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A Neural Network Approach to Plant Procurement

Modèle de réseau neuronal pour l'acquisition de biens d'équipement

Einsatz eines neuronalen Netzwerks zur Baumaschinenbeschaffung

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SUMMARY
The authors introduce a neural network model that was developed to assist in the selection of the method of plant procurement. An outline of the characteristics that make the problem suitable for neural network modelling is followed by a presentation of the procedure for developing, training and testing of the model. The paper demonstrates the feasibility and desirability of the model, but concludes that a significant amount of research work is required before a reliable tool can be realised.

RÉSUMÉ
L'article présente un modèle de réseau neuronal qui a été développé comme une aide pour l'acquisition de biens d'équipement. Après avoir présenté les différentes caractéristiques qui permettent de traiter le problème au moyen d'un modèle neuronal, l'article présente le développement du modèle, son calibrage et son utilisation. La faisabilité et les avantages de ce type de modèle sont présentés. Un travail de recherche important est cependant encore nécessaire avant qu'un outil fiable ne puisse être réalisé.

ZUSAMMENFASSUNG
Die Autoren stellen ein neurales Netzwerk-Modell vor, das entwickelt wurde um die Auswahl der Anschaffungsmöglichkeiten von Baumaschinen zu unterstützen. Einer Beschreibung der Eigenschaften, die das Problem für ein neurales Netzwerk-Modell behandelbar machen, folgen die Vorgehensweise zur Entwicklung des Modells und die Methoden des Trainings und des Testens. Der Artikel zeigt, dass das Modell realisierbar und sehr hilfreich ist, aber auch dass die Entwicklung eines verlässlichen Werkzeugs noch eine beachtliche Menge an Forschungsarbeit erfordert.

1. INTRODUCTION

Over the years the construction industry has experienced an underlying trend towards greater use of plants in the construction and maintenance processes. Several factors have encouraged this shift to mechanisation. These factors include technical improvements in construction equipment, the increasing size and complexity of construction projects, short construction periods required by clients and economic pressures. Furthermore, the increasing cost of labour has increased the relative benefits that can be derived from mechanisation. Construction is a high risk business environment where any decision that has any bearing on the financial wealth of construction firm or project demands a realistic approach to the appraisal of the options available and of the consequences of taking a particular course of action. The selection of both the plant required [1] and the method of procurement is an important element in cost and time [2, 3]. This paper introduces a neural network model for applications in the selection of plant procurement method.

There are essentially 4 methods of procuring plant:

1. Outright Purchase
2. Hire Purchase
3. Rental from a plant hire company
4. Leasing.

The choice of procurement method will have a significant effect on the financial status of any construction company and consequently on its day to day operations as will as its long term performance. The plant procurement decision can be split into two processes:

1. Technical Analysis to establish the utilisation rate, type of application and length of service for the plant.
2. Financial Assessment to establish the profitability of operating a type of plant.

The method of procurement is influenced by the former and has a profound effect on the latter.

Often the decision on the method of procuring plant is made on purely financial principles. This is not advisable for two principle reasons. First the data used to compute cash flows ensuing from the procurement and use of plant is often only a deterministic [4] estimate of the expected revenue. The reliability of such estimates is inversely proportional to the length of the period which they cover. Secondly, the outcome of the assessment is largely dependant on the discount rate used to produce the Net Present Value. Depending on the discount rate chosen it is possible to make a case for any given method and show that it is superior to any other.

Furthermore vendors offering the different options are regularly adjusting their price structures to a point where there is little difference in the annual equivalent cost between any two methods of procurement. It is therefore the rule rather than the exception for managers of construction firms to examine various qualitative factors when considering which method to use in the procurement of plant. Some of the factors that affect the procurement method are shown in Table 1. A few of the factors in this Table, like active life can be incorporated in the financial models used in analysis and thus be accounted for in the financial assessment. Other factors like the risk of technological obsolescence are difficult and often impossible to incorporate into these financial models. This hampers the use of conventional computing methods. Expert systems, which are among the most popular artificial intelligence techniques, are also not suitable for application to this problem. Their IF THEN procedures do not mirror the decision making process. Furthermore the factors shown in the table are considered simultaneously, a process that is difficult to model using traditional artificial intelligence techniques. [5].

TABLE 1: Factors Affecting the Selection of Plant Procurement Method

	FACTORS
1	Period over which plant is required
2	Type of application to which plant is to be put
3	Utilisation rate
4	Active life
5	Financial Status of company purchasing the plant
6	The magnitude of the risk of technological obsolescence
7	The probability of continuation of use
8	Annual equivalent cost, internal rate of return or Net present value
9	Urgency with which plant is required

2. NEURAL NETWORKS

A neural network is a computer model designed to emulate some of the features of the human brain. It is a non programmable adaptive information processing system capable of producing it's own algorithm in response to its environment [6,7,8]. Neural networks as shown in Figure 1 are built of numerous highly interconnected, simple processing units designed to resemble biological neurones.

