Performance Evaluation of ANN and Neuro-Fuzzy System in Business Forecasting

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Abstract-In recent years, Artificial intelligence based algorithms are being widely used as prediction models in different domains. However, the suitability and performance of a particular technique depends on the essence of the prediction problem at hand. In this paper we perform a comparison of prediction performance of two widely used AI techniques namely Adaptive Neuro-fuzzy inference system (ANFIS) and Artificial neural network (ANN). For performance analysis two forecasting problems have been considered. First one is the sales forecasting for which the real sales dataset of cold drinks collected by authors for five months has been used. Second is the stock price prediction problem for which the daily stock market data of BSE obtained from Yahoo Finance has been used. Root mean square error and prediction accuracy have been used to evaluate the performance of the two models.

Keywords—Neuro-fuzzy system, artificial intelligence, neural network, business, forecasting.

I. INTRODUCTION

Artificial intelligence is used in a wide range of fields as is evident from a considerable amount of research done in this field during last years in different domains. AI field comprises of various techniques like artificial neural networks, genetic algorithms, fuzzy logic including different hybrid systems combining these techniques such as Neuro-genetic systems, Neuro-fuzzy systems which are valuable in a number of real world problems. Each of these AI methods has different approaches to adapting and learning in order to emulate the intelligent behavior. Such Artificial Intelligence methods are particularly useful in modeling complex relationships where the relationship cannot be computed directly or easily interpreted by a human. Most AI methods can be used for function approximation in which predictions of continuous variables can be generated.

Among the different AI techniques used for prediction problems, ANN and ANFIS are among the most widely used.
These two techniques differ in the various performance measures like the accuracy of the prediction, training time required, complexity of implementation and the speed of execution on unseen data. ANN is a nonlinear method that nowadays has a wide range of applications in industries, businesses, sciences etc. ANN can estimate any continuous nonlinear functions with desired accuracy [1].
Although neural network is an efficient technique for forecasting but has black box architecture as it does not furnish any information regarding the predicted output. Fuzzy systems on the other hand in addition to managing the imprecise constitution of the financial prediction problems adequately supply user with the expert knowledge about the results obtained through a fuzzy rule base which enables the user to comprehend the influence of the input variables on the results obtained. Using Neuro-fuzzy hybrid systems, the ability of the fuzzy systems to generate knowledge and use it to solve prediction problems in an uncertain environment, is combined with the learning property in neural networks, thus providing a more complete intelligent system. The Neuro-fuzzy systems have been used in a number of areas like process control, medical diagnosis, cognitive simulation, engineering design etc. for forecasting purpose. These systems are also being successfully used in business and the use is proliferating into different business domains like finance, marketing, production, human resource, business planning etc.
The paper outline is as follows: In section II literature review is given. In section III, the theory and general structure of the two compared methods i.e. ANN and ANFIS is presented. Section IV, discusses the implementation of the two models. In section V, results of the study are provided. Lastly, in section VI conclusions are discussed.

II.LITERATURE REVIEW

ANN and Neuro-fuzzy systems both are widely used in business domain for a variety of tasks such as forecasting, decision analysis, inventory management, operations management and so on. The literature in the financial applications of neural networks is vast. Neural networks have been used for stock market prediction [2,3,4,5], business failure prediction [6,7,8,9,10,11], foreign exchange rate forecasting [12,13,14,15,16,17] and others [18,19,20,21]. In 2012, Suresh Kumar Sharma et al. [31] performed a

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comparative analysis of neural network, KNN and moving average methods. The authors concluded that both neural network and moving average provide more accurate results than KNN. Neuro fuzzy applications also are attaining huge attention of many researchers in business field and a number of relevant researches have been conducted. In 2005, Quek et al. [22] proposed a rough set-based pseudo outer-product for stock market prediction. The proposed model combines simple moving average rules and the time delayed price difference forecast approach. Later Lin et al. [23] provided a model using neuro-fuzzy approach to describe the online English auction process for final price prediction. Authors also investigated the complicated nonlinear relationship between the final price and auction mechanisms. In 2009, Didehkhani et al. [24] used an ANFIS based model for evaluating supply chain flexibility. Various flexibility attributes for supply chain such as operation, responsiveness and new product were used. In 2010, Georgios Mantas et al. [25] analyzed and compared various artificial neural networks like feed forward, radial basis networks and ANFIS for their accuracy and convergence for the problem of sales forecasting of medical products. In 2011, Carolin Kaiser et al. [26] proposed a warning system based on neuro-fuzzy approach for online market research. It is based on identifying the critical situations in the online opinion formation which are then sent to the marketing managers. This can enable the marketers to take preventive measures. In 2012, Kit Yan Chan et al. [27] proposed a customer satisfaction model based on neuro-fuzzy approach. Authors used a method for obtaining significant rules from a set of rules indicating the significant customer requirements for a new product. In 2013, Hiziroglu et al. [28] proposed a neuro-fuzzy system to determine non-strict customer segments according to purchasing behavior, recency, frequency and monetary value. Besides these a number of researchers have employed neuro-fuzzy systems in domains finance, marketing and distribution, production/operations, business planning and human resource management.

