Journal of Engineering and Applied Sciences 11 (5): 1122-1127, 2016
ISSN: 1816-949X

Claim Causing Assessment in Construction Projects in Iran Using Artificial Neural Networks Model: Radial Basis Function (RBF)

[1]Majid Gholhaki, [2]Ali Kheiroddin and [3]Ali Ghorbani
[1]Asistant Professor, Department of Civil Engineering, Semnan University, Semnan, Iran
[2]Professor, Department of Civil Engineering, Semnan University, Semnan, Iran
[3]PhD Student in Construction Management and Engineering, Department of Civil Engineering, Semnan University, Semnan, Iran

Abstract: This study presents the model that uses Radial Basis Function (RBF) from Artificial Neural Networks (ANNs) to predict and decision about claim causes and their responsibility that helps project organizations such as owners and consultants in their construction project decisions to control and minimize claims. The model is composed of twenty ANNs that work based on radial basis function that predict the percent of owner, consultant and contractor in twenty mail claims that occurs in Iran construction projects. The framework is implemented using actual data from civil projects and Literature review, interviews with pertinent experts with filling questionnaire. Different weights were assigned as variables to the different layers of each ANN and the total square error was used as the objective function to be minimized. Data was collected from 138 construction projects in order to train and test the model which predicted relationships between contracting parties. It implements an intelligent input interface which helps project parties in their decisions on the project's for claim causing assessment.

Key words: Claims, artificial neural networks, radial basis function, claim causes, assessment

INTRODUCTION

Construction projects are dynamic, globally competitive and increasingly challenging. According to uniqueness of the projects, claims can be evolved in the same rate as events during the project span, contract span as well as legal relationship between parties. In other words, dealing with changes and unpredictable conditions are inherentparts of managing a construction project. Although, an intelligently formed contract could diminish future claims to some extent, butit cannot entirely remove probability of occurrence of such disagreements. In additions, different participants of projectsmay find a claim as a way to protect their forecasted payback, orat least as a preventive measure.

A claim is an unavoidable consequence of the construction processes. Thus, some gaps and conflicts may exist in the contract that may result in disagreements and disputes regarding the contractual obligations of its parties (Fisk, 2005). As such when any of the parties to a contract feels that his or her rights have not been met by the other party, according to contract conditions; he or she will file a claim against the other party which will probably have an impact on both parties.

Civil projects of Iran are experiencing dissimilar condition. Monopoly of governmental organization and their bureaucratic obstacle to resolve disputes, special cultural, social, economic and political condition of the country and technical complexity and multidisciplinary nature projects are important aspects which necessitate a separate study for its construction environment. Claim and disputes in this atmosphere are common and finding the mail causes of claims and their sources in this research is a main object. The findings could also be applicable to project parties to identifying diagnose the main claim causes.

This study reports a study that aims to investigate the effectiveness of using past performance records to predict future claim. The paper is organized as follows: Firstly, the process of collecting data on claim and dispute information is described. Secondly, the research methodology for investigating the prediction power of the claim information on the civil projects is introduced. Thirdly, the sensitivities of the model for claims of the contractors' are examined.

Literature review: Since, the 1980s, researchers have described that there has been a good potential for applying Artificial Intelligence (AI) tools to claims prediction and analysis (Diekmann and Kruppenbacher, 1984). They recommended conducting further research work to develop claim analysis tools for construction professionals. Somecases of these AI techniques are Case-Based Reasoning (CBR), rule-based expert systems

Corresponding Author: Majid Gholhaki, Asistant Professor, Department of Civil Engineering, Semnan University, Semnan, Iran

and Artificial Neural Networks (ANNs). Case-Based Reasoning (CBR) is an Artificial Intelligence (AI) problem solving paradigm thathas been previously applied to predict claims and resolve litigation cases (Arditi and Tokdemir, 1999; Ashley, 1990; Ashley and Rissland, 1988; Chua *et al*., 2001; Ren *et al*., 2001). It has many advantages such as its ability to propose prompt solutions to problems as well as its excellence in proposing solutions in domains that a decision-maker may have not experienced before. Expert systems are rule-based techniques that have been historically applied in the area of claims management, owing to their capability of representing "factual knowledge" in specific areas of expertise and providing the problem-solving results that "simulates experts' decisions" (Kim and Adams, 1989). Not only have expert systems been capable of processing data but they have also been capable of processing experts' knowledge (Kim and Adams, 1989).

