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ARTIFICIAL NEURAL NETWORKS AS AN EFFECTIVE PROJECT MANAGEMENT TOOL

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ABSTRACT

Effective project management is crucial to the success of any project. In the past, several projects have failed, not for want of competent technical professionals, neither for the lack of resources but due to the faulty project management practices. Scheduling the projects and hence predicting the duration of the project is a critical project management activity to ensure successful completion of the project. This paper proposes an artificial neural network model for predicting the time duration of the project. Important factors that affect the project duration have been selected from the literature after an extensive study. The proposed neural network model has been tested using several cases. The ratio of the actual duration to the project planned duration has been calculated in each case. The results have been compared with the other project planning techniques. The variance of the proposed neural network model has been found to be the least, which makes it the most effective and reliable tool for predicting the project duration.

***Keywords*: *Artificial Neural Network, Back-propagation, Project delay, Project duration, Project planning*.**

I. INTRODUCTION

The importance of planning was specified in general as follows: First, to offset uncertainty and change; Second, to focus attention on objectives; Third, to gain economical operation; Fourth, to facilitate control. It also has an important role in cash flow prediction and resources management. One of the major functions of time schedule is the prediction of the expected project completion time. The reliability of such prediction is greatly affected by many uncertain but predictable factors. So, certain time changes are required in the scheduled completion time to arrive at a more reliable prediction for that time. An accurate estimation of project duration is seen as a major factor for achieving a successful construction projects.

Project management that we know today, started with the development of the first methods of network planning, at the beginning of 1960s. The appearance of personal computer and the project management software further improved the field of project management, and the corresponding methods and techniques expanded even more. Starting from 1990s, the concept of project management is getting the forms that are being widely used and introduced as project realisation practice. One of the reasons for the development of project management concept and its increasing application is connected with the changes that happened in the preceding period. The enterprises started to introduce and adjust the management concept, as their way of carrying out the changes and improving the business process as a whole. Today, the projects are seen as the means of carrying out the organisation's strategy. If the planned realisation time and costs cannot be obtained, then the goal is to minimize the time and costs overruns. Investment projects contain the following characteristics: they are long-lasting, there is a large number of participants, numerous resources are involved, a great deal of financial resources are used, they are very complex, there exists the realisation duration, the application of standard software is necessary, as well as monitoring and control of the realisation for a long time, etc. A neural networks model has been presented in the paper in order to help project planner to have a more reliable prediction for the actual duration of project from planned duration

II. ARTIFICIAL NEURAL NETWORKS

In a broad sense, the artificial neural network (ANN) itself is a model because the topology and transfer functions of the nodes are usually formulated to match the current problem. Many network architectures have been developed for various applications. The performance of a neural network depends on its architecture and their parameter settings. There are many parameters governing the architecture of the neural network including the number of layers, the number of nodes in each layer, and the transfer function in each node, learning algorithm parameters and the weights which determine the connectivity between nodes. There is no clearly defined theory which allows for the calculation of the ideal parameter settings and as a rule even slight parameter changes can cause major variations in the behavior of almost all networks. So far, the technique in the use of the neural network for predicting software cost estimation is back propagation trained multilayered feed forward networks with sigmoidal activation function. But, there are some limitations that prevent it from being accepted as common practice in cost estimationThe main reason for slow convergence in back propagation is the sigmoid activation function used in its hidden and output layer units. Furthermore, inappropriate selection of network patterns and learning rules may cause serious difficulties in network performance and training. The problem at hand decides the number of layers and number of nodes in the layers and the learning algorithm as well. However, the guiding criterion is to select the minimum nodes which would not impair the network performance so that memory demand for storing the weights can be kept minimal. So, the number of layers and nodes should be minimized to amplify the performance. A proper selection of tuning parameters such as momentum factor, learning coefficient are required for efficient learning and designing of stable network.

