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ABSTRACT

In this paper, an innovative approach is presented to decision making using self-organizing multi-layered neural networks. The model helps make a decision whether to use a conventional "stick-built" method or to use some degree of modularization when building an industrial process plant - a problem considered very important in construction management because of its economic impact. The objective of this paper is to show that both expert system and neural network approaches can be useful for decision making problems. However, in some situations a neural network approach can outperform the expert system approach.

A brief overview of prior approach to modular construction decision making is provided in this paper and the reasons for using a neural network approach are also discussed. The architecture, knowledge representation, and training procedure for the neural network paradigms used are described. The performance of the trained neural network system and its comparison with the recommendations provided by human experts and the expert system are also presented.

INTRODUCTION

This paper deals with the design and development of a neural network based decision making model. The model helps management personnel in the construction industry decide whether to use a conventional construction method or to use certain degree of modular construction method when planning to build an industrial process plant either within or outside the United States. The feasibility of construction modularization depends on the specific project situation, organizations involved, social, legal and environmental conditions. In some obvious project environments, such as remote sites, harsh weather conditions, etc., modularization represents the only feasible choice. On the other hand, in some other situations the decision to modularize is not as obvious. Therefore, at the initial stage of a project, management must decide whether to investigate the modularization potential.

In the past, there has never been an easy-to-use method that can be used to determine modularization feasibility. The only way in which companies have utilized modularization in the past has been when an expert in the field was consulted from within the organization or from another organization. However, there are many engineering and construction and owner companies which need to be able to determine modularization feasibility of a project in a simpler and more easily accessible way. An expert system has already been designed to achieve this goal (Murtaza, Fisher and Skibniewski, 1993). However, the results of the research presented here show that a neural network approach outperforms an expert system for the present problem. Additionally, the neural network based system can handle the inexact and incomplete inputs in order to reach a conclusion (Kamarthi, Sanvido & Kurmara, 1992) and, thus, is more appropriate for unstructured decision making environments like construction modularization.

The next section of this paper presents a brief overview of expert system approach developed previously for modular construction decision making. The paper then discusses the architecture of the neural network paradigms used, and also describes the overall architecture and training procedure of the neural network system. The performance of the neural network system and its validation results are also provided.

EXPERT SYSTEM APPROACH

Modular construction is a method for constructing units of a project in a remote location from the final project site. Modularization brings the advantage of the manufacturing process to the construction industry, such as a controlled environment (temperature and lighting), improved quality control, improved safety, etc. Modularization offers an opportunity to improve a variety of performance parameters relating to the project, such as cost and schedule. A module is a remotely assembled unit. It is usually the largest transportable unit or component of a facility. It has all structural elements, finishes, and process components fitted. Modules may contain prefabricated components or preassemblies.

An expert system for construction modularization decision making has already been developed (Murtaza, Fisher & Skibniewski, 1993). During the knowledge-base development phase, several hours of knowledge acquisition sessions were held with the experts at the major engineering and construction, fabrication and owner firms in the construction industry. These sessions with modularization experts provided an extensive amount of information about the modularization feasibility study process. The most important discovery was the determination of factors to consider when such a study is performed. These factors can be categorized in the following five groups: Plant Location, Labor Considerations, Environmental and Organizational Factors, Plant Characteristics, and Project Risks (Murtaza, 1993).

The analysis of project location includes such factors as accessibility, climatic conditions, bulk commodity quality and availability, construction equipment quality and availability, transportation mode, transport equipment availability and timing. Labor skills, productivity and type (union or non-union) are some of the factors included in the labor related category. Some of the factors related to the project characteristics are repeatability, proprietary security, project type (evolutionary or non-evolutionary), system density, and existing facility impact. Project risks factors category includes schedule, height of construction, quality requirements, etc. Environmental factors include module import restrictions, offsite access concerns, environmental restrictions and social issues. There are some other factors to be evaluated and are included in the organizational factors category. These factors relate to engineering and construction firms (climate towards modularization, willingness to early involvement with owner, etc.), fabricators (availability and capability) and owners (receptivity to modularization, understanding of modularization, willingness to live with the design constraints of modular construction, etc.).

In addition to the five influencing factor categories described above, economics also was determined to be an important factor. Some costs increase with modularization, such as transportation, steel, and engineering; however, total labor costs are reduced due to higher productivity. The potential reduction in schedule, when converted to dollar figures, can become a considerable advantage in the selection of modular construction over traditional methods. In fact, schedule savings are often the driving force for modularization as capital costs for both "stick-built" and modular projects can be comparable.

The expert system - MODEX (MODularization EXpert) contains a three-step analysis as described below. The first step is *prescreening,* which can be performed with a minimum of information, and is usually available at the very early stages of a project. The purpose of this step is to quickly find out whether the modularization is worth considering for a given project. If the modularization is worth considering for the project, then the system continues to the second step which is *detailed feasibility study.* This step determines which design and construction method is more advantageous for a given project - conventional "stick-built" or some degree of modularization. This is determined based on the relevant qualitative factors and on other preferences expressed by the user. The system also determines the level of confidence assigned to the advice given to the decision maker. The third and final step is *economic study.* At this step, the system determines what cost savings (or loss) and reduction in the construction schedule is possible if some degree of modularization is used on the project.

The expert system was designed and fully implemented. After validation, the performance of the system was at an acceptable level. However, later on, based on several reasons, the authors decided that a neural network approach would be more appropriate for construction modularization which is an unstructured decision making problem. One reason for using a neural network approach is that it was discovered during knowledge acquisition process that the decision-makers for the problem are not aware of exactly what motivates the decision, and that they base decisions on experience without weighing each decision-making attribute separately. An artificial neural network approach is better suited for modeling these kinds of decision processes (Burke, 1991; Moselhi, Hehazy, & Frazio, 1991). Also, apart from being more efficient (due to parallel processing at the classification stage), the architecture presented here resembles more the human decision-making process, since the proposed neural network paradigms use unsupervised learning.

NEURAL NETWORK APPROACH

Instead of using deduction or collection of rules, neural networks rely on their ability to recognize patterns through experience. Although neural networks are considered essentially adaptive pattern recognition systems, their applicability can easily be extended to other types of problems. With little effort, a decision situation can be converted to a pattern recognition problem. Several researchers have applied neural networks to business decision making situations in the past (Collins, Ghosh, & Scofield, 1988; Dutta & Shekhar, 1988; Fletcher & Goss, 1993; Kimoto, Asakawa, Yoda & Takeoda, 1990; Lodewyck & Deng, 1993; Odom & Sharda, 1990; Surkan & Singleton, 1990).

The authors have designed and implemented a multi-layered self-organizing neural network to perform the decision making (classification) for the construction modularization problem. The multilayered network utilizes two neural network paradigms, namely, Kohonen's self-organizing feature maps and competitive learning. Both of these paradigms essentially use unsupervised learning approaches. The unsupervised learning methods try to adjust the weights in such a way that the input vectors that are sufficiently similar produce the same output vector (Dadashzadeh & Bahr, 1993).

Kohonen (1989) has developed self-organizing maps and used them for pattern recognition and signal processing tasks. In general, these maps classify a pattern represented by a vector of values in which each component of the vector corresponds to an element of the pattern. Kohonen's algorithm is essentially based upon an unsupervised learning technique, although some variants do use some supervision. The benefit of Kohonen's algorithm lies in its simple computational form, which besides providing a plausible neural model allows its efficient application to pattern recognition and control tasks, such as speech recognition, image processing and motor learning for robots (Ritter & Schulten, 1988). In a series of papers, Kohonen (1982a, 1982b, 1982c) has proved effectiveness of the algorithm through mathematical proofs and computer simulation results.

Competitive learning systems are usually feedforward multilayered neural networks. Neurons compete for the activation induced by randomly sampled input patterns. At an iteration, the neuron whose weight vector is closest, in Euclidean distance, to the random pattern wins. In competitive learning, only one output neuron is "on" at a time. Since output neurons compete for being the one that fires, these neurons are called 'winner-take-all' neurons. The aim of competitive learning networks is to cluster or categorize the input data. Similar inputs are clustered as being in the same category, and therefore they should activate the same neuron. Since competitive learning is essentially unsupervised, the classes must be found by the network itself from the correlations of input data. The competitive learning is closely related with the feature mapping mentioned earlier.

NETWORK ARCHITECTURE AND TRAINING

The basic competitive learning networks have a single layer in which only one neuron wins for each input pattern. In order to generalize it to multiple layers, several winners should be allowed for each layer so that subsequent layers can analyze different patterns. In this way, it is expected that the network can detect successively higher order patterns in the data (Hertz, Krogh, & Palmer, 1991). It has been shown that a hierarchical hybrid neural network comprised of simple neural networks provided higher accuracy in information retrieval than single neural network architectures (Gersho & Reiter, 1990).

