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Prediction of outcome of construction dispute claims using multilayer perceptron neural network model

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Abstract

The occurrence of disputes in Indian construction contracts results in damaging the relationship between the parties apart from the time and cost overruns. However, if the parties to a dispute can predict the outcome of the dispute with some certainty, they are more likely to settle the matter out of court resulting in the avoidance of expenses and aggravation associated with adjudication. Dispute resolution process is mainly based upon the facts about the case like conditions of the contracts; actual situations on site; documents presented during arbitrational proceedings, etc., which are termed as 'intrinsic factors' in this research. These facts and evidences being intrinsic to the cases have been explored by researchers to develop dispute resolution mechanisms. This study focuses on determining the intrinsic factors for construction disputes related to claims raised due to variation from 72 arbitration awards through Case Study approach and furthermore statistically proving their importance in arbitral decision making by seeking professional cognizance through a questionnaire survey. It also further asserts the feasibility of the multilayer perceptron neural network approach based on the intrinsic factors existing in the construction dispute case for predicting the outcome of a dispute. Data from 204 variation claims from the awards is employed for developing the model. A three-layer multilayer perceptron neural network was appropriate in building this model, which has been trained, validated, and tested. The tool so developed would result in dispute avoidance, to some extent, and would reduce the pressure on the Indian judiciary.

Keywords: Construction disputes; Dispute resolution; Intrinsic factors; Extrinsic factors; Artificial intelligence techniques

1. Introduction

A dispute is a regular feature in construction and consumes resources that would otherwise be used in a more productive manner (Cheung et al., 2007). A dispute arises due to the involvement of disagreement (Cheung et al., 2002). When one party to the contract denies a claim made by the other party to the contract, it results into a dispute (Patil, 2005). Traditionally, construction disputes were settled in courts through litigation (Pinnel, 1999). However, litigation being too cumbersome for the dynamic nature of the construction sector; arbitration proceedings became the main mechanism for settling construction disputes (Gajria, 2000). Modern techniques of dispute resolution of commercial conflicts have drifted from litigation to arbitration (Rao, 2013). The use of arbitration has been regarded effective than litigation as an arbitral tribunal makes a determination based on facts and not precedence, and they interpret the contact rather than having a judge or jury to interpret the contract (Patil, 2005). Although this method is effective, expeditious, and economical as compared to regular court proceedings many a time the awards of the arbitrators are challenged in the higher court of laws and set aside for some valid reasons and exceptional cases (Iyer et al., 2008). The whole process becomes quite difficult to both the owner and the

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contractor (Iyer et al., 2002). If the parties knew the decision of the court ahead of time with some certainty, they are more likely to settle the matter out of court rather than encountering the expenses and aggravation associated with court proceedings (Iyer et al., 2012).

The decisions of construction disputes are affected by a large number of complex and interrelated technical factors in construction, which makes it difficult to interpret (Chau, 2007). This has resulted in adopting technologies as a way to deliver better, faster, and cheaper alternatives to litigation in court (Chaphalkar and Patil, 2012). The role of technology can be further enhanced with the integration of artificial intelligence (AI) techniques (Carneiro et al., 2010). Research in AI has provided more suitable tools to the construction industry (Moselhi et al., 1991). Arditi and Patel (1989) developed an expert system using forensic scheduling concepts to prevent and resolve time-related construction disputes; Raid et al. (1991) developed a Knowledge-Based Expert System (KBES) for time based claim management. Case-based Reasoning (CBR) systems as intelligent prediction tools to predict the outcome of construction litigation (Arditi and Tokdemir, 1999a, 1999b); Generic methodology for analyzing delay claims (Kartam, 1999); Artificial Neural Network applications in geotechnical engineering (Shahin et al., 2001); Boosted Decision Trees (BDT) for litigation prediction (Arditi and Pulket, 2005); and Delay Analysis method in resolving construction claims (Pattanakitchamroon and Arditi, 2006) are employed in various researches. Further, Ant Colony Optimization Model (Pulket and Arditi, 2008), Universal Prediction Model for Construction Litigation (Pulket and Arditi, 2009), Integrated Prediction Model (IPM) (Arditi and Pulket, 2010), Machine Learning (ML) models (Mahfouz and Kandil, 2012) for predicting outcome of construction litigation; and Innovative ANN model for predicting failure/cracking load of masonry wall panel under lateral load (Zhou et al., 2010) are developed using AI techniques. Hence, the use of one of the AI technologies — Neural Network (NN) is proposed to reach predictions that are close to court decisions based on the various factors influencing the decisions of arbitrators. The research comprises of identification of these factors and development of a dispute resolution framework for variation and deviation clause related claims in Indian construction contracts by using NN.

