An Ensembel Model for Modelling Chaotic Behaviour of Bursa Malaysia Time Series Data

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Abstract. Financial data is characterized as non-linearity, chaotic in nature and volatility thus making the process of forecasting cumbersome, hence a successful forecasting model must be able to capture long-term dependencies from chaotic data. In this study, an ensemble model, called UKF-NARX, consists of unscented kalman filter and parallel non-linear autoregressive network with exogenous input trained with bayesian regulation algorithm is modelled for chaotic financial forecasting. The proposed ensemble model is compared with the conventional non-linear autoregressive network and financial static forecasting model employed by financial analysts when applying in multi-step-ahead forecasting. Experimental results on Burssa Malaysia KLCI show that the proposed ensemble model outperforms the other two commonly used models.

Keywords: chaotic time-series, ensemble model, non-linear autoregressive network, financial forecasting.

1 Introduction

Forecasting is a dynamic process and perplexing task in the financial division. 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 forecasts by planning some required interventions to meet their business performance targets [12]. Furthermore, stock trading companies are usually scrutinized by short and long term investors while concerning the expectations from shareholders. Stockholders may also like to analyze their investments by comparing the analysis of forecasting companies.

An example of financial time-series forecasting is stock prices in the share market which are characterized by non-linearity, noisy, chaotic in nature and volatile thus making the process of forecasting cumbersome. The goal of financial forecasters is to innovate a numerous techniques that can effectively forecast by following legal trade strategies and avoiding losses. The general idea of successful stock market prediction is to achieve best results by using minimum required input data and the least complex stock market model [3]. The intricate nature of stock market forecasting has led to the need for further improvements in the use of intelligent forecasting techniques that would drastically decrease the dangers of inaccurate decision making.

Financial controllers who adhere to the ideas of an efficient market hypothesis and random walk theories disbelieve that stock market can be predicted [13]. Nevertheless, fanatics of technical and fundamental analysis have shown numerous ways to counter the claim by adherents of random walk theory and efficient market hypothesis. Therefore, numerous approaches for tackling the chaotic nature of forecasting have been suggested. However, new improvements in the area of soft computing through the use of computational intelligence have offered new ideas in forecasting chaotic data in stock market and also modelling its non-linearity.

In this paper, deriving from computational intelligence method, an ensemble neural network model consisting of unscented kalman filter and parallel non-linear autoregressive neural network is developed to enhance the performance of financial forecasting based on Kuala Lumpur Composite Index (KLCI) data. The remainder of the paper is organized as follows: section 2 outline some related work in financial forecasting and its development; in section 3, the proposed ensemble neural network model is discussed; while section 4 addresses the experimental setup and performance analysis followed by the conclusion in the last section.

2 Related Works

Computational Intelligence forecasting techniques such as fuzzy logic, genetic algorithms (GA) and artificial neural networks (ANN) are the most famous used techniques to cope with problems that have not been solved by complex mathematical systems. ANN applications have been widely used in a variety of areas in financial markets [19], [9], [7], [14], [11]. ANN was used for the solution of numerous financial problems [7]. It is also used in forecasting of financial markets, particularly forecasting of stock market indexes which are considered to be a barometer of the markets in many countries [19, 17]. However, the problem of over-fitting [5] arises when a model describes noise instead of the underlying relationship, hence affecting the accuracy of forecasting. The forecast of Kuala Lumpur Composite Index (KLCI) has been investigated using ANN [19], fuzzy logic [2] and artificial neural fuzzy inference system (ANFIS)[21]. However, ANFIS has strong computational complexity restrictions and translates prior knowledge into network topology hence being sensitive to the number of input variables.

The advances of ANNs over the last few years is its ability of easily allowing more than one model to be combined with itself with multiple training, which is also referred to as ensemble model [5]. This technique has huge advantages because each part of the model performs and captures patterns within the data applied hence increasing the forecasting ability of each model inside the ensemble model. A number of studies have employed the use of ensemble modelling in financial forecasting, such as an ensemble model consisting of neural networks and support vector machines (SVM) [8], a radial basis function (RBF) neural network model ensembles with SVM [16], an ensemble forecasting model integrated with generalized linear auto-regression (GLAR) and neural networks (ANN) [20]. Apart from that, an ensemble of neural networks and fuzzy regression was applied in foreign exchange rate forecasting too [6]. In those previous ensemble models for financial forecasting, they encounter the main issues of vanishing gradient [10] and over fitting [5].

