Influencing Cost Factors in Road Projects in Gaza Strip Using ANN

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Abstract— Conceptual cost estimate can serve the owners' feasibility estimate and assists in the establishment of the owner's funding which aids the engineers in designing to a specific budget. Conceptual estimating exhibits low accuracy level due to the lack of project information and the high level of uncertainty at early stage of project development. The purpose of this paper is to determine the most influencing cost factors in road projects using Delphi technique and Artificial Neural Networks. These factors were employed in a neural network (NN) for building a multi-layer perceptron (MLP) model to estimate the road project cost. Historical data of Gaza strip road projects were used to train and test the MLP model. The model developed showed a reduced error rate of 6.3% which demonstrates the ability to estimate the cost of road projects at early stage with higher accuracy.

Index Terms— Cost factors, Conceptual cost estimate; Artificial neural networks.

I. Introduction

Early stage cost estimate plays a significant role in any initial road projects decisions; despite the project scope has not yet been finalized. Major problems faced are lack of preliminary information, database of road works costs and appropriate cost estimation methods [2, 3]. Project managers in Gaza Strip, often need to estimate the cost of road projects at early stage quickly and approximately to provide funding or to obtain the adoption of the budget from decision-makers. Therefore, it is important to know the cost of the road projects in a short time with acceptable accuracy. Artificial Neural Networks (ANN) is well suited to model complex problems where the relationship between the model variables is unknown [4].

The main objective of this research is to develop ANN model to estimate the cost of road projects in Gaza strip at early stage to reduce the error in estimation. To achieve this, the factors that affect the cost of road projects that can be available at early stage were identified and modeled.

II. Literature Review

Cost is on the mind of every business. Every business is expected to do more with less. The objective is to minimize cost, maximize profit, and maintain the competitive edge. Methods for cost estimation vary as the project evolves from the early stages of conception to the construction phase.

Conceptual cost estimate is made at the early stage of the project where the budgets are to be decided, and available information is limited. It is conducted without working drawings or detailed specifications. The estimator may have to make such an estimate from rough design sketches, without dimensions or details and from an outline specification and schedule of the owner's space requirements [5]. The conceptual cost estimate can serve several purposes, such as:

- It supplements or serves as the owners feasibility estimate.
- It aids the Architect/Engineer in designing to a specific budget.
- It assists in the establishment of the owner's funding.

A. Parameters Affecting Cost of Road Projects

There are a lot of parameters that affected the cost of road projects, Hegazy and Ayed [2] relied on ten parameters to determine highway construction cost in Canada. Those parameters were project type, project scope, year, construction season, location, duration, size, capacity, water body, and soil condition. Wilmot and Mei [6] took on price of labor, price of material, price of equipment, pay item quantity, contract duration, contract location, quarter in which contract was let, annual bid volume, bid volume variance, number of plan changes, and changes in standards or specifications for estimating the escalation of highway construction costs over time in Louisiana state. Whilst for estimating the cost at conceptual phase of highway projects in poland and thailand, sodikov [7] picked out construction factors which are predominant work activity (asphalt or concrete), work duration, pavement width, shoulder width, ground rise fall, average site clear/grub, earthwork volume, surface class (asphalt or concrete), and base material (crushed stone or cement stab). likewise in the West Bank – Palestine Mahamid and Bruland [8] adopted construction factors. which are road length, pavement width, pavement thickness after compaction, asphalt hauls distance, pavement area, base coarse thickness after compaction, base coarse haul distance, the base coarse area, terrain condition (semi even, hilly), soil drillability (good, poor), and soil suitability (good, poor) to predict the cost of road construction activities. Pewdum et al. [9] used traffic volume, topography, weather condition, evaluating date, construction budget, contract duration, % of as planned completion, and % of actual completion to forecast final budget and duration of a highway construction project during construction stage. Attal [10] employed norm cost estimate, location of the project, area location (rural, urban, etc.), loops and ramps, new signal counts, construction length, sidewalks, curb and gutter, crossover count, average daily traffic, and geometric design standard for predicting highway construction cost in Virginia.