2. Neural network applications in construction litigation

Neural Network (NN) uses a learning algorithm automatically to generate functional relationships between inputs and outputs that are presented in a set of historical data, even though the data may be noisy and incomplete (Kaushik, 2011; Rajasekaran and Pai, 2003). Applications of NN in construction management cover a range of studies grouped as construction scheduling and management, construction cost estimation, resource allocation, and construction litigation (Dikmen and Birgonul, 2004). NN based methodology has been applied for estimating the construction resource requirements at the conceptual design stage (Elazouni et al., 1997); predicting the level of organizational effectiveness in a construction firm (Sinha and McKim, 2000); predicting the adoption potential or acceptability of a new form work system (Elazouni et al., 2005); quantifying the impact of change orders on construction productivity (Moselhi et al., 2005); and evaluating the knowledge management practices of construction firms (Kale and Karaman, 2011). In risk management, neuro fuzzy decision support system for efficient risk allocation (Jin, 2010); a back-propagation NN application for bridge risk assessment to model bridge risk score and risk categories (Taha et al., 2007) and Neuronet model as a decision support tool that can classify international projects with respect to attractiveness and competitiveness based upon the experiences of contractors in overseas markets (Dikmen and Birgonul, 2004) are developed. Application of NN is common for Civil Engineering but not so common in the area of construction disputes. Although researchers like Arditi et al. (1998) employed NN for predicting the outcome of litigation by identifying the hidden relations between the factors influencing the court decision. Cheung et al. (2000) presented NN technique of analysis in determining the important factors affecting the outcome of construction dispute resolution process in Hong Kong. Chau (2007) adopted particle swarm optimization model to train perceptrons in predicting the outcome of construction claims in Hong Kong. Despite the success of these systems in litigation outcome's prediction, they were not designed for a specific claim of dispute nor based on detailed analysis of legal concepts that govern such outcomes (Mahfouz and Kandil, 2009). Nevertheless, taking a drive from the above researches, this paper attempts to fill this gap by modeling a frame work for a specific type of construction dispute claim arising from variation clause in the Indian construction industry. It aims at developing an NN prediction model based on the significant legal factors governing verdicts in this type of disputes. The model will help in the faster resolution of disputes and can also be considered as a means of litigation avoidance to some extent.

3. Factors influencing the arbitral decision making

Arbitral decision making is mainly based on the facts and findings of the case related to the claims, conditions of contracts, and factual situations experienced on site during the execution of a project, the actual documents presented during arbitration proceedings, etc. (Al Qady et al., 2013). Literature review of legal studies conducted by Robbennolt and Studebaker (2003), Wiener et al. (2006), Feigenson and Park (2006); Singhi and Jangir (2010), Goel (2011), Motiwal (2011), and Seth (2011) revealed that apart from the facts about the case, evidence and documents put forth during the arbitral proceedings, there are several other indirect factors, which influence the decision making of arbitrators. The experience, technical expertise, cognitive skills, decision making approach, background characteristics, humane nature, etc. of the arbitrators can be cited as examples of the factors apart from facts and evidence of the case. The factors can be broadly segregated into two groups — one, which is directly related to the facts and situations of the case termed as "Intrinsic Factors" and the other that is not directly related to the case but are related to the arbitrator's personality traits, and demographic characteristics termed as "extrinsic factors".

4. Methodology of the study

In view of the scope of this research paper, it mainly focuses only on the identification of the intrinsic factors and further using them in development of NN model for prediction of construction dispute outcomes related to Indian construction industry. To achieve this aim, the study followed the methodology shown in Fig. 1.

4.1. Development of data set

Case Study approach is a powerful technique to study systems in their natural settings. Robert Yin (2003) was an early proponent of Case Study research methodology and defined it to be an "empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between the phenomenon and context are not clearly evident". Documentation, archival records, interviews, direct observation, participant observations are the sources of data for case studies (Yin, 2003).