For the present problem, the input data vector consists of thirty-nine components, corresponding to problem attributes for decision making as discussed earlier. The architecture of the network proposed here is parallel and multi-layered (Murtaza & Fisher, 1991). There are certain benefits obtainable by layering networks (Thacker & Mayhew, 1990) that can be outlined as follows: the different layers of the network could represent semantic descriptions of the input data at different levels of abstraction, or the first layer may be used for feature recognition and the next layer for recognition of groups of features with this or some further layer eventually providing object recognition.

The architecture of the network is truly parallel, self-organizing, and hierarchical. There are five self-organizing feature map networks (see Figure 1) in parallel. This number of networks is selected heuristically, since these networks represent broad categories of decision factors. These individual networks consist of two layers, the first layer comprised of input neurons and the second layer is made up of Kohonen neurons. The second layer Kohonen neurons are activated when the input is fed from the first layer. The third layer uses competitive learning, and the Kohonen neurons of the second layer provide input to the competitive layer neurons through their connection links. The number of neurons in the first layer of each network is equal to the number of problem attributes (decision factors) and the number of neurons in the second layer is chosen arbitrarily. The number of third layer neurons is more than four, since after training they are expected to represent at least four possible final choices (clusters). The overall architecture of neural networks is given in Figure 2.

The objectives in developing this type of parallel, self-organizing hierarchical neural network include decreasing system complexity, increasing classification accuracy, avoiding local minima, reducing learning and recall times, and obtaining a higher degree of robustness and fault tolerance (Ersoy & Hong, 1990).

To train each Kohonen layer, self-organizing feature map (single winner unsupervised learning) is used. However, there are other vector quantization methods which can also be utilized and are proven more efficient, such as frequency-sensitive competitive learning [1] but those methods were not needed for the present problem. Each time an input vector **x** is given to input layer (layer h), competition is held among the neurons of Kohonen layer (layer i) and the one whose weight vector **w** is closest of **x** wins. This neuron's output signal z_i is then set to 1 and the other neurons' outputs are set to 0. Once the winner is determined, it adjusts its weight vector in accordance with the following equation:

Figure 1. Self-Organized Feature Map for Each Decision Factor Category

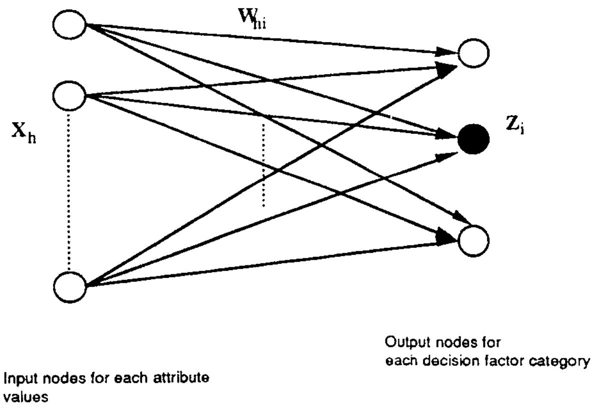
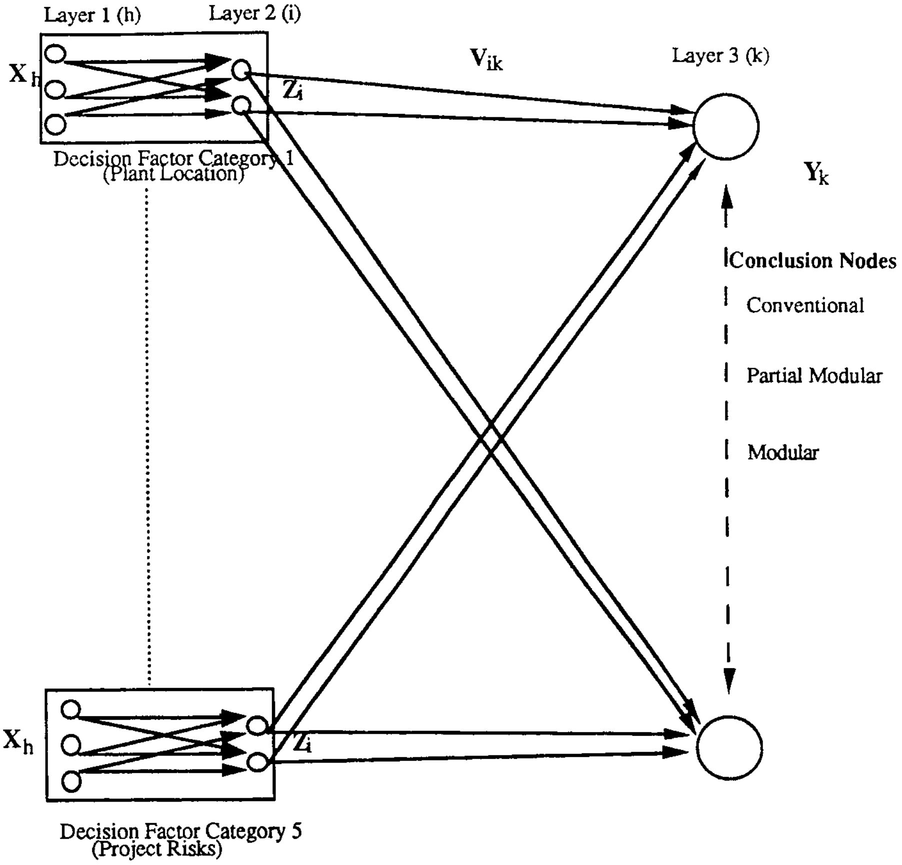


