NEURAL NETWORK MODELING FOR REWORK RELATED COST OVERRUN AND CONTRACTUAL CLAIMS IN CONSTRUCTION PROJECTS

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ABSTRACT

The dynamics of rework related transactions in construction projects become very complicated because of various influencing factors such as multiple stakeholder interactions and overlapping interfaces. In order to understand the significance of rework based impacts on different performance related aspects in construction projects (e.g. cost overrun, time overrun, contractual claims), a pilot study was recently launched in Hong Kong. The knowledge-mining exercise aimed to consolidate the rework experiences from various recently completed construction projects, and this mainly included (i) a set of exploratory interviews and (ii) a questionnaire survey. It was considered that artificial neural network modeling approaches can be developed for mapping rework related impacts on different aspects of project performance. Applications of advanced neural network architectures such as General Regression Neural Networks (GRNN) have been explored for modeling rework based cost overrun and contractual claims in construction projects. A consolidated summary of initial findings from the neural network modeling for rework related cost overrun and contractual claims is presented in this paper.

KEY WORDS

rework, artificial neural network, cost overrun, contractual claims, construction projects.

INTRODUCTION

Construction projects are usually complicated for example, the needs to manage several intricate interfaces and segregated design and construction tasks. In poorly managed construction projects, rework could significantly impact on the time, cost and quality aspects. Rework transactions often arise from the unnecessary redoing/ rectifying efforts of incorrectly implemented processes or activities (Love, 2002). Earlier studies indicated that the costs of rework in poorly managed projects can be as high as 25% of contract value and 10% of the total project costs (e.g. Barber et al, 2000, Love and Li, 2000). In the US, for

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example, the Construction Industry Institute has estimated that the annual loss due to rework could be as high as US$ 15 billion for industrial construction projects (CII, 2001a). Rework is a significant contributor to time wastage and time/ schedule overruns (Kumaraswamy and Chan, 1998; CII, 2001b), which will eventually impact on costs (e.g. indirect costs such as overheads), resources and quality as well (Love et al 2004). Rework also triggers claims for extra costs and time wasted in redoing or repairing, given that contractors for example, would seek compensation from those they may consider responsible, wherever possible.

Artificial Neural Networks (ANNs) have high capacities to learn and model process behaviors using a set of relevant observed parameters. In general, ANNs are mainly used for prediction/ forecasting and classification problems. A multilayer perception type neural network trained with the back propagation algorithm (Rumelhart et al., 1986), which belongs to the category of error correction learning rules, is the most widely used network paradigm in prediction. The increasing trend of neural network applications in various domains including construction industry is due to various inherent advantages such as (a) potentials for implicitly detecting simple linear relationships as well as complex nonlinear relationships between dependent and independent variables, (b) comprehensive mapping of almost all possible interactions between input variables used for predictions or classifications, and (c) rapid simulations and convenient interpretations from modeling complex relationships between observed parameters. However, the disadvantages include over-fitting dangers and lack of credibility due to black box/ empirical nature of modeling. Different neural network architectures and wide-range of training algorithms are available. This paper describes the application of two specific networks in particular, i.e. Back Propagation Neural Network (BPNN) and General Regression Neural Network (GRNN) for mapping the project performance parameters from a set of rework related data from recently completed construction projects in Hong Kong.

OVERVIEW OF NEURAL NETWORK ARCHITECTURE

BACK PROPAGATION NEURAL NETWORK (BPNN)

The architecture of 3-layer Back Propagation Neural Network (BPNN) is shown in Figure 1.

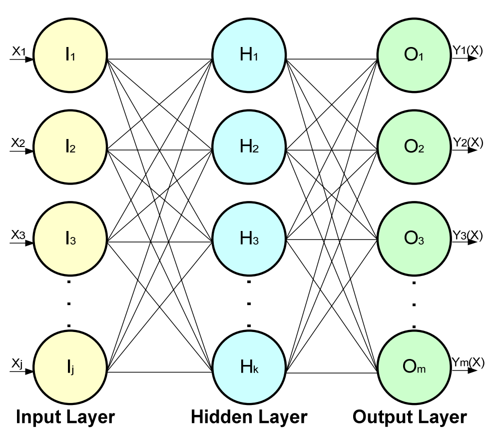

Figure 1: Architecture of standard Back Propagation Neural Networks

This popular form of BPNN has 3 layers such as one input layer, one hidden layer and one output layer. The training procedure in the BPNN architecture is mainly based on back propagation of errors using a supervised training mode. In the traditional 3-layer BPNN, the input function performs a specific weighted summing, the activation function is mostly a sigmoid or logistic function and the output function is a linear function deriving from an activation function (Peretto, 1992, Haykin, 1994, Arbib, 2003).

