Advances in Mathematical Finance & Applications, 1(2) (2016), 95 - 104

Published by IA University of Arak, Iran
Homepage: www.amfa.iau-arak.ac.ir

Forecasting the Profitability in the Firms Listed in Tehran Stock Exchange Using Data Envelopment Analysis and Artificial Neural Network

Maryam Saberi [a,*], ***Mohammad Reza Rostami*** [a], ***Mohsen Hamidian*** [b], ***Nafiseh Aghami*** [c]

[a] *Department of Management and Accounting, Tarbiat Modares University,Tehran, iran*
[b] *Department of Economics and Accounting, Islamic Azad University South Tehran Branch, iran*
[c] *Department of Management and Accounting, Al-Zahra University, Tehran,iran*

ARTICLE INFO

Article history:
Received 12 Septamber 2016
Accepted 29 December 2016

Keywords:
Artificial Neural Network (ANN),
Fuzzy DEA,
Earnin predicting,
Decision Making.

ABSTRACT

Profitability as the most important factor in decision-making, has always been considered by stakeholders in the company's profitability. Also can be a basis for evaluating the performance of the managers. The ability to predict the profitability can be very useful to help decision-makers. That's why one of the most important issues is the expected profitability. The importance of these forecasts depends on the amount of misalignment with reality. The amount of deviation is less than the forecast of higher accuracy. Although there are various methods for predicting but the use of artificial intelligence techniques is increasing due to fewer restriction. The aim of this study is to evaluate the predictive power of profitability using DEA and neutral network, to enhance the decision-making users of 2012 to 2015of 7 premier financial ratios were used as independent variables. Test results show that both of ANN and DEA have ability to forecast profitability and given that neutral network prediction accuracy is higher than the DEA, the model predict better the profitability of companies.

1 Introduction

Financial statement analysis is often undertaken to provide insight on the future profitability of the firm. Return on assets (ROA) is one of the most popular measures used to assess firms' future profitability. Financial statement analysis textbooks suggest that disaggregating the return on assets into asset turnover and profit margin can increase the ratio's usefulness by providing information about industry characteristics, firms' strategies, and firms' performance. Fairfield and Yohn document that disaggregating change in return on assets into change in asset turnover and change in profit margin can be useful in forecasting profitability. They show that change in asset turnover is the primary driver of their results. We investigate the usefulness of those traditional financial statement analysis tools for the oil and gas industry. However, traditional ratio analyses may not provide the same insights for future profitability of firms that engage in oil and gas production due to a long time horizon between initial investment and the realization of benefits from the investment, and because of the capitalization of exploration (EXP) cost. Due to the long time horizon and the capitalization of EXP costs for oil and gas firms, we propose an efficiency measure using data envelopment analysis (DEA). We examine the incremental usefulness of our proposed efficiency measure over the components of change in return on assets in forecasting changes in future profitability.

* Corresponding author. Tel.: 09378477436
E-mail address: **accmsaberi@gmail.com**

Traditional financial ratios such as ROA and its components are likely to reflect success in resource utilization and performance. However, historical cost based accounting information and traditional financial metrics may be less effective in reflecting efficiencies in acquisition, exploration and development activities of oil and gas companies. Although providing supplemental oil and gas reserves could mitigate such a deficiency in the financial reporting model of oil and gas firms, they do not address the differential ability among oil and gas firms in converting investments in acquisition, exploration and development into oil and gas reserves. Our study fills such a gap by proposing and testing an efficiency measure for acquisition, exploration and development activities using DEA methods.

DEA is a Linear-Programming (LP) based approach used to evaluate the relative efficiency of a set of peer organizations called decision making units (Talluri). Using LP, DEA can compute a relative efficiency between zero and one for each decision making unit (DMU), with consideration of financial and non-financial inputs and outputs. Hence, performance measures generated during investments in acquisition, exploration and development of oil and gas reserves may be defined as inputs and outputs, and used to formulate efficiency. Then, by solving the LP, the DEA provides an optimal value of efficiency for each DMU. In this way, decision makers can quantitatively evaluate the relative performance of each oil and gas firm based on reserve acquisition, exploration and development activity information, which is provided in the footnotes to the financial reports. This relative efficiency may improve investors' ability to predict financial performance of oil and gas firms beyond traditional financial performance metrics.

