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Conceptual cost estimates using evolutionary fuzzy hybrid neural network for projects in construction industry

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ABSTRACT

Conceptual cost estimates are important to project feasibility studies and impact upon final project success. Such estimates provide significant information that can be used in 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 conceptual cost estimate precision. This approach first integrates neural networks (NN) and high order neural networks (HONN) into a hybrid neural network (HNN), which operates with alternating linear and non-linear neuron layer connectors. Fuzzy logic (FL) is then used in the HNN to handle uncertainties, an approach that evolves the HNN into a fuzzy hybrid neural network (FHNN). As a genetic algorithm is employed on the FL and HNN to optimize the FHNN, the final version used for this study may be most aptly termed an 'EFHNN'. For this study, estimates of overall and category costs for actual projects were calculated and compared. Results showed that the proposed EFHNN may be deployed effectively as an accurate cost estimator during the early stages of construction projects. Moreover, the performance of linear and non-linear neuron layer connectors in EFHNN surpasses models that deploy a singular linear NN.

1. Introduction

Cost estimates are fundamental to all project-related engineering and greatly influence planning, design, bidding, cost management/budgeting and 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 standard estimators to estimate project costs. As such, intuition plays a significant role in decision making. Researchers have worked to develop cost estimators that maximize the practical value of limited information in order to improve the accuracy and reliability of cost estimation work and thus enhance the suitability of resultant designs and project execution work.

Statistical methods have traditionally been used to develop cost estimating models (Singh, 1990). While regression analysis represents a common alternative (Bowen & Edwards, 1985; Khosrowshahi & Kaka, 1996), an inherent disadvantage is the requirement of a defined mathematical form for cost functions. In general, all traditional methods are hampered in estimating accurate project costs by the large number of significant variables and interactions between these variables. Traditional methods, as a result, face significant limitations in application.

Artificial intelligence approaches are applicable to cost estimation problems related to expert systems, case-based reasoning (CBR), neural networks (NNs), fuzzy logic (FL), genetic algorithms (GAs) and derivatives of such. Many research studies have been done in this area. For instance, an integrated knowledge-based system for alternative design decisions, materials selection and cost estimating used mainly in pre-design analysis was proposed by Mohamed and Celik (1998). Serpell (2004) proposed a model of this problem based on existing knowledge and demonstrated how the model could be used to develop a knowledge-based assessment system. Arditi and Suh (1991) developed an expert system that proposed decision criteria used in the classification of available cost estimating packages. An, Kim, and Kang (2007) developed a case-based reasoning model that incorporated experience using an analytic hierarchy process. Yau and Yang (1998) applied CBR to estimate construction project implementation duration and costs during the preliminary design stage. NNs represent 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. Adeli and Wu (1998) also employed NNs to estimate highway construction cost and identified noise in the data. Williams (1994) used NNs to predict change in the ENR construction cost index and concluded that

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the back-propagation neural network model cannot accurately predict cost index movement due to the complexities involved.

Hybrid models have also been developed to estimate construction costs. Rao, Grobler, and Kim (1993) developed a hybrid neural-expert system approach to obtain conceptual cost estimates for construction projects. Hegazy and Ayed (1998) used NNs to develop a parametric cost estimating model for highway projects, with NN weightings optimized by GA. Kim, Seo, and Kang (2005) applied hybrid NN and GA models to residential building cost estimation in order to predict preliminary cost estimates. One of the models used GA to optimize back-propagation network parameters and the other employed GA to determine NN weightings. Boussabaine and Elhag (1997) developed a neurofuzzy system to predict construction project cost and duration. Yu, Lai, and Lee (2006) proposed a web-based intelligent cost estimator incorporating a neurofuzzy system.

In past research, NN, GA and FL have been employed due to their powerful abilities to estimate construction costs. They are also widely applied to other issues and to fields not construction industry-related. NN affords a capacity to learn from past data and generalize solutions for future applications; FL allows for tolerance of real world imprecision and uncertainties; and GA facilitates global optimization of parameters. The feasibilities of these three approaches have already been evidenced, although none represent an ideal solution when applied alone.

Various critical factors must be identified in order to estimate construction costs effectively. Factors that impact on various project stages (i.e., conceptual, design, tendering, and preconstruction) should be identified individually to improve estimation accuracy (Liu & Zhu, 2007). Because preliminary estimates greatly influence subsequent cost management efforts, the accuracy of preliminary estimation work is of critical importance. Therefore, conceptual cost estimate accuracy at the early stage of construction projects has been a major concern and focus of study over the past four decades.

