



Prediction of Related Party Transactions Using Artificial Neural Network

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ABSTRACT

Recent scandals of companies in America (Adelfia, Enron) and Europe (Parmalt) have magnified transactions with related parties. Experience has shown that transactions with related parties not only can disrupt in create value for shareholders, but also can provide caused of the collapse of firms. In this line, the aim of this study is to predict the amount of transactions with related parties using artificial neural network in companies listed in the Tehran Stock Exchange. Multi-layer artificial perceptron neural network with backwards propagation algorithm, the duality of the board of directors, the independence of the board of directors, financial leverage, institutional ownership, the ratio of market value to book value of assets, company size and profitability were used to predict the amount of transactions with related parties, the predictor variables of board size. Finally, a network with the mean square error 0.229, 0.424, 0.299, 0.268 were chosen respectively for educational data, validation, test and total data, and coefficient of determination more than 76%, as the best network to predict the amount of transactions with related people were selected.

Keywords: Forecast Transactions with Related Parties, Propagation Algorithm, Related Parties Transaction

JEL Classifications: C32, O13, O47

1. INTRODUCTION

According to Iran's Accounting Standard 12, transactions with related parties is defined as the transfer of resources, services or obligations between related parties, regardless of demand or lack of demand for it. Relationships with related parties may have an impact on financial position, financial performance and financial flexibility of entity. Related parties may do some transactions may not carry out independent entities. Also, the amount of transactions between related parties may not be the same with similar amounts between independent parties. Due to the above-mentioned reasons, awareness of transactions, parties account balance, and relation with the parties may impact on user's assessment of financial statements of commercial operations including risk assessment and opportunities of commercial unit. According to the financial analysts, one of the reasons of the financial crisis of the company's includes transactions with related parties and their coverage through their financial statements. Transactions with related parties may provide a suitable opportunity for related people to exit cash of company by underground activities (Jiang et al., 2008). Experience has shown that transactions with related parties can

not only cause a disturbance on value creation for shareholders, but also can lead to the collapse of companies.

That's why, after the bankruptcy of Enron, America's Congress passed the Sarbanes-Oxley Act in part of it referred to the transactions with related party. Accordingly, the Stock Exchange of America issued some strict rules about the necessity of disclosure of transactions with related parties for listed companies (Gordon and Henry, 2005). As a result, it can be said that transactions with related party and the possibility of opportunistic behavior of manager, is due to dealers conflict. The formation of the agency relationship, is combined with conflicting interests that occurs as a result of the separation of ownership from management, different goals and information asymmetry between managers and shareholders (Djankov et al., 2008).

One of the basic assumptions of agency theory is that manager consumes the company's resources to win to maximize their personal interests. Transactions with related party is often considered as this type that is in the interests of managers and shareholders losses (Kohlbeck, 2004). These management abuses,

In addition to interfering in the value creation for shareholders, can also endanger job security of administrators. For this reason, managers for the preservation of the adverse effects of these transactions may attempt to distort the faces of their financial statements which results in problem in value-creation for shareholders, because it forecloses the awareness decision-making possibility of owners due to providing distorted information (Henry et al., 2007).

As a result, the need for a monitoring mechanism such as auditors was essential to build confidence about the performance of managers (Ming, 2007).

Audit of transactions with related parties is of the complex issues and the inability of auditors to identify these deals, is one of the shortcomings of the audit. America Society of Certified Public Accountants (2001) has offered three reasons for the difficulty of auditing related parties and transactions with related parties. Firstly, the transactions are not identified simply. Secondly, to identify related parties and related party transactions, auditor relies on the CEO and major shareholders. Thirdly, these transactions are not followed easily by internal controls of company.

On the other hand, traditional processes of accounting deal with some limitations such as time, human force, cost, and extended financial information. Therefore, designing a model is essential for forecasting the trading amount with people to help owners (shareholders) and creditors in assessing the risk and opportunities of commercial unit and decreasing conflicts of representation theory to help the accountants in better programming of accounting of these transactions.

2. LITERATURE FRAMEWORK

2.1. Related Party Transactions

Related party transactions can be examined from two perspectives that each one expresses different aspects of these transactions.

The first perspective is compatible with representation issue and expresses these transactions are used to obtain personal interests for managers are causing damage to the company and shareholders.