III. MATERIALS AND METHODS.

A. Data sets used.

Two datasets have been used for the performance analysis of the models in this study. The first dataset is the daily BSE stock market data from Yahoo Finance which includes five stock quantities (opening price, closing price, maximum price, stock trading volume and minimum price). The stock market data of four years form 01/01/2009 to 17/12/2014 consisting of total 1966 records has been used. The second dataset consists of sales dataset of cold drinks collected by authors for a period of five months form 01/06/2013 to 22/11/2013. This dataset includes maximum daily temperature, minimum temperature, previous day sale, current day sale data and holiday attribute as input. The information about the type of day has been included as input as sale is usually more on weekdays. This input has a value 1 if it is a holiday and 0 if it is a weekday.

B. Algorithms used for Analysis

B.1 Feed Forward Neural Network

The ANN used for this study is the Feed Forward Neural Network (FFNN). FFNN consists of neurons ordered into layers. The first layer is the input layer, the last layer being the output layer and the layers between are called hidden layers. A single hidden layer FFNN is shown in Figure-3.1. The neurons in the network receive inputs from other neurons in the network or from the outside world and the outputs of the neurons are connected to other neurons or to the outside world. The interconnections between neurons are weighted based on the importance of connections between the nodes.

Feed forward neural networks are commonly trained using the Backpropagation algorithm. The Backpropagation algorithm proposed by Rumelhart et al.[29] is a supervised learning technique involving presentation of a set of pairs of input and output patterns to the neural network being trained. The algorithm utilizes gradient descent technique to reduce a cost function. The cost function that the back propagation network tries to minimize is the squared difference between the actual network output and the target/desired output value summed over the all the output units. The error on input/output pattern n is given by:

$$E(n) = \frac{1}{2}\sum_{j=1}^{K}(d_j(n) - o_j(n))2$$

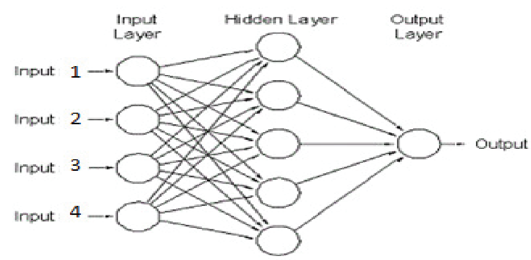

Fig. 3.1 General structure of a two layer feed forward neural network.

Where, $d_j(n)$ is the target or desired output for the jth output vector for input pattern n, $o_j(n)$ is the jth element of the obtained output vector produced by the presentation of input pattern n and K is the total number of output units.

Let $s_j = \sum_{i=1}^{N} w_{ij} x_i(n)$

be the weighted sum input to unit j in the hidden layer due to application of input pattern n. N is the number of input patterns and w_{ij} is the weight on the link connecting input unit i and hidden unit j.

Let $a_j = \sum_{i=1}^{H} w_{ij} o_i(n)$

be the weighted sum input to the output unit j due to input pattern n. Here $o_i(n)$ is the output produced by the hidden layer unit 'i' on presentation of the input pattern n, and w_{ij} is the weight connecting output unit j and hidden unit i and H is the number of hidden units in the hidden layer, The outputs of the hidden units and output units are, respectively

$$o_j = f\left(s_j(n)\right) \text{and} o_j^- = f(a_j(n))$$

Where, f is a differentiable and non-decreasing non-linear transfer function.
The overall error can be given as :

$$E = \sum_{n=1}^{S} E(n)$$

Where, S is the total number of the input training samples, E is the cost function of the network. Backpropagation algorithm utilizes gradient descent learning, and therefore each weight in the network can be adapted by correcting the present value of the weight with a value proportional to the present error and input at the weight, i.e

$$w_{ij}(n+1) = w_{ij}(n) + \rho\mathcal{E}_i(n)x_j(n)$$

Where, $\mathcal{E}_i$ (n) is the local error and is calculated as a weighted sum of errors at the internal neurons or error value at the output layer. $'\rho'$is a constant called the learning rate.