As shown above the factors varied widely. This is referred to several reasons like the location of study and the tools, which was used to determine the parameters. A number of techniques were available to determine the influencing factors on road projects costs. Delphi technique is one of these methods. It provided the opportunity to evaluate knowledge based on the experience of individual practitioners and it is suitable for this research [11]. While this research focused on the "implementation factors" that affected the budget of road projects in the Gaza Strip. The research adopted the most nine influential factors in roads budgets, which are determined by using Delphi technique.

B. Artificial Neural Networks (ANN)

Neural networks are the preferred tool for many predictive data mining applications because of their power, flexibility, and ease of use [12].

A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data [13]. During training, both the inputs (representing problem parameters) and outputs (representing the solutions) are presented to the network normally for thousands of cycles. At the end of each cycle, or iteration, the network evaluates the error between the desired output and actual output. Then use this error to modify the connection weights according to the training algorithms used [14].

Over the last few years, the use of artificial neural networks (ANN) has increased in many areas of engineering. Many research in construction management have been carried out to use ANN in various topics.

Moselhi et al [15] are among the first scholars to research ANN as a promising management tool in construction. Following on from their work, Moselhi and Hegazy [16] used neural network methodology to markup estimation. Then ANN became widely spread and, it is used in construction management.

Recently Hola and Schabowicz [17] estimated earthworks execution time cost by means of artificial neural networks. Wang and Gibson [18] studied pre project planning and project success by using ANNs and regression models. Chen [19] developed hybrid ANN-Case Based Reasoning (CBR) model for disputed change orders in construction projects and Oral et al [20] predicted productivity of the construction crew by using NN with supervised versus unsupervised learning.

Many researchers focused on predicting the cost of construction by using NN, like Arafa and Alqedra [4] who developed ANN model to predict the early stage cost of buildings. The analysis of the training data revealed that there are seven key parameters. Kim et al [21] developed a hybrid conceptual model for estimating cost of large building projects. Gunaydın and Dogan, [22] also, built a neural network model to estimate the cost in early phases of building design process. Cost and design data were used for training and testing the neural network methodology with eight design parameters utilized in estimating the square meter cost of reinforced concrete structural systems of 4–8 storey residential buildings in Turkey, an average cost estimation accuracy of 93% was achieved. Likewise, in Korea Kim et al. [23] used the construction cost data for residential buildings constructed between 1997 and 2000. The back-propagation network (BPN) model incorporating genetic algorithms (GAs) were used to improve the accuracy of construction cost estimation.

ANN technique was also used in highway projects. Pewdum, Rujirayanyong and Sooksatra [9] presented a study of back-propagation neural networks for predicting final budget and duration of highway construction projects by using the actual data collected from project progress reports of 51 highway construction projects in Thailand between 2002 and 2007. Sodikov [7] focused on the development of a more accurate estimation technique for highway projects in developing countries at the conceptual phase using artificial neural networks. He used database of road works cost data from two developing countries Poland and Thailand, which have a relatively large number of projects. Therefore, they investigated the relationship between project cost and other variables such as work activity, terrain type, road parameters, etc. The ANN model was developed by multilayer perception (MLP) with back-propagation algorithm. Wilmot and Mei [6] developed an artificial neural network model, which relates overall highway construction costs to improve a procedure that estimates the escalation of highway construction costs over time. The model was able to replicate past highway construction cost trends in Louisiana with reasonable accuracy.

The multilayer feed-forward network structure for ANNs was chosen for this study, and for training, the backpropagation learning algorithm was used.

This research used multi-layer perceptron architecture of ANN applications to introduce a model for estimating the cost of road projects in Gaza strip at the early stage.

