International Journal of Soft Computing 8 (3): 218-222, 2013
ISSN: 1816-9503

Computationally Intellectual Structure for Forecasting Share Price

[1]M.P. Rajakumar and [2]V. Shanthi
[1]Sathyabama University, [2]St. Joseph's College of Engineering,
600119 Chennai, Tamil Nadu, India

Abstract: Earnings significant profit is the prime concern of the investor and it is rather competent to determine the future value of a company's stock. To introspect challenges in stock market researchers need to overcome the impediments and strive for further improving the focus on prediction of share market. As the market prices are flexible it is nevertheless to say a volatile and dynamic pattern of prediction is inevitable. In the present scenario application of soft computing in stock market has taken a faster face of advancement thereby inducing the hope of extracting market patterns at a speeder rate. The research is concerned with development of forecasting the company's stock price by utilizing the facilities of fuzzy inference system and neural network. The methodology employed is based on fundamental analysis and financial market theory. Based on the literature review done the current valuation of the stock-price to earnings ratio and future growth of the stock-price to earnings growth ratio could have been employed to build successful investment strategies in predicting stock market high. The empirical results obtained with stock data of NSE shows that the proposed system can be effective to improve the accuracy of stock price prediction.

Key words: Price to earnings ratio, price to earnings growth ratio, neural network, fuzzy inference system, NSE

INTRODUCTION

During the 1970s and 80s many researchers have been probing into the various traditional and technical approaches of stock prediction system and their combinations for effective predictions was extremely amazing. A prediction algorithm uses a set of known entities to produce a prediction of the future values of the same or other entities. These entities can be broadly divided into three categories: Technical data, fundamental data and derived data. The technical data is the only data used by the technical analysts. Their prognoses are based on past stock data only (Hellstrom and Holmstrom, 1997). The fundamental analysts include data related to the companies actual activity and the market situation. By combining these two categories the derived data can be produced.

A fundamental analysis of a company typically focuses the general economy (company inflation, interest rates and trade balance, etc.) the condition of the industry (other stock prices presented as indexes and the value of the competitors stock) and the condition of the company. This is normally taken from the financial statement of the company. From the financial statement there are number of useful variables can be derived like price earnings ratio, book values per share, debt ratios and prognoses future profit and sales (Adebiyi *et al*., 2012).

An earning per share is an important indicator of share value to assess a company's performance by investors (Casson and Mckenzie, 2007). An integrated ANFIS Model is used to forecast the EPS (Wei *et al*., 2011). The price to earnings ratio is also the most popular metric of stock analysis. The price to earnings looks at the relationship between the stock price and the company's earnings. This is calculated as dividing the market value per share by earnings per share. The high levels of price to earnings ratio could have resulted in the fall of stock market returns. Hence, the determinants of PE ratio can be the expected growth rate of dividends, estimated required rate of return and the expected dividend payout ratio (Ong *et al*., 2010). A price to earnings growth ratio cannot be used alone but it is a very powerful tool when integrated with the basics (price, volume and chart reading). If the PEG ratio is equal to one, it means that the market is pricing the stock to fully reflect the stocks. If the PEG ratio is greater than one, it indicates that the stock is possibly overvalued. If the PEG ratio is <1, it is a sign of a possibly undervalued stock (Easton, 2004). The price to earnings growth ratio = price to earnings ratio/short time earnings growth rate. The high levels of price to earnings growth ratio could have also resulted in the fall of stock market also.

The hybrid system is an attempt to take NN flexibility of design with logic support of time series model even in the absence of large historical data (Agarwal *et al*., 2010). High speed time delay neural networks are used for fast forecasting of stock prices (El-Bakry and Mastorakis, 2010). In a nutshell, a stock prediction system is

Corresponding Author: M.P. Rajakumar, Sathyabama University, 600119 Chennai, Tamil Nadu, India

developed based on a fuzzy neural network by using past stock data which are called as input data. The input data to each network is the high, low and average value of the daily stock data which is corresponding to the output data which also expressed as high, low and average values of daily stock data. The above data is used to discover fuzzy rules and for future predictions. Web search techniques are used to collect input data for search of specific term from the website and later the system is trained for future predictions. The proposed technique is demonstrated by considering the popular HCL TECH from NSE of stock market.

Stock forecasting is done by preprocessing input data by using principal component analysis and fed to an artificial neural network. Then, the analysis of trend of the market is done by feeding the predicted stock values on a neuro fuzzy system. The results based on forecasting and trend prediction using the proposed hybrid system are highly flexible and warrants future research and analysis.