We find that current change in asset turnover is positively associated with future change in return on assets and future change in operating income when we examine the whole sample from the oil and gas industry and firms that use the successful efforts method for EXP costs (SE firms). This is consistent with Fairfield and Yohn. However, we find that change in asset turnover is not useful in forecasting future profitability for firms that use the full cost method for EXP costs (FC firms). Also, the amount of reserves reported in the financial statement footnotes is useful in predicting future profitability for SE firms but not for FC firms. Unlike change in asset turnover, our DEA based efficiency measure is useful in predicting future profitability for both FC firms and SE firms of the oil and gas industry. In addition, we find that current change in profit margin is negatively associated with future change in return on assets and future change in operating income, which is inconsistent with Fairfield and Yohn.

Artificial neural networks have increased attention for solving many real complex world problems. ANN compared to traditional methods have solved many complex problems successfully where traditional methods have failed. In addition, numbers of research and development works are increasing rapidly in recent years. A lot of research about Artificial Neural networks dealt with predicting and decision making problems in last few decades. These researches have improved and developed in methods of forecasting which led to make better decisions. Many forecasting and decision modeling problems have used ANN as solving process. Artificial neural networks have strong potential advantages over than statistical methods and can be strongly deal with non-linear functions. Hawley, Johnson, and Raina were one of the first who have applied neural networks in real business world [2].

In the last ten years, neural network is particularly applicable to risk management and forecasting [3]. ANN also has property of non-linear behavior where it can estimate non-linear functions well and extract any remaining of non-linear elements from the data as well [4], [5]. Hornik [6] has found that artificial neural networks are able to make the best approximation functional form as long as use good data characteristics. In addition, ANN has potential power to transform the input data [7]. Kang [8] found that artificial neural networks give better forecasting in monthly and quarterly period than in the annual. However, recent studies including our study on artificial neural networks have proved the opposite. Artificial neural network has strong ability to generate fitting to the data as good as the fit of the true functional forms where's performed with high noise and low sample sizes by high reliability [9]. Artificial neural network has ability to provide good solution, of which regenerate an existing system behavior that leads to right decision-making [10]. Crone [11] and Wang [12] have found that artificial neural network training is able to inaugurate the behavior of the original system. They applied that successfully to predict cost of manufacturing, control of system quality, etc.

2. Literature review, institutional context and hypothesis development

Earnings are said to be of higher quality when they provide more information about the features of a firm's financial performance for decision making. Earnings quality thereby depends on the specific situation. This makes the term earnings quality conditional on the frame of reference. Even though a vast stream of accounting research on earnings quality demonstrates its consequences, for instance, on stock prices and returns, cost of capital, or information asymmetry, little is known of how earnings quality impacts the forecast accuracy of ratio-based forecast models. Earnings quality is jointly determined by both the accounting system and by the firm's fundamental performance (Barth et al). Accordingly, if a firm experiences a change, either in its operating profitability or in its accounting system, it might also have an impact on earnings quality or, as a result, on the accuracy of an earnings forecast model. By omitting one of these partly joint earnings quality determinants, forecast models might lose information which lowers the explanatory power.

Previous forecast models in the FSA literature predominantly focus on firms' performance without considering the influence of the accounting system. However, the earnings quality literature presents growing evidence that firm performance and the accounting system both affect future profitability and market reactions. For example, Lipe and Sloan find differences in the persistence of earnings components, suggesting that forecasts should weigh the influence of each component differently. Amir et al. provide evidence that the market reacts differently to the conditional and unconditional persistence of DuPont ratios. Another approach analyzing the impact of earnings quality on firms' future profitability is the examination of the total magnitude of accruals or the error term from regressing accruals on their economic drivers. Xie observes that non-discretionary accruals have more predictive ability than residuals from the Jones model for explaining one-year-ahead earnings. Dechow and Dichev conclude that accrual quality is positively related with earning quality proxies. These studies suggest that an extreme magnitude of accruals decreases earnings persistence and, ultimately, forecast accuracy. To this extent, Tucker and Zarowin find that firms which actively manage the smoothness of earnings (firms with a stronger negative correlation between discretionary accruals and earnings) provide earnings with more information about future earnings.