Disputes arising in the Indian construction industry are majorly resolved by arbitration whereby, the appointed arbitrator gives his decision in the form of a document known as the award which is binding on the parties in a dispute. The case study of 831 claims of various types in seventy two arbitration awards related to disputes in construction contracts included i) development of a data set of variation claims from arbitration awards containing details of the parties, arbitration tribunal, contract conditions, important dates of the project execution, claims and their causes, the amount claimed, whether the claim allowed, rejected or partially allowed, the amount awarded, claimant's contentions, respondent's arguments, and reasons behind the arbitrators' judgment and ii) extraction of a set of intrinsic factors that constitute the basis of judgements in variation claims.

4.2. Identification of intrinsic factors

The 821 claims raised were categorized into various types namely variation claims, delay claims, interest claims, cost of arbitration claims, claims related to inappropriate billing, price escalation, time extension, loss of profit, claims related to retention money, claims for office overheads and claims related to balance payment. Out of the total 821 claims, 239 were raised for variations which were considered for further study. Sixteen intrinsic factors were identified from the data set of these 239 variation claims. The identification of the factors was carried out by studying the cause of the claim, the claimant's contentions, respondent's arguments, and reasons behind the arbitrators' judgment for each and every 239 claims. The study revealed certain logics followed by the arbitrators while deciding to allow or reject claims. These logics are in the form of probing questions based on the facts and findings of the case and the contract conditions that consequently help the arbitrators in their decision making. Hence, as the next step, the logics or the probing questions that are considered by the arbitrator while giving decisions are traced and are termed as 'intrinsic factors'. It is explained by the help of sample cases in the following Table 1 which illustrates the brief background of a claim (column 2) and the reasoning of Arbitrator in deciding the result of that claim (column 3) and factors identified from the decisions taken by the arbitrators for the claim (column 4). It should be noted that due to space constraint only three cases are illustrated to explain the methodology.

In the above cases, it can be observed that the factors identified can be considered as the important facts based on which the arbitrators decided their judgments, whether to allow the claim, reject the claim or partly allow the claim. These can be considered as intrinsic factors influencing the decisions of the arbitrators. Consequently, by studying the reasoning of the arbitrators for each of the extracted data set of variation claims a list of 16 factors is identified, which is enlisted in Table 2.

A questionnaire survey was also carried out where questionnaire was sent to 50 arbitrators and counsels out of whom thirty eight responded. The respondents were asked to rate their agreeableness to the importance of identified intrinsic factors in a Likert scale of 1 (strongly disagree) to 5 (strongly agree). Subsequently, a statistical test namely, Friedman Chi-square test was carried on the responses collected with a level of significance $\alpha = 0.05$. The test statistics show Chi-square as 73.881; degree of freedom as 15 and asymp. significance (P) as 0.000. In the statistical test carried out for the factors related to variations, the 'P' value is 0.000, which is less than the level of significance (0.05). Thus, the null hypothesis that "there is no difference in the importance attached to the factors influencing the arbitral decision making for variation claims" is rejected and it is concluded that "there is a significant difference in the importance attached to the factors influencing the arbitral decision making for variation claims".

The mean ranks obtained from the test are depicted in the column 3 of Table 2. It can be seen that change orders issued in writing have a mean rank of 11.29 followed closely by the factor provision of express condition of variation work having a

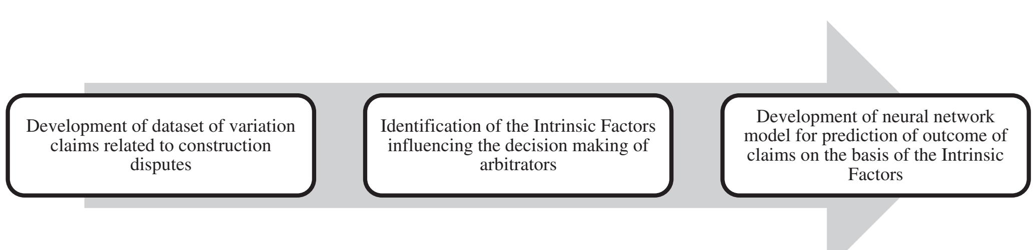

Fig. 1. Methodology of the study.

mean rank of 11.23. The factor change in work/variation ordered by the owner received a mean rank of 10.44 whereas factors — variation work outside the scope of work/extra work; extra work or revised rates mutually agreed by both parties; uncontemplated item of work at the time of tendering; and extra work necessary for completion of work have mean ranks 9.96; 9.42; 9.38 and 9.0 respectively. The factors — variation within the deviation limit and miscalculation/recalculation of claim amount scored the least ranks as 5.33 and 5.27 respectively.