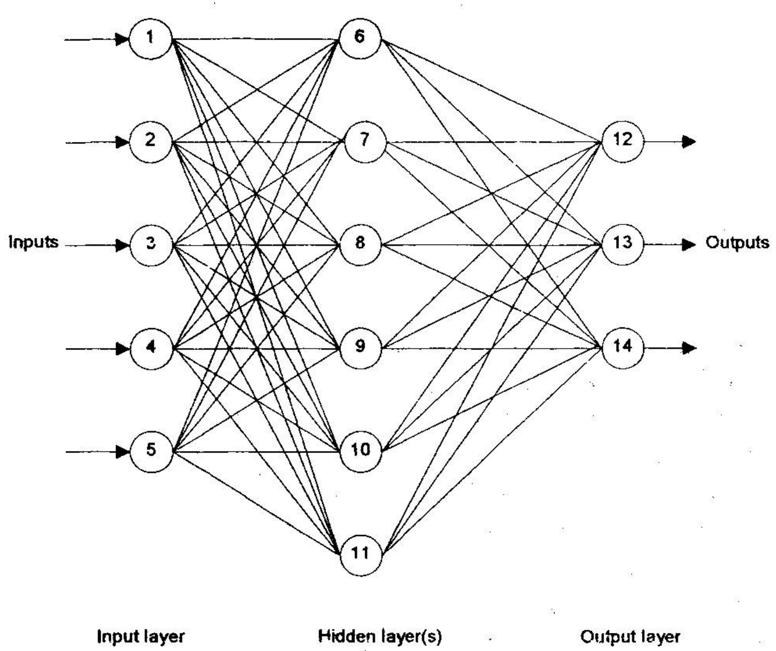

Fig. 1 Structure of a Neural Network

Each processing unit represents a specific concept: features, letters, data or an indescribable part of a larger concept [9]. All information processing is carried out by these units which only receive inputs and compute outputs which they send to neighbouring units, Neural networks are inherently parallel because the processing units can carry out their computations simultaneously [10]. Figure 1 shows how processing units are arranged in structural units called layers. Interaction between any two processing units depends on the weighting factor assigned to the connection between the two units.

Unlike standard software, a neural network is not a carefully developed series of linear instructions [11]. They are not programmed but rather they are trained using a series of input and output data. The network undergoes internal changes as it formulates the correct relationship between the input and output data. It stores what it has learnt as connection weights between processing units. The characteristic that has been the critical factor in raising interest in neural networks is this ability to learn. Other interesting and valuable characteristics of neural networks are their capacity of generalisation and induction, which enable them to give nearly correct responses when exposed to incomplete inputs. Parallelism endows neural network with processing speeds which allows them to overcome limitations imposed on conventional systems.

3. MODEL DEVELOPMENT

The first step in developing a neural network modelling is to identify the type of input that the network would require and the output desired. For the problem of selection of a plant procurement method this involves the selection of the factors that would need to be considered in order to identify the optimal procurement method. Seven factors were chosen from Table 1 to test the feasibility of a neural network approach. These factors were:

* The period over which the plant is required
* The type of application the plant is put to
* The utilisation rate
* The probability of continued use
* The company's financial status
* The risk of technological obsolescence and
* The urgency with which the plant is required

Table 2 shows the stages of development of the input and output representations used for the neural network "***NeuroPlant***". The various levels of input from the final model used for NeuroPlant was a ranking of the different methods on a scale of 0 to 1: the different methods would be ranked to show their suitability relative to one another of achieving the desired objective under given conditions. The sum of the rankings given to each method under any set of circumstances was not to exceed a value of 1. The choice of this presentation was due to two principle reasons. First, the software was more amenable to this form of representation. Second, it was our opinion that a system that ranked the methods was superior to one that gave a single output showing the optimal method. Such a system would allow the user to identify the next best method if s/he does not wish to use the optimal one.

