



PREDICTION OF ECONOMIC VALUE ADDED OF IRANIAN LISTED COMPANIES

Mahmoud Mousavi Shiri¹, Mehdi Salehi², Mostafa Bahrami³
(Assistant Prof¹, Assistant Prof², M.A Holder in Management³)

Payame Noor University¹
(Islamic Republic of Iran)

Ferdowsi University of Mashhad²
(Islamic Republic of Iran)

Hidaj Branch, Islamic Azad University³
(Islamic Republic of Iran)

Mousavi1973@pnu.ac.ir¹
mehdi.salehi@um.ac.ir²

Bahrami.mostafa@yahoo.com³

Corresponding author: mehdi.salehi@um.ac.ir

Abstract

Economic value added (EVA) is an important issue for economic analysts and investors. This article proposes a method for predicting economic value added of the automotive and steel listed companies on the Tehran Stock Exchange (TSE) using neural networks. The data were collected from the audited financial statements during 2006-2011. EVA was predicted using linear regression and neural networks and the results were compared with actual data. The findings suggested that neural networks method outperforms linear regression in predicting EVA.

Keywords: Neural networks; economic value added; financial ratios; Tehran Stock Exchange; Iran.

Additional data:

UDC 336.7

GRNTI 06.73.35

JEL Code G320

Received 13 June 2013

Accepted 28 July 2013

Introduction

With the separation of ownership and management and the subsequent conflict of interest between managers and owners, evaluating the performance of organizations and managers became the focus of attention of creditors, owners, and governments. The most important goal of organizations is to create value and increase shareholders' wealth which results from optimal performance. For shareholders also the increase of wealth is of utmost importance, whether in the form of increased value of the company or cash profit. However, this issue is critical for investors, for they are not willing to invest in high-risk companies or if they do they expect higher returns for their venture. Both groups look for indices to evaluate the performance of the companies and decide whether or not to invest. Agents and joint venture companies also use these indices to promote investment goals, for they will suffer irretrievable losses if they make mistakes in their analyses.

In Iran, institutions that provide financial counseling services have not yet been developed. Thus, it is not easy for most investors and shareholders to access valid financial/economic analyses and to interpret the events that affect their activities, which increases the risk involved in buying and selling stocks. In these conditions, the capital market of the country needs to reinforce the institutions that regulate the market and to support shareholders and the free flow of information. On the other hand, it needs to establish entities that provide financial counseling and portfolio management services. Financial analysts play an important role in converging the price and value of stocks by acquiring economic and financial information of firms, thus reducing price bubbles.

Managers do not have much information about the value of assets or about the process through which an investment project is accepted by an entity and rejected by another. Therefore, managers, as users of financial information, require additional data. On the other hand, each business unit needs to evaluate its performance and investigate the strengths and weakness of its past operations. This entails appropriate strategic planning by the management.

An important issue for managers in their value creation decisions is economy which is closely linked to value creation. Economy refers to effective use of resources for long-term profitability. There are different measures for valuing assets: return on assets (ROA), return on equity (ROE), profit margin, etc. ROA and ROE were developed by DuPont and have been widely used since the 1980s.

Another measure which was introduced in the 1990s is economic value added (EVA). This measure focuses on the loss of capital (firm value). EVA is equal to the profit earned by the firm less the cost of financing the firm's capital. EVA has proven to be a more effective measure of performance, for unlike ROA it accounts for the entire financing costs of firms (including investment opportunity cost).

Finding methods for predicting the future conditions of businesses has always been a major concern for economists. Indeed only those methods that have the least error in prediction will remain and will be widely used. The advent of AI techniques, especially neural networks, has been very promising, particularly in areas where traditional mathematical approaches fails to create a proper relationship between the

dependent and independent variables. The main question of the present research is whether such methods can be applied to predict the future economic value added of firms.

Economic value added

EVA measures the true economic profit, or the amount by which the earnings of a project, an operation, or a company exceed (or fall short of) the total amount of capital that was originally invested by the company's owners. EVA is equal to the profit earned by the firm less the cost of financing the firm's capital. It measures the economic profit rather than the accounting profit that has been created by the business after all the costs of all equity and debt have been taken into consideration.