III. Methodology

The research was carried out to achieve the objective of the study. In the first step, Delphi technique was used for determining the influencing implementation factors on the cost of roads. Secondly, historical data of road projects implemented between 2011 and 2012 in Gaza was collected. In the third step, this data was used in developing the neural networks proposed models. The model was tested on separate data for best-possible architecture. These steps will be explained in the following sections.

IV. Influencing Factors and data collection

To obtain the factors, which have the most effect on the cost of road projects, the Delphi method was utilized and the following steps were followed[1]:

- Seven exploratory interviews were done with experts. The experts worked in various positions: cost engineers, managers and site engineers. They worked with consulting offices, municipalities and contractors.
- The factors that affect the cost of road projects, which have been drawn from previous studies were presented to them.
- Then the experts' opinions were showed consensus on nine factors, which have the greatest impact on the road project cost in Gaza strip.

Neural networks models require many data. Therefore, Eighty-six (86) projects were collected from municipalities, Ministry of Public Works and Housing, contractors and consultants.

As a result for using Delphi technique, the following nine factors were recommended which cover the parameters of the cost of road projects influencing:

Project scope: The collected data includes 26 projects that have a "new project with a good soil" scope, 27 projects that have a "new project with a poor soil" scope and 33 projects that have a "rehabilitation" scope. This is a clear indication that the collected projects are distributed as per the project scope so it was considered a representative sample and can be used in modeling.

Pavement type: The sample was representative of two types; 48 projects with asphalt pavement and 38 with interlock pavement.

Pavement area: There is no data for projects, which have pavement area less than 2,000 m^2, while 65% of projects in the data set have pavement area between 2000 to 10,000 m^2. The low rate of projects that have an area more than 20,000 square meters may lead to reducing the accuracy of the model in estimating the cost for this category.

Length of road: Gives an indication for the size of works in the project. The shortest length in the data set is 250m and the number of projects that have road lengths more than 2,250m is less than five percent. While 77% of the projects in the data set, have road lengths between 250 to 1,250 m.

Sewage, water and lighting networks: The cost of projects in the data set contains the cost of implementing one or more of the networks listed in Table 1. The data represented all feasible possibilities in the presence or absence of the three networks. This supports the possibility of the adequacy of this data to build the model.

Curbstone length: A quarter of the projects in the data set do not include the cost of curbstones, which means it was well represented. The projects, which include curbstones with more than 5000 meter are few. This may reduce the accuracy of the model in estimating the cost of this category of projects.

Pavement area of (side walk+ island): Forty-two percent of the projects in the data set did not include the cost of paving sidewalks and islands.

Table 1: Number of projects including different networks

Networks	No. of projects	%
Sewage only	7	%8.1
Water only	3	%3.5
Lighting only	14	%16.3
No Networks	35	%40.7
Sewage &Water	6	%7.0
Sewage &Lighting	4	%4.7
Water &Lighting	6	%7.0
Sewage, Water &Lighting	11	%12.8

Projects Budget for the gathered cases are presented in Figure 2. It is very clear that more than 67 percent of the projects in the data set have a budget less than 400,000 dollars. This means that the accuracy of the model will be good for projects that have cost within this range.

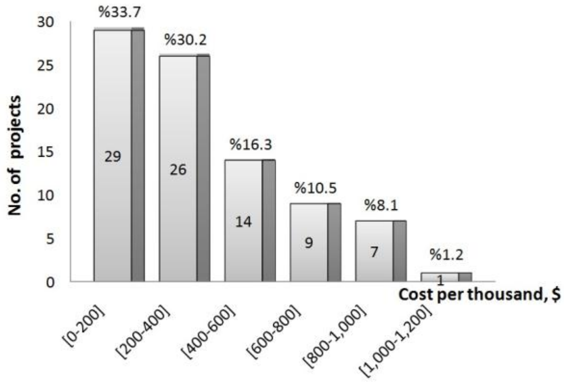


Figure 2: Number of projects according to their budget

V. Model Development

To obtain the best models with minimum error, the research followed the procedures explained in Figure 1.

A. Model Structure Design

The choice of ANN architecture depends on a number of factors such as the nature of the problem, data characteristics and complexity, the number of sample data, etc.[7]. The models designed to include an input layer of nine processing elements (neurons) corresponding to the nine input parameters and an output layer of one processing element (neuron) as the target. In this research, the data is textual and numeric, so it is encoded to be only numeric or integer according to Table 2.

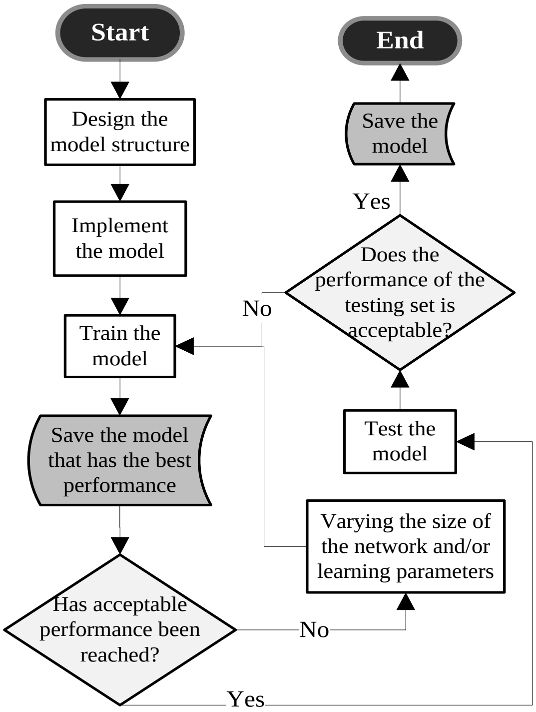


Figure 1: Modelling Procedures Flowchart [1].

Table 2: Inputs/Output encoding.

No	Input Parameters	Code
1.	Project scope	New with a good soil = 1 New with a bad soil = 2 Rehabilitation = 3
2.	Pavement type	Interlock = 1 Asphalt = 2
3.	Pavement area	in m^2
4.	Sidewalk & Island pavement area	in m^2
5.	Road length	in meters length
6.	Curbstone length	in meters length
7.	Water networks	Exist = 1 Not exist = 0
8.	Lighting networks	Exist = 1 Not exist = 0
9.	Sewage networks	Exist = 1 Not exist = 0
	Output Parameter	**Code**
1	Project budget	in thousand dollar's

The design of the neural network architecture is a complex and dynamic process that requires the determination of the internal structure and rules (i.e., the number of hidden layers and neurons, update weights method, and the type of activation function) [22].

This research depended on the backpropagation algorithm, which is a type of supervised learning algorithms that is mostly used in civil engineering applications. Also, Levenberg-Marquardt learning rule is selected. The choice of ANN in this study is based on optimum design and prediction using multilayer perceptron neural network architectures.

NeuroSolution 6.07 application and Microsoft Excel 2007 were selected to build the models. There are many types of activation functions, which are used to transform an input signal into output. The hyperbolic tangent (Tanh) was used.

B. Model Implementation

The problem at hand needs to identify and tag the data as input or as output. So the data was organized in the preliminary stage to neural network modeling. Then three processes were followed in modeling:

Data Sets: Any model selection strategy requires validation by the process data. Traditionally, available data is divided into three sets [24]; training set (in-sample data), cross-validation set and a test set (out-of-sample). Learning is performed on the training set, which is used for estimating the arc weights while the cross validation set was used for generalization that is to produce better output for unseen examples [7]. However, the test set is used for measuring the generalization ability of the network and network performance evaluation [25].

The total available data is 86 exemplars that are divided randomly into three sets:

- Training set (includes 60 exemplars ≈ 70%),
- Cross validation set (includes 16 exemplars ≈ 18%) and
- Test set (includes 10 exemplars ≈ 12%).

