

A Comparison of Intelligent Soft Computing Techniques for Forecasting Earnings Per Share

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Abstract: Market share price prediction plays a significant role in the current era for any economy which is on the development stage. In general, Earnings per share (EPS) is considered to be the most vital variable to determine the market share price. EPS forecasts are of important concern to investors, financial analysts and market investment researchers. Soft computing is a promising compilation of methodologies which learn, model and evaluate multifaceted phenomenon. This paper reviews recent literature in the field of intelligent soft computing to forecast the EPS. Classification is made in terms of hybrid soft computing techniques, independent variables, performance measurement and other useful modeling information. Through the examined documents, it is shown that hybrid soft computing techniques are extensively acknowledged and it evaluates market behavior more accurately compared to standalone soft computing methods and other statistical methods.

Keywords: stock market, earnings per share forecasting, hybrid soft computing techniques, statistical methods, standalone soft computing techniques.

1 Introduction

Intelligence is described as widespread cognitive problem-solving ability. It is straightly associated to the way of thinking and decision making. Computational intelligence (CI) is defined as the learning of adaptive methods to facilitate the intelligent activities in composite and changing environment to which explicit modeling are unproductive or unrealistic. The good aspirant for CI is imprecise data, non-availability of mathematical model, unknown optimal solution, need of robust system and rapid prototyping. CI produces solutions for such and other complex problems. CI mainly comprises of manv-

computation. In addition, it also includes swarm intelligence and artificial immune system.

Soft computing (SC) is a promising compilation of methodologies which learn, model and evaluate multifaceted phenomenon. SC is a promising approach to computing which analogous the outstanding capability of the human mind to cause and learn in an atmosphere of uncertainty and imprecision [1]. The goal of SC is to develop acceptance for vagueness, partial truth in order to realize robustness, uncertainty and tractability with total low cost. The major components of SC are the combined set of CI pattern and probabilistic methods.

A company's earnings are merely its revenues. Shareholders and investors often use EPS to evaluate the earnings of different companies. EPS is calculated by dividing the net profit for a particular quarter by the total number of outstanding shares in the market. A company reports its EPS in each quarter. So, we can get this figure from the quarterly result. EPS represents the profitability of a common stock and the financial performance of the company. An earnings per share is a very important figure. EPS is considered to be the most vital variable to determine the market share price. It reveals a lot about the financial health of a company. Increasing EPS is a very good sign for a particular company. Moreover, it can come handy while choosing stocks from a bunch of stocks.

EPS is considered to be a sign of the healthy or bad financial situation of the business and its raise was reflected in the market price, profit earnings ratio, earnings yield, dividend coverage and dividend-price ratio [2]. There is a considerable impact of earnings declaration on stock prices and extremely strong constructive relationship between EPS on its stock price [3]. The impact of EPS and profit earnings ratio elucidates 63 percent of change in one time ahead stock returns [4]. In the long-run investment there exists a solid rapport between stock prices and EPS. Furthermore, EPS has strong impact in share prices especially for the industry with a low level of growth rate [5].

Although the concept of EPS is simple and straightforward, EPS forecasting is a very challenging task. Forecasting EPS are of important concern to investors, financial analysts, market investment researchers and practitioners [6]. Investors use these forecasts as a basis to configure their investment portfolios, market risks and top management use for a host of important decisions including capital investment and operational budgeting [7][8]. The more accurately you can determine the path of a company's future earnings, the more accurately you can determine the price path of that company's stock. Prediction of stock price trends and EPS has been considered as both attractive and complicated research topic in the field of trade finance and engineering because of its potential monetary gain. This paper reviews forecasting of EPS using time series model and traditional statistical model. This paper also reviews literature in the domain of intelligent soft computing techniques which comprises of NN, NN variants, GA and DM to forecast the earnings. The hybrid model can supplement its separate standalone components.

The purpose of this work is to review and classifying the hybrid soft computing techniques to stock market earnings prediction. Results are presented in 3 tables. The first table lists the various models, descriptions, enhanced features and scope for future work. The second table presents the

stock market, data preprocessing techniques used and performance measures. The last table summarizes some useful modeling information like sample size of the work, validation set, training process, network structure and the membership function used.

