Global Advanced Research Journal of Engineering, Technology and Innovation Vol. 1(3) pp. 063-074, June, 2012
Available online http://garj.org/garjeti/index.htm

Full Length Research Paper

Assessment of the Expected Construction Company's Annual Work Volume Using Neural Network and Multiple Regression Models

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Accepted 14 June 2012

Annual work volume of any construction company can be considered as an important indicator for the company's financial performance. Business success heavily depends on the ability of financial executives to maximize the company's net profit and annual work volume. Consequently, the firm financial managers should continuously strive to maximize their company's annual work volume. Modelling the company's annual work volume can help financial management to investigate the serious effect that the different financial conditions can have on the expected annual work volume of their companies. Stated differently, financial managers can make sure that business operations of their companies are running in a successful manner. For example, inadequate working capital may interrupt the normal operations of the business which impairs the company's annual work volume and consequently its profitability. To elaborate more, excessive levels of current assets may have a negative effect on firm's work volume and profitability whereas a low level of current assets may lead to lower level of liquidity and stock outs which results in difficulties in maintaining smooth operations that leads to a corresponding decline in the annual work volume. The objective of this research is to develop a mathematical model for the assessment of the expected construction companies' annual work volume. First, the main factors affecting firms' annual work volume were identified based on a comprehensive literature review. Next, pertinent data regarding these factors were collected. Such data are mainly concerned with the companies' financial statements as well as the economic environment. Then, two different annual work volume models were developed using the Multiple Regression (MR) and the Neural Network (NN) techniques. The validity of the proposed models was also investigated. Finally, the results of both MR and NN models were compared to investigate the predictive capabilities of the two models.

Keywords: Construction Company's Annual Work Volume, Neural Network, Multiple Regressions.

INTRODUCTION

The annual work volume of any construction company can be generally defined as the accumulated contract values executed and delivered to clients over the whole year. This annual work volume is an important indicator for the company's financial performance. For instance, it can be considered as an indicator for the effectiveness of

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using the firm's total assets. It can also measure the ability of the company to successfully compete in the construction market. Consequently, the annual work volume maximization can be generally considered as one of the main targets that company's are seeking to achieve. So, firm's financial managers should have a reliable tool to investigate the serious effect of the different financial conditions on the expected annual work volume of the firm. Such, conditions should reflect the different scenarios of the company financial policy. They should also represent the important inputs of the construction market as well as the local economic conditions.

The objective of this research is to develop a suitable tool for construction companies' annual work volume assessment. Such tool can help financial planners to arrive at a reliable assessment for the expected annual work volume of their companies. Moreover, the companies' stockholders can have a clear picture regarding the future performance of their investment. Again, such tool should take into consideration the different conditions regarding the company's financial policy as well as the market and economic conditions. This study was conducted through a number of sequential steps. First, the main factors affecting construction companies' annual work volume were identified based on a review of the corresponding literatures. Next, financial data of a selected sample of the Egyptian construction companies were collected from the Egyptian Stock Exchange (ESE). Moreover, data regarding the local construction market and the Egyptian local economy were also collected. Such data definitely include the Demand on Construction, Inflation rate and Gross Domestic Product (GDB) data. Then, two different models were developed to be used as a tool for construction companies' annual work volume assessment. These two models were developed using Multiple Regression (MR) and Neural Network (NN) techniques. Finally, the results of the two models were compared to explore the more reliable tool for the construction companies' annual work volume assessment.

Factors Affecting Annual Work Volume of a Construction Company

Through this paper a comprehensive literature review was performed in order to identify the most significant factors affecting the annual work volume of any construction company. Annual work volume, as a main indicator for the companies' financial performance, was the main issue of many researches. Smith (1980) signified the implications of working capital management on the value, risk and profitability of firms. Referring to his earlier studies, he made a search on the factors that might determine the financial performance of a firm. Such, factors mainly include: leverage, level of economic activity on the country, firm growth, operating cash flow, firm size, and nature of industry, firm operating cycle and return on assets. Pinches (1991) stated that, there is a long debate on the risky/return trade off between different working capital polices. More aggressive working capital polices are associated with higher return and risk, while conservative working capital polices are concerned with the lower risk and return. Deloof (2003) explained that the level of the company's current assets and working capital, in respect of the company's total corporate structure and flow off funds is a trade off relationship between profitability and risk. He analyzed a sample of large Belgian firms. His results confirmed that Belgian firms can improve their financial performance by reducing the number of day's accounts receivable and reducing inventories. Jose (1996) examined the relationship between aggressive working capital management and financial performance of US firms using the Cash Conversion Cycle (CCC) as a measure of working capital management where, a shorter CCC represents the aggressiveness of working capital management. His results indicated a significant negative relationship between the cash conversion cycle and profitability. Rehman (2006) studied the impact of the different variables of working capital management including: average collection period, inventory turnover in days, and average payment period and cash conversion cycle on the firm financial performance. He concluded that there is a strong negative relationship between the above working capital factors and the profitability of firms. Moreover, Afza and Nazir (2007) concluded that there is a negative relationship between the profitability measures of firms and the degree of aggressiveness of these firms working capital investment and financing polices.

