Evolutionary Fuzzy Hybrid Neural Network for Conceptual Cost Estimates in Construction Projects

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Abstract

Conceptual cost estimates are important to project feasibility studies, even the final project success. The estimates provide significant information for project evaluations, engineering designs, cost budgeting and cost management. This study proposes an artificial intelligence approach, the evolutionary fuzzy hybrid neural network (EFHNN), to improve precision of conceptual cost estimates. The approach incorporates neural networks (NN) and high order neural networks (HONN) into a hybrid neural network (HNN). The HNN operates with the alternative of linear and non-linear neuron layer connectors. Besides, fuzzy logic (FL) is employed for handling uncertainties, the approach therefore evolve into a fuzzy hybrid neural network (FHNN). For FHNN optimization, the genetic algorithm is used for both FL and HNN, consequently the approach is named as EFHNN. In practical case studies, two estimates including overall and category cost estimates are provided and compared. Results show that the proposed conceptual cost estimates can be deployed as accurate cost estimators during early stages of construction projects. Moreover, considering linear and non-linear neuron layer connectors in EFHNN surpasses models with singular linear deployment of NN.

Keywords： Construction Cost, Conceptual Estimates, Genetic Algorithm, Fuzzy Logic, Neural Network, High Order Neural Network, Hybrid Neural Network

1. Introduction

Cost estimates are fundamental to all project-related engineering and greatly influence planning, design, bidding, cost management/budgeting and even construction management. Such estimates allow owners and planners to evaluate project feasibility and control costs effectively in detailed project design work. Due to the limited availability of information during the early stages of a project, construction managers typically leverage their knowledge, experience and estimators to estimate project costs, i.e., they usually rely on their intuition. Researchers have worked to develop cost estimators that maximize the practical value of limited information available in order to improve cost estimate accuracy and reliability, which should improve the suitability of resultant designs and subsequent project execution work.

Artificial intelligence approaches are applicable to cost estimating problems related to expert systems, case-based reasoning (CBR), neural networks (NN), fuzzy logic (FL), genetic algorithms (GA), and derivatives of such. Many research studies have been done in this area. For instance, Serpell (2004) proposed a model of this problem based on existing knowledge and demonstrated how the model was used to develop a knowledge-based assessment system. An et al. (2007) developed a case-based reasoning model, where an analytic hierarchy process was employed to incorporate experience. NN represents the most frequently applied approach in this type of application. Wilmot and Mei (2005) developed an NN model to estimate highway construction cost escalation over time.

Furthermore, hybrid models have also been developed to estimate construction costs. Hegazy and Ayed (1998) used NN to develop a parametric cost estimating model for highway projects, with optimal NN weightings optimized by GA. Yu et al. (2006) proposed a web-based intelligent cost estimator that incorporated a neurofuzzy system.

In past research work, NN, GA, and FL have been employed for their powerful abilities to estimate construction costs. They are widely applied as well to other topics and even to fields unrelated to the construction industry.

High order neural networks (HONN) usually introduced a nonlinear equation to a specified layer. It allowed the networks to capture high order correlations easily and attained the nonlinear mapping effectively. As HONN uses high order correlations, it may perform better than linear NN (Zurada, 1992). HONN not only allowed a fuller degree of adaptability in the form of the nonlinear mapping than linear model, but has a structure that can make it easier to determine how the network inputs come to be mapped into the network outputs (Abdelbar, Tagliarini, 1996).

In previous studies (Cheng et al. 2008a; Cheng et al. 2008b), the authors had contributed on a GA-optimized Neural-fuzzy model for studying various engineering problems. This study incorporates the linear neural networks (NN) and high order neural networks (HONN) as a hybrid neural network (HNN). Each HNN layer connector is dominated by an alternative of selecting a linear or high order layer connector. The HNN model evolved into a fuzzy hybrid neural network (FHNN) model with participation of fuzzy logic. Within the proposed evolutionary fuzzy hybrid neural network (EFHNN) model, GA optimized both of FL's membership functions and HNN's connection types, topology, and coefficients, etc. This study further applied proposed EFHNN for the uses of conceptual cost estimators. Two kinds of estimates - overall estimates (total cost estimates) and category estimates (estimating respectively with engineering categories) – were provided at the planning or preliminary design stage.

