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PREDICTION OF EARNINGS MANAGEMENT BY USE OF MULTI-LAYER PERCEPTRON NEURAL NETWORKS WITH TWO HIDDEN LAYERS IN VARIOUS INDUSTRIES

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Abstract
Over the last few years, increase in the number of financial crisis cases has attracted the attention of a great number of investors and creditors to the prediction of these cases by using the data available from financial statements of the corporations in order to prevent losses which are caused by them. Many of the studies about the earning management only focus on identifying the factors which affect the earnings management and relation between earnings management and these factors and not on using these factors in order to predict the earnings management. On the other hand, in the present study, 12 influential factors, which are introduced by former studies, are used to evaluate the predicting ability of the neural networks for prediction of earnings management and its different levels. Multilayer perceptron neural network with 2 hidden layers is used for prediction. Moreover, the required data is obtained from the financial statements of the listed companies of Tehran Stock Exchange (TSE). The results show that the applied neural network method has an acceptable ability for the prediction of earnings management and its different levels in all different studied industries.

Research paper

Keywords: Earnings management, Neural network, Multilayer perceptron, Accrual items

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Introduction

For a long time the earnings figures reported in the financial statements for shareholders, creditors, employees, financial analysts, customers and suppliers is very attractive. Users of financial statements generally make decision based on information derived from financial statements. Thus, financial reporting should effectively through a reliable and timely manner provide financial information to users outside the organization. This is while managers always have the opportunity to mislead the users of financial statements. Investors give higher value for companies with stable earnings, so managers due to different incentives such as increasing stock prices of their company may go toward earnings management (Elias, 2002).

Earnings management includes a wide range which begins conservative accounting and ends to its extreme state fraudulent accounting. Managers due to different reasons and motivations and using various tools and employing various methods, attempt to manipulate earnings and their ultimate purpose is to exhibit desirable status of firm and provide a positive image of the firm's performance. While millions of people based on information and earnings reported by the company administrator invest their savings in such company's securities and rely on the financial statements provided by them. Also a lot of people give their savings to banks and financial institutions then them, in turn, invest these funds in stocks of the companies or lend them (Lo, 2008).

Many people either directly or indirectly have interests in joint stock companies and preserving public interests requires reliable and timely financial reports of operations and financial health of the companies. In recent years the number of financial crises related to public companies is increased, while investors and creditors are barely able to predict financial crises, especially when earnings management is done in the financial statements. Some of the financial crisis are related to companies that are well-known and has high stock prices that were bankrupt as well (such as Enron, WorldCom, etc.). The important issue in such financial crisis is that it was too late for creditors and shareholders to give back their loans or sale their stocks. So these cases strongly damage shareholders and creditors and indicate that shareholders and creditors can not fully recognize earnings manipulated by management (Healy & Wahlen, 1999).

Many studies on earnings management only focus on recognizing related factors which may significantly affect the earnings management. Earnings management is done by managers in various ways. Among earnings management practices, manipulation of accounting accruals, especially discretionary accruals, is the easiest and most common way to manage profits that at the same time is the most difficult way to determine whether the earnings management is performed. Therefore, the adoption of accounting accrual to manage earnings is often considered in studies of earnings management. In the meantime, it is important to note that in most of the research and the methods used only attempt to identify the factors used in earnings management and in few studies these factors are directly used to predict the level of earnings management (Cohen & Zarowin, 2010).

Thus, finding a way which able shareholders and creditors to detect earnings management before it is too late and firms are now bankrupt, is very valuable. Therefore, determining the strategy and finding tools to predict the level of earnings management to use in decision making of financial statements users can be very beneficial. One of the tools that can be used to predict the level of earnings management is artificial intelligence and techniques and tools related to it like neural network. Artificial intelligence in addition to applications in various fields, like earthquake prediction problems (Mahmoudi et al, 2015 & 2016), has long been finds its position in accounting and finance (Pandya, 2014; Azhar, 2015). Accounting researchers take advantage of artificial intelligence techniques to specific tasks in auditing and assurance (Koh and Low, 2004; Etheridge et al., 2000).

Neural networks have the three major advantages compared to statistical methods. First, neural networks are able to learn any complicated design and nonlinear mapping. Second, neural networks, does not consider any default in data distribution and third that neural networks are very flexible against incomplete, missing and caustic data (Vellido et al., 1999). Accordingly, the use of neural networks in accounting, auditing and finance is increased dramatically.

This study tries to answer the question that multilayer Perceptron neural network model with two hidden layers with how much precision can predict earnings management and its different levels in companies listed on the stock exchange for various industries. According to the above facts and following previous studies in this study we attempt to evaluate the neural network techniques to predict the level of earnings management and capabilities and application of neural network model. For this purpose we first study the literature on earnings management identification techniques and the application of neural networks in prediction. Then research methodology is described and then findings related to studied industries are presented and finally, according to the findings, some suggestions for future research are presented.

Literature review

Chen et al. (2015) discuss the complexities involved in biotech industry in financial statement analysis and detection of earnings management is the central focus of the research paper. The adoption of data mining techniques has also resulted in better detection of accounting manipulation. This study examines the Earnings manipulation state in biotechnology by incorporating computing models. Bereskin et al. (2015) in the study examined US firms for a period of 1990-2012. The study examined the effect of operating environment on the earnings management. Both accruals based and real earnings management was taken into consideration.

Hoglund (2010) tries to identify a model to replace the traditional statistical models which are not able to detect non-linear relationships. Their findings show that models based on neural networks by learning non-linear relationships is able to analyze total accrual and non-discretionary accruals and discretionary accruals (as the basis for earnings management). Tsai and Chiou (2009) in their study act to predict earnings management using neural networks. The findings of this study indicate that the ability of neural networks in predicting earnings management is in general 54.25%.

Wang (2007) said that when estimating the final cost many factors, including the constantly changing nature of technology, the availability of materials and direct labor, currency value should be considered. The results of this study indicate that input information are too much and sometimes incomplete, so neural networks can be a good choice to estimate the final cost. Kumar and Bhattacharya (2006) in their study began to compare the ability of neural networks with linear models. The results suggest that neural network model compared to linear models is more effective in predicting financial solvency.

Koskivaara (2004) examines the application of neural networks by auditors. The results show that neural networks in auditing can help to analytical review procedures by auditors. Etheridge et al (2000) investigate the application of neural networks by auditors. The results show that neural networks can help auditors in decision-making regarding the continuation of customer activity and financial viability.

Pourheydari and Azami (2010) in their study predict the type of auditors’ opinions using neural networks. Research results indicate that multilayer perceptron artificial neural network has high potential in identifying and prediction of auditors’ opinions. This network with87.75% has the best performance in identifying audit report, while logistic regression performs poorly in identifying qualified opinion and is unbalanced pattern in identifying auditor opinion.

Rai (2006) compares the neural network model and Markowitz model in investment portfolio theory. The results show that the neural network model portfolio after the test period, also has more efficiency and its risk was also lower than Markowitz model. Sinai et al. (2005) in their study predict the stock price index. The findings suggest that neural networks perform better than linear ARIMA model to predict price index and MSE acceptable value for network error test data and estimation indicate that there are chaotic movements in the price index.

Research hypothesis

According to research aim and conducted research and theoretical framework, research hypothesis for the companies listed on the Tehran Stock Exchange has been formulated as follows: Applying multilayer perceptron neural network with two hidden layers, has the ability to predict earnings management in listed companies in various industries of Tehran Stock Exchange.

Sampling & data

The target population included all Iranian companies listed on Tehran Stock Exchange with the following conditions: (i) Prior to 2003, be accepted on the stock exchange; (ii) for consistency of the reporting date, remove the seasonal effects, increasing comparability of information and given that the data for a period of six months also must taken into account, their financial period ended to 21 September or 19 March; (iii) All companies that have all the data needed to calculate discretionary accruals; (iv) All companies that have presented their interim financial statements to the stock exchange; (v) Do not be of financial intermediation companies, including investment companies, banks, insurance and leasing.

The scope of research topic is assessing the ability of neural networks to predict and development of tools available to users of financial statements to understand the earnings management used in information ahead of them. Research local territory is Tehran Stock Exchange and its period is from 2003 to 2009. At first sample size according to the constraints mentioned above, 61 companies in 16 different industries were selected for 6 years. But given that in order to use of cross-sectional Jones model, every industry must contain at least 8 samples, so from all observations collected in this study, which included 61 samples in 16 different industries, 16 companies were removed and 45 companies in five different industries were used to conduct research as described Table 1. Because to get some of the variables, data for one year ago are needed so year 2004 were considered as first year and data for 2003 also were considered as year ago.

Table 1. Number of samples divided by industry

#	Industry type	Sample size
1	Automobile and spare parts	13
2	Other non-metallic mineral products	8
3	Basic metals	8
4	Equipment and machinery	8
5	Chemical materials and products	8
	Total	**45**

Considering that the data for six months data of each sample company is collected, so every year the number of 90 companies/ period has been analyzed that the total number of observations for 6 years (2004 to 2009) is 540.

