

A Conceptual Framework for Forecasting Noisy Multivariate Financial Time-Series Data

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ABSTRACT

Financial prediction is the manner in which businesses anticipate future projections, by making risky decisions based on the anticipated historical stock market. An example of financial time-series forecasting is stock market prices, nevertheless the process of forecasting is met with numerous difficulties which are obtained by the continuous fluctuations in the daily trading market. Financial data are characterized by nonlinearity, noise, chaotic in nature and volatile thus making the process of prediction cumbersome. The biggest impediment is due to the colossal nature of the capacity of transmitted data from the trading market. Hence, the main aim of forecasters is to develop an approach of forecasting that focuses on increasing profit by being able to predict future stock prices based on current stock data. However the intricacy of stock market prices, there is the need of intelligent forecasting techniques that will reduce decision making risks and predicting future stock market trends.

Keywords: Colossal, intelligent forecasting, stock prices

1. INTRODUCTION

Financial prediction is the manner in which companies envision and strategize for the future, by making marketing decisions based on current and past stock prices. Forecasting is a dynamic process and perplexing task in the financial division for numerous reasons. First, it helps financial market analysts to evade stock trading losses and obtain huge profits by coming up with promising business policies. Hence, financial companies can make precise predictions by being able to “see what interventions are required to meet their business performance targets” [1]. Secondly, the shareholders who are commonly referred to as the stockholders have expectations which are the main cause for concern among trading companies because there usually scrutinized by short and long term shareholders. Stockholders analyse their investments which are in the form of shares by comparing their analysis from the forecaster’s analysis. This scrutiny has an effect on any financial institution because it leads to the lack of trust on any failed financial model presented by financial institutions.

Financial data are characterized by nonlinearity, noise, chaotic in nature and volatile thus making the process of prediction cumbersome. The biggest impediment is due to the colossal nature of the capacity of transmitted data from the trading market. Precise timing of buying and selling stock shares is very important because of the continuous variations of stock prices within the stock exchange. Market volatility is a regular occurrence in any stock market hence in order to avoid the regular instability, accurate timing is important [2]. The main difficulty of stock data is the size of stock data obtained in daily intervals which are massive hence having a direct impact on the ability of performing predictions.

Predictors’ goal is to develop and change numerous techniques that can effectively forecast stock shares with one main objective of following legal trade strategies and avoiding losses. “The central idea to successful stock market prediction is achieving best results using minimum required input data

and the least complex stock market model” [3]. The intricate nature of stock market prediction has led to the need for further improvements in the use of intelligent prediction techniques that would drastically decrease the dangers of inaccurate decision making.

2. RELATED WORK

Financial controllers plan on the major part of any economy thus making finance the central pivotal point. Controllers who adhere to the ideas of an efficient market hypothesis and random walk theories disbelieve that stock market shares are predictable. Nevertheless, fanatics of technical and fundamental analysis have shown numerous ways to counter claim adherents of random walk theory and efficient market hypothesis. Undeniably due to stock’s nature of being highly volatile, this has made forecasting really cumbersome. This directly affects the modelling process of any proposed techniques, thus the need of a near perfect modelling process which is characterized by the highs and lows of market volatility. These problems rise from the trading rates being also volatile in nature as a result of short term variations in demand. Hence, new improvements in the area of soft computing through the use of swarm intelligence have offered new ideas in prediction of noisy data like stock market shares and also modelling its nonlinearity [4].

Computational Intelligence forecasting techniques such as fuzzy logic, genetic algorithms (GA) and artificial neural networks (ANN) are the famous used techniques, since they cope with problems that have not been solved by complex mathematical systems. In recent years, forecasters have turned to artificial neural networks (ANNs) because of its precise nature when applied to numerous applications including the field of engineering. Many unique characteristics of neural networks have made it a preferable tool for forecasting e.g. it is a self-adaptive unique technique that is data feed; another feature is that ANN can generalize applied data on its network as it has a supervised way of learning and ANN can infer applied data like stock prices which are noisy in nature[5].