LITERATURE REVIEW

The use of intelligent systems for stock market deals with glimpse of application of hybridized soft computing techniques for automated stock market forecasting and trend analysis. NN is applied to the investor's financial decision making to invest all types of shares (Ravichandran *et al*., 2005). The predicted value from the system is combined political and economical situation in a fuzzy inference system. These variables are fuzzy by nature. The final value is produced as a fuzzy one and as crisp one after the defuzzification process.

In case of stock market the fundamental factors influencing share prices might include performance of the company's earnings, price to earnings ratio, price to earnings growth ratio, price to sales ratio, market value of equity, growth of the company, change in board of directors and the creation of new assests, dividend, etc. (Cohen, 2010).

The flow of the proposed framework is given in Fig. 1. It can be seen from Fig. 1 that the framework consists of 8 steps. The following elaborates the steps proposed by the framework.

Data selection: In any prediction problem the first is to select the input to be used in building the Forecast Model. Data selection normally consists of three main stages namely prior information, technical indicators and exploratory data analysis (Rahou *et al*., 2007). The most common fundamental data which is pertinent to the stock market typically focus the following three factors namely general economy includes inflation, interest rates and trade balance, the condition of the industry and finally the condition of the company. The condition of the company normally extracted from the company's financial statements. These are the stock prices divided by the earnings per share, the relationship between the price earnings ratio and earnings growth expressed linguistically as high, medium and low.

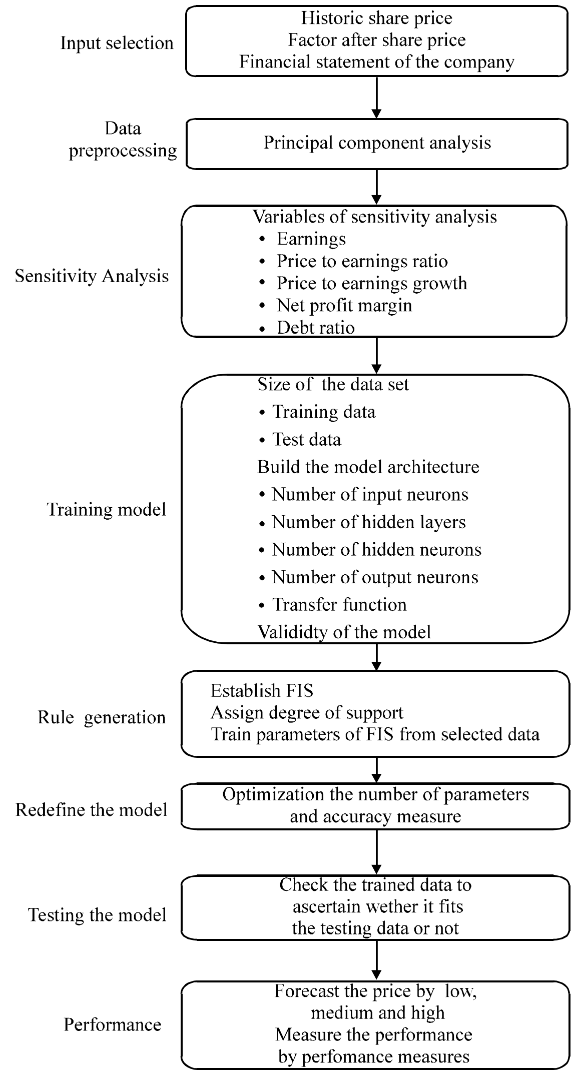

Fig. 1: Proposed framework

Data preprocessing: To facilitate the learning process of the neural network and to increase the accuracy of the prediction the data has to be processed. Input data were preprocessed using principal component analysis and fed to an artificial neural network for stock forecasting. These values are fed to neuro fuzzy system to analyze the trend of the stock market.

Sensitivity analysis: Sensitivity analysis is a kind of revision about evolutionary economical plan and uses from artificial neural network for implementing complicated functions in different fields including discriminating pattern, classification, learning and control system (Roodposti and Rasi, 2011). Data of sensitivity analysis executed using Matlab. Variables for sensitivity analysis include as it is obvious the factors of earnings, price to earnings and price to earnings growth ratio, net profit margin and debt ratio.

