Quantities Predictor Model (QPM) Based on Artificial Neural Networks for Gaza Strip Building Contractors

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Abstract—The management of resources is an essential task in each construction company. The aim of this study is to develop a new technique for predicting the quantities of key construction materials “cement, reinforced steel and aggregate” for building projects in Gaza Strip, through developing a model that is able to help parties involved in construction projects (owner, contractors, and others) epically contracting companies to go ahead or leave the project . This model build based on Artificial Neural Networks. In order to build this model, quantitative and qualitative techniques were utilized to identify the significant parameters for the predicting quantities of key construction materials (cement, steel, Aggregate). A database of 72 weeks was collected from the construction industry in Gaza Strip. The ANN model considered eleven significant parameters as independent input variables affected on three dependent output variable " Passing (Cement, steel, Aggregate) per ton ". Neurosolution software was used to train the models. The results of the trained models indicated that neural network reasonably succeeded in predicting the quantities of three key materials. The correlation coefficient (R) is 0.98, 0.99, 0.97 for cement, reinforced steel, aggregate respectively, indicating that; there is a good linear correlation between the actual value and the estimated neural network quantities. The performed sensitivity analysis showed that the “open crossings” factor has the highest rate of influence on the total quantities of materials.

Index Terms— Construction Materials, Artificial Neural Networks (ANN), Neurosolution.

I INTRODUCTION

Buildings are part of the built environment in which many activities are performed. In many countries, the building industry is a major economic driver. As such, facilities need to be constructed efficiently while meeting the aesthetic and functional requirements. One of the key factors affecting the successful delivery of construction projects is managing the construction resources in a good way [1]. This study aimed at developing a new technique for predicting the quantities of key construction materials “cement, reinforced steel and aggregate” for building projects in Gaza Strip based on Artificial Neural Networks.

II ARTIFICIAL NEURAL NETWORKS (ANNS)

There is no universally accepted definition of Neural Network (NN), but most of definitions are similar to some extent with each other, as such, Swingler (1996) defined neural networks as "statistical models of real world systems which are built by tuning a set of parameters. These parameters, known as weights, describe a model which forms a mapping from a set of given values known as inputs to an associated set of values the outputs"[7]. Artificial Neural Networks (ANNs) as the name suggests are inspired by the biology of a brain‟ s neuron. Human brain can perform a wide range of complex tasks in a relatively easier way as compared to computers. Therefore, researchers were looking for ways in which human intelligence can be incorporated into machines so that they can also perform certain complex tasks easily. ANNs resembles the human brain in two aspects; the knowledge acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights used to store the knowledge [2]. In early stage of a project, there is a limited availability of information, and limited application of traditional methods that require a precise knowledge of all parameters and their interrelations. Therefore, the researchers have worked to develop a new technique for predicting the quantities of key construction materials “cement, reinforced steel and aggregate” for building projects in Gaza Strip. Weckman, et al., (2010) see that, the major benefit of ANN is its ability to understand and simulate complex functions including those dimensions, attributes, and other factors. In concerning of the structure of ANNs, they are inspired to the human brain functionality and structure which consist of a set of neurons, grouped in one or more hidden layers connected by means of synapse connections [4]. The connections between neurons are called synapses and could have different levels of electrical conductivity, which is referred to as the weight of the connection. This network of neurons and synapses stores the knowledge in a „„„distributed‟ ‟ manner: the information is coded as an electrical impulse in the neurons and is stored by changing the weight (i.e. the conductivity) of the connections [5].

III NEUROSOLUTION 5.07 APPLICATION

Several applications support the establishment of neural networks like SPSS, MATLAB, etc. In this research, NeuroSolution application was selected. Where NeuroSolutions is the premier neural network simulation environment. As mentioned in NeuroDimension, Inc., (2012) NeuroSolutions combines a modular, icon-based network design interface with advanced learning procedures and genetic optimization. Perform cluster analysis, sales forecasting, sports predictions, medical classification, and much more with NeuroSolutions, which is:

- powerful and flexible: neural network software is the perfect tool for solving data modeling problems, so it's flexible to build fully customizable neural networks or choose from numerous pre-built neural network architectures. Modify hidden layers, the number of processing elements and the learning algorithm (NeuroDimension, Inc., 2012).
- Easy to use: NeuroSolutions is an easy-to-use neural network development tool for Microsoft Windows and intuitive, it does not require any prior knowledge of neural networks and is seamlessly integrated with Microsoft Excel and MATLAB. NeuroSolution also includes neural wizards to ensure both beginners and advanced users can easily get started. (NeuroDimension, Inc., 2012).

