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A Back Propagation Artificial Neural Network based Model for Detecting and Predicting Fraudulent Financial Reporting

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ABSTRACT
Fraudulent financial reporting has become an important issue in accounting profession, the implementation of self-assessment system appears as incentives to companies to misstate their financial reports to reduce tax obligation. Fraudulent financial reporting may cause fast losses to government income, as well as losses to the users of financial reports; several recent Studies have examined the feasibility of using various machine learning techniques in business and industrial applications. The purpose of this research is to propose a back propagation based artificial neural network model for Fraudulent Financial Reporting detection and prediction. Another main objective for this proposed model is using it in measuring the financial performance assessment by detecting the positive and negative deviations in certain important accounts balances such as net sales, and accounts receivable, which will support top managers in taking important strategic financial decisions for their companies. The proposed model was implemented using NeuronsSolution ANN software and has been applied on two large Egyptian companies managing electricity distribution in Egypt. The implementation results of this proposed model showed that the model is successful, efficient and reliable in detecting and predicting fraudulent financial reporting, and also the assessment of any company's financial performance.

General Terms
Machine Learning, Artificial Neural Networks

Keywords
Machine Learning, Multilayer Perceptron (MLP) Artificial Neural Networks, Fraudulent Financial Reporting Prediction.

1. INTRODUCTION
ANNs are computer software that simulates the way of human brain functions. The basic building blocks of human brains are neurons which process a number of inputs to produce output. ANN consists of simulated neurons in the format of layers and nodes. The main advantage of an ANN over other traditional programming methods is its ability to learn. Through a trial and error process, neurons adjust their weights of input variables to model the behavior or patterns of output variables. Financial fraud detection is one the important applications for ANNs. Financial statements fraud is one of the biggest challenges in the modern business world, this is when corporations engage in certain practices designed to hide or maneuver the accounts of a corporation to help it continue to remain attractive to investors, and it costs the world’s economies billions of dollars a year, in the US alone the cost of corporate fraud is estimated at $600 billion annually and is said to be responsible for severely reducing investor confidence in the nation’s capital markets. [1] Although Bemardi [2] supported and defined the ability of auditor to detect the fraud as the previous beliefs and experiences about the fraud while Eining& Jones and Loebbecke [3] have proved that most of auditors did not know how to manage fraud which affect in the auditor’s ability to detect and evaluate such fraud. Kaminski, Wetzel and Guan described fraudulent financial reporting as a matter of grave social and economic concern. Fraudulent can be either through the falsification of financial statements or through misappropriation of assets, and since the Traditional Statistical Model need to data which has available assumptions or certain conditions (such as that the data distributed naturally, and that the matrix of variance and covariance of such data equal), these assumptions are rarely available in the data actually. [4] As a result, Siegel et al, doubted on the reliability and confidence of these methods. [5] Khormuji et al. presented a cascade artificial neural network model for the recognition of credit card fraud detection by utilizing a cascade artificial neural networks for enhancing recognition rate and reducing rejection rate. [6] To estimate the risks of fraudulent financial reporting using Artificial Neural Networks financial Ratios and account trends that are related either to revenue recognition and measurement or to the use of accounting estimates in the sales and accounts receivable cycle are used. It’s no surprise that accounts affected by transactions in the revenue cycle were presented in fraudulent financial reports because revenue recognition and measurement and the use of accounting estimates are among the most difficult auditing issues such as allowance for doubtful accounts as percentage of net sales, allowance for doubtful accounts as percentage of accounts receivable, accounts receivable as percentage of net sales. Green and Choi identified neural networks as being able to “simultaneously examine the changes and relationships between multiple accounts or groups of account balances. [7] Bell and Carcello developed and tested a logistic regression to estimate the likelihood of fraudulent financial reporting using a sample of 77 fraud and 305 non-fraud engagements, based on the incidence of red flags as explanatory variables. [8] Lin et al. created a fuzzy neural network (FNN) “to investigate the utility of information technologies such as an integrated system of neural networks and fuzzy logic for fraud detection”. The network had constructed using ratios and trends associated with either revenue recognition and measurement, or the use of accounting estimates in the revenue cycle. [9] Kotsiantis .et al. explored the efficacy of ANNs in detecting firms that issue fraudulent financial statements (FFS) and in predicting corporate bankruptcy. [10] Kirkos et al. investigated the usefulness of Decision Trees, Neural Networks and Bayesian Belief Networks in the identification of fraudulent financial statements. In terms of

