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An Approach to Identify a Model for Efficient Prediction of Exchange Rates Using Setty Volatile Index (SVI)

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ABSTRACT

In recent years forecasting of financial data such as stock market, exchange rate, interest rate and bankruptcy has been observed to be a potential field of research due to its importance in financial and managerial decision making. Survey of existing literature reveals that there is a need to develop efficient forecasting models involving less computational load and fast forecasting capability. Our proposed work aims to fulfill this objective by analyzing and comparing different ANN and Fuzzy models with some specified attributes. These networks involve nonlinear inputs and simple ANN structure with few neurons. The models are functional link artificial neural network (FLANN) as well as Dynamic Radial Basis Functional Networks (RBF) model and hybrid NEURO-FUZZY model.

These models have been tested to predict currency exchange rate between US dollar Indian Rupees and Japanese Yen and also stock market data like US-RUPEE and IBM etc. The performances of the proposed models have been evaluated through simulation and compared with those obtained from other models. Experimental results are compared on basis of various parameters including Normalized Root Mean Square Error (NRMSE), Mean Absolute Percentage Error (AMAPE), Volatility and Error Convergence. An approach is designed with the key parameter SVI (Setty Volatility Index) to classify the dataset and further decide the right model for the prediction problem.

I. INTRODUCTION

1.1 Introduction to Financial Prediction

Financial Forecasting or specifically Stock Market prediction or Exchange rate prediction is one of the hottest fields of research lately due to its commercial applications owing to the high stakes and the kinds of attractive benefits that it has to offer. Forecasting the price movements in financial markets has been a major challenge for common investors, businesses, brokers and speculators. The primary area of concern is to determine the appropriate time to buy, hold or sell. In their quest to forecast, the investors assume that the future trends in the stock market are based at least in part on present and past events and data**.** However financial time-series is one of the most 'noisiest' and 'non-stationary' signals present and hence very difficult to forecast. Many researchers in the past have applied various statistical and soft computing techniques such as neural networks to predict the movements in these finance market indices.