On the other hand, managers to cover the negative effects of these transactions start to distort financial statements (Gordon et al., 2004; Jiang et al., 2008 and Aharony et al., 2010).

Examples of related parties' transactions opportunistically can be seen in Enron Company where managers gain personal benefits through transactions with related parties due to weaknesses in internal control structure, and distorted the financial statements in order to avoid the consequences of this action because many of these transactions were not disclosed in the financial statements of the company that was considered as one of reasons of the bankruptcy of Enron in 2001 (Kohlbeck, 2004).

Second perspective, sees transactions with related parties as part of a business unit demand and knows it as a factor to ensure work of managers in the company.

Effectiveness of related party transactions viewpoint follows the concept of transaction costs offered by Coase (1937) and Williamson (1975). According to this view, related party transactions not only is not harmful, but notes that such transactions may also be beneficial for shareholders (Stein, 1997; Chang and Hong, 2000; Khanna and Palepu, 2000; Jian and Wong, 2010).

2.2. Artificial Neural Networks (ANNs)

ANNs are educable and analysis tool that attempts to mimic the patterns of information processing in the human brain. These networks are dynamical systems consisting of parallel processing units, or neurons which is a propensity to keep their experiential knowledge and making it available for use. Learning property of neural networks is important. The network as the learning systems has the potential to learn from past experience and environment and improve their behavior during the learning.

Improve learning network over time is measured based on the criteria for improvement, the goal is to model learning system (Menhaj, 2002). In Figure 1 is shown the components of a neuron.

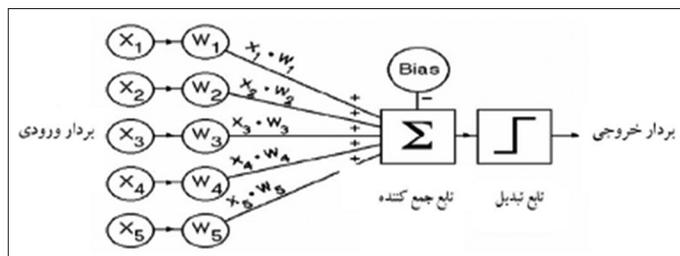
In this model, the input vector x with the size $xw + b$ enters into neurons. Then, it is under other action or process that is called as transfer function that provides neurons function. W parameter is called weight parameter. When a great neural network was created by putting together a large number of neurons, a network is available that is completely dependent on b and w amounts in addition to output function.

In such a large network, a large number of parameters w and b should be set by the network designer. The process of the work, in terms of neural networks, is known as the learning process. In fact, in a real test, after the presentation of the input vector, network is educated by measuring the output with the by selecting parameters w and b such that the desired output is achieved. Therefore, after such a network trained for a set of inputs to create the desired outputs, it can be used to solve the problems made by different compounds of inputs (Kordstani et al., 2013).

3. MULTI-LAYER ARTIFICIAL PERCEPTRON NEURAL NETWORK

Multi-layer artificial perceptron neural network is one of the strongest models of ANN including input, hidden (center) and

Figure 1: The components of a neuron. Picker : مَدَنَك عَمَج رَادَرِب
 victor : لِي دَبَت عِبَا
 Input vector : يَدُورُ رَادَرِب
 Output vector : ي جُورُخ رَادَرِب



output layers. The structure of each of these layers is composed of a large number of neurons or nodes.

Figure 2 shows a multi-layer artificial perceptron neural network.

The number of neurons in the input and output layers tasked with only incoming and outgoing data, depends on the number of input variables (training) and output variables of network. But, unlike the input and output layers, determine the number of neurons in the middle layer with the number of repeat cycles, are considered as the main problem in the design of ANNs. Almost there is no proven formula for determining the optimal structure of network. This structure (the number of middle layers, number of neurons in the middle layers, the number of repeated cycles of learning) is determined experimentally. If the number of neurons in the middle layer and number of repeated cycles is selected underrepresented, the network will have the ability to adapt to the mapping.

On the other hand, high amount of these neurons and number of the repeated cycles, result in high fitness and lack of network generalizability, so that the network is experiencing a large increase in input becomes unstable. Thus, the low cycle of neurons should be used in the middle layer and are gradually used for the improvement of error, increases their number. Different methods are suggested solving this problem, the extent we can add to the number of neurons in the middle layer and the repeats cycle to avoid network with too fit, including early stopping rule using validation data (Rigor and Geatz, 2003).