Table 1
Identification of intrinsic factors.

Sr. no.	Claims	Questions raised during decision making	Factors identified for each of the claims
01	For use of Extra Cement in executing the work of M-25 concrete Design mix for M25 was adopted as per instructions of engineer which involved excess cement consumption. This was due to the change in the slump of 10 cm instead of 7.5 cm. Respondents argue claim is vague; no fixed minimum quantity specified in the contract; the earlier mix was not workable and quality control circle suggested new mix design. As the increase in the cement content in the mix design M25 was ordered as per instructions of the Engineer, it amounts to Variation Work as per provision of clause No. 51.1 of GCC. As per the quantity of work carried out the calculations were done by the arbitrator.	• Is there an express provision in the contract for compensation in case of variation works? • Were the changes in design, drawings, and specifications ordered by the owner or done by the contractor? • Were the variation orders communicated in writing or any other mode by the owner? • Was the change in work necessary for completion of work? • Whether the change in specifications was due to inconsistency in documents? • Has the contractor transacted with the owner by issuing a notice in writing about the change in the rate of item of work/change in the cost of work? • Whether the execution of variation work was supported by documents?	• Provision of express condition in the contract for compensation of variation work. • Change in work/variation ordered by owner • Change orders issued in writing • Extra work necessary for completion of work • Change in specifications due to inconsistency in documents • Contractor conveyed the change in rate of item of work to owner • Execution of variation works supported by documents
02	For extra cost of second coat of primer to MDF wood work Manufacturer recommended two coats of paint for MDF door frames. The contract stipulated to provide only one primer coat under BOQ rates as per technical specifications. However, 2 coats were provided. The respondent deny that second coat was applied; claim has no basis; claim not supported by any documentary proof The arbitrator accepted the claim as claimants informed the engineer about the application of second coat. Work executed as per manufacturer's specifications. As per clause 51 of GCC, work was considered as variation and payable to claimants.	• Is there an express provision in the contract for compensation in case of variation works? • Was the change in work necessary for completion of work? • Whether the variation was necessitated due to change in the specifications of work? • Whether the change in specifications was due to inconsistency in documents? • Whether there was a change in the rate of item of work? • Has the contractor transacted with the owner by issuing a notice in writing about the change in the rate of item of work? • Whether the extra work was executed as rework for reasons attributable to contractor/owner? • Whether the revised rates have been mutually agreed by both the parties? • Whether the variation work was outside the scope of work/extra work? • Whether the execution of variation work was supported by documents?	• Provision of express condition in the contract for compensation of variation work. • Extra work necessary for completion of work • Change in specifications due to inconsistency in documents • Change in the rate of item of work due to change in specifications • Change in work/variation ordered by owner • Contractor conveyed the change in rate of item of work to owner • Extra work/change caused due to reasons attributable to contractor/owner • Work/revised rates mutually agreed by both parties • Variation work outside the scope of work • Execution of variation works supported by documents
03	Extra for providing 45 mm thick layer of water proofing mortar in suite room toilet. Claimants were directed to provide additional water proofing layer; extra payment for extra work. Respondents contended that it was claimants fault and incorrect workmanship; respondents not responsible to pay for faulty work. Arbitrators rejected the claim. The work is as per tender and is already paid. Hence no additional claim. Work was carried out incorrectly by the claimants.	• Is there an express provision in the contract for compensation in case of variation works? • Whether the change in design, drawings and specifications were ordered by the owner or done by the contractor. • Whether there was a change in the rate of item of work? • Has the contractor transacted with the owner by issuing a notice in writing about the change in the rate of item of work? • Whether the extra work was executed as rework for reasons attributable to contractor/owner? • Whether the variation work was outside the scope of work/extra work? • Whether the unforeseen conditions were present and beyond the control of contractor?	• Provision of express condition in the contract for compensation of variation work. • Change in work/variation ordered by owner • Change in the rate of item of work due to change in specifications • Contractor conveyed the change in rate of item of work to owner • Extra work necessary for completion of work • Extra work/change caused due to reasons attributable to contractor/owner • Variation work outside the scope of work • Unforeseen/physical conditions beyond the control of contractor

Table 2
Intrinsic factors influencing the decisions of arbitrators related to variation claims along with their Friedman mean ranks.