performance, the Bayesian Belief Network model achieved the best performance managing to correctly classify 90.3% of the validation sample in a 10-foldcross validation procedure. [11] Nonyelum, et al. presented an automated credit card fraud (CCF) detection system based on neural network technology and rule-based component. The Self-Organizing Map (SOM) algorithm had used to create a model of a typical cardholder's behavior and analyze the features of transactions, thus detecting fraudulent transactions. [12] Hsueh-Ju Chen et al. presented a model aims to predict fraud Gap on internal control, which leads to reduce the auditor's ability to make sure that the data contained in the books and records. [13] Gupta et al. presented a data mining framework for prevention and detection of financial statement fraud. This framework used association rules, a descriptive data mining technique, for preventing fraudulent financial reporting along with the use of predictive data mining techniques such as classification for successful identification and detection of financial statement fraud. [14]

2. THE PROPOSED ANN BASED MODEL FOR PREDICTING FRAUDULENT FINANCIAL REPORTS ARCHITECTURE

This paper proposes a supervised learning back propagation artificial neural network based model for detecting and predicting fraudulent financial reporting. Supervised learning incorporates an external teacher, so that each output unit had told what its desired response to input signals ought to be. During the learning process, global information may be required; Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning, an important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights, which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

2.1 The Proposed Model Architecture

The architecture of the proposed Artificial Neural Networks Based Model for Predicting Fraudulent Financial Reports is shown in Figure 1. The proposed ANN model is a Multilayer Perceptron (MLP) network which is a layered feed forward network typically trained with static back propagation as the most used supervised learning scheme. The architecture of the proposed ANN consists of the input layer which contains a vector of seventeen PEs (input parameters), two hidden layers with a vector of eight PEs each, and output layer with eight PEs (output parameters). Listing of the input and output parameters of the proposed ANN model is explained in section 2.2. Where x_1 .. x_{17} represent the input parameters for the ANN classified into 4 categories, h_{1-1} .. h_{1-8} represent the eight processing elements PEs in the first hidden layer (h_1), h_{2-1} ..h_{2-8} represent the eight processing elements of the second hidden layer (h_2), and y_1.. y_8 are the processing elements of the output vector. W_{ij} represent weights of connections between PEs in the input layer and the PEs in the hidden layer (h_1), w_{jm} represent weights of connections between PEs in the hidden layer (h_1) and the PEs in the hidden layer (h_2), and w_{mk} represent weights of connections between PEs in the hidden layer (h2) and the PEs in the output layer. Each PE in the hidden layers or the output layer will do summation to combine and modify the inputs from the previous layer using the following equation:

$$m_i = \sum_{j=1}^{i} x_i w_{ij} + b_j \qquad (1)$$

where m_i is the net input to PE j in hidden or output layer, x_i are the inputs to PE j (or outputs of previous layer), i is the number of PEs in previous layer and bj is the bias associated with PE j. The activation (transfer) function used in the two hidden layers, and the output layer is the TanhAxon function. Each axon represents a layer, or vector, of PEs. All axons will also be equipped with a summing junction at their input and a splitting node at their output. This allows multiple components to feed an axon, which then processes their accumulated activity.

