AN ARTIFICIAL NEURAL NETWORK MODELING APPROACH TO PREDICT CRUDE OIL FUTURE

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ABSTRACT

This study is an attempt to predict the crude oil future series by using the Artificial Neural Networks (ANN) models. Twenty various ANN models with four architectures are constructed to predict the series. Forecasting errors when calculated by using two forecasting error measures, it has been observed that the 4-3-1 (α=0.8 and ε=0.8) model has the minimum forecasting error and hence, best suits to predict the estimated series. MSE is found to be best suitable as a forecasting error measure for the crude oil series.

Keywords: ANN, Crude oil, Error, Forecasting, Models

1. INTRODUCTION:

In the business and economic environment, it is very important to predict various kinds of financial variables accurately in order to develop proper strategies and avoid the risk of potential large losses. In the literature, there are numbers of classical models that have been developed in predicting financial time series data. Among them, there is a powerful model available in the literature for univariate time-series forecasting, popularly known as Box and Jenkins ARMA approach on the stationary time series. In conventional econometric models, the variance of the disturbance is assumed to be constant. But many econometric and financial time series such as exchange rate, stock market indices, market returns, inflation rate, etc., exhibit periods of unusual large volatility, followed by periods of relative tranquility (i.e., time series exhibits clustering of large and small disturbances). Such circumstances suggest a form of heteroskedasticity in which the variance of the disturbance depends on the size of preceding disturbance and hence, the conditional variance is non-constant over the sample period.

Evidence on the forecasting abilities of the GARCH type of models is somewhat a matter of analysis. As an alternative, some more approaches have been advocated by numbers of researchers from the perspective of estimation and forecasting financial time series data. Neural Network (NN) is one of such methods. ANNs are developed to meet the increasing demand that can predict, detect, classify and summarize the structure of variables and define the relationship between them-without relying too much on the assumptions of linearity or no error distributions like normality.

All predictions are subject to errors and these errors arise for many reasons. Some are called as specification errors because the econometric model being tested has left out (i.e., not specified) important explanatory variables. Others are called measurement errors because the variable could not be accurately measured. Because it is not possible to know all the potential sources of error, the actual size of the error is unknown. The conventional procedure is to assume that there is an unobservable world where the true values of all the desired parameters exist. But, because one cannot obtain all the data on all the variables we desire, we settle for what is available- a sample of observations on the variables in which we are intended.

2. REVIEW OF RELATED LITERATURES:

The very first use of ANN to predict share market prices was derived by Kimoto et al. (1990) who were used this technique to predict Tokyo stock exchange index. Tang and Fishwick (1993) and Wang and Leu (1996) provided the general introduction of how a neural network should be developed to model financial and economic time series. Further more, Minzuno et al. (1998) applied ANN technique to Tokyo stock exchange to predict the buying and selling signals with an overall prediction rate of 63 per cent. Phua et al. (2000) applied neural network with genetic algorithm to the Singapore stock exchange market and predicted the market direction with an accuracy of 81per cent. Sarangi and Sarangi (2010) examined and analysed the use of ANN as a forecasting tools for predicting the future electric load demand and the impact of different neurons in the hidden layer in a three layered ANN architecture. They concluded ANN as a powerful tool for decision making in forecasting. Khan et al. (2011) used the back propagation algorithm for training session and multilayer Feedforward network as a network model for predicting Bangladesh stock exchange market index values. Perwej and Perwej (2012) were investigated to predict the daily excess returns of Bombay Stock Exchange (BSE) indices by using the feed-forward ANN. Sarangi and Dublish (2013) used the gold return series data with both the GARCH family and ANN models. Their study revealed that ANN models better predict the series than the traditional GARCH family of models. Sarangi (2014) studied bullion trading, more particularly, gold by suing both GARCH types and ANN models as is of high interest for analysts, researchers, more particularly to investors as it will pave them away with an opportunity to benefit financially by investing their limited resources. Among both the types of models, ANN models are proved to be better models with less forecasting error than GARCH types of models.

3. OBJECTIVES OF THE STUDY:

This study is based on following objectives:

i. To develop twenty ANN models with four architectures with crude oil series for forecasting with changing numbers of hidden neurons, learning rate and momentum value, and

ii. To evaluate the prediction errors by using two different error measures.

4. METHODOLOGY:

Since the scope of the study is widened, hence, the models adopted in this study to justify the formulated objectives have been categorized in following sub-sections separately:

4.1 *Data:*

A total of 2892 days of data has been used in the study ranging from 1st January 2009 to 31st March, 2017. The detailed division of data into various patterns are derived in the section 4.2 under heading '*the implementation design'* derived below.