2. Evolutionary Fuzzy Hybrid Neural Network (EFHNN)

The proposed EFHNN incorporates four artificial intelligence approaches which are neural network (NN), high order neural network (HONN), fuzzy logic (FL), and genetic algorithm (GA) (see Fig. 1). Of which, NN and HONN are composed for the inference engine, i.e. the proposed hybrid neural network (HNN); FL dominates both fuzzifier and defuzzifier layers; and GA optimizes the HNN and FL. According to the definitions of "neuro with fuzzy input-output" (Hayashi et al. 1998), this study proposes a fuzzy hybrid neural network (FHNN) which is structured of HNN with both fuzzy inputs and fuzzy outputs (see Fig.2). Each NN connection can select a linear or high order NN connector. Sequentially, the FHNN is optimized through GA adaption process (see Fig. 3). The process simultaneously searches for the optimum FL's membership functions, defuzzification coefficients, HNN topologies, and HNN parameters (including linear/high order connection types) using GA. In the process, P(t) denotes a population at generation t, PO(t) is an offspring population at generation t, and PM(t) indicates a mutation population at generation t. Details of FL and HNN and GA are described in the following sections.

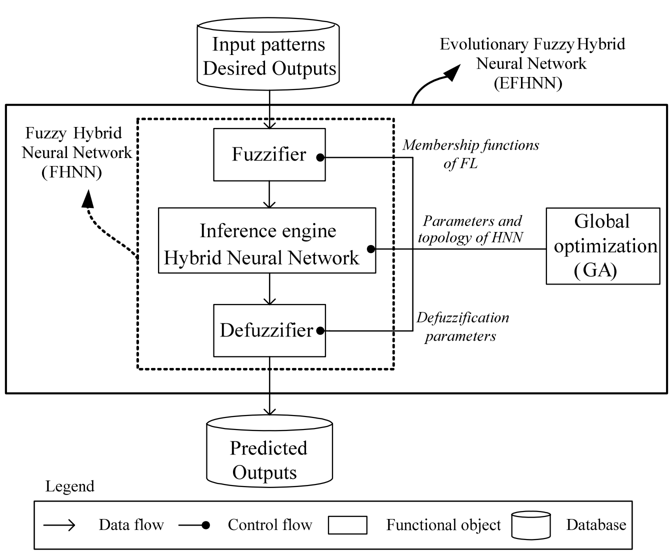

Fig. 1. EFHNN Architecture

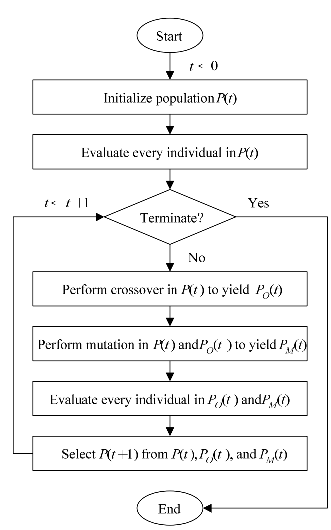

Fig. 3. EFHNN Adaption Process

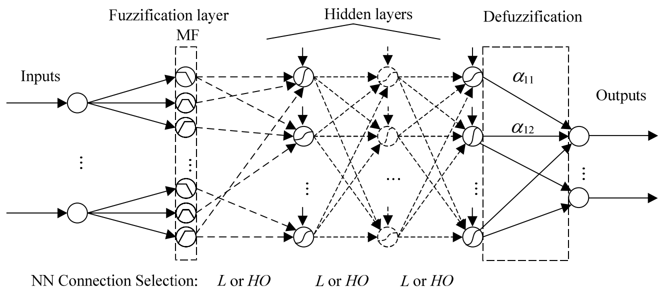

Fig. 2. FHNN with FL and HNN

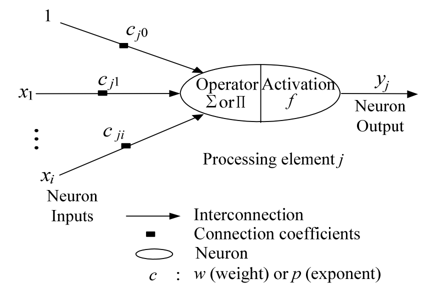

Fig. 4. A HNN Neuron

2.1 Proposed Hybrid Neural Network

Originally, "hybrid" means anything derived from heterogeneous sources, or composed of elements of different or incongruous kinds. For the proposed hybrid neural network (HNN), "hybrid" is used for representing the combination of traditional neural network and high order neural network. The high order neural network that this paper uses was proposed by HONEST model (Abdelbar and Tagliarini, 1996) which was structured of three layers with a high order connection and a linear connection between 1st – 2nd layers and 2nd – 3rd layers respectively . This study extends uses of high order connection for all connection alternatives, i.e. all layer connections can switch to linear or high order type (see Fig.2). An HNN neuron is dominated by an alternative of following equations:

Linear connection: $$y_j = f\left(\sum w_{ji}x_i + b_{j0} \times 1\right) \quad (1)$$

High order connection: $$y_j = f\left(\prod x_i^{p_{ji}} \times 1^{b_{j0}}\right) \quad (2)$$

Activation function: $$f(x) = \frac{1}{1+e^{-ax}} \quad (3)$$

where yj is a HNN neuron output calculated by neuron inputs xi. cji represents a coefficient of a interconnection, which can be linear or high order format related to a weight wji or exponent pji respectively (see Fig. 4). An activation function f uses sigmoid function with a slope coefficient of a. Therefore, each layer connection has an attached connection type to represent thereof operation selection (see Fig. 2). All the HNN parameters will then be optimized by GA evolution. As above mentions, a HNN with 2 layers can select a linear layer connection (L) or a high order connection (HO); with 3 layers number of HNN models according to connection types, four possible scenarios of L-L, L-HO, HO-L, and HO-HO exist. If adopting a maximum number of HNN layers as N, i.e. the final HNN model can be a HNN with layer not beyond N, there are 21, 22,…, 2N-1 HNN model candidates respectively related to HNN with 2, 3,…, N layers. Summarily, there are 2N-2 HNN model candidates. Of which, only N-1 models select all L connections, all the remainders are categorized into high order neural networks in this study. The proposed HNN includes all the linear and high order neural networks according connection type selections.

2.2 Fuzzy Logic Facilities

In Fig. 2, the HNN is enclosed by a fuzzification layer and a defuzzification layer. All of these compose a fuzzy hybrid neural network. In the defuzzification layer, an input firstly transfers into several membership grades by membership functions (MF). In this study, a complete MF set which uses trapezoidal MF is adopted. A general way to describe the shapes of MF is to depict summit positions (smi) and widths (wdi) of MF (Ishigami et al., 1995; Hayashi et al., 1998). An input can be transferred into several membership grades with the membership functions. Originally, the membership function inputs of are bounded between the range of layer inputs and the membership function inputs are usually set within [0,1]. However, owing to the adopted equation (2), while one of the membership function outputs has zero value, the related HNN neurons will output zero values through the sigma-pi Π operator. To prevent such, this study modified the original MF to the output range of [0.0001,1] (see Fig. 5). Following the aforementioned descriptions, all the membership functions are characteristic of values of sm and wd. Besides, in defuzzification layer (see Fig. 2), this study adopts weighted average formula:

$$y_i = \psi(x) = \frac{\sum \alpha_{ji} x_i}{\sum \alpha_{ji}} \quad (4)$$

where ψ is a defuzzification function; α represent defuzzification weights; x denotes the eventual outputs of HNN; and y are the final FHNN outputs. Consequently all the sm, wd, and α will then be dominated by GA evolution.