IV Factors affecting the quantities of resources from Gaza crossings

In fact, one of the most significant keys in building the neural network model is identifying the factors that have real impact on the quantities of resources from crossing. Depending on this great importance of selecting these factors, several techniques were adopted carefully to identify these factors in Gaza Strip building projects; as reviewing literature studies, and Delphi technique by conducting expert interviews.

V Delphi Technique

Different technique has been used to determine the effective factors on the quantities of resources from crossing. This technique relies on the concept of Delphi technique, which aimed to achieve a convergence of opinion on factors affecting the quantities of resources. It provides feedback to experts in the form of distributions of their opinions and reasons. Then, they are asked to revise their opinions in light of the information contained in the feedback. This sequence of questionnaire and revision is repeated until no further significant opinion changes are expected [16]. For Delphi process, several rounds should be conducted where first round begins with an open-ended questionnaire. The open-ended questionnaire serves as the cornerstone of soliciting specific information about a content area from the Delphi subjects, then after receiving the responses, the researcher converts the collected information into a well-structured questionnaire to be used as the survey instrument for the second round of data collection. In the second round, each Delphi participant receives a second questionnaire and is asked to review the items summarized by the investigators based on the information provided in the first round, where in this round areas of disagreement and agreement are identified. However, in third round Delphi panelist are asked to revise his/her judgments or to specify the reasons for remaining outside the consensus. In the fourth and often final round, the list of remaining items, their ratings, minority opinions, and items achieving consensus are distributed to the panelists. This round provides a final opportunity for participants to revise their judgments. Accordingly, the number of Delphi iterations depends largely on the degree of consensus sought by the investigators and can vary from three to five [17]. Five experts in construction field were selected to reach a consensus about specifying the key parameters. The results with those five experts were significantly close to the questionnaire results, and only three rounds were conducted due to largely degree of consensus. Where they proposed to exclude retaining wall and curtain wall from these factors because of their rarity in Gaza's projects.

VI Model Development

A Introduction

A Neural Network training program, NeuroSolution, was used as a standalone environment for Neural Networks development and training. Moreover, for verifying this work, a plentiful trial and error process was performed to obtain the best model architecture. The following sections present the steps performed to design the artificial neural network model, the limitation of adopted model, and finally the discussion and analysis of results.

B Model Limitations

In spite of great accuracy of using ANN in construction material prediction, it has a considerable defect, as it depends mainly on historical data; this dependency has several disadvantages as the following;

- Diversity of variables for effective factors is imited to what available in collected data.
- New variables which were not included in adopted model will not be handled.

Therefore, in this study most of construction variables used in Gaza Strip was included except those that haven't enough frequency. After analyzing the collected data, there was found that some limitations on input parameters should be assigned to give the best output. Table 1 illustrates the available range of input data in ANN model as; Number of crossings is from one to three…etc

TABLE 1
Input limitation in model

Model Variables	Minimum value	Maximum value
Number of crossings	1	3
Maximum Capacity of one crossing	0	700

C Model Building

There are several types of ANNs softwares are used to predict the future values based on the past data like SPSS, MATLAB, NeuroSolution …etc. Many researchers used NeuroSolution application in building their neural networks that it achieved good performance as (Edara, 2003; Gunaydın & Dogan, 2004; Bouabaz & Hamami, 2008; Dowler, 2008; Attal, 2010; Wang, et al., 2012). The developed model in this research based on NeuroSolution 5.07 for Excel program. It was selected for its ease of use, speed of training, flexibility of building and executing the NN model. In addition, the modeler has the flexibility to specify his own neural network type, learning rate, momentum, activation functions, number of hidden layers/neurons, and graphical interpretation of the results. Finally, It has multiple criteria for training and testing the model.

D Data Encoding

Artificial networks only deal with numeric input data. Therefore, the raw data must often be converted from the external environment to numeric form (Kshirsagar & Rathod, 2012) [18]. This may be challenging because there are many ways to do it and unfortunately, some are better than others are for neural network learning [19].In this research data were converted to numeric form as shown in Table 2.1. And Table 2 shows the data organization for eleven factors.

TABLE 2
Inputs/Output encoding

No	Input factor	Encode	Code
1	Numbers of opened crossings	Number form For Example Tunnels, Rafah, Karm Abo Salem	1 or 2 or 3
2	The percentage of closed time	Percentage	%
3	Amount of first payment	Complex Middle Easy	= 1 = 2 = 3
4	Type of project	International Projects Governmental Projects People & Special Projects	= 1 = 2 = 3
5	The value of NIS in Dollars	Number form	i.e.:3.55 NIS
6	Transportation fees	More than Normal Normal Less than Normal	= 1 = 2 = 3

1) Data Organization

TABLE 2
Inputs/Output encoding

No	Input factor	Encode	Code
7	Taxes	More than Normal Normal Less than Normal	= 1 = 2 = 3
8	Needed quantities of cement by tons per week	Number form	ton
9	Needed quantities of reinf. steel by tons per week	Number form	ton
10	Needed quantities of aggr. by tons per week	Number form	ton
11	labour wages	More than Normal Normal Less than Normal	= 1 = 2 = 3
No.	**Output Parameter**	**Encode**	**Code**
1	Quantities of passing Cement from all crossings/week	Number form	ton
2	Quantities of passing Steel from all crossings/week	Number form	ton
3	Quantities of passing Aggregate from all crossings/week	Number form	ton

Initially, the first step in implementing the neural network model in NeuroSolution application is to organize the Neurosolution excel spreadsheet. Then, specifying the input factors that have been already encoded, which consist of 11 factors; Numbers of opened crossings, the percentage of closed time, amount of first payment, type of project, the value of NIS in

Dollars for example (1$ = 3.55 NIS), transportation fees, taxes, needed quantities of cement by tons, needed quantities of reinforced steel by tons, needed quantities of aggregate by tons, and labour wages. The desired parameter (output) are the quantities of cement, steel, and aggregate that reach from several crossings.

2) Data Set

The available data were divided into three sets namely; training set, cross-validation set and test set. Training and cross validation sets are used in learning the model through utilizing training set in modifying the network weights to minimize the network error, and monitoring this error by cross validation set during the training process. However, test set does not enter in the training process and it hasn‟ t any effect on the training process, where it is used for measuring the generalization ability of the network, and evaluated network performance [15].

In the present study, the total available data is 75 exemplars that were divided logical randomly, according to previous literatures in section (2.9.4), into three sets with the following ratio:

- Training set (includes 54 exemplars ≈ 75%).
- Cross validation set (includes 10exemplars ≈ 14%).
- Test set (includes 8 exemplars ≈ 11%).

3) Building Network

Once all data were prepared, then the subsequent step is represented in creating the initial network by selecting the network type, number of hidden layer/nodes, transfer function, learning rule, and number of epochs and runs. An initial neural network was built by selecting the type of network, number of hidden layers/nodes, transfer function, and learning rule. However, before the model becomes ready, a supervised learning control was checked to specify the maximum number of epochs and the termination limits, Figure 1 presents the initial network of Multilayer Perception (MLP) network that consists of one input, hidden, and output layer.

Before starting the training phase, the normalization of training data is recognized to improve the performance of trained networks by Neurosolution program which as shown in Figure 2 which ranging from (0 to +0.9).

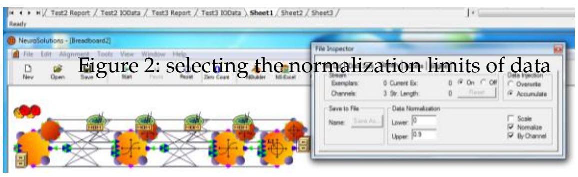


Figure 2: selecting the normalization limits of data

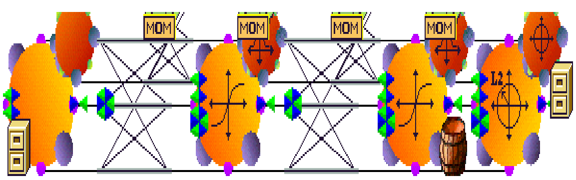
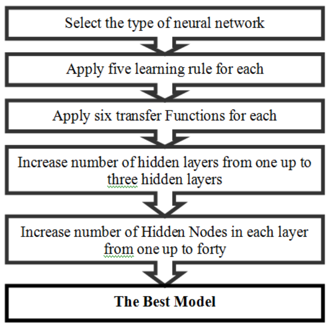