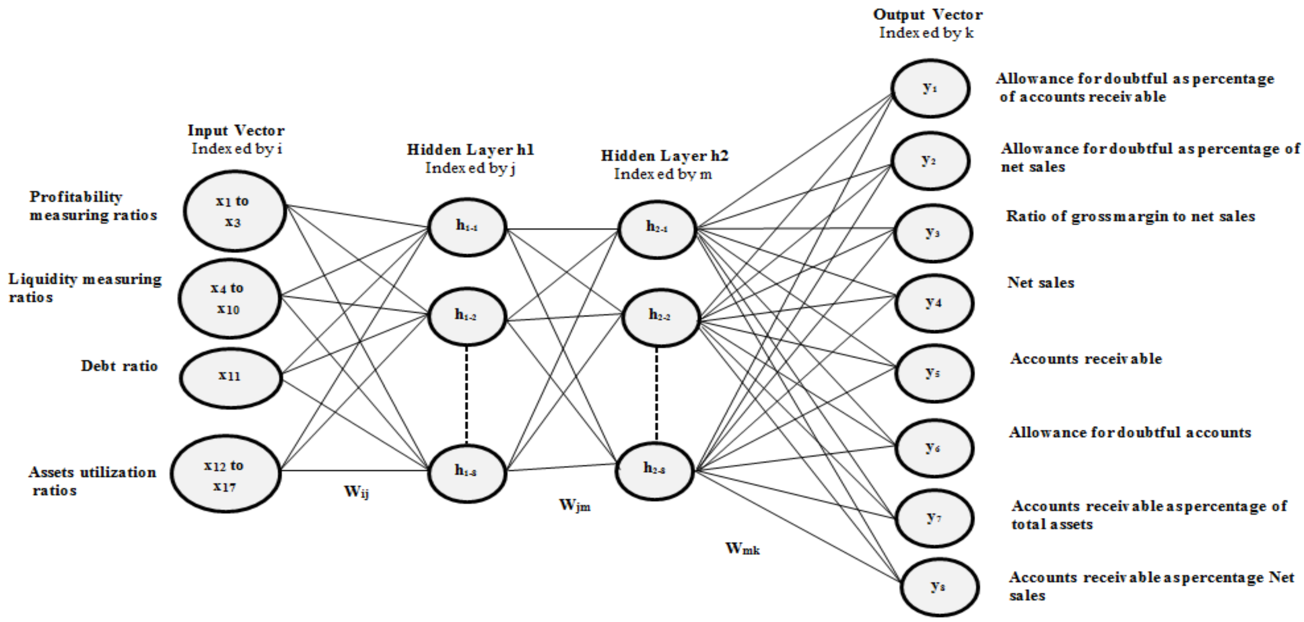

Fig 1: The proposed Multilayer Perceptron Back Propagation ANN Based Model for Detecting and Predicting Fraudulent Financial Reporting

The TanhAxon applies a bias and tanh function to each neuron in the layer. This will squash the range of each neuron in the layer to between -1 and 1. Such nonlinear elements provide a network with the ability to make soft decisions. The used TanhAxon function in each hidden layer h_1, h_2, and the output layer is as follows:

$$f(h_{ij}, w_{ij}) = \tanh[\, h_{ij}^{lin}] \qquad (2)$$

Where $h_{ij}^{lin} = \beta\, h_{ij}$ is the scaled and offset activity inherited from the LinearAxon.

2.2 The Proposed ANN Model Input and Output Parameters

Based on a review of practice and empirical literature, the proposed model uses four categories of input parameters for the ANN: profitability measuring ratios, liquidity measuring ratios, debt ratios, and assets utilization ratios. These categorized input parameters are shown in Table 1, and Table 2. In addition eight important related financial ratios were selected thoroughly based on a review of practice and empirical literature to be considered as the main output parameters for the ANN. These output parameters are shown in Table 3. All financial ratios that were used are related rather to revenue recognition and measurement or to the use of accounting estimates in the sales and accounts receivable cycle. It is no surprise that accounts affected by transactions in the revenue cycle were presented in fraudulent financial reports because revenue recognition and measurements and the use of accounting estimates are among the most difficult auditing issues. These financial parameters were measured as percentage changes in respective to financial ratios and account balances between the year the fraud was first committed and the preceding year.