It must be noted that EVA is also equal to the difference of what the customer pays and what the business spends on raw materials and other production factors. That is, EVA not only measures the economic profit of the business, but also reveals customer satisfaction. In the literature on measures of performance, the closest concept to EVA is residual income. Today, EVA is regarded as a financial management system whose main goal is to maximize shareholders' wealth. It is a basis for setting goals, capital budgets, and incentives.

Neural networks

Neural networks, which were first investigated by Rosenblatt (1959) and Widrow and Hoff (1960), are computational structures with the ability to learn and be generalized. Recently, artificial neural networks have received much attention for their capacity to solve financial problems. Some of the applications of neural networks in the area of finance are to predict: financing behavior (Steiner et al., 2006), stock market index (Kim & Chun, 1998), foreign exchange rate (Safer, 2003), bankruptcy (Atiya, 2001), and fraud detection (Smith & Gupta, 2000). Moreover, there many software applications have been developed to solve many modern problems using artificial neural networks (Rosenberger et al., 2009).

Artificial neural networks (ANN) are inherently non-linear, which makes them much more accurate and practical in modeling complex pattern of data. ANN models are able to mimic the brain function by mimicking its simplest and most basic neurons. Like a human brain, neural networks models contain one or more processing units that are interconnected by a network of simple processing elements that interact with each other through weighted connections. The neural network model has to be fed a set of data to be learned for a forecast to be generated as a result (Mira et al., 2009).

Neural networks basically consist of an array of processors or cells and their interconnections. The input data is processed by this array to give the output or results. Neural networks are also defined as a mathematical model that consists of numerous processing elements that are inspired by the biological model of the brain (Lubis, 2001).

Questions

1. Are neural networks able to predict the EVA of the studied firms?
2. Can we predict the future EVA and financial assets of firms using neural networks and financial ratios?
3. Does prediction of EVA using neural networks have any advantages over linear regression?

Hypotheses

- The mixture of neural networks and financial ratios can predict EVA.
- The model proposed in the present research has a better performance in predicting EVA than linear regression.

Methodology

The purpose of this research is to predict EVA using neural network. The population consists of all the firms listed on the TSE for the period 2006-2012. The data were collected from the audited financial statements of the firms that were included in the software provided by TSE. 50 leading firms in automobile and metal industries were selected as sample.

Limitations

1. EVA is calculated using the financial statements of the firms, and these statements were modified in certain years.
2. Although the financial statements were audited, certain numbers that were not important or relevant were excluded.
3. Costs such as deferred costs, cost of depreciation, or cost of doubtful receivables were included in one single category and could not be separately examined.
4. Growth rate involved many limitations and was calculated with much difficulty.
5. Historical numbers were recorded in financial statements and were not adjusted to inflation.

Variables

This research examines the effect of financial ratios (independent variables) on EVA (dependent variable) after controlling for industry type. The relationship is examined using both a neural networks model and a multivariate linear regression model and the results are compared.

EVA is equal to the profit earned by the firm less the cost of financing the firm's capital. As mentioned earlier, historical numbers were used to calculate EVA. The issues of overlap were considered when selecting financial ratios, i.e. those ratios with the least overlap were selected as independent variables: current ratio, quick

ratio, Receivables Turnover, Inventory Turnover, Sale Return, Assets Turnover, Return on Assets, Return on Equity, Payout Ratio, Debt Ratio, and Interest Coverage.

EVA is calculated using the following formula:

$$EVA = (r - c) \times \text{capital}, \quad (1)$$

where r is the Return on Invested Capital (ROIC).

c is the weighted average cost of capital (WACC).

Some adjustments are made in the above approach to calculating EVA: converting accounting profit to net operating profit after taxes (or NOPAT) and equity to Capital. The purpose of these adjustments is to:

- Remove the biases due to conservatism in accounting;
- Approximate accounting profit to economic profit;
- Limit the ability of managers to manipulate profit.

