Artificial Intelligence Approaches to Dynamic Project Success Assessment Taxonomic

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Abstract: Artificial Intelligence (AI) approaches are widely applied to various civil engineering problems. This paper focuses on an approach to assessing project success using AI approaches including K-means Clustering, Genetic Algorithm (GA), Fuzzy Logic (FL), and Neural Network (NN). As various factors at different construction stages affect project performance, project success criteria change dynamically and are hard to estimate accurately through reliance on experience alone. Information that is uncertain, vague, and incomplete is an inherent feature of this problem. CAPP (Continuous Assessment of Project Performance) software was used to study in a dynamic manner the significant factors that influence upon project performance. K-means clustering was employed to conduct an unsupervised clustering to extract similar cases for comparison. FL for was used to examine uncertainties, NN was employed for data mining, and GA was used for optimization. A developed Evolutionary Fuzzy Neural Inference Model (EFNIM) was used to achieve optimal mapping of input factors and project success output. Results show that EFNIM is able to estimate the degree of project success well and case clustering can greatly enhance project success assessments.

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1. Introduction

In the construction industry, construction project success infers that certain expectations of participants, including owners, planners, designers, architects, contractors, and operators, are fulfilled. Once a construction project has been bid, the prime contract is typically subdivided into multiple subcontracts. Large numbers of participants are, therefore, involved in the project planning and implementation phases. Expectations can only be met by conducting a comprehensive analysis of participants (Sanvido et al., 1992). Project success is determined in terms of cost, schedule, performance, and safety by many events and resultant interactions, plans, facilities, participant changes and changes in the environment. Project managers who identify the key determinants to project success can monitor project performance continuously and make proper decisions based on objective performance predictions related to targeted project success.

Many published papers over the past several decades have reported the results of research conducted to identify critical project success factors. Griffith et al. (1999), using data collection and telephone interviews, developed an index designed to assess the success of industrial project execution for different types and sizes of projects. Hughes et al. (2004) developed a tool, the Construction Project Success Survey, to identify important success metrics prior to the start of a project and evaluate the level of success achieved at project completion. Wang and Huang (2006) surveyed Chinese construction supervisors to identify correlations between the performance of key stakeholders and project success. Ling et al. (2006) used tailored questionnaires, respectively, for international architecture, engineering, and construction firms to study key factors of foreign firm project success in China. Drawing from articles published in seven major construction industry journals, Chan et al. (2004) developed a conceptual framework on critical project success factors, in which five major groups of independent variables were identified, namely project-related factors, project procedures, project management actions, human-related factors, and external environment, as crucial to project success. Nguyen et al. (2004) expounded on the success factors typical to large construction projects in Vietnam, focusing his study on four factor categories and using a questionnaire survey returned by 109 valid respondents in 42 organizations.

The construction industry is replete with myriad an uncertainty that makes management exceedingly complex. Factors for success, therefore, vary from project to project. Although human experts can often achieve a satisfactory project outcome, shortfalls nearly always occur due to managers failing to take all relevant factors into consideration and lacking access to all relevant information.

Artificial intelligence, a novel technology for extracting knowledge, is already widely applied to various civil engineering problems, including project management (Cheng and Ko, 2003). To predict project performance, Chua et al. (1997) employed a neural network with eight key factors for project success. Georgy et al. (2005) utilized a neurofuzzy intelligent system to predict the engineering performance in a construction project and compared such with the results of statistical variable reduction techniques.

An appreciation of critical factors is crucial to assess the requirements of project success and to achieve successfully project objectives. Statistical methods represent a basic approach to identify significant factors from historical data or questionnaire results. However, the dynamic nature of critical factors means that changes in project conditions must be monitored continuously. The Construction Industry Institute (CII, 1996) cooperated with the University of Wisconsin at Madison to develop a prediction software tool, named Continuous Assessment of Project Performance (CAPP) (Russell et al., 1997), which allows managers to identify significant factors continuously and dynamically.

