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An artificial neural network model for estimating the influence of change orders on project performance and dispute resolution

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Abstract

Most construction projects today experience changes at different phases due to a number of reasons. Since contract recognition by two parties is diverse, communication between the parties is likely to be destructive even though owners and contractors may gradually realize that the project changes are reasonable. These changes may raise disputes between owners, contractors and subcontractors as change orders can have adverse effects on project performance and are difficult to quantify and manage. Many studies have sought methods to quantify the impact of change orders on project performance, and to resolve construction disputes but only few exist involving Artificial Neural Network (ANN) approaches for dispute resolution. The aim of this paper is to present an ANN Model so that the influence of change orders can be estimated and probable disputes may be avoided or resolved before litigation occurs. For this purpose, various factors that describe the adverse effects of change orders on project performance have been identified from a background research. Based on the survey conducted to the contractors in North Cyprus construction industry, an ANN Model has been developed to manage change orders through all phases of a project such that construction operations can continue with the least amount of interruption that usually results from of disputes between different parties involved in a project.

Keywords: change orders, project performance, dispute resolution, artificial neural networks

1 Introduction

Most construction projects today experience changes at different phases due to a number of reasons. Unplanned for changes in construction projects can cause additional work beyond that expected, resulting in extra cost and time (Chivitello, 1987). Since contract recognition by two parties is diverse, communication between the parties is likely to be harmful even though owners and contractors may gradually realize that the project changes are reasonable. These changes may raise disputes between owners, contractors and subcontractors as change orders can have adverse effects on project performance and are difficult to quantify and manage. Change orders have long been identified to have a negative impact on construction productivity, leading to a decline in labor efficiency and, in some cases, sizeable loss of man hours. Change orders continue to pose serious challenge to owners and contractors alike (Moselhi et al., 2005). Quantifying the impact of change orders on project performance remains to be a challenging task, despite the reported findings of many studies and documented cases (Moselhi et al. 1991; Thomas and Napolitan 1995; Ibbs 1997; Hanna et al. 1999a,b; Moselhi et al., 2005; Ibbs 2005; Yitmen et al. 2006; Ibbs et al. 2007).

The ANN approach is an information processing technology based on simulating the human brain and nervous system. It is usually applied to establish forecast models (Arditi et al., 1999). Among the algorithms fitting the approach, the Back-propagation (BP) algorithm serves as the most representative and practical, being an efficient approach for training multiple-layer artificial networks derived from the supervised learning concept. The input layer receives inputs in relation to question-inquiring from the outside. The hidden layer(s) calculate interactions among the neurons where the optimal numbers of neurons and layers are configured as a result of trial-and-error. The output layer produces the outcomes that are the solution of the initial question-inquiring (Chen and Hsu, 2007). Arditi and Tokdemir (1998) use the ANN and CBR approaches respectively to predict the outcomes of disputed construction project litigation in Illinois. Cheung et al. (2000) presents an artificial neural network to classify projects in accordance with their project dispute resolution satisfaction (DRS). Chau (2007) presents a particle swarm optimization (PSO)-based neural network to train perceptrons in predicting the outcomes of construction claims in Hong Kong. Chen and Hsu (2007) provide a method that can be used to solve potential lawsuit problems caused by change orders in construction projects.

Many studies have sought methods to quantify the impact of change orders on project performance, and to resolve construction disputes before litigation occurs but only few exist involving ANN approaches for dispute resolution. The aim of this paper is to present an ANN Model so that the influence of change orders can be estimated and probable disputes may be avoided or resolved before litigation occurs.

2 Data for model development

The field investigation was conducted for data collection. 35 projects, referred to here as cases, extracted from projects constructed in North Cyprus between 2003 and 2008, were analyzed and used in the developments made in this study. Only 35 work packages, extracted from the 57 projects, were found to have sufficient data that can be used for the intended developments. Of these work packages, 29 were building construction, and 6 infrastructure construction, respectively. These work packages, have an original total value of more than $90 million.

Based on the field investigation conducted and a comprehensive literature review, 11 change order factors were found to have influences on project performance. The development of the model depends very much on the data available. A data analysis has revealed the main input factors to be used in the modeling and training of the network. These factors were the predominant influence drivers of the case examples. They described the adverse effects of change orders on project performance. The change orders factors, their rank and rate of influence on project performance are shown in Table 1.