Training the model: Training the model includes the size of the data set, model construction and finally validating the model. Choosing the size of the dataset required to train the model is the initial stage of this process. Most of the research done by the analyst is not publically available. But there is plenty of high quality of data published in financial magazine. Experimental data were gathered from NSE for a period starting from April 01, 2000 to Dec. 31, 2011. This data set was taken for training and testing.

The training function trains the collected data and they are generally used for mapping error tolerant problems they have much data trained. Neural networks use a learning rule by which the connections weights are determined in order to minimize the error between neural network output and desired output. After successful training, the input data are presented alone to the NN (that is input data without the desired result) and the NN will compute an output value that approximates the desired result (Abbasi and Abouse, 2009). The most common training algorithm used when designing financial neural networks is the back-propagation algorithm (Lawrence, 1997). Back-propagation is a systematic method of back propagating errors through the system from the output layer towards the input layer during training and it is necessary because hidden units have no training target value that can be used, so they must be trained based on errors from earlier layers. Back propagation provides a computationally efficient method for changing the weights in a feed forward network with differentiable activation function units, to learn a training set of input-output examples (Choudhary and Rishi, 2011). A back-propagation network which only used past share prices as input had some predictive ability. The most common network architecture for financial neural networks is a multilayer feed-forward network trained using back-propagation (Lawrence, 1997). After the training process is completed, the network with specified weights can be used for testing a set of data different from those used for training (Egeli *et al*., 2003). The results achieved can then be used for generalization of the approximation of the network

The training method involves selecting the training pair from the training set and fed into the network. Calculate the error using actual output and desired output. Weights can be adjusted to minimize the error. This procedure is repeated until error is acceptable for each training data set.

Rule generation: The fuzzy inference system establishes the fuzzy rules. The inference process evaluate all the listed rules in the rule based system and combine the weighted consequences of all relevant rules into a single output fuzzy set. The base rules consists of the following:

- The high price to earnings ratio could have resulted in a fall of stock market returns
- The high level of price to earnings growth ratio could have resulted in a fall of stock market returns
- The high level of price to earnings growth implies that the price to earnings is also high
- The low level of price to earnings growth implies that the price to earnings is also low

The value called degree of support is assigned to each rule. Consider the inputs which are trained by neural network and determine the degree to which they belong to each of the appropriate fuzzy sets using membership functions. The price to earnings, price to earnings growth ratio are considered as input variables for fuzzy system.

These values are always crisp in nature limited to the universe of discourse and the output is a fuzzy degree membership in the qualifying linguistic set. In this research, the input linguistic variables adopted are low price, high price and average share price. To accomplish this task appropriate membership function were developed.

After proper weights assigned to each rule the implication method is implemented. The input for the implication process is a single number and the output is a fuzzy set. The aggregate of fuzzy set encompasses a range of output values and must be defuzzified in order to get a single output value and the share price whether it is high, low or medium.

Redefine the model: The non-significant inputs that are input that have smaller or no effect on output. Some of the data's here like prognoses of the future profit and sales are removed as they have little impact on output. This leads the parsimonious form of the model.

Testing the model: This step entails checking the trained model to ascertain whether it fits the testing data or not (Table 1 and 2).

Performance evaluation: The forecasted value will be checked to ascertain whether they are acceptable in terms

Table 1: Training results for price to earnings ratio

No. of layers	Layer	No. of neurons	Training function	Transfer function	Performance
4	1	8	TRAINCGF	PURLIN	0.0236873
	2	9			
	3	6			
	1	9	TRAINCGF	TANSIG	0.00823333
	2	8			
	3	7			
	1	7	TRAINLM	PURLIN	0.00316262
	2	9			
	3	5			
	1	10	TRAINLM	TANSIG	$3.14834e^{-008}$
	2	10			
	3	9			
3	1	7	TRAINCGF	PURLIN	0.0258684
	2	9			
	1	8	TRAINCGF	TANSIG	0.00439166
	2	10			
	1	8	TRAINLM	PURLIN	0.00344849
	2	7			
	1	5	TRAINLM	TANSIG	0.000739221
	2	6			
2	1	9	TRAINCGF	TANSIG	0.0791614
	1	7		PURLIN	0.054321
	1	8	TRAINLM	TANSIG	0.000915528
	1	4		TANSIG	0.054321