In recent years, more hybrid forecasting models have been proposed for example, Auto-regressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN) are applied to time series forecasting as it reduces model uncertainty which typically occurs in statistical inference and time series forecasting. Pai and Lin [6] proposed a hybrid methodology to exploit the unique strength of ARIMA models and support vector machines (SVMs) for stock prices forecasting. Chen and Wang [7] constructed a combination model incorporating seasonal auto-regressive integrated moving average (SARIMA) model and SVMs for seasonal time series forecasting. Voort and Watson [8] introduced a hybrid method called KARIMA using a Kohonen self-organizing map and auto-regressive integrated moving average method for short term prediction. Zhou and Hu [9] proposed a hybrid modelling and forecasting approach based on Grey and Box-Jenkins auto-regressive moving average (ARIMA) models. The ARIMA approach is elegant in theory but has been of little practical use in business because of its complexity and limited increase in accuracy over less sophisticated methods.

Data modelling for Kuala Lumpur Composite Index (KLCI) was forecasted [10] using Artificial Neural Fuzzy Inference System (ANFIS). However studies have pointed out that ANFIS can only be applied to prediction tasks where there is only one output unlike the nature of complex financial stock data. Armano, et al. [11] presented a new hybrid approach that integrated artificial neural network with genetic algorithms (GAs) to stock market forecast. Yu, et al. [12] proposed a novel nonlinear ensemble forecasting model integrating generalized linear auto regression (GLAR) with artificial neural networks in order to obtain accurate prediction in foreign exchange market. Kim and Shin [13] investigated the effectiveness of a hybrid approach based on the artificial neural networks for time series properties, such as the adaptive time delay neural networks (ATNNs) and the time delay neural networks (TDNNs), with the genetic algorithms in detecting temporal patterns in stock market prediction tasks. Tseng, et al. [14] proposed to use a hybrid model called SARIMABP that combines the seasonal auto-regressive integrated moving average (SARIMA) model and the back-propagation neural network model to predict seasonal time series data. Khashei, et al. [15] proposed a new hybrid model to overcome the data limitation of neural networks and yield more accurate forecasting model, especially in incomplete data situations.

3. PROPOSED FORECASTING MODEL

Analysis on recent published articles in financial forecasting shows that Artificial neural networks (ANNs) was preferred over the other methods. This is because forecasters have turned to artificial neural networks (ANNs) because of its precise nature when applied to numerous applications including the field of engineering. Many unique characteristics of neural networks have made it a preferable tool for forecasting. However to reduce the limitations of ANN's, there is the need for modifications in the training phase of neural networks. Hence, with the purpose of improving the accuracy of forecasted stock prices, Artificial Neural Network (ANN) has been chosen as the basis of prediction. This study

will hybridize a new nonlinear model which will be used to forecast the Malaysian stock market. The new developed hybrid model will be known as Kalman Back propagation Two Based Swarm Particle Swarm Optimization enhanced with Lavenberg-Marquardt algorithm (KBPSO-LM) Model.

Kalman filter employs the use of observed measurements over time, the data applied for filtration and smoothing contains random variations in the form of noise. Kalman filter will be used in data pre-processing thus making it as a filter method to be used in the process of selecting the minimum subset of features from the datasets based on certain reasonable criteria in order to remove irrelevant and redundant features and hence noise.

One technique commonly used as a supervised learning method is Back propagation (BP) algorithm which is used in training and employs a technique that moves the error signal forward and backward within the network until the least error signal is found. Back propagation algorithm relies on the selection of initial weights and threshold that is normally randomly chosen, thus convergence becomes slow and it easily gets stuck in shallow minimum [16]. Therefore Particle Swarm Optimization technique has been introduced in the new hybrid model to solve these problems by being applied in the training phase to obtain weights and biases that will minimize the error function which is the objective function to be minimized by PSO. The key reasons for selection of Two Based PSO as an optimizing technique in artificial neural network are; its ability to easily model up forming hybrid models, it has few parameters unlike other optimizing techniques which use the same idea of swarm intelligence thus being less time consuming. In training of neural networks, the network tends to converge and getting stuck in the local minima, however when PSO is used the network tends to escape the local minima and its algorithm can be easily programmed and finally it has shown to be a free-derivative algorithm unlike other optimization techniques [17].