Table 1. Comparison of different forecasting techniques

Forecasting models	Descriptions	Comparative performance analysis	Main features	Future work
AR & ANFIS [9]	Hybrid model consists of AR into an ANFIS was proposed to predict the EPS. The order of AR is set to one by setting the lag period of the EPS. FIS was generated followed by training of FIS from the training data set.	This fusion model outperforms the linear regression, AR (1), MLP and RBF models in forecasting accuracy in 5 out of 8 dataset considered.	Combines both the advantages of time series model and soft computing model.	The fusion model can be extended to predict the individual stock price and future market. The performance can be evaluated using minimal entropy principle.
ARMA & ANFIS [10]	AN integrated ANFIS model by adopting the ARMA concept into ANFIS model was developed forecast the EPS. Correlogram was used to find the terms of AR and MA.	The hybrid model is superior compared to NN, fuzzy system, ANFIS, combined AR – ANFIS model.	Combines both the advantages of time series model and soft computing model.	Forecasting model may consider other useful variables such as profit earnings ratio along with EPS to depict clear picture of the entire situation of the company's market value.
GGM [11]	A GGM (1, 1) was used to predict quarterly accounting EPS. This GGM consists of data preparation, grey group model and validation stages. Data preparation step consists of data cleaning, completeness and rearranging. GM construction can be conducted by utilized those observations. The validation step authenticates with validations data set.	This model do better than the statistical methods such as Foster model	Easy calculation, only few observation needed than statistical modeling, liberated the user from the procedure of model based selection	Finding the appropriate mean factors, finding appropriate number of observation for different applications
ANN & BP [12]	The study proved that an ANN with BP can able to forecast the EPS with less error. This model used number of independent variable to predict the EPS.	The ANN with BP forecasts EPS with less error than the ANN with GA model.	NN does not force boundaries on the number of input data, not sensitive to noise, unreliable data and provide tolerance to missing or erroneous values.	
ANN & GA [13]	NN model using GA is used to forecast the EPS. This hybrid model used various number of accounting variables	The ANN, GA with fundamental variables is superior to ANN & BP without fundamental variable, with fundamental accounting variable, ANN & GA without fundamental variable.		Nature of the data set can be extended. Comparative study can be done between Chinese listed companies and US companies.
ANFIS & DT [14]	The combined process of ANFIS & DT is used to predict the EPS. The key attributes are selected using feature selection method. For data discretization, C.45 DT is used. Generating FIS followed by training parameters of FIS was done to decide on the best possible FIS model.	The integrated ANFIS model outshines the time series model, NN, logit-based financial statement model, ANFIS and cash flow information	Combines the features of NN & FIS, modeling the qualitative aspects easily, deal uncertainty and nonlinear problem, minimize entropy copy, keep dividing attribute well into a number of parts	To acquire the boarder data set, time spanning may be extended backward and forward, verification can be done by introducing more experiments
Rule extracted by GA from NN [15]	This work studied EPS forecasting using MLPNN and rule extraction from NN by GA. The work also observed the most advantageous model between RE and MLP by estimating their forecasting correctness.	The final outcome shows that the rule extraction from NN by GA technique is more precise than MLP.	It takes into account of several number of hidden layers, does not depend on the training algorithms of NN, Does not modify the training result, can be employed	

NN with BP & NN with GA [16]	The author studied the relative effectiveness of NN models estimated with a GA in predicting future EPS.	Univariate NN models do better than univariate ARIMA. It also outperforms the linear regression models. The addition of fundamental accounting variables adds considerable expounding influence to EPS forecasting models.		
Time series models [17]	This study compared the accuracy of four different methods for forecasting EPS namely Holt-Winter exponential smoothing model, ARIMA modeling also known as Box-Jenkins model, X11 and X11ARIMA.	In the four models (Holt-Winter exponential smoothing model, ARIMA modeling, classical decomposition by census-X11 methods coupled with time series regression analysis, classical decomposition by X11-ARIMA methods coupled with time series regression) no one technique established to be better statistically for short term forecasting.		Long term forecasting can be done using these for model with different on different economic time series.
NN [18]	The author used NN model to forecast the quarterly EPS. The study concludes that NN not essentially better than time series model even for highly non-linear data and/or non-stationeries data.	NN model are not inevitably superior to the time series linear models such as and Griffin-Watts time series model and Brown-Rozeff. NN models are superior to the Foster model.	Linear time series models works better even for the firms which exhibit important non linearity and non-stationeries	The hype about NN and the bias against the negative results for the state of the art techniques should be examined carefully.
Genetic programming [19]	The author estimated the capability of genetic programming as both a forecasting model estimator and a forecast-combining methodology.	Genetic programming is not superior to traditional methodologies such as ARIMA, value line method in forecasting EPS.	Genetic programming has no significant advantage over the other traditional model such as ARIMA.	
SWMR & MOGA [20]	A combination of SWMR-MOGA is proposed for accurate earnings forecast. This hybrid method is used to select only critical and minimal financial ratio	Proposed method is superior than simple exponential model, moving average model, stepwise model and AR model	Combine the advantages of MOGA and multiple regression, intellectual selection of nominal significant financial ratios, robustness, stability	
SWMR & PSO [21]	A hybrid swarm intelligence based mechanism to predict EPS was proposed. The hybrid model also evaluates the forecasting accuracy of other statistical tools such as exponential, moving average and AR model.	Execution efficiency, convergence speeds are better than SWMR-MOGA, simple exponential model, moving average model, stepwise model and AR model.	Combines the advantages of statistical methodologies and PSO, nonlinear searching methodology, execution efficiency, convergence speed, intellectual selection of nominal significant financial ratios	
RBF [22]	The forecasting accuracy of EPS evaluated using three different models using linear regression, RBF and MLP. The paper concluded that different models should be used for different data sets.	MLP and linear regression model performs better than RBF model for linear data. For highly nonlinear data MLP is superior to linear regression and RBF.	Parameter selection process, 10 fold cross validation	Different data sets should be included for different models.
RBF [23]	NN model to forecast EPS was developed with the help of various RBF models namely RBF1 (simple naïve model), RBF2 (includes financial ratios) and RBF3 (comprehensive model - includes financial ratios, macro-economic variables and market variables).	This approach does better than regression and financial analyst forecast in EPS. RBF3 model provides better accuracy compared to RBF1 and RBF2 since it includes macro-economic and market variables)	No need of any assumption of the relationship between variable, even work with in times of instability and crisis time period, deals with irregularity placed data points, clustering algorithm is used in hidden layer to	i) Different groups of variables may be considered for better accuracy ii) investigation should be done to find the relationship between the variables and earnings iii) methods to be developed to deal the missing data points