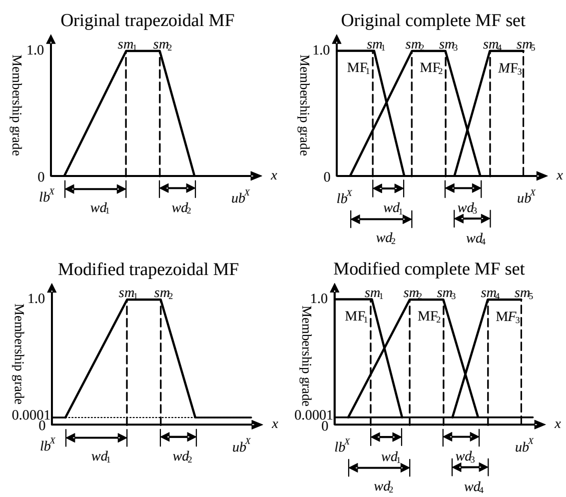

Fig. 5. Membership Function Example

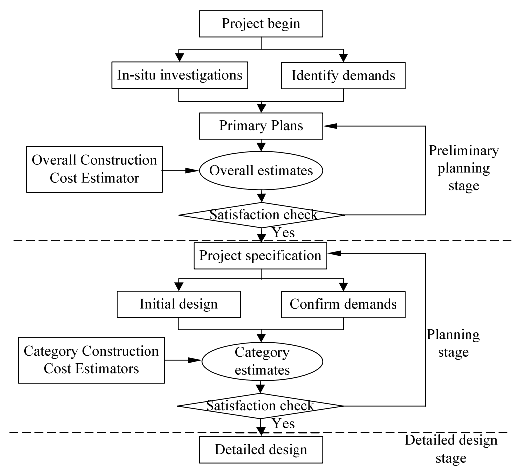

Fig. 6. Cost estimators during project planning stage

2.3 Genetic Algorithm Facilities

To apply GA for problem optimization, one should identify all essential parameters to determine the length of chromosome. A chromosome (an individual) in this study is to represent a FHNN with parameters of HNN and FL. HNN's Parameters have interconnection coefficients c (w and p), connection types (CT: L or HO), slope coefficient of activation function a (1~6), and network topology (number of layers and number of layer neurons). FL's parameters include MF summit points (sm), MF widths (wd), and defuzzification weights α. It deservers to be mentioned is that an interconnection coefficient c can be used for the alternative of w or p. However, w and p perform totally different, they should be recorded in different sub-string. Therefore the aforementioned c should be a combination of w and p. As the chromosome of an individual is identified, the FHNN can be optimized through the adaption process with crossover, mutation, and selection mechanisms (see Fig. 3). Each model result is evaluated with the root mean square error (RMSE).

3. Conceptual Cost Estimators

In the planning stage of projects (i.e. initial design has not yet been produced), the overall estimator is identified by six quantitative factors and four qualitative ones (see Cheng 2008c). These factors will be treated as EFHNN inputs.

Once a project design has been drafted, category cost estimators can be employed to calculate engineering cost by categories. Comparing with the overall estimate, the summation of all category estimates is another alternative. Therefore, the category estimators will be more applicable and useful to the overall estimator for project management. One category estimate will be evaluated for each engineering category according to particular factors. There were seven types of engineering work generalized for category construction cost estimates (see Cheng 2008c).

The range of construction project data spans the years 1997 through 2001. Construction cost range was assigned between NTD40,179 and NTD98,285 per square meter. All 28 projects were designed using reinforced concrete in main structural members. All but five (23) cases were used as training cases, with the remainder (5) used for testing the approach in this paper. Ten inputs were set as the overall construction cost estimator and one output served as the overall estimate of total unit cost (i.e., construction cost per square meter). Seven category estimates (respective outputs, i.e. unit cost by categories) are calculated by engineering category (see Cheng 2008c), where 4 inputs for temporary construction; 7 for geotechnical construction; 8 for structural construction; 9 for interior decoration; 8 for electromechanical infrastructure; 5 for miscellaneous construction; and 4 for indirect construction. Construction costs used as training targets reflect Taiwan's published price index for calendar year 2001. Therefore, the proposed estimators are capable of dealing with unit price fluctuation of the wok and material items in the market. These estimators were developed to meet the goal of assisting construction project planning and design through the use of evaluated cost estimates. In Fig. 6, an overall construction cost estimator is used in the preliminary planning stage, when detailed project plans have not yet been drafted. Preliminary plans can be drafted with in-situ investigations and identified demands, after which the generated overall cost estimate can be used to check the relevance and accuracy of those plans. Initial design will be done next in the planning stage, and then demands and designs will be checked against category estimates. Detailed planning and design can be executed once all data and estimates meet project management needs. These conceptual estimates significantly influence project construction and management.

4. Results and Comparisons

As noted above, this study developed two kinds of estimators and used 23 training cases and 5 testing cases. The capabilities of EFHNN were employed in these estimates. However, the EFHNN is time-consuming due in large part to its use of GA. Therefore, experiments should be run to set parameters to a practicable range (see Table 1). All the results will be compared with the results of previous model (evolutionary fuzzy neural inference model, EFNIM, which did not employ high order neural network and changes in FL and GA).

Table 1 Parameter Settings for EFHNN

Parameters	Values
No. of input neurons	Number of influenced factors
No. of output neurons	1
No. of maximum hidden layers	5
No. of maximum neurons in each layer	5
Selected activation function	Logistic Sigmoid Function
Slope of activation function	1~6
Shape of membership function	Trapezoidal
Number of membership functions	5
Crossover rate	0.9
Mutation rate	0.025
Population size	50
Iteration set	5000

4.1 Overall construction cost estimator results

This estimates construction cost, obtained while the project is in the preliminary concept stage, i.e. without detailed engineering plans organized by category, has significant bearing on detailed planning. After a process of evolutionary training, achieved through applying the 23 training cases, five testing results are shown in Table 2.