Table 1. ANN Categorized Input Parameters Part 1

Profitability measuring ratios	
No	**Variable Name**
1	Gross profit ratio = (gross profit/net sales)
2	operating profit margin = operating income/ net sales
3	Return on invested capital = net profit / invested capital
Liquidity measuring ratios	
No	**Variable Name**
1	Quick ratio = (current assets – inventory)/ current liabilities
2	Working capital to total assets ratio
3	Current ratio = current assets/ current liabilities
4	cash to total assets ratio
5	Receivables to current assets ratio
6	Current assets / total assets ratio

Table 2. ANN Categorized Input Parameters Part 2

Debt ratio	
No	**Variable Name**
1	financial leverage = total debts / Shareholders Equity
Assets utilization ratios	
No	**Variable Name**
1	Assets turnover ratio = net sales/ total assets
2	Inventory to invested capital ratio
3	Net profit to total assets ratio
4	inventory to sales ratio
5	Invested capital turnover ratio = sales / invested capital
6	Accounts receivable turnover ratio = net credit sales / average accounts receivable
7	Inventory to current assets ratio

Table 3. ANN Output Parameters

No	Variable Name
1	Allowance for doubtful as percentage of accounts receivable
2	Allowance for doubtful as percentage of net sales
3	Ratio of gross margin to net sales.
4	Net sales.
5	Accounts receivable
6	Allowance for doubtful accounts
7	Accounts receivable as percentage of total assets
8	Accounts receivable as percentage Net sales

2.3 The Proposed ANN Model Learning and Testing Phases

Learning is the process by which the weights of the network get optimal values. The weights are updated using supervised learning. With supervised learning, the network is able to learn from the input and the difference between the output and the desired response (error). In supervised learning the most popular learning law is back propagation. Back propagation changes each weight of the network based on its localized portion of the input signal and its localized portion of the error. The back propagation slowness of convergence can be improved by speeding up the original gradient descent learning. Momentum learning is used in the learning process of this proposed model as a learning rule due to its simplicity and efficiency with respect to the standard gradient. Backpropagation requires that all PEs of the output layer and hidden layers perform two operations. First, given an error at their output, BackAxon function must calculate gradient information for all adaptive weights. Second, they must derive the relative error at their input to be back propagated to any components which precedes them. The general learning equation used in the proposed model is as follows:

$$\Delta w_{ij}(k) = \gamma \Delta w_{ij}(k-1) - \mu \nabla w_{ij} E(k) \qquad (3)$$

where γ is a constant (normally set between 0.5 and 0.9), and μ is the learning rate, and E(k) is the error (the difference between the desired response and the actual system response) at iteration step k. A momentum value used in this model in the hidden layers, and the output layer = 0.7.

The learning process of the proposed ANN model will be terminated based on two conditions:

- Mean Square Error (MSE) with threshold = 0.01

Where the Mean Square Error is defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_{di})^2 \qquad (4)$$

where n is the number of PEs, y_i is the predicted value obtained from the neural network model, y_{di} is the actual value.

- Cross validation

Also maximum epochs (iterations) = 1000 is specified and is applied if other termination conditions are not matched.

Network testing is completely similar to the learning process, but the network at this phase do not adjust their weights. Only the processes of summation, transfer and comparing the output produced by the network with the target output are performed in this phase. Testing data set contain a set of inputs and outputs associated with each input. If the network was able to pass and give the correct answers, the Learning of the network is successful, and the network is ready for use. The neural network give us the result in the form of prediction using the input data to detect if there is fraud in the financial reporting or not.