Sr. no.	Factors influencing the decisions of arbitrators related to variation claims due to change in specifications	Friedman mean rank
1	Provision of express condition in the contract for compensation of variation work	11.23
2	Change in work/variation ordered by the owner	10.44
3	Change orders issued in writing	**11.29**
4	Change in specifications due to inconsistency in documents	7.42
5	Variation work outside the scope of work/extra work	9.96
6	Insufficient data at the time of tendering	7.75
7	Uncontemplated item of work at the time of tendering	9.38
8	Unforeseen/physical conditions beyond the control of the contractor	8.52
9	Extra work necessary for completion of work	9.00
10	Change in the rate of item of work due to change in specifications	7.92
11	Contractor conveyed the change in the rate of item of work to the owner	6.94
12	Extra work/change caused due to reasons attributable to the contractor/owner	7.17
13	Execution of variation work supported by documents	8.98
14	Extra work/revised rates mutually agreed by both parties	9.42
15	Variation within the deviation limit	5.33
16	Miscalculation/recalculation of claim amount	5.27

4.3. Development of neural network model

The development of the NN model comprises of data conversion, training, validating and testing of the neural network, and finally, implementation or production. The *Neuro Solutions* software was used for the study. The data set was organized into a data file that is compatible with the software which requires input and output variables. The 16 extracted intrinsic factors, upon, which the arbitral decision of the variation claims is based on, were utilized as input variables for the NN model. The output of the NN model was 'claim allowed', 'claim rejected' and 'claim partially allowed'. For every single claim in the case study, the input and output variables were identified. Considering the missing values, finally 204 cases were regarded for the NN model. Considering the presence or absence of the input variables, they were assigned values −1; 0; 1. For example, for the factor 'instructions ordered by owner' will be assigned value '1' if specific orders to change in work are given by the owner, and it will be '−1' if there is a mention that orders are not given and if there is no reference regarding this factor in the case, the value will be '0'. The outcome of the claim is considered as the output of the NN model which is expressed as '1' for a claim allowed, '−1' for a claim rejected and '0' for a claim partly allowed. The process of training the network includes feeding the training cases and the corresponding inputs and outputs to the network. The network performs a number of training runs and acquires the complete knowledge of the database fed to it and allots the appropriate weights to the interconnections. In the validation process, based on the data training, the network when fed with input data of a known case not belonging to the training pairs generates the output of it, which is compared with the desired output. If any discrepancy is observed between the desired output and obtained output, it is clarified by adjusting the weights and minimizing the error by the network tool itself. Once the error is minimized, the network is said to be accurately validated. For the testing process, cases whose outputs are to be predicted are fed to the network which generates output through a number of training runs. Finally, the production process is carried out where cases are fed without output, and the results obtained are compared with the actual output, and the prediction rate is calculated. The whole process is repeated with different combinations of input parameters, permutations, and shuffling of training and validation data and changes in other parameters, on the rate of prediction and testing performance.

Out of the 204 cases considered for the development of the neural network model, 10 cases were randomly selected for production. NNs undergo effective training when training cases are in random order and shuffling may be used to create randomness (Arditi et al., 1998). Taking cognizance of earlier research studies (Arditi et al., 1998; Chaphalkar and Sandbhor, 2014) that maximum data set considered for training gives better results, 70% (135 cases) of the remaining cases, were considered for training, 15% (29 cases) for validation and 15% (29 cases) for testing purposes. The *Neuro Solutions* provides a quick method for tagging multiple rows of data with user-specified percentages of the data as training, cross validation, and testing. However, a reversed tagging option causes the tagging order to be reversed such that the data is tagged as testing, cross validation, and training. Trials were conducted using both these options and by varying the training parameters like (a) number of hidden layers from one to three (HL1, HL2, HL3) (b) processing elements from one to four (PE1, PE2, PE3, PE4) and (c) number of epochs as 1000, 2000, and 3000. In these trials the transfer function – TahnAxon, learning rule – Levenberg was used. In these trials, two neural models Multilayer Perceptron (MLP) and General Feedforward (GFF) were used. Multilayer perceptrons (MLPs) are layered feedforward networks typically trained with static

Table 3
Details of the trials.

Trial	Neural model	No. of epochs
1	MLP	1000
2		2000
3		3000
4	GFF	1000
5		2000
6		3000

Table 4
Details of the trial runs of each trial set.