2. A Survey Of Existing Ann Models For Finance market Prediction

A lot of research has gone into the development of models based on a range of intelligent soft computing techniques over the last two decades. Early models employed the Multi-Layer Perceptron (MLP) architecture using Back propagation algorithm, while a lot of recent work is based on evolutionary optimization techniques such as Genetic Algorithms (GA). This section describes briefly some of work that has gone into the field of application of ANN to stock price prediction. In Japan, technology major Fujitsu and investment company, Nikko Securities joined hands to develop a stock market prediction system for TOPIX, the Tokyo based stock index, using modular neural network architecture **[1]**. Various economic and technical parameters were taken as input to the modular neural network consisting of multiple MLP used in parallel. A study was done on the effect of change of network parameters of an ANN Back propagation model on the stock price prediction problem **[2]**. The paper gives insights into the role of the learning rate, momentum, activation function and the number of hidden Neurons to the prediction. In addition to ANN using Back propagation, the Probabilistic Neural Network (PNN) has also been employed to stock prediction **[3]**. In their work, the model is used to draw up a conservative thirty day stock price prediction of a specific stock: Apple Computers Inc. Due to their bulky nature owing to the large training data, the PNN are not popular among forecasters. In the process lots of newer architectures came to the fore (Ornes & Sklansky) **[4]** in their paper present a Visual Neural Network (VNN), which combines the ability of multi expert networks to give low prediction error rates with visual explanatory power of nonlinear dimensionality reduction **[5]** and applied to the TOPIX Tokyo 7 Stock Exchange). The simulations show that MBNN, based on the concept of Universal Learning Networks (ULN), have higher accuracy of prediction than conventional NNs. In their paper, (Chen, Dong & Zhao, 2005) **[6]** investigate how the seemingly chaotic behavior of stock market could be well represented using Local Linear Wavelet Neural Network (LLWNN) technique. Hybrid architectures are also being deployed in recent times (Raymond Lee, 2004) **[7]** propose a Hybrid Radial Basis function Recurrent Network (HRBFN) stock prediction system called the iJADE stock advisor. The stock advisor was applied to major Hong Kong stocks and produced promising results in terms of efficiency, accuracy and mobility. Another Hybrid AI approach to the implementation of trading strategies in the S&P 500 index futures market is proposed by (Tsiah, Hsu & Lai,) **[8]**. The Hybrid AI approach integrates the rule-based systems techniques with Reasoning Neural networks (RN) to highlight the advantages and overcome the limitations of both the techniques. Hiemstra proposes a fuzzy logic forecast support system to predict the stock prices using parameters such as inflation, GNP growth, interest rate trends and market valuations **[9]**. According to the paper, the potential benefits of a fuzzy logic forecast support are better decision making due to the model-based approach, knowledge management and knowledge accumulation Another effort towards the development of fuzzy models for stock markets has been made by (AlaaSheta, 2006) **[10]** using Takagi-Sugeno (TS) fuzzy models. Sheta uses the model for two non-linear processes, one pertaining to NASA and the other to prediction of next week S&P 500 index levels. The application of evolutionary optimization techniques such as Genetic Algorithm has given an entirely new dimension to the field of stock market prediction (Badawy, Abdelazim&Darwish) **[11]** conducted simulations using GA to find the optimal combination of technical parameters to predict Egyptian stocks accurately (Tan, Quek& Ng, 2005) **[12]** introduce a novel technique known as Genetic complementary Learning (GCL) to stock market prediction and give comparisons to demonstrate the superior performance of the method. GCL algorithm is a confluence of GA and hippocampal complementary learning. Another paper introducing Genetic algorithm approach to instance selection (GAIS) (Kyoungjae-Kim, 2006) **[13]** for ANN in financial data mining has been reported. Kim introduces this technique to select effective training instances out a large training data set to ensure efficient and fast training for stock market prediction networks. The GA also evolves the weights that mitigate the well-known limitations of the gradient descent algorithm. The study demonstrates enhances prediction performance at reduced training time. A hybrid model proposed by (Kuo, Chen & Hwang, 2001) **[14]** integrates GA based fuzzy logic and ANN. The model involves both quantitative factors (technical parameters) and qualitative factors such as political and psychological factors. Evaluation results indicate that the neural network considering both the quantitative and qualitative factors excels the neural network considering only the quantitative factors both in the clarity of buying-selling points and buying, selling performance. Another hybrid model involving GA proposed by (Hassan, Nath & Kirley, 2006) **[15]** utilizes the strengths of Hidden Markov Models (HMM), ANN and GA to forecast financial market behavior. Using ANN, the daily stock prices are transformed to independent sets of values that become input to HMM. The job of the GA is to optimize the initial parameters of HMM. The trained HMM is then used to identify and locate similar patterns in the historical data. A similar study investigates the effectiveness of a hybrid approach based on Time Delay Neural Networks (TDNN) and GA (Kim & Shin, 2006) **[16]**. The GA is used to optimize the number of time delays in the neural network to obtain the optimum prediction performance. The functional link ANN is a novel single Neuron based architecture first proposed by Pao**[17]**.This study proposes a Functional Link or FLANN architecture based model to predict the movements of prices in the DJIA and S&P500 stock indices. A NEURO-FUZZY system composed of an Adaptive NEURO FUZZY Inference System (ANFIS) controller used to control the stock market process model, also identified using an adaptive NEURO-FUZZY technique, is derived and evaluated for a variety of stocks **[18]**. Radial basis function (RBF) networks have advantages of easy design, good generalization, strong tolerance to input noise, and online learning ability. This paper presents a review on different approaches of designing and training RBF networks **[19]**.

II. APPROACH

3.1.1 SVI Index for a data set

The nature of the data set is to be studied in prior. To analyze the nature many approaches are present in the real world. One fetching technique is volatility. Volatility index is calculated as the maximum of return value array. This indicates the extent to which the data set is instable. The new volatility index (averaged value of normal volatility) of a dataset is key parameter in our approach to classify the dataset in to one group based on which the right model can be determined. The below is an illustration for plot of SVI index for US-RUPEE dataset.

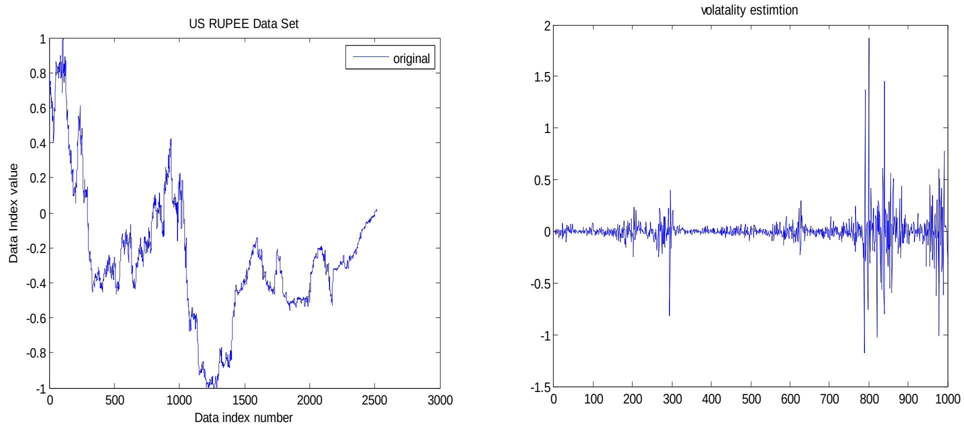


Fig 1(a), 1(b): plot of normalized us-rupee data set and volatility plot.