B.2 Adaptive-Network-Based Fuzzy Inference System

Fuzzy logic and Fuzzy Inference system were proposed by Zadeh (1965). In fuzzy logic, if-then rules and linguistic variables are used to represent models. Every fuzzy inference system comprises of three parts: fuzzy rules, a reasoning mechanism and membership functions. Fuzzy inference systems can be one of three types namely the Mamdani system, which produces fuzzy output, the Takagi–Sugeno system, that gives a real number as output and the Tsukamoto system, which uses monotonous functions.

Jang (1993) proposed the Adaptive Network-based Fuzzy Inference System. ANFIS uses a Takagi–Sugeno type fuzzy system. Fig. 2 shows the general architecture of ANFIS which has 2 inputs and output.

The details of the functioning of each layer of the ANFIS are as follows:

Layer 1: This is the input layer and consists of nodes with adaptive node functions. Each node has an output equal to:

$$O1,i = \mu Ai(x) \qquad \text{for } i = 1,2 \tag{1}$$

Here output of each node is the value of the membership function 'A' of that node and $O_{k,I}$ is the node in the i-th position of the k-th layer.

Various types of membership function are used, but the bell-shaped function is the most usually employed one.

Layer 2: In this layer each node computes the product of incoming signals with output given by:

$$O_{2,i} = w_i = \mu A_i \mu B_i(y) \text{ , } i = 1,2 \tag{2}$$

Layer 3: in this layer each j-th node computes the ratio of the firing strength of the j-th rule and the sum of all the firing strengths, with output

$$O3,j= \quad w_j = \frac{w_j}{w1+w2} \text{ , } j = 1,2 \tag{3}$$

Layer 4: in this layer function for i-th node is:

$$O4,1 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i x + r_i) \tag{4}$$

Layer 5: this layer has a single node that computes the overall output as the sum of all incoming signals:

$$O5,1 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

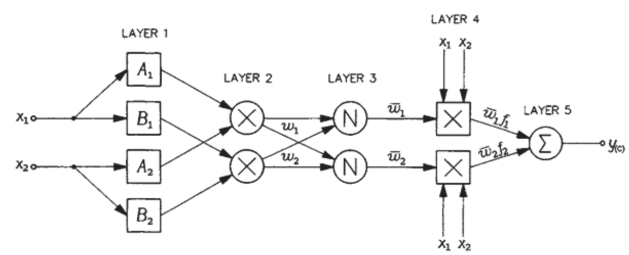

Fig. 3.2 Architecture of ANFIS with two inputs.

IV. IMPLMENTATION.

For comparison purpose the data preprocessing, training and testing of the models has been done in MATLAB R2013a environment using neural network toolbox for ANN and fuzzy toolbox for ANFIS.

A. Implementation using feed forward neural network

The artificial neural network used for this study is the two layer Feed forward neural network trained using back propagation algorithm. The number of neurons in hidden layer found optimum with least error was 10 for stock data and also for sales data. The transfer function used for hidden layer is the Tansig function and for output layer Logsig function has been used. The learning rate was set to 0.01, maximum number of epochs was set to 1000 and the performance goal was set to 0.0. For both datasets, 80% of data was used for training, 10% for validation and 10% for testing purpose. For stock price prediction inputs to the neural network are high price, low price, close price, open price and stock trading volume. Output is the present day's predicted close price. For sales price prediction the inputs to ANN are previous day sale, maximum temperature, minimum temperature, current day sales, day and the output is the next day sale forecast.

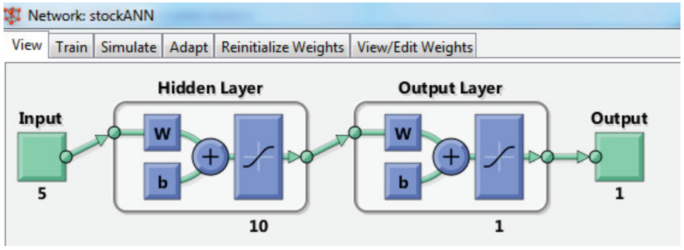

Fig. 4.1 Feedforward Neural network for stock data in MATLAB

B. Implementation using ANFIS

For stock price prediction ANFIS with five inputs (high price, low price, close price, open price and volume) and one output (present day close price) has been used. For sales forecasting ANFIS with five inputs (maximum temperature, minimum temperature, previous day sale, current day sales and day information) and one output(next day sale) has been used. For each input three membership functions of gbell typehave been used and for output linear membership function was used. Optimization method used was hybrid learning algorithm. To identify the inference parameters subtractive clustering proposed by [30] was used as it is more intuitive and does not have dimensionality issues. Error tolerance was set to 0.0. of the data was used for training, 10% as checking dat 10% as testing data for both datasets.

