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A Split-Step PSO Algorithm in Predicting Construction Litigation Outcome

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Abstract. Owing to the highly complicated nature and the escalating cost involved in construction claims, it is highly desirable for the parties to a dispute to know with some certainty how the case would be resolved if it were taken to court. The use of artificial neural networks can be a cost-effective technique to help to predict the outcome of construction claims, on the basis of characteristics of cases and the corresponding past court decisions. This paper presents the application of a split-step particle swarm optimization (PSO) model for training perceptrons to predict the outcome of construction claims in Hong Kong. The advantages of global search capability of PSO algorithm in the first step and local fast convergence of Levenberg-Marquardt algorithm in the second step are combined together. The results demonstrate that, when compared with the benchmark backward propagation algorithm and the conventional PSO algorithm, it attains a higher accuracy in a much shorter time.

1 Introduction

It is highly desirable for the parties to a dispute to know with some certainty how the case would be resolved if it were taken to court. This would effectively help to significantly reduce the number of disputes that would need to be settled by the much more expensive litigation process. Artificial neural networks (ANN), in particular the feed forward back-propagation (BP) perceptrons, have been widely applied in different fields [1-2]. ANN can be a cost-effective technique to identify the hidden relationships among various interrelated factors and to mimic decisions that were made by the court. However, slow training convergence speed and easy entrapment in a local minimum are inherent drawbacks of the commonly used BP algorithm [3]. Levenberg-Marquardt (LM) optimization technique [4] is a commonly used ANN that has attained certain improvements such as convergence rates over the BP algorithm. Swarm intelligence is another recent SC technique that is developing quickly [5]. These SC techniques have been applied in construction problem and accomplished satisfactory results [6-7].

In this paper, a split-step PSO algorithm is employed to train multi-layer perceptrons for prediction of the outcome of construction litigation in Hong Kong. It is believed that, by combining the two algorithms, the advantages of global search capability of PSO algorithm in the first step and local fast convergence of LM algorithm in the second step can be fully utilized to furnish promising results.

2 Nature of Construction Disputes

Prior to the actual construction process, the involving parties will attempt to sort out the conditions for claims and disputes through the contract documents. However, since a project usually involves thousands of separate pieces of work items to be integrated together to constitute a complete functioning structure, the potential for honest misunderstanding is extremely high. The legislation now in force requires that any disputes incurred have to be resolve successively by mediation, arbitration, and the courts [8].

3 Characteristics of PSO Algorithm

Among other advantages, the more significant one is its relatively simple coding and hence low computational cost. One of the similarities between PSO and a genetic algorithm is the fitness concept and the random population initialization. However, the evolution of generations of a population of these individuals in such a system is by cooperation and competition among the individuals themselves. The capability of stochastic PSO algorithm, in determining the global optimum with high probability and fast convergence rate, has been demonstrated in other cases [9-10]. PSO can be readily adopted to train the multi-layer perceptrons as an optimization technique.

4 Training of Perceptrons by PSO

Without loss of generality, a three-layered preceptron is considered in the following. $W^{[1]}$ and $W^{[2]}$ represent the connection weight matrix between the input layer and the hidden layer, and that between the hidden layer and the output layer, respectively. During training of the preceptron, the i-th particle is denoted by $W_i = \{W^{[1]}, W^{[2]}\}$ whilst the velocity of particle i is denoted by V_i. The position representing the previous best fitness value of any particle is denoted by P_i whilst the best matrix among all the particles in the population is recorded as P_b. Let m and n represent the index of matrix row and column, respectively, the following equation represents the computation of the new velocity of the particle based on its previous velocity and the distances of its current position from the best experiences both in its own and as a group.

$$V_i^{[j]}(m,n) = V_i^{[j]}(m,n) + r\alpha[P_i^{[j]}(m,n) - W_i^{[j]}(m,n)] + s\beta[P_b^{[j]}(m,n) - W_i^{[j]}(m,n)] \quad (1)$$

where j = 1, 2; m = 1, …, M_j; n= 1, …, N_j; M_j and N_j are the row and column sizes of the matrices W, P, and V; r and s are positive constants; α and β are random numbers in the range from 0 to 1. In the context of social behavior, the cognition part $r\alpha[P_i^{[j]}(m,n) - W_i^{[j]}(m,n)]$ denotes the private thinking of the particle itself whilst the social part $s\beta[P_b^{[j]}(m,n) - W_i^{[j]}(m,n)]$ represents the collaboration among the particles as a group. The new position is then determined based on the new velocity as follows:

$$W_i^{[j]} = W_i^{[j]} + V_i^{[j]} \tag{2}$$

The fitness of the i-th particle is determined in term of an output mean squared error of the neural networks as follows:

$$f(W_i) = \frac{1}{S}\sum_{k=1}^{S}\left[\sum_{l=1}^{O}\{t_{kl} - p_{kl}(W_i)\}^2\right] \tag{3}$$

where f is the fitness value, t_{kl} is the target output; p_{kl} is the predicted output based on W_i; S is the number of training set samples; and, O is the number of output neurons.

5 The Study

The system is applied to study and predict the outcome of construction claims in Hong Kong. The data from 1991 to 2000 are organized case by case and the dispute characteristics and court decisions are correlated. Through a sensitivity analysis, 13 case elements that seem relevant in courts' decisions are identified. They are, namely, type of contract, contract value, parties involved, type of plaintiff, type of defendant, resolution technique involved, legal interpretation of contract documents, misrepresentation of site, radical changes in scope, directed changes, constructive changes, liquidated damages involved, and late payment.

Some of the 13 case elements can be expressed in binary format; for example, the input element 'liquidated damages involved' receives a 1 if the claim involves liquidated damages or a 0 if it does not. However, some elements are defined by several alternatives; for example, 'type of contract' could be remeasurement contract, lump sum contract, or design and build contract. These elements with alternative answers are split into separate input elements, one for each alternative. Each alternative is represented in a binary format, such as 1 for remeasurement contract and 0 for the others if the type of contract is not remeasurement. In that case, only one of these input elements will have a 1 value and all the others will have a 0 value. In this way, the 13 elements are converted into an input layer of 30 neurons, all expressed in binary format. Table 1 shows examples of the input neurons for cases with different types of contract. The court decisions are also organized in an output layer of 6 neurons expressed in binary format corresponding to the 6 elements: client, contractor, engineer, sub-contractor, supplier, and other third parties.

In total, 1105 sets of construction-related cases were available, of which 550 from years 1991 to 1995 were used for training, 275 from years 1996 to 1997 were used for testing, and 280 from years 1998 to 2000 were used to validate the network results with the observations. It is ensured that the data series chosen for training and validation comprised balanced distribution of cases.

Table 1. Examples of the input neurons for cases with different types of contract

Input neuron	Cases		
	Remeasurement	Lump sum	Design and build
Type of contract - remeasurement	1	0	0
Type of contract - lump sum	0	1	0
Type of contract – design and build	0	0	1

Sensitivity analysis is performed to determine the best architecture, with variations in the number of hidden layers and number of hidden neurons. The final perceptron has an input layer with thirty neurons, a hidden layer with fifteen neurons, and output layer with six neurons. In the PSO-based perceptron, the number of population is set to be 40 whilst the maximum and minimum velocity values are 0.25 and -0.25 respectively.

Table 2. Comparison of prediction results for various perceptrons

Algorithm	Training		Validation	
	Coefficient of correlation	Prediction rate	Coefficient of correlation	Prediction rate
BP-based	0.956	0.69	0.953	0.67
PSO-based	0.987	0.81	0.984	0.80
LM	0.964	0.70	0.957	0.68
Split-step	0.990	0.84	0.987	0.83

6 Analysis and Discussions

The performance of the split-step multi-layer ANN is evaluated in comparison with the benchmarking standard BP-based network, a PSO-based network and a LM network. In order to provide a fair and common initial ground for comparison purpose, the training process of the BP-based perceptron or LM network commences from the best initial population of the corresponding PSO-based perceptron or split-step network. Table 2 shows comparisons of the results of network for various perceptrons. It can be observed that the split-step algorithm performs the best in terms of prediction accuracy. It is noted that testing cases of the split-step PSO-based network are able to give a successful prediction rate higher than 80%, which is much higher than by pure chance. It is believed that, if the involving parties to a construction dispute become aware with some certainty how the case would be resolved if it were taken to court, the number of disputes could be reduced significantly.

7 Conclusions

In this paper, a perceptron based on a split-step PSO algorithm is employed for prediction of outcomes of construction litigation on the basis of the characteristics of the individual dispute and the corresponding past court decisions. The results show that the split-step PSO-based perceptron outperforms the other commonly used optimization techniques in prediction of outcomes of construction litigation, in terms of both convergence and accuracy. The final network presented in this study is recommended as an approximate prediction tool for the parties in dispute, since the rate of prediction is higher than 80%, which is much higher than chance. It is, of course, recognized that there are limitations in the assumptions used in this study. Other factors that may have certain bearing such as cultural, psychological, social, environmental, and political factors have not been considered here.

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