Results

Prediction through regression

The following table provides the results of analyzing the data using linear regression in SPSS software.

Table 1.

Regression coefficients

Variable	Coefficient
Constant	613082.24
Current assets ratio	-464335.89
Quick ratios	1503714.7
Receivables Turnover	-5542.301
Inventory Turnover	-319597.55
Sale Return	2823558.3
Assets Turnover	824388.39
Return on Assets	-2363386.6
Return on Equity	80495.842
Payout Ratio	-11661.669
Debt Ratio	-154514.15
Interest Coverage	-245.206

The regression line is as follows:

$EVA = C + B + \beta_1$ Interest Coverage + β_2 Receivables Turnover + β_3 Return on Equity + β_4 Payout Ratio + β_5 Inventory Turnover + β_6 Quick ratios + β_7 Assets Turnover + β_8 Sale Return + β_9 Debt Ratio + β_{10} Return on Assets + β_{11} Current assets ratio.

Replacing the coefficients with the values in Table 1 gives:

$EVA = 613082.24 - 245.206$ Interest Coverage – 5542.301 Receivables Turnover + 80495.842 Return on Equity – 11661.669 Payout Ratio – 319597.55 Inventory

Turnover + 1503714.7 Quick ratios + 824388.39 Assets Turnover + 2823558.3 Sale Return – 154514.15 Debt Ratio – 2363386.6 Return on Assets - 464335.89 Current assets ratio

After estimating the regression model, the data were used to evaluate the error of the model and to illustrate it using MATLAB software. As shown in Figure 1, error of the regression model increases with high diffraction.

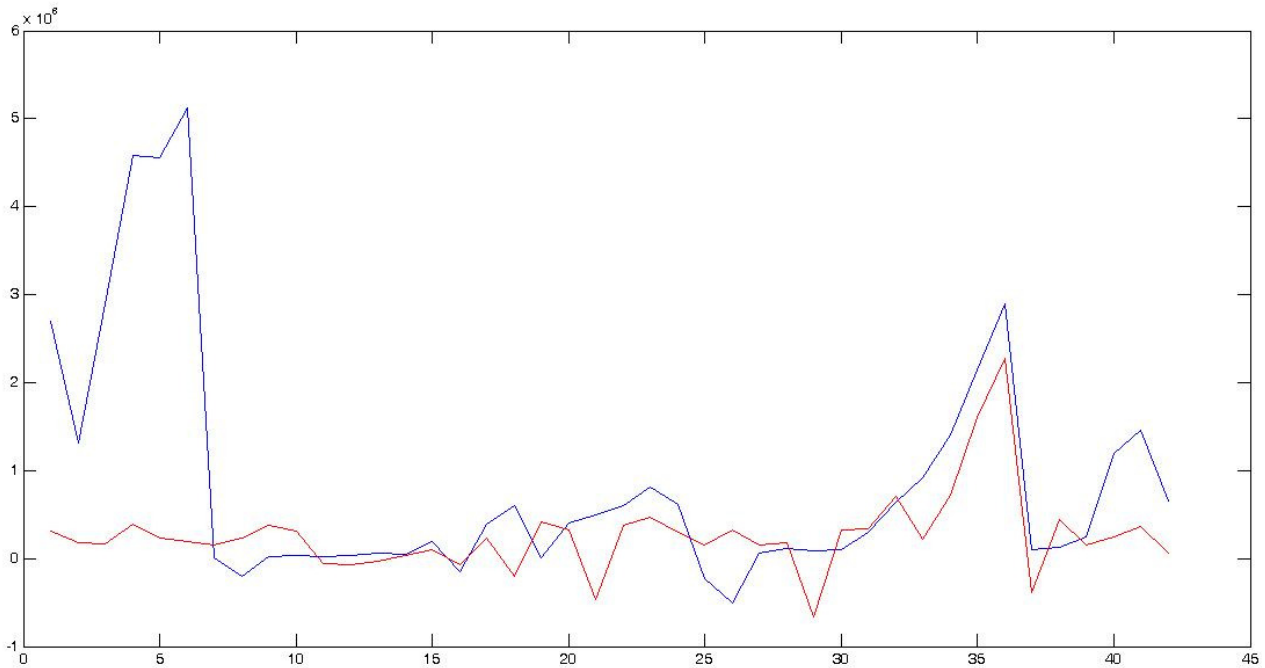


Figure 1. Diagram of the linear regression model

Neural networks

The weights of the input layer and the hidden layer are provided in Table 2, and EVA can be predicted according to these eight.