According to early stopping rule, data is divided into three groups as training data, validation data, and test data. Training data is used for determining weights.

Validation data are used when training, but they play no role in determining weights. Duty of validation data includes monitoring the generalization of network in line with network training. After offering all training data to network completely, using the weights, validation data enters the network and the network amounts are calculated based on them. The calculated amounts are calculated by network for training data, and validation data are calculated by main amounts, and error amounts of training data and validation data. These errors are calculated again after each complete cycle of presenting the training data to the network.

Since a cycle, error of validation data increases. This means the network misses its generalization ability little by little, and keeps training data, without the ability to receive correct relationship between input and output data. Therefore, after presenting more validation error by network after consecutive times, the training process stops, and the weights of the least validation error are considered as the best result of the network training. If the error amount is not desired, it is essential to start a new training cycle. After the error on the training data and validation reached the desired level, test data that has not been used until this stage of the work, is used for final testing of network interoperability. This data group enters into the training network its optimal weight coefficients are calculated, their output is calculated, and finally are compared with main amounts.

If you have a good amount of test data error, the job is finished.

“Movement technique” is another method that is helpful in network training, especially in cases where limited data is available.

In this method, after network training of the obtained weights are used as the initial weights of the second round of training network, but in this new round of education, training and validation of the data changes. The previous validation data are used as training data and previous training data are used instead of the current validation data (Dezfoolian and Akbarpor, 2011).

4. LITERATURE REVIEW

Kohlbeck (2004) argue that based on agency theory, related party transactions increases concern, because managers by improper transfer of wealth, reduce financial statement reliability and decrease the effect of incentive contracts designed to reduce conflicts of representation and ultimately damage of corporate shareholders.

According to Skaife et al. (2006) when there is no closer examination about related party transactions or there is a few tests done, managers have powerful incentives to expropriate the company’s resources and profit management.

Chen and HSu (2010) investigated on the relationship between related party transactions and the company’s performance and also determine a positive impact of corporate governance on the relationship between related party transactions and firm performance. According to the results, corporate governance mechanisms change the transactions of opportunistic transactions to more efficient transactions and independence of the board, plays a moderating role in these transactions.

Moscariello (2010) investigated motives of related party transactions on the Stock Exchange of Italy. His goal was to identify the reasons behind the transactions with related parties or opportunistic and efficiency of these transactions. Due to the concentrated ownership structure in Italian companies, the possible use of related party transactions by major shareholders to acquire the company’s resources was evaluated to seize the company’s resources to the detriment of small shareholders. There is evidence of opportunistic behavior in these transactions. Accordingly, there is significant relationship between the amount of these transactions and effective variables on motivations and costs of seizing properties.

Srinivasan (2013) investigated on related party transactions in Indian companies for 3 years. According to his results, 1 - There is negative significant relationship between related party transactions and company performance. 2 - The related party transactions with companies audited by large institutions, are less than the rest of the company. 3 - There is no significant relationship between ownership structure and related party transactions.

Kohlbeck (2014) investigated on the relationship between the related party transactions and restated paid after the balance

sheet date to assess if this type of transaction is a warning to increase the risk of distortion with importance of financial statements for accountants and users of financial statements. The researchers analyzed data on 1500 companies came to the conclusion that (1) there is a significant relationship between this type of transactions and revised after the balance sheet date and the probability of revised after the balance sheet date when they are trading with affiliated entities, is 15% more than the time companies have no trading with related people. (2) In particular, transactions with employees and managers have a strong positive correlation with the restated after the balance sheet date.

Lee et al. (2014) investigated on the relationship between the transactions with related parties and comparability of financial statements of companies in South Korea. The following results were obtained:

1. There is negative significant relationship between the total amount of related party transactions and comparability of financial statements
2. There is negative significant relationship between fluctuations related party transactions and comparability of financial statements
3. There is negative significant relationship between transactions with non-cash related parties and comparability of financial statements.

5. METHODOLOGY

In this study, after the preparation of the data in Microsoft Excel and perform calculations for the required variables, three-layers perceptron neural network was made for prediction of related party transactions. It has 8 neurons in the input layer and one neuron in the output layer, according to the number of input variables (training) and output.

The optimal number of neurons in the middle layer is achieved by trial and error, i.e., starting from the small number of neurons in the middle layer and then gradually increasing them and check the error changes, the optimum number is determined. To avoid overheating and improve network fit, the early stopping rule using data validation is used. For this purpose, according to this rule, the data is divided into three categories:

60% as educational data, 20% as validation data, and 20% as data for network testing. Stopping rule is such that if validation error increase over six consecutive step, even if the training data error is increasing, the training process is stopped. Criteria to measure network performance in the training process, is considered the mean square error. Also, according to the surveys conducted, tangent sigmoid transfer function was used in the middle layer, and linear transfer function was used in output layer.

Network training was done using error back propagation algorithm and Levenberg Markvardet method. Because setting a linear efficient structure was difficult to predict the amount of related party transactions, and basically there is no knowledge of linear

or non-linear relationship between the amount of related party transactions and the relevant variables (predictors), the ANN with specifications, is considered as the best tools to predict the related party transactions.

5.1. The Population and Sample

The study population consists of all companies listed on Tehran Stock Exchange during the period from 2006 to 2013. Taking into account the following restrictions for the companies, sample was selected:

1. 1 in terms of increased comparability, the fiscal period ended March
2. Do not change its financial year during the period
3. During the period under review, trading symbol is not out of foreign exchange
4. Because to calculate the market value of the entity, stock market value is required, the companies during the period should work constantly, and their shares have been traded without interruption significantly
5. The investment holding companies, banks, leasing and intermediary company (due to differences in the nature and type of activity of the company)
6. The required information is available. According to the terms listed, 55 companies were selected in the period from 2006 to 2013, as samples.

5.2. Variables of Research

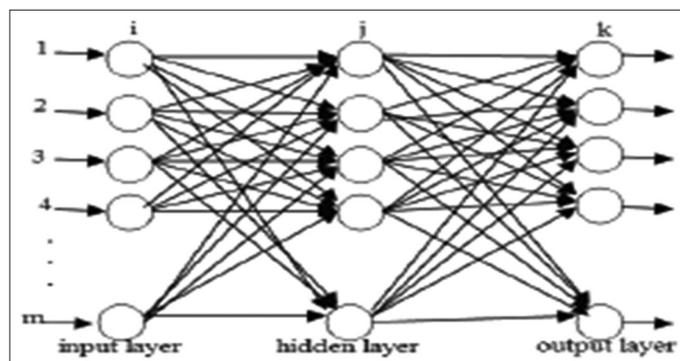
In the present study, the related party transaction is used as output for training the neural network. The amount of these transactions was obtained of natural logarithm of total amount of transactions with dependent people (LOGRPTS) disclosed in the notes to the annual financial statements of the investigated companies.

5.3. The Predictor Variables

In the theoretical foundations of related party transactions, most of studies investigated on factors impact significantly on the amount of such transactions. But of the variables directly have not been used to predict the amount of related party transactions.

Therefore, in this study, of the variables used in research related to transactions with related parties have been examined, based on the importance and the ability to calculate in the business environment in Iran, eight variables were used as input variables for the neural network training as follows:

Figure 2: A multi-layer artificial perceptron neural network



1. Size of board of directors: It is defined as the number of members of board of directors
2. Role DUAL board: This variable is a dummy variable i.e., if chairman of the board is CEO, its amount is 1 otherwise, and it is 0
3. Independence of the board of directors (%NED): This variable can be obtained by dividing the number of not-bound directors of the board of directors and board members
4. Leverage (LEV): In this study, the purpose of financial leverage is defined as the ratio of total debt to total assets
5. Ownership: In this investigation, ownership means a percentage of shares of company that is provided for owners of more than 5% of shares
6. The ratio of market value to book value of assets: This ratio is the result of dividing the company's market value to net book value of assets
7. Size of company (LOGTA): In this research, size of company is defined as natural logarithm of total assets of company each year
8. Profitability: It is obtained of dividing profit before financial costs and tax on total assets of each company in each year.

6. RESULTS

After multiple tests and make changes in network parameters, the model structure had the lowest error rate was (1-13-10), that was stopped using the data validation.

According to purpose of research, including predicting the transactions amount with dependent people among 55 companies accepted in Tehran Stock Exchange during 8 years, a multi-layer artificial perceptron neural network was designed in MATLAB.