Thus, expert systems offer means of storing and sharing knowledge that allow more people to have access to expertise when no expert is available for consultation (Hosny *et al*., 1994; Elbarkouky and Robinson, 2010). However, expert systems are deficient in a major aspect compared to other artificial intelligence tools as they do not support the self-learning function. Artificial Neural Networks (ANNs) are AI techniques that provide a "self-organizing" and "self-learning" forecasting tool that have been inspired by the structure of the "humanbiological system" (Caudill and Butler, 1990). Artificial neural networks technique can be successfully applied to resolve complex and imprecise information processing problems as one of its hallmarks is its ability to learn from past experiences (Sun and Xu, 2010). Chau (2007) who adopted a Particle Swarm Optimization (PSO) model to train perceptrons in predicting the outcome of construction claims in Hong Kong, concluded that ANN has resolved the modeling problem in a cost effective manner. This technique provides an "adaptive" forecasting method that performs well when the environment or the system being modeled varies with time (Boussabaine, 1996) and it does not require an assumption of a specific data distribution (Elhag and Wang, 2007). The previous characteristics of ANNs suit the dynamic and multifaceted problem of time and cost prediction of construction claims than those of the traditional approaches such as statistical and mathematical models. For example, statistical prediction models including regression analysis may require predicting the relationship between project cost and time in advance using regression functions. This is, sometimes, impossible because the relation between time and cost is non-linear and may vary based on the project situation (Sun and Xu, 2010). Moreover, unlike expert systems, the ANNs technique does not require setting predestined rules between its inputs and outputs. This is an advantage of the ANNs because projects, especially those of global contexts are dynamic and unique in nature whose specific circumstances may vary or develop over time. Finally, ANNs technique has been successfully applied to similar construction prediction problems because it is capable of dealing with numerical input data (Moselhi *et al*., 1991; Gaber *et al*., 1992; Williams, 1994; Chua *et al*., 1997; Hegazy and Ayed, 1998; Emsley *et al*., 2002; Attalla and Hegazy, 2003; Hosny, 2006; Taormina *et al*., 2012).

Although, very studies done in predicting a claim causes but in the scope of recognizing the amount of each party rolling in claim happening no study is done. In this study, ANNs are used to develop a claims' impact prediction from any party (owner, consultant, contractor) and decision awareness framework for construction projects in Iran. The application of this method clarifies the relationship between the input and output parameters of the model.

The effective factors were selected and an appropriate ANN architecture was determined to be able to predict the percentage of shared amount of each party of project to make a claim and develop it. In addition, a statistical analysis of the data was performed to determine main parties that causes claims. Among the various types of ANN, Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) are the most commonly used predictive neural network models. However, previous studies had also identified a number of advantages of RBF over MLP neural networks. First, RBF neural network training is faster, simpler, generates less standard error and requires fewer training samples than the MLP neural network. Second, RBF neural network can model any nonlinear function usinga single hidden layer. This removes tedious trial-and-error procedures in design-decisions about the number of hidden layers. This study employed the RBF neural network to examine the prediction power of claim causes and percentage of three parties to make it.

MATERIALS AND METHODS

The next step of this study is to select a tool to investigate the prediction power of the claim causes.

Input data collection and analysis phase: Iranian construction projects were conducted to determine the input parameters of the Claim Model (CM). Those

Table 1: Data of 138 Iranian construction projects

Contract type	Original value ranges	Increase in cost (%)	Increase in duration (%)
LS (2).U/P (20)	<10M (3). 10-100M (8). >100M (1)	<10% (10) 10-20% (2). 20-100% (8).>100% (2)	<10.00% (6) 10-20% (1).20-100% (12).>100% (3)
U/P	<10M (4). 10-100M (8)	<10% (5) 10-20% (2). 20-100% (3).>100% (2)	<10% (1) 10-20% (2).20-100% (4).>100% (5)
LS (1).U/P (1)	<10M (1). 10-100M (1)	<10% (1) 20-100% (1)	20-100% (1) >100% (1)
LS (2) U/P (3)	<10M (3). 10-100M (2)	<10% (3) 10-20% (2)	<10.00% (2). 20-100% (3)
LS (4). UP (5)	<10M (5). 10-100M (4)	<10% (3) 10-20% (2) 20-100% (4)	10-20% (2). 20-100% (5). >100% (2)
LS	<10M	<10%	<10%
UP	<10M (2). 10-100M (1)	10-20% (3)	10-20% (1). 20-100% (2)