In summary, the aforesaid literature unfolds some interesting debate in the determining factors of the annual work volume. The determining factors include both internal and external components. Researchers have investigated numerous factors in this regard. Leverage, operating cash flows, return on assets, debt ratio, business indicators, market performance and ratio of fixed to total assets make a list of internal micro level factors. The external micro/macro level factors include: cost of financing, level of economic activity, firm growth, industry effects, seasonal implications on sales volume and supplies. There are some factors identified by literature that can be attributed both to internal and external categories. Firm growth depends on both internal and external conditions. Likewise are higher market share of business, product image relevant to competition and size of the firm.

Based on the above comprehensive review of literature, twenty three factors were being identified as the most significant factors affecting the construction companies' annual work volume. According to Table 1 these factors were classified into two

Table 1. Factors Affecting Construction Companies' Annual Work Volume

Category	Category Description	Factor Description	Symbol
(1)	Internal Factors (firm related factors)	(1) Business Size	BS
		(2) Sales Growth	G
		(3) Operating Cash Flow	OCF
		(4) Return On Assets	ROA
		(5) Leverage	Lev
		(6) Firm Debt Ratio	Debt
		(7) Firm Market Power	FM
		(8) Cash Conversion Cycle	CCC
		(9) Working Capital Policy	WCP
		(10) Inventory Turnover Rate	Inv
		(11) Inventory Management Efficiency	IME
		(12) Receivables Management Efficiency	RME
		(13) Liabilities Management Efficiency	LME
		(14) Tangible Assets Ratio	Tang
		(15) Average Collection Period	ACP
		(16) Average Payment Period	APP
(2)	External Factors (market related factors)	(17) Level of Economic Activity	GDP
		(18) Market Performance	Q
		(19) Inflation Rate	IR
		(20) Financial Distress	Z- score
		(21) Demand on Construction	DC
		(22) Competition	Comp
		(23) Cost of External Financing	CEF

categories: internal factors (firm related factors) and external factors (market and economy related factors).

Data Collection

Two hundred financial statements were collected from twenty construction companies listed in the Egyptian Stocks Exchange (ESE) for a period of 2000 to 2010. They represent all the available data in the Egyptian Stock Exchange, since (ESE) can provide financial statements for the last ten years only. Thirty six financial statements which include missing data were abanded and not used through the models development process. As a consequence, the final numbers of financial statements that have been used through the analysis were one hundred and sixty four financial statements. The annual work volume of the selected construction companies ranges from (28 million to 4985 million) Egyptian pounds. Some of these companies' are related to private sector while, the others are related to public sector. All of these companies are qualified and registered in the Egyptian Federation for Construction and Building Contractors as first class companies.

In order to design reliable models for assessing the expected construction companies' annual work volume, companies were classified into three groups according to their business size. Such size is represented by the natural log of total assets of firm. This classification divided companies into three groups: Group (1) with business size < 8.00, Group (2) with business size ranges from 8.00 to 8.50 and Group (3) with business size > 8.50. The number of financial statements used for model development for each group was 48, 63 and 44 for: Group (1), (2) and (3) respectively. For each group three financial statements were being held to be used in the model validation process.

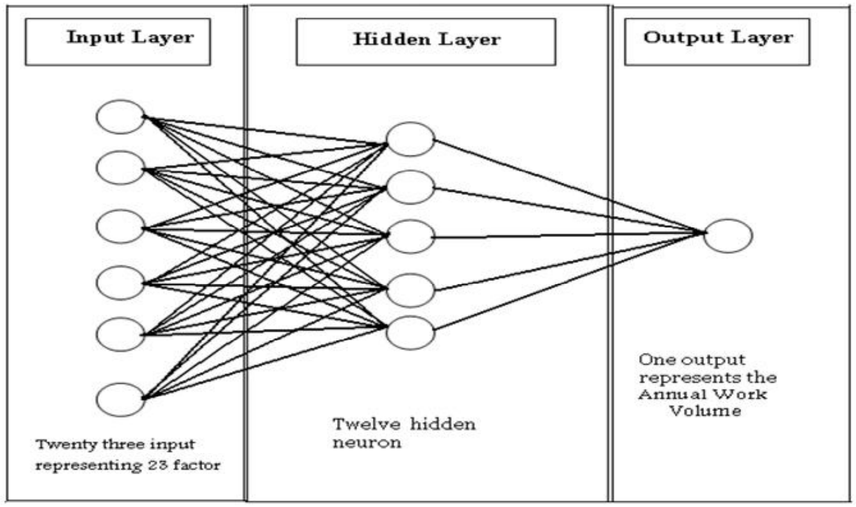
Data regarding the previously mentioned twenty three variables were extracted by analysing the selected financial statements. These data were used as model inputs. The construction company's annual work volume will be the target model output. Inflation rate data, growth domestic production and demand on construction data were identified from the annual reports issued by the Central Bank of Egypt.

Neural Network Model Development

Three different NNM were designed for the three groups: (1), (2) and (3) respectively. The twenty three factors listed in Table 1 were used as the model inputs while; the construction companies' annual work volume represents the model output. To determine the number of hidden layers, Bailey and Thompson (1990) suggested, as a rule of thumb, start with one hidden layer and add more as long as the performance of the network is improved. The size of the hidden layer (number of hidden neurons) can be specified by using a number of heuristics include: 1) Bailey and Thompson suggested the number of neurons to be around 75% of the size of the input layer, 2) BrainMaker Professional user's guide suggested that the number of neurons in hidden layer to be calculated according to the following formula:

Number Of hidden neurons = [(Input Variables + Output Variables) /2].