Calculation of normal volatility index

The formula for this is calculated as logarithmic difference of two successive values. This is represented as an array. The maximum of that array (v1) is volatility index of the data range.

Return value (i) = ln (i) - ln (i-1). **(1)**

In case of US-RUPEE dataset which is plotted below is (0.18-(-0.3)) =0.48.

Setty volatility index (SIV)

In this new index average of first eight maximum volatile values are considered as the actual volatility index. The v1, v2, v3, v4, v5, v6, v7, v8 when averaged gives the actual value called SVI.

SVI value	**very short (next day)**	**short term(up to 2 months)**	**Long term(3 months to 1 year)**
low (-0.2 to +0.2)	NEURO-FUZZY Works well	FLANN works very well	FLANN is used widely with many Technical indicators. Online RBF May also be used
high (other values)	NEURO-FUZZY/FLANN	FLANN/Online RBF	Online RBF is the only choice in most cases

Table 1: proposed approach to decide the appropriate model

III. MODELS DESCRIPTION

4.1 Introduction to Online RBF

Radial basis function (RBF) networks have advantages of easy design, good generalization, strong tolerance to input noise, and online learning ability. The properties of RBF networks make it very suitable to design flexible control systems. This project presents a review on different approaches of designing and training RBF networks. The recently developed algorithm is introduced for designing compact RBF networks and performing efficient training process. At last, several problems are applied to test the main properties of RBF networks like generalization ability, tolerance to input noise, and online learning ability. RBF networks are also compared with traditional neural networks and fuzzy inference systems

Structure of Online RBF

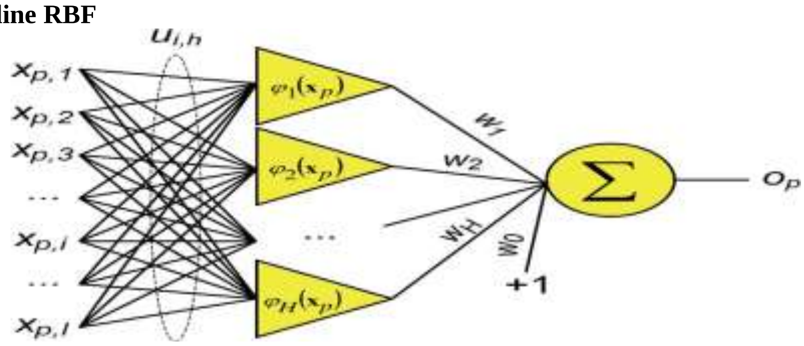


Fig 2. Structure of standard RBF model with three layers

Levenberg–Marquardt Algorithm

The update rule of Levenberg–Marquardt algorithm is

$$\Delta_{k+1} = \Delta_k + \left(J_k^T J_k + \mu_k I\right)^{-1} J_k^T e_k \qquad (2)$$

Where μ is combination coefficient, Δ is the variable vector, e is error vector, and J is Jacobian matrix. This algorithm is used in our Online-RBF model.

4.2Introduction to NEURO-FUZZY System

A NEURO-FUZZY system composed of an Adaptive NEURO FUZZY Inference System (ANFIS) controller used to control the stock market process model, also identified using an adaptive NEURO-FUZZY technique, is derived and evaluated for a variety of stocks. Obtained results challenge the weak form of the Efficient Market Hypothesis(EMH)by demonstrating much improved and better predictions, compared to other approaches of short-term stock market trends and in particular the next day's trend of chosen stocks. The ANFIS controller and the stock market process model inputs are chosen based on a comparative study of fifteen different combinations of past stock prices performed to determine the stock market process model inputs that return the best stock trend prediction for the next day in terms of the minimum Root Mean Square Error (RMSE).Guassian-2 shaped membership functions are chosen over bell shaped Gaussian and triangular ones to fuzzify the system inputs due to lowest RMSE. Real case studies using data from emerging and well developed stock markets-the Athens and the NewYork Stock Exchange(NYSE)-to train and evaluate the proposed system illustrate that compared to the "buy and hold" strategy and several other reported methods, the proposed approach and the forecasting trade accuracy are by far superior.

The Structure of NEURO-FUZZY Model

The methodology presented in this paper considers historical/past stock prices as inputs (predictors) to create a forecasting system that captures the underling "laws of the stock market price motion" thus, predicting next day's trend of a stock. The proposed NEURO-FUZZY model uses an ANFIS technique which is superior in modeling time series data as shown in Abraham et al. (2005), jang et al. (1997). A block diagram of the proposed NEURO-FUZZY system, during the training and the application-evaluation phase is shown in Fig 3.2(a) and 3.2(b).