GENERAL REGRESSION NEURAL NETWORK (GRNN)

The General Regression Neural Network (GRNN) is a kernel regression based feed-forward type of network using supervised training (Specht, 1991, Rutkowski, 2004). A basic architecture of GRNN is portrayed in Figure 2. According to this architecture, GRNN has different layers such as input layer, patter layer, summation layer and output layer. Also, there are 'j' input nodes, 'k' pattern nodes, 'm+1' summation nodes and 'm' output nodes in the GRNN architecture. For single output problems, the summation layer consists of one numerator node and one denominator node. For every additional output unit, one numerator is included additionally, while the denominator remains the same. GRNN is capable of quick training, even with sparse data sets. GRNN is a type of supervised network that can handle multidimensional inputs. The main advantages of GRNN include faster training times and capability to handle both linear and non-linear models. Unlike BPNN which requires training parameters such as learning rate and momentum, GRNN operates with a smoothing factor applied after the network is trained.

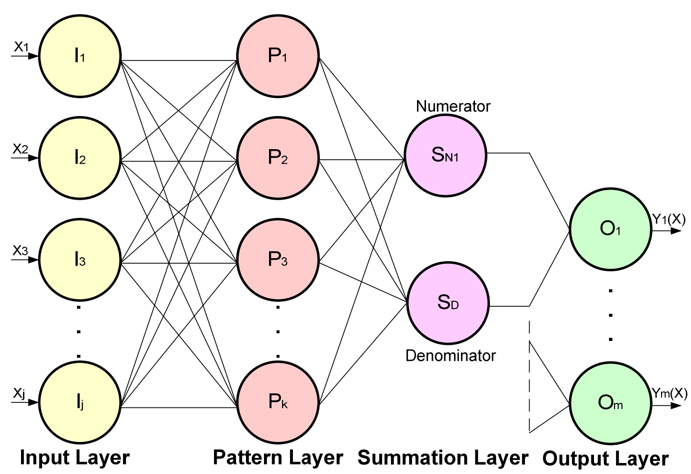

Figure 2: Architecture of General Regression Neural Networks

NEURAL NETWORK MODELS FOR PREDICTING PROJECT PERFORMANCE

DATASETS FOR MODELING PROJECT PERFORMANCE FROM REWORK SYMPTOMS

In this research, a triangulation approach is adopted. This mainly includes (i) knowledge networking with domain experts and experienced practitioners in the construction industry through exploratory correspondence and semi-structured interviews, (ii) targeted questionnaire surveying, (iii) knowledge mining from relevant literature and forensic case-studies on recently completed projects. The questionnaire used in this study was mainly derived from a recent Australia-based study (Love et al, 2004) and pilot tested in Hong Kong before distributing to the targeted respondents in the local construction industry. The questionnaire included a set of questions to be answered against a 5-point scale, for 87 rework related variables and a cluster of questions regarding 18 other information sets such as time and cost related datasets, project parameters and respondent details. All the targeted respondents were asked to relate their responses to any one of the recently completed projects that they were involved with and they were encouraged to submit multiple responses if they have been involved in more projects recently. In this neural network modeling, 112 such datasets were used (of which 75 were derived from building projects and 37 are from other civil engineering/ infrastructure projects).