The number of hidden neurons for the proposed model was taken to be twelve neurons. All trial models experimented in this study was trained in a supervised



(Note that not all neurons and connections are drawn)
Figure 1. NN Architecture for Modelling Construction Companies' Annual Work Volume

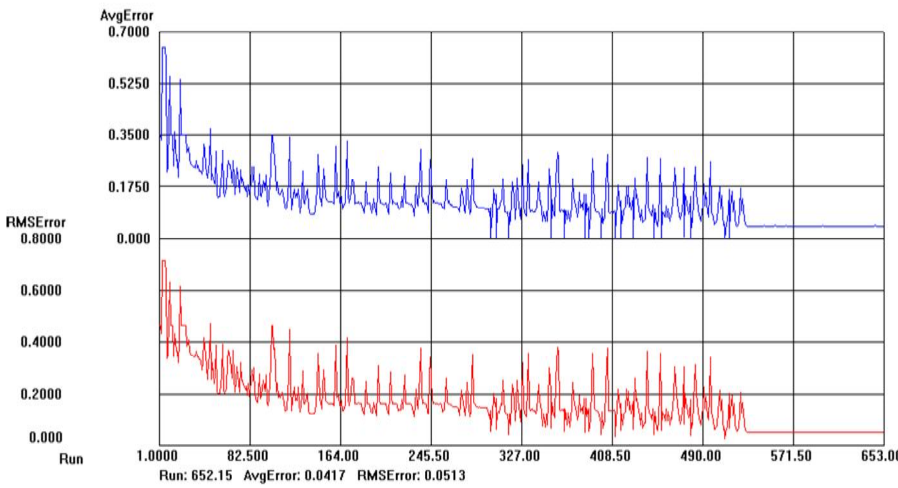


Figure 2. Statistical Graph of Training Results for Group (1)

mode by a back propagation learning algorithm. Data for 48 construction companies' financial statements with business size < 8.00, 63 construction companies' financial statements with business size ranges between 8.00 to 8.50 and 44 construction companies' financial statements with business size > 8.50 are presented to the model as a training data set. Inputs were fed to the proposed network and the output was predicted. Differences between the calculated output and the actual output were then evaluated.

The back propagation algorithm develops the input to output mapping by minimizing the Root Mean Square Error (RMS Error). Figure 1 shows the neural network architecture that give the minimum error during the training process and the best results when applied to the validation set for the three developed models of Groups (1), (2) and (3). In this research, twelve hidden neurons were found to be capable of achieving the best results for assessing construction companies' annual work volume.

Training and Testing the Proposed Neural Network Model

Training is required to continuously adjust the connection weights between neurons until they reach values that allow the Artificial Neural Network (ANN) to predict outputs that are very close to the actual outputs while being able to generalize well on new cases. In order to develop the (NNM), BrainMaker Professional software package 3.75 has been used for its ease of use; speed of training, and for its host of neural network architectures including back propagation with flexible user selection of training parameters. BrainMaker Professional 3.75 includes a simplified set of procedures for building and executing complete and powerful neural network applications. The user has the ability to specify the learning rate, tolerance, activation functions, number of hidden layer and number of hidden neurons. It also has multiple criteria for stopping training in addition to

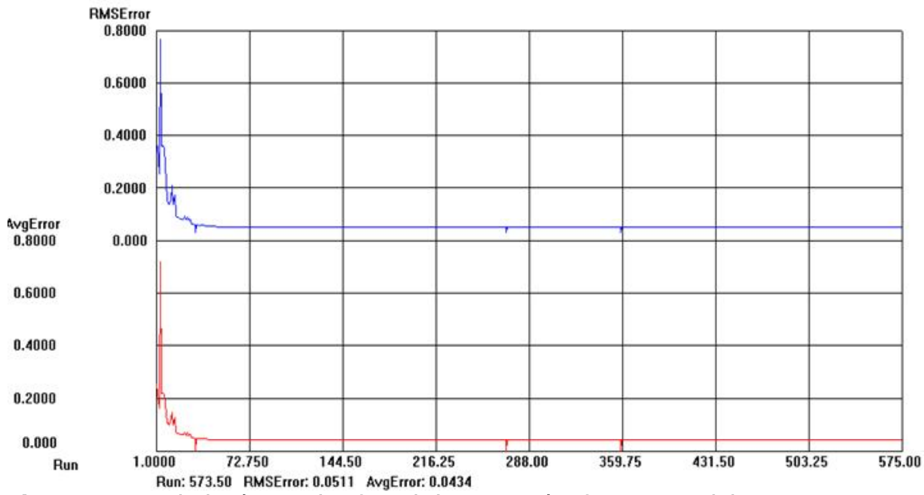


Figure 3. Statistical Graph of Training Results for Group (2)