Normalizing Data: Data is generally normalized for confidentiality and for effective training of the model being developed. The normalization of training data is recognized to improve the performance of trained networks [22].

The input/output data is scaled, zero is the lower bound and the upper bound is one to suit neural networks processing. NeuroSolution 6.07 automatically scales input values to {Lower Upper} according to Equations (1), (2) and (3).

$$(\mathrm{Data_i})_{\mathrm{Nor}} = \mathrm{Amp_i} \times \mathrm{Data_i} + \mathrm{Off_i}0 \qquad (1)$$

Where:

$(\mathrm{Data_i})_{\mathrm{Nor}}$: data represent value for one input for one sample after normalization.

$\mathrm{Data_i}$: data represent value for one input for one sample.

$$\mathrm{Amp_i} = \frac{(\mathrm{UpperBound} - \mathrm{LowerBound})}{(\mathrm{Max_i} - \mathrm{Min_i})} \qquad (2)$$

$$\mathrm{Off_i} = \mathrm{UperBound} - \mathrm{Amp_i} \times \mathrm{Max_i} \qquad (3)$$

Where $\mathrm{Max_i}$ and $\mathrm{Min_i}$ are the maximum and minimum values found within channel i, and Upper-bound and Lower-bound are equal 0 and 1 respectively.

Initial Networks Building: The modeling was started with small networks and increased their size until the performance in the test set is appropriate. This proposed method of growing neural topologies ensures a minimal number of weights, but the training can be fairly long [13].

C. Training Models and Testing

Training a NN is an iterative process of feeding the network with the training examples and changing the values of its weights in a manner that is mathematically guaranteed to reduce consecutively the error between the network's own results and the desired output. Neural networks are able to generalize solutions to problems by learning from pairs of input patterns and their associated output pattern [16].

After building a small topology as viewed above, training with cross-validation and testing phase will begin. The optimum architecture is often achieved by trial and error according to the complexity of the respective problem, also by testing few proposed designs to select the one that gives the best performance[26]. Figure 3 explains the series of processes to get the best weights, which give the minimum percentage error.

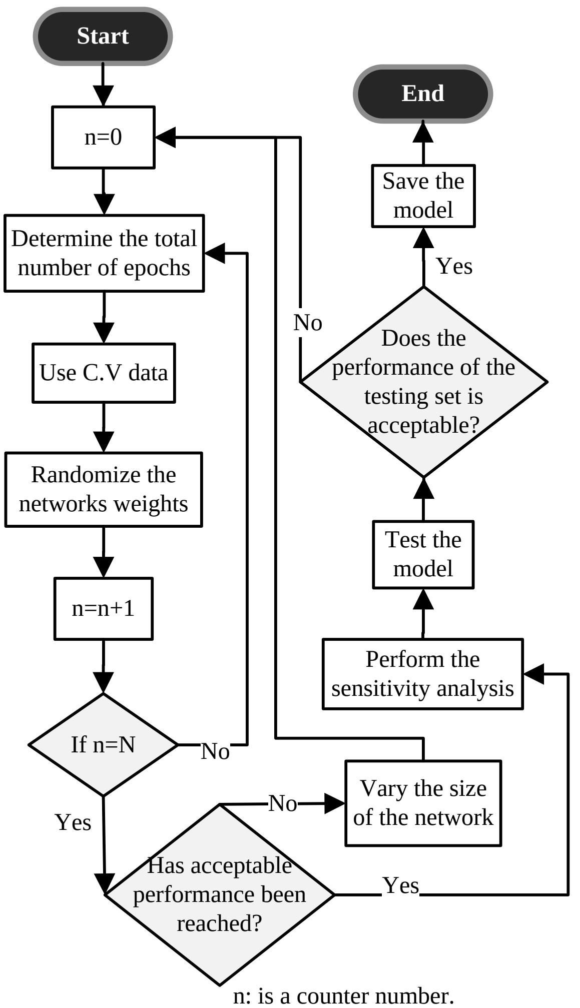
VI. PERFORMANCE MEASURES

The Performance Measures are important to evaluate the models. There are five values that can be used to measure the performance of the network for a particular data set.