Table 2. Testing Results of Overall Estimates

Case No.	Actual output (NTD/m2)	Desired output (NTD/m2)	Diff. (NTD/m2)
1	49697	61591	-11894
2	63763	56334	7429
3	51988	49139	2849
4	87454	84631	2823
5	63654	70843	-7189

Note: Diff. = Actual – Desired.

4.2 Category construction cost estimator results

Although the overall construction cost estimator has been developed, construction plans in each category must still be designed. Construction costs for engineering categories should be estimated to ensure costs are controlled effectively and facilitate project management. Although it is difficult to completely categorize construction work into types of engineering, such is essential in order to estimate category cost values and helpful in project planning and design. Table 3 not only shows estimation results, but also category cost ratios (take the structural category as an example). It is apparent that category cost ratios bear significantly on project planning and design. This result allows cost management to be effectively implemented into construction engineering categories.

Table 3. Testing Results of Category Estimates

Engineering categories	Case No.	Actual output (NTD/m2)	Desired output (NTD/m2)	Diff. (NTD/m2)	Ratio of category cost (%)
Structural construction	1	17398	18843	-1444	28.00
	2	16721	15795	926	28.15
	3	15725	15781	-55	30.67
	4	15726	14531	1195	20.99
	5	17416	17777	-360	26.54

Table 4. Result Comparisons of Overall and Category Estimates

Case No.	EFHNN prediction errors		EFNIM prediction errors	
	Error of overall estimates (%)	Error of total category estimates (%)	Error of overall estimates (%)	Error of total category estimates (%)
1	19.312	0.900	20.541	2.504
2	13.187	5.452	23.783	7.458
3	5.797	4.349	21.201	9.699
4	3.336	11.447	5.082	10.018
5	10.148	7.373	9.755	4.082
Avg.	**10.356**	**5.904**	**16.072**	**6.753**

4.3 Comparisons between EFHNN and EFNIM

In practice, overall estimates accurate to within 25% and category estimates accurate to within 15% using engineers' experience are typically considered acceptable. Estimators developed in this paper achieve a high level of precision for construction cost estimation during the early stages of a project (see Table 4). Estimating construction costs more precisely will help make designs more feasible and projects more efficient by enhancing project management. Moreover, the proposed EFHNN which employs both linear and non-linear layer connectors surpasses the previous version EFNIM which use the traditional NN connection only in the conceptual cost estimates (Cheng et al., 2008c).

5. Conclusions

This paper presents comprehensive descriptions of the proposed Evolutionary Fuzzy Hybrid Neural Network and thereof application of construction conceptual estimators. The EFHNN mechanism is a fusion of HNN, FL, and GA. HNN is composed of a traditional neural network (linear) and a high order neural network, FL uses a fuzzification and a defuzzification layers to sandwich the proposed HNN for a FHNN model, and GA is used to optimize FHNN's parameters for the proposed EFHNN. EFHNN innately different from various GA-FL-NN approaches, even if the previously proposed EFNIM, basing on layer connection types of HNN, modifications for FL's membership functions, and GA-optimized parameters. Therefore, the EFHNN address problems further with a huge amount of HNN models along with fuzzy concepts and GA optimization.

This study proposed two kinds of construction cost estimators. The overall construction cost estimator was established to estimate a total cost in the absence of categorized engineering plans. The category estimators, with additional data inputs, were established to evaluate engineering costs within categories. The advantages of proposed estimators:

1. An overall construction cost estimate can be provided during the preliminary project planning stage to facilitate project execution even when only a minimal amount of available data is available.
2. Category construction costs, categorized by engineering type, offer an alternative to overall estimates that provides results that are more reasonable and practicable.
3. Category estimators supply useful information on the relative ratios of engineering categories, which is essential for detailed construction cost management.
4. All estimates, come from EFHNN results, address problems with a newly developed HNN architecture with figure out an input-output mapping with both linear and nonlinear layer connections.
5. The EFHNN results for construction conceptual cost estimates surpass results from EFNIM which use the traditional NN connection only. It evidences that the HNN concept not only makes NN innately different but also performs well in EFHNN with both FL and GA.

This paper presents the application EFHNN to estimate construction costs during the early stage of construction projects in order to facilitate designers, owners and contractors for decision-making. Results show that EFHNN is relevant and applicable to construction management in Taiwan and may be implemented worldwide with modifications to account for specific regional/national factors.

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