After obtaining best possible initial weights the proposed hybrid model will be enhanced using second order method of BPNN which is the Levenberg-Marquardt algorithm that excels in local fast convergence which could avoid falling into local mini-mum. Studies have shown that Levenberg-Marquardt algorithm excels in fast local optimization by calculating the derivatives of the network in terms of nonlinear least squares. Hence by merging the two methods, Two Based PSO will provide great skill in global search and Lavenberg-Marquardt algorithm in local fast optimization.

4. METHODOLOGY

From the above discussions and findings, the methodology for the stock market prediction model will be sub-divided into the following steps:

- i. Collection of stock market data which are categorized as multivariate data.
- ii. The data will be smoothed and filtered then normalized.
- iii. The neural network nodes will be determined i.e. input, hidden and output nodes.
- iv. Two swarm PSO will be used for optimization on parameters in the neural model.
- v. The training phase will be done using LM algorithm.

- vi. The model will generate output as predicted stock market prices.
- vii. Model validation of obtained prices against original stock market prices.

The limitations of nonlinear time series data were identified through previous re-researches as mentioned in the literature review section, the review lead in forming a strong theoretical understanding in coming up with the proposed model. This model will be validated using multivariate data obtained from Bursa Malaysia. The proposed research framework is shown in Figure 1.

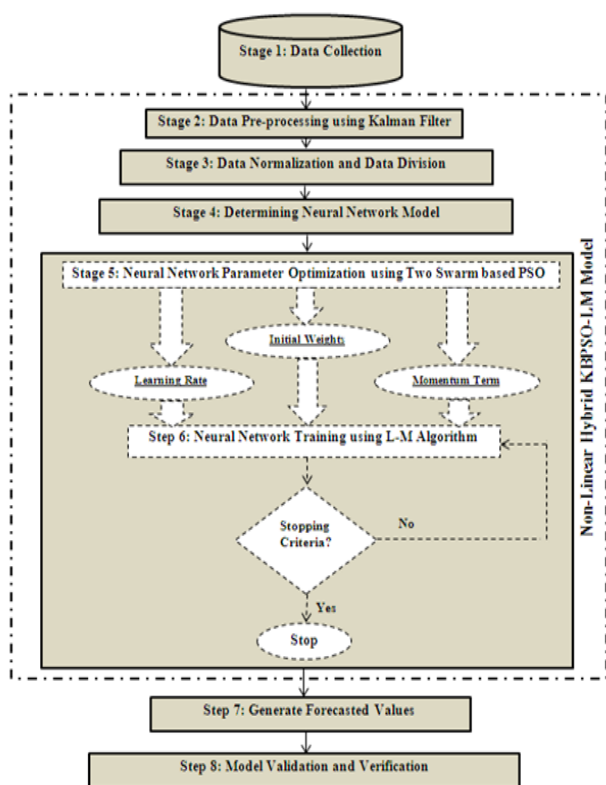


Figure 1: Proposed Research Framework

5. CONCLUSION

This literature survey proposes a present day related problem that can be solved by applying the newly formulated prediction model on stock market data which is an example of financial time series data. A broad argument on the prediction of stock market data and its characteristics are discussed. Hence from previous researches, studies have shown that forecasters goal is to progress on finding numerous ways and approaches that can predict stock market prices with one aim of maximizing profits while following the best legal trading ways. "The central idea to successful stock market prediction is achieving best results using minimum required input data and the least complex stock market model".

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