Mean Square Error (MSE): According to Principe et al [13] the MSE formula is:

$$\mathrm{MSE} = \frac{\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{N} \qquad (4)$$

Where: N= number of exemplars in the data set.
y_{ij}= network output for exemplar i at PE j.
d_{ij}= desired output for exemplar i at PE j.



n: is a counter number.
N: is a number of the required runs.

Figure 3: Training and testing model flowchart [1].

Correlation Coefficient (r): According to Principe et al [13], the correlation coefficient between a network output x and a desired output d is:

$$r = \frac{\frac{\sum_i (x_i-\bar{x})(d_i-\bar{d})}{N}}{\sqrt{\frac{\sum_i (d_i-\bar{d})^2}{N}}\sqrt{\frac{\sum_i (x_i-\bar{x})^2}{N}}} \qquad (5)$$

Mean Absolute Error (MAE): According to Willmott and Matsuura [27], the MAE is defined by the following formula:

$$\mathrm{MAE} = \frac{\sum_{i=0}^{N} |dy_{ij}-dd_{ij}|}{N} \qquad (6)$$

Where: N= number of exemplars in the data set.

dy_{ij}= denormalized network output for exemplar i at PE j.

dd_{ij}= denormalized desired output for exemplar i at PE j.

Mean Absolute Percentage Error (MAPE): According to Principe et al., (2010) [13], the MAPE is defined by the following formula:

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=0}^{N}\frac{|dy_{ij}-dd_{ij}|}{dd_{ij}} \qquad (7)$$

This research considered Hegazy and Ayed [2] methodology in determining the total MAPE. The training phase was represented by fifty percent of the total MAPE while the test set equals the remaining fifty percent. Total MAPE can be calculated by the following formula:

$$\text{Total MAPE} = \frac{(\mathrm{MAPE_T}\times \mathrm{N_T}+\mathrm{MAPE_C}\times \mathrm{N_C})/(\mathrm{N_T}+\mathrm{N_C})+\mathrm{MAPE_S}}{2} \qquad (8)$$

Where:

$\mathrm{MAPE_T}$= MAPE for training data set.

$\mathrm{N_T}$ = number of exemplars in the training data set.

$\mathrm{MAPE_C}$ = MAPE for cross validation data set.

$\mathrm{N_C}$= number of exemplars in the cross validation data set.

$\mathrm{MAPE_S}$ = MAPE for test data set.

Total Accuracy Performance (TAP): According to Wilmot and Mei [6], the accuracy performance is defined as (100−MAPE) %. Total Accuracy Performance (TAP) can be calculated by the following formula:

$$\mathrm{TAP} = 100 - \text{Total MAPE} \qquad (9)$$

VII. RESULTS AND DISCUSSION

From the previous procedure of training and testing, many multilayer perceptron topologies were trained for several trials. The best structure has one hidden layer with five neurons although two hidden layers topologies were trained, see Figure 4.

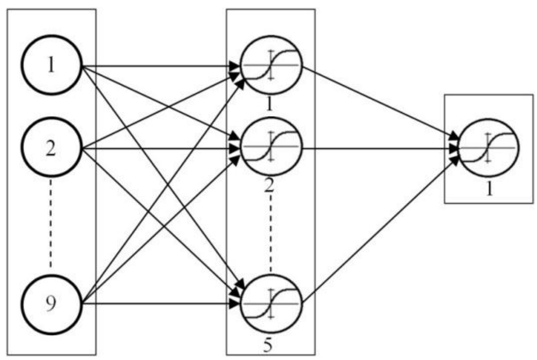


Figure 4: The architecture of the MLP model.

The models were trained on sixty exemplars while sixteen exemplars of cross validation set were used for generalization to produce better output for unseen examples. The models were tested on ten exemplars. The results are summarized in Table 3.