3. MODEL IMPLEMENTATION AND RESULTS DISCUSSION

For implementing the proposed model, an ANN software called NeuroSolutions was used which is considered one of the leading software available for implementing neural networks. The proposed model was applied on the financial reporting of two large Egyptian companies for electricity distribution which are the North Delta Electricity Distribution company, and the South Delta Electricity Distribution company. The collected dataset was divided into three data subsets: first data subset (60% of the whole dataset) was used as inputs for the ANN training phase, and second data subset (30% of the dataset) was used as inputs for the ANN validation and testing phase. The last data subset (10% of the dataset) represent the target years that the system will predict for them whether a financial reporting fraud has happened or not, and this data subset was divided into two sets of parameters: the seventeen input parameters, and the eight output parameters which were used as the actual output values that are going to be compared with the predicted output eight values from the implemented ANN model. If there is a big gap (deviation) between the output parameters actual values and the predicted values, there is a high probability of fraud in the financial reporting, otherwise there is not. In the following two subsections, results of applying the proposed model on the two companies are presented and discussed.

3.1 Case One Experiment

After running the implemented ANN using NeuroSolutions on the data of the first company the North Delta Electricity Distribution company, the result of the training phase is shown in table 4, result of testing phase is presented in table 5, and finally the result of the prediction phase is shown in table 6, and figure 2. Table 4 shows that the max number of iterations for training and cross validation was 1000. The assessment and measurement of the proposed back propagation based ANN is done with the minimum and final mean square error (MSE) during training and validation phases. The value of the final mean square error MSE for the training phase in the output is 0.00017, and the value of mean square error MSE for the cross validation in the output is 0.2574.

Table 4. Result of training phase for case one

Best Networks	Training	Cross Validation
Epoch #	1000	1000
Minimum MSE	0.000173717	0.257466573
Final MSE	0.000173717	0.257466573

From the presented results of prediction phase in table 6, and figure 2, it is found that the implemented ANN model had predicted values of Allowance for doubtful as percentage of accounts receivable, Allowance for doubtful as percentage of net sales, Ratio of gross margin to net sales, Accounts receivable as percentage of total assets, Accounts receivable as percentage Net sales. It was found that the predicted values by the implemented model almost equal to the actual values; however the model had predicted the value of Net sales, Accounts receivable , Allowance for doubtful accounts (1189171335 - 25625349.32 - 40313347.66) Less than the actual value (75350000 -67165763.43 - 2057063794.56) with large deviations. This result shows the importance of the proposed ANN model as an indicator proving that the company had succeeded in increasing sales and this is a positive phenomenon, and become more useful when they are in the form of cash or at least the percentage of cash sales is greater than credit sales in order to avoid the risk of non-payment in case of credit sales.

Table 5. Result of testing phase for case one

Performance	Allowance for doubtful as percentage of accounts receivable (1)	Allowance for doubtful as percentage of net sales (2)	Ratio of gross margin to net sales (3)	Net sales (4)	Accounts receivable (5)	Allowance for doubtful accounts (6)	Accounts receivable as percentage of total assets (7)	Accounts receivable as percentage Net sales (8)
MSE	0.0736558	3.23833E-05	9.65398E-05	3.41567	1.50373E+14	6.64435E05	1.950E-05	8.327E-07
NMSE	1518.2779	1.3202669	1.1472399	28.6892507	3.080462059	4.25238092	1.2810955	0.1068773
MAE	0.271017116	0.0054121	0.0089386	580464021	11415363.99	22577857.9	0.0042602	0.0009119
Min Abs Error	0.25667963	0.0036539	0.0048593	512428835	6936300.217	10141023.5	0.0030971	0.0008779
Max Abs Error	0.285354602	0.007170	0.0130179	648499207	15894427.77	35014692.3	0.0054233	0.0009459
R	1	-1	1	1	1	1	1	1
Percent Correct	#N/A	#N/A	#N/A	100	#N/A	#N/A	#N/A	#N/A