Table 2: Training results for price to earnings growth ratio

No. of layers	Layer	No. of neurons	Training function	Transfer function	Performance
4	1	7	TRAINCGF	PURLIN	0.1244890
	2	9			
	3	8			
	1	9	TRAINCGF	TANSIG	0.01121730
	2	8			
	3	6			
	1	10	TRAINLM	PURLIN	0.00979024
	2	7			
	3	5			
	1	10	TRAINLM	TANSIG	$2.6571e^{-007}$
	2	10			
	3	9			
3	1	9	TRAINCGF	PURLIN	0.01400320
	2	7			
	1	5		TANSIG	0.0129736
	2	6			
	1	8	TRAINLM	PURLIN	0.1606930
	2	6			
	1	7		TANSIG	0.00279856
	2	7			
2	1	9	TRAINLM	TANSIG	0.00142753
	1	7		PURLIN	0.14003200
	1	3	TRAINCGF	TANSIG	0.05801060
	1	6		PURLIN	0.21402300

of the application. The accuracy of the prediction is evaluated using various traditional performance measures like MAPE, MSE and RMSE.

TRAINING RESULTS

For the system described the Feed Forward Back Propagation Model were applied with varying the number of hidden layers and the number of neurons in each hidden layer to find the minimum error for the obtained data. Based on the analysis in the table it was found that the number of hidden layer is 3 and the number

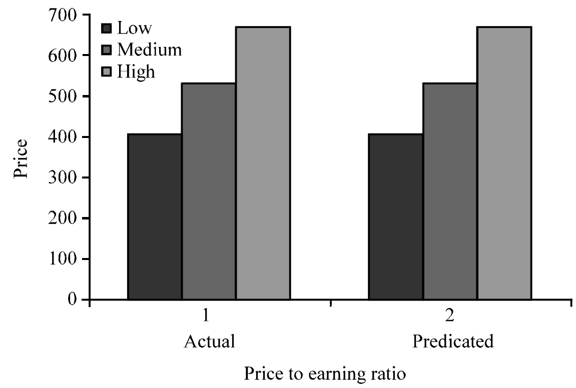

Fig. 2: Price to earnings:price comparison graph

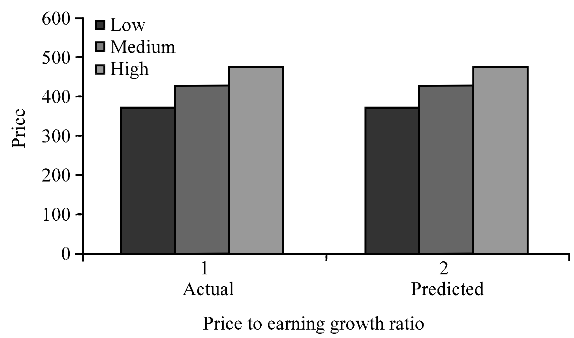

Fig. 3: Profit to earnings growth:price comparison graph

of neurons in each hidden unit is 10, 10 and 9, respectively provides better performance. For the prediction, Eq. 1 was utilized to calculate the relative error for each case in the testing set. Then, the calculated values were averaged and factored by 100 to express in percentages (Egeli *et al*., 2003). Table 1 shows the training results for price earnings ratio:

$$\frac{\left|(f_{HCL})_{actual} - (f_{HCL})_{predicted}\right|}{(f_{HCL})_{actual}} \quad (1)$$

Figure 2 shows the comparison of actual and predicted share price expressed linguistically as low, medium and high for price to earnings ratio. Figure 3 shows the comparison of actual and predicted share price expressed linguistically as low, medium and high for price to earnings growth ratio. These linguistic variables with non-crisp information are consistent with the imprecise nature.

PERFORMANCE EVALUATION

An obvious way to assess the quality of the learned model is to see on how long term the predictions given by

Table 3: Price to earnings error index values

Error indexes	Errors Low	Medium	High
Mean absolute percent error	8.955E-06	1.3861E-050	9.9948E-060
Mean squared error	0.0131071	0.048277800	0.025888900
Root mean square error	0.1144863	0.219722100	0.160900300
Mean absolute error	0.0886667	0.163333300	0.111111100
Hit ratio	0.8888889	0.888888889	0.888888889

Table 4: Price to earnings growth error index values

Error indexes	Errors Low	Medium	High
Mean absolute percent error	8.22E-05	7.7065E-05	4.1168E-05
Mean squared error	0.30304711	0.5260222	0.22656667
Root mean square error	0.55049715	0.7252739	0.47599020
Mean absolute error	0.44577778	0.5955556	0.35
Hit ratio	0.8888889	0.888888889	0.88888888

the model are accurate. The accuracy of the prediction model is evaluated using the traditional performance measures such as Mean Absolute Percent Error (MAPE), Mean Squared Error (MSE), Root Mean Square (RMS), Mean Absolute Error (MAE) and Hit Ratio (HR). Table 3 shows the performance measures for price to earnings ratio. Table 4 shows the various performance measures for price to earnings growth ratio.