Table 3: Performance measurements for the model.

	Training set	C.V set	Test set
MSE	152.2	1446	2819
R	0.999	0.992	0.99
MAE	8.812	30.97	43.3
MAPE	3.49%	9.59%	7.80%
AP	96.52%	90.41%	92.20%

The back-propagation algorithm involves the gradual reduction of the error between model output and the target output. It develops the input to output by minimizing a mean square error cost function measured over a set of training examples [28]. The value of the MSE for MLP model has MSE 152, 1446 and 2819 at training, cross validation and testing sets respectively.

The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it does not necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, we can change the MSE without changing the directionality of the data. The correlation coefficient (r) solves this problem [13]. As show in Table 3 the correlation coefficient (r) for any set of data is not less than 0.989, this means that the fit of the model to the data is reasonably good.

Mean absolute error is another factor to measure the models performance. The MLP model has MAE of 8.8, 31 and 43.3 at training, cross validation and testing sets respectively.

Note that MAE factor alone is not enough because its value can easily be misleading.

For example, say that output data is in the range of 0 to 10. For one exemplar, the desired output is one and the actual output is two. Even though the two values are quite close and the MAE for this exemplar is one but the mean absolute percentage error is 100. Therefore, this research used the MAPE. The values of the MAPE for the MLP model were 3.5, 9.6 and 7.8 at training, cross validation and testing sets respectively.

The accuracy of the best model developed by multilayer perceptron sounds very favorably with data based from the test set. It can be seen from the results that the model performs well and no significant difference could be discerned between the estimated output and the desired budget value. Results of training, cross validation and test set are shown in Figure 5, Figure 6 and Figure 7 respectively.

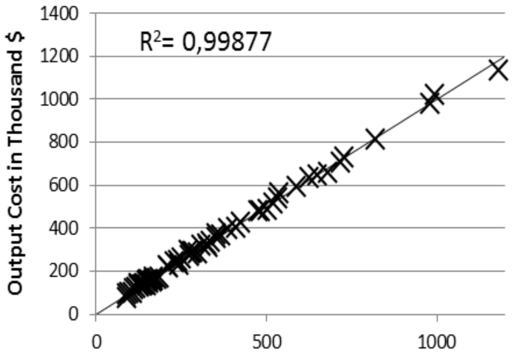


Figure 5: Desired output and actual network output for training set exemplar.

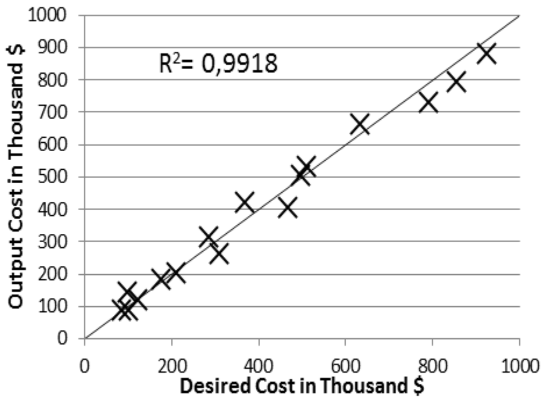


Figure 6: Desired output and actual network output for cross validation set exemplar.

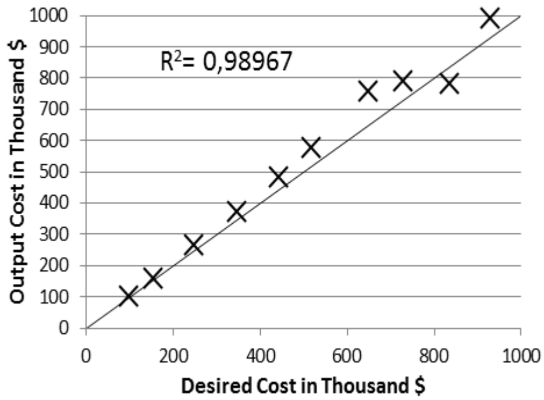


Figure 7: Desired output and actual network output for test set exemplar.