A further group of studies on earnings quality examines the consequences of the accounting system. Research investigates how the selection of accounting principles impacts the quality of accounting numbers disclosed in firms' financial statements. In this vein, great effort has been undertaken to understand the impact of conservative accounting on earnings and profitability ratios. Conservatism is broadly interpreted as the choice of accounting treatments that are likely to understate net assets and cumulative income. More recent research distinguishes between unconditional and conditional conservatism. Unconditional conservatism reflects the application of conservative accounting policies (e.g. expenditure of R&D and advertising) whereas conditional conservatism is event driven. Normative and empirical research examines how the joint influence of conservative accounting and growth in investments affect earnings quality. Under conservative accounting, firms build reserves and understate their reported earnings when investments in operating assets increase. In contrast, if investments decrease, built reserves could get released. Either way, changes in growth under conservative accounting affect earnings quality due to earnings becoming temporarily bloated or inflated. Ignoring these changes could consequently distort forecasts which naively fixate on earnings as reported in the financial statements. [1] find that the association of conservatism in combination with growth and future book return on equity is less negative for firms with higher investments. [5] developed a diagnostic measure that captures the joint effect of conservative accounting and growth on earnings quality. The diagnostic measure predicts differences of firms' future profitability and stock returns, indicating the usefulness of information on earnings quality in forecast models [2]. They analytically and empirically investigate the joint effect of conservatism and growth on return on investments (ROI). Explaining the joint impact of both variables on future ROI, they find that these two variables are substitutes. They argue that, under conservative accounting, growth not only tends to lower ROI, but also initiates a downward effect where more conservatism further magnifies this joint effect. This contradicts previous beliefs regarding how conservatism and growth interact.

3. Methodology

3-1- Data Envelopment Analysis (DEA)

DEA is a data-oriented tool that uses LP to evaluate the efficiency levels of multiple homogeneous organizations, or DMUs. The DEA tool first identifies inputs and outputs for a given set of peer organizations. Then it defines the relative efficiency of a DMU. Using the ratio of the weighted outputs to the weighted inputs for each DMU, the DEA tool attempts to maximize the relative efficiency for each DMU under the constraint that the efficiency of each DMU is less than or equal to one. To better explain the concept of DEA, we use the following notations:

n = number of DMUs $\{j = 1, 2, \ldots, n\}$;
m = number of inputs $\{i = 1, 2, \ldots, m\}$;
s = number of outputs $\{r = 1, 2, \ldots, s\}$;
yrj=positive quantity of rth output of jth DMU;
xij=positive quantity of ith input of jth DMU;
ur=weight of rth output; and
vi=weight of ith input.

The relative efficiency score of a specific $j*$ (DMU) is given by solving the linear program shown below.

Maximize: $h_{j0}=\Sigma u_r y_{rj}*s_r$ (1)

Subject to

$\Sigma u_r y_{rj} s_r=1\Sigma v_i x_{ij} m_i=1 \leq 1$ for each DMU j (2)

The objective function in equation (1) is to maximize the efficiency for a specific DMU, $j*$ under the equation (2) constraint that the relative efficiency for each DMU is less than or equal to 1. The decision variables are weights ur, for outputs and inputs, respectively. If the efficiency is unity, then the DMU is said to be *efficient*. Otherwise, it is said to be *relatively inefficient*. Equations (1) through (3) can be translated into a corresponding LP form through normalization of the denominator in the equation (1) objective function, as seen in equations (4) through (7).

Max $\Sigma u_r y_{rj}*s_r$ (3)

subject to

$\Sigma v_i x_{ij}*m_i=1$ (4)

$\Sigma u_r y_{rj} s_r-\Sigma v_i x_{ij} m_i=1\leq 0$ for all j (5)

$u_r,>0\ for\ all\ r,$

Thus, the objective function is the weighted sum of outputs in equation (4) while the weighted sum of inputs is constrained to be unity in equation (5). Based on the denominator normalization, $\Sigma vixij{*}mi$=1, the maximized objective function itself represents the efficiency of DMU j*. The model shown in equations (4) to (7) is referred to as the input-oriented multiplier model. This input-oriented model is frequently used when the input factors are more manageable than the output factors. The model also implicitly assumes a positive linear relation between inputs and outputs, referred to as a constant return to scale (CRS). It should be mentioned here that optimally all DMUs are homogeneous when applying the DEA approach since DEA evaluates the relative efficiency of each DMU. Readers are encouraged to refer to Zhu for a detailed understanding of DEA theories and formulae.