III. LITERATURE SURVEY

Garza and Rouhana [2] compared the results of Neural Networks with those of regression models for predicting the material cost of carbon steel pipes. Ten sets of cost data were used to train the Neural Networks and six sets were used in testing. The 6 sets were estimated using three methods (linear regression, non-linear regression and Neural Networks). The mean square error was calculated for each model. It was found that Neural Networks produced the lowest mean square error when compared with the other two models. The accuracy level was between 66.8% and 77.96%. This study proves that the Neural Networks approach must be used to resolve some of the major drawbacks of the regression-based pararnetric estimation. A similar study was conducted by Creese and Li [1]. In this study. Three models were developed to estimate the cost of timber bridges. A set of actual cases of 12 timber bridges was collected from West Virginia department of highways. Three variables were used as the main factors affecting the total cost: cost of the web. cost of the deck. and weight of the steel used. The study experimented with three Neural Network models to identify the optimum one. The three models consider

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either one input variable, two input variables, or three input variables, respectively, to predict the total cost. It was observed that the overall training accuracy increased as more input variables were used and as such. The model with three input variables was the best. The initial training of the Neural Networks used al1 available bridges' data and 1.500 training cycles were used. The standard linear regression approach was used to predict the actual cost for the three models using the same variables and r-square values (coefficient of detemination) were calculated to evaluate the three models. The study also compared the Neural Networks approach to linear regression analysis and concluded that the estimation accuracy of Neural Networks approach is better than linear regression analysis in timber bridges' types. Another important conclusion of the study is that the cost prediction ability of Neural Networks to improves when more independent variables are introduced. in training. Williams [6] developed two Back-propagation Neural Network models to predict change in ENR construction cost index for one month and six months ahead. The models used many different factors such as the prime lending rate and the month of the year) as input variables. A training set of 215 cases and a test set of 63 cases were used for the one-month model while a training set of 207 cases and test set of 66 cases were used for the six-month model.. When comparing the predicted results from the Neural Network models with those predicted from the other two models, it was found that the Neural Networks produced close but poorer predictions of changes in construction cost indexes. These poor predictions were attributed to the extrapolation, rather than estimation, nature of the application. Another study was conducted by Mckim [4]. The results were compared to other industrial methods commonly used in practice for predicting pumps' cost. These methods were: 1) 0.6 exponent scaling method, 2) Best-fit exponent scaling method. and 3) Empirical best-fit equation method. The standard deviation error and the coefficient of determination were calculated for each method. Similar to the previous study by Greece, it was concluded that the Neural Networks method provides a more accurate estimate than the other regression methods. Moselhi et al. applied “Fuzzy logic” to forecast potential cost overruns and schedule delays on the construction project [7]. The results of the methods are useful to assess the project status at certain times and to evaluate the benchmarks depicting profit efficiency of the project. This helps the project staff to complete the project by the time limit. Furthermore the data are crucial for managing cost and time of highway construction. The earned value method is currently used as a tool to evaluate the project status in terms of schedule and cost variances compared with planned value which is normally based on a deterministic method like CPM [8]. CPM scheduling in general creates an unrealistic expectation regarding project schedule performance [9]. In addition, the earned value method generally assumes either that the performance efficiency achieved up to the reporting date remains unchanged throughout the rest of the project, or that the performance will be as planned beyond the reporting date [7]. William R. identified the project factors which influence highway construction duration early in the design development [10]. His work quantified the relationship between the duration-influential factors and highway construction duration using statistically significant relationship and developed a regression model for highway projects. Pewdum et. al developed an artificial neural network to forecast the final budget and duration of highway construction projects in Thailand using data for 51 highway construction projects between 2002 and 2007 [11]. They found that the developed ANN model (with a mean absolute percentage error of 8.51%) forecasts the duration for highway projects better than the current earned value method (with a mean absolute percentage error of 19.90%). Duration overrun is problematic in the construction industry and has generated much concern [12]. Petruseva et. al used the linear regression and artificial neural network to develop models for the prediction of duration of building projects in Bosnia and Herzegovina using data for 75 building projects with good predictive ability (Coefficient of determination, R2 = 0.97) and mean absolute percentage error of 2.5% [13]. Mensah et. al developed both regression and artificial neural network (ANN) for small span bridges. They indicated that the developed ANN model is superior to estimating the duration of bridge projects as compared to the regression model [14]. Jin et. al developed a case based reasoning (CBR) model for estimating the duration of building projects using 83 multi housing projects [15]. Their test results confirmed the strong potential of the applicability of the CBR model with minimum information at the preliminary stage.