Table 2.

The weights of the input and the hidden layers

	Current	Quick	GHD	GMK	BF	GD	BD	BHSS	NPS	NBD	TDPB
Neuron 1	0.8331	0.79726	0.042246	1.7479	-1.1724	-0.0396	-0.51115	0.1283	-1.0819	-0.97678	-0.659
Neuron 2	0.61911	-1.1628	0.080098	-0.1104	0.2687	0.58883	-0.60796	0.77355	0.086905	0.38143	0.061153
Neuron 3	0.85912	-0.8097	0.23068	0.69292	-0.3818	-0.26816	0.073947	-0.30432	0.98412	-0.20838	0.23146
Neuron 4	0.7448	0.027024	-0.85115	0.60572	-0.81867	0.6137	0.43243	0.37119	-1.0442	0.62149	0.64893
Neuron 5	-0.21581	0.19112	-0.77252	-0.15697	-0.77347	-0.31905	-0.3251	1.0628	-0.54275	-0.51296	0.45455
Neuron 6	0.73105	0.063883	-0.72367	0.54662	-0.92286	-0.05502	-0.24502	0.47058	0.48803	0.87685	0.53333
Neuron 7	0.55522	0.5141	-0.25806	-0.05391	0.66755	-0.89577	0.57508	-0.90886	-0.59836	0.63901	0.11944
Neuron 8	-0.89693	-0.01878	-0.59564	0.26224	-1.2078	-0.89727	0.49237	-0.38571	0.76556	1.0105	0.54083
Neuron 9	-0.54153	-0.68535	0.75254	-0.56619	0.057369	-0.89611	-0.29839	-0.72042	0.64299	0.89145	0.59641
Neuron 10	0.68341	0.54528	-0.85764	0.5179	-0.17551	-0.23207	0.82588	0.030142	-0.61456	-0.024	-0.24863
Neuron 11	-0.42023	-0.0317	-0.51034	0.14799	-0.91327	-0.64872	0.16717	-0.82962	-1.0702	1.0272	-0.43761
Neuron 12	0.39329	-1.3487	-0.30093	0.42086	-0.72957	0.98605	0.35154	0.052562	0.36388	-0.40252	-0.59852
Neuron 13	0.091972	0.73807	0.44005	-0.45299	-0.91345	0.055005	0.14162	0.62241	1.5773	-0.26524	-0.49227
Neuron 14	1.0291	-0.84956	0.6831	1.0129	0.18042	0.77235	0.47895	0.25275	0.15859	-0.2093	0.99789
Neuron 15	0.10192	0.044513	0.57493	0.67354	-0.67955	-0.188	-0.83473	-0.66028	0.65831	0.22643	-0.69075

The following diagram illustrates neural networks' prediction based on the input data and compares it with actual values (the red line indicates the predicted values and the blue one indicates the actual values).