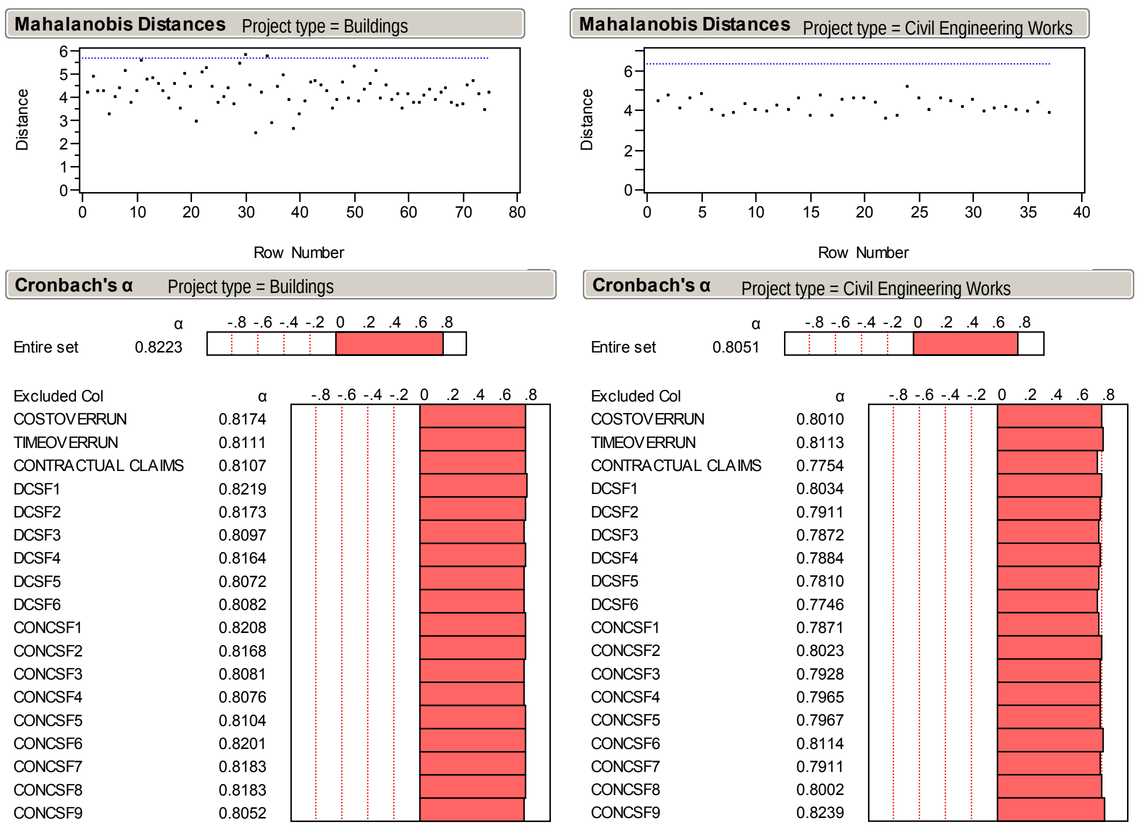

Figure 3: A snapshot of multivariate statistical checkings

The qualitative checking of validity and reliability were performed through meaningful questionnaire designs as well as careful data collection measures such as pilot testing, selecting appropriate experienced/ knowledgeable respondents and filtering. For example, there was a conscientious selection of the respondents. They were well-experienced persons from the Hong Kong construction industry, with a majority being senior executives and project managers (from several contractor organizations) who have more than 10 years experience. In addition, some multivariate statistical tests were conducted for quantitative checking, e.g. item reliability through Croanbach's Alpha (α) and outliner analysis through Mahalanobis distance measures. Figure 1 portrays a snapshot of some statistical checking.

NEURAL NETWORKS FOR PREDICTING PROJECT PERFORMANCE FROM REWORK SYMPTOMS

ANN 1: Predicting cost overrun from 15 cost attributes

In this neural network model, the datasets regarding 15 cost attributes were used as inputs for predicting the cost overrun. Both inputs and output were gauged on a 5 point scale. The inputs include a set of design and construction related sources as follows:

- 6 design-related sources such as (i) changes made at the request of the contractor during construction (DCS1), (ii) changes made at the request of the client (DCS2), (iii) changes initiated by an end-user/ regulatory bodies (DCS3), (iv) revisions/ modifications/ improvements of the design initiated by the contractor or subcontractor (DCS4), (v) errors made in the contract documentation (DCS5), and (vi) omissions of items from the contract documentation (DCS6)
- 9 construction related sources such as (i) changes made to the method of construction to improve constructability (CONCS1), (ii) changes in construction methods due to site conditions (CONCS2), (iii) changes initiated by the client or an occupier after some work has been undertaken on-site (CONCS3), (iv) changes initiated by the client or an occupier when a product or process had been completed (CONCS4), (v) changes made during the manufacture of a product (CONCS5), (vi) changes initiated by a contractor to improve quality (CONCS6), (vii) errors due to inappropriate construction methods (CONCS7), (viii) omissions of some activity or task (CONCS8), and (ix) damages caused by a subcontractor (CONCS9).

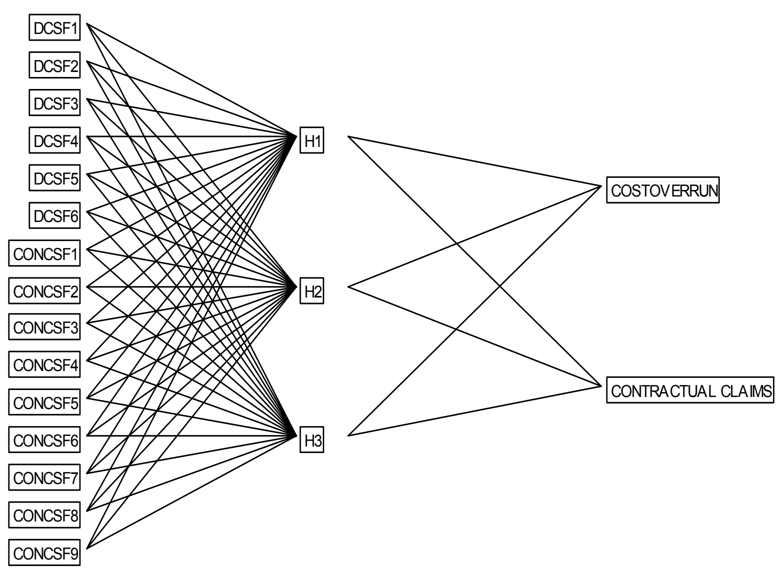

Figure 4: A neural network model for predicting some project performance parameters

Figure 4 portrays a sample neural network model for predicting project performance parameters such as cost overrun, time overrun and contractual claims from 15 rework related cost attributes. A comparison of network results from BPNN and GRNN for the 'ANN 1' predictions is provided in Table 1. The parameters used for comparing the network results are (i) coefficient of multiple determination (R squared), (ii) coefficient of determination (r squared), (iii) mean squared error (i.e. the mean of squares of the difference between actual and predicted values), (iv) mean absolute error (i.e. the mean of absolute values of 'actual minus predicted' for the corresponding data), (v) correlation coefficient (r), and (vi) a set of actual versus predicted comparisons expressed in percent ranges (i.e. the percent of network predictions that are within the specified percentage of the actual values).

Table 1: Comparison of results for ANN 1

	GRNN				BPNN			
	Buildings		Civil Works		Buildings		Civil Works	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R squared	0.8290	0.5592	0.9411	0.7375	0.1875	0.2294	0.8833	0.5566
r squared	0.8308	0.5862	0.9435	0.8121	0.2186	0.2464	0.8893	0.8706
Mean squared error	0.265	0.972	0.081	0.429	1.351	0.808	0.161	0.284
Mean absolute error	0.205	0.621	0.081	0.429	0.982	0.688	0.260	0.454
Correlation coefficient	0.9115	0.7656	0.9713	0.9012	0.4676	0.4964	0.9430	0.9330
Percent within 5%	78.667	57.143	91.892	57.143	8.333	26.667	45.946	0
Percent within 5% to 10%	1.333	0	0	0	5.000	6.667	27.027	20.000
Percent within 10% to 20%	8.000	0	0	0	11.667	20.000	13.514	60.000
Percent within 20% to 30%	0	0	2.703	14.286	18.333	6.667	0	0
Percent over 30%	12.000	42.857	5.405	28.571	56.667	40.000	13.514	20.000

Among the two groups (i.e. buildings and civil works), the genetic adaptive GRNN results are generally better than the BPNN outcomes. However, the BPNN results are basically better for the civil/ infrastructure category than the corresponding values of the buildings datasets.

ANN 2: Predicting contractual claims from 15 cost attributes

This neural network model is similar to the previous one (i.e. ANN 1) in which the same set of inputs were used for predicting contractual claims gauged on a 5 point scale. Similarly, a comparison of results is captured in Table 2.

Table 2: Comparison of results for ANN 2

	GRNN				BPNN			
	Buildings		Civil Works		Buildings		Civil Works	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R squared	0.8990	0.7359	0.9377	0.8359	0.2846	0.2829	0.7198	0.3378
r squared	0.9005	0.7680	0.9408	0.9462	0.3394	0.3083	0.7319	0.9008
Mean squared error	0.104	0.333	0.066	0.289	0.694	0.905	0.516	0.441
Mean absolute error	0.093	0.203	0.072	0.333	0.698	0.783	0.654	0.613
Correlation coefficient	0.9490	0.8764	0.9700	0.9727	0.5826	0.5552	0.8555	0.9491
Percent within 5%	88.000	86.667	91.892	60.000	10.000	6.667	0	0
Percent within 5% to 10%	1.333	0	0	0	10.000	26.667	0	33.333
Percent within 10% to 20%	4.000	0	0	0	25.000	13.333	60.000	33.333
Percent within 20% to 30%	4.000	6.667	5.405	20.000	25.000	6.667	40.000	33.333
Percent over 30%	2.667	6.667	2.703	20.000	30.000	46.667	0	0

The comparisons portrayed in Table 2 indicate some generic similarity between ‘ANN 1’ and ‘ANN 2’ and the distributions are slightly different.

ANN 3: Predicting cost overrun from 28 rework factors

In this neural network model, the datasets regarding 28 rework factors were used as inputs for predicting cost overrun. The inputs include a set of client-related, design-related, site management-related and subcontractor-related factors as detailed below:

- 6 client-related factors such as (i) lack of experience and knowledge of design and construction process (CR1), (ii) lack of funding allocated for site investigations (CR2), (iii) lack of client involvement in the project (CR3), (iv) inadequate time and money spent on the briefing process (CR4), (v) poor communication with design consultants (CR5), and (vi) payment of low fees for preparing contract documentation (CR6)
- 10 design-related factors such as (i) ineffective use of quality management practices (DR1), (ii) ineffective use of information technologies (DR2), (iii) poor coordination between different design team members (DR3), (iv) time boxing/ fixed time for a task (DR4), (v) poor planning of workload (DR5), (vi) lack of manpower to complete the required tasks (DR6), (vii) staff turnover/ re-allocation to other projects (DR7), (viii) incomplete design at the time of tender (DR8), (ix) insufficient time to prepare

contract documentation (DR9), and (x) inadequate client brief to prepare detailed contract documentation (DR10)

- 6 site management-related factors such as (i) ineffective use of quality management practices (SMR1), (ii) ineffective use of information technologies (SMR2), (iii) setting-out errors (SMR3), (iv) poor planning and coordination of resources (SMR4), (v) staff turnover/ re-allocation to other projects (SMR5), and (vi) failure to provide protection to construction works (SMR6)
- 6 subcontractor-related factors such as (i) ineffective use of quality management practices (SCR1), (ii) damage to other trades work due to carelessness (SCR2), (iii) inadequate managerial and supervisory skills (SCR3), (iv) low labour skill level (SCR4), (v) use of poor quality materials (SCR5), (vi) multi-layered subcontracting (SCR6)

A comparison of network results from BPNN and GRNN for the ‘ANN 3’ predictions is provided in Table 3. Basically, the comparisons indicate a similar pattern as mentioned before. However, the network predictions from 15 cost attributes seems to be slightly better than using 28 rework factors in the BPNN modeling for buildings category.