High order neural networks (HONN) typically introduce a non-linear equation into a specified layer, which allows networks to capture high order correlations easily and attain non-linear mapping effectively. As HONN uses high order correlations, it holds the potential to perform better than linear NN (Zurada, 1992). HONN not only allows a fuller degree of adaptability than linear model in terms of non-linear mapping, but further features a structure that makes it easier to determine how network inputs are actually mapped into network outputs (Abdelbar & Tagliarini, 1996).

Previous studies (Cheng, Tsai, Ko, & Chang, 2008; Cheng, Tsai, & Liu, 2009) contributed by the authors have addressed the application of GA-optimized Neural-fuzzy models to various engineering problems. The current study incorporates linear neural networks (NN) and high order neural networks (HONN) into a hybrid neural network (HNN). Each HNN layer connector is dominated by an alternating linear or high order layer connector. The participation of fuzzy logic facilitates HNN model evolution into a fuzzy hybrid neural network (FHNN) model. Within the proposed evolutionary fuzzy hybrid neural network (EFHNN) model, we further employed GA to optimize FL membership functions and HNN connection types, topology, and coefficients. This study further applied the proposed EFHNN in conceptual cost estimation. Both overall (total cost) estimates and (engineering) category estimates were provided at the planning/preliminary design stage. An overall cost estimate was provided for each construction project, with the value of construction cost per unit of area calculated to reflect in situ conditions and preliminary design concepts. In addition, category cost estimates were determined based on various engineering categories (i.e., temporary, geotechnical, structural, decorative, electromechanical, miscellaneous, and indirect construction). Category estimates offer greater reference opportunities than overall estimates due to the more detailed data involved.

2. The evolutionary fuzzy hybrid neural network (EFHNN)

The proposed EFHNN incorporates four artificial intelligence approaches, namely the neural network (NN), high order neural network (HONN), fuzzy logic (FL), and genetic algorithm (GA) (see Fig. 1). NN and HONN comprise the inference engine, i.e. the proposed hybrid neural network (HNN); FL dominates fuzzifier and defuzzifier layers; and GA optimizes the HNN and FL. In accordance with the definition of "neuro with fuzzy input–output" given by Hayashi, Umano, Maeda, Bastian, and Jain (1998), this study proposes a fuzzy hybrid neural network (FHNN) comprising an HNN with fuzzy inputs and fuzzy outputs (see Fig. 2). Each NN connection may select a linear or high order NN connector. Sequentially, the FHNN is optimized through a GA adaptation process (see Fig. 3). The process uses GA to search simultaneously for optimum FL membership functions, defuzzification coefficients, HNN topologies, and HNN parameters (including linear/high order connection types), with $P(t)$ denoting a population at generation t, $P_O(t)$ an offspring population at generation t, and $P_M(t)$ a mutation population at generation t. Details of FL and HNN and GA are described in the following sections.

2.1. Proposed hybrid neural network

The term "hybrid" typically refers to anything derived from heterogeneous sources or composed of different or incongruent elements. For the proposed HNN, "hybrid" refers to the combining of traditional neural and high order neural networks. The high order neural network that this paper uses was proposed by the HONEST model (Abdelbar & Tagliarini, 1996), and is constructed of three layers with a high order connection and a linear connection between the 1st and 2nd layers and 2nd and 3rd layers, respectively. This study extends the use of high order connections for all connection alternatives, i.e. all layer connections can switch between linear and high order formats (see Fig. 2). An HNN neuron is dominated by an alternative of the following equation:

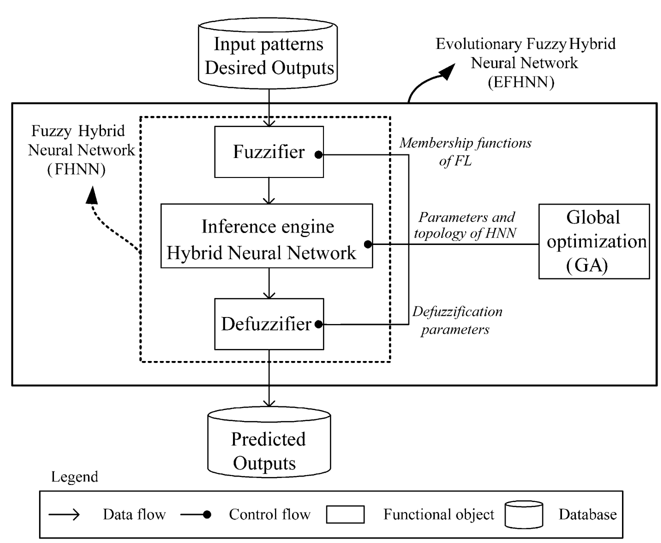

Fig. 1. EFHNN architecture.

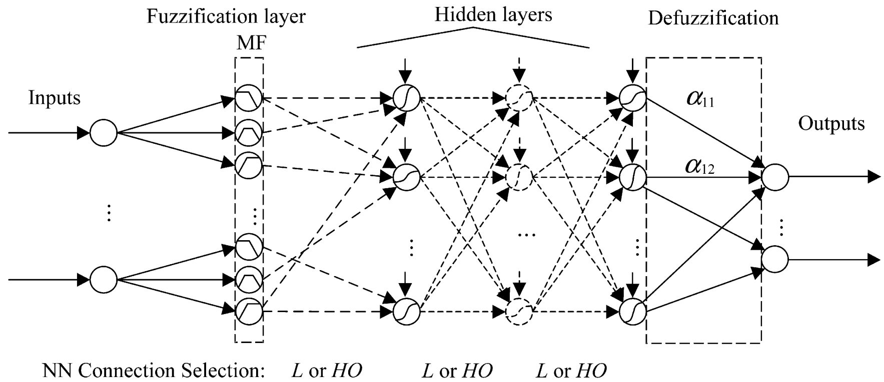

Fig. 2. FHNN with FL and HNN.

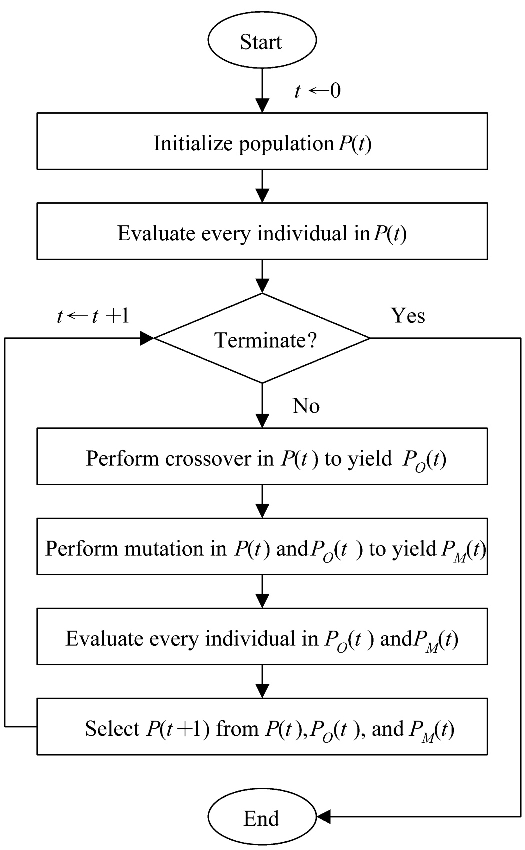

Fig. 3. EFHNN adaption process.

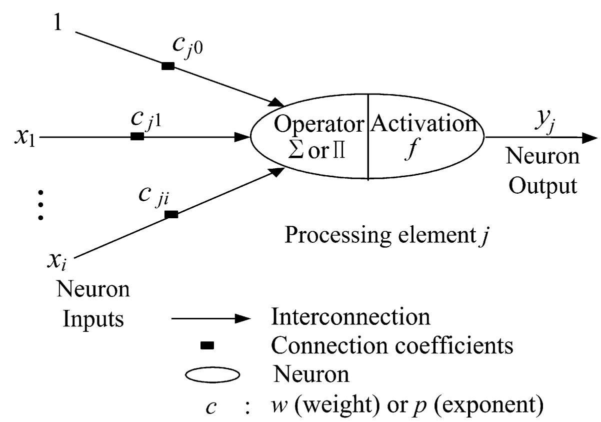

Fig. 4. A HNN neuron.