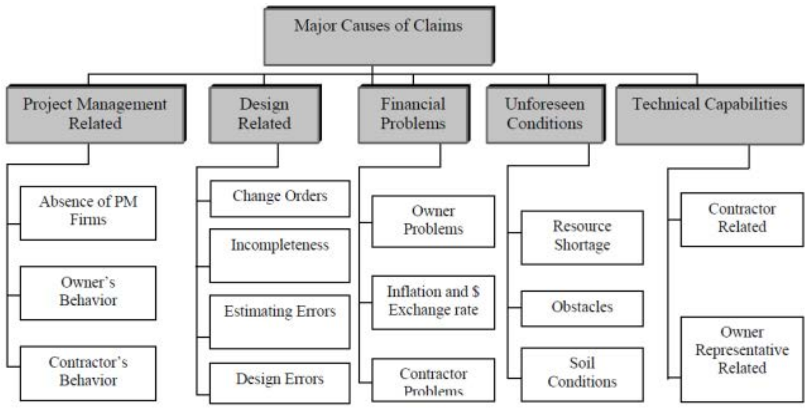

Fig. 1: Major factors of claims

parameters comprised the project decision variables such as: contract type and duration of project and cost of contract and the changes in cost and time such as project.

Several research studies in the area of construction claims were reviewed, particularly those concerned with the analysis of the effect of different project characteristics on the occurrence of claims and those relevant to identifying the sources of construction claims in both developing and developed countries (Diekmann and Girard, 1995; Hosny, 2006; Bramble and Callahan, 2010; Mohamed *et al*., 2011). Then, interviews with construction industry experts who had >15 year of experience in managing construction projects in Iran were conducted to screen the identified variables and determine their possible values.

Finally, 138 civil projects in Iran were analyzed to determine the major claims that caused delays and cost overruns in these projects. Table 1 illustrates the information gathered from these projects such as project category, owner type, contractor type, contract condition, payment method, contract, percentage increase in the original contract value and duration of these projects. The projects' counts of each category are illustrated between brackets in Table 1. Also, the major causes of claims resulting in cost overruns and scheduledelays of international projects in Iran are illustrated in Fig. 1. This phase resulted in determining fourteen inputs parameters to the CM that instigated project claims in construction projects in Iran.

CM model training and testing phase

Identifying RBF neural network model: The architecture of the RBF neural network model in this study is presented in Fig. 1. The model consists of the input variable, hidden and the output variable layers. In this study, the project information of the 138 projects were used as the input variables and the percentages of owner, consultant and contractor rolling in claims was used the output variable. The hidden layer placed between the input and output variable layers is where the basic functions operate to intervene between the input parameters and the network output. It is crucial to note that the number of neurons included in the hidden layer has considerable infiuence on the network performance. If the number of neurons is increased, the larger number of network connections resulted may encourage memorizing rather than true learning. On the otherhand, the network learning performance will deteriorate with decreasing neuron numbers. Nevertheless, there is no hard and fast rule to determine the number of neurons to be included for developing the most effective RBF neural network model (i.e., a model that can deliver the most accurate prediction results (Diekmann and Kruppenbacher, 1984). Dikmen and Birgonul (2004) suggested identifying the most effective RBF neural network model among others by evaluating their Root Means Square Error (RMSE) values (Diekmann and Kruppenbacher, 1984).