In this study, CAPP software is employed to determine significant factors for project success and AI approaches are used to assess project success. Project managers can use the model to predict the degree of success of a new project, allowing managers to enhance their effective control over projects and prevent problems. The remaining sections of this paper include Section II: a introduction of AI approaches which comprehend K-mean clustering and Evolutionary Fuzzy Neural Inference Model with GA, FL, and NN involved; Section III: significant factors for project success are determined using CAPP software; Section IV: AI approaches apply to project success prediction; Section V: conclusions are described.

2. Artificial Intelligence Approaches

2.1 K-means Clustering

Many algorithms are able to identify specific domains. K-means clustering is a simple and fast approach to data clustering that starts with k centroids (seeds), which are usually generated randomly. Each data set (sample) is assigned to the cluster with closer centroid of the Euclidean distance measurement. It is customary to set a threshold on iteration numbers to prevent excessive calculation times. After a number of iteration steps, every clustering feature can be determined. As desired number of clusters can be set as a limitation for target convergence, perfect convergence cannot be guaranteed. K-means usually converges in practical applications, especially in pattern recognition problems. K-means clustering is widely and commonly employed owing to its simplicity, although it does present some inherent drawbacks such as a fixed setting for the optimal solution or time consumption (MacQueen, 1967).

While the input data set S is composed of n points (n d-dimensional vectors), the k cluster centroids C must be satisfied using the following descriptions (Maulik and Bandyopadhyay, 2000):

$$S = \{x_1 \quad x_2 \quad \ldots \quad x_n\} \quad \text{(1)}$$

$$C_m \neq \Phi, \quad m = 1 \sim k \quad \text{(2)}$$

$$C_m \cap C_n = \Phi, \quad m, n = 1 \sim k, \quad m \neq n \quad \text{(3)}$$

$$\bigcup_{i=1}^{k} \text{dataset}(C_m) = S \quad \text{(4)}$$

$$d(x_i, C_j) = (x_i - C_j)^T (x_i - C_j), \quad \text{(5)}$$

$$i = 1 \sim n, j = 1 \sim k$$

The above definition describes each cluster as having at least one dataset, with each belonging to a cluster of one-to-one relationships. Also, each dataset must attach to a cluster. k cluster centroids are initially selected at random from S. During each iteration process, every data point x is assigned to a particular cluster set by closest Euclidean distance measurement d. Once each data point has been assigned to its cluster, all centroids C can be re-calculated by means of all attaching points. This describes the major concept of K-means algorithm: that K-means iterates until stable cluster centroids are found (Tou and Gonzalez, 1974).

2.2 Fuzzy Logic

Zadeh (1965) first proposed Fuzzy Logic (FL) as a tool to describe uncertainty and imprecision. Because it imitates the high order mode in which the human brain makes decisions in the face of uncertainty or vagueness, FL provides an effective way for automated systems to describe highly complex, ill-defined, or difficult-to-analyze subjects. In general, FL is composed of a fuzzifier, rule base, inference engine and defuzzifier (Cheng and Ko, 2003). The FL approach still has certain problems to overcome such as membership function configuration, composition operator determination, and application-specific fuzzy rule acquisition (Maier et al., 2000). Although the FL parameters can be determined using the experience and knowledge of experts, determining these parameters in the absence of such experts remains difficult for particularly complex problems (Gorzalczany and Gradzki, 2000).