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

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

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

where y_j is a HNN neuron output calculated by neuron inputs x_i. c_{ji} represents a coefficient of an interconnection, which can be in linear or high order format based on the weight w_{ji} or exponent p_{ji}, respectively (see Fig. 4). An activation function f uses a sigmoid function with a slope coefficient of a. Therefore, each layer connection features an attached connection type that represents the corresponding operation selection (see Fig. 2). All HNN parameters are then optimized by GA evolution. As noted above, a HNN with 2 layers may select either a linear layer connection (L) or high order connection (HO). Four possible scenarios, based on connection type, exist for 3-layer HNN models, including L–L, L–HO, HO–L, and HO–HO. If N is adopted as the maximum HNN layer number (i.e., the final HNN model is an HNN with a number of layers not greater than N), then the number of HNN model candidates are $2^1, 2^2, \ldots, 2^{N-1}$, respectively, related to HNN $2, 3, \ldots, N$ layers. In sum, of the $2^N - 2$ HNN model candidates, only $N - 1$ models select all L connections. All others are categorized into high order neural networks in this study. The proposed HNN includes all linear and high order neural networks according connection type selections.

2.2. Fuzzy logic facilities

Zadeh (1965) first proposed Fuzzy logic as a tool with which to describe uncertainty and imprecision. In Fig. 2, the HNN is enclosed between fuzzification and defuzzification layers. The complete structure is a fuzzy hybrid neural network. In the defuzzification layer, the membership function (MF) initially assigns inputs into one of several membership grades. In this study, a complete MF set using trapezoidal MF has been adopted. A general approach to describing MF shapes is to depict MF summit positions (sm_i) and widths (wd_i) (Ishigami, Fukuda, Shibata, & Arai, 1995; Hayashi et al., 1998). An input can be assigned to several membership grades with MF. Initially, MF inputs are bound between the range of layer inputs, and membership function inputs are usually set within $[0, 1]$. However, owing to adopted Eq. (2), if one of the membership function outputs has a value of zero, 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 descrip-

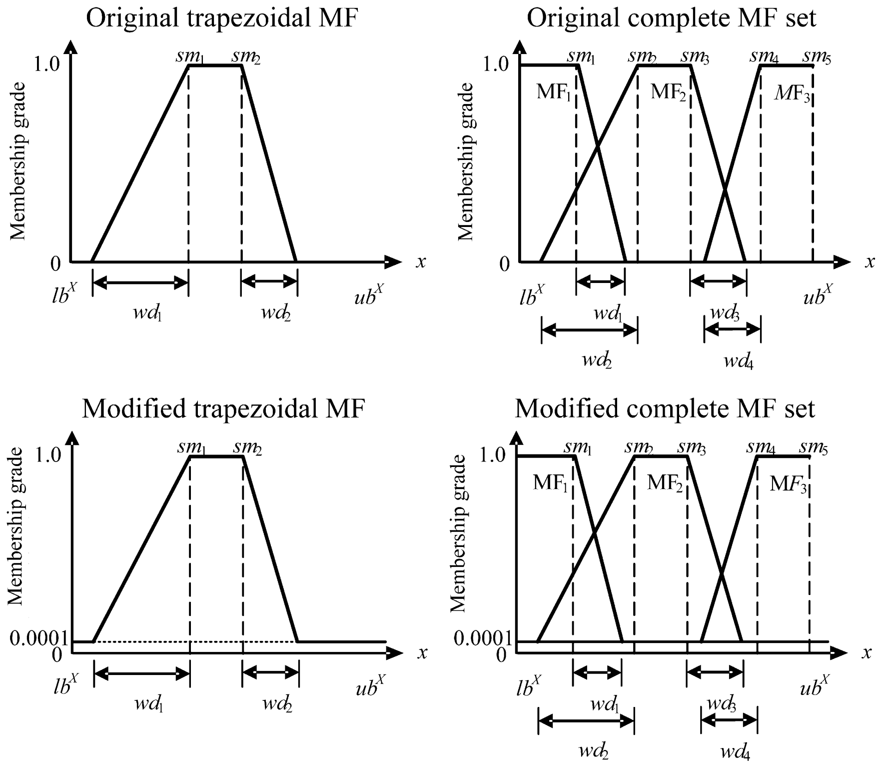

Fig. 5. Membership function examples.

tions, all membership functions are characteristic of values of *sm* and *wd*. In the defuzzification layer (see Fig. 2), this study adopted a weighted average formula, as follows:

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

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

2.3. Genetic algorithm facilities

Genetic Algorithms (GA), which imitates elements of the natural evolution process, were first proposed by Holland (1975). To apply GA to problem optimization, one must identify all essential parameters to determine chromosome length. The chromosome (i.e., one individual) in this study represents an FHNN with HNN and FL parameters. HNN 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 (total layers and layer neurons). FL's parameters include MF summit points (sm), MF widths (wd), and defuzzification weights α. It deserves mentioning that an interconnection coefficient c can be used for alternatives w or p. However, w and p perform totally differently, as they must be recorded in different sub-strings. Therefore, the aforementioned c should be a combination of w and p. Once an individual's chromosome is identified, FHNN can be optimized through the adaption process with crossover, mutation, and selection mechanisms (see Fig. 3). Each model result is evaluated using root mean square error (RMSE).

3. Conceptual cost estimators

Two conceptual cost estimators, i.e. overall and category estimators, were developed as the basis of conceptual construction cost. Various factors must be identified to describe these two construction cost estimates at the planning (or preliminary design) stage. In the planning stage (i.e., the stage prior to developing an initial design), the overall estimator can be identified by six quantitative and four qualitative factors (listed in Table 1). These factors are treated as EFHNN inputs.

Once a project design has been drafted, category cost estimators can be employed to calculate engineering cost by category. As an alternative to the overall estimate, all category estimates can be summed. Therefore, the category estimators are more applicable and useful for whole project management. One category estimate is evaluated for each engineering category according to particular factors. There were seven types of engineering work generalized

Table 1
Overall estimator impact factors.

Features	Impact factors	Values or units
Quantitative factors	1. Floors underground	Floors
	2. Total floor area	Meter2
	3. Floors aboveground	Floors
	4. Site area	Meter2
	5. Number of households	Households
	6. Households in adjacent buildings	Households
Qualitative factors	7. Soil condition	Stiff, medium, soft
	8. Seismic zone	Type A, B
	9. Interior decoration	Luxurious, common, basic
	10. Electro-mechanical infrastructure	Luxurious, common, basic

for category construction cost estimates. Their impact factors are listed in Table 2 (by category).

The range of construction project data used in this study spans the years 1997 through 2001. The construction cost range was limited to between NTD40,179 and NTD98,285 per square meter. All 28 projects identified were designed using reinforced concrete for main structural members. We employed 23 cases for training purposes, with the remainder (5) used for testing the approach. As shown in Table 1, 10 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 category) were calculated by engineering category in Table 2, where 4 inputs were for temporary construction; 7 inputs were for geotechnical construction; 8 were for structural construction; 9 were for interior decoration; 8 were for electromechanical infrastructure; 5 were for miscellaneous construction; and 4 were for indirect construction. Construction costs used as training targets reflect Taiwan's published price index for calendar year 2001. Therefore, proposed estimators are capable of dealing with fluctuations in unit costs for labor and materials. 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 was used in the preliminary planning stage, before detailed project plans had been drafted. Preliminary plans can be drafted based on in situ investigations and identified demands, after which the overall cost estimate generated can be used to check plan relevance and accuracy. Initial design will be handled in the planning stage, which immediately follows, when 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 influence project construction and management significantly.

Table 2
Category estimator impact factors.