Figure 1 Multilayer Perceprtorn (MLP) network

4) Model Training

The objective of training neural network is to get a network that performs best on unseen data through training many networks on a training set and comparing the errors of the networks on the validation set [20]. Therefore, several network parameters such as number of hidden layers, number of hidden nodes, transfer functions and learning rules were trained multiple times to produce the best weights for the model. As a preliminary step to filter the preferable neural network type, a test process was applied for most of available networks in the application. Two types Multilayer Perceptron (MLP) and General feed Forward (GFF) networks were chosen to be focused in following training process due to their good initial results. It is worthy to mention that, previous models that have been applied in the field of quantities estimation by neural networks used earlier two types of networks because of giving them the best outcome. The following chart illustrates the procedures of training process to obtain the best model having the best weight and minimum error percentage.



The chart shows the procedures of the model training, which starts with selecting the neural network type either MLP or GFF network. For each one, five types of learning rules were used, and with every learning rule six types of transfer functions were applied, and then one separate hidden layers were utilized with increment of hidden nodes from 1 node up to 40 nodes this layer. By another word, thousand trials contain 40 variable hidden nodes for each was executed to obtain the best model of neural network. Figure 3 clarifies training variables for one trial. It compromises of number of epochs, runs, hidden nodes, and other training options.

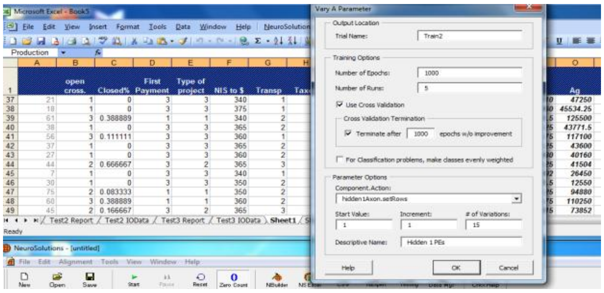


Figure 3: Training options in Neurosolution application

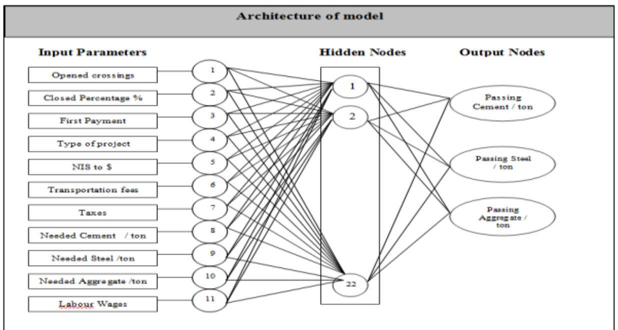
Ten runs in each one 3000 epochs were applied, where a run is a complete presentation of 3000 epochs, each epoch is a one complete presentation of all of the data [19].However, in each run, new weights were applied in the first epoch and then the weights were adjusted to minimize the percentage of error in other epochs.

To avoid overtraining for the network during the training process, an option of using cross-validation was selected, which computes the error in a cross validation set at the same time that the network is being trained with the training set. The model was started with one hidden layer and one hidden node in order to begin the model with simple architecture, and then the number of hidden PEs was growing up by one node up to 40 hidden nodes.

5) Model Results

As mentioned above, the purpose of testing phase of ANN model is to ensure that the developed model was successfully trained and generalization is adequately achieved. Through a system of trial and error. The best model that provided more accurate quantities estimate without being overly complex was structured of Multilayer Perception (MLP) includes one input layer with 11 input neurons and one hidden layer with (22 hidden neurons) and finally three output layer with three output neuron (Passing quantities of Cement, Reinforced steel and Aggregate from Gaza Strip crossings). However, the main downside to using the Multilayer Perception network structure is that it required the use of more nodes and more training epochs to achieve the desired results. Table 3 summarizes the architecture of the model .