Table 2: Input and output variables of the ANNs of the CIPM

Input variables	Output variables (%)
Project duration	RBFI owner
The cost of project	
The area of project	RBF2 consultant
Time changes (%)	
Cost changes (%)	RBF3 contractor
The type of contract	

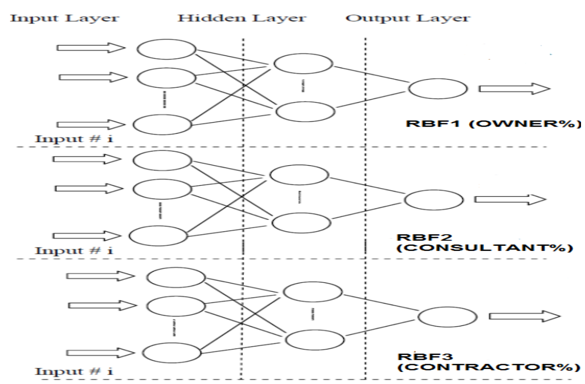

Fig. 2: The external and internalschematic structure of the three ANNs and theircomponents

RMSE is the measure of the deviations between the actual and the predicted values of the output variable. The smaller the value of the RMSE, the more accurate the output variable value (i.e., the PASS score of the successful bidder) predicted by the RBF neural network model. Regarding this approach, Kim suggested testing the networks with different hidden neurons ranged from 0.5*-3* input variables. This study adopted the approach suggested by Kim and analyzed the prediction performance of the RBF neural network model with hidden neurons ranged from 3 (i.e., 0.5×6)-18 (i.e., 3×6 input variables). The model with the lowest RMSE value was consequently selected for prediction of the best percentage.

The Claims Cause percentage Prediction Model (CM) iscomposed of three stand-alone ANNs. Each has a different prediction purpose based on the training and testing results of the six parameters (input nodes) and the output node of eachANN. The first artificial neural network (RBF1) predicts the percentage category of owner due to possible claims. The second artificial neural network (RBF2) predicts the percentage category of consultant due to possible claims. The third artificial neural network (RBF3) the percentage category of contractor due to possible claims: one input layer, one hidden layer and one output layer that can be outlined as follows.

The input layer had 6 neurons that represented the fourteen input parameters illustrated in Table 2. The hidden layer had 3 neurons which is half the number of neurons of the input layer as recommended by Hegazy and Ayed (1998). The output layer of each ANN included one neuron which represents the percentage impact category of the Owner, consultant and contractor in RBF1, RBF2 and RBF3, respectively. The external and internal structure of the three ANNs of the CM and their components are shown schematically in Fig. 2. The 96 projects were selected from the 138 projects illustrated in Table 1 for training and 42 projects for testing purposes, based on the available data of the six input parameters of each project. A computer program calledMatlab was used for the RBF neural network analysis. There are five major algorithm of using the collected data to train the RBF neural networks:

Specify input and output variables and randomly assign the data set for training and testing the network using. In this study, data of claim information (i.e., the input variables) and the owner, consultant and contractor percentage (i.e., the output variable) were obtained from 138 projects. Of the data source 42 sets were randomly assigned fortraining the RBF neural network models that were built with different numbers of hidden neurons. The 30 sets of the data were randomly selected to form the ‘‘testing set’’ that is used to validate the reliability of the trained network models.

Select RBF insert ‘‘3’’ in ‘‘Hidden Layers’’ in order to build a RBF neural network with three hidden neurons for analysis. Train the network as built in Step 2 either until the network has been trained for 500 epochs or until the means square training error becomes lower than 0.01. Save the network training results. Repeat steps 1-4, yet building the RBF neural networks with four to 18 hidden neurons. Evaluating the prediction results obtained from the identified model. To test the claim information in predicting the percentage of three parties in claim making with the identified RBF. A percentage error of 5% was used as the demarcation. That means if the difference between the predicted and the actual PASS score is within 5% (both positive and negative); the prediction result obtained is considered satisfactory.

RESULTS AND DISCUSSION

Results of model selection and validation: The prediction results obtained from the RBF neural network analyses are shown in Table 3. By detailing the RMSE values the 16 RBF neural network models, a 6-4-1 network model (i.e., a network model with six input variables, four hidden neurons and 1 output variables) isidentified as the most effective in predicting the percentage of each three