3 Proposed Model

In this paper, an ensemble model, called UKF-NARX model, consists of Unscented Kalman Filter (UKF) and parallel non-linear autoregressive network with exogenous input is proposed to enhance multi-step-ahead forecasting of chaotic financial data. The ensemble model addresses the problem of vanishing gradient [10] experienced in network training by employing the use of bayesian regulation in training of the ensemble model and also the problem of over-fitting [5] by filtering the chaotic data before forecasting. The function of UKF is to create a better forecasting model by filtering the chaotic KLCI data because tiny errors in noise form [1] will be amplified hence affecting the forecasting performance of non-linear autoregressive with exogenous input network.

3.1 Unscented Kalman Filter (UKF)

Unscented Kalman Filter addresses the approximation issues of Extended Kalman Filter[15]. In UKF, a minimal number of sigma points are selected that captures the mean and covariance of the state distribution which are obtained using a gaussian random variable.

The random variable undergoes the process of non-linear unscented transformation. Assuming X has mean $\bar{X}$ and covariance P_k, each sigma point is propagated through the non-linear process model:

$$X_k^{f,j} = f(X_{k-1}^j) \tag{1}$$

The transformed points are used to compute the mean and covariance of the forecast value of X_k:

$$X_k^f = \sum_{j=0}^{2n} w^j X_k^{f,j} \tag{2}$$

$$P_k^f = \sum_{j=0}^{2n} w^j (X_k^{f,j} - X_k^f)(X_k^{f,j} - X_k^f)^T + Q_{k-1} \tag{3}$$

The sigma points were propagated through the non-linear observation model:

$$Z_{k-1}^{f,j} = h(X_{k-1}^{j}) \tag{4}$$

With the resulted transformed observations, their mean and covariance (innovation covariance) computed as:

$$Z_{k-1}^{f} = \sum_{j=0}^{2n} w^j Z_{k-1}^{f,j} \tag{5}$$

$$Cov(\tilde{Z}_{k-1}^{f}) = \sum_{j=0}^{2n} w^j (Z_k^{f,j} - Z_k^f)(Z_{k-1}^{f,j} - Z_{k-1}^f)^T + R_k \tag{6}$$

The cross covariance between $\tilde{X}_k^f$ and $\tilde{Z}_{k-1}^f$ is:

$$Cov(\tilde{X}_{k-1}^{f}, \tilde{Z}_{k-1}^{f}) = \sum_{j=0}^{2n} w^j (X_k^{f,j} - Z_k^f)(Z_{k-1}^{f,j} - Z_{k-1}^f)^T + R_k \tag{7}$$

The information obtained form the time update step is combined with the measurement step Z_k. The gain K_k is given by:

$$K_k = Cov(\tilde{X}_k^f, \tilde{Z}_{k-1}^f) Cov^{-1}(\tilde{Z}_{k-1}^f) \tag{8}$$

The posterior covariance is updated from the following formula:

$$P_k = P_k^f - K_k Cov(\tilde{Z}_{k-1}^f) K_k^T \tag{9}$$

3.2 Recurrent network

Non-linear autoregressive network with exogenous input (NARX) can be easily applied for prediction of time series data with the embedded input reconstruction of the network [18]. Hence, the filtered dataset is then fed into the non-linear autoregressive with exogenous input model in parallel mode as shown in Figure 1, which is mathematically expressed as:

$$y(n+1) = f[y(n), ..., y(n-d_y+1); u(n-k), u(n-k+1), ..., u(n-d_u-k+1)] \tag{10}$$

where $u(n)\epsilon\mathbb{R}$ and $y(n)\epsilon\mathbb{R}$ denote, respectively, the input and output of the model at discrete time step n, while $d_u \geq 1$ and $d_y \geq 1$, $d_u \leq d_y$, are the input-memory and output-memory orders respectively. The parameter of z^{-1} is the unit time which is applied to each input with the same value of 1. The parameter $k(\geq 0)$ is a delay term assumed to be zero hence referred to as the process dead-time.

When gradient algorithms are used for training, the value decreases to zero as the number of time steps increases. This problematic outcome is commonly referred to as the vanishing gradient problem that results in reduced network performance on standard neural network models [10]. In the proposed model, Bayesian regulation is used as a training algorithm to adjust the parameters of the network so as to move the equilibrium in a way that will result in an output that is close as possible to the target output [4].

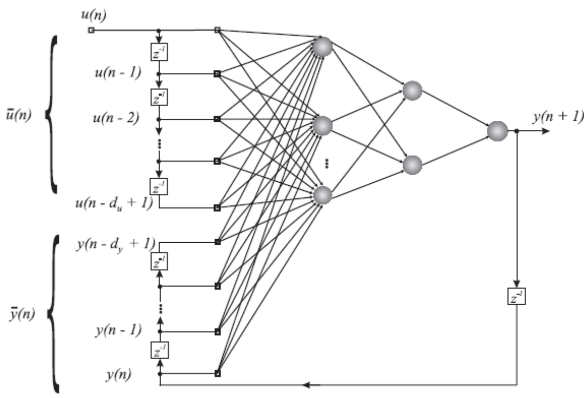


Fig. 1: Parallel-NARX recurrent network architecture.

4 Experimental Setup

The daily financial indices (Kuala Lumpur Composite Index) traded in FTSE Bursa Malaysia are used as real life financial time series datasets to be experimented in this paper. The transaction date was from 12 April, 1988 to 12 April, 2013 with a total of 6524 daily samples over a period of 25 years. 3156 daily data points were used as training data and the remaining 3368 points are used for testing of the proposed ensemble model which translates to around 12 years of forecasting.

UKF with $Q_k = 1$ and $R_k = 0.001$ is used for filtering and the filtered outputs are fed into the parallel non-linear autoregressive with exogenous input network trained using Bayesian regulation algorithm. The P-NARX network was