CONCLUSION

The overall result throws light to the fact that the current valuation of the stock-price to earnings ratio and the future growth of the stock-price to earnings growth ratio apart from earnings plays significant role in predicting the company's stock price accurately. This research enhances the role of the fundamental factors thereby striving towards successful prediction. This research can be a base for further research where it can be elaborated by adding other input variables such as earnings status ratio, earnings per share, book value, price to book value ratio, price to sales ratio and linguistic terms for fuzzy logic concern decision making. It can also be extended by combining with other methods to assess stock price volatility for investment purpose. Further exploration in the field of fuzzy logic can be associated by using other artificial intelligent technique.

REFERENCES

Abbasi, E. and A. Abouse, 2009. Stock price forecast by using neuro-fuzzy inference system. Int. J. Busi. Econom. Finan. Manage. Sci., 4: 11366-1139.

Adebiyi, A.A., C.K. Ayo, M.O. Adebiyi and S.O. Otokiti, 2012. An improved stock price prediction using hybrid market indicators. Af. J. Comput. ICT., 5: 124-135.

Agarwal, D.J.P., V. Singhal, A. Singh and R.K. Murmu, 2010. Comparative study of volatility forecasting between ann and hybrid models for indian market. Int. Res. J. Finan. Econom., 45: 68-79.

Casson, P. and G. Mckenzie, 2007. A comparison of measures of earnings per share. Eur. J. Finan., 13: 283-298.

Choudhary, A. and R. Rishi, 2011. Improving the character recognition efficiency of feed forward bp neural network. Int. J. Comput. Sci. Info. Technol., 3: 1-85.

Cohen, G., 2010. P/E Versus PEG: Which better predicts abnormal return? Int. J. Econ. Res., 1: 38-46.

Easton, P.D., 2004. PE ratios PEG ratios and estimating the implied expected rate of return on equity capital. Accounting Rev., 79: 73-95.

Egeli, B., M. Ozturan and B. Badur, 2003. Stock market prediction using artificial neural networks. Proceedings of the 3rd International Conference on Business, June 18-21, 2003, Hawaii, pp: 1-8.

El-Bakry, H.M. and N. Mastorakis, 2010. Fast forecasting of stock market prices by using new high speed time delay neural networks. World Acad. Sci. Engin. Technol., 37: 705-711.

Hellstrom, T. and K. Holmstrom, 1997. Predicting the stock market. Tech. Report Series IMa-TOM-1997-07. Vasteras, Malardalen University, http://www.e-m-h.org/HeHo98.pdf.

Lawrence, R., 1997. Using neural network to forecast stock market prices. Department of Computer Science, University of Manitoba, Canada, http://sharesforcast.googlecode.com/svn-history/r77/nn.pdf.

Ong, T.S., Y.N. Yichen and B.H. Teh, 2010. Can high price earnings ratio act as an indicator of the coming bear market in the Malaysia? Int. J. Busin. Soc. Sci., 1: 194-211.

Rahou, A.A.M., H. Al-Madfai, H. Combs, D. Gilleland and A. Ware, 2007. A generalized algorithm for modeling and forecasting the share prices of the banking sector. Proceedings of the World Congress on Engineering, Volume 2, July 2-4 2007, U.K., London, pp: 948-955.

Ravichandran, K.S., P. Thirunavukarasu, R. Nallaswamy and R. Babu, 2005. Estimation of return on investments in share market through ANN. J. Theor. Applied Infor. Technol., 3: 44-54.

Roodposti, F.R. and R.E. Rasi, 2011. Sensitivity analysis based on artificial neural networks for evaluating economical plans. Proceedings of the World Congress on Engineering, Volume: I. July 6-8, 2011, U.K., London.

Wei, L.Y., C.H. Cheng and H.H. Wu, 2011. Fusion ANFIS model based on AR for forecasting EPS of leading industries. Int. J. Innov. Comput. Info. Cont., 7: 5445-5458.