Time series and AI model [24]	The author evaluated the forecasting accuracy of two time series model (ARIMA and TF) and two artificial intelligence model (ANN and GA). Both basic and diluted EPS were considered for predicting the future basic EPS. Further the author shows that no evidence in terms of better accuracy between basic and diluted EPS.	i) The TF model that includes CRR into the ARIMA model reveals superior forecasting precision than the ARIMA model. ii) Linear time series model yield better quarterly basic EPS forecasts accuracy than the ANN model. iii) GA is superior to TF and ANN model. iv) Finally ANN model demonstrates the least precision in predicting courses and the GA model confirms the greatest accuracy in predicting directions.	GA evidently leads in logic methods and discriminate analysis	In addition, GA can be applied in other monetary fields such as commodity markets and futures to inspect its soundness in projecting power.
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Table 2. Stock market, independent variables, data preprocessing and performance measurements of SC and hybrid SC techniques

Hybrid neural network	Stock Market	Independent variables	Data Preprocessing	Performance measurement
AR & ANFIS	Taiwan stock exchange	Historical Earnings Per Share	Testing the lag period of EPS	RMSE
ARMA & ANFIS	Bombay stock exchange	Historical Earnings Per Share	Augmented dickey fuller test, Testing the lag period of EPS	Mean error, MSE, MAD, MAPE, RMSE
GGM	Taiwan stock exchange	Historical Earnings Per Share		MSE, MAE
ANN with BP	Tehran stock exchange	INV, AR, non-commercial accounts, CAPX, gross earnings, SA, ETR, LFP.	Normalized to [0,1]	MSE, MAE
ANN & GA	Chinese stock market	Historical Earnings Per share and fundamental accounting data such as INV, AR1, CAPX, GM, SA, ETR, LFP		MSE, MAPE, F-statistic
ANFIS & DT	Taiwan stock exchange	Historical Earnings Per Share	Normalized to [0,1]	RMSE
Rule extracted by GA from NN	Tehran stock exchange	Historical EPS and fundamental accounting variables such as INV, AR1, CAPX, GM, SA, ETR, LFP		MSE, MAPE, R ² , Adjusted R ²
NN with BP & NN with GA	United states	Historical EPS and fundamental data such as INV, AR1, CAPX, GM, SA, ETR, LFP		MAPE, MSE
Time series model	United states corporation	Historical EPS data		MSE, MEAN RMS, MAPE
NN	New York stock exchange	Historical EPS data	Normalized between 0 and 1	MAPE, MAD, MSD
Genetic Programming	New York stock exchange	Lagged model error, lagged EPS data, Value line data, different ARIMA model value		SSE, Sum of absolute errors
SWMR & MOGA	Taiwan stock exchange	Net sales, total assets, market value of equality, sales growth rate, return on total assets, current ratio, leverage, turnover	Normalized between 0 and 1	SSE, mean and standard deviation
SWMR & PSO	Taiwan stock exchange	Selection of financial ratio based on binary PSO	Normalized between 0 and 1	Mean and standard deviation
RBF	software			RMSE, Correlation