TABLE 2(A): *NeuroPant* INPUT AND OUTPUT PATTERN

INPUT PATTERN

Requirement Period	< 1 year	1 - 2 years	2 - 5 years	5 - 10 years	
Application	Universal	Specialised			
Utilisation Rate	Very Poor	Poor	Average	> Average	High
Probability of continued use	No Possibility	Highly Possible			
Financial Status	Poor	Average	Good	Very Good	
Obsolescence Risk	Very Low	Low	Average	> Average	High
Requirement Urgency	None	Urgent			

OUTPUT: METHOD

Outright Purchase	Hire Purchase	Lease	Rental

TABLE 2(B): INITIAL INPUT AND OUTPUT PATTERN USED IN *NeuroPlant*

INPUT PATTERNS RANKINGS

Requirement Period	1	2	3	4	
Application	1	2			
Utilisation Rate	1	2	3	4	5
Probability of continued use	0	1			
Financial Status	1	2	3	4	
Obsolescence Risk	1	2	3	4	5
Requirement Urgency	0	1			

OUTPUT: METHOD

Outright Purchase	Hire Purchase	Lease	Rental

TABLE 2(C): THE FINAL INPUT AND OUTPUT PATTERN USED IN *NeuroPlant*

INPUT PATTERNS RANKING

Requirement Period	1	2	3	4	
Application	1	2			
Utilisation Rate	1	2	3	4	5
Probability of continued use	0	1			
Financial Status	1	2	3	4	
Obsolescence Risk	1	2	3	4	5
Requirements Urgency	0	1			

OUTPUT: METHOD

Outright Purchase	Hire Purchase	Lease	Rental
0	0	1	0

4. KNOWLEDGE ACQUISITION, TESTING AND TRAINING

From the very start it was realised that these will present significant problems. The selection of procurement strategy depends on a number of interrelated factors. Presented with identical information different managers arrive at different decisions. Furthermore, the same manager often makes a different decision when presented with identical input some time later. The underlying cognitive and emotive biases in humans make managers unsuitable as trainers. What is required is a training set of reliable character and adequate size. The results of the work reported here led to the realisation that a more reliable set of training data will produce a very significant improvement in the performance of the system. The next step involves the creation, through simulation, of an "expert" capable of producing any number of training sets rendered reliable by eliminating the biases. The details of this approach will be the subject of a separate paper to be published in 1994.

The network's architecture was defined using "Brainmaker" a proprietary back propagation neural network software package developed by California Scientific Software. The neural network developed had 7 neurones in its input layer, 4 neurones in its output layer and 32 neurones in the middle layer.

The neural network was trained using 33 examples. Training was done in Brainmaker and carried out on an Elonex computer with 808486 SX processor working at a speed of 25 MHz. The network converged in about 3 minutes after 425 runs. Testing was done by introducing the two categories of input patterns. The first category of inputs consisted of all the data used in training. The second category of test data consisted of examples which the network had not encountered during training.

5. DISCUSSION

The results of testing the network show that a neural network can be used to capture the relationship between qualitative factors that influence a decision. ***NeuroPlant*** was capable of producing independent outputs to patterns used in training. The network outputs had an average error of 6.1% corresponding to an average aggregated deviation of 0.064 from the desired responses. Though maximum error for the network was 20.9%, errors greater than 10% were few in number. As expected both the average and maximum error from tests on data that the network had not encountered during training was higher than the corresponding results from tests on the training data. The error was largest for input patterns where the factor representing the probability of continued use had a value of 1. The reason for this result is the dearth of training examples that had this factor taking a value of 1. Even where the factor took this value its effect on the decision was often overshadowed by the effect of the other features. When NeuroPlant was presented with examples that had an abundance of patterns where continuity was an important factor the average error was 17.5% and the maximum error was 83.3%, corresponding to aggregated deviations of 0.175 and 0.833 respectively. The average error for test data with only a few patterns where continuity of use was a crucial factor was 7.6% with a maximum error of 34.4%. The test data consisted of 12 examples. It is worthy of note that the sum of rankings given to each method by the network often exceeded the desired value of 1. This problem could not be remedied but such a system could be used to give each method a rank on a scale of 0 to 1.

The accuracy of the neural network model can be improved by:

1) Identifying the optimal size of the hidden layer and training parameters (the large maximum error indicated that the optimal size had not been identified).

2) Increasing the number of examples used in training.

3) Incorporating more factors that affect plant procurement into the model

4) Incorporating examples that are obtained from a survey of professionals with experience in plant procurement.

A valuable lesson from this study was derived through experiencing the difficulty of identifying the optimal size of the hidden layer in a network. The trial and error process used to select network architecture was made more difficult by the network's sensitivity to changes in size of the hidden layer. Furthermore the performance of the network was also dependant upon the size and quality of the training data. It will therefore be difficult to convince potential users of the reliability of neural networks until we are able to understand the working of the hidden layer and subsequently formulate rules to help select the hidden layer characteristics. Secondly the issue of optimal training size requires to be resolved. Experience shows that a network that is trained with too few examples will not learn while too many examples will hamper the network's ability to generalise. The reason for this is not well understood though it is thought that a network presented with a large training set memorised the individual patterns rather than capturing the essential relationship embodied in the data.