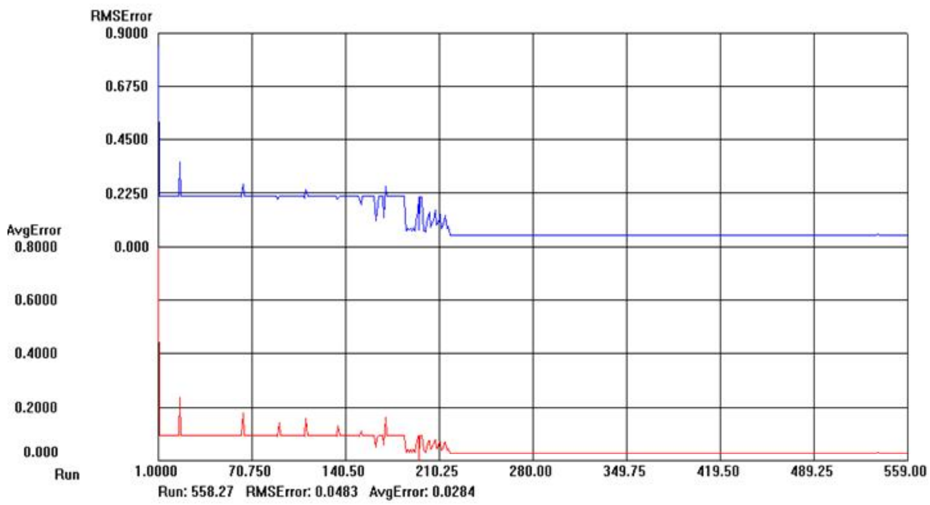


Figure 4. Statistical Graph of Training Results for Group (3)

different methods for handling missing data, pattern selection and viewing weight and neuron values throw the training phase.

During training, data were presented to the neural network many thousands of times (called cycles or epochs). After each cycle, the error between the neural network predicted outputs and the actual outputs are propagated backwards to adjust the weights in a manner that is mathematically guaranteed to converge. Several training experiments were conducted to arrive at the best trained model. In these experiments, parameters of the networks structure such as the number of hidden layers, the number of hidden neurons, learning rate, tolerance, and transfer function such as sigmoid function, threshold function, and other functions available on the software were changed and the best results were documented.

After training the network, the user can evaluate the training and testing processes by using the training and testing statistical files. The best model was selected based on reaching acceptable minimum values of the Root Mean Square Error (RMS Error). For each group the collected data were divided into two sections, training data and validation data. During training, the RMS Error between the actual and predicted values of the construction company's net profit was plotted as shown in Fig. 2, 3 and 4 for groups: (1), (2) and (3) respectively.

From Figures, the horizontal axis is the number of runs attempted by the BrainMaker software to achieve the best architecture which gives the least RMS Error while the vertical axis introducing the RMS Error and the average error at each run. It is obvious that the average error decreases as the number of runs increases and then become stable. The network that was found to be the best architecture for the study on hand has a minimum RMS Error of approximately 5.13, 5.11, 4.83% for groups: (1), (2) and (3) respectively. The network stabilized at this error rate and training was stopped at 652, 574 and 558 runs for groups: (1), (2) and (3) respectively. The architecture, parameters and training results of the best NNM are tabulated in Table 2.

Table 2. NNM Architecture, Parameters and Training Results

NNM best Architecture					Learn Rate	Transfer Function (1)	Transfer Function (2)	RMS Error %
Group	Neurons in Input layer	Neurons in Hidden Layers Layer 1	Layer 2	Neurons in Output Layer				
1	23	12	-	1	0.1	Sigmoid	Threshold	5.13
2	23	12	-	1	1.0	Sigmoid	Sigmoid	5.11
3	23	7	5	1	0.1	Sigmoid	Threshold	4.83

Table 3. NNM Validation Results

Group	Actual Value	Model Output	MAPE	RMS	R^2
	56092079	45090000	-19.61	229209.98	.98
(1)	28080403	20800000	-25.93	151675.06	.98
	28554252	32355000	-17.53	104255.25	.98
	Average Absolute Values		***21.02***	***161713***	***.98***
	5138289782	4241000000	-17.46	14242694.95	.98
(2)	4282786408	3395000000	-20.73	14091847.75	.98
	8340194454	6550000000	-21.46	28415784.98	.98
	Average Absolute Values		***19.89***	***18916775***	***.98***
	442226262	555500000	25.61	2574403.14	.98
(3)	300523494	266000000	-11.49	784624.86	.98
	177703503	133000000	-25.16	1015988.70	.98
	Average Absolute Values		***20.75***	***1458338***	***.98***

As it can be seen from Table 2 the best architecture for Group (1) was found to have the following characteristics: one input layer with twenty three neurons,
one hidden layer with twelve neurons and an output layer with one neuron. Sigmoid activation function was used between input / hidden layers and the threshold activation function was used between hidden/output layers. For Group (2) the best architecture was found to have the following characteristics: one input layer with twenty three neurons, one hidden layer with twelve neurons and an output layer with one neuron. Sigmoid activation function was used between input / hidden layer and also was used between hidden/output layers. For Group (3) the best architecture was found to have the following characteristics: one input layer with twenty three neurons, two hidden layer with seven neurons in first one, five neurons on second one and an output layer with one neuron. Sigmoid activation function was used between input / hidden layers and Threshold activation function was used between hidden/output layers.

Neural Network Model Validation

Once the network was trained and a satisfactory error level was achieved, the validation data that had not been presented to the network during the training process were used to check how well the best trained model predicts the construction companies' annual work volume for a new data that the proposed model never seen before. Three evaluation parameters were used as a basis for evaluating the performance of the trained neural network model: (1) Root Mean Square Error (RMS Error); (2) Mean Absolute Percentage Error (MAP Error); (3) Adjusted Square Multiple (R^2). Mathematically, these parameters are defined as follows:

RMS Error = $1/N * (\sum (A-P)^2)^{0.5}$ ……………………………………. (1)

MAPE =$1/N * (A-P)/A*100$……………………………………………. (2)

$R^2 = [N*\sum(AP-\sum A*\sum P]^2 / \{[N*\sum A^2-(\sum A)^2]*[N*\sum P^2-(\sum P)^2\}$………..(3)

Where: N= total number of cases presented to the model; A= actual value; P= predicted value. For each group (1), (2) and (3); three observation cases were being held for the validation process. The validation results are summarized in Table 3. The results shown reveal that the developed NNM has good predictive capabilities as the Average Mean Absolute Error (MAPE) for the three groups is about 20.55%.

Multiple Regression Model

Many problems in engineering and science involve exploring the relationships between two or more variables. Regression analysis is a statistical technique that is very useful for solving these types of problems. In this research, the Multiple Regression Model (MRM) will be used to determine the statistical relationship between a dependent variable (e.g. construction companies' annual work volume) and the independent variables (e.g.,

Table 4. MRM (Group (1)) - Using Forward Technique

Adjusted square multiple R^2 = 1.00 ***F* ratio = 476638 , *P*- value = 0.000**			
Variables	**Coefficients**	**t-ratio**	**Partial F**
(Constant)	-4.859E8	-68.139	0.000
Inv	2007223.386	425.279	0.000
Comp	0.479	110.805	0.000
IME	501997.945	134.073	0.000
Q	-427780.338	-136.778	0.000
Z-score	-1.882E7	-106.403	0.000
LME	792693.863	148.989	0.000
LEA	1.382E-5	77.139	0.000
DC	-1.227	-130.343	0.000
Lev	357426.004	82.049	0.000
ACP	-34168.109	-6.201	0.000
RME	-2.381E6	-28.049	0.000
APP	-859.165	-103.647	0.000
BS	7.484E7	75.214	0.000
Tang	450497.637	21.212	0.000

business size, operating cash flow,…etc.). The responses to the regression model are what the financials ultimately want to estimate. For each of the previously identified companies groups (1), (2) and (3) three multiple regression techniques namely: stepwise, Stepwise and forward techniques were used in order to achieve the best technique that gives the best results in the validation process. MRM was given by the equation:

$Y = ß_0 + ß_1 * x_{i1} + ß_2 * x_{i2} + \ldots\ldots + ß_p * x_{ip} + €_i$…………………… (4)

Where: i = 1, 2, 3…. and the following were assumed:

• Y_i is the response that corresponds to the levels of the explanatory variables: x_1, x_2, x_3…. at the i-th observation.

• $ß_0$, $ß_1$…….. $ß_p$ are the coefficients in the linear relationship. For a single factor (p = 1), $ß_0$ is the intercept, and $ß_1$ is the slope of the straight line defined.

• $€_1$, $€_2$, ………$€_i$ are the errors that create scatter around the linear relationship at each of the i = 1 to n observations.

In order to make estimates of the coefficients in the regression model, the method of least squares is used for its mathematical convenience and its ability to provide explicit expressions for these estimates [12].

Regression Model Development

SPSS 18 package was used to develop the proposed regression model. SPSS enables the user to select one of the three different techniques stepwise, backward and forward individually. For each of the three groups of construction companies' group (1), (2) and (3) data used for the model development process were organized and saved in Microsoft Excel spreadsheet. The SPSS 18 package is compatible with Microsoft Excel. Therefore, the data exported from Excel to SPSS using the file import option in SPSS.

For a model, that includes twenty three independent variables (complete model) with the use of forty eight, sixty three and forty four case studies (observations) for groups (1), (2) and (3):

$F_{critical} = F_{\alpha,}$ p-1, n-p = 1.98………………………………**(5.a)**

$F_{critical} = F_{\alpha,}$ p-1, n-p = 1.79………………………………**(5.b)**

$F_{critical} = F_{\alpha,}$ p-1, n-p = 2.09………………………………**(5.c)**

Where: n= number of observations; p= number of independent variables in the complete model plus the constant (total 24). P-1= degree of freedom for the regression, n-p = degree of freedom for the error. Several modelling experiments were conducted; the three most suitable models are shown in Tables 4, 5 and 6 (Appendix-A) for groups (1), (2) and (3) respectively. Table 4 shows that for group (1) the best model was achieved by using the forward technique. The model used fourteen independent variables in order to predict the dependent variable (the construction companies' annual work volume). The results obtained from the statistical analysis showed that, the tolerance value for all of the independent variables was < 0.1 except for one independent variable (Receivables Management Efficiency); its tolerance value was > 0.1. This concludes that, multi-collinearity exist among all of the independent variables except for this variable (Receivables Management Efficiency).The tolerance is an indicator of multi-collinearity, which inflates the variance of the least square estimators and possibly predictions made (M., Attalla, T., Hegazy ,2003).

It can be seen at Table 5 that, the best model for group (2) was achieved throw using the stepwise technique. The model used nineteen independent variables in order to predict the dependent variable (the construction companies' annual work volume). It is observed from the output of the statistical analysis that their were seven independent variables (Liabilities Management Efficiency, Average Payment Period, Growth, Inventory

Table 5. MRM (Group (2)) – Using Stepwise Technique

Adjusted square multiple R^2 = 1.00 ***F* ratio = 1845093 , *P*- value = 0.000**			
Variables	**Coefficients**	**t-ratio**	**Partial F**
(Constant)	-2.026E9	-128.319	0.000
FMP	1.470E8	214.658	0.000
LEA	0.042	252.025	0.000
CCC	-161.711	-48.595	0.000
LME	7.029E6	-153.10	0.000
APP	-192.176	-6.828	0.000
G	-0.103	-68.806	0.000
Lev	960860.3	116.057	0.000
Inv	6871461	180.431	0.000
Debt	-2.510E6	-176.036	0.000
Comp	-0.022	-160.206	0.000
BS	2.590E8	130.953	0.000
CEF	1155543	73.857	0.000
DC	-0.155	-49.583	0.000
IME	-1.695E6	-70.041	0.000
ACP	864.226	62.799	0.000
WCP	-830336.858	-69.711	0.000
Q	-44053.590	-44.046	0.000
Z-score	3.794E7	27.673	0.000
RME	169164.102	15.376	0.000

Table 6. MRM (Group (3)) – Using Stepwise Technique

Adjusted square multiple R^2 = 1.00 ***F* ratio = 24261 , *P*- value = 0.000**			
Variables	**Coefficients**	**t-ratio**	**Partial F**
(Constant)	-2.274E8	-8.930	0.000
Comp	0.055	12.613	0.000
FMP	3.981E7	10.939	0.000
G	1.531	36.094	0.000
ROA	4.284E7	15.644	0.000
Debt	6334615.46	18.401	0.000
DC	-0.081	-17.076	0.000
RME	-2.648E7	-11.602	0.000
CEF	-2.116E6	-13.315	0.000
Q	1205862.222	10.655	0.000
Z-score	-8.467E8	-10.354	0.000
IR	3785792.117	5.246	0.000
LEA	0.020	-5.405	0.000
APP	-18826.972	-3.962	0.000
Tang	-1.171E7	-3.579	0.001

Management Efficiency, Average Collection Period, Market Performance, Receivables Management Efficiency) have tolerance value > 0.1 while all the other independent variables have a tolerance value < 0.1, which indicates that multi-collinearity doesn't exist among these seven variables.

Table 6 shows that, for group (3) the best model was achieved also by using the stepwise technique. The model used fourteen independent variables in order to predict the dependent variable (the construction companies' annual work volume). There were seven independent variables (Debt Ratio, Receivables Management Efficiency, Cost of External Financing, Financial Distress, Level of Economic Activity, Average Payment Period, Tangible Assets Ratio) have a tolerance value > 0.1 this indicates that multi-collinearity doesn't exist among these variables.

Based on statistical tests, it can be concluded that the regression model developed by using the stepwise technique is the most accurate in predicting the dependent variable (construction companies' annual work volume) for Group (2) and (3) while for Group (1) the Forward technique is more accurate in predicting the dependent variable (construction companies' annual work

Table 7. Multiple Regression Model Validation Results

Group	Technique	Actual Value	Model Output	MAPE	RMS	R^2
		56092079	70912651	26.42	308761.91	.98
(1)	**Forward**	28080403	23515389	-16.26	80104.47	.98
		28554252	25565594	-10.47	62263.71	.98
		Average Absolute Values		***17.72***	***150376***	***.98***
		5138289782	6056707230	17.87	14577976.51	.98
(2)	**Stepwise**	4282786408	5100917836	19.10	12986213.14	.98
		8340194454	9112642103	9.26	12261073.79	.98
		Average Absolute Values		***15.41***	***13275087***	***.98***
		442226262	496294979	12.23	1228834.48	.98
(3)	**Stepwise**	300523494	240460711	-19.99	1365063.24	.98
		177703503	221623871	24.72	998190.18	.98
		Average Absolute Values		***18.98***	***1197362.63***	***.98***