Table 6. Result of Prediction phase for case one

No.	Ratio	Actual	Predicted	Change
1	**Net sales**	2057063794.56	1189171335	867892459.3
2	**Accounts receivable**	67165763.43	25625349.32	41540414.11
3	**Allowance for doubtful accounts**	75350000	40313347.66	35036652.34
4	**Allowance for doubtful as percentage of accounts receivable**	1.12185	1.335804861	-0.21395355
5	**Ratio of gross margin to net sales**	.09277	0.074047107	0.018727593
6	**Accounts receivable as percentage of total assets**	0.03390568	0.018415718	0.015489962
7	**Accounts receivable as percentage Net sales**	0.032651279	0.021131044	0.003029836
8	**Allowance for doubtful as percentage of net sales**	0.03663	0.033600044	0.01152023

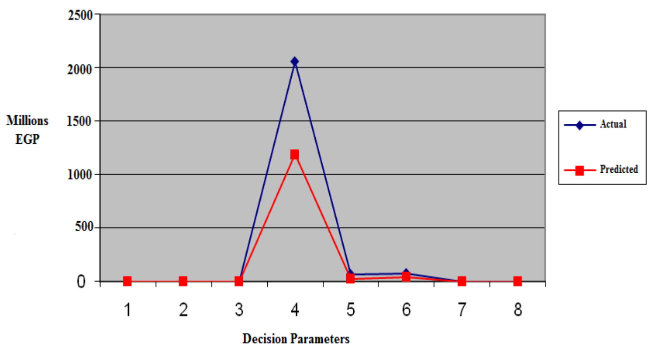

Fig 2: Relationship between the predicted and actual values for case one

It was found that the company achieved sales of bulbs saving about 3830 million pounds free of charge in the budget, which shows that the company has to sell part of its sales on credit, and in the date of sale, sales was recorded as accounts receivable, if it is found later that some of the accounts receivable cannot be collected, allowance for doubtful debts will be established and its estimated value will be added to the expenditure and this in turn leads to increased allowance for doubtful debts. The investment in accounts receivable leads to increase in sales, because accounts receivable is considered a part of sales. However, it is found that there is an increase in allowance for doubtful accounts as the company applied the principle of caution by making allowance for doubtful accounts. In business, the company may not be able to collect debts from other people; in this case the debts are called bad debts. The company should take into consideration at the end of the next financial Cycle that there is Allowance for doubtful accounts will be collected. The increase in this account has an effect on the achieved revenue in Income statement and cash flow statement.

The gap between the values of allowance for doubtful accounts (the difference between actual and predicted) may be caused by fraudulent reporting by increasing allowance for doubtful accounts to increase expenses and this will decrease the revenue of the period as a result. This gap may be also resulted from the probability that the used input data subset in training phase will lead to more efficient training if they covered the financial statements of more years. As a result, if the used input data subset for the training phase covered more number of years, the probability of that the gap in accounts like net sales, and allowance for doubtful accounts between actual values and predicted values by the ANN is caused by fraud in financial reporting is very high.

3.2 Experiment on Case Two

After running the implemented ANN on the data of the second company the South Delta Electricity Distribution company, the result of the training phase is shown in table 7, result of testing phase is presented in table 8, and finally the result of the prediction phase is shown in table 9, and figure 3.

Table 7. Result of training phase for case two

Best Networks	Training	Cross Validation
Epoch #	1000	1000
Minimum MSE	7.15933E-06	0.91516433
Final MSE	7.15933E-06	0.91516433

Table 7 shows that the max number of iterations for training and cross validation was 1000. The assessment and measurement of the proposed back propagation based ANN is done with the minimum and final mean square error (MSE) during training and validation phases. The value of the final mean square error MSE for the training phase in the output is 7.15933E-06, and the value of mean square error MSE for the cross validation in the output is 0.91516433.