Therefore, the best neural network structure in this research includes 13 neurons in middle layer. Overview of the neural network implemented by software is displayed in Figure 3.

Early stopping rule was used in this research to avoid high fit level of network in this method, according to settings in network planning process, if validation data error increases more than 6 repetitive steps, training process is stopped even if training data error is decreasing.

Designed neural network training process, as shown in Figure 4 is stopped after 12 iterations, because validation data error increased six consecutive steps.

In Figure 5, mean square error curve in terms of the number of repeat cycles is designed for input data (the predictor variables). This figure shows the process of neural network training of input data. Accordingly, after 12 repeat cycles, the designed ANN reaches its best efficiency i.e., the least mean square error. If the network error continues, the training error increases, and network keeps the patterns. According to the figure, the best efficiency of the designed ANN, is in a point with mean square error for training data as 0.299, mean square error for validation data as 0.424, mean square error of test data as 0.299, and error square mean is 0.268. Also, according to Figure 6 reveals that behavior of the

Figure 3: The neural network implemented by MATLAB

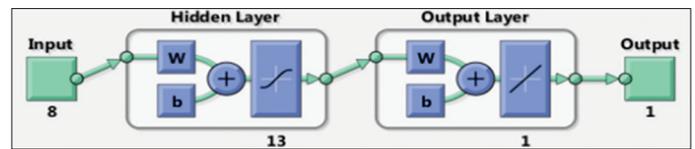


Figure 4: Validation data error in the process of education

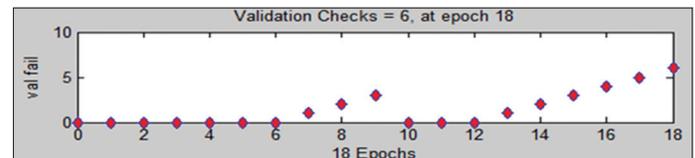
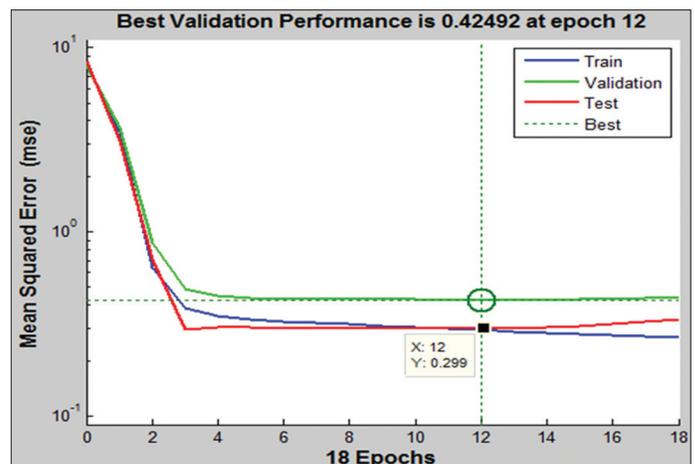


Figure 5: curve in the number of repetitions performed in the states of training, validation and test



training data error with validation data error and characteristics are almost identical. Also, no fit was seen until stage 12 (where the best efficacy occurs for validation data).

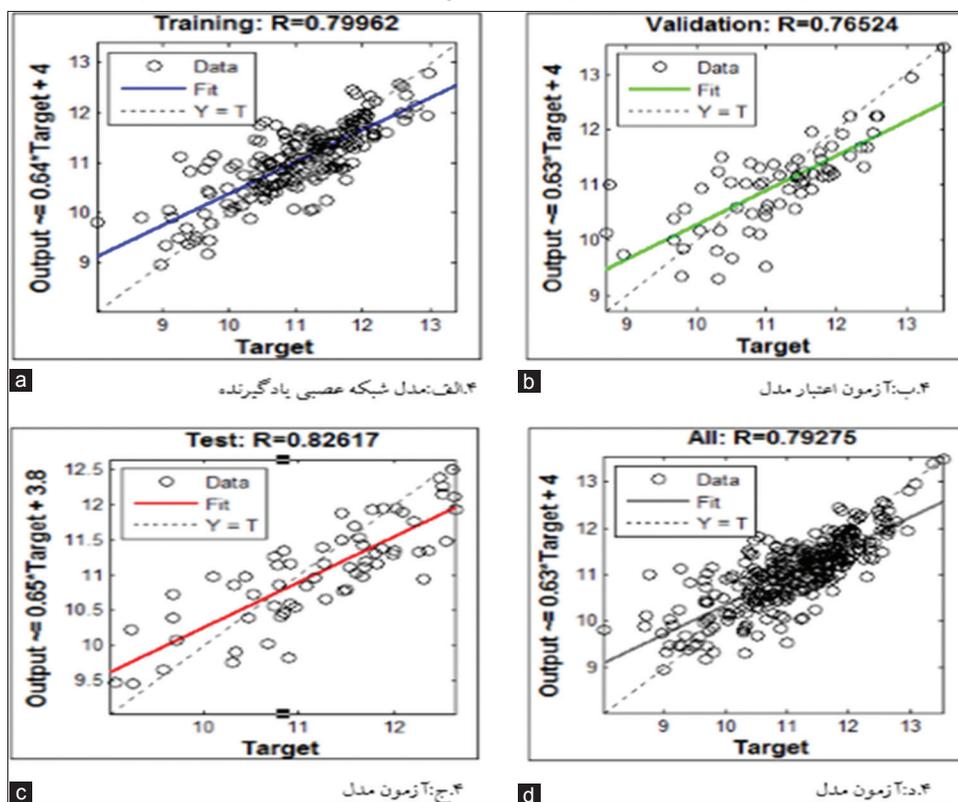
Figure 6 shows the accuracy and the ability of the neural network, for modeling each training data, validation, and test and the entire dataset to predict the amount of transactions with related parties. The vertical axis shows actual values of the data and the horizontal axis shows the output amount of ANN. If the neural network output is precisely equal to the actual values of data, all points will be on the line $Y = T$. If the data are concentrated around the line $Y = T$, show the appropriate identification of data by neural network. Line FIT is regression error of fit of data.

Figure 6a shows total results of training. This figure explains model test using the training data. As can be seen, the model is validated by a factor of 79%. To reaffirm, as shown in Figure 6b, the model confirms itself by validation data and retesting with 76% coefficient of determination.

Figure 6c is testing model by test data. This model is validated for test data by 82% coefficient of determination.

In Figure 6d, 79% coefficient of determination factor confirms this validation where model is tested using total data.

Figure 6: Evaluation the efficiency of artificial neural network using regression analysis. (a) Learner neural network model - دای یبصع هکبش لدم - ددنریگ, (b) model validation test - لدم رابتعاً نومزا, (c) model test - لدم نومزا, (d) model test



7. CONCLUSION

Related party transactions is defined as the transfer of resources, services or obligations between related parties, regardless of demand or lack of demand for it. Relationships with related parties may impact on financial position, financial performance and financial flexibility of the entity.

Experience has shown that transactions with related parties not only cause a disturbance on value creation for shareholders, but also lead to the collapse of companies. In this regard, for the first time, this study is to predict the amount of related party transactions conducted using ANNs. The use of these predictive models is useful to increase the accuracy of predictions based on financial data. Multi-layer artificial perceptron neural network with backwards propagation algorithm was used in this research. Network parameters were found after multiple tests.

Finally, network with mean square error, 0.299, 0.424, 0.299 and 0.268 respectively for training data, validation, test, and total data and the coefficient of determination more than 76 percent has been selected as the best network for prediction of related party transactions of listed companies in Tehran Stock Exchange.

Therefore, it is possible to explain more than 76% of the related party transactions by neural networks and predictor variables (board size, role ambiguity board of directors, board independence, financial leverage, and institutional ownership, the ratio of market value to book value of assets, firm size and profitability).

7.1. Suggestions

1. Due to the limitations of auditors in identifying and exploring related party transactions the auditors recommended to use neural networks technique and predictive variables of the study to predict the related party transactions
2. The board of directors and inspectors to identify not disclosed related party transactions is recommended to use neural network and predictor variables in this study
3. Investors and creditors are suggested to assess the risks and opportunities facing business units and reduce opportunistic behavior of manager not rely only on related party transactions disclosed by admin, and estimate the amount of such transactions through neural network and predictor variables of the study
4. The Stock Exchange as an entity to monitor on the company is recommended to use neural networks and predictive variables of the study to identify the related party transactions in order to reduce financial crises in companies and reduce distortions in the financial statements.

REFERENCES

- Aharony, J., Wang, J., Yuan, H. (2010), Tunneling as an incentive for earnings management during the IPO process in China. *Journal of Accounting and Public Policy*, 29, 1-26.
- Chang, S.J., Hong, J. (2000), Economic performance of group-affiliated companies in Korea: Intragroup resource sharing and internal business transaction. *Academy of Management Journal*, 43(3), 429-448.
- Chen, C.U., Hsu, J. (2010), The Role of Corporate Governance in Related

- Party Transactions. Working Paper, National Yunlin University of Science and Technology.
- Coase, R.H. (1937), The nature of the firm. *Economica*, 4(16), 386-405.
- Dezfoolian, M., Akbarpor, S.M. (2011), Modeling of lithology in south pars gas field using artificial neural network. *Petroleum Research*, 21(66), 12-22.
- Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A. (2008), The law and economics of self-dealing. *Journal of Financial Economics*, 88(3), 430-465.
- Gordon, E.A., Henry, E. (2005). *Related Party Transactions and Earnings Management*. Rutgers University. Available from: <http://www.papers.ssrn.com>.
- Gordon, E.A., Henry, E., Palia, D. (2004), *Related Party Transactions: Associations with Corporate Governance and Firm Value*. Available from: <http://www.papers.ssrn.com>.
- Henry, E., Gordon, E.A., Reed, B., Louwers, T. (2007), *The Role of Related Party Transactions in Fraudulent Financial Reporting*. University of Miami. Available from: <http://www.paper.ssrn.com>.
- Jian, M., Wong, T.J. (2010), Propping through related party transactions. *Review Accounting Studies*, 15, 70-105.
- Jiang, G., Lee, C.M.C., Yue, H. (2008), *Tunneling in China: The Remarkable Case of Inter-Corporate Loans*. Working Paper, Peking University.
- Khanna, T., Palepu, K. (2000), Is group affiliation profitable in emerging markets? An analysis of diversified Indian business groups. *The Journal of Finance*, 55(2), 867-891.
- Kohlbeck, M.J., Mayhew, B. (2014), *Are Related Party Transaction Red Flags?* Available from: <http://www.ssrn.com/abstract=2427439>.
- Kohlbeck, M., Mayhew, B.W. (2004), *Agency Costs, Contracting, and Related Party Transactions*. University of Wisconsin-Madison.
- Kohlbeck, M., Mayhew, B.W. (2004), *Related Party Transactions*. Madison, WI: University of Wisconsin-Madison.
- Kordstani, G.H., Masomy, J., Baghay, V. (2013), Anticipated of earnings management using artificial neural networks. *Accounting Developments*, 5(1), 190-169.
- Lee, M.G., Kang, M., Lee, H.Y., Park, J.C. (2014), Related-party transactions and financial statement comparability: Evidence from South Korea. *Asia-Pacific Journal of Accounting and Economics*, 23(2), 1-29.
- Menhaj, M.B. (2002), *Computational Intelligence, Fundamentals of Neural Networks*. Tehran: University of Technology Tehran Polytechnic.
- Ming, L. (2007), *Corporate Governance, Auditor Choice and Auditor Switch, Evidence from China*. A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy. Hong Kong Baptist University.
- Moscariello, N. (2010), *Related Party Transactions: Opportunistic or Efficient Behavior? Evidence from the Italian Listed Company*. Working Paper, Second University of Naples.
- Rigor, R.J., Geatz, M.W. (2003), *Data Mining: A Tutorial-based Primer*. Boston, MA: Addition Wesley.
- Skaife, H., La Fond, R., Lang, M. (2006), *The Effects of Governance on Smoothing and Smoothing Consequences: International Evidence*. Available from: <http://www.fisher.osu.edu/supplements/10/4880/Lafond20paper.pdf>.
- Srinivasan, P. (2013), *An Analysis of Related-Party Transactions in India No. 402*. Bangalore: Indian Institute of Management.
- Stein, J.C. (1997), Internal capital markets and the competition for corporate resources. *The Journal of Finance*, 52(1), 111-133.
- Williamson, O.E. (1975), *Markets and Hierarchies; Analysis and Antitrust Implications; A Study in the Economics of Internal Organization*. New York, NY: The Free Press.