An Empirical Comparison between Artificial Neural Network and Traditional Financial Forecasting Models in Indian Context

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In this paper, efficacy of two classes of models e.g., Artificial Neural Network based models and Econometric based models has been compared in the context of Indian stock market to determine which class predict more effectively and with greater efficiency. Predictive ability of both classes of models has been tested using price values of BSE 500 index as well as all stocks within it over 16 calendar years from 1st January 2001 to 31st December, 2016.Artificial Neural Network based models have been found to be superior in terms of minimizing forecasting errors. The paper concludes that if ANN can be used properly, then its predictive ability is more than Econometric models. However, improper use may not justify its forecasting power over Econometric models.

Keywords: Artificial Neural Network (ANN), Genetic Algorithm(GA), Auto Regressive Conditional Heteroscedasticity (ARCH), Discrete Wavelet Transformation (DWT)

SECTION 1: INTRODUCTION

Among commonly available investment avenues for investors, like high risk avenues (e.g. stock market, foreign exchange market,commodity market), moderate risk avenues (e.g. mutual fund, real estate, gold) and low risk avenues (e.g. government bond, bank fixed deposits), an equity investment for a period ranging moderate to log term offers highest return as evidenced by recent literatures. Despite having mathematical proof in support of this claim, stock market around the world could not attract more than a very meager percentage of its population simply because of uncertainty in return. Here lies the importance of predicting stock price which is complex and challenging task, as large number of interrelated variables interact with each other to determine the market movement. While numerous scientific attempts have been made, no single method has yet been discovered to predict stock price movement even with reasonably degree of accuracy.

Objective of this paper is to use various types of Artificial Neural Network (ANN) based prediction models for financial forecasting as compared against financial Econometric models (such as Auto Regressive Conditional Heteroscedasticity (ARCH), Generalised Auto Regressive Conditional Heteroscedasticity (GARCH)) in order to judge the superiority and suitability for practical use.

After we submit rational of our study in this introduction, Section 2 depicts literature review. Section 3 describes our experiment. Section 4 depicts the results of our study followed by final conclusion in section 5. Harvard referencing system is used in this paper for valuable references at the end.

SECTION 2: LITERATURE REVIEW

It is evident from the literature review that very few studies have been made in Indian context (which is our main focus). As a developing country Indian financial markets are highly influenced by rapid reforms and gradually highly dependent on Foreign Direct Investment and Foreign Institutional Investment. Such liberalization and globalization influence Indian system so rapidly that innovative predictive methods are highly challenging to be used in Indian context. Moreover, the closely related research works do not include all ANN parameters to vary simultaneously (i.e. learning rate, network topology, learning algorithm, number of hidden layers etc). In addition to that, we noticed that in literature previous researchers mainly compared soft computing based forecasting models with other traditional models (like various types of regression models but very few studies are available to compare performance with econometric models. In view of the above research gap, our study is an attempt to verify predictive benefit of ANN based forecasting over ARCH/GARCH models.

There is also a growing trend towards using the ensemble approaches (combining features from two

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or more approaches) to leverage the synergy effect.The majority of the ensembles draw their components from a variety of soft computing methods (like ANN, GA, Fuzzy Logic, Swarm Intelligence, ACOetc) .Kumar, Mand Thenmozhi, M. (2012) developed a hybrid model that combines Autoregressive Integrated Moving Average (ARIMA), Exponential GARCH (EGARCH) and ANN to predict the daily returns of S&P CNX Nifty and S&P 500 indices and shows superiority than traditional models.

Dhar et al., (2010) did the same thing in Indian context and got more success than them but failed to address the prediction for multi-step ahead.To the best of our knowledge, Nag, A and Mitra, A (2002) applied ANN optimized with GA first in Indian context nicely and got limited success.The research of Das et al., (2015) adopted Functional Link Artificial Neural Network (FLANN) model for predicting the closing price of three companies. The FLANN model trained by GA has been compared with Particle Swarm Optimisation (PSO). It provides better accuracy and less time. Typically the FLANN-fuzzy approach is seen to provide better results in predicting financial distress. The effect of using technical analysis, fundamental variables and experts judgement for stock price prediction is examined by Adebiyi et al., (2011). Input variables extracted from these market hybrid indicators are fed into a fuzzy-neural network for improved accuracy of stock price prediction. The empirical results obtained with published stock data shows that the proposed model can be effective to improve accuracy of stock price prediction. Nair et al., (2011) demonstrated nicely how ACO algorithms can be used to produce a robust and adaptive search system. This paper uses, a Support Vector Machine (SVM) to forecast stock markets. The proposed method of Baboli, M and Abadeh, M. (2015) is MA-SVR, which is a combination of memetic algorithm (MA) and support vector regression (SVR). Lakshmi, Pand Visalakshmi, S. (2016) enquired the inter-linkage of the Indian spot market with other global markets and the predictability of S&P CNX NIFTY Index returns with a set of five new international market returns as input variables in artificial neural networks (ANNs). They pointed out that identifying the right set of exogenous input variables using conventional techniques like OLS, Granger causality and cross correlation substantially increased the predictability of financial time series like stock return in the Indian context.

SECTION 3: EXPERIMENT IN THIS STUDY

3.1: DATA SET: All of the prices and related information in the sample used in our study are taken from CMIE PROWESS (Prowess is a database of Indian corporate maintained by CMIE . However, BSE website is referred for possible cross-checking.

The data used in this research are the daily stock prices (open, high, low and close) of all the stocks included in BSE 500 index and the index itself. The data set covers the period from 1st Jan 2001 to 31st Dec 2016 (16 calendar years).

Hence our data set is panel data set though we have not used them together as panel. The reason is to maintain the scope and consistency with soft computing models (i.e. training & testing) for our comparative study.

3.2: TRAINING SET & TESTING SET: For ANN models to use, it is essential to divide the entire sample into two disjoint parts- training set and testing set. Firstly ANN must be trained to learn the unknown patterns in the data set and then that model is supposed to be tested for its performance. Out of these 16 years price data of our sample, 20% values are reserved for testing performance of our newly constructed model, while initial80% observations are used to train (i.e. parameter optimization) the ANN model before using for forecasting. However we have used historical data based performance evaluation but not real time performance evaluation.

3.3: SPECIFICATION OF OUR ANN: Neural networks that we have used in this study are different in terms of different parameters as given below. We considered three types of networks such as Fixed Geometry Neural Network (FNN), Genetically Optimized Neural Network (GNN), and Wavelet Decomposed Genetically Optimized Neural Network (WDGNN) with all possible combination of these parame-ters.

The parameters include the network topology (feed forward and feedback), the number of hidden layers (8 or 16),the number of hidden neu-rons in each layer (3 or 6), the type of activation function (sigmoid i.e. SIG or tan hyperbolic i.e. TANH). We have chosen two types of learning algorithms such as Supervised (Generalized delta rule) and Unsupervised (Hebbian learning rule).The error loss function (which is an important parameter in ANN based models) can be of different types. For this study we consider the two types say Absolute Error Loss (AEL) and Square Error Loss (SEL) functions only.Another parameter, learning rate, should be between 0 and 1 for any neural system. Typically we have taken it as 0.50 as the mid representative value, which determines the effect of past weight changes on the current direction of movement in weight space.

3.4: TYPES OF OUR ARCH and GARCH MODELS: Various conditional heteroscedastic models have also been considered for comparison with the ANN based forecasting mod-els. In this study, we considered the following ARCH/GARCH type models for comparison with the ANN models: ARCH(l), GARCH(1,1), Absolute GARCH(1,1), exponential GARCH(1,1) and GARCH-in mean (1,1) or GARCH-M(1,1).