Table 3: Architecture of the model



Model Type	Transfer Function	Update Methods	Gradient Search
Multilayer Perception	Tanh Axon	Batch	Momentum
No. off hidden layer	No. of PEs in the 1st Input layer	No. of PEs in the 1st Hidden layer	Model Type
1	11	22	1

6) Results Analysis

The testing dataset was used for generalization that is to produce better output for unseen examples. Data from 8 cases were used for testing purposes.

A Neurosolution test tool was used for testing the adopted model accordingly to the weights adopted. Table 4 and Table 5 present the results of these 8 cases with comparing the real quantities of tested cases with estimated quantities from neural network model, and an absolute error with both price and percentage are also presented.

TABLE 4

Results of neural network model at testing phase

Case	Actual quantity of cement (ton)	Actual quantity of steel (ton)	Actual quantity of aggregate (ton)	Estimated quantity of cement (ton)	Estimated quantity of steel (ton)	Estimated quantity of aggregate (ton)	Absolute Percentage Error(%) for cement	Absolute Percentage Error(%) For steel	Absolute Percentage Error(%) For aggregate
1	13990	2260	45325	13066	2221	43458	7%	2%	4%
2	13090	1850	45300	13066	2221	43458	0%	20%	4%
3	11660	3185	31618	11552	3081	29817	1%	3%	6%
4	13090	2280	45586	13066	2221	43458	0%	3%	5%
5	56928	23878	121032	55589	23566	120774	2%	1%	0%
6	50122	20143	130620	50062	20117	123818	0%	0%	5%
7	57600	22360	121503	57283	22292	131209	1%	0%	8%
8	38604	14511	90656	45681	17483	101933	18%	20%	12%

TABLE 5

Results of neural network model at testing phase

Absolute Error AE of Cement (ton)	Absolute Error AE of Steel (ton)	Absolute Error AE of Agg. (ton)	Absolute Error AE of Cement %	Absolute Error AE of Steel %	Absolute Error AE of Agg. %
924.3343	39.27626	1867.1	7%	2%	4%
24.33432	370.7237	1842.1	0%	20%	4%
108.0029	104.2349	1801.453	1%	3%	6%
24.33432	59.27626	2128.1	0%	3%	5%
1339.272	312.0733	257.0527	2%	1%	0%
59.34351	25.39074	6802.272	0%	0%	5%
316.9003	68.37791	9705.52	1%	0%	8%
7077.461	2971.878	11277.49	18%	20%	12%

➢ Mean Absolute Error

The Mean Absolute error (MAE) for the presented results in Table 5.3 equals (59.3 tons for cement, 25.4 tons for reinforced steel, and 25.7 tons for aggregate), it is largely acceptable for Gaza Strip construction industry. However, it is not a significant indicator for the model performance because it proceeds in one direction, where the mentioned error may be very simple if the project is large, and in turn; it may be a large margin of error in case the project is small.

➢ Mean Absolute Percentage Error

The mean absolute percentage error of the model is calculated from the test cases as shown in Table 5.3, which equals 4% for cement, 6% for steel and 6% for aggregate; this result can be expressed in another form by accuracy performance (AP) according to Wilmot and Mei, (2005) which is defined as (100−MAPE) %.

AP= 100% - 6% = 94% for steel and aggregate, and 96% for cement. That means the accuracy of adopted model for estimating quantities of the important construction materials is 94% for steel and aggregate, and 96% for cement. It is a good result especially when the construction industry of Gaza Strip is facing a lot of obstacles.

➢ Correlation Coefficient (R)

Regression analysis was used to ascertain the relationship between the estimated quantities and the actual quantities. The results of linear regressing are illustrated in table 6. The correlation coefficient (R) is 0.98, 0.99, 0.97 for cement, reinforced steel, aggregate respectively, indicating that; there is a good linear correlation between the actual value and the estimated neural network quantities.

TABLE 6

Results of performance measurements

Performance	Cement / ton	Steel /ton	Aggregate /ton
MSE	16716008.43	2525194.80	113330607.53
NMSE	0.05	0.03	0.09
MAE	2999.60	971.88	8594.01
Min Abs Error	59.34	25.39	257.05
Max Abs Error	7610.85	3251.87	21053.52
r	**0.98**	**0.99**	**0.97**

The results of performance measures are presented in Table 5.4, where the accuracy performance of adopted model is 98%, 99%, 97%. Figure 4 describes the actual quantities comparing with estimated quantities for cross validation (C.V) dataset. It is noted that there is a slight difference between two quantities lines.