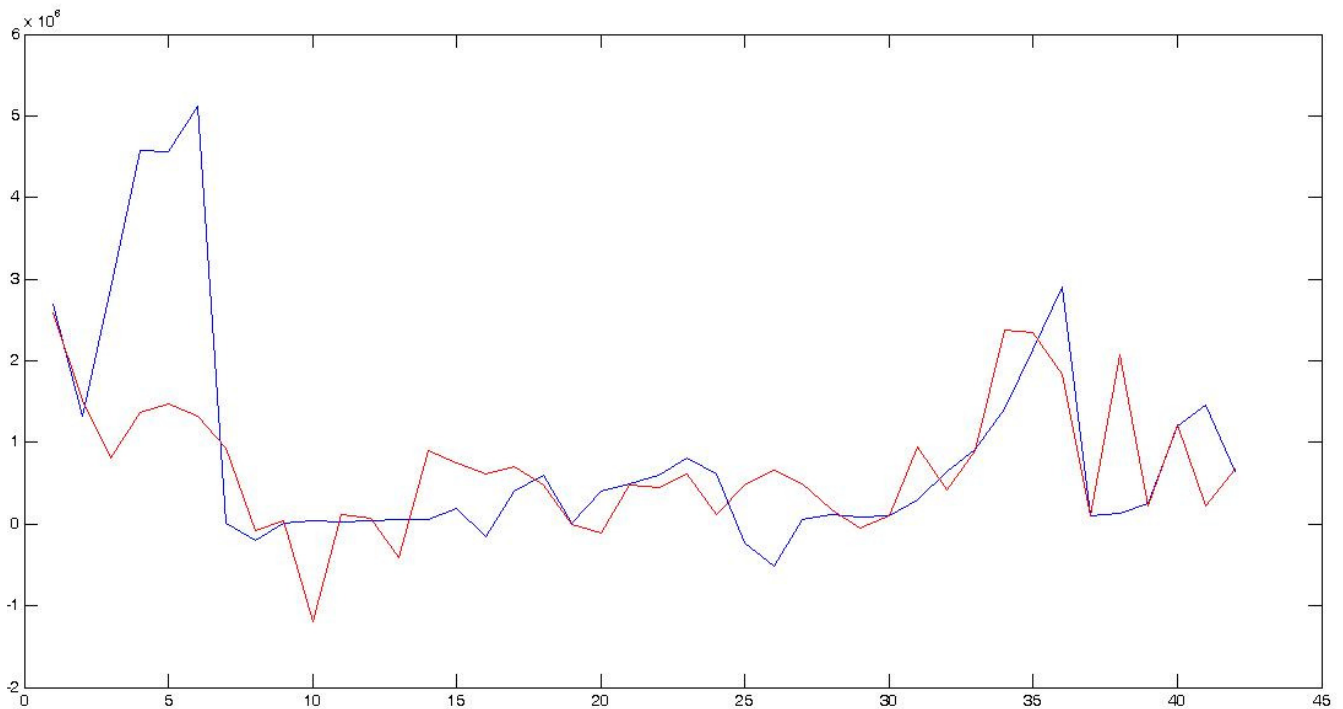


Figure 2. Prediction based on neural networks and its comparison with actual values

Neural networks vs. regression

Minimum mean square error (MMSE) is used as a measure for comparing the predictive power of neural networks and regression models. The closer the predicted values are to actual values, the better is the performance of the model. Table 3 shows the predicted and actual values.

Table 3.

Predicted and actual values

Neural Networks	Regression	Actual
2588412	444534	921006.7
1510402	607192.1	790774.7
809912.4	118993.7	785794.2
1370524	471081.2	997552.7
1469583	654372.5	841832.3
1326516	487489.9	808850.7
932492.7	179186.7	771525.4
-74614	-46918.1	841383.5
46234.97	97591.76	993677.3
-1200640	946633.7	930086.6
111613.2	422911.5	554843.9
75570.87	906908.8	544144.7
-409399	2378703	583278.4
906062.5	2345335	654203

756334.5	1839623	708267.6
618245.5	98014.58	544857.2
707163.4	2069548	841716.1
474278.8	223201.4	411050.7
-1093.38	1214243	1032403
-106553	220624.2	937937.7
480200.3	668135.1	145504.8

Here, root-mean-square error (RMSE) is used as a measure to compare the predictive power of the models. First the error rates of both approaches are measured and then RMSE is calculated. This involves estimating EVA using both approaches. Then, the difference between the estimated values and the actual values is obtained using Excel software. Estimation with the lowest RMSE is the desirable one.

Table 4.