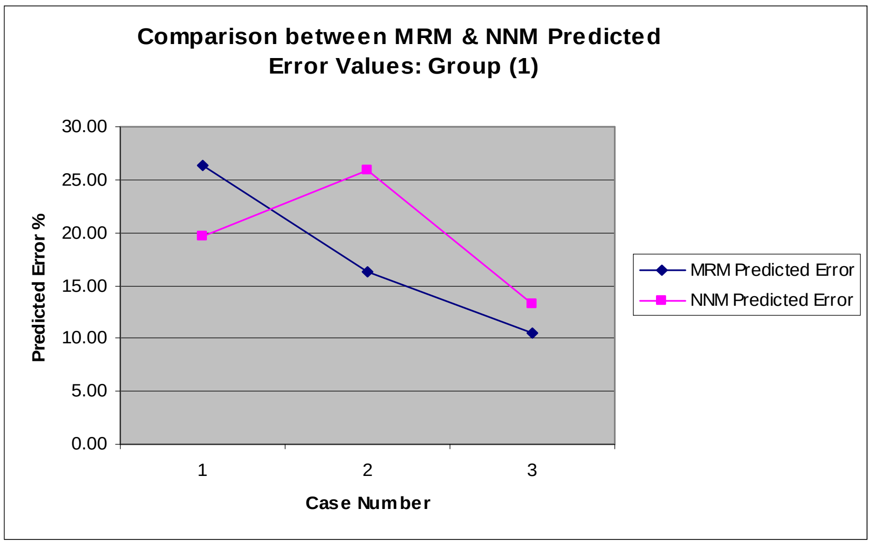


Figure 5. Prediction Error of NNM and MRM (Group 1)

volume) since these techniques provide a better statistical diagnostics with regard to its F-ratio, t-ratio, Adjusted Square Multiple R^2. R^2 = 1.00 for the three groups (1), (2) and (3) which means that, the three developed models have the capability to explain 100% of the variability of the data presented for models development process.

Regression Model Validation

For each group: (1), (2), (3) three cases were being held for the validation process. Three evaluation parameters were used to measure the MRM performance: (1) Root Mean Square Error (RMS Error); (2) Mean Absolute Percentage Error (MAPE); (3) Adjusted Square Multiple (R^2). The results of the validation were tabulated in Table 7. As shown in Table 7, for groups (1), (2) and (3); the Mean Absolute Error was 17.72%, 15.41% and 18.98% respectively. These results reveal that the developed model has good predictive capabilities.

Comparison between Neural Network Model and Multiple Regression Model

The results (i.e. predicted values) obtained by using NNM were compared to those obtained by using MRM. Table (8) illustrates a comparison between the predictive capabilities of NNM versus the predictive capability of MRM. This comparison was based on four evaluation parameters: Mean Absolute Percentage Error (MAP Error), Root Mean Square Error (RMS Error), Adjusted Square Multiple (R^2), Number of variables.

As shown in Table 8 the results indicated that the MRM performance was better than NNM performance in the four evaluation parameters. For group (1) the values of MAPE, RMS, and R^2 for the MRM were found to be 17.72 %, 150376 and 0.98 respectively, while the values of the same parameters, for NNM were found to be 21.02%, 171013 and 0.98. On the other hand, the number of variables used by NNM to predict the construction companies' annual work volume was twenty three variables, whereas the MRM utilized only fourteen

Table 8. Performance Comparison between NNM and MRM

Group	Case Number	Actual Value	Multiple Regression Model					Neural Network Model				
			Predicted Value	MAPE	RMS	R^2	Nu. of variables	Predicted Value	MAPE	RMS	R^2	Nu. of variables
(1)	Case 1	56092079	70912651	26.42	308761	.98	14	45090000	-19.61	229209	.98	23
	Case 2	28080403	23515389	-16.26	80104	.98	14	20800000	-25.93	151675	.98	23
	Case 3	28554252	25565594	-10.47	62263	.98	14	32355000	-17.53	104255	.98	23
Average Absolute Values				***17.72***	***150376***	***.98***			***21.02***	***161713***	***.98***	
(2)	Case 1	5138289782	6056707230	17.87	14577976	.98	19	4241000000	-17.46	14242694	.98	23
	Case 2	4282786408	5100917836	19.10	12986213	.98	19	3395000000	-20.73	14091847	.98	23
	Case 3	8340194454	9112642103	9.26	12261073	.98	19	6550000000	-21.46	28415784	.98	23
Average Absolute Values				***15.41***	***13275087***	***.98***			***19.89***	***18916775***	***.98***	
(3)	Case 1	442226262	496294979	12.23	1228834	.98	14	555500000	25.61	2574403	.98	23
	Case 2	300523494	240460711	-19.99	1365063	.98	14	266000000	-11.49	784624	.98	23
	Case 3	177703503	221623871	24.72	998190	.98	14	133000000	-25.16	1015988	.98	23
Average Absolute Values				***18.98***	***1197362***	***.98***			***20.75***	***1458338***	***.98***	

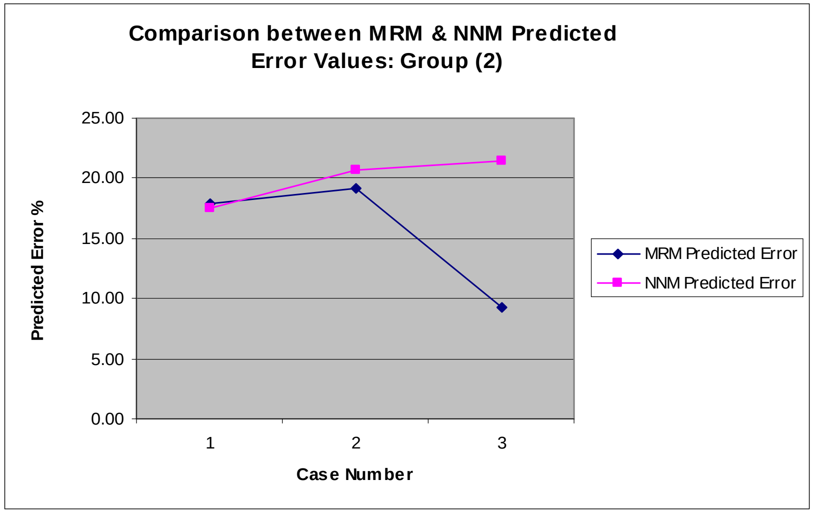


Figure 6. Prediction Error of NMM and MRM (group 2)

