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A CBR-BASED COST PREDICTION MODEL FOR THE DESIGN PHASE OF PUBLIC MULTI-FAMILY HOUSING CONSTRUCTION PROJECTS

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ABSTRACT: Korean public owners who order public multi-family housing construction projects have yet to gain access to a model for predicting construction cost. For this reason, their construction cost prediction is mainly dependent upon historic data and experience. In this paper, a cost-prediction model based on Case-Based Reasoning (CBR) in the design phase of public multi-family housing construction projects was developed. The developed model can determine the total construction cost by estimating the different Building, Civil, Mechanical, Electronic and Telecommunication, and Landscaping work costs. Model validation showed an accuracy of 97.56%, confirming the model's excellent viability. The developed model can thus be used to predict the construction cost to be shouldered by public owners before the design is completed. Moreover, any change orders during the design phase can be immediately applied to the model, and various construction costs by design alternative can be verified using this model. Therefore, it is expected that public owners can exercise effective design management by using the developed cost prediction model. The use of such an effective cost prediction model can enable the owners to accurately determine in advance the construction cost and prevent increase or decrease in cost arising from the design changes in the design phase, such as change order. The model can also prevent the untoward increase in the duration of the design phase as it can effectively control unnecessary change orders.

Keywords: Case-Based Reasoning; prediction model; design phase; construction cost

1. INTRODUCTION

1.1 Research Background and Purpose

To ensure the efficiency of one's investment in a construction project, it is necessary to accurately predict the construction cost. The technique of predicting the construction cost in public multi-family housing construction projects is focused, however, on the steps after the completion of the design. As such, it is very difficult to predