Quest for Behavioural Traces the Neural Way : A Study on BSE 100 along with its Oscillators

** Bikramaditya Ghosh*

Abstract

S&P BSE 100 is a broad-based index in the Indian capital market. They have many a diverse investor groups investing on a daily basis with contrasting ideas, knowledge bases, information inputs, and organic expertise. Presence of cognitive errors or overconfidence in the prediction methodology, heuristic simplification or decisions using mental shortcuts to arrive at quicker but uncertain outcomes, familiarity bias or selecting familiar stuff over more efficient, however, unfamiliar conditions and variables cannot be ruled out. This study, using neural networks on the said index, attempted to identify and determine traces of all the behavioural biases along with the construction of a reasonably accurate prediction model at the same time.

Keywords : **neural network, CNX Nifty, predictive modelling, cognitive error, heuristic simplification and familiarity bias**

JEL Classification : C45, B26, D53, G02, G11, G18

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Oscillators in bourses in the world are indicators of the short to near term directionality. RSI, stochastic drift, bollinger bands, MACD indicate momentum towards the market and more often than not come out with a clear direction. They ideally determine the closing of the market with a fair share of accuracy. However, often it has been noticed that behavioural biases such as overconfidence, heuristic simplification, choice hypothesis, and familiarity bias lowers their predictive capacity by a large extent. This study focuses on S&P BSE 100 and its oscillators, and tried to search for behavioural traces. The more the behavioural bias is found, the more difficult it is to predict the final closing of the index under consideration. The most important bias is called "cognitive error", that is, wrong assessment before any test is conducted not considering all the relevant parameters. Then "familiarity bias" comes under consideration, where the decision comes from staying inside a comfort zone, despite it being erroneous or faulty. The final frontier is arrived when the concept of "heuristic simplification", where human brain automatically makes a short-cut key to arrive at a point pre-test itself comes.

Simplification of any problem though is considered to be good, over-simplifying means omission of important parameters. So, though the present status is different, however the mind considers the past only, completely ignoring the present, thus generating a high probability of cognitive error by doing so. Many ways and methods were used in the past and are going to be used in the future (GARCH, e-Garch, logistic regression, quantile regression, classification, and regression tree etc.) as well to predict some stochastic time series like closing of the index. However, so far artificial neural network with a back-propagating error corrective option seems to be the most efficient as far as accuracy of output is concerned. So, artificial neural network has been used extensively in this study.

* *Associate Professor*, Christ University, Hosur Road, Koramangala, Bangalore - 560 029.
E-mail : bikramaditya.ghosh@christuniversity.in; bikram77777@gmail.com

Literature Review

Though similar kind of study was not found during literature review, many studies were found around this central theme. Researchers especially, from 1999 onwards used ANN extensively in predicting stock prices/index closings etc. Some used back-propagation and some used radial bias function. Most researchers used time series approach. However, few used regressive methods using various factors. The second one yielded results with higher accuracy. Some other methods that emerged out of this review are functional link neural fuzzy network (FLNFN), artificial fish swarm algorithm (AFSA), artificial immune systems (AIS), and improved bacterial chemotaxis optimization (IBCO). The interesting thing to note here is, no researcher has identified the gap areas, and on the contrary researchers have tried to construct only a predictive model with high degree of precision. The establishment of linkage between oscillator driven bourses and the various behavioural biases(such as cognitive error, familiarity bias, and heuristic simplification etc.)have not been attempted earlier for the Indian capital market.

The earliest literature, which I found was as early as 1990. Japanese researchers - Kimoto, Asakawa, Yoda, & Takeoka (1990) developed a number of innovative algorithms to track and predict the stock prices of Tokyo Stock Exchange Price Index (TOPIX). Their algorithm worked and produced excellent profits for both the traders and investors. Another noted researcher, Brownstone (1996) developed a model on FTSE or Footsie, as known popularly. The model was made in two parts from the prediction angel. Daily market close of 5 days ahead and 25 days ahead was predicted. As the result was highly accurate and the model was quite user friendly, he received plenty of accolades. In the same year a couple of Chinese research workers (Wang & Leu, 1996) developed a mid-term price trend model of Taiwan Stock Exchange (TSEWSI). This neural network system was a recurrent one extracting traits from ARIMA (1,2,1). This paper found that neural networks that run on secondary and processed data allow highly accurate predictive model.

A decade later from the auspicious start provided by the Japanese scientists, Chinese researchers (Kuo, Chen, & Hwang, 2001) mixed fuzzy neural network and artificial neural network for a decision support system for the purpose of buying and selling stocks. They used the Taiwan stock market for this genetic algorithm based code for a successful outcome. Ghosh and Srinivasan (2015a) too found profound trace of sentiment in CNX Nifty by using artificial neural network. Some noted researchers (Merh, Saxena, & Pardasani, 2010) in their study used artificial neural network (ANN) and ARIMA model to analyze the trends of some selected Indian indices such as Sensex, BSE IT, BSE Oil and Gas, and BSE 100. They used ARIMA to predict the following day price and used ANN to reduce error. Some of the researchers (Chakravarty & Dash, 2009) used functional link neural fuzzy network (FLNF) to predict both BSE and S&P500 by constructing a robust model.

Dutta, Jha, Laha, and Mohan (2011) found that prediction of Sensex closing figures with the help of ANN was possible with higher accuracy level. Nayak, Misra, and Behera (2012) used neuro-genetic hybrid network for forecasting of stock exchange rates. An Indian team of researchers, Gunasekaran and Ramaswami (2011) predicted that Sensex trends with ANN using a pricewise linear method. In fact, they were pioneers of artificial immune systems (AIS) in structuring the network. The Chinese researchers - Shen, Guo, Wu, and Wu, (2011) used radial bias function neural network (RBFNN) for forecasting Shanghai Stock Exchange. They used a unique algorithm called "Artificial Fish Swarm Algorithm".

Zhang and Wu (2009) carried out a study on S&P 500 using back-propagation neural network; the study proposed improved bacterial chemotaxis optimization (IBCO) to be merged with ANN to come up with a new range of accurate predictions. Turkish researchers - Guresen, Kayakutlu, and Daim (2011) predicted NASDAQ very efficiently with multi-layer perception (MLP) of ANN, though it was supposedly difficult as NASDAQ is an integral part of an efficient economy like the USA. The American researchers - O'Connor and Madden (2006) applied artificial neural network on Dow Jones (DJIA) with the help of external factors like commodity price, currency exchange rates etc. ; their prediction accuracy was also found to be quite high. Altay and Satman

(2005)compared the performance of ANN against performance of linear regressive (LRM) strategies in Istanbul stock market and found thatANN results beat LRM hands down by a handsome margin. Ghosh and Srinivasan (2015a, 2015b) detected a trace of sentiment or behavioural bias in CNX Nifty using probabilistic neural network (PNN) and constructed the Nifty predictor model using artificial neural network (ANN).

Objective of the Study

Artificial Neural Network (ANN) with neural layers [6, 15, 20, 1] was run to construct a model of BSE 100 based on technical oscillators and finding traces of behavioural biases in it.

Research Methodology

Technical oscillators such as RSI, SMA, Bollinger band, and stochastic drift were considered to predict the closing of S&P BSE 100. RSI or relative strength index tries to identify the overbought and oversold territories of an asset by comparative momentum gain or loss. SMA (50) shows the moving average of a time series, and clearly hints the trends and trend reversals as well. Since this study is on technical oscillators, 50 day SMA is more apt over 100 days or 200 days. Bollinger band (upper and lower)is a momentum driven band, which also has a clear link with market volatility (and its expansion or contraction) for determining the overbought and oversold regions. Stochastic drift (fast and slow)is the change of the average value of a stochastic or random time series. Generally all these parameters themselves are considered on a standalone way to buy or sell a stock. Traders or analysts either observe stochastic drift or Bollinger band or even SMA to guide their clients about the range to buy and sell stocks. The reason these were chosen as control variables in this study has its thread in the 1996 work by Wang and Leu (1996). They found out that the processed data, if used as control variable to construct a neural network produce a highly accurate model more often than not.

Artificial neural network is a machine learning tool inspired by the central nervous system of the human race. It has a series of inter-connected layered "neuron" or censors. These layers process data and ultimately lead to the final answer. Although McCulloch and Pitts introduced the concept way back in 1943 and Farley and Clark used it in real around 1954, yet it reached its efficient best during 1975 when back propagation algorithm was created by Paul Werbos. It became a unique tool for pattern recognition, regression, compression, and filtering.

The Neural Layers are [6, 15, 20, 1] in this back propagation neural network. These multi-layer neural networks are quite complex in nature as they try to replicate the function of the human brain. They operate in a back-propagating way, so at each level of learning through back-propagation the error of prediction gets reduced. The output layer here is the Closing of S&P BSE 100. That closing is an outcome of the technical oscillators that are present in the market. Six input layers consisting of six technical oscillators here. In back propagation method, a model has been built on the basis of the "training set" and the same model has been superimposed on the "testing set". Here 75% of the initial data set is considered as training dataset and left over 25% of the latest data set is kept reserved as the testing dataset. Training set in ANN study holds an important thread as the divergence and depth of the series or cross-sectional data opens up the door for efficient model construction, which in turn is tested on the testing set. Apart from building the model for prediction of the closing price with a higher level of accuracy, the second most important objective is to identify the importance of the variables. This, in turn, shows us the way to select the correct set of variables to focus on, especially when the numbers of variables are many and the decision is tough to select the most apt ones out of the entire bunch.

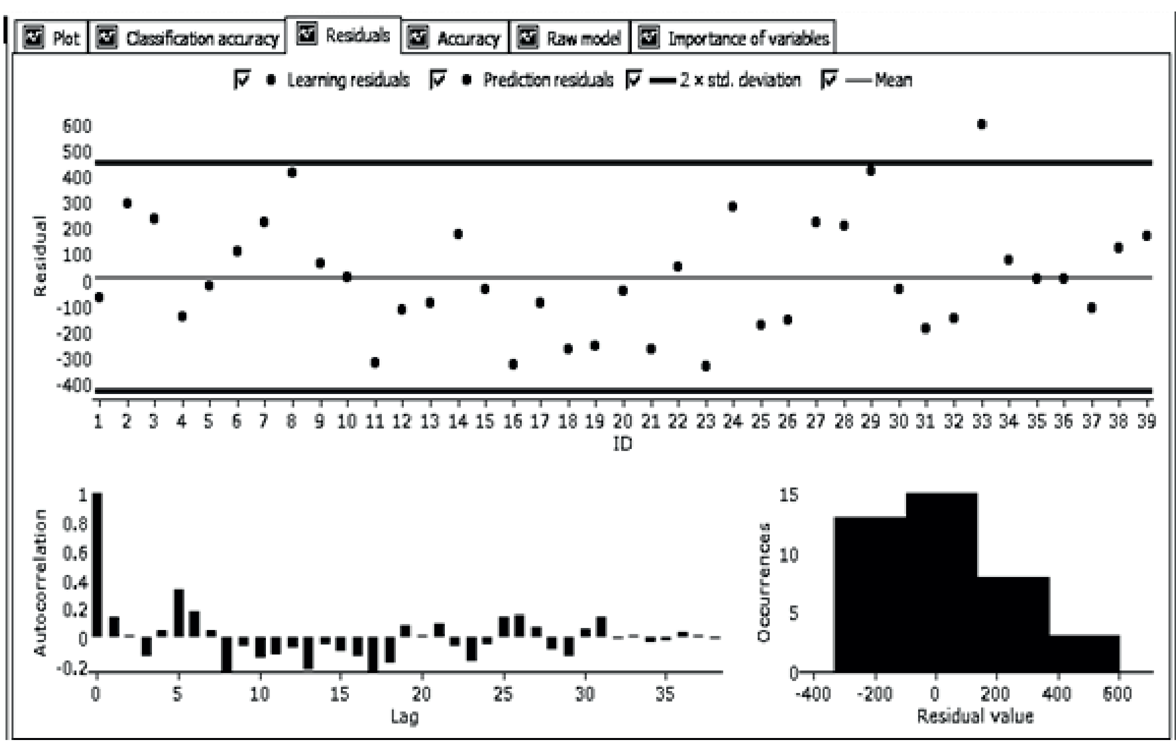
With these two tests, we will be able to identify presence of cognitive error, heuristic simplification, and familiarity bias within BSE 100. Oscillators were taken into consideration for the very fact that they are considered for a comparatively short time investments when compared to the fundamental parameters. So, the behavioural trace could be prominent in a short range when compared to a long range. Data of these technical oscillators have been under consideration from January 2013 to March 2016. Reason behind that time period is inbuilt volatility in S&P BSE 100 from 2013 to 2016. After running a GARCH (1, 1) model successfully in the mentioned time period, it was evident that the volatility was present in high octave as AIC recorded 12684.04, and standard deviation was found to be 0.56, and both ARCH Coefficient and GARCH Coefficient were found to be 0.49.

Since these are technical oscillators, the time horizon was kept under a check. Otherwise dilution effect would have made the model and the accuracy far lower. Total dataset was 273 and the data was considered for the month end. In most cases, last Thursday of the month was quite close to the closing day, adding fair bit of volatility to the entire set for calculation.

Interpretation and Results

ACF function output (Figure 1) shows that ACF drops substantially after a few lags and continues to move in a narrow band with specified volatility. This confirms that either the model is auto regressive in nature or it is a mixed model called ARMA. Since most of the stock markets do follow moving averages quite significantly, here we can conclude that this model could well be a mixed one or ARMA. Though conclusively it cannot be proved to be following ARMA 100%, yet the evidences are fairly strong in favour of ARMA. From the same Figure 1, we can also observe that though the residuals are not completely "homoscedastic", but tend to be so with the fair Histogram representation. The length of the tails or wings are similar in nature (-400 to +600)which confirms steadiness in distribution as well. This is reaffirmed from Table 1, where we have found that R^2 is 96% and coefficient of correlation is about 98%. This confirms the solidity in the model but finds minor traces of behavioural bias.

Figure 1. Depiction of Residual Movements, ACF, PACF, and Symmetry Histogram



Source: GMDH Shell Neural Network output

Table 1. Depiction of Accuracy Measurements of the Model

Error Measure	Model Fit
Max Negative Error	-333.576
Max Positive Error	600.462
Mean Absolute Error (MAE)	177.013
Root Mean Square Error (RMSE)	221.478
R Squared	0.963671

Source: GMDH Shell Neural Network output

Table 2. Depiction of Impact of Different Variables

Variable	Impact on RMSE
SMA (50)	54.75%
Bolling Band Up	21.19%
Bolling Band Low	2.94%

Source: GMDH Shell Neural Network output

Table 3. Depiction of the Neural Model Alongside Sub - Models

Model
Y1 = 3.41269 + 1.26935 N6 - 0.269839 N8
N8 = -24.7558 + 0.7886 N11 + 0.2149 N14
N14 = -1.952 + 2.89 Fast Stock + 0.986 SMA
N6 = -117.88 + 0.0824 Bolling Band Low + 0.9388 N11
N11 = 234.06 + 0.694 SMA + 0.265 Bolling Band Up

Source: GMDH Shell Neural Network output

The Table 2 decodes major behavioural bias, as SMA (50) and upper bollinger band emerge out as clear winners, consisting of more than 75% of the decisions being taken while considering both. Overconfidence on SMA(50) and upper bollinger band is shown as an indicator of "cognitive error" and "heuristic simplification," where dependence on these two costed those 4% less accuracy in prediction. Both the variables being easy, uncomplicated, known and time tested were preferred by the diverse investor groups. This proves "familiarity bias "in a clear way. "Heuristic simplification" has been proved that out of six technical oscillators one holds more than 50% importance. So, we can specify that investors have mentally developed a short cut to predict the closing of S&P BSE 100 based on two parameter i.e. SMA (50) and upper bollinger band.

The Table 3 is a clear proof of effectiveness of the "neural variables" over the input variables, as the closing of the index (*Y*1) was developed by two neural variables (namely N6 and N8). Neural variables came out as various combinations of the selective input variables. Very interestingly "choice overload hypothesis," or the theory that excessive options can limit participation because decision makers generally prefer a manageable number of decision alternatives, has been spotted in the study outcome. In this case six input variables were possibly too many for the target investor group, so they preferred only two out of six.

Implications and Concluding Remarks

It can well be concluded that though the technical oscillators were quite apt in determining the closing figure of S&P BSE 100, yet a gap has been noticed in the process. That could well be because of the fact that behavioural traces do play a crucial role; even in short term investing and trading strategies. Heuristic simplification, familiarity bias and cognitive error played the spoilsport in the prediction. Also, neural variables replaced the X variables in a study where short term specific X-variables are quite accurate in nature. X variables have been reduced to a functional part of each neural variable. Choice of one or two X-variables in a certain manner takes us to the world of cognitive error along with heuristic simplification. In trying to answer the question of behavioural trace, often the researchers were found to have overridden primacy and showed the error as a gap in the study. However, behavioural trace has been cobbled together in this piece of work along with the technical counterpart.

In an attempt to answer the question of insulating the investors from an inaccurate prediction, it becomes evident that a mixed model is the need of the hour. Those glaring research warts, could however be covered to certain extent post this investigative attempt. This study echoes another investigative piece of work (the study of Gunasekaran and Ramaswami, 2011) as far as accuracy is concerned. So, for all practical purposes, this will help making an uncertain world certain.

Limitations of the Study and Scope for Further Research

At the outset, the current study serves as the base of many future studies in the same domain. Similar kind of study could have been conducted over a wide range of bourses in a specific economic block, such as Portugal, Ireland, Italy, Greece, and Spain (PIIGS). These kind of studies have been found to define and validate the rationale of an economic block as well. Moreover, market dependency and trade relationships too could be delved upon.

References

Altay, E., & Satman, M. H. (2005). Stock market forecasting: artificial neural network and linear regression comparison in an emerging market. *Journal of Financial Management & Analysis, 18*(2), p. 18.

Brownstone, D. (1996). Using percentage accuracy to measure neural network predictions in stock market movements. *Neurocomputing, 10* (3), 237 - 250. DOI: http://dx.doi.org/10.1016/0925-2312(95)00052-6

Chakravarty, S., & Dash, P. K. (2009). Forecasting stock market. *Nature & Biologically Inspired Computing, NaBIC 2009. World Congress,* 1225 - 1230. DOI:10.1109/NABIC.2009.5393749

Dutta, G., Jha, P., Laha, A. K., & Mohan, N. (2011). Artificial neural network models for forecasting stock price index in the Bombay stock exchange. *Journal of Emerging Market Finance, 5* (3), 283 - 295.doi: https://doi.org/10.1177/097265270600500305

Ghosh, B., & Srinivasan, P. (2015a). Comparative predictive modeling on CNX Nifty with artificial neural network. *SDMIMD Journal of Management, 7*(1), 1-12.

Ghosh, B., & Srinivasan, P. (2015b). Detection of sentiment in CNX Nifty – An investigative attempt using probabilistic neural network. *International Journal of Business Quantitative Economics and Applied Management Research, 1*(12), 1 - 11.

Gunasekaran, M., & Ramaswami, K. S. (2011). Evaluation of artificial immune system with artificial neural network for predicting Bombay stock exchange trends. *Journal of Computer Science, 7* (7), 967 - 972. https://doi.org/10.3844/jcssp.2011.967.972

Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications, 38* (8), 10389 - 10397. DOI: https://doi.org/10.1016/j.eswa.2011.02.068

Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990). Stock market prediction system with modular neural networks. *IJCNN International Joint Conference on Neural Networks* (pp. 1- 6). DOI: 10.1109/IJCNN.1990.137532

Kuo, R. J., Chen, C. H., & Hwang, Y. C. (2001). An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. *Fuzzy Sets and Systems, 118* (1), 21 - 45. DOI:http://dx.doi.org/10.1016/S0165-0114(98)00399-6

Merh, N., Saxena, V. P., & Pardasani, K. R. (2010). A comparison between hybrid approaches of ANN and ARIMA for Indian stock trend forecasting. *Business Intelligence Journal, 3*(2), 23 - 43.

Nayak, S. C., Misra, B. B., & Behera, H. S. (2012). Index prediction with neuro-genetic hybrid network: A comparative analysis of performance. *Computing, Communication and Applications (ICCCA), 2012 International Conference* (pp. 1 - 6). DOI: 10.1109/ICCCA.2012.6179215

O'Connor, N., & Madden, M. G. (2006). A neural network approach to predicting stock exchange movements using external factors. *Knowledge-Based Systems, 19*(5), 371- 378.DOI : http://dx.doi.org/10.1016/j.knosys.2005.11.015

Shen, W., Guo, X., Wu, C., & Wu, D. (2011). Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm. *Knowledge-Based Systems, 24* (3), 378 - 385. DOI: http://dx.doi.org/10.1016/j.knosys.2010.11.001

Wang,J.-H., & Leu,J.-Y. (1996). Stock market trend prediction using ARIMA-based neural networks. In *the 1996 IEEE International Conference on Neural Networks* (pp. 2160 - 2165). doi: 10.1109/ICNN.1996.549236

Zhang, Y., & Wu, L. (2009). Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network. *Expert Systems with Applications, 36* (5), 8849 - 8854. DOI: http://dx.doi.org/10.1016/j.eswa.2008.11.028