Comparison of the errors of the neural networks and linear regression models

Regression Error		Neural Networks Error	
3143016716407	151949753000	11119730619	25862824533
276056427831	71069717445	37720077973	42606741128
4442551118802	93801269190	4341463309723	240138733828
12853620478817	999144353796	10318377405610	495028647361
13807529400374	2075139786710	9536349819146	1353164712505
18580018462753	494454917665	14385248933881	182358966380
586385242203	461304372541	858819574360	4788057553
1091332172277	19553492030	16556194001	18118189547
951951934835	698694962202	797378692	4580885
796167462933	412255769821	1533745023138	413365278432
281593242999	464186762739	7642772750	48580720123
257508147829	6694473825	1511558692	180830625
273998048787	6728897086	220176442822	939968400474
364311677218	5143613633	731780772492	42483155983
263275583838	121042703	314912715540	1117140965855
489273290328	16191231731	597326544393	23367421
198053661338	858019374365	96397566737	3748099142996
36326064628	275721372478	16222082457	486914730
1047344610194	115323293359	101975610	233566251
282796062145	225505975869	262866298537	1533418755323
125432590130	494562373	379043611	325998654
RMSE = 1268670.483		RMSE = 1128588.391	

As can be seen in the above table, RMSE of the neural networks model is less than that of the linear regression model. This higher accuracy can be attributed to the non-linear nature of the neural networks model. The result indicates that the first hypothesis is accepted, i.e. EVA can be predicted using financial ratios and neural networks.

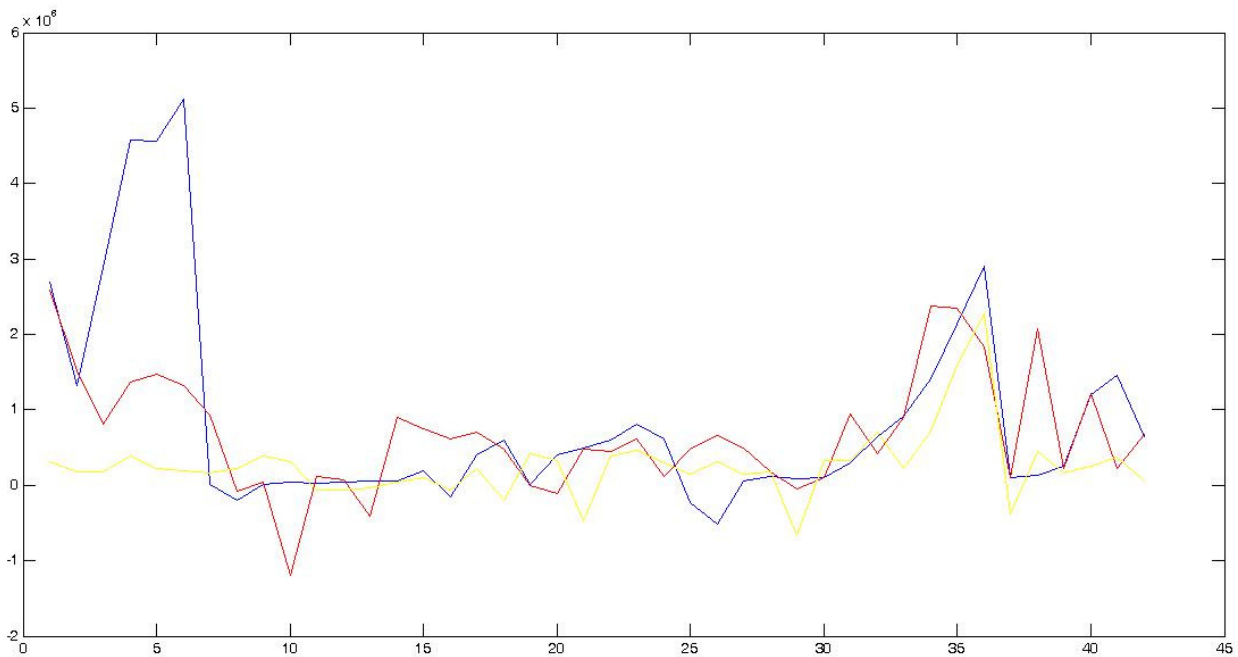


Figure 3. Neural networks vs. linear regression (the blue line is the actual values, the red line is prediction based on neural networks, and the yellow line is prediction based on regression).

