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

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Most construction projects today experience changes at different phases due to a number of reasons. Unplanned 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.

Many studies have sought methods to quantify the impact of change orders on project performance (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), but only few exist involving ANN approaches (Arditi et al. 1998; Cheung et al. 2000; Chau 2007; Chen and Hsu 2007) 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.

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. These factors were Process change/Functional Change, Added/Deleted Scope of Work, Safety Change, Environmental Change, Regulatory/Permit Change, Purchase Order, Aesthetic Change, Productivity Change, Schedule Change, Cost Change, Force Majeure.

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. 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 X1 through X11 in this work. The NN model was developed in three phases: the modelling phase, the training phase, and the testing phase.

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. The records of thirty five cases collected from twenty building contractors 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 expectations. Adding new data to the training samples and retraining the network may enhance the performance of NN. In this work, the input and output values are normalized for training and testing purposes. Input parameters \( x_i \) 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 value. The neural network structure is as follows. First, we store the argument values in an input vector. The inputs are fed into the 10-neuron hidden layer through an input weight matrix. To complete the structure of NN at this stage, a bias vector is also fed into the 10-neuron hidden layer. The hidden layer will produce 10 outputs that are multiplied by the output weight matrix and is added to the bias vector 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. 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 2.65x10-5. This error value indicates the average difference between desired value (used in teaching) and actual NN output. The training resulted in a satisfactory error value. Based on the results, proposed ANN model has shown an efficient approach to find the probability of dispute with respect to the mentioned parameters. Future research would consider the impact of the different management approach and the project owner-contractor relationship.

References