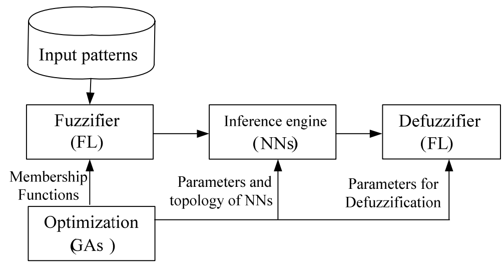

Figure 1 EFNIM Architecture

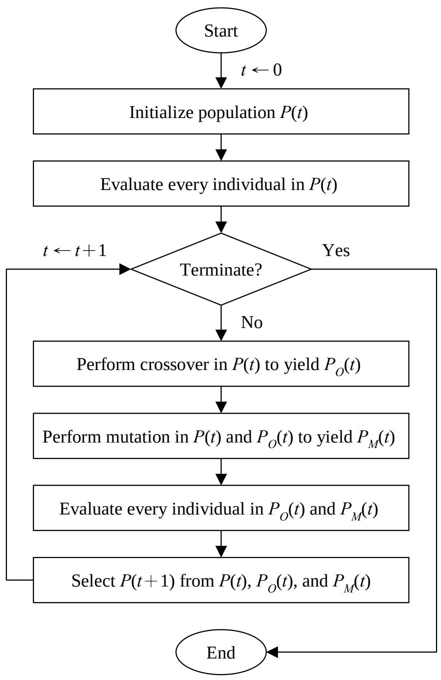

Figure 2. EFNIM Adaptation Process

2.3 Neural Network

Neural Networks (NN) focus primarily on computing and storing information within a structure composed of many neurons. Because NN imitates the human brain in terms of learning, recall and generalization, they are usually designed to solve non-linear or ill-structured problems (Haykin, 1999). An NN model frequently used is multilayer perceptron learning with error back-propagation. However, appropriate NN structures and parameters are essential to accurate problem assessment. As the optimal network topology is highly problem-oriented, such are difficult to determine (Liatsis and Goulermas, 1995). In addition, some real world applications are hampered by lack of training techniques able to find reliably a global optimum set of weights (Jagielska et al., 1999).

2.4 Genetic Algorithm

Genetic Algorithms (GA), which imitate parts of the natural evolution process, were first proposed by Holland (1975). GA is a stochastic search approach inspired by natural evolution that involves crossover, mutation, and evaluation of survival fitness. Genetic operators work from initial generation to offspring in order to evolve an optimal solution through generations. Also, its relatively straightforward and simple implementation procedure give the GA exceptional flexibility to hybridize with domain-dependent heuristics to create effective implementation solutions tailored to specific problems. Based on its merits, the potential of using GA in optimization techniques has been intensively studied (Gen and Cheng, 1997). However, simple GA is difficult to apply directly and successfully to a large range of difficult-to-solve optimization problems (Michalewicz, 1996).

2.5 Evolutionary Fuzzy Neural Inference Model (EFNIM)

EFNIM, which fused GA, FL, and NN to solve civil engineering problems, was proposed by Cheng and Ko (2006). The complementary combination of its three elements maximizes the positive merits of each and helps compensate for their individual inherent weaknesses. GA is used for optimization; FL deals with uncertainties and handles approximate inferences; and NN is employed in input-output mapping. The model architecture is shown in Figure 1.

Although FL can describe the high-order human inference process, making decisions regarding the appropriate distribution of membership functions, operator composition and regulations is not easy. EFNIM introduces NNs to resolve this issue as well as to infuse into FL a capacity for self-learning. The combination of FL and NNs is regarded as a “neuro with fuzzy input-output,” i.e., a neural network with both fuzzy inputs and fuzzy outputs. For convenience, the term “neuro with fuzzy input-output” is termed a Fuzzy Neural Network (FNN), which is a general phrase used to express the fusion/union of FL and NNs (Hayashi et al., 1998). Even if FNN is more relevant than either the traditional FL in the inference process or the single NN in the imitating process, determining the fittest distribution of membership functions (MF), NN topology, and parameters of NN (including number of hidden layers and neurons, synaptic weights, bias shifting, slopes of activation functions) remains difficult. GA represents an effective approach to overcoming FNN drawbacks (Gorzalczany and Gradzki, 2000). GA, which is applied to optimization over wide territories, addresses the above-mentioned problems by searching for optimal MFs and identifying optimum network parameters. The EFNIM is able to self-adapt, as shown in Figure 2, where *P(t)* represents ξ parents in generation *t*; *PO(t)* means that performing crossover ξ parents yield σ children; *PM(t)* means τ

mutant individuals. The EFNIM can be constructed once all these constituent components are in place.

3. Factors of Project Success

Using CAPP software, 54 historical construction projects were collected from 17 CII member companies and analyzed using 76 variables.

3.1 CAPP analyzing process

Current project progress and the level of significance of each factor should be identified first using CAPP software. The analysis process is illustrated as follows:

Step 1: Progress setting.

Significant factors vary during project stages. To identify factors, a completion percentage should be selected for this analysis. For purposes of research in this paper, project progress is set at 67% complete.

Step 2: Significant level for factors.

A threshold level of significance should be selected to identify factors of greatest significance. CAPP recommends that an attached alpha below 0.1 identifies a referenced factor. In this paper, a threshold for the alpha was set at less than 0.025 in order to reduce the number of identified factors.

3.2 Project Success definition

According to project performance, CAPP defined the four degrees for project success of “successful”, “on time or on budget”, “less-than-successful”, and “disastrous” (Russell et al., 1997). Basing on this definition, this paper assigned four quantitative values for project success linearly (see Table 1).

Table 1 Quantitative Project performance

Project performance	Value
Successful	1.000
On time or on budget	0.667
Less-than-successful	0.333
Disastrous	0.000

3.3 Significant Factors of Project Success

Sequentially, CAPP can be employed to calculate significant factors. Factors can be analyzed using CAPP software (see Figure 3). Histogram in CAPP Graphics shows level of significance, denoting high effectiveness at low quantity. With project progress set at 67% (selected in Section 3.1), the value of histogram is about 0.02 (below the threshold 0.025), indicating that the factor “cost of change orders” is identified as a significant factor in this study. Eleven factors significant to project success were identified in total (see Table 2). Forty-six of the 54 valid projects in the CAPP database met the criterion that all eleven factor values are non-null. Forty-two of the 46 were selected for training, leaving four valid projects available for testing (see Table 3).

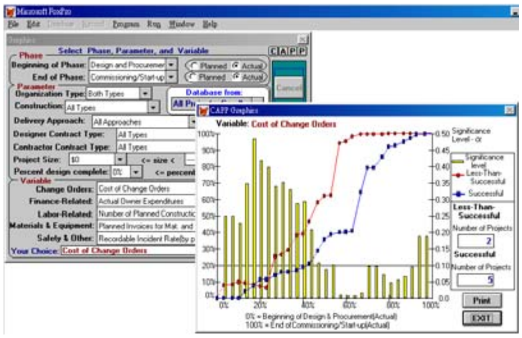

Figure 3. CAPP Graphics for Cost of Change Orders

Table 2. Time-dependent factors identified by CAPP

Factors	Column I.D. in CAPP	Analyzed Significant Level
1. Actual design % complete	C5_16	0.01
2. Actual owner expenditures	C3_10	0.01
3. Invoiced construction costs	C2_14	0.02
4. Designer planned effort hours	C2_13	0.01
5. Actual invoices for material and equipment	C3_28	0.01
6. Paid construction costs	C3_14	0.01
7. Cost of owner project commitments	C2_24	0.01
8. Recordable incident rate (by period)	C2_38	0.01
9. Cost of change orders	C2_17	0.02
10. Quantity of change orders	C3_17	0.01
11. Actual overtime work	C3_41	0.02

4. Project Success Assessment Model

4.1 Model design

To develop a dynamic project success assessment model, significant factors, which are time-dependent, were selected by the CAPP software with an assigned project completion percentage. A K-means algorithm was used to cluster similar projects. The Evolutionary Fuzzy Neural Inference Model (EFNIM), which, as stated above, fuses GA, FL and NN, employed project success learning to determine the relationships between quantities of significant factors (at 67% completion herein) and degree of final project success. Consequently, one can assess the degree of project success using significant factor quantity inputs (at 67% completion). Specific processes and employed facilities of the developed assessment model are shown in Figure 4. In EFNIM, GA plays an important role for global optimization. The fittest result was obtained through the following sequence: define initial population, evaluate individuals, evaluate fitness function, perform crossover, perform mutation, and select individuals.