IV. DATA COLLECTION

This research aims to identify the main factors which affect projects time of construction projects in India. Identifying these factors can help to accurately assess the planned project duration. Eighty four factors were identified to affect the project duration of construction projects through extensive literature survey. These factors are listed below:

A. Project Conditions

1 Project Location
2 Project Design complexity
3 Equipments shortage [Construction technology]
4 Material shortage [Market]
5 Project location [Near from governmental Buildings[i.e. embassies, ministries, .etc]
6 Preparing the plan during project preliminary Stages [i.e. Initiation, Tender phase]
7 Limited time allowed for preparation of the schedule
8 Missing Project Scope Items [conflicts between project documents].
9 High Level of Quality requirements
10 Lack of Experience in similar projects.
11 Lack of Consultant Experience
12 Unexpected onerous requirements by client’s supervisors

B. Management Conditions: Contractual

13 Great Scope Changes [i.e. change scope from core & shell to complete finishing]
14 Contract Risks [Force Majeure]
15 Change orders
16 Deficiencies, errors, contradictions, ambiguities in contract documents
17 Inadequacy of detailed drawings
18 Contract type: Lump sum
19 Contract type: Re-measured
20 Context of Contract
21 Inadequacy of dispute settlement procedures

C. Management Conditions: Time

22 Payments [Delays]
23 Risks related to Governmental Authority Constraints which limit the project completion date

24 Imposed Holidays

25 Inaccurate planning by any party

26 Inaccurate control & follow up

27 Workload on the contractor resources

28 Client delays commencement date.

29 Client suspend works

30 Late project changes

31 Long time to make or take a decision

32 Delays in resolving litigation/ arbitration disputes

33 High Percentage of critical activities in the baseline

D. General

34 Amount of interference [lack of knowledge or experience in any party]

35 Inadequate supply, quality, timing of information and drawing by designer

36 Unfavorable interference in work sequence

37 Unexpected inadequacy of pre-construction site investigation data

38 Poor dispute resolution mechanism

E. Environmental Conditions:

39 Bad Weather conditions

43 Unknown geological conditions

40 Labor strike

44 Labor restrictions

F. Economical Conditions:

45 Economical stability [Unexpected conditions such as Economic Crises]

46 Material Market rates [Escalation, Inflation or fluctuation]

47 Design changes due to Market Demand [i.e. town houses instead of large villas]

G. Country Conditions:

48 Administration [Bureaucratic delays, Attitude towards foreign investment etc.]

49 Laws and regulations [e.g. Import and export regulations]

50 Unavailability & Bad Quality of Resources

51 Changes in regulations and law

52 Fraudulent and kickbacks in laws

53 Political instability

54 Influence of power groups [i.e. environmental laws]

H. Factors related to Contractor:

55 Shortage of experienced staff and labors

56 Contractor start delay [i.e. project starting or concrete pouring milestones…etc]

57 Contractor poor performance

58 Efficiency of planning by contractor

59 Bad Relationship between top management and site staff

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60 Bad Relationship between site management and laborers

61 Bad relationship between Contractor's representative and Client representatives

62 Inadequate control over subcontractors

63 Bad co-ordination between laborers

64 Poor productivity of equipments

65 Fire

66 Theft

67 Contractually defined "expected risks"

68 Unforeseen events [i.e. Great Accidents…etc]

69 Inadequate tender pricing

70 More than estimated waste of materials in site

71 Poor productivity of laborers

72 Disputes on site between laborers

73 Poor performance of claim engineer

74 Lack of coordination between Engineer and Contractors

75 Contractor financial difficulties

I. Factors related to Subcontractor:

76 Uncertainties related to subcontractor's technical qualifications

77 Uncertainties related to subcontractor's financial stability

78 Uncertainties related to subcontractor's quality of material and equipment

79 Extra duration due to variability of subcontractors' bid

J. Factors related to Planner:

80 Clerical errors

81 Planner's biases in technical issues

82 Wrong method of estimating

83 Planner's lack experience

84 Planner's personality traits

5. The most important factors

Through a questionnaire to the construction managers of fifty different construction projects, the factors that have maximum affect on project duration were identified. These important factors are listed below:

1. Change orders
2. Payments [Delays]
3. Long time to make or take a decision
4. High Percentage of critical activities in the baseline
5. Late project changes
6. Missing Project Scope Items due to conflicts between project documents.
7. Workload on the contractor resources
8. Inaccurate control & follow up
9. Unexpected onerous requirements by client’s supervisors

10. Efficiency of planning by contractor
11. Inadequate supply, quality, timing of information and drawing by designer

Further, through a questionnaire, the construction managers were asked to assign a score from 1 to 10 to the identified factors found to have maximum effect on project duration. A score of ten is assigned to the factor found to have maximum effect on the project duration and score of one indicates minimal effect of the corresponding factor on project duration. The data obtained is shown in the table below:

Table no. 1: Variation of Ratio of Actual duration to Project planned duration (K) with important factors discussed in section

Case No.	Important Factors											Ratio of Actual duration to Project planned duration (K)
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	
1	6	9	1	5	3	2	9	6	3	3	6	1.11
2	3	1	1	6	4	7	9	6	4	3	9	1.14
3	1	0	3	3	2	2	2	3	4	5	5	1.29
4	6	6	2	5	4	6	6	9	3	5	5	1.05
5	1	9	4	4	0	2	4	2	9	1	9	1.27
6	6	0	2	9	7	1	7	10	7	2	6	1.03
7	4	5	7	2	3	0	6	1	9	5	0	1.28
8	10	1	9	6	1	9	4	3	3	3	7	1.05
9	9	1	0	4	8	3	1	0	2	9	4	1.28
10	7	1	9	1	7	5	6	3	5	1	9	1.1
11	8	8	0	8	4	8	10	3	2	7	0	1.01
12	2	2	8	5	5	1	9	4	8	8	2	1.1
13	7	6	9	2	3	6	2	3	5	1	1	1.27

14	3	3	8	9	2	4	5	0	8	3	3	1.23
15	10	10	4	2	7	1	6	5	5	5	6	0.89
16	3	3	3	1	4	4	7	0	5	0	8	1.28
17	3	2	3	8	8	2	1	4	5	5	9	1.19
18	5	1	4	8	4	6	1	10	7	7	7	0.99
19	9	0	1	1	6	7	1	8	7	9	4	1.12
20	2	5	3	7	9	5	2	2	9	6	4	1.11
21	2	4	7	2	7	4	8	8	5	0	2	1.22
22	4	7	2	8	6	9	1	1	6	5	1	1.18
23	4	7	8	6	5	6	6	5	2	9	2	1
24	4	8	7	0	8	6	9	1	4	1	8	1.08
25	9	4	10	3	10	9	7	0	5	9	3	0.85
26	9	5	3	6	7	9	8	6	5	6	8	0.81
27	6	1	2	9	9	2	4	1	3	10	9	1.06
28	5	9	4	4	1	7	4	10	1	2	3	1.19
29	2	4	2	3	8	10	4	4	8	7	8	0.99
30	0	3	9	9	0	4	9	3	9	1	0	1.24
31	1	1	2	5	4	5	3	4	3	5	5	1.28
32	2	2	7	7	3	8	10	4	10	3	9	0.87
33	9	5	5	9	9	6	1	1	4	10	4	0.88