Test runs	Tagging of data rows	Hidden layers	Processing elements
1 to 4	70% training 15% CV 15% testing (normal tags)	1	1 to 4
5 to 8		2	1 to 4
9 to 12		3	1 to 4
13 to 16	70% training 15% CV 15% testing (reversed tags)	1	1 to 4
17 to 20		2	1 to 4
21 to 24		3	1 to 4

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Table 5
Summary results of trail set 2.

Trial 2: Neural model — MLP; transfer function — TanhAxon; learning rule — Levenberg Marqua

Training parameters		Performance parameters	Training parameters 2000 epochs			
			PE = 1	PE = 2	PE = 3	PE = 4
70% training 15% CV 15% testing	Hidden layer = 1	MSE	0.18	0.20	0.36	0.26
		R	0.86	0.80	0.66	0.79
		Testing % age	75.87	86.21	72.41	89.65
		Production % age	90	80	80	100
70% training 15% CV 15% testing	Hidden layer = 2	MSE	0.13	0.26	0.23	0.21
		R	0.88	0.79	0.80	0.83
		Testing % age	93.1	93.1	89.65	89.65
		Production % age	100	80	100	100
70% training 15% CV 15% testing	Hidden layer = 3	MSE	0.34	**0.01**	0.03	0.23
		R	0.71	**0.99**	0.98	0.81
		Testing % age	86.21	**100**	96.55	75.87
		Production % age	100	**100**	100	90
70% training 15% CV 15% testing (reversed tags)	Hidden layer = 1	MSE	0.13	0.19	0.07	0.28
		R	0.86	0.79	0.93	0.66
		Testing % age	82.76	79.31	93.1	69.97
		Production % age	90	80	90	80
70% training 15% CV 15% testing (reversed tags)	Hidden layer = 2	MSE	0.07	0.08	0.09	0.08
		R	0.93	0.91	0.91	0.93
		Testing % age	93.1	93.1	89.65	89.65
		Production % age	100	90	90	90
70% training 15% CV 15% testing (reversed tags)	Hidden layer = 3	MSE	0.08	0.10	0.11	0.10
		R	0.92	0.89	0.88	0.89
		Testing % age	93.1	89.65	89.65	89.65
		Production % age	100	90	100	90

backpropagation. These networks have found their way into countless applications requiring static pattern classification. Generalized feedforward networks are a generalization of the MLP such that connections can jump over one or more layers. Levenberg–Marquardt Optimization is a virtual standard in nonlinear optimization, which significantly outperforms the gradient descent and conjugate gradient methods for medium-sized problems. The transfer function translates the input signals to output signals. The Axon family sums all the incoming vectors from multiple connections and then applies a transfer function to the sum. The implementation for the LinearTanhAxon is the same as that of the LinearAxon except that the transfer function is clipped at −1 and 1.

5. Trial runs for development of NN model

In view of the variation in the input rows and the training parameters, three trial sets for each neural model MLP and GFF

Table 6
Effect of varying hidden layers for different epochs (1000, 2000, 3000) and neural models (MLP and GFF) and processing elements = 4.

Data tagging details	Neural model	Performance parameters	1000 epochs			2000 epochs			3000 epochs		
			HL1	HL2	HL3	HL1	HL2	HL3	HL1	HL2	HL3
70% training 15% CV 15% testing	MLP	MSE	0.34	0.11	0.23	0.26	0.21	0.23	0.64	0.11	0.37
		R	0.71	0.90	0.77	0.79	0.83	0.81	0.47	0.91	0.71
		Testing % age	89.65	89.65	82.75	89.65	89.65	75.87	79.31	82.76	79.31
		Production % age	80	100	100	100	100	90	90	100	90
70% training 15% CV 15% testing (reversed tags)		MSE	0.15	0.06	0.24	0.28	0.08	0.10	0.11	**0.07**	**0.08**
		R	0.85	0.94	0.73	0.66	0.93	0.89	0.88	**0.93**	**0.92**
		Testing % age	89.65	93.1	75.86	69.97	89.65	89.65	89.65	**93.1**	**93.1**
		Production % age	90	100	100	80	90	90	90	**100**	**100**
70% training 15% CV 15% testing	GFF	MSE	0.20	0.45	0.05	0.20	0.39	0.06	0.41	0.16	0.15
		R	0.82	0.60	0.95	0.82	0.62	0.95	0.63	0.86	0.87
		Testing % age	86.21	72.41	93.1	86.21	68.97	89.65	82.76	82.76	89.65
		Production % age	100	70	100	90	90	100	80	90	100
70% training 15% CV 15% testing (reversed tags)		MSE	0.21	0.09	0.20	0.10	0.27	0.26	0.28	0.08	0.18
		R	0.78	0.90	0.79	0.89	0.76	0.71	0.70	0.91	0.80
		Testing % age	79.31	86.21	93.1	89.65	75.86	82.76	86.21	89.65	75.86
		Production % age	70	80	90	90	70	90	100	90	70

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Table 7
Performance of MLP neural network with hidden layers = 3 for different epochs (1000, 2000, 3000) and by varying processing elements (PE1; PE2; PE3; PE4).