RBF	Hong Kong stock market	Macro-economic variables, general market statistic, company specific market measures, company specific accounting ratios	Wasserman model normalization	MAPE, MSD, SSE, Standard deviation, Theil U-statistic
Time series and AI model	S&P 500, data gathered from COMPUSTAT database	Basic EPS, diluted EPS, CRR, firm's stock return data and market value		MAE, MAPE

Table 3. Modeling information

Hybrid neural network	Sample size	Validation set	Training process	Company	Membership function
AR & ANFIS	15 Quarter data from first quarter of 2005 to third quarter of 2008	Training data: two-thirds of data (10 quarter from first quarter of 2005 to second quarter of 2007) Testing data: one-thirds of data (5 quarter from third quarter of 2007 to third quarter of 2007)	ANFIS: Least-square method and BP gradient descent method, Training stopping criterion - 0.05	7 industries and 8 firms of Taiwan stock exchange	FIS: Triangular membership functions for input variables and constant type for output variables.
ARMA & ANFIS	39 quarter data from march 2002 to December 2011	Training data: 80 % (31 quarter data) Testing data: 20 % (08 quarter data)	Combination of least-squares and BP gradient descent method. The number of epochs is given as forty and error tolerance is close to zero	Company from information sector	For independent variable set the triangle type membership function and for dependent variable EPS (t + 1) set the constant type of membership functions.
GGM	48 quarter data from First quarter of 1996 to fourth quarter of 2007	Training data from First quarter of 1996 to fourth quarter of 2006 Testing data from First quarter of 2007 to fourth quarter of 2007	A GGM (1,1) is the solution of the pseudo difference equation formed as $\frac{dy^{(1)}}{dt} + az^{(1)} = b$, where $z^{(1)}(i) = \frac{1}{2}(y^{(1)}(i) + y^{(1)}(i-1))$ for $2 \leq i \leq N$ and $y^{(1)}_1$ is accumulated generating sequence	50 companies	
ANN with BP	Seven financial years of data	Training data: six financial years (86 %) Testing data : one financial year (14 %) from 3843 data points	8-24-1 architecture that is 8 input layers, 24 hidden layers and one output layer.	14 different industries and 61 firms	MLP with sigmoid transfer function, epoch number =1000 , error= $10^{-6.5}$
ANN with GA	36 quarter data from First quarter of 1999 to fourth quarter of 2006	Training data: 75 % Testing data 25 % (9 forecasts based upon the previous 27 quarters data)	Input layer, a hidden layer and a output layer	22 industries and 723 firms	Logsig transfer function
ANFIS & DT	Nine quarterly EPS data from first quarter of 2006 to first quarter of 2008	Training data: 66 % Testing data 34 %	ANFIS: Least-square method and BP gradient descent method	Electronic industry	Decision tree : C.45 for data discretization
Rule extracted by GA from NN	11 years of data	Training data : 9 years of data from 2000 to 2008 Testing data : 2 years of data from 2009 to 2010	GA parameters: Population size =120, iteration=250, crossover probability 0.4, mutation probability 0.6, chromosome size = 20	24 industry and 90 firms	MLPNN: activation function: sigmoid, learning rate: 0.20, number of hidden neurons: 25, iteration:19400, momentum:0.15