Figure 2. Overall Architecture of the Neural Network



$$w_{hi}\,(t + 1) = w_{hi} + a(x_h - w_{hi}\,(t))z_i\,,$$

where $w_{hi}\,(t + 1)$ = weight after the update. At the beginning of training, the weights of neurons within certain distance from the winner are also updated using the same equation. However, this distance is slowly reduced to 0 so after few iterations the weight of only the winning neuron is updated.

The identity $z_i = 1$ if $\sum_i (x_h - w_{hi}) < \sum_j (x_h - w_{hj})$ where $i \neq j$, and 0 otherwise.

At the beginning "a" is close to 0.2 and slowly reduced to very close to zero. Also, the neighborhood training region is slowly reduced to zero.

Once the Kohonen layers are trained, the third layer (layer k) starts to learn using the training equations given below:

$$v_{ik}\,(t + 1) = v_{ik}\,(t) + a\,[z_i - v_{ik}\,(t)]\,y_k',$$

where $v_{ik}\,(t)$ = the connection weight from second layer Kohonen neurons,

z_i = output from each Kohonen layer,

a = the training rate coefficient, which starts around 0.1 and is gradually reduced during the training process,

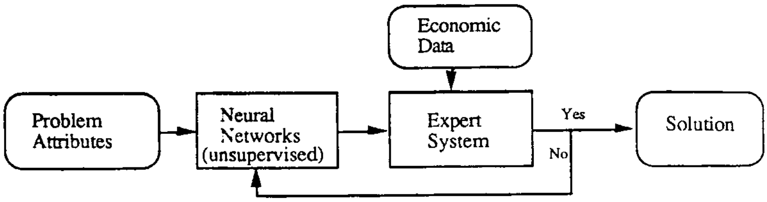
y_k' = is set equal to 1 for that third-layer neuron w which has highest value output value y_k, and zero otherwise, where

$$y_k = v_{ik}\,(t)\,.\,z_i^T.$$

During post-training operation the network can be operated in interpolative mode, i.e., more than one neuron can win the competition in the Kohonen layers (Simpson, 1989). The output from non-winning neurons remains equal to zero. Finally, during post-training operation when provided with the input in the first layer, activations are propagated through second layer to the third layer. As a result, one of the third layer neurons wins, the one with the highest activation, representing the final choice.

In this model, the neural network is only used to find the best choice based on mostly

Figure 3. Overall Architecture of the System



PERFORMANCE RESULTS AND VALIDATION

As described earlier, the neural network consists of three layers and the third layer provides the final conclusion for modularization decision. In the final simulation runs, there were five neurons in the third layer and since the training procedure used was unsupervised, it is only after the training that it could be determined what decision a particular neuron represents. The five neurons used in the network represent the following decision clusters: [1] Conventional with High Confidence, [2] Conventional with Low Confidence, [3] Low Partial Modularization, [4] High Partial Modularization, and [5] Extensive Modularization. The input neurons could take continuous values from 0 to 1, and each neuron represents one of the factors important to modularization decision making. To train the network, forty cases were run several hundred times while the learning rate was continuously reduced until the connection weights stabilized.