Table 3: RMSE values of the RBF neural networks with different hidden nodes

	Training RMSE				Testing RMSE			
Hidden noodes	1st	2nd	3rd	Average	1st	2nd	3rd	Average
3	1.095	1.093	1.094	1.094	3.021	3.070	3.957	3.349
4	1.116	1.077	1.089	1.094	3.024	2.594	3.034	2.884
5	1.092	1.091	1.092	1.092	3.122	2.686	2.947	2.919
6	1.092	1.088	1.092	1.091	3.087	3.312	3.092	3.164
7	1.091	1.090	1.090	1.091	3.117	3.692	3.314	3.375
8	1.092	1.088	1.092	1.091	3.181	3.299	4.197	3.559
9	1.092	1.095	1.086	1.091	3.371	3.555	3.598	3.508
10	1.092	1.092	1.089	1.091	3.253	3.192	4.158	3.534
11	1.092	1.090	1.091	1.091	3.390	3.605	3.694	3.563
12	1.092	1.090	1.092	1.091	3.162	3.617	3.810	3.530
13	1.090	1.092	1.092	1.091	3.575	3.410	3.703	3.563
14	1.076	1.093	1.086	1.085	3.852	3.765	3.249	3.622
15	1.070	1.092	1.092	1.085	3.889	3.249	3.752	3.630
16	1.075	1.092	1.080	1.082	3.954	3.643	3.486	3.694
17	1.070	1.080	1.090	1.082	3.766	3.896	3.434	3.698
18	1.072	1.082	1.092	1.082	3.768	3.437	4.241	3.815

Table 4: Actual and network predicted pass scores of training and testing projects of the prediction model developed by the 6-4-1 RBF neural networks

Project no.	Actual pass scores	Network predicted pass scores	Percent error*	Percent error <1%	Percent error <2%	Percent error <3%
Training set						
1	89.89	90.51	0.69	-	-	-
2	82.61	82.49	-0.14	-	-	-
3	91.25	90.87	-0.41	-	-	-
4	88.96	89.94	1.10	-	-	-
5	88.57	87.75	-0.93	-	-	-
6	85.46	84.91	-0.64	-	-	-
7	87.84	87.61	-0.26	-	-	-
8	85.88	87.46	1.84	-	-	-
9	90.35	88.69	-1.83	-	-	-
10	81.16	80.41	-0.92	-	-	-
11	89.05	88.82	-0.26	-	-	-
12	83.47	83.28	-0.23	-	-	-
13	89.14	88.85	-0.32	-	-	-
14	95.06	94.50	-0.59	-	-	-
15	91.63	90.24	-1.52	-	-	-
16	86.49	86.68	0.22	-	-	-
17	87.22	86.49	-0.84	-	-	-
18	90.57	89.75	-0.90	-	-	-
19	90.07	89.61	-0.52	-	-	-
20	84.86	86.17	1.55	-	-	-
21	83.93	83.88	-0.06	-	-	-
22	90.48	87.81	-2.95	-	-	-
23	87.43	86.54	-1.02	-	-	-
24	91.14	89.82	-1.45	-	-	-
Tesimg set						
A	90.63	90.26	-0.93	-	-	-
B	82.61	82.53	0.14	-	-	-
C	86.88	84.96	-2.21	-	-	-
D	87.83	85.34	-2.84	-	-	-
E	85.08	85.51	-0.50	-	-	-
F	93.08	90.40	-2.88	-	-	-

Percnt error = (Actual contractora's pass score-output contractora's pass coores)/output contractora's pass score* 100%

parties. The values of the determination of coefficient (R^2) for the training and testing results are 0.899 and 0.510, respectively. Furthermore, as the percentage errors between the network predicted PASS scores and the actual PASS scores of the projects in the testing set are <3% (Table 4) such relatively low prediction errors further support the predictive power of the input variables (i.e., the claim information).

CONCLUSION

Understanding the main parameters that causes claim and each of parties of one project roles to make claims has become more and more important in Iran. This information help te project parties to prevent from future claims and also help them to project judgment instead of other methods such as mediation and lawyer process. A RBF neural network model is developed on the data collected from 138 civil projects in Iran. The prediction accuracy attained is within 3% and is considered satisfactory. This model is a expanding data model and in each new project is updated and its accuracy is updating. The power claim banc consist of 140 claims of Iran projects also inside this model that help project element to better deciding.

REFERENCES

Arditi, D. and O.B. Tokdemir, 1999. Comparison of case-based reasoning and artificial neural networks. J. Comput. Civil Eng., 13: 162-169.