NN with BP & NN with GA	Second quarter of 1992 to the first quarter of 2002 (40 quarters of EPS data 5 quarter data for differencing)	Training data from second quarter of 1992 to third quarter of 1999 and Testing data from fourth quarter of 1999 to first quarter of 2002	input layer, a hidden layer and a output layer	41 industries and 283 firms.	Logsig transfer function
Time series model	Data selected from COMPUSTAT data file and published financial reports from 1975-1987	Training data: 1975- 1984 Testing data : 1984-1987		47 firms	
NN	40 quarters of data	Each rolling trials is broken down to 36 adjacent point 4 tuples as key in and 36 equivalent outputs.	Input layer, a hidden layer and a output layer	296 Firms	Sigmoid function
Genetic programming	First quarter of 1963 to fourth quarter of 1980	Training period: 1963Q1-1980 Q4 Validation period: 1981 Q1-1981 Q3 Testing period: Not applicable.	Selection method – best, fitness Population size - 100,500,1000 Generations-2,5,10 error weights - equal, front	17 firms	
SWMR & MOGA	First quarter of 1991 to the fourth quarter of 1999	Training data: 16 quarters (80 %) Testing data: 04 quarters (20 %)	Population size=50, chromosome length = 65, number of generations =2000 selection method- roulette wheel, crossover method- one-point cross over crossover rate=0.6, mutation rate = 0.001	17 different industries and 109 companies	
SWMR & PSO	First quarter of 1991 to the fourth quarter of 1999	Training data: 16 quarters (80 %) Testing data: 04 quarters (20 %) Validation data : four quarters data	Population size = 50, chromosome length = 65, number of generations = 2000 selection method - roulette wheel, crossover method- one point cross over crossover rate = 0.6, mutation rate = 0.001	17 different industries and 109 companies	PSO parameters: Population size = 50, dimension size = 65, number of generations = 2000, maximum velocity = 6.0, acceleration constants = 2.0, 2.0
RBF	14 years of quarterly data (56 quarterly EPS data)		Linear regression model, MLP: Sigmoid function	6 companies	RBF: input layer, one hidden layer , a output layer, Gaussian functions
RBF	From 1989 to 1998 with 5659 observations	Training data : 4338 observations testing data :1321 observations	Input layer, one hidden layer, a output layer	64 companies	Linear activation function
Time series and AI model	First quarter of 1992 to the fourth quarter of 2003 consists of 48 observations	Training data : 40 quarters data Testing data : 08 quarters data 8 periods (out-of sample) are employed to compute the performance	BPN, Input layer, a hidden layer and a output layer, Transfer function : TanH, Learning rule: Norm-com delta rule	109 firms	Cross over probability = 0.8, mutation probability = 0.05

2 Findings

Soft computing techniques achieve better forecasting accuracy compared to customary statistical based methods.

Hybrid soft computing techniques outperform standalone soft computing and conventional models and provide more robust and consistent problem solving models.

(for testing). 50–50 and two thirds for training and one third for testing are commonly used. Since information regarding stock is normally complex, involves more number of independent parameter and contain huge data set size different training set and of testing data is used.

In order to get better forecasting accuracy, particularly for stock market data which consists high noise and unusual scales forecasting models should carry out data preprocessing in the forecasting process. The data preprocessing stage facilitate the learning process, enhance the precision of the prediction model and decrease the computational cost.

The architecture of an artificial neural network has a great impact on the generalization power. More precisely, by varying the number of layers and neurons in each hidden layer generalization capability can be appreciably changed. Hence, designing the hidden layer construction has turn out to be a research challenge. Optimal number of hidden layer is decided based on minimal error and highest accuracy.

3 Conclusions

This study has surveyed articles of intelligent soft computing techniques to predict stock market earnings per share. This study has focused on independent data, data preprocessing methods, network structure, membership function used, comparative studies, performance measures and other useful modeling information. Information regarding a stock is normally incomplete, complex, uncertain and vague, hybrid soft computing techniques are suitable for forecasting stock market data. The analysis demonstrates that hybrid soft computing techniques outperform standalone soft computing and conventional models. The hybrid model provides extremely accurate predictions since it focuses on different data set characteristics. However, difficulties arise while defining the structure of the network, number of hidden layer and number of hidden neurons, etc.

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Appendix:

ADF	Augmented dickey-fuller test
AI	Artificial intelligence
AMAPE	Average mean absolute percentage error
ANFIS	Adaptive neuro fuzzy inference system
ANN	Artificial neural network
AR	Autoregressive
AR1	Accounts receivable scaled by the number of common shares
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BP	Back Propagation
CAPX	Capital expenditure scaled by the number of common shares
CC	Correlation coefficient
CI	Computational intelligence
CRR	Cash reinvestment ratio
EPS	Earnings per share
ETR	Effective tax rates
FFNN	Feed forward neural network
GA	Genetic algorithm
GGM	Grey group model
GM	Gross Margin scaled by the number of common shares
INV	Dollar value of inventory scaled by the number of common shares
LFP	Log of Labor force productivity
MA	Moving average
MAD	Mean absolute deviation
MAP	Maximum absolute percentage error
MAPE	Mean absolute percentage error
MLP	Multi-layer perceptron
MOGA	Multi objective genetic algorithm
MSE	Mean squared error
NMSE	Normalized mean squared error
PSO	Particle swarm optimization
R ²	Squared correlation
RBF	Radial basis function
RMSE	Root mean squared error
RR	Rate of return
RST	Rough set theory
SA	Selling and administrative expenses scaled by the number of common shares
SC	Soft computing
SSE	Sum of squared errors
SVM	Support vector machine
SVR	Support vector regression
SWMR	Sliding window multiple regression
TF	Transfer function model
TIC	Theil inequality coefficient