Define initial population:

Initial solutions are generated randomly, with each solution composed of two FL and NN substring segments.

Evaluate individuals:

A fitness function is designed for global optimization of MF shapes, NN topology, and NN parameters. The objective function f^{ob}, which addresses model accuracy and model complexity, is defined as following:

$$f^{ob} = w^a m^a + w^c m^c \quad \text{……………………………...………(6)}$$

where w^a is a weight of model accuracy; ma denotes model accuracy calculated by the discrepancy between predicted and desired outputs; w^c represents a weight of model complexity; mc indicates model complexity formulated by number of activation connections.

Evaluate fitness function:

Fitness function f^{fi}, defined as the reciprocal of f^{ob}, is used to evaluate chromosomes. The larger the fitness value, the more objectives are achieved.

$$f^{fi} = \frac{1}{f^{ob}} \quad \text{……………………………………...……(7)}$$

Perform crossover:

Crossover rate is used to select fitter parent individuals (crossover rate is 0.2 herein). One-cut-point crossover and exchanging the right-hand part of the parents are used for adaptation. All FL and NN parameters can be exchanged from parents to children.

Perform mutation:

A mutation rate is set to perform mutation operations (mutation rate is 0.02 herein). A probability is assigned to genes. The mutation operator will be excited when the probability reaches the mutation rate.

Select individuals:

Fitness for survival is the criterion for individual selection. To prevent fit chromosomes being lost during evolution, a new generation is composed of several parents, offspring, and their mutations.

Table 3. Testing data from the CAPP database

No.	Inputs											Output
	C5_16	C3_10	C2_14	C2_13	C3_28	C3_14	C2_24	C2_38	C2_17	C3_17	C3_41	
1.	0.000	0.000	0.118	0.150	0.154	0.135	0.000	0.000	0.251	0.456	0.961	0.000
2.	0.074	0.841	0.657	0.079	0.622	0.000	0.000	0.249	0.000	0.000	0.000	1.000
3.	0.000	0.277	0.166	0.000	0.000	0.000	0.000	0.941	0.138	0.200	0.635	0.333
4.	0.000	0.807	0.585	0.000	0.000	0.000	0.000	0.000	0.081	0.211	0.000	0.667

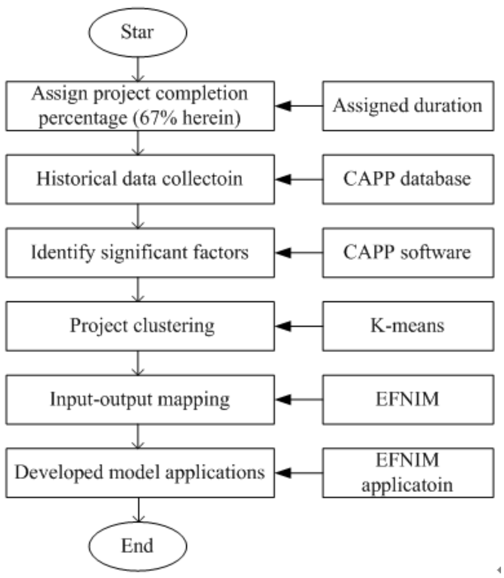

Figure 4. Model Processes

4.2 Project Success Assessment without Data Clustering

With CAPP's kind permission, 54 projects in CAPP database were employed in this study. Firstly, significant factors were analyzed using CAPP software, with a threshold of significant level set at 0.02 and project completion set at 67%. Eleven significant factors of influence in project success were determined. Forty-six projects fulfilled our criteria and were treated as raw data for project success learning. Of the 46 data sets, 42 were treated as training data and 4 were assigned as testing data for EFNIM learning. Although model complexity may lead to an over-learning result, model accuracy is more important than model complexity. Therefore, the weight of model accuracy in equation (6) was set as 1 and relatively 0.0001 for weight of model complexity. Model accuracy varies in correspondence with the dynamic factors of influence on project success. After 5,000 generations were trained / searched, the fitness value of the fittest individual was 0.1198, with mean fitness for all individuals determined as 0.06843. Training and testing RMSE were 0.1812 and 0.1303, respectively. Detailed training results are shown in Figure 5. While result trends are positive, they are not categorized well to determine project success, identify successful projects (project performance=1.000), or determine on-time or on-budget (project performance=0.667) projects. Additional strategies should be employed to overcome such deficiencies.

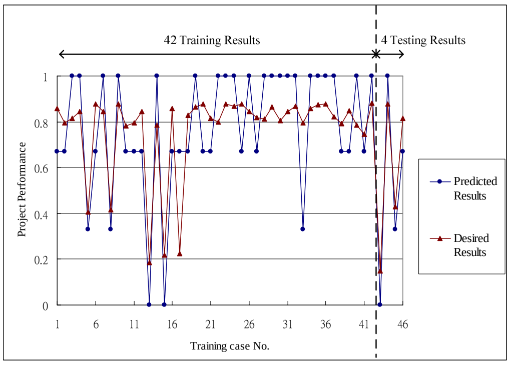

Figure 5 Results for Project Success Assessment without Prepared Data Clustering

4.3 K-means Cluster Analysis

K-means clustering is a multi-variable analysis data clustering method that aggregates similar data and identifies discrepancies between clustered categories. CAPP database data used in this study were gathered from different construction companies and vary in terms of project attributes (e.g., type of construction, cost, procurement approaches, etc.) To improve assessment accuracy, K-means clustering was used prior to EFNIM learning to collate training data sets that were most similar to the assessment target. SPSS, a commercial statistics software package, was the tool used to conduct K-means clustering analysis for this purpose. After the number of clusters been set, each cluster center iterated toward the fittest location by Euclidean distance measurement (see Figure 6). The number of clusters was chosen as 2 to represent positive and negative quality. The four testing data (CS1, CS2, CS3, and CS4) were treated as clustering targets respectively. For CS1, K-means clustering was employed for the 42 training data and CS1. The clustering results are shown in Table 4, in which the CS1 is attached to cluster 2, where there are 17 data sets in this cluster. Similarly, there are 24 training cases for CS2, 25 for CS3, and 17 for CS4. In other words, for each new project assessment, K-means clustering was applied to the assembly of the 42 training projects as well as the new one with 2 sets of clusters having been set. Thus, SPSS generated 2 cluster centers. Finally, data sets in which the new project had been clustered were treated as training data (part of 42 training projects, without the new one) for sequential EFNIM learning to assess new project performance. The reason for setting 2 sets of clusters was to avoid having only a small number of projects for EFNIM learning. Therefore, if the data pool is large enough in other studies, the selected number of clusters could be increased. In summary, time-dependent factors were not the only factors that changed dynamically with CAPP analysis. Training data sets also varied for different project performance assessment targets with SPSS K-means clustering.

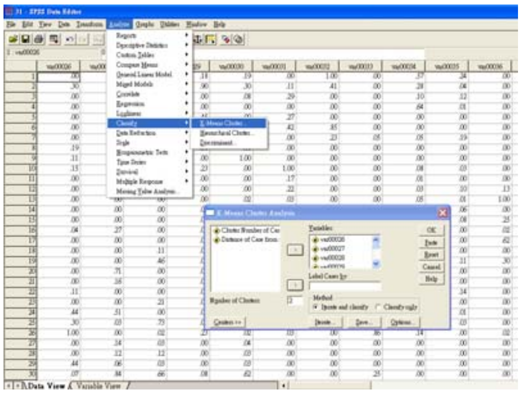

Figure 6 K-means Clustering Analysis of SPSS

Table 4 Results of K-means Clustering

	Initial Cluster Centers		Final Cluster Centers	
	Cluster		Cluster	
Variable	1	2	1	2
C5_16	1.00	0.00	0.11	0.10
C3_10	0.00	1.00	0.07	0.48
C2_14	0.02	0.33	0.08	0.33
C2_13	0.23	0.00	0.06	0.15
C3_28	0.02	0.68	0.03	0.27
C3_14	0.03	0.42	0.05	0.27
C2_24	0.00	0.85	0.02	0.27
C2_38	0.86	0.00	0.12	0.03
C2_17	0.14	0.00	0.07	0.17
C3_17	0.00	0.00	0.11	0.15
C3_41	0.20	0.00	0.13	0.03