Table 1. Change Order Factors

Influence Items	Type of Change Orders	Rank	% of Influence
x_1	Process change/Functional Change	4	13
x_2	Added/Deleted Scope of Work	3	15
x_3	Safety Change	9	3
x_4	Environmental Change	11	1
x_5	Regulatory/Permit Change	8	5
x_6	Purchase Order	6	9
x_7	Aesthetic Change	7	7
x_8	Productivity Change	5	11
x_9	Schedule Change	2	16
x_{10}	Cost Change	1	18
x_{11}	Force Majeure	10	2

3 Development of the Back-Propagation ANN Model

We have used the error back-propagation learning algorithm which is a type of supervised learning to solve our problem. This algorithm has been shown to be theoretically sound and performs well in modeling nonlinear functions, and is simple to program. In our work, Matlab 7.5 Neural Network Toolbox has been used in all simulation. A neural network model was developed to manage change orders through all phases of a project such that construction operations can continue with the least amount of interruption that usually results from disputes between different parties involved in a project. For this purpose, various factors that describe the adverse effects of change orders on project performance have been identified from a background research. These factors have been designated as X_1 through X_{11} in this work. The NN model was developed in three phases: the modelling phase, the training phase, and the testing phase.

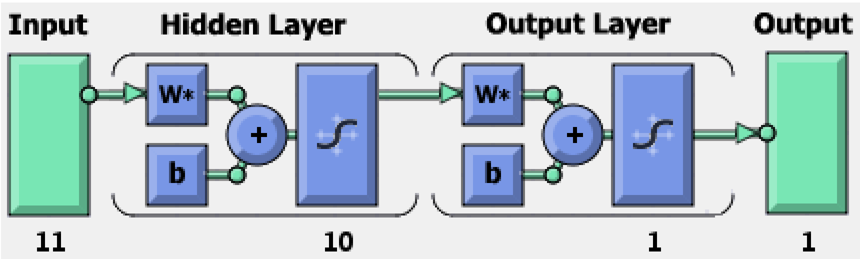

Figure 1. Structure of the multi-layer ANN Model

The NN model includes an input layer of eleven processing elements (neurons) corresponding to the eleven input factors, a hidden layer of 10 neurons and an output layer of a single neuron, the output of which will determine the probability of a dispute. The function of the hidden layer is to extract and store the useful features and the sub features from the input patterns to predict the outcome of the network. Therefore, an effective number of processing elements is usually determined by trials for the hidden layers, since there is no rule to determine it. The 11-key factors (i.e., type of change orders) for the input layer were selected from the analysis of experimental data to evaluate the output data (i.e probability of dispute).

The records of thirty five cases collected from twenty building contractors in North Cyprus construction industry contain data on all of the selected eleven change orders factors and the corresponding influences on project performance. The training algorithm or the training pattern set (input-output pairs) can be modified if the performance of the model does not meet the expectations. Adding new data to the training samples and retraining the network may enhance the performance of NN. Data are generally normalized to fit into the neural network model. In this work, the input and output values are normalized for training and testing purposes. Input parameters x_1 through x_{11} were normalized by dividing by the maximum value in the corresponding column. The probability of dispute was normalized by dividing by the maximum probability value. Since neuron outputs are confined to the interval [0,1], all externally provided values for training purposes must also fall in the same interval.

Table 2 represents the probability of dispute based on the changes (in percent) in parameters of different factors. The probabilities calculated in Table 2 are the product of the weight of each factor by the probability of the occurrence of that factor. Table 2 has been used to train the neural network using back propagation algorithm. The factors X_1 to X_{11} are the inputs and probability of dispute is the desired output used in teaching the neural network.