34	6	8	8	6	5	7	1	7	10	6	7	0.85
35	4	5	10	0	2	2	4	8	4	2	7	1.23
36	9	6	9	0	5	6	8	4	4	7	2	0.96
37	9	5	1	2	10	9	1	0	1	4	3	1.26
38	8	5	1	4	7	3	6	9	5	9	8	0.87
39	10	8	3	4	4	8	3	5	6	9	3	0.87
40	6	7	8	6	3	7	3	0	2	8	6	1.05
41	4	7	9	1	8	9	1	4	4	4	10	0.9
42	2	4	5	8	5	6	0	10	5	6	4	1.09
43	2	3	1	4	6	5	6	9	8	0	7	1.16
44	2	5	1	5	0	10	1	1	0	2	2	1.3
45	6	2	8	3	7	8	7	8	0	4	7	0.97
46	5	8	4	2	7	8	9	1	8	1	5	1.02
47	4	2	8	3	9	8	10	1	7	0	9	0.94
48	2	6	5	6	2	6	2	1	7	10	2	1.2
49	5	7	5	10	6	1	4	6	8	2	1	1.08
50	2	1	6	2	6	8	6	8	2	3	1	1.26

VI. MODEL DEVELOPMENT

In this paper, Artificial Neural Networks were used as a modeling tool that can enhance current automation efforts in the construction industry. Many applications were previously prepared using artificial neural networks such as Markup estimation, Estimating Resource Requirements at Conceptual Design Stage and many other applications. There are two types of neural networks. The first type handles classification problems [e.g., into which category of customers targeted by a company does an individual fall]. The second type handles prediction problems [e.g., if certain conditions exist, will a child protective service worker stay or leave his or her job?]. The structure of a neural network model includes an input layer that receive input from the outside world, hidden layers that serve the purpose of creating an internal representation of the problem, and an output layer, or the solution of the problem. All trial models experimented in this research were trained in supervised mode by a back propagation learning algorithm. The rating of the factors was taken as the input while the ratio of actual duration and predicted duration was taken as the target values. Inputs were fed to the proposed network model and the outputs were calculated. The differences between the calculated outputs and the actual outputs were then evaluated. The best model is obtained by use of one hidden layer containing 20 neurons. The model architecture is 11-20-1 with minimum root mean square error of 0.9845. The predicted ratio of actual duration to project planned duration is very much close to field observations which can be visualized from Fig no. 1.

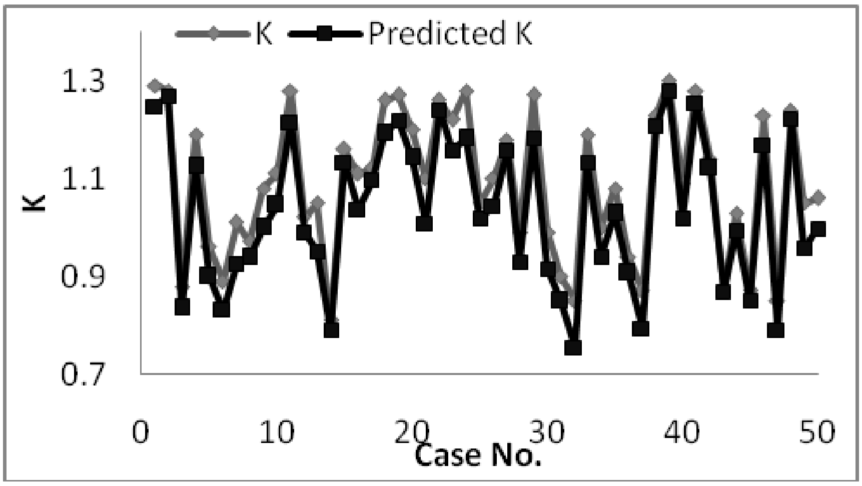

FIG. NO.1: Prediction of ratio of actual duration to project planned duration (k) by ANN

VII. CONCLUSION

Neural networks model was introduced as a management tool that can enhance current automation efforts in the project management. ANN model was prepared in order to predict the duration of any ongoing project in addition to conventional techniques of project planning. A large number of trials were applied for model training. The absolute variance of model's results varies from 1.7% to 2.6% which is less than variance calculated by use of PERT network technique (3.8 to 7.8%) in cases studied. Therefore the model testing is successfully passed and it can be concluded that Artificial Neural Networks are an effective project management tool that can be used to effectively predict the project duration and hence prevent scheduling and project duration overruns.

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