Non-Linear Regression Analysis)	Extensions that are more Powerful may outperform this model.
2	D.C. Indro, C.X. Jing, B.E. Patuwo, G.P. Zhang [19]	Multilayer Perceptron Model and GRG2 Non-linear Optimizer.	The result is superior in forecasting the performance of growth and blend funds to Back propagation and other linear models.	It uses only fund specific operating characteristics. It has to be used under different macroeconomic environment.
3	H. Yan, W. Liu, X. Liu , H. Kong, C. .Lv [20]	Back Propagation Neural Network Model	This method has good nonlinear reflection ability, learning ability and prediction precision.	The predicting model is effective and applicable in forecasting NAV tendency and inflexion of funds.
4	H. Li, H. Zhou, Q. Cai [21]	Back Propagation Neural Network Model	The proposed method is effective for the asset evaluation.	ANN can be combined with other methods for better performance

4. Flann model

FLANN structure consists of only input and output layers without any hidden layers. It is a flat network. So it provides very less computational complexity and uses simple learning algorithm. The functional expansion of input features increases the input dimensions. Various researchers have used FLANN model in financial time series forecasting purpose. R. Majhi et al. applied FLANN model using trigonometric expansion function in predicting the short term and long term stock prices [22]. For training the weights of the FLANN model, they used least mean square (LMS) and recursive least square (RLS) algorithm. The authors concluded that the FLANN model is computationally efficient that other ANN models. For the currency exchange rate prediction between Indian rupees to Japanese Yen, US dollar to British pound, R. Majhi et al. developed a FLANN model and cascaded FLANN model [23] for forecasting of exchange rate. The exchange rate forecasting performance of the cascaded FLANN model was compared with the FLANN and LMS based prediction model through simulation. It was shown that the cascaded FLANN model was relatively better as compared to FLANN and LMS based forecasting model. C. Anish and B. Majhi used the FLANN model for the NAV prediction of different Indian Mutual Funds [24]. The authors compared the prediction performance of FLANN model with MLP and found that the FLANN model was better in terms of Mean Average Percentage Error, Computational complexity and convergence. A. Rout et al. proposed a recurrent computationally efficient FLANN (RCEFLANN) model for the prediction of stock market indices [25]. They determined the optimal weights of the proposed FLANN model using evolutionary algorithms like PSO and DE. The results suggested that the proposed RCEFLANN model was efficient as compared to FLANN trained with DE. C.M. Anish & B. Majhi proposed the Feedback FLANN (FFLANN) method using recursive least square (RLS) training for stock market prediction. This method involved very fast forecasting capability as compared to FLANN and Multilayer ANN (MLANN) [26]. B. Majhi et al. used a hybrid adaptive ensemble model comprising of AMA, Adaptive ARMA and FLANN model for the NAV prediction of different Indian Mutual Funds [27]. The authors concluded that the prediction performance of the ensemble model was better than that of the individual model. The performance comparison of FLANN model with other neural network models for NAV prediction is shown in Table-2 [24, 27].

Table 2: NAV Prediction Using FLANN Model

Sl No	Authors	Methodology	Findings	Limitations / Future Scope
1	C.M. Anish & B. Majhi [26]	FLANN	Computationally efficient, Less Mean Average Percentage Error	FLANN model may be hybridized with other models for better prediction performance
2	B. Majhi et al. [27]	AMA+ARMA +FLANN model	The proposed ensemble model produced better prediction performance with respect to other individual models.	The ensemble model can be applied in different day ahead NAV prediction.

5. Conclusion

From this survey, it is concluded that neural network model has been extensively used in the financial time series data forecasting task, especially in NAV prediction of various mutual funds. The ability of neural network models to handle the nonlinearity and chaotic behaviour of NAV data make them successful and efficient in the forecasting task as compared to other linear models. The review suggests that the prediction performance is measured in terms of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) of the testing NAV data, but the neural network model is trained using the training NAV data. The direction of research is now moving towards application of bio inspired algorithms with neural network models in NAV prediction task.

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