The neural network structure is as follows. First, we store the argument values x_1 to x_{11} in an input vector such that $\mathbf{x} \in \mathbb{R}^{11\times1}$ will represent 11 inputs. The inputs are fed into the 10-neuron hidden layer through an input weight matrix $\boldsymbol{W}_h \in \mathbb{R}^{10\times11}$. To complete the structure of NN at this stage, a bias vector $\boldsymbol{b}_h \in \mathbb{R}^{10\times1}$ is also fed into the 10-neuron hidden layer. The total input $\boldsymbol{v} \in \mathbb{R}^{10\times1}$ of the hidden layer before the activation function, then, is the algebraic sum of W_hx and b

$$\boldsymbol{v} = \boldsymbol{W}_h \mathbf{x} + \boldsymbol{b}_h \tag{1}$$

The neurons at the hidden layer produce an output $y \in \mathbb{R}^{10\times1}$ based on the value of v using the sigmoid function

$$\boldsymbol{y} = \frac{1}{1+e^{-av}} \tag{2}$$

Where the constant a can be generalized to unity.

Table 2. Probability of Dispute based on the changes (%) in parameters of different factors.

Case No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	Probability of Dispute %
1	10	4	1	6	7	23	16	21	19	24	5	15.72
2	9	5	2	4	6	22	14	20	20	25	3	15.45
3	7	3	0	6	4	25	13	22	18	22	2	13.71
4	8	5	1	5	4	22	15	20	22	23	2	14.12
5	7	4	1	4	5	23	16	21	21	22	1	14.16
6	8	4	2	5	6	23	15	22	19	24	3	15.58
7	9	4	1	4	5	24	13	20	20	25	3	14.49
8	8	5	2	6	4	23	14	21	22	23	2	14.87
9	7	5	1	4	5	22	15	20	19	24	3	14.30
10	8	3	2	5	4	23	16	22	21	22	2	15.33
11	9	4	2	6	5	24	14	21	22	23	2	15.34
12	9	5	3	6	4	23	15	21	20	24	1	14.74
13	7	4	2	5	4	22	14	20	21	22	3	14.98
14	7	3	1	4	5	23	13	21	22	22	1	13.95
15	8	3	2	5	4	22	16	20	21	23	2	15.12
16	10	3	2	4	5	24	15	22	22	24	1	15.47
17	7	5	3	4	6	22	14	21	19	22	2	15.13
18	8	4	3	5	5	23	15	21	20	23	2	15.33
19	9	3	2	4	6	24	13	20	22	22	2	14.96
20	7	4	1	5	4	23	15	22	20	24	1	14.29
21	8	5	2	4	3	22	16	20	21	23	2	14.67
22	9	3	2	5	4	22	15	19	18	22	1	14.32
23	7	4	3	4	5	23	14	20	22	24	2	15.50
24	9	4	2	4	5	24	15	21	21	23	2	15.34
25	7	4	2	4	4	23	13	20	19	22	3	14.51
26	8	3	2	5	3	22	15	21	18	23	2	14.75
27	7	4	1	4	4	22	16	22	22	23	3	14.80
28	8	5	2	5	3	23	14	20	21	23	2	14.57
29	9	4	2	3	4	22	14	21	22	24	2	14.93
30	7	3	2	4	3	22	15	20	19	22	2	14.39
31	8	3	3	5	4	21	14	22	22	24	1	15.04
32	8	4	2	4	3	24	14	21	21	22	2	14.81
33	9	4	1	5	4	22	15	22	92	83	2	14.69
34	8	5	3	4	3	22	14	20	22	24	2	15.00
35	7	4	3	4	5	24	14	22	21	23	1	12.04

The hidden layer will produce 10 outputs that are multiplied by the output weight matrix $\boldsymbol{W}_o \in \Re^{1\times10}$ and is added to the bias vector $b_o \in \Re^{1\times1}$ and is then fed into the activation function of the output layer. After the feed-forward stage, error is calculated during training stage and is fed back to update the weights. One hundred thousand epochs at a learning rate of $\eta = 0.6$ and *gradient descent with momentum* algorithm are used to train the neural network. Note that at the first 1000 epoch, error drops from 0.1 to 4×10^{-4}. To avoid oscillation in weight values, we make the change in weights dependent of the past weight change by adding a momentum term, which we have chosen to be 0.9 here. The training was carried out for 100,000 epochs; each epoch contained 60 items that consisted of 11 to 1 data pairs each. The training resulted in an error value of $2.65\text{x}10^{-5}$. This error value indicates the average difference between desired value (used in teaching) and actual NN output. Performance (how close is the actual network output to the desired probability value used in teaching) curve is shown in Fig.2. The Correlation between desired and actual network output for 60 elements is shown in Figs. 3-4.