DEA has been used extensively for benchmark purposes in applied research. Borenstein, Becker and Prado evaluate the performance of 85 post office stores using both financial and non-financial inputs such as physical area, number of employees, etc. and outputs such as average waiting time in line, home delivery satisfaction rate, etc. They conclude that compared to a financial oriented analysis, the DEA-based benchmark provides more differentiation power across stores and allows more flexibility for future process improvement. Chen and Chen combine both DEA and the Balanced Scorecard (BSC) to evaluate the performance of 30 Taiwanese semi-conductor firms. They use the BSC to identify factors to be utilized in DEA. Cherchye et al. shows that DEA can be easily integrated into the development of another performance index. They use the efficiency from DEA to develop Composite Indicators (CIs) to work as a technology achievement index. Many references consistently support a DEA-based approach overcoming the disadvantages of a purely financial performance-based analysis; and DEA can also be used to develop an index. Those successful DEA applications motivate us to adopt DEA-based efficiency measures to predict future profitability. and W_j is the original weight given to the indicator $v_j, j = 1, 2, ..., n.$

3-2- Artificial Neural Network (ANN)

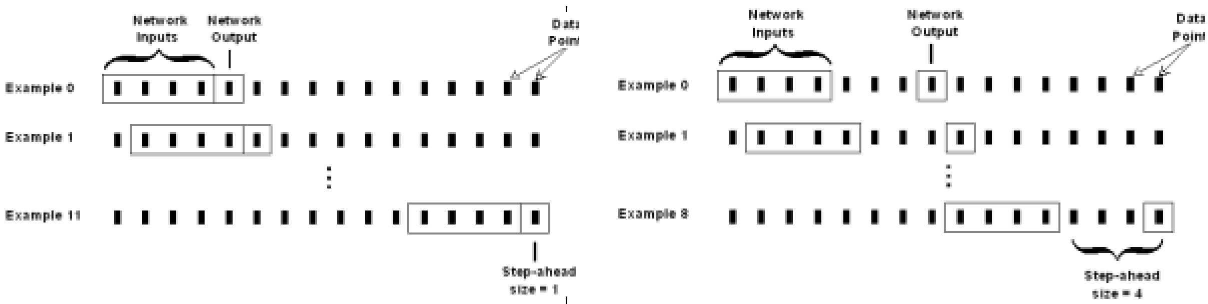
There are two types of data on which a neural network can be trained: time series data and classification data. Examples of time series data were given in Section. In contrast, classification data consist of *n*-tuples, where there are *m* attributes that are the network inputs and $n - m$ classifications that are the network outputs[1]. Forecaster parses time series data from a single column of newline-separated values within a text file (*.txt). Forecaster parses classification data from multiple columns of comma-separated values within a comma-separated-values text file (*.csv).

To create the examples in the form of <**input**, **output**> pairs referenced in Section 3**Error! Reference source not found.**, first Forecaster parses the time series data from the file into a one-dimensional array. Second, any preprocessing the user has specified in the Neural Network Wizard (discussed in Section) is applied. Third, as shown in Figure1, a moving window is used to create the examples, in this case for a network with four inputs and one output.

In Figure1 (a), the network will be trained to forecast one step ahead (a *step-ahead size* of one). When a forecast is made, the user can specify a forecast horizon, which is the number of data points forecasted, greater than or equal to one. In this case, a forecast horizon greater than one is called *iterative forecasting*—the network forecasts one step ahead, and then uses that forecast to forecast another step ahead, and so on. Figure2 shows iterative forecasting. Note that the process shown in *Figure2* can be continued indefinitely. In Figure1 (b), the network will be trained to forecast four

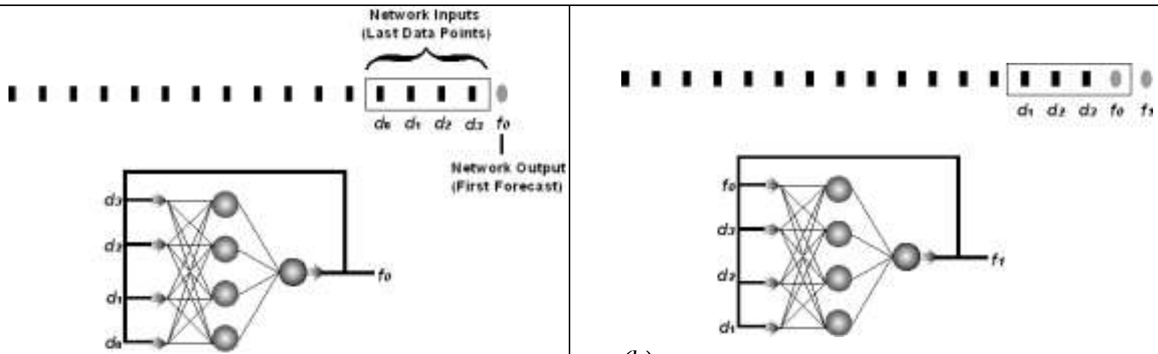
[1] An example of a classification problem is real-estate appraisal, where the attributes may be acreage, view, and utilities, and the classification is price.