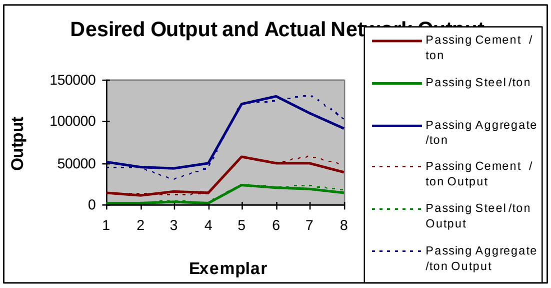


Figure 4 Comparison between desired output and actual network output for Test set

7) Sensitivity Analysis

Sensitivity analysis was carried out by Neurosolution tool to evaluate the influence of each input parameter to output variable for understanding the significance effect of input parameters on model output. Figure 5 presents the sensitivity analysis results for each input parameter.

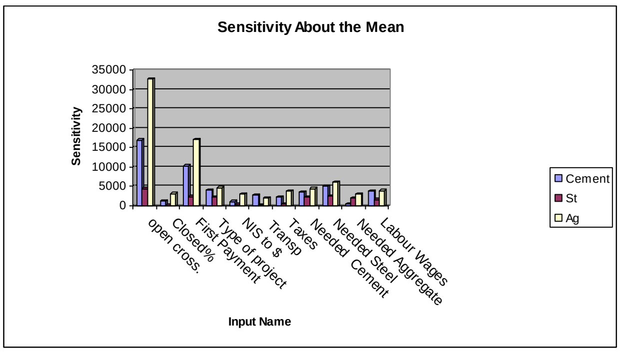


Figure 5: Sensitivity about the mean

The increase of Standard Deviation refers to the strength influence of this parameter on the overall quantities; Figure 5 shows that the “open crossings” factor has the highest rate of influence on the total quantities of materials.

8. Users Interface Building

After testing QPM model using varied projects and the results of the sensitivity analysis has been a logical then the model can be generalized. For more facilitation, Visual Basic interface was developed to facilitate data entry for the model. This interface provides the user with many alternatives options according to the nine input parameters, which describe the project.

8.1 Custom Solution Wizard (CSW)

The Custom solution wizard is a tool that will take an existing neural network created with NeuroSolutions and automatically generate and compile a Dynamic Link Library (DLL). This allows programmer to incorporate neural network models easily into other NeuroDimension products and other application, such as Visual Basic (VB) [21]. While using the wizard to create the DLL, it is gives the option of creating a shell for any of the following programming environments:
[Visual Basic, Visual C++, Microsoft Excel, Microsoft Access, Active Server Pages (Developers level only)]. Each shell provides a sample application along with source code to give programmer a starting point for integrating the generated DLL into the desired application. The generated neural network DLL provides a simple protocol for assigning the network input and producing the corresponding network output [21].

8.2 Generating DLL

The following steps were followed to generate DLL file using CSW tool:
Choose Breadboard Type. After run, CSW the first panel appears is the "choose breadboard type" panel. This panel gives the option of using the active NeuroSolutions breadboard or allows opening an existing NeuroSolutions breadboard for generating the neural network DLL. The active NeuroSolution breadboard was shown in Figure 6 is the breadboard of the best GFF model, which was chosen to create the DLL

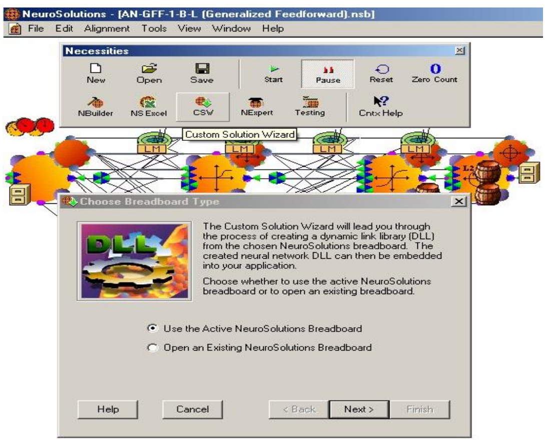


Figure 6: Choose breadboard type

- **Choose Project Type**

In this step as shown in Figure 7, the panel allows choosing the type of project with which the programmer prefers to use the generated DLL. In this research, the type that was chosen is Visual Basic 6.