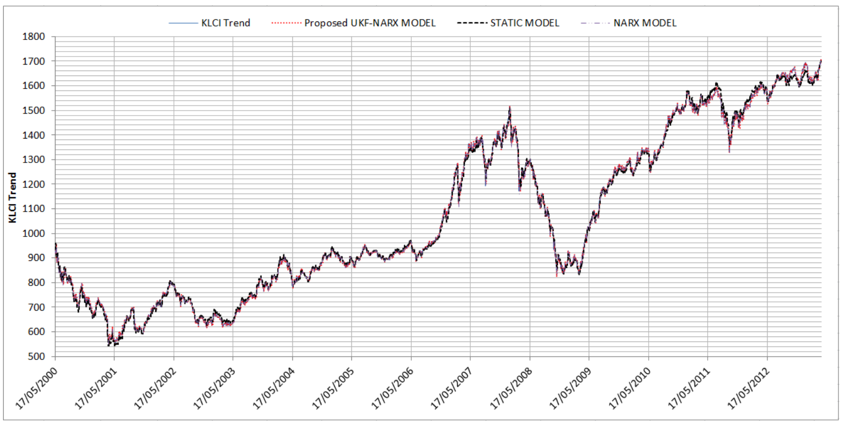


Fig. 2: Graph showing 12 years forecasted KLCI Trend output

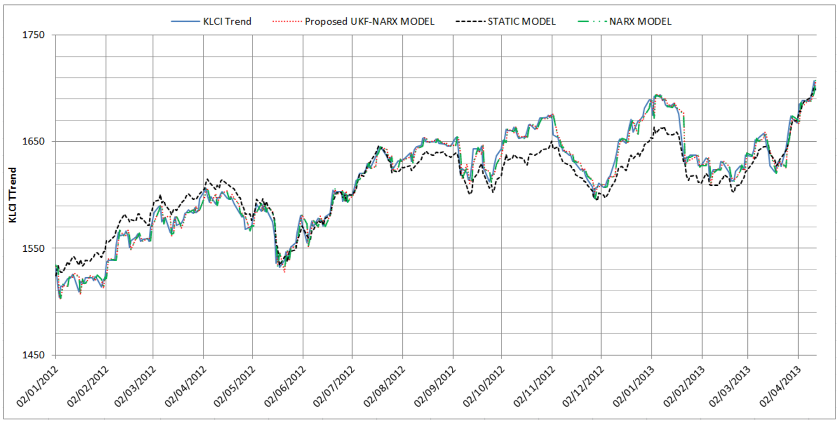
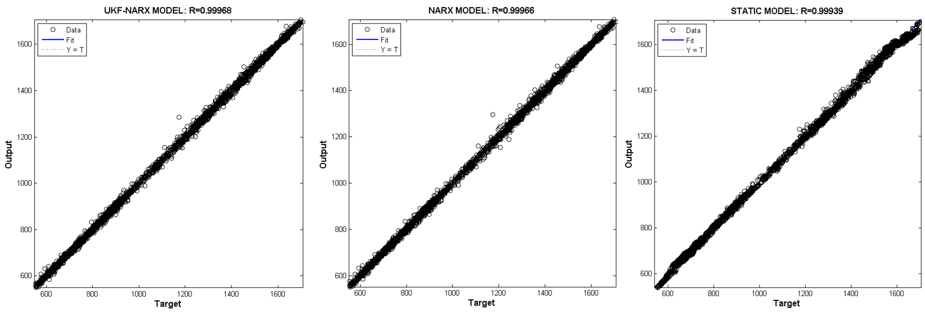


Fig. 3: Graph showing 1.5 years forecasted sample from the total forecasted period of 12 years



(a) UKF-NARX model (b) NARX model (c) Financial static model

Fig. 4: Regression values

set up with 10 neurons in the hidden layer, input delay $d_y = 3$ and feedback delay $d_n = 4$. Figure 2 shows the total forecasted period of 12 years using three different models and an in-depth graphical representation for a period of one and half years is shown in Figure 3.

Three commonly used performance metrics are employed to evaluate the forecasting accuracy in different aspects. Those metrics are Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The obtained forecasting errors from the three models are shown in Table 1. The results show that the proposed UKF-NARX model outperforms other commonly used forecasting models by having the least value of error i.e. 0.5641, 5.7331, 8.3878 for MAPE, MAE and RMSE respectively.

The regression (R) value is obtained by measuring the correlation between the forecasted and target output in the testing phase, the importance of this value is to check the model success in forecasting the dependant variable within

Table 1: Model comparison for forecasted KLCI trend

FORECASTING MODEL	**MAPE**	**MAE**	**RMSE**
Financial Static Model	0.8769	9.0408	11.4886
NARX Recurrent Network Model	0.7654	6.3147	9.9556
UKF-NARX Model	**0.5641**	**5.7331**	**8.3878**

the KLCI sample. The proposed model had a regression value of 0.99969, NARX model had a value of 0.99966 and the static model had a regression value of 0.99939 as shown in Figures 4a and 4. All the three models had an accepted regression value which is closer to the value of 1 translating to a close model relationship with almost a perfect fit.

5 Conclusion

In this study, a novel modelling technique is proposed for multi-step-ahead chaotic forecasting of the KLCI trend. The experimental results showed that the UKF-NARX model outperformed other commonly used models in terms of accuracy and regression value. It should be noted that NARX and static models tested can also be used for forecasting because the error and regression values obtained are within the accepted range. However, in terms of model enhancement, the proposed UKF-NARX model is better for financial forecasting bearing in mind the improved accuracy rate of about 18.7 percent when forecasting for a period of 12 years.

Future research may further explore the selection parameter settings for input and feedback delays in the proposed model and the forecasting effect of increasing the period to over 12 years. Furthermore, the daily KLCI time series trend has not been applied for multi-step-ahead forecasting with a forecasting horizon of over 10 years, hence no model comparison was reported in the literature based on the forecasting horizon.

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