steps ahead. If the network is trained to forecast *n* steps ahead, where $n > 1$, then when a forecast is made, the user can only make one forecast *n* steps ahead. This is called *direct forecasting* and is shown in Figure3 for four steps ahead. Note that the number of examples is reduced by $n-1$. In Figure2 and ***Figure3***, the last data points, saved for forecasting to seed the network inputs, are the last data points within either the training set or validation set, depending on which set is "closer" to the end of the data series. By seeding the network inputs with the last data points, the network is making *out-of-sample* forecasts. The training set and validation set are considered *in-sample*, which means the network was trained on them. The training set is clearly in-sample. The validation set is in-sample because the validation error determines when training is stopped (see Section for more information about validation error).



(a) *(b)*

Figure1 *Creating examples with a moving window for a network with four inputs and one output. In (a), the step-ahead size is 1; in (b), the step-ahead size is 4.*



(a) *(b)*

Figure2 *Iteratively forecasting (a) the first forecast and (b) the second forecast. This figure corresponds to Figure1 (a).*

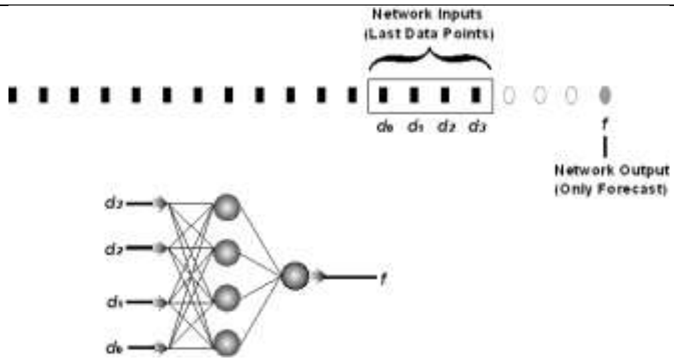


Figure3 *Directly forecasting the only possible data point four steps ahead. This figure corresponds to Figure1 (b).*

4. Empirical results

In the present study, the variables are calculated annually, so we have: 864 = 6 x 141, where 144 represents the relationship between the number of companies in the sample and the number 6 represents the study period (1388 1393), respectively. The number of firm-year observations from this study for each variable is equal to 864.

Table 1: Data set

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
P	846	1.00	.00	1.00	.1596	.36643	.134	1.862	.084	1.472	.168
R1	846	5.95	-2.39	3.56	.0056	.99666	.993	.137	.084	-.009	.168
R2	846	6.50	-2.94	3.56	-.0231	.99459	.989	-.151	.084	.054	.168
R3	846	5.28	-2.37	2.91	.0096	.98817	.976	.071	.084	-.221	.168
R4	846	.00	.00	.00	.0000	.00001	.000	.995	.084	20.315	.168
R5	846	7.50	-3.75	3.75	.5860	1.06797	1.141	-1.918	.084	3.479	.168
R6	846	5.59	-2.55	3.04	.0090	.98233	.965	.023	.084	-.221	.168
R7	846	.00	.00	.00	.0000	.00003	.000	-9.104	.084	199.200	.168

One of the assumptions of normality of the residuals of the regression model that represents the credit Kolmogorov-Smirnov test regression tests is continued using the normal distribution is related variables including variables studied. The normality of the dependent variable to normality of the residuals (difference between the estimated value of real values), respectively. So it is necessary to estimate the normality of the dependent variable parameters to be controlled and in case of non-normal condition suitable solution for them (including conversion of it) would be taken. In this test the null hypothesis and the alternative hypothesis can be written as.