Notes:

1. Convergence achieved due to no or minimal distance change. The maximum distance by which any center has changed is 0.000. The current iteration is 3. The minimum distance between initial centers is 2.053.
2. There were 43 valid cases. Of which, 25 cases were in cluster 1 and 18 cases were in cluster 2. No cases were missing.

4.4 Project Success Learning with K-means Clustering Results

After K-means clustering analysis, EFNIM project performance learning for a particular case can follow sequentially. 5,000 generations were similarly set for GA iteration. Results of fitness values and RMSE are listed in Table 5, with results (not using prepared data clustering) shown in Section 4.2. Results show that K-means clustering does indeed improve project performance assessment. Therefore the project success assessment processes in Figure 4 have been demonstrated as representing a reasonable, feasible, and effective approach.

Table 5 Comparisons for K-means Clustering of Performance Assessment Results

	Testing Case	Predicted Output	Desired Output	Best Fitness Value	Overall Fitness Value	Training RMSE
Without K-means Clustering	1	0.1476	0.0000	0.1198	0.0684	0.1812
	2	0.8772	1.0000			
	3	0.4287	0.3330			
	4	0.8151	0.6670			
With K-means Clustering	1, CS1	0.0285	0.0000	0.4012	0.1563	0.0956
	2, CS2	0.9963	1.0000	3.1162	2.4366	0.0175
	3, CS3	0.3835	0.3330	0.3338	0.1456	0.1150
	4, CS4	0.7209	0.6670	0.6676	0.2702	0.0826

Notation: A larger fitness value or smaller RMSE indicates smaller differences between predicted and observed values.

5. Conclusion

This paper proposes a model for assessing project success using AI approaches that employ fuzzy logic, genetic algorithm, neural network, and K-means clustering. The two commercial software packages used include CAPP for project access and SPSS for data clustering. The results achieved in this paper can be summarized as follows:

1. Using CII's copyrighted CAPP software, the time-dependent factors that dynamically influence project performance can be managed in order to achieve precise project success assessment.
2. Although data in the CAPP database are representative of typical construction projects, their features vary widely. Extracting similar historical cases using K-means clustering can improve prediction accuracy. This study performs clustering using SPSS software.
3. The uncertain information and complex mapping in project performance assessment are conducted using EFNIM. EFNIM uses FL to handle uncertainties, NN to perform input-output mapping and GA to achieve global optimization. As its feasibility for project performance assessment has been demonstrated, therefore EFNIM is proposed herein.
4. Project assessment helps managers to make strategies in a time efficient manner and take correct actions to achieve final project success. With the proposed model, dynamic project performance assessment can be achieved using CAPP, SPSS, and EFNIM.