Data tagging details	Performance parameters	1000 epochs				2000 epochs				3000 epochs			
		PE1	PE2	PE3	PE4	PE1	PE2	PE3	PE4	PE1	PE2	PE3	PE4
70% training 15% CV 15% testing	MSE	0.33	0.07	0.10	0.23	0.34	**0.01**	0.03	0.23	**0.01**	0.04	0.11	0.37
	r	0.72	0.95	0.91	0.77	0.71	**0.99**	0.98	0.81	**1.00**	0.97	0.91	0.71
	Testing % age	79.31	93.1	93.1	82.75	86.21	**100**	96.55	75.87	**100**	96.55	89.65	79.31
	Production % age	90	100	80	100	100	**100**	100	90	**100**	100	100	90
70% training 15% CV 15% testing (reversed tags)	MSE	0.24	0.13	0.21	0.24	0.08	0.10	0.11	0.10	0.08	0.21	0.07	0.08
	r	0.73	0.87	0.77	0.73	0.92	0.89	0.88	0.89	0.94	0.79	0.92	0.92
	Testing % age	82.76	86.21	89.65	75.86	93.1	89.65	89.65	89.65	93.1	89.65	89.65	93.1
	Production % age	100	80	100	100	100	90	100	90	100	90	100	100

were carried out for 1000, 2000, and 3000 epochs. Each trial set comprised of 24 trial runs wherein keeping processing elements constant, the number of hidden layers was varied from one to three. The first 12 test runs were carried by normal tagging of a data set with 70%; 15% and 15% for training, validation and testing respectively and the second set of 12 test runs was carried by a reversed tagging option. The details of the parameters of the trial sets and trial runs of each trial set are illustrated in Tables 3 and 4 respectively.

The performance of all the trial runs was compared mainly on the basis of four parameters namely — (i) mean squared error (MSE), (ii) linear correlation coefficient (r), (iii) testing rate (no. of cases predicted right in the testing phase), and (iv) prediction rate (no. of cases predicted right in the production phase). The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it doesn't necessarily reflect whether the two sets of data move in the same direction. The correlation coefficient (r) solves this problem. Calculating the correlation coefficient for two variables can give an indication of the strength of the relationship between them. The correlation coefficient measures the degree, to which two variables move together. The correlation coefficient ranges from −1.0 to +1.0, with a value of 0 indicating no correlation, 1.0 indicating a high positive correlation (when x is high y is high), and −1.0 indicating a high negative correlation (when x is high y is low). The results of each trial set are displayed in a tabular format. A sample table of the results is shown as Table 5.

Further the performance of the network models was compared wherein the three hidden layers were constant, and processing elements are varied from 1 to 4 and 1000, 2000, and 3000 epochs were used for the MLP neural model, which is illustrated in Table 6. Most of the trial runs have given 100% prediction rate but along with the prediction rate, the testing rate, value of MSE and r is also compared. It is observed that using 'normal tagging of data option' with 2000 epochs and PE2, the results are MSE is 0.01; r is 0.99, and both testing and prediction rate is 100%. This combination was labeled as MLP_HL3_PE2_2000. Another neural network with 3000 epochs and PE1 also gave similar results with MSE equal to 0.01; r equal to 1.00 and both testing and prediction rate equal to 100%. This network model was marked as MLP_HL3_PE1_3000 (Table 7). From the graphs of the 'desired output versus actual output' for models, as shown in Figs. 2 and 3, it is observed that the profiles for the desired and actual output coincide to a large extent. Both these models were further validated for a real time situation wherein the inputs of only one case are fed to the networks for the prediction of output. For this four Supreme Court cases were considered for the implementation of the neural network model and the outputs of the model were compared with the actual result of the cases. The comparative of outputs of the neural models and the actual outputs are illustrated in Table 8. It is observed that both the models give a similar prediction rate wherein out of the four cases three cases were predicted rightly. In the first, third and fourth court cases, the claims were allowed (1) and the neural network also predicted correctly. The claim raised in the second case was rejected (−1) in reality, and the model prediction was nearly equal to partially allowed (0) output.