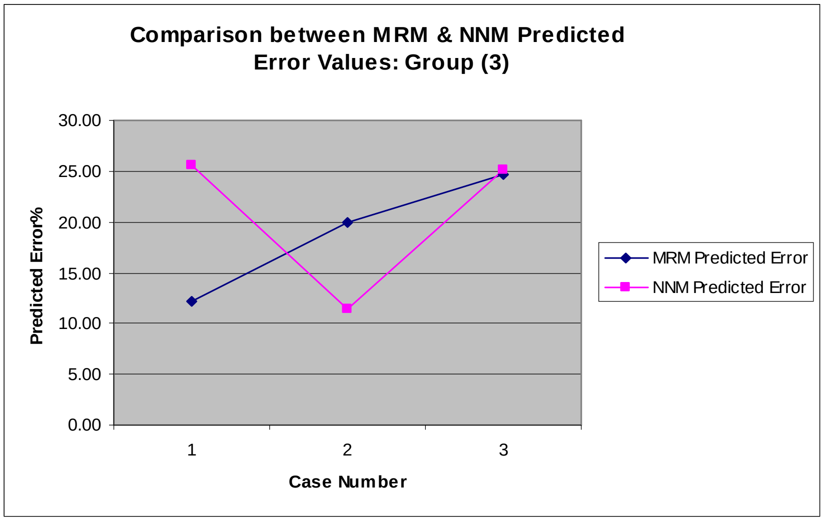


Figure 7. Prediction Error of NNM and MRM (Group 3)

variables. For group (2) the values of MAPE, RMS, and R^2 for the MRM were found to be 15.41 %, 13275087 and 0.98 respectively, while the values of the same parameters, for NNM were found to be 19.89 %, 18916775 and 0.98. On the other hand, the number of variables used by NNM to predict the construction companies' annual work volume was twenty three variables, whereas the MRM utilized only nineteen variables. For group (3) the values of MAPE, RMS, and R^2 for the MRM were found to be 18.98 %, 1197362 and 0.98 respectively, while the values of the same parameters, for NNM were found to be 20.75 %, 1458338 and 0.98. On the other hand, the number of variables used by NNM to predict the construction companies' annual work volume was twenty three variables, whereas the MRM utilized only fourteen variables. From a planner or user's point of view , the ability to use more variables in predicting the construction companies' annual work volume may be advantageous.

Another useful comparison is to plot the prediction error (Actual-Predicted), for each case, for NNM and MRM. This comparison gives clear indication about the accuracy of each model. This was made for the three Groups (1), (2) and (3) as shown in Figures 5, 6, 7 For Group (1): Fig. 5 shows that, the predicted Error obtained from MRM for case (2) and (3) were smaller than the predicted error obtained from NNM. Conversely, for case (1) the predicted error obtained from NNM is smaller than those obtained from MRM. For Group (2): Fig. 6 shows that, the predicted error obtained by using MRM for cases (2) and (3) was smaller than the predicted error obtained by using NNM, while for case (1) the two predicted errors are nearly the same. For Group (3): Fig. 7 shows that, the predicted error obtained from MRM for case (1)and (3) was smaller than the predicted error obtained from NNM, while for case (2) the predicted error obtained from MRM was greater than the predicted error obtained from NNM. In general, the prediction error plot indicates that MRM was found to be more accurate and reliable tool for construction companies' annual work volume assessment than NNM.

CONCLUSION

This paper introduced an attempt to develop NNM and MRM models which can be effectively used to predict the construction companies' annual work volume. A comprehensive literature review was made to identify the most important factors affecting construction companies' annual work volume. Twenty three factors were identified as the most significant factors affecting the construction companies' annual work volume. Financial statements for 164 Egyptian construction companies were analyzed and data regarding the twenty three significant factors were extracting. The companies were classified into three groups (1), (2) and (3) according to their business size. Each group has a number of cases for model development and other cases for model validation. It can be concluded from the results of this study that:

1. The use of the NNM and MRM helps financial managers to assess the expected annual work volume of their construction companies which leads to profit maximization and raises the confidence level between stockholders and companies' managers.
2. The results indicated that both NNM and MRM can be effectively used to asses the construction companies annual work volume, but MRM performance showed more accuracy than NNM.
3. The accuracy of the developed MRM model was about ***81%*** which might be a result of that the developed models were based on the available financial statements on the Egyptian Stocks Exchange (ESE). It is expected that with the availability of more data, in the future, the accuracy of the developed model can be greatly enhanced. So, it is recommended that the developed

models should be continuously revised to arrive at a better level of accuracy and a more reliable tool for construction companies' annual work volume assessment.

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