Research methodology

Data required is collected from financial statements of sample firms. The multilayer perceptron neural network technique with two hidden layers is used to predict earnings management calculated via a modified Jones model. Also discretionary accruals have been considered as a proxy for earnings management. Multilayer Perceptron Neural Network (MLP) is one of the most powerful neural network models which include multiple layers of nodes (Haykin, 1999), in turn includes one input layer, one output layer and one or multiple hidden layers. The input layer is defined based on research variables.

In the present study the balance sheet approach with some changes has been used to calculate the all accruals. Change in the calculation of all accruals under the balance sheet approach is as follows, according to the ineffectiveness of the dividend payable as a current liability but non-operational items the effect of this balance sheet item in the calculation of accruals is removed from all accruals. By applying changes the formula for calculating all accruals on the balance sheet approach is provided in equation 1 (Tsai and Chiou, 2009):

$$TA_{i,t} = (\Delta CA_{i,t} - \Delta Cash_{i,t}) - (\Delta CL_{i,t} - \Delta STD_{i,t} - \Delta DIV_{i,t}) - Dep_{i,t} \qquad 1$$

Where

$TA_{i,t}$: is the sum of all accruals

$\Delta CA_{i,t}$: change in current assets of firm i on year t

$\Delta Cash_{i,t}$: change on cash and Cash equivalents of firm i on year t

$\Delta CL_{i,t}$: Change in current liabilities of firm i on year t

$\Delta STD_{i,t}$: Change in current portion of long term debts of firm i on year t

$Dep_{i,t}$: The cost of depreciation of tangible and intangible fixed assets of firm i on year t

$\Delta DIV_{i,t}$: The difference of dividends payable of firm i in year t compared to last year

Variables measure (network input data)

Twelve important variables based on previous studies (Tsai and Chiou, 2009, Sajjadi and Habibi, 2008) are used as input variables of neural networks:

(1) Supervised effects from outsider (%INST)

$\%\text{INST} = \frac{TRUST_{ih}}{SHARES_{ih}}$, where

$TRUST_{ih}$ refers to the outstanding shares held by the trust institutions in firm i in the latest quarter h. $SHARES_{ih}$ refers to the outstanding shares in firm i in the latest quarter h.

(2) Performance threshold (THOD)

$THOD_{in} = NDA_{ih} - NDA_{ih-2}$

NDA_{ih} refers to the amount of non-discretionary accruals based on four quarters before in firm i in the latest quarter h.

(3) Pay-performance sensitivity (PPS):

PPS_{in}= 1, when (ROE_{in}-ROE_{mn}) . ($COMP_{in}$-$COMP_{mn}$) > 0,

Otherwise,

PPS_{in}=0 where

ROE_{in} refers to the rate of return on equity in firm i at the beginning of year n.

$COMP_{in}$ refers to the compensation of the CEO in firm i at the beginning of year n.

ROE_{mn} and $COMP_{mn}$ means the median of the variables at the beginning of year n.

(4) Leverage rate (LEV)

LEV_{ih}=TL_{ih}/TA_{ih}, where

TL_{ih} refers to the total liabilities in firm i in the latest six months h.

TA_{ih} refers to the total assets in firm i in the latest six months h.

(5) Corporate risk (RISK)

$RISK_{ih}=\beta_{ih}$, where

β_{ih} refers to the one-year corporate risk. We adopted the latest six months data.

(6) Prior discretionary accruals (DA_{n-1})

The discretionary accruals in the prior year (DA_{n-1}) have a negative effect on earnings management in the current period. In other words, the discretionary accruals have a mean-reverting effect.

$DA_{in-1}= DA_{ih-3}$, where

DA_{ih-3} refers to the amount of discretionary accruals in firm i in the latest same quarter h of the predicting quarter.

(7) Earnings persistence (PERS)

$$PERS = \frac{\sum_{h=2}^{12}\left(UE_h - \overline{UE}\right)\left(UE_{h-1} - \overline{UE}\right)}{\sum_{h=1}^{12}\left(UE_h - \overline{UE}\right)^2}$$

, where

$$\overline{UE} = \frac{\sum_{h=1}^{12} UE_h}{12}$$

$UE_h=e_h- e_h$-4; e_h refers to earnings in the latest six months,

(8) Corporate size (SIZE)

$SIZE_{in} = ln\ (\sum_{p=h-1}^{h} SALES_{ipn})$, where $\sum_{p=h-1}^{h} SALES_{ipn}$ refers to the summation of the six months sales amounts in firm i.

(9) Firm performance (CFO)

$$CFO_{in} = \frac{\sum_{p=h-1}^{h} OCF_{ipn}}{ASSET_{inh-2}}$$

, where

$\sum_{p=h-1}^{h} OCF_{ipn}$ refers to the summation of cash from operations six months amounts in firm i in year n.

$ASSET_{inh-2}$ refers to total assets in firm i at the same date of six months in the last year.

(10) Financing activities (SHARVAR)

$SHARVAR_{in}$ when the outstanding shares increased or decreased by 10% in firm i from the latest six months, otherwise, $SHARVAR_{in}$= 0

(11) HALF

In this paper, we gather the six months data in data collection. The level of earnings management may be affected by different six years. In order to control the effect of the periods, we use the number from 1 to 2 to stand for 2 six months periods.

(12) Prediction of the future earnings growth (MV/BV)

This is determined by considering the proportion of market value to book value.

After identifying the research variables the following steps are carried out to use artificial neural network:

1. The definition of earnings management levels based on the distribution of accruals

There is a range of discretionary accruals from - 2.09455 to 2.54948 in used sample. Of course the real range is considered from -1 to 1 and values outside of this range were very small and that number was deleted. In addition, the majority of discretionary accruals are close to zero, according to Table 2, different levels of earnings management had been tagged.

Table 2. The definitions of earnings management levels and its label (Tsai & Chiou, 2009)

Tag	Description	How to determine
2	Extreme upward earnings management	It accounts discretionary accruals greater than or equal to 0.4 for itself
1	High upward earnings management	The data that their discretionary accrual figure is greater than 0.2 and less than 0.4.
0	Earnings management close to zero	The data that their accrual figure is between -0.2 and 0.2.
-1	High downward earnings management	The data that their discretionary accrual figure between -0.02 and -0.04
-2	Extreme downward earnings management	The data that their discretionary accrual figure is lower than -0.04.

2. Assigning variables to the neurons in neural network

At this stage the research variables and criteria related to neurons are assigned. The output branches of neural networks are prediction label or outlets, which as can be seen in Table 2, earnings management is classified into 5 groups. After collecting the data, and determining tags of defined output, the networks become ready for model training.

3. MLP neural network design

The data is divided into two parts. The first part is data for years 2004 to 2006 that provides the data required for network training and the second part is data for years 2007 to 2009 and provides prediction data. It should be noted that, as this division is summarized in Table 3, the data of training course is divided into two parts: training and test. This is done that network to be able in this way to measure its prediction error and prevent from excessive training, which is one of the major problems of neural networks. According to Table 3, 200, 70 and 270 companies / period are used respectively for the training, testing and prediction. The next part is about the hidden layer that according to network architecture, two hidden layers were used. In the hidden layers, because there is no way to directly determine the number of hidden nodes, five different numbers of hidden nodes is selected which are 8, 12, 16, 24 and 32. One famous point of concern for neural network is excessive training. To fix this problem, Roiger and Geatz (2003) have suggested that experiences continuously done by various parameters. So, a bunch of different learning period includes 1000, 1500, 2000 and 2500 have been used. As a result, there are four learning period; each period has 25 models (according to 5 different nodes in each hidden layer) in neural network.

4. Training and test of neural networks

In training part the first three years data (2004 to 2006) calculated for variables affecting in research and also calculated data for discretionary accruals have been given as alternate representative to earnings management of neural network. It should be noted that part of the training data, itself as test data is used to determine the learning error. So, for each year and for each company data for variables affecting are introduced as neural network input neurons and data for discretionary accruals are introduced as final data of neural network (Target). By increasing the number of data for each company and for each year and determining training courses neural network started studying relationships between independent and dependent variables and have discovered their linear or non-linear relationships. In prediction part, neural networks go toward the data for next three years of the effective variables and by giving it to the neural network as the network inputs attempt to specify the number of discretionary accruals that figures obtained has been classified in the aforementioned groups (between -2 to 2).

5. Determining the best prediction model

5 defined categories have been tested using neural networks and the results obtained were compared with the actual results which have been pre-calculated through Jones model, and prediction accuracy rate is determined for each category. After the prediction phase is complete, the model that has the highest average rate of forecast accuracy as predictive models will be chosen as earnings management.

Results

With regard to the content expressed, neural networks are used to test the hypothesis that results are presented in the following section. As mentioned above, research data have been extracted from 45 companies in five different industries. Given that the characteristics of each industry can be effective factor, so this study examines the results of earnings management prediction using neural networks to separate industries. The results of the best prediction model in different industries are as follows:

Table 3. Results of the best prediction model in different industries

#	Industry type	The best prediction model		Prediction %	The best prediction of the level of earnings management	Prediction %
		1st hidden layer	2nd hidden layer			
1	Automobile and spare parts	12	24	60.5	Earning management close to zero	81.1
2	Other non-metallic mineral products	12	12	56.5	Earning management close to zero	88.5
3	Basic metals	8	8	74.5	High upward earnings management	100
		8	12	74.5	Earning management close to zero	91.4
4	Equipment and machinery	8	8	67.4	Earning management close to zero	87.1
5	Chemical materials and products	16	12	80.5	High upward earnings management	66.7
		8	24	80.5	Earning management close to zero	94.1

The table shows the highest percentage of predictive power in different industries, that for example in the Automobile industry, the best prediction model, is related to the model of the first hidden layer with 12 node and to the second hidden layer with 24 node that in general could predict as much as 60.5% of earnings management and in earnings management levels it predicts earnings management close to zero by as much as 81.1%. As is clear from Table 3 the best prediction results of earnings management is related to materials and chemical products industry by 80.5% and basic metals by 74.5 percent true prediction, also the lowest percentage of prediction is related to non-metallic mineral products industry with 56.6%.

Table 4 Indicates the importance of the independent variables and the standardized importance of independent variables in prediction process using neural networks. As can be seen the highest importance rate among input variables is for company risk, company size and performance threshold.

Table 4. Importance of input variables

Input variable	Importance	Standardized importance
Risk	183	100.00%
Corporate size	128	70.00%
Performance threshold	112	61.00%
Financial leverage	90	49.20%
Firm performance	82	44.80%
Prior discretionary accruals	78	42.40%
Earnings persistence	66	36.00%
Supervised effects from outsider	63	34.10%
Prediction of the future earnings growth	59	32.10%
Pay-performance sensitivity	54	29.50%
Acquisition and financing activity	43	23.50%
Interim period	42	23.10%

This study investigates the power of Perceptron neural network with two hidden layers on predicting earnings management at different levels in various industries.The selected sample contains 45 companies during period of six years (2004 to 2009) which is extracted for two periods of six months in each year (a total of 12 periods) using Tehran Stock Exchange database.

The results indicate that the MLP neural network with two hidden layers is able to predict earnings management in the Automobile industry in general by 60.5% and in the best classifier up to 81.1% for earnings management close to zero, other non-metallic mineral products industry in general by 56.5% and in the best classifier up to 88.5% for earnings management close to zero, basic metals industry in general by 74.5% and in the best classifier up to 91.4% for earnings management close to zero, and 100% for upward earnings management, in machinery and equipment industry in general by 67.4% and in the best classifier up to 87.1% for earnings management close to zero and at chemical materials and products industry which has the best results in general by 81% and in the best classifier up to 66.7% for upward earnings management and 94.1% for earnings management close to zero which shows the high feasibility of this model.

Conclusion

According to the results of Tsai and Chiou (2009) MLP neural networks, able to predict earnings management in the electronics industry in general by 54.25%. Results of present study showed that the MLP neural network with two hidden layers are able to predict earnings management in various industries, at the highest rate up to 81% in the chemical product industry and at the lowest rate up to 57% in non-metallic mineral products industry that compared to similar research has the best results for prediction.

The recommendations are as follows: (i) The Tehran Stock Exchange using this software as practical software can detect companies which manage earnings and through this draw shareholder confidence; (ii) Shareholders and creditors as those who earnings management can cause irreparable losses for them in this way can protected themselves from the risk of losses; (iii) Auditors can also using software obtained from this research can take advantage of research results in the process of auditing.

This study as a template can provide the necessary background for further research in the future, including the following topics: (i) In this study

Perceptron neural network is used. Researchers can also make use of other neural network techniques (propagation, linear elements, etc.); (ii) In this research six-month period of sample companies are studied. The researchers can study the three-month period data. This research is done through the SPSS software tool for neural networks. Researchers can through the use of programming, act to produce special software related to predicting earnings management through neural networks as practical software.

Research limitations

The present research limitations are as follows: (i) due to lack of required data for all stock exchange companies in the research period a large number of companies were excluded, so this can affect the results; (ii) Given that to control the industry effects there should be at least 8 companies in every industry and since the number of observations in most industries were less than 8 companies therefore the test was only done on 5 industries; and (iii) Investment companies, leasing and insurance due to the specific nature of the activity and figures contained in the financial statements, have been excluded from population examined in this study. So, generalizing the results to these companies should be used with caution.

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