The results suggest that the neural networks model outperforms the linear regression model in predicting EVA.

Conclusion

The results showed that financial ratios and neural networks are capable of predicting EVA. The neural networks model was trained over six steps, thus defining weights that have the least difference from reality when tested. Moreover, the results suggested that for firms in automobile and metal industries the non-linear model outperformed the linear model in predicting EVA. Overall, the results of this research can be used in investment decisions as well as evaluation and valuation of firms.

References:

- Atiya, A. F., 2001, Bankruptcy prediction for credit risk using neural networks: A survey and new results. *IEEE Transactions on Neural Networks*, 12(4), 929-935. <http://dx.doi.org/10.1109/72.935101>
- Kim, S. H. & Chun S. H., 1998, Graded forecasting using an array of bipolar predictions: Application of probabilistic neural networks to a stock market index. *International Journal of Forecasting*, 14, 323-337.
- Lubis, H. Y., 2001, *Initial Public Offering Prediction Using Neural Network*, Doctoral Dissertation, George Washington University.
- Mira, J., Cabestany, J. & Prieto, A., 2009, *New Trends in Neural Computation*, Springer.
- Rosenberger, L. E., Nash, J & Graham A., 2009, *The Deciding Factor: The Power of Analytics to Make Every Decision a Winner*, Jossey-Bass.
- Rosenblatt, F., 1959, The perceptron: A probabilistic model for information storage and organization in the brain. *Psych. Rev.*, 65: 386-407. DOI: 10.1037/h0042519
- Safer, A. M., 2003, A comparison of two data mining techniques to predict abnormal stock market returns. *Intelligent Data Analysis*, 7, 3-13.
- Smith, K.A., and J.N.D. Gupta, 2000, Neural networks in business: techniques and applications for the operations researcher. *Computers and Operational Research* 27: 1023-1044.
- Steiner, M. T. A., Neto, P. J. S., Soma, N. Y., Shimizu, T., & Nievola, J. C., 2006, Using Neural Network Rule Extraction for Credit-Risk Evaluation. *International Journal of Computer Science and Network Security*, 6(5A), 6-16.
- Widrow, G., M.E. Hoff, 1960, Adaptive switching circuits. In *Institute of Radio Engineers, Western Electronic Show and Convention, Convention Record, Part 4*, pp. 96–104.

ПРОГНОЗИРОВАНИЕ ЭКОНОМИЧЕСКОЙ ДОБАВЛЕННОЙ СТОИМОСТИ КОМПАНИЙ ИРАНА, КОТИРУЮЩИХСЯ НА БИРЖЕ

Махмуд Моусави Шири
Мухди Салехи
Мустафа Бахрами

Университет Пайам Нур¹
(Иран)

Университет имени Фирдоуси, Мешхед²
(Иран)

Исламский университет Азад, филиал в городе Хидадж³
(Иран)

Аннотация. Экономическая добавленная стоимость (EVA) является важным элементом для аналитиков и инвесторов. В настоящей статье предлагается метод прогнозирования экономической добавленной стоимости для автомобильных и сталелитейных компаний, котирующихся на Тегеранской фондовой бирже (TSE) с использованием нейронных сетей. Статистические данные были собраны из аудированной финансовой отчетности в 2006-2011 гг. EVA была спрогнозирована с использованием линейной регрессии и нейронных сетей, а результаты были сопоставлены с фактическими данными. Полученные результаты свидетельствуют, что нейронные сети превосходит метод линейной регрессии в прогнозировании EVA.

Ключевые слова: нейронные сети; экономическая добавленная стоимость; финансовые коэффициенты; Тегеранская фондовая биржа; Иран.