An average accuracy of 93.7% was achieved, this means that the total MAPE equals 6.3%. The previous results show that MLP model has excellent performance with minor error.

As shown in Figure 5, Figure 6 and Figure 7 perfect agreement between the actual and predicted values draws a 45-degree line; this line means that the actual cost values equal the predicted ones. Figure 5, Figure 6 and Figure 7 indicate reasonable concentration of the predicted values around the 45-degree line. The coefficient of determination between the actual and the predicted cost values were 0.998, 0.992 and 0.99 for training, cross validation and test set respectively.

VIII. Sensitivity Analysis

Sensitivity analysis is the method that discovers the cause and effect relationship between input and output variables of the network [13].

The NeuroSolution program provides a useful tool to identify sensitive input variables called ‘‘Sensitivity about the Mean’’. The sensitivity analysis was run by batch testing on the MLP model after fixing the best weights then started by varying the first input between the mean ± one standard deviation, while all other inputs are fixed at their respective means. The network output was computed for 50 steps above and below the mean. This process was then repeated for each input. Figure8, summarizes the variation of output with respect to the variation of each input generated.

As shown in Figure 8, the pavement area parameter has the value 56.6 that is the greatest effect on the budget output. The second parameter affecting the total budget is pavement type, which has 41.15.

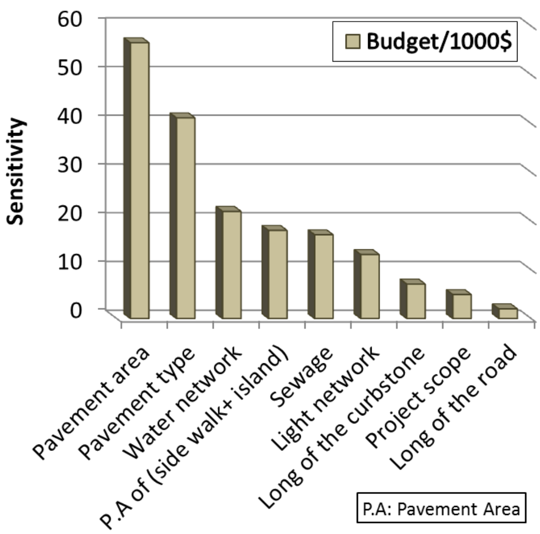


Figure 8: sensitivity output

These results are logical when compared to actual practice. On the other hand, project scope has a weak impact; likewise, road length has the weakest impact, which may be due to the presence of the pavement area parameter.

IX. Conclusion

This research was achieved the ability to estimate the road projects cost at early stage with high accuracy and minor error. MLP model had error rate equal 6.3% and MAPE 3.49 %, 9.59% and 7.8% for training, cross validation and test sets respectively. In addition, the value of correlation coefficient does not less than 0.989 for any set.

This research focused on the "implementation factors" that affected the budget of road projects in the Gaza Strip. The research adopted nine factors, which are determined by using Delphi technique. The remarkable, that the sensitivity analysis results were very logical and showed the impact of each parameter on the cost. Which the pavement area parameter had the greatest effect on the budget output. Nevertheless, project scope and road length had low impact.

ANN are well suited to model complex problems where the relationship between the model variables is unknown. Also, ANN does not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANN has compared with most empirical and statistical methods. Although the ANNs have advantages, on the other hand there are disadvantages. The principal disadvantage being that they give results without being able to explain how they were arrived to their solutions. Their accuracy depends on the quality of the trained data and the ability of the developer to choose truly representative sample inputs. In addition to trial and error method is the best solution to obtain the formula to decide what architecture of ANN should be used to solve the given problem and which training algorithm to use. One looking at a problem and decide to start with simple networks or going on to complex ones to get the optimum solution is within the acceptable limits of error.

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