Table 2: Analysis of the variable

Var	**N**	**Normal P**		**Max D**			**Z of K-S**	**Sign**
		Mean	std	Abs	Positive	Negative		
R1	846	1.4452	0.93193	0.192	0.192	-0.151	0.192	.000[c]
R2	846	29.3627	110.26731	0.395	0.363	-0.395	0.395	.000[c]
R3	846	1.3307	0.59819	0.115	0.115	-0.074	0.115	.000[c]
R4	846	751.8441	5708.58416	0.415	0.402	-0.415	0.415	.000[c]
R5	846	0.1311	1.48926	0.376	0.376	-0.313	0.376	.000[c]
R6	846	1.8132	1.02354	0.117	0.117	-0.077	0.117	.000[c]
R7	846	3334643.07	12225089.2	0.393	0.388	-0.393	0.393	.000[c]

Kolmogorov-Smirnov is seen as a possibility for financial ratios R1, R2, R3, R4, R5, R6 and R7 is lower than 05/0 The independent variables were not normal and should be looked normal. It should be noted in this study, normalization of independent variables, use Minitab software, which is Johnson's conversion results are in Appendix 3. Also to check the normality of the dependent variable of the P

Rian Jenior test is used when the test showed that the dependent variable, the predicted profitability is normally distributed.
In this section, two-variable analysis of the study variables, correlation matrix in tables (2- 4) are provided.

Table 3: Correlations

	P	R1	R2	R3	R4	R5	R6	R7
P	1 846	.027 .431 846	.052 .134 846	.034 .326 846	.045 .189 846	.060 .080 846	.021 .551 846	.022 .521 846
R1	.027 .431 846	1 846	.056 .102 846	.099** .004 846	-.007 .830 846	.052 .133 846	-.004 .912 846	-.003 .935 846
R2	.052 .134 846	.056 .102 846	1 846	-.068* .050 846	.013 .716 846	-.283** .000 846	-.035 .311 846	-.034 .329 846
R3	.034 .326 846	.099** .004 846	-.068* .050 846	1 846	.025 .467 846	.094** .006 846	.533** .000 846	.018 .595 846
R4	.045 .189 846	-.007 .830 846	.013 .716 846	.025 .467 846	1 846	.052 .130 846	.055 .108 846	-.136** .000 846
R5	.060 .080 846	.052 .133 846	-.283** .000 846	.094** .006 846	.052 .130 846	1 846	.086* .013 846	.051 .142 846
R6	.021 .551 846	-.004 .912 846	-.035 .311 846	.533** .000 846	.055 .108 846	.086* .013 846	1 846	.050 .148 846
R7	.022 .521 846	-.003 .935 846	-.034 .329 846	.018 .595 846	-.136** .000 846	.051 .142 846	.050 .148 846	1 846

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The level of significance (P- Value) correlation coefficient between the variables in the table above, the second Drstr shown. If the level is significantly lower than 05/0, the correlation coefficient is statistically significant at the 95% confidence level.
The result of the comparison in the table below is shown.

Table 4: Comparisons

Groups	**Ann Forecasting**		**DEA Forecasting**		**Difference**	
	Num	**Per**	**Num**	**Per**	**Num**	**Per**
Profitable	12	8.51	7	31.81	5	20
Non-profitable	66	46.81	54	46.55	12	10.34
sum	78	55.32	61	43.26	17	12.05

Above table shows that the percentage of correct prediction given by a Ann model for profitability level of 20, a higher percentage of correct prediction is provided by DEA. The percentage of correct prediction provided by the Ann to unprofitable levels by as much as 10% more than the forecast provided by data envelopment analysis is correct. Finally, we can say that Ann to the data envelopment analysis with 05/12 percent, higher accuracy in the prediction of profitability is much stronger.

5. Conclusions

The main objective of this study was to compare two techniques are artificial neural network and data envelopment analysis capability and superior techniques for predicting the profitability of the Company's financial decision makers. Thus, according to the results obtained may be used technique ANN to different groups offered for the following purposes:

- To investors to evaluate the company's future profitability in order to take appropriate decisions in buying or selling stocks
- Capital market managers to assess the future profitability of the applicant companies to enter this market.
- To managers and directors of companies with the aim of achieving an overview of the status of your company's profitability in order to take appropriate measures to address the problems underlying losses or reduced profits.
- To banks and other creditors with the aim of reducing risk through assessment of future profitability and give preference to companies profitable lending.
- The society and the government to use future profitability of companies in allocation visible from a distance.

References

[1] Abdipoor, S. Nasseri A, Akbarpour M, *Integrating Neutral Network and Colonia Competitive Algorithm:" A new approach for predicting bankruptcy in Tehran security exchange, Asian economic and financial review*, 2013, 3(11): P. 1528-1539.