Table 8. Result of testing phase for case two

Performance	Allowance for doubtful as percentage of accounts receivable (1)	Allowance for doubtful as percentage of net sales (2)	Ratio of gross margin to net sales (3)	Net sales (4)	Accounts receivable (5)	Allowance for doubtful accounts (6)	Accounts receivable as percentage of total assets (7)	Accounts receivable as percentage Net sales (8)
MSE	0.0745244	0.0001118	4.7974E-05	2.1928E+17	4.9087E+14	1.97993E+12	0.00035076	3.54905E-05
NMSE	1.1517236	41.3809439	2.77635921	27.7819660	27.1283276	#DIV/0!	18.2564645	1.98157612
MAE	0.2535884	0.0105200	0.0067317	46367698.3	20322002.2	1220521.72	0.01653077	0.004990499
Min Abs Error	0.1525073	0.0094473	0.0051015	39821547.2	11496301.7	520336.959	0.00772727	0.001736972
Max Abs Error	0.3546694	0.0115926	0.0083620	52913849.4	29147702.6	1920706.4	0.02533426	0.008244026
r	1	1	1	1	-1	#DIV/0!	-1	1
Percent Correct	#N/A	#N/A	#N/A	100	#N/A	#N/A	#N/A	#N/A

From the presented results of prediction phase in table 9, and figure 3, the gap that was found between the actual values and the predicted values by the implemented ANN model is so small for the South Delta Electricity Distribution company, and this means that the company had succeeded to achieve the targeted predicted sales, and the company has no credit sales, but cash sales instead. Also, it is apparent that the company had invested in accounts receivable, which leaded to increasing total sales, since the accounts receivable is part of total sales.

Table 9. Result of Prediction phase for case two

No.	Ratio	Actual	Predicted	Change
1	Net Sales	1697718436	1696889347.49565	829088.50435
2	Allowance for doubtful accounts	40,000,000.00	39970315.45	29,684.55
3	Accounts receivable as percentage Net sales	0.0177478	0.0188637	-0.00111589
4	Allowance for doubtful as percentage of accounts receivable	1.327539	1.33005	-0.00251
5	Allowance for doubtful as percentage of net sales	0.023561	0.02753	-0.00397
6	Ratio of gross margin to net sales	0.067444	0.07392	-0.00648
7	Accounts receivable as percentage of total assets	0.020063	0.0272154	-0.00715236
8	Accounts receivable	30130927.36	30223983.85	-93056.4921

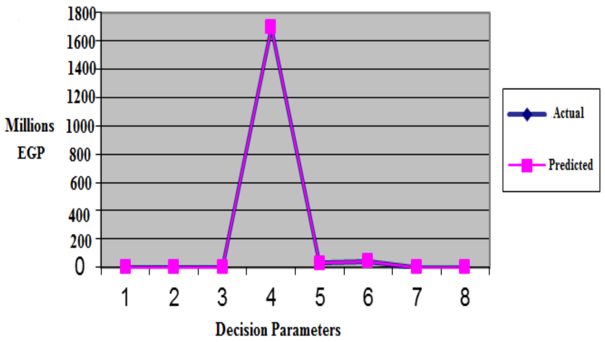

Fig 3: Relationship between the estimated and actual values for case two

4. CONCLUSIONS

The purpose of this research was to develop a Multilayer Perceptron (MLP) Artificial Neural Network model that is capable of detecting and predicting the risk of fraudulent financial reporting. The proposed model used the Tanhaxon as a nonlinear activation function to provide the network the ability to make soft decisions, and the Momentum learning rule due its simplicity and efficiency with respect to the standard gradient. It is proven in this work that the proposed back propagation based artificial neural networks model can be used in the discovery of manipulation and fraud prediction in the accounts balances by comparing the predicted values and the actual values. In addition, it is proven that the proposed ANN based model can be used in exploring the advances that are implemented in certain accounts balances if the probability of fraud is excluded, and this will support the auditors and companies' top managers in doing financial performance assessment. It is recommended to take advantage of the artificial neural networks - as one of the important techniques of machine learning – with other intelligent techniques to build hybrid models that can be used effectively in the analysis and treatment of various accounting problems, especially those related to financial fraud and financial performance appraisal.

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