Ashley, K.D. and E.L. Rissland, 1988. A case-based approach to modeling legal expertise. IEEE. Expert, 3: 70-77.

Ashley, K.D., 1990. Modeling Legal Argument: Reasoning with Cases Andhypotheticals. MIT Press, Cambridge, England, UK., ISBN: 9780262011143, Pages: 329.

Boussabaine, A.H., 1996. The use of artificial neural networks in construction management: A review. Constr. Manage. Econ., 14: 427-436.

Bramble, B. and M. Callahan, 2010. Construction Delay Claims. Aspen Publishers, Netherlands, USA.,.

Caudill, M. and C. Butler, 1990. Naturally Intelligent Systems. MIT Press, Cambridge, ?England,.

Chau, K.W., 2007. Application of a PSO-based neural network in analysis of outcomes of construction claims. Autom. Constr., 16: 642-646.

Chua, D.K.H., D.Z. Li and W.T. Chan, 2001. Case-based reasoning approach in bid decision making. J. Constr. Eng. Manage., 127: 35-45.

Chua, D.K.H., Y.C. Kog, P.K. Loh and E.J. Jaselskis, 1997. Model for construction budget performance-neural network approach. J. Constr. Eng. Manage., 123: 214-222.

Diekmann, J.E. and M.J. Girard, 1995. Are contract disputes predictable?. J. Constr. Eng. Manage., 121: 355-363.

Diekmann, J.E. and T.A. Kruppenbacher, 1984. Claims analysis and computer reasoning. J. Constr. Eng. Manage., 110: 391-408.

Elbarkouky, M.M. and F.A. Robinson, 2010. Fuzzy preference relations consensus approach to reduce conflicts on shared responsibilities in the owner managing contractor delivery system. J. Constr. Eng. Manage., 137: 609-618.

Elhag, T.M. and Y.M. Wang, 2007. Risk assessment for bridge maintenance projects: Neural networks versus regression techniques. J. Comput. Civil Eng., 21: 402-409.

Emsley, M.W., D.J. Lowe, A.R. Duff, A. Harding and A. Hickson, 2002. Data modelling and the application of a neural network approach to the prediction of total construction costs. Construct. Manage. Econo., 20: 465-472.

Fisk, E., 2005. Construction Project Administration. 8th Edn., Prentice Hall, New Jersey, USA.

Gaber, M.T., L.C. Rabelo and O.A. Hosny, 1992. An integrated artificial neural networks model for industrial projects risk assessment. Proceedings of the 1992 IEEE International Conference on Managing in a Global Environment Engineering Management, October 25-28, 1992, IEEE, New York, USA., ISBN: 0-7803-0854-9, pp: 206-210.

Hegazy, T. and A. Ayed, 1998. Neural network model for parametric cost estimation of highway projects. J. Constr. Eng. Manage., 124: 210-218.

Hosny, O., 2006. An artificial neural network approach for predicting theeffect of claims on project time and cost. Eng. Res. J., 106: 87-106.

Hosny, O.A., C.O. Benjamin and Y. Omurtag, 1994. An al-based decision-support system for planning housing construction projects. J. Eng. Technol., 11: 12-19.

Kim, M.P. and K. Adams, 1989. An expert system for construction contract claims. Constr. Manage. Econ., 7: 249-262.

Mohamed, K.A., S.S. Khoury and S.M. Hafez, 2011. Contractor's decision for bid profit reduction within opportunistic bidding behavior of claims recovery. Intl. J. Project Manage., 29: 93-107.

Moselhi, O., T. Hegazy and P. Fazio, 1991. Neural networks as tools in construction. J. Constr. Eng. Manage., 117: 606-625.

Ren, Z., C.J. Anumba and O.O. Ugwu, 2001. Construction claims management: Towards an agent based approach. Eng. Constr. Archit. Manage., 8: 185-197.

Sun, C., and J. Xu, 2010. Estimation of time for Wenchuan Earthquake reconstruction in China. J. Constr. Eng. Manage., 137: 179-187.

Taormina, R., K.K. Chau and R. Sethi, 2012. Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. Eng. Applic. Artif. Intell., 25: 1670-1676.

Williams, T.P., 1994. Predicting changes in construction cost indexes using neural networks. J. Constr. Eng. Manage., 120: 306-320.