[2] Alkali, J, Rashid, Z, *Relationship Between Profitability and Voluntary Disclosure: A case of Banks in Kenya, Available at SSRN: http:// ssrn.com/abstract*=2706027.2015.

[3] Anders,I, Landajo, M & Larca, P, *Forecasting Business Profitability by Using Classification Techniques* : A Comparative Analysis Based on a Spanish CSE. European Journal of Operational Research, 2015, 167, (3), P. 518-542.

[4] Beynon, M, Clatworthy M, *The Prediction of Profitability Using Accounting Narratives: A variable precision rough set approach intelligent systems in accounting, financial finance & management*, 2004, 4, P. 227-242.

[5] Cao,Q & Gan ,Q , *Forecasting EPS of Chinese Listed Companies Using Neutral Network With GA*, International of Society Systems Science, 2011, 2(3), P. 207-225.

[6] Collopy, F &Armstrong J.S, *Error Measures for Generalizing About Forecasting Methods: Empirical Comparisons*. International Journal of forecasting, 1992, 3, P. 69-80.

[7] Dai, W, Jui-Yu W, Chi-Jie L., *Combining Nonlinear Independent Component Analysis and Neutral Network for the Prediction of Asian Stock Market Indexes, Export System with Applications*, 2011, 39(4), P. 4444-4452.

[8] Demuth H and Beal M, *Matlab 6.5/Neutral Network Toolbar*", Version 4, The Math works, inc, (CD-ROM), 2002, P. 1-840.

[9] Kanam, E, Sinoeraya, M.S., Al Rini W., *The effect of Reported Comprehensive Income, Firm Size*, Profitability & Leverage on Income Smoothing. http://ssrn.com/abstract = 2731472. 2016.

[10] Galal, H, Muamar Bennisa, S, Vasin, S, *Optimization Optimal Production Program Using Profitability Optimization by Genetic Algorithm and Neutral Network*, International Journal of Mechanical Aerospace, industrial, Mechatronics & Manufacturing Engineering, 2014, 8, P. 913-918.

[11] Göçken, M, Ozçalici, M, Boru, A, Dosdogru, T, *Integrating Metaheuristics and Artificial Neutral Networks for Improved Stock Price Prediction*, Expert Systems with Applications, 2016, 44, P. 320-331.

[12] Guoqiang Z., Eddy B., Patuwo, M., Hu, Y., *Forecasting With Artificial Neutral Network*: The State of The Art, International Journal of Forecasting, 1998, 14, P. 35-62.

[13] Hagan, MT, Demuth, H.B. and Beal, M., *Neutral Network Design PWS Publishing CO*. Boston, MA. ISBN:0-534-94332-2. 2004.
[14] Hipper, Henrique S, Perdeira, Eduardo, C & Souza Reinaldo, C; *Neutral Networks for Short term load Forecasting: A Review and Education*, IEEE Transactions on Power System, 16:6, 2001, P. 44-55.
[15] Radu, M, Delia, M, Todea, N, *Structure Ratios of Profit & Loss Account-Source of Information for Performance Analysis*, Procedia Economic and Finance, 2015, 26, P. 396-403.
[16] Mohiuddin, K, M. Mao, J. K, Jain., A, *Artificial Neutral Networks: A Tutorial, Computational Science & Engineering*, 1996, 29(3), P. 31-44.
[17] Montgomery, C.D., Ynwood, A, I & Gardiner. J.S, *Forecasting Time Series Analysis, Second Ed, Mc Grow Hill.1990.*
[18] Ravi Kumar, P. and Ravi, V., *Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent Techniques*, European Journal of Operational Research, 2007, 180(1), P. 1-28.
[20] Shanker, M., Hu Y. & Hugan, M.S., *Effect of Data Standardization on Neutral Network Training Omega*, 1996, 24, P. 385-397.
[21] Shumway, T, *Forecasting Bankruptcy More Accounting: A Simple Model, Journal of Business*, 2004, 74, P.101-124.
[22] Tzafestas, S. Tzafestas, E, *Computational Intelligence Techniques for Short Term Electric Load Forecasting*, Journal of Intelligent and Robotic System, 2001, 31, P. 7-68.
[23] Ju-Jie, W, Jain-Zhou, W, Zhe-George, ZH, Shu-Po, G, *Special Issue on Forecasting in Management Science Stock Index Forecasting Based on Hybrid Model. Omega*, 2012, 40(6), P. 758-766.