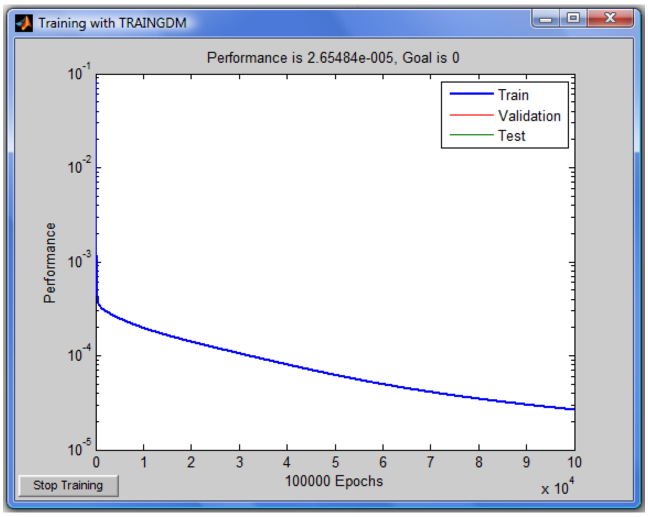

Figure 2. Performance of back-propagation NN versus number of epochs.

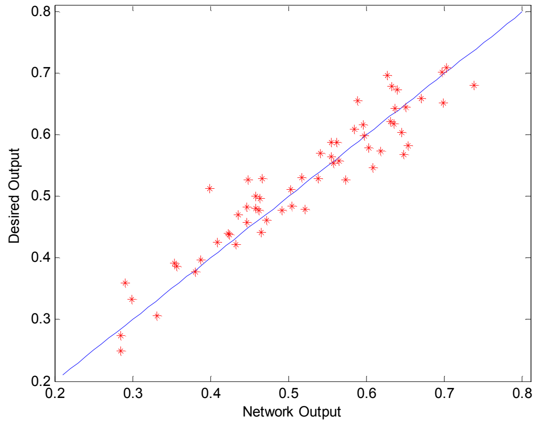

Figure 3. In ideal learning (almost never realizable in practice) all values would be exactly on the diagonal line

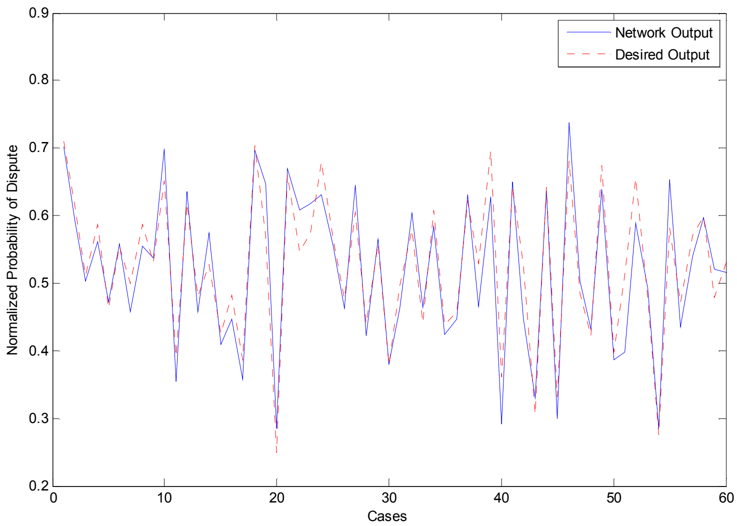

Figure 4. Desired Response and Actual Probability Dispute Values after training

The concept of desired response and actual network output is made clear in Figure 4. Values plotted indicated desired values and actual NN output values after training is completed.

As a final word, it must be stated that number of neurons in the hidden layer should be maintained at a reasonable level such that all input-output relationship properties are stored in the network. Number of input elements and output elements will depend on the type of problem to be solved. It is the flexibility of NN models towards accepting general number of inputs and outputs that makes it an attractive tool in solving engineering problems.