Learning in NEURO-FUZZY Model

The parameters set {p, q, r} in functional formula of every neuron is updated with the help of learning law called **"Woodrow's Learning Law".** The formula is given by equation below

$$\Delta w = \eta * (b - x) * a \qquad (3)$$

Where η is the learning rate parameter, b is the actual output and x is the calculated output, b-x is the error generated by the network and a is the input applied

IV. EXPERIMENTS AND RESULTS

5.1. Experiment for Long Term Prediction

Prediction problem is three types very short term prediction, short term prediction and long term prediction. In case of long term prediction we have to test data over range of 90 days to 360 days. Here we implemented three models which clearly indicate the prediction over US-RUPEE data set for 1000 points in training phase and for 100 data we go for testing to check the performance of the network where the parameters are freezed. The models are FLANN, Online RBF and NEURO-FUZZY model. The table below shows that Online RBF performs well in case of long term predictions.

Model/parameter	FLANN	NEURO-FUZZY	Online RBF
NRMSE	-1.1099e+04	-6.9065e+002	-3.7020e+009
MAPE	-0.2024	-1.202	-15.0480
AMAPE	7.3824	8.2999	5.6402

Table 2: Table showing various performance measures of 3 models.

5.2. Experiment for Very Short Term Prediction

In case of very short term predictions we go for hit ratio. Here we implemented two models which clearly indicate the prediction over US-RUPEE data set for 1000 points in training phase and for 20 data we go for testing to check the performance of the network where the parameters are freezed. The models are FLANN, NEURO-FUZZY model.

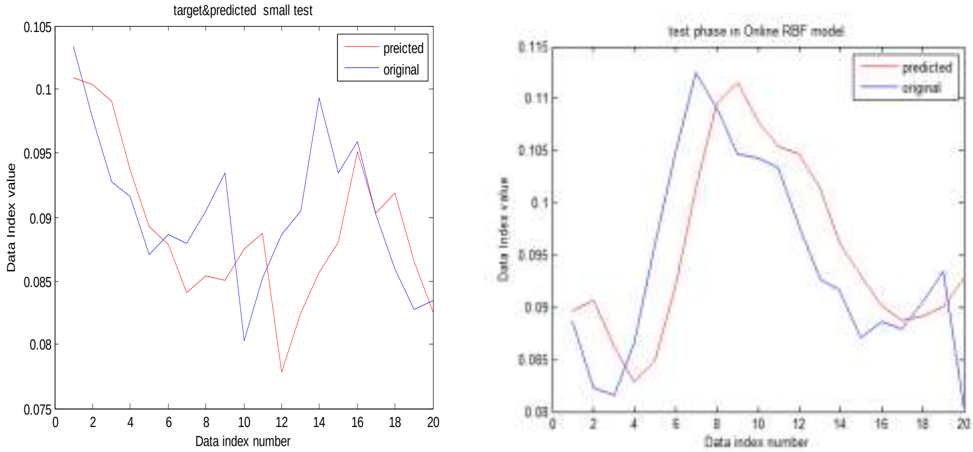
Hit Ratio

In case of very short prediction generally we consider number of exact matches done in the range which varies from 2 days to 20 days. The hits are crossovers indicated after identification with the help of square blocks. The formula for hit ratio is given by

$$\boldsymbol{hitratio} = \frac{\boldsymbol{numberofexactmatches}}{\boldsymbol{totalnumberofdatatested}} \qquad (4)$$

Plot of NEURO-FUZZY and Online RBF performance (20 test data)

In these plots we observe that number hits for twenty data points tested in part of test case after training phase of 1000 data are 8 and 4 and the hit ratios are 8/20 =0.40 and 4/20=0.2 for Neuro-fuzzy and online RBF model respectively. The Neuro-fuzzy model out performs in case of very short term predictions. This experiment when further extended to Flann model yielded 5/20=0.25. Thus Neuro fuzzy model is best for very short term predictions in case of low SVI values.



4(a) 4(b)

Fig 4(a), 4(b). Plot of very short term prediction problem in NEURO-FUZZY model and Online RBF model

5.3 Discussion

The experiment for long term prediction shows that various performance measures like normalized root mean square error, mean absolute percentage error, average mean absolute percentage error over US-RUPEE dataset in case of long term prediction problem that online RBF performs at par with FLANN but, NEURO-FUZZY model doesn't work well over US-RUPEE data set. Online RBF works well in both cases of data set with less volatility (low SVI) and high volatility but FLANN is used only in case of low **SVI** value.

In experiment for very short term prediction, the case is very short term prediction problem , hit ratio which is taken as measure of performance and accuracy says that NEURO-FUZZY model works well in case of very short term prediction problem. The results of experiment indicate that NEURO-FUZZY outstands Online-RBF model for SVI data sets. Flann model also can be preferred in case of high **SVI** value sets after further experiments. Thus the tabulated results are proved valid.

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