After completion of the training process, three types of comparison tests were performed on the system in order to validate it. Since the unsupervised training was used, after the training it was determined what cluster a particular neuron represented. Therefore, one performance test was made to determine whether the network could cluster the training patterns correctly. The second test was made on the data that were not used for training purposes. These data included three cases on which consensus of more than one expert was received, and three hypothetical cases that could easily be divided into modular, partial modular, and conventional cases. These hypothetical cases were compiled based on the knowledge acquired during interviews with experts. One of the cases included highest possible values for all the decision factors, second case included middle values for all the factors, and the third case included lowest possible values for all the factors. Finally, the third test was made using incomplete data sets, so as to determine the network's capabilities of decision making under incomplete information.

As mentioned earlier, one type of validation test that was performed on the network was comparison of its recommendation with the decision that was actually made on a case. This test, however, was made on some of those cases that were used for the training. The results of neural network matched with the actual decisions in 27 out of 36 cases (75%).

For the second kind of validation test, six cases were compiled. On these cases, more than one expert agreed on the decision. Three of these cases were actual, and three were hypothetical as described earlier. Out of these six cases, the neural network made the correct decision in five cases (83%). These cases are presented in Table 1. The first three cases are actual and cases 4 to 6 are hypothetical.

Table 1. Comparison of Neural Network Results with Actual Decisions

Case	Actual Decision	Neural Network Decision
1	Extensive modularization	Extensive modularization
2	High partial modularization	High partial modularization
3	High partial modularization	High partial modularization
4	Extensive modularization	Extensive modularization
5	High partial modularization	High partial modularization
6	Conventional	High partial modularization
7	High partial modularization	High partial modularization
8	Low partial modularization	Conventional
9	Extensive modularization	Extensive modularization
10	Low partial modularization	Low partial modularization

A third validation test was performed on the data collected from the literature (Tatum, Venegas & Williams, 1987). Out of four cases, the network made correct decisions in three cases (see cases 7 to 10, Table 1). For these cases, the actual input set was incomplete, as the cases presented in the literature did not provide complete information about all of the relevant decision making factors. Therefore, this validation illustrated the networks' capabilities to cluster under incomplete information. A word of caution is needed here—the only feasible way to validate the system here is to compare its performance against the recommendation of the experts. And if the judgment of the experts is inaccurate then the validation results would also be inaccurate, therefore extreme caution is required when compiling test cases.

A nonparametric statistical test was performed on the results of the previously described ten cases.The appropriate test is the Wilcoxon Signed Rank Test for the paired difference experiment. In this experiment, the difference between the results is analyzed. The nonparametric approach requires that the ranks of the absolute values of the differences between the measurements be calculated (McClave & Benson, 1985). In the case of ties, one-half of the ties are considered positive and the other half as negative (Gibbons, 1971). After the absolute differences are ranked, the sum of the ranks of the positive differences, T_+, and the sum of the ranks of the negative differences, T_-, are calculated.

The test hypothesis of this test is as follows:

Ho: The probability distribution of the actual decisions and the neural network decisions are identical.

Ha: The probability distribution of the actual decisions is shifted to the left or right of the probability distribution of neural network decisions.

Test statistic: T = Smaller of the positive and negative rank sums T_+ and T_-

The rejection region for the hypothesis can be determined by consulting the table of critical values of T_0 for the Wilcoxon Paired Difference Signed Rank Test. For $n = 10$ pairs of observations, the value of T_0 is 3 for $\alpha=.01$ (McClave & Benson, 1985, Appendix B, Table XI). Thus, the rejection region for this particular test is given below.

Rejection region: $T \leq$ for $\alpha = .01$

For the test, it was found that the sum of positive ranks T_+ is 9, and the sum of negative ranks T_- is 10. Since the smaller rank sum, T_+ , does not fall within rejection region, the alternate hypothesis cannot be concluded at $\alpha = .01$. Thus, the probability distribution of the actual decisions and the neural network decisions are identical.

Thus the validation tests have shown the accuracy of neural network based systems. However, the tests were limited to ten cases and, therefore, there is a need to compile several more test cases and compare the performance of the system against the conclusions provided by the experts.

CONCLUSIONS

The focus of this research was on developing a decision model using a neural network system. The results obtained from the neural network system were compared with the recommendation provided by experts and the expert system. The test cases for validation were compiled from experts and from literature. The validation tests showed that neural network results were highly accurate.

The present paper shows that neural networks offer a viable alternative to traditional artificial intelligence methods as a means of developing powerful decision making tools. The model presented here or any variant of it can easily be utilized in several similar decision making situations that involve a consideration of several decision factors.

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