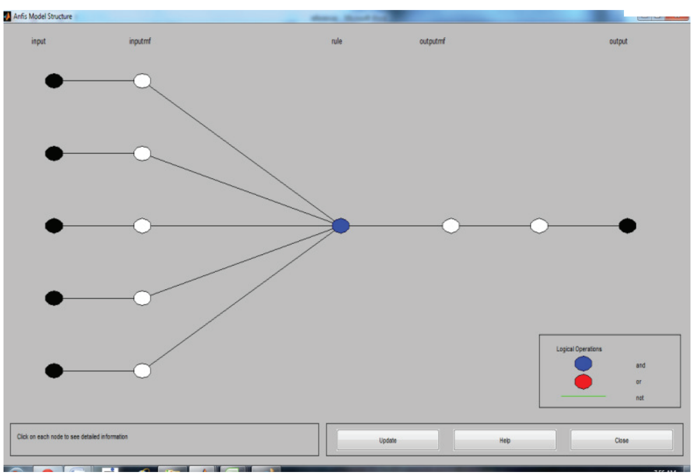

Fig.4.2 ANFIS implementation in MATLAB for stock market data

V. PERFORMANCE EVALUATION.

In order to compare the performance of the two models, RMSE and accuracy performance criteria have been used. RMSE is frequently used performance criteria which measures the difference between values predicted by a model or forecaster and the target or desired values. It is the square root of the mean square error and is given by the equation:

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2}$$

Accuracy is the degree of matching between the predictions and the actual data which is given by:

$$\text{Accuracy} = 100 - 100 * \frac{\sum_{i=1}^{N} |x_i - y_i|}{N}$$

Where, x_i is the actual vaue and y_i is the predicted value. After training the two algorithms on the same datasets, RMSE and accuracy was calculated for both the algorithms on the test data for each dataset. The results are shown in Table 1 and Table 2. Graphical representation of performance of models is shown in Figure 5.1

TABLE I. PERFORMANCE FOR STOCK DATASET

Model	Accuracy	RMSE
ANFIS	98.91	0.0148
ANN	98.70	0.0175

TABLE II. PERFORMANCE FOR SALES DATASET

Model	Accuracy	RMSE
ANFIS	98.63	0.021
ANN	98.77	0.0151

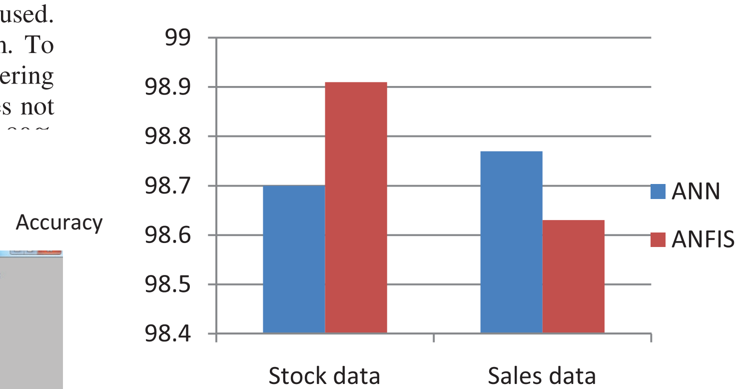

Fig. 5.1 Graph for accuracy of prediction.

VI. CONCLUSION.

In this paper a comparison between ANN and ANFIS as predictive models has been presented. The results show that both ANFIS and ANN are powerful tools for forecasting problems. However, the learning duration of ANFIS is shorter implying that ANFIS reaches the target earlier than ANN. Moreover, the accuracy of the ANFIS for stock market dataset is higher than ANN which indicates that ANFIS is better prediction model. But for sales data ANN performs better. The reason for different results is that the sales dataset is much lesser than stock market data which is not enough in case of ANFIS for good learning

In this study, the data set comprising of five daily stock market quantities viz. maximum price, minimum price, price at the time of opening, volume and price at the time of closing has been used. In future, this data set would be converted into dataset of various popular technical indicators like Moving Average, Momentum etc and used as input to the models. Moreover, the comparison is based on the basic implementation of the two models, different artificial neural network architectures and various performance optimization techniques for both models can be used.

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