3.5: ERROR METRICS USED IN THIS STUDY: The forecasting performance of the artificial intelligence and conditional heteroscedastic models are evaluated in terms of the following criteria (i.e. error metrics in our study) such as Average Absolute Error (AAE), Mean Square Error (MSE) , Mean Absolute Percentage Error (MAPE) and Percentage of Correct Movement (PCM).

3.6: PREDICTION TIME HORIZON: This paper attempted next day prediction for opening, high, low and closing prices initially. Then it extended the time horizon for multi-step ahead prediction. Typically we considered 2days ahead, 3 days ahead and 4 days ahead for this present paper.

3.7: SOFTWARES USED IN THIS STUDY: For ANN based financial prediction model, we have utilized our programming abilities and implemented such models using C++. Outputs from such programs are recorded as results in following tables. For ARCH/ GARCH models and we have taken help of Eviews software to calculate the results. Other statistical computations for hypothesis testing are done through Stata software.

3.8: RESEARCH HYPOTHESIS: Main aim of this paper is to compare the predictive ability of ANN based financial forecasting models with that of ARCH and GARCH models in the context of Indian stock market.The performances of such models have been observed experimentally.

We started initially with FNN to compare its predictive ability over ARCH and GARCH models. However, result produces no remarkable benefit to use FNN. Realizing such limitation, we planned some recovery way out. Hence, to improve prediction accuracy of ANN models, we have used GA for parameter optimization of ANN models.

Thus taking the null hypothesis that there is no difference in predictive ability (average error) of two classes of model, we proceed to further sections of this paper.

Typically we considered 13 research hypotheses to test empirically in this paper. These include Predictive ability of FF & FB Networks are same, Predictive ability of SEL & AEL functions are same, Predictive ability of TANH & SIG Activation functions are same, FNN predict better than Econometric Models, Prediction accuracy does not improve from FNN to GNN, Prediction accuracy does not improve from GNN to WDGNN, Prediction accuracy is not inversely proportional with prediction horizon, Between Supervised Learning & Unsupervised Learning, there is no difference in prediction accuracy, Change in number of Hidden Layer has impact on prediction accuracy, Change in number of neurons in each Hidden Layer has no impact on prediction accuracy, All Error Metrics are consistent with a particular model, Prediction accuracy of a particular model varies with open, close, high and low financial time series, Predictive ability of all variations of Econometric Models are same. All such hypotheses are tested statistically using z test with following justification.

SECTION 4: RESULT OF THE EXPERIMENT

This paper is supposed to present huge number of tables with respect to 13 hypotheses and all possible combinations of parameters of forecasting models. Due to limitation of space and word count, we are keeping some of the representative tables in each case. Table 1(a) depicts prediction errors against WDGNN with TANH for next day prediction of opening price of BSE 500. Such tables also have been constructed for each 500 stocks within it, also for high/low/closing prices, for SIG, for GNN, for FNN, for Econometric models and for multi-step ahead (i.e. 2/3/4 days ahead) predictions. Thus a total of (1+500) X 4 (open, high, low, and close) X 4 (one day, two days, three days and four days) X 7 ((WDGNN,TANH),(WDGNN,SIG), (GNN,TANH), (GNN,SIG), (FNN,TANH),(FNN,SIG) and Econometric) = 56112 tables are not possible to represent. So we are keeping only three representatives of them as in Table 1(a), Table 1(b) and Table 1(c) as follows.

Table 1(a) :Model Vs. Prediction Errors towards One Day ahead prediction of Opening price for BSE 500 for WDGNN with TANH

Model Specification					Error Metric			
Model Name	**Model Type**	**Number of Hidden Layers**	**Number of neurons in each Hidden Layer**	**Learning type**	**AAE**	**MAPE**	**MSE**	**PCM**
WDGNN	WDGFB,AEL,TANH	8	3	Supervised (Generalized delta rule)	0.62	0.51	0.71	0.54
				Unsupervised (Hebbian learning rule)	0.63	0.57	0.77	0.52
			6	Supervised (Generalized delta rule)	0.60	0.49	0.65	0.53
				Unsupervised (Hebbian learning rule)	0.62	0.52	0.71	0.55
		16	3	Supervised (Generalized delta rule)	0.63	0.52	0.70	0.53
				Unsupervised (Hebbian learning rule)	0.63	0.52	0.71	0.54
			6	Supervised (Generalized delta rule)	0.60	0.50	0.67	0.51
				Unsupervised (Hebbian learning rule)	0.59	0.51	0.72	0.54
	WDGFF,AEL,TANH	8	3	Supervised (Generalized delta rule)	0.63	0.52	0.72	0.55
				Unsupervised (Hebbian learning rule)	0.61	0.52	0.70	0.50
			6	Supervised (Generalized delta rule)	0.56	0.47	0.67	0.50
				Unsupervised (Hebbian learning rule)	0.54	0.48	0.70	0.49
		16	3	Supervised (Generalized delta rule)	0.62	0.50	0.70	0.52
				Unsupervised (Hebbian learning rule)	0.62	0.52	0.72	0.44
			6	Supervised (Generalized delta rule)	0.53	0.42	0.64	0.53
				Unsupervised (Hebbian learning rule)	0.61	0.50	0.69	0.51
	WDGFB,SEL,TANH	8	3	Supervised (Generalized delta rule)	0.64	0.53	0.71	0.54
				Unsupervised (Hebbian learning rule)	0.63	0.57	0.79	0.54

			6	Supervised (Generalized delta rule)	0.60	0.49	0.67	0.55
				Unsupervised (Hebbian learning rule)	0.63	0.53	0.71	0.55
		16	3	Supervised (Generalized delta rule)	0.64	0.52	0.70	0.53
				Unsupervised (Hebbian learning rule)	0.63	0.53	0.73	0.54
			6	Supervised (Generalized delta rule)	0.60	0.51	0.68	0.51
				Unsupervised (Hebbian learning rule)	0.59	0.50	0.72	0.54
	WDGFF,SEL,TANH	8	3	Supervised (Generalized delta rule)	0.63	0.53	0.72	0.55
				Unsupervised (Hebbian learning rule)	0.64	0.58	0.78	0.53
			6	Supervised (Generalized delta rule)	0.60	0.49	0.65	0.53
				Unsupervised (Hebbian learning rule)	0.62	0.52	0.71	0.55
		16	3	Supervised (Generalized delta rule)	0.63	0.52	0.70	0.53
				Unsupervised (Hebbian learning rule)	0.64	0.56	0.73	0.53
			6	Supervised (Generalized delta rule)	0.60	0.51	0.68	0.55
				Unsupervised (Hebbian learning rule)	0.59	0.51	0.72	0.54

Source : Authors own computation

Table 1(b) :Model Vs. Prediction Errors towards One Day ahead prediction of Opening price for BSE 500 for WDGNN with SIG

Model Specification					Error Metric			
Model Name	**Model Type**	**Number of Hidden Layers**	**Number of neurons in each Hidden Layer**	**Learning type**	**AAE**	**MAPE**	**MSE**	**PCM**
WDGNN	WDGFB,AEL,SIG	8	3	Supervised (Generalized delta rule)	0.61	0.51	0.71	0.54
				Unsupervised (Hebbian learning rule)	0.62	0.57	0.77	0.52
			6	Supervised (Generalized delta rule)	0.60	0.48	0.65	0.53
				Unsupervised (Hebbian learning rule)	0.62	0.51	0.71	0.55
		16	3	Supervised (Generalized delta rule)	0.64	0.52	0.70	0.53
				Unsupervised (Hebbian learning rule)	0.62	0.52	0.71	0.54
			6	Supervised (Generalized delta rule)	0.60	0.51	0.67	0.51

			Unsupervised (Hebbian learning rule)	0.59	0.51	0.73	0.51
WDGFF,AEL,SIG	8	3	Supervised (Generalized delta rule)	0.63	0.54	0.72	0.55
			Unsupervised (Hebbian learning rule)	0.64	0.57	0.78	0.53
		6	Supervised (Generalized delta rule)	0.61	0.48	0.65	0.53
			Unsupervised (Hebbian learning rule)	0.62	0.52	0.72	0.54
	16	3	Supervised (Generalized delta rule)	0.63	0.52	0.70	0.52
			Unsupervised (Hebbian learning rule)	0.64	0.57	0.73	0.51
		6	Supervised (Generalized delta rule)	0.60	0.52	0.68	0.55
			Unsupervised (Hebbian learning rule)	0.59	0.51	0.72	0.54
WDGFB,SEL,SIG	8	3	Supervised (Generalized delta rule)	0.64	0.53	0.71	0.54
			Unsupervised (Hebbian learning rule)	0.63	0.57	0.79	0.54
		6	Supervised (Generalized delta rule)	0.61	0.47	0.67	0.55
			Unsupervised (Hebbian learning rule)	0.62	0.53	0.71	0.55
	16	3	Supervised (Generalized delta rule)	0.64	0.52	0.71	0.47
			Unsupervised (Hebbian learning rule)	0.66	0.53	0.74	0.44
		6	Supervised (Generalized delta rule)	0.60	0.51	0.68	0.51
			Unsupervised (Hebbian learning rule)	0.65	0.51	0.72	0.50
WDGFF,SEL,SIG	8	3	Supervised (Generalized delta rule)	0.63	0.52	0.72	0.55
			Unsupervised (Hebbian learning rule)	0.66	0.58	0.78	0.53
		6	Supervised (Generalized delta rule)	0.60	0.48	0.65	0.63
			Unsupervised (Hebbian learning rule)	0.63	0.52	0.79	0.55
	16	3	Supervised (Generalized delta rule)	0.63	0.50	0.70	0.53
			Unsupervised (Hebbian learning rule)	0.65	0.56	0.71	0.43
		6	Supervised (Generalized delta rule)	0.60	0.50	0.68	0.55
			Unsupervised (Hebbian learning rule)	0.59	0.51	0.74	0.44

Source : Authors own computation

Table 1(c) :Model Vs. Prediction Errors towards One Day ahead prediction of Opening price for BSE 500 for Econometric Models

Econometric	ARCH(1)	0.63	0.54	0.77	0.50
	GARCH(1,1)	0.64	0.55	0.78	0.54
	AGARCH(1,1)	0.67	0.52	0.75	0.53
	EGARCH(1,1)	0.62	0.50	0.69	0.55
	GARCH(1,1)-M	0.66	0.51	0.71	0.52

Source : Authors own computation

Table 2.0 :Model Vs. Error metric performance superiority towards prediction for BSE 500

1 DAY AHEAD PREDICTION	Model Class	AAE	MAPE	MSE	PCM	AAE	MAPE	MSE	PCM	AAE	MAPE	MSE	PCM	AAE	MAPE	MSE	PCM
				(Open)				(Close)				(High)				(Low)	
									(in percentage)								
	WDGNN	42	43	44	42	42	42	43	42	44	42	47	42	42	43	45	40
	GNN	28	27	28	29	27	28	27	31	28	29	23	28	27	27	25	28
	FNN	11	10	10	11	12	11	10	10	10	11	12	11	12	13	12	14
	Econometric	19	20	19	18	19	19	20	18	19	18	18	19	19	17	19	18
	Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source : Authors own computation

Similar to Table 2, we have other three tables for 2 days, 3 days and 4 days ahead prediction, which are not kept due to paucity of space. Table 3 represents the result of hypothesis testing for all the 13 hypotheses stated earlier. This table is complete in the sense, it includes all possible cases but not any specific representative.

Table 3.0 :Summary of Hypothesis testing (at 5% level)

		Open	Close	High	Low	Observations
1	Number of stocks rejecting Null hypothesis H_0 : Predictive ability of FF & FB Networks are same	415	413	416	410	Most of the time, FB networks performed better than FF networks.
	Number of stocks failed to reject null hypothesis	86	88	85	91	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
2	Number of stocks rejectingNull hypothesis H_0 : Predictive ability of SEL & AEL functions are same	300	307	300	301	SEL function performed better for FB networks but not in case of FF networks.
	Number of stocks failed to reject null hypothesis	201	194	201	200	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
3	Number of stocks rejectingNull hypothesis H_0 : Predictive ability of TANH & SIG Activation functions are same	367	368	360	362	Prediction accuracy of TANH activation function is better than SIG for one day ahead prediction

						but not for multiday ahead prediction.
	Number of stocks failed to reject null hypothesis	134	133	141	139	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
4	Number of stocks rejectingNull hypothesis H_0 : FNN predict better than Econometric Models	425	425	422	424	FNN are trapped in local optima and not fruitful for financial prediction.
	Number of stocks failed to reject null hypothesis	76	76	79	78	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
5	Number of stocks rejectingNull hypothesis H_0 : Prediction accuracy does not improve from FNN to GNN	350	355	356	355	GA based Neural Net performed much better than both FNN and Econometric models.
	Number of stocks failed to reject null hypothesis	151	146	147	146	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
6	Number of stocks rejectingNull hypothesis H_0 : Prediction accuracy does not improve from GNN to WDGNN	396	395	390	397	Wavelet Decomposition improves prediction accuracy than GNN.
	Number of stocks failed to reject null hypothesis	105	106	111	104	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
7	Number of stocks rejectingNull hypothesis H_0 : Prediction accuracy is not inversely proportional with prediction horizon	380	387	378	380	With the increase in prediction horizon, accuracy of prediction decreases for all the models. It is quite natural due to uncertainty.
	Number of stocks failed to reject null hypothesis	121	114	123	121	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
8	Number of stocks rejectingNull hypothesis H_0 : Between Supervised Learning & Unsupervised Learning, there is no difference in prediction accuracy	355	350	349	351	Supervised Learning did better always. We could not get any improvement for using Unsupervised Learning algorithm.
	Number of stocks failed to reject null hypothesis	146	151	152	150	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
9	Number of stocks rejectingNull hypothesis H_0 : Change in number of Hidden Layer has impact on prediction accuracy	403	400	404	400	Increase in number of Hidden Layer has no role towards prediction accuracy in case of FNN but it played a good job for GNN and WDGNN.
	Number of stocks failed to reject null hypothesis	98	101	97	101	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
10	Number of stocks rejectingNull hypothesis H_0 : Change in number of neurons in each	292	290	295	289	Increase in number of Hidden neuron in each hidden layer,

	Hidden Layer has no impact on prediction accuracy					found to be successful to improve prediction accuracy but it takes more iteration to converge. Hence prediction result came in delay but accuracy improved.
	Number of stocks failed to reject null hypothesis	209	211	206	212	
	Total	500+1	500+1	500+1	500+1	
		Open	Close	Open	Open	Open
11	Number of stocks rejectingNull hypothesis H_0 : All Error Metrics are consistent with a particular model	125	121	122	120	Choice of error metrics does not found to be successful for proving the predictive superiority of any model.
	Number of stocks failed to reject null hypothesis	376	380	379	381	
	Total	500+1	500+1	500+1	500+1	
12	Number of stocks rejectingNull hypothesis H_0 : Prediction accuracy of a particular model varies with open, close, high and low financial time series		447			Predictive superiority of a model over another does not depend on the choice of financial time series. All the models performed consistently with respect to open, close, high and low time series.
	Number of stocks failed to reject null hypothesis		54			
	Total		500+1			
13	Number of stocks rejectingNull hypothesis H_0 : Predictive ability of all variations of Econometric Models are same	377	375	370	372	EGARCH (1, 1) produced better result for one day ahead prediction and AGRACH (1, 1) found to be good for other cases.
	Number of stocks failed to reject null hypothesis	124	126	131	129	
	Total	500+1	500+1	500+1	500+1	

Source : Authors own computation

SECTION 5: CONCLUSION

It is evidenced from literature that recent trend is to use soft computing techniques for error minimization of financial time series prediction, than that of traditional models. Newly introduced techniques like Neural Net, Genetic Algorithm, Fuzzy Logic, Ant Colony Optimization, Simulated Annealing, Swarm Intelligence, and Collective Intelligence are commonly used techniques under the umbrella of soft computing, which is a part and parcel of the broad domain of Artificial Intelligence.

This study is an attempt to judge the suitability of Neural Net model for financial prediction in comparison to traditional Econometric model. In addition to that, this study also enquires the optimal parameter setting for Neural Net model to minimize prediction error. Statistically all the variations of Neural Net model and Econometric model have been compared to determine the optimized model for financial prediction.

It has been found that Fixed Geometry Neural Net is not very promising than traditional Econometric model. When Genetic Algorithm is clubbed with Neural Net, then we got significant improvement due to synergy effect. Role of Genetic Algorithm is to optimize connection weights for Neural Net. Going one step further, when we decomposed financial time series using Discrete Wavelet Transformation, before being fed into genetically optimized neural net, then this study found more better prediction in terms of error minimization. All of the above predictions are for the next day value (i.e. one day ahead prediction). We further investigated for multi-step ahead prediction (i.e. for 2 days, 3 days etc). However all the models including Econometric, FNN, GNN, WDGNN failed to maintain prediction accuracy for increased time horizon.

A Neural Net model for financial time series predictioncanbe specified by a number of parameters like topology, connection weights, error loss function, activation function, number of hidden layer, number of neurons in input layer, output layer and in each hidden layer, learning rate, learning algorithm etc.

It is evident from the study that selection of Neural Net topology plays a significant role in prediction accuracy. With respect to all the Error metrics like AAE, MAPE, MSE and PCM, FB type of topology produced better result than FF type in our study. However whenever we used SEL type of error loss function with FB network, then we got much better result than AEL function.For activation function, this study found better result with TANH than SIG. Thus gradually it motivates us to use FB topology with SEL error loss function and TANH activation function. However, for multi-step ahead prediction, TANH function is not recommended and we found better result with SIG activation function. We experimented with various numbers of hidden layers and it has been found that for FNN it has no role but for GNN and WDGNN, we got enhanced prediction. When we investigated the role of number of neurons in each hidden layer, then it has been found that increase in the number would always be beneficial but it will increase the number of iteration, which is not an important issue during this age of advanced computer technology. In compared to Unsupervised Learning, this study found Supervised Learning as better option for financial prediction. Hence optimal recommendation of this paper for financial prediction includes WDGNN with FB type network topology, SEL error loss function, TANH activation function, 6 hidden neurons in each of 16 numbers of hidden layers, Supervised Learning Algorithm with generalized delta rule.

On the other hand, among various types of Econometric models we found better result for EGARCH (1, 1) for one day ahead prediction but AGARCH (1, 1) for multi-step ahead prediction.

Last but not least finding of this study is that each model performs consistently with each of the open, close, high and low time series. It means that when a particular model deteriorates its performance for opening price prediction, then it follows the same trend for closing price, high price and low price series. This finding is quite natural for a stable financial prediction model.

However, this paper tested the performances of newly proposed forecasting models with reference to historical price data. It is expected that future researchers will test their models with real time data, so that feasibility of the models can be well under stood in practical sense.

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