6. Discussions of the data analysis

From the study, it is seen that there is no relation observed as more the number of PEs or greater the number of hidden layers, better is the accuracy. The results of different combinations when compared help in discarding the combinations, which do

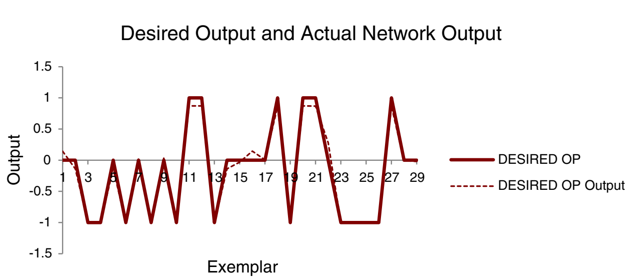

Fig. 2. Result for combination — 2000 epochs, hidden layer 3, PE2, MLP network, Tanh, Levenberg Marquardt (HL3_PE2_2000).

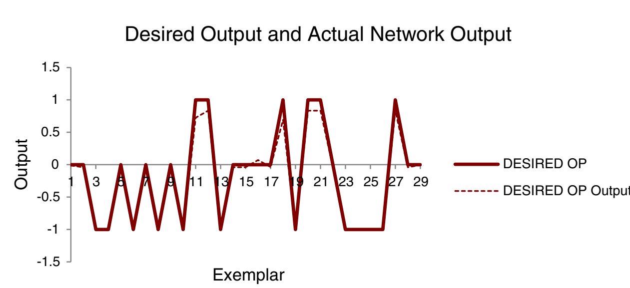

Fig. 3. Result for combination — 3000 epochs, hidden layer 3, PE1, MLP network, Tanh, Levenberg Marquardt (HL3_PE1_3000).

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Table 8
Prediction rate/validation of the final neural network models.

Case no.	Output of final neural network models		Actual output of Supreme Court
	HL3_PE2_2000	HL3_PE1_3000	
Case 1	1	1	1
Case 2	0	0	−1
Case 3	1	1	1
Case 4	1	1	1

not give a good performance. As the number of training cases increases, the correlation coefficient, i.e. the ratio of the desired output and actual output and eventually rate of prediction improves. Shuffling of training, testing, and cross validation cases also yields varied rate of prediction. As the software is data sensitive, reliability and adequacy of the data provided to the software, and the corresponding output vary as soon as any one case set is changed. NN having the following parameters gives the best prediction rate and a testing rate of 100%.

Type of network model: Multilayer perceptron network

- Transfer function = TanhAxon
- Learning rule = Levenberg Marquardt
- Number of hidden layers: 3
- Number of processing elements and epochs: (i) 2 and 2000 (ii) 1 and 3000.

These models can be implemented to resolve the dispute related to escalation and have a high percentage of prediction rates. For the ten cases extracted from awards, the prediction rate was 100% while for the Supreme Court cases prediction rate was 75%. Therefore, it can be decisively concluded that the model developed has the utility for arbitration as well as litigation. The system acts in a neutral way and is not in favor of any of the parties involved in the dispute hence, avoiding the bias of the decision maker. The system may be consulted by arbitrators, negotiators, and mediators to facilitate their decision-making process. It could also be used by contractors and owners independently to test the consequences of planned changes in the contract. Strategic decision making may be performed by the decision makers with the help of this model leading to a smoother settlement and resolution of disputes due to escalation claims. The heavy costs and the time lost due to litigation could be saved effectively as the model developed gives around 100% rate of prediction.

7. Conclusions

The study identified sixteen intrinsic factors, which influence the decision making of the arbitrators in resolving the claims related to variation in Indian construction contracts. The study explored the feasibility of using the NN model for the prediction of the outcome of disputes related to variation. Several test runs were conducted by varying the training parameters. It was observed that the MLP network gave better results as compared to GFF. This framework can offer a more cost-effective solution to dispute resolution than existing methods. The same methodology can be expanded for the resolution of construction disputes arising out of other dispute prone claims and when fully developed, the proposed NN model may be consulted by contractors, owners, or arbitrators to facilitate their decision-making process.

Conflict of interest

None.

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