4.2 Models:

Following are the methodologies adopted to implement ANN architecture:

- Construction of four ANN architectures having three neurons in input layers, one neuron in the output layer and varying the number of neurons in single hidden layer from 3 to 6 (i.e., 3-6-1 to 3-3-1). The basic structure of an ANN architecture is derived in Figure-1:

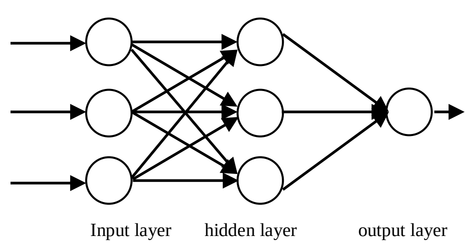

Figure-1: ANN Architecture

- Training of the networks using back propagation algorithm with different learning rates (0.7 to 0.9), momentum value (0.7 to 0.9) and keeping the tolerance ratio at 0.001 as constant *(see **table-3** column-1 for details on models)*. The ANN back-propagation is a feed-forward neural network structure that takes the input to the network and multiplies it by the weights on the connections between neurons or nodes; summing their products before passing it through a threshold function to produce an output. The tolerance value is the amount of accuracy that the network is required to achieve during its learning stage on the training data set and determine the predictive result at the test data set.

- Leaning rate coefficient (ε) determines the size of the weight adjustments are made at each iterations and hence, influences the rate of convergence. In this study, the 'ε' values lies from 0.7 to 0.9. There is another way possible to improve the rate of convergence by adding a momentum to the gradient expression. The addition of such a term helps to smooth out the descent path by preventing extreme changes in the gradient due to local anomalies. This study has three values for 'α' as 0.7, 0.8 and 0.9. Besides the considered values, other values of 'ε' and 'α' are also experimented with all the four architectures, but are not included for inferences in this study because of their inappropriateness.
- The architectures have been constructed for the validation.
- The forecasted values of models have been observed and the errors are calculated.

4.3 *The Implementation Design:*

Following are the steps adopted for implementation of the architectures:

1. A total of 2892 days data has been divided into two patterns. The first set is training pattern and the second set is validation pattern. Beside 2892 days, next 21 days data is used to test the forecasting efficiency of the constructed models.
2. With the four architectures, twenty models are formulated both for training and validation with various combinations of 'ε' and 'α' values. The inputs are new on each trial and are presented cyclically until weights stabilize. Here, the return values of Open (O), High (H) and Low (L) of previous day

are inputs of day 1. The Close (C) returns value of next day is Target value of day-1.

3. The training node consists of 2313 days data patterns (80% of the total data). The basic structure is arranged as below:

Days	Input			Target
Day-1	O_{t-1}	H_{t-1}	L_{t-1}	C_t
Day-2	O_t	H_t	L_t	C_{t+1}
Day-3	O_{t-+1}	H_{t+1}	L_{t+1}	C_{t+2}
:	:	:	:	:
Day-2313	O_{t+2312}	H_{t+2312}	L_{t+2312}	C_{t+2212}

4. The twenty models are estimated with 579 (20 % of the total data) patterns for validation. Data of day-2313 consists of first validation pattern and the validation pattern ends with day-2892 data. Above structure is used for implementing the models.
5. After validation, 21 days further are forecasted (April 2017). These constitute the desire output of our research.
6. The neural network architecture used as the predictor is the Sigmoid Diagonal Recurrent Neural Network (SDRNN) to calculate output at hidden layers.
7. The output with the target or desired outputs are compared with actual output. The errors are calculated by using six forecasting error measures.

4.4 *Validity of the Models:*

Separate programming have been developed for all the considered specifications and models in Matlab 7.0 software to predict the daily return series. On the other hand, actual return data for April 2017 i.e., 21 days of trading are calculated. Two most frequently used measures by most of the researchers separately are considered all together in this study and calculated by using the following formulas:

Mean Error (ME):	Mean Square Error(MSE):
$ME=\frac{1}{h}\sum_{t=1}^{h}\left(\hat{\sigma}_t^2-\sigma_t^2\right)$	$MSE=\frac{1}{h+1}\sum_{t=1}^{h}\left(\hat{\sigma}_t^2-\sigma_t^2\right)^2$

Where '*h*' is the number of day's forecasts. In this study *h=21*. Symbol '$\hat{\sigma}_t$' stands for 'forecasted value' and 'σ_t' for 'actual value'.

5. EMPERICAL FINDINGS:

From the **table-1** derived below, Model-8 (4-3-1) has been ranked first by both the two measures with minimum value. The minimum values reported for model-8 by the respective measures are as ME-0.00127, and MSE-0.00072. The lowest is reported by MSE. The table reflects few interesting incidences also. From the table it can be seen that in case of ME, except model-8 all other error values are reported to be negative. Similarly, in MSE, except model-8 and model-12, the error values for all other models are reported to be negative. This implies the ANN models for other models except the above mentioned three models are over predicting the values than the original value of the series.