Figure 7: Choose project type.

After the network DLL has been created, the Custom Solution Wizard created a project shell in the format of Visual Basic 6. The shell is provided as a guide to help programmer get started with developing a custom application using the generated neural network DLL.

8.3 Visual Basic Interface

The NeuroSolutions Object library is NeuroSolutionsOL.dll, which was installed in the Windows\System or Winnt\System32 directory (depending upon your operating system) during the Custom Solution Wizard installation. The NeuroSolutions Object Library provides a simple protocol (made up of properties and methods) for communicating with neural network DLLs generated by the Custom Solution Wizard. This protocol makes it extremely easy to use the generated network DLLs from within the application. The object library allows creating the NeuroSolution recall network type of neural network objects. The easiest way to build a visual basic application for using a neural network DLL is to start with a project shell. A VB project shell was generated automatically as described in the previous section by choosing the VB project type on the choose project type panel during the creation of the neural network DLL. This creates a sample application (with source code) that will load in the DLL and allow training the network and getting the networks output.
The main aim of the VB application interface for the QPM model is to facilitate the data entry for the model. Therefore, the interface was drawn using VB buttons, see Figure 8 and then the VB code was written into the VB shell code panel.

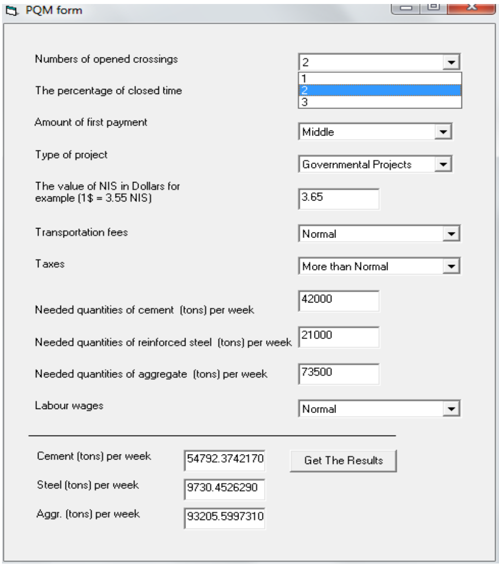


Figure 8: The VB interface for the QPM model.

9. Conclusion

- Quantities Predictor Model (QPM) gives the contractor a mechanism to decide if he can go ahead on the construction project or no according to the predicting quantities of the key materials (cement, steel, and aggregate).
- Developing ANN model passed through several steps started with selecting the application to be used in building the model. The Neurosolution5.07 program was selected for its efficiency in several previous researches in addition to its ease of use and extract results. The data sets were encoded and entered into MS excel spreadsheet to start training process for different models.
- Many models were built but the best model that provided more accurate results was Multilayer Perception network model (MLP) which structured from one input layer included 11 input neurons, one hidden layer contained 22 hidden neurons, three output neuron, tanhAxon transfer function, and Moentum learning rule .
- The accuracy performance of the adopted model recorded 98%, 99%, and 97% for cement, reinforced steel, and aggregate respectively where the model indicating that; there is a good linear correlation between the actual value and the estimated neural network quantities.
- Sensitivity analysis was performed using Neurosolution tool to study the influence of adopted factors on predicting quantities of the key materials (cement, steel, and aggregate)., the concept of calculating sensitivity analysis of input factors based on determining the standard deviation of each. However, the performed sensitivity analysis was in general logically where the number of opened crossings had the highest influence.
- According to Quantities Predictor Model (QPM) the result shows that the quantities of key materials (cement, steel, and aggregate) which passing from all Gaza Strip crossings can be affected by several factors such as numbers of opened crossings, the percentage of closed time, Amount of first payment, type of project, the value of NIS in Dollars for example, transportation fees, and taxes, respectively.
- Some assumption and limitation were assumed in the study according to available collected data. These limitations include: the first one, the number of crossings (1 to 3). This limitation is assumed because the other crossings don't use for materials. And the other limitation, the maximum Capacity of one crossing (700 trucks).

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