The study suffered from one major limitation. This was the factors used and the patterns developed for training the networks were all identified by a very small number of individuals. The networks' abilities therefore reflected the expertise and opinion of these individuals. Any further work in this area should obtain training examples from a large number of managers who are involved in the administration of plant divisions for construction companies. There is a danger that the variability in the training examples introduced by the different perceptions of the experts would make training the network more difficult. Clearly the best method of implementation would involve each interested company training the neural network on data that would represent its own perception on how the different factors affect the choice of procurement method.

6. FUTURE WORK

Anyone carrying out future work should be encouraged to investigate the feasibility of combining the neural network with two important elements:

A user interface and a spreadsheet application housing cost information.. Figure 2 shows the probable structure of the resulting hybrid system. The user interface would perform the following tasks:

1) Get information about the problem from the user

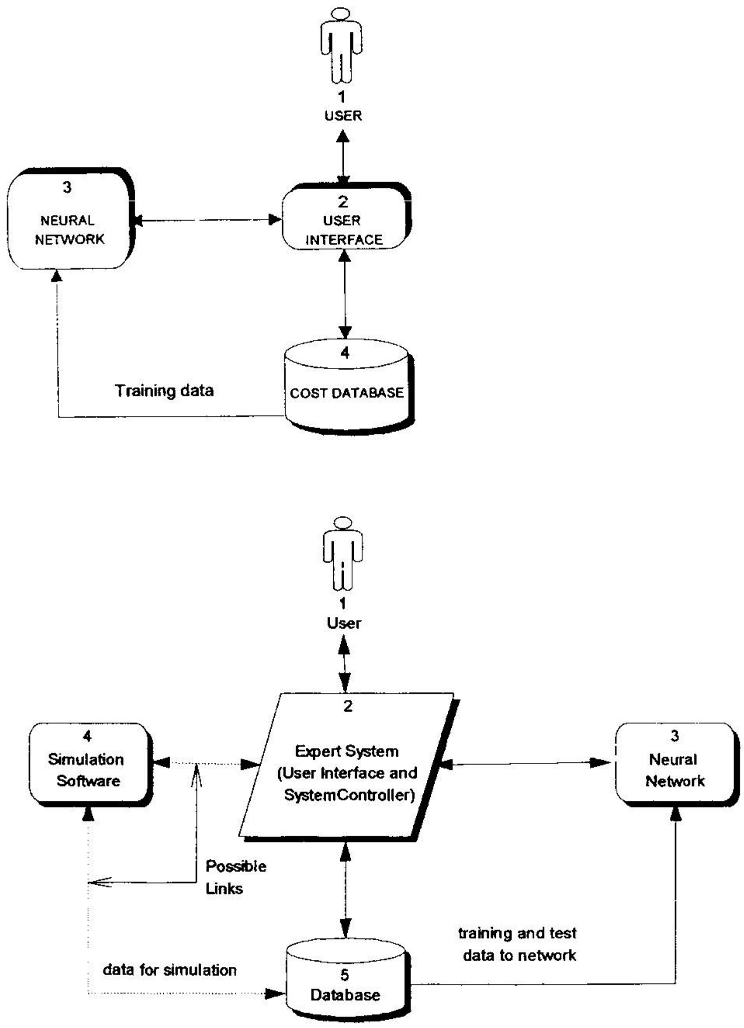

Fig. 2 Possible Structures of a Hybrid System

2) Translate the information into an input representation that the neural network can understand

3) Translate the information provided by the user and the output from the neural network into a form that the spreadsheet can use

4) Display the recommendation from the neural network into a form that the user can understand.

Once a recommendation has been given the management would wish to see the financial implications of this recommendation. This can be achieved by linking the neural network to a spreadsheet package containing a cost database for each method and a procedure for computing cash flows. The user would input various parameters like the type of plant, cost, capital allowances and other pertinent information which would be used together with the neural network's output to compute a cash flow stream. It would be advisable for future work to include an investigation on the performance of the neural network when equipped with two or more hidden layers. The results of such an investigation would allow the identification of the optimal neural network model.

7. CONCLUSIONS

The prototype presented in this paper demonstrates that a back propagation neural network can be developed to assist plant managers in the choice of a plant procurement method. Characteristics like learning and generalisation capabilities combine to make neural networks a potentially powerful decision support system. Additional work will however be required before this application can be developed into a commercially viable tool.

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