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References

1. Sanvido, V., Grobler, F., Parfitt, K., Guvenis, M., Coyle, M. Critical success factors for construction projects. Journal of Construction Engineering and Management 1992;118(1):94-111.
2. Griffith, A.F., Gibson, G.E., Jr., Hamilton, M.R., Tortora, A.L., Wilson, C.T. Project success index for capital facility construction projects. Journal of Performance of Constructed Facilities 1999;13(1):39-45
3. Hughes, S.W., Tippett, D. D., Thomas, W. K. Measuring project success in the construction industry. Engineering Management Journal 2004;16(3):31-37.
4. Wang, X., and Huang, J. The relationships between key stakeholders' project performance and project success: Perceptions of Chinese construction supervising engineers. International Journal of Project Management 2006;24(3):253-260.
5. Ling, F.Y.Y., Ibbs, C.W., Hoo, W.Y. Determinants of international architectural, engineering, and construction firms' project success in China. Journal of Construction Engineering and Management 2006;132(2):206-214.
6. Chan, A.P.C., Scott, D., and Chan, A.P.L. Factors affecting the success of a construction project Source. Journal of Construction Engineering and Management 2004;130(1):153-155.
7. Nguyen, L.D., Ogunlana, S.O., Lan, D.T.X. A study on project success factors in large construction projects in Vietnam. Engineering. Construction and Architectural Management 2004;11(6):404-413.
8. Cheng M.Y., Ko C.H. Object-Oriented Evolutionary Fuzzy Neural Inference System for Construction Management. Journal of Construction Engineering and Management 2003;129(4):461-469.
9. Chua, D.K.H., Loh, P.K., Kog, Y.C., Jaselskis, E.J. Neural networks for construction project success. Expert Systems with Applications 1997;13(4):317-328.
10. Georgy, M.E., Chang, L.M., Zhang, L. Prediction of engineering performance: A

neurofuzzy approach. Journal of Construction Engineering and Management 2005;131(5):548-557.
11. CII. Predictive tools: closing the performance gap. Research Summary, RS107–1. The Construction Industry Institute, Austin Tex, 1996.
12. Russell, J.S., Jaselskis, E.J., and Samuel P. Lawrence, S.P. Continuous Assessment of Project Performance. Journal of Construction Engineering and Management 1997;123(1):64-71.
13. MacQueen, J. B. Some methods for classification and analysis of multivariate observations. Proc. 5th Berkeley Symp. Probability Statistics, University of California Press, Berkeley1967;281-297.
14. Maulik, U. and Bandyopadhyay, S. Genetic algorithm-based clustering technique. Pattern Recognition 2000;33(9):455-1465.
15. Tou J.T., Gonzalez R.C. Pattern recognition principles. Addison-Wesley, 1974.
16. Zadeh L A. Fuzzy sets. Information Control 1965;8:338-353.
17. Maier, H. R., Sayed, T., Lence, B. J. Forecasting cyan bacterial concentrations using B-Spline networks. Journal of Computing in Civil Engineering 2000;14(3):183-189.
18. Gorzalczany, M. B., Gradzki, P. A neuro-fuzzy-genetic classier for technical applications. Industrial Technology. Proc., of IEEE Int. Conf. 2000;1:503-508.
19. Haykin, S. Neural networks: A comprehensive foundation, Prentice-Hall, New York, 1999.
20. Liatsis, P., Goulermas, Y. J. P. Minimal optimal topologies for invariant higher-order neural architectures using genetic algorithms. Industrial Electronics 1995 ISIE. Proc., IEEE Int. Symp. Greece 1995;2:792-797.
21. Jagielska, I., Matthews, C., Whitfort, T. An investigation into the application of neural networks, fuzzy logic, genetic algorithms, and rough sets to automated knowledge acquisition for classification problems. Neurocomputing 1999;24(1-3):37-54.
22. Holland, J. H. Adaptation in neural and artificial systems, The University of Michigan Press, Ann Arbor, Mich, 1975.
23. Gen, M., Cheng, R. Genetic algorithms and engineering design, Wiley, New York, 1997.
24. Michalewicz, Z. Genetic algorithms data structures–evolution programs, Springer, Berlin, 1996.
25. Cheng M.Y., Ko C.H. A Genetic-Fuzzy-Neuro Model Encodes FNNs Using SWRM and BRM. International Scientific Journal Engineering Applications of Artificial Intelligence 2006;19:891-903.
26. Hayashi, I., Umano, M., Maeda, T., Bastian, A., Jain, L. C. Acquisition of fuzzy knowledge by NN and GA. Knowledge-Based Intelligent Electronic Systems. Proc. KES 1998;1:69-78.

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