6. CONCLUSIONS:

From all these evidences, there will be no harm if we will conclude model-8 is the most efficient single combination of model among the calculated nineteen models as the most efficient model for crude oil index series. Similarly, when the forecasting efficiencies of the error measures are compared, MSE can be proved as the most efficient measure than ME while calculating forecasting errors for the crude oil return series. Similar advanced modeling techniques could be explored to other vast areas like financial derivatives, economic analysis, financial markets, and business operations and in professions, more particularly in various core areas that Company Secretaries are dealing with.

Table-1: Forecasting Errors of ANN Models for Crude Oil Future Return

ANN Models	ME	RANK	MSE	RANK
α=0.9,ε=0.9; 4-6-1 (Model-1)	-0.04768	17	-0.02274	17
4-5-1 (Model-2)	-0.07881	02	-0.03062	03
4-4-1 (Model-3)	-0.0781	04	-0.03054	10
4-3-1 (Model-4)	-0.05905	10	-0.02507	15
α=0.8,ε=0.8; 4-6-1 (Model-5)	-0.07804	08	-0.03061	06
4-5-1 (Model-6)	-0.0585	12	-0.02525	11
4-4-1 (Model-7)	-0.05826	13	-0.02534	13
4-3-1 (Model-8)	**0.00127**	**01**	**0.00072**	**01**
α=0.9,ε=0.8; 4-6-1	-0.04747	18	-0.02268	18

(Model-9)				
4-5-1 (Model-10)	-0.0781	05	-0.03061	07
4-4-1 (Model-11)	-0.0782	03	-0.03062	04
4-3-1 (Model-12)	-0.05892	11	0.02551	02
α=0.7,ε=0.7; 4-6-1 (Model-13)	-0.07799	09	-0.03059	09
4-5-1 (Model-14)	- 0.055841	16	-0.02451	16
4-4-1 (Model-15)	-0.05807	14	-0.02531	12
4-3-1 (Model-16)	-0.00046	20	-0.00945	20
α=0.8,ε=0.9; 4-6-1 (Model-17)	-0.07809	06	-0.03062	05
4-5-1 (Model-18)	-0.04178	19	-0.02122	19
9; 4-4-1 (Model-19)	-0.07808	07	-0.03061	08
4-3-1 (Model-20)	-0.05785	15	-0.02521	14

Note: 1. Calculated value. 2. Bold values are minimum error values.

REFERENCES:

Khan, Z.H., Alin, T.S. and Hussain, M.A. (2011), Price Prediction of Share Market Using Artificial Neural Network, International Journal of Computer Applications, Vol- 22, No-2.

Kimoto, T., Asakawa, K., Yoda, M. and Takeoka, M. (1990), Stock Market Prediction System with Modular Neural Network, in Proceedings of the International Joint Conference on Neural Network, (pp 1-6).

Klassen, F. (2002), Improving GARCH Volatility Forecasts. Empirical Economics, Vol- 27, No-3, pp. 363-94.

Mizuno, H, Kosaka, M., Yajima, H. and Komoda, N. (1998), Application of Neural Network to Technical Analysis of Stock Market Prediction, Studies in Information and Control, Vol- 7, No-3, pp. 111-120.

Perwej, Y. and Perwej, A. (2012), Prediction of the Bombay Stock Exchange (BSE) Market Returns Using Artificial Neural Network and Genetic Algorithm, Journal of Intelligent Learning Systems and Applications, Vol- 4, No-4, pp.108-119.

Phua, P.K.H., Ming, D. and Lin, W. (2000), Neural Network with Genetic Algorithms for Stocks Prediction, Fifth Conference of the Association of Asian- Pasific Operations Research Societies, 5th -7th July, Singapore.

Sarangi, P.K. and Sarangi, P. (2010), Load Forecasting using Artificial Neural Networks: Performance Evaluation with Different Numbers of Hidden Neurons, The IUP Journal of Information Technology, Vol.VI, No-1, pp. 34-42.

Sarangi, P. and Dublish, S. (2013), Prediction Of Gold Bullion Return Using GARCH Family And Artificial Neural Network Models, Asian Journal of Research in Business Economics and Management, Vol-3, No-10.

Sarangi (2014). Are GARCH Specifications Superior Among GARCH Types of Models in Estimating Financial Volatility?: An Experiment, Productivity, Vol-55, No-2.

Tang, Z and Fishwick, P.A. 91993), Back-propagation Neural Nets as Models for Time Series Forecasting, ORSA Journal on Computing, Vol.- 5, No-4, pp.374-384.

Wang, J.H. and Leu, J.Y. (1996), Stock Market Trend Prediction Using ARIMA-based Neural Network, Proceedings of IEEE Conference on Neural Networks, Vol-4, No.3, pp. 2160-2165.