Engineering	Features	Impact factors	Values or units
Temporary construction	QT	1. Site area	Meter2
	QT	2. Floors underground	Floors
	QT	3. Floors aboveground	Floors
	QT	4. Total floor area	Meter2
Geotechnical construction	QT	1. Site area	Meter2
	QT	2. Excavation depth	Meter
	QT	3. Floors underground	Floors
	QT	4. Households in adjacent buildings	Households
	QL	5. Soil condition	Stiff, medium, soft
	QL	6. Bracing system	Tied-back, Inside bracing
	QL	7. Retaining structure	None, sheet-pile, soldier pile, rail pile, diaphragm wall, others
Structural construction	QT	1. Total floor area	Meter2
	QT	2. Floors underground	Floors
	QT	3. Floors aboveground	Floors
	QT	4. Area of exterior wall	Meter2
	QL	5. Seismic zone	Type A, B
	QL	6. Soil condition	Stiff, medium, soft
	QL	7. Type of foundations	Raft, pile
	QL	8. Type of Excavation	Partial-braced, top-down, bottom-up, slope excavation
Decorative construction	QT	1. Total floor area	Meter2
	QT	2. Area of exterior wall	Meter2
	QT	3. Households planned	Households
	QT	4. Type of flooring	Ceramic tile, archaized brick, quartz tile, terrazzo tile, wooden, granite tile
	QT	5. Type of ceiling	Emulsion paint, light rigid frame, waterproof, wood board, calcium silicate board, metal
	QT	6. Interior wall decoration	Emulsion paint, ceramic tile, granite tile
	QT	7. Exterior wall decoration	Strip tile, facial cut terrazzo, facial washed terrazzo, granite tile, curtain wall, cast plate
	QT	8. Material of doors	Wooden, aluminum, copper vitriol, stainless steel, fireproof
	QT	9. Material of Windows	Aluminum, plastic-steel, airtight, stainless steel
Electro-mechanical infrastructure	QT	1. Total floor area	Meter2
	QT	2. Households planned	Households
	QT	3. Elevators	Number
	QL	4. Air conditioner	Non-central, central
	QL	5. Kitchen	Luxurious, common, basic
	QL	6. Shower room	Luxurious, common, basic
	QL	7. Fire control	Common, basic
	QL	8. Parking	Mechanic parking system, parking lot
Miscellaneous construction	QT	1. Site area	Meter2
	QT	2. Total floor area	Meter2
	QT	3. Households planned	Households
	QT	4. Floors underground	Floors
	QT	5. Floors aboveground	Floors
Indirect construction	QT	1. Total floor area	Meter2
	QT	2. Floors underground	Floors
	QT	3. Floors aboveground	Floors
	QL	4. Type of excavation	Partial-braced, top-down, bottom-up, slope excavation

Notations: QT – quantitative factor; QL – qualitative factor.

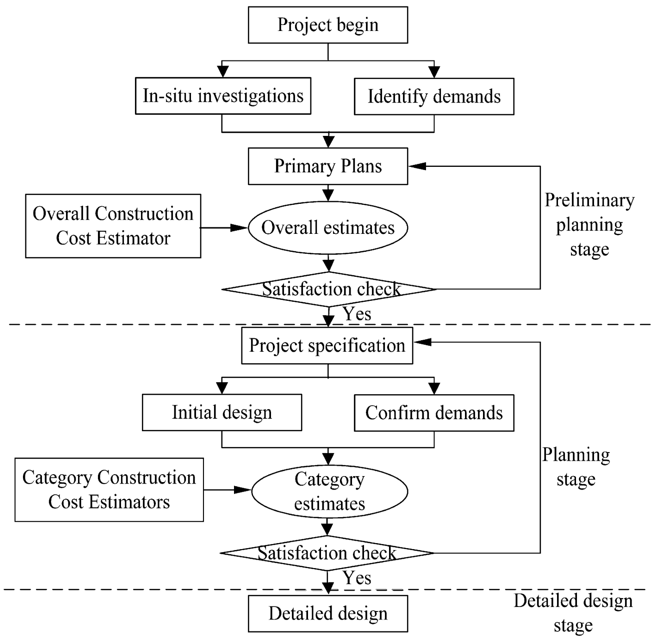

Fig. 6. Cost estimators during the project planning stage.

4. Results and comparisons

This study developed two distinct estimators using 23 training cases and 5 testing cases. While EFHNN was employed to obtain these estimates, this approach is time-consuming due in large part to its use of GA. Therefore, experiments run should set parameters within a practicable range (see Table 3). Results obtained were compared with those obtained using the evolutionary fuzzy neural inference model (EFNIM), which did not employ high order neural network and changes to FL and GA.

4.1. Overall construction cost estimator results

The ability to estimate construction cost while a project is in the preliminary concept stage (before categorized engineering plan details have been made) can help engineers adjust planning details appropriately to improve the chances of project success. After an evolutionary training process using the 23 training cases, five testing results were obtained (Table 4). Fig. 7 shows the resultant model for the overall cost estimate.

4.2. Category construction cost estimator results

Although an overall construction cost estimator had been developed, construction plans in each category remained to be designed.

Table 3
EFHNN parameter settings.

Parameters	Values
No. of input neurons	Number of factors influenced
No. of output neurons	1
Maximum hidden layers	5
Maximum neurons in each layer	5
Selected activation function	Logistic sigmoid function
Activation function slope	1–6
Membership function shape	Trapezoidal
Number of membership functions	5
Crossover rate	0.9
Mutation rate	0.025
Population size	50
Iteration set	5000

Table 4
Testing results for overall estimates.

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

Note: Diff. = Actual–Desired.

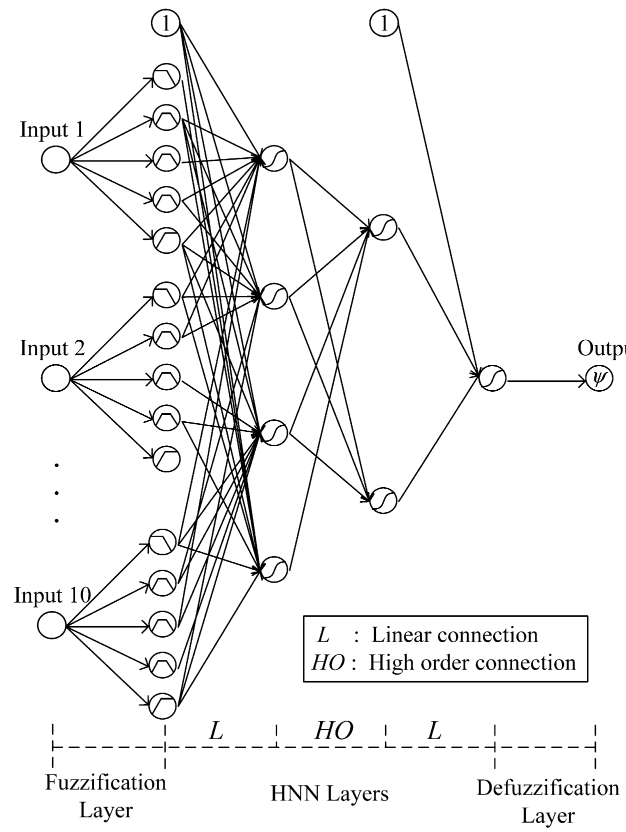

Fig. 7. FHNN model phenotype of overall cost estimation.

Construction costs for engineering categories should be estimated to ensure costs are controlled effectively and facilitate project management. Although it is difficult to assign construction work neatly into distinct project type categories, such is essential in order to estimate category cost values and facilitate project planning and design. Table 5 shows both estimation results and category cost ratios. It is apparent that category cost ratios bear significantly on project planning and design. This result allows cost management to be implemented effectively in construction engineering categories. Seven cost estimation models were learned. Structural construction cost, which bears significantly on total cost, is shown in the model structure in Fig. 8.

4.3. Comparing EFHNN and EFNIM

In practice, overall estimates accurate to within 25% and category estimates accurate to within 15% obtained based on engineer experience are typically considered acceptable. Estimators developed in this paper achieved high levels of precision for construc-

Table 5
Testing results of category estimates.

Engineering categories	Case no.	Actual output (NTD/m^2)	Desired output (NTD/m^2)	Diff. (NTD/m^2)	Ratio of category cost (%)
Temporary construction	1	1352	1863	−510	2.18
	2	2783	2868	−84	4.69
	3	1594	1120	474	3.11
	4	1623	1803	−179	2.17
	5	1649	1921	−271	2.51
Geotechnical construction	1	5141	5275	−133	8.27
	2	3326	2918	408	5.60
	3	5979	4411	1568	11.66
	4	10316	14,610	−4293	13.77
	5	6252	5658	594	9.53
Structural construction	1	17398	18843	−1444	28.00
	2	16,721	15,795	926	28.15
	3	15,725	15,781	−55	30.67
	4	15,726	14,531	1195	20.99
	5	17,416	17,777	−360	26.54
Interior decoration	1	16,811	14,724	2087	27.05
	2	18,330	18,756	−425	30.86
	3	14,359	17,850	−3490	28.01
	4	24,076	25,650	−1573	32.13
	5	18,848	21,072	−2223	28.72
Electromechanical infrastructure	1	14467	14582	−114	23.28
	2	11,293	9400	1893	19.01
	3	8185	6938	1247	15.96
	4	15,978	19,101	−3122	21.32
	5	12,430	14,553	−2122	18.94
Miscellaneous construction	1	2042	2079	−36	3.29
	2	2766	2787	−20	4.66
	3	2202	728	1474	4.30
	4	1995	3493	−1497	2.66
	5	3238	2652	586	4.94
Indirect Construction	1	4932	4225	707	7.94
	2	4183	3809	374	7.04
	3	3227	2311	916	6.29
	4	5225	5443	−217	6.97
	5	5785	7211	−1425	8.82
Total construction cost	1	62,145	61591	554	100
	2	59,404	56,333	3071	100
	3	51,275	49,139	2136	100
	4	74,943	84,631	−9687	100
	5	65,620	70,844	−5223	100

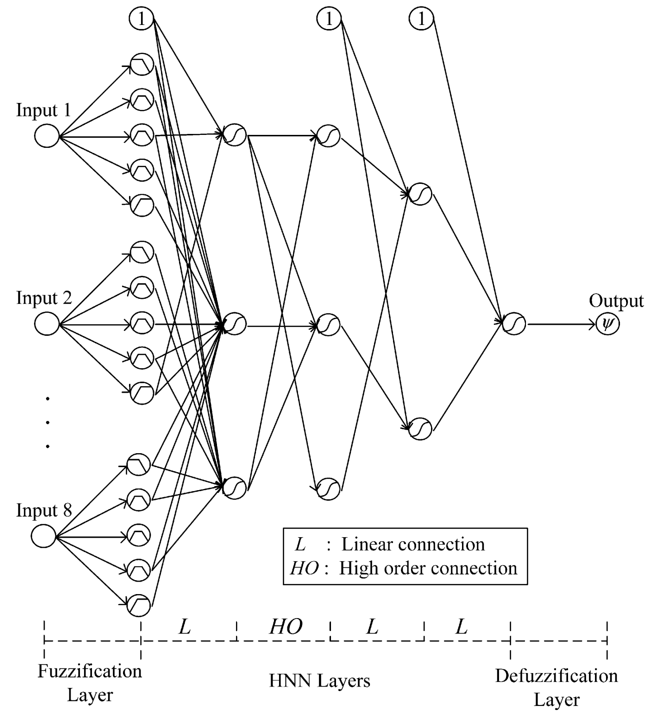

Fig. 8. FHNN model phenotype of structural cost estimation.

Table 6
Comparison of results obtained by overall and category estimates.

Case no.	EFHNN		EFNIM	
	Overall estimate error (%)	Total category estimate error (%)	Overall estimate error (%)	Total category estimate error (%)
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

tion cost estimation during the early stages of a project (see Table 6). 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 previously developed EFNIM, which only uses traditional NN connections in conceptual cost estimation (Cheng, Tsai, & Hsieh, 2009).

5. Conclusions

This paper presents comprehensive descriptions of the proposed Evolutionary Fuzzy Hybrid Neural Network (EFHNN) and its application in conceptual cost estimation for construction projects. The EFHNN mechanism integrates HNN, FL, and GA. In the proposed EFHNN, HNN includes both traditional neural (linear) and high order neural networks; FL uses fuzzification and defuzzification layers to sandwich the proposed HNN; and GA optimizes FHNN parameters. The proposed EFHNN is innately different from various GA-FL-NN approaches, even the previously proposed EFNIM, due to unique HNN layer connection types, modification of FL membership functions, and GA-optimized parameters. Therefore, EFHNN is able to address problems in greater depth with its large number of HNN models, fuzzy concepts and GA optimization.

This study proposed two distinct construction cost estimators. The overall construction cost estimator was established to estimate total cost in the absence of categorized engineering plans. Category estimators, relying on additional data inputs, were designed to evaluate engineering costs within categories. The advantages of proposed estimators include:

1. Overall construction cost estimates 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 derived from EFHNN results address problems with a newly developed HNN architecture able to perform input–output mapping with both linear and non-linear layer connections.

5. EFHNN results for construction conceptual cost estimates surpass results obtained using EFNIM, which uses only traditional NN connections. Such evidences that the HNN concept not only makes NN-related parts innately different, but also performs well in EFHNN with both FL and GA.

This paper presents an EFHNN application able to estimate construction costs during the early stage of construction projects in order to improve the ability of designers, owners and contractors to make decisions that enhance the chances of project success. 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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