Table 3: Comparison of results for ANN 3

	GRNN				BPNN			
	Buildings		Civil Works		Buildings		Civil Works	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R squared	0.6732	0.4592	0.9208	0.9137	0.2103	0.1808	0.8594	0.8478
r squared	0.6984	0.5311	0.9299	0.9241	0.3167	0.2403	0.8611	0.8969
Mean squared error	0.499	0.880	0.109	0.132	1.206	1.270	0.194	0.075
Mean absolute error	0.515	0.740	0.211	0.243	0.941	0.968	0.359	0.251
Correlation coefficient	0.8357	0.7288	0.9643	0.9613	0.5627	0.4902	0.9279	0.9471
Percent within 5%	16.667	13.333	62.162	60.000	5.000	4.000	13.514	14.286
Percent within 5% to 10%	18.333	6.667	10.811	6.667	3.333	4.000	45.946	71.429
Percent within 10% to 20%	33.333	20.000	10.811	13.333	21.667	20.000	18.919	14.286
Percent within 20% to 30%	5.000	20.000	5.405	6.667	23.333	22.667	13.514	0
Percent over 30%	26.667	40.000	10.811	13.333	46.667	49.333	8.108	0

ANN 4: Predicting contractual claims from 28 rework factors

This neural network model is similar to the previous one (i.e. ANN 1) in which the same set of inputs were used for predicting contractual claims. Similarly, a comparison of results is captured in Table 4.

Table 4: Comparison of results for ANN 4

	GRNN				BPNN			
	Buildings		Civil Works		Buildings		Civil Works	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R squared	0.8485	0.7440	0.9148	0.8974	0.1956	0.2146	0.9345	0.6515
r squared	0.8847	0.7553	0.9189	0.9099	0.2410	0.2198	0.9362	0.7240
Mean squared error	0.202	0.265	0.090	0.109	0.893	0.572	0.069	0.502
Mean absolute error	0.218	0.191	0.173	0.214	0.760	0.646	0.186	0.635
Correlation coefficient	0.9406	0.8691	0.9586	0.9539	0.4909	0.4688	0.9676	0.8509
Percent within 5%	80.000	68.000	70.270	62.162	13.333	13.333	62.162	20.000
Percent within 5% to 10%	0	17.333	13.514	18.919	5.000	6.667	18.919	0
Percent within 10% to 20%	0	6.667	10.811	8.108	25.000	26.667	13.514	20.000
Percent within 20% to 30%	0	2.667	0	5.405	21.667	20.000	2.703	20.000
Percent over 30%	20.000	5.333	5.405	5.405	35.000	33.333	2.703	40.000

In this model also, the GRNN found to respond much better than the BPNN for the building projects.

DISCUSSIONS AND CONCLUSIONS

The observations in this study indicated that the mapping of rework symptoms could be useful for developing some useful neural network based predicting/ forecasting constructs on project performance parameters such as cost overrun, time overrun, contractual claims and client satisfaction. For brevity, only the most notable findings related to modeling of cost overrun and contractual claims are presented in this paper.

Two types of neural network architecture (i.e. BPNN and GRNN) were used for modeling the outputs (i.e. cost overrun and contractual claims) from various rework symptoms and related cost attributes. Several trials were conducted with various combinations of network design parameters (e.g. hidden neurons, number of epochs/

generations) to arrive at a set of best combinations of training and testing sets by carefully avoiding/ minimizing the over-fitting problems.

Through comparison, it has been observed that the genetic adaptive form of GRNN is more suitable to analyze the rework symptoms and their impacts in construction projects. However, the number of datasets (used for training and testing) and characteristics of input parameters (i.e. cost attributes, rework factors), as well as the number of input parameters might have some influence on the network results. Further research is being carried out to study the impacts of these parameters e.g. by conducting multivariate statistical constructs (such as factor analysis) and using other modeling approaches (e.g. regression analysis, genetic programming). In addition, some longitudinal studies for mapping the rework impacts on various performance and productivity aspects are also planned.

ACKNOWLEDGMENTS

The ongoing research study is supported by a URC research grant (under Seed Funding for Basic Research') from the University of Hong Kong (Ref: 10205236). The authors are also grateful for the valuable knowledge-based contributions from many Hong Kong construction industry practitioners who shared their valuable experiences with the research team.

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