4 Limitations and future research directions

The developed ANN Model does not consider the impact of the different management approach and the project owner-contractor relationship. In this paper the adverse effects of change orders on project performance were identified and probability of dispute was estimated. Future research would involve considering options for effective dispute avoidance and management. For this purpose, firstly innovative dispute resolution processes generally described as alternative dispute resolution (ADR) techniques should be identified concerning the different mechanisms which most effectively fit together to form an entire dispute resolution procedure. Then the application of an ANN approach for selection of the appropriate ADR technique could be cost effective. Furthermore the factors affecting the outcome of construction dispute resolution processes can be determined through a case-based reasoning approach.

5 Conclusions

The development of an ANN model for estimating the influence of change orders on project performance and dispute resolution has been presented in this paper. The model consists of two main components i.e. identifying the adverse effects of change orders on project performance and probability of dispute. The model has been developed in three main phases. An input sample of 11 parameters has been considered and the corresponding probability of dispute has been used for teaching the NN using back-propagation algorithm. Sixty cases (11 input 1 output pairs) were used to for training purposes. The training resulted in a satisfactory error value. Based on the results, proposed ANN model has been shown to be an efficient approach to find the probability of dispute with respect to the mentioned parameters.

References

ARDITI, D., OKSAY, F.E. and TOKDEMIR, O.B., 1998. Predicting the outcome of construction litigation using neural networks, *Computer-Aided Civil and Infrastructure Engineering* 13 (2), 75–81.

ARDITI, D, AND TOKDEMIR, O.B., 1999. Predicting the outcome of construction litigation using Case Based Reasoning, *Computer-Aided Civil and Infrastructure Engineering* 14 (6), 385–393.

CHAU, K.W., 1992. Resolving construction disputes by mediation: Hong Kong experience, *Journal of Management in Civil Engineering*, 4, 384–393.

CHAU, K.W. 2007. Application of a PSO-based neural network in analysis of outcomes of construction claims, *Automation in Construction,* 16 (5), 642-646.

CHEN, J.H., and HSU, S.C., 2007. Hybrid ANN-CBR model for disputed change orders in construction projects, *Automation in Construction* 17, 56–64.

CHEUNG, S.O., TAM, C..M., and HARRIS. F.C., 2000. Project Dispute Resolution Satisfaction Classification Through Neural Network, *Journal of Management in Engineering*, 16(1), 70-79.

CIVITELLO A.M., 1987. *Contractor's Guide to Change Orders, Englewood Cliffs*: Prentice–Hall, Inc.

HANNA, A., RUSSEL, J., GOTZION, T., and NORDHEIM, E., 1999a. Impact of change orders on labor efficiency for mechanical construction. *J. Constr. Eng. Manage.,* 125~3!, 176–184.

HANNA, A., RUSSEL, J., NORDHEIM, E., and BRUGGINK, M., 1999b. Impact of change orders on labor efficiency for electrical construction. *J. Constr. Eng. Management.*, 125~4!, 224–232.

IBBS, C. 1997. Quantitative impacts of project change: Size issues. *J. Constr. Eng. Managment.,* 123(3), 308–311.

IBBS, W. 2005. *Impact of Change's Timing on Labor Productivity,* ASCE JCEM Nov. 2005, p 1219-1223.

IBBS, W., NGUYEN, L.D., LEE, S. 2007. Quantified Impacts of Project Change, *Journal of Professional Issues in Engineering Education and Practice,* ASCE January 2007, p. 45-52.

MOSELHI, O., ASSEM, I., and EL-RAYES, K., 2005. Change Orders Impact on Labor Productivity, *Journal of Construction Engineering and Management, 1*31(3), 354-359.

MOSELHI, O., CHARLES, L. and FAZIO, P. 1991. Impact of change orders on construction productivity. *Can. J. Civ. Eng.,* 18(4), 484–492.

THOMAS, R. and NAPOLITAN, C., 1995. Quantitative effects of construction changes on labor productivity. *J. Constr. Eng. Manage.*, 121(3), 290–296.

YITMEN, I. SEVAY, I TANERI, C and YALÇINER, H., 2006. An Expert System for Quantifying the Impact of Change Orders on Project Performance. *Proceedings of ICCCBE-ICCC-ASCE-DMUCE-CIB-W78-W102 Joint International Conference on Computing and Decision Making in Civil and Building Engineering,* June 14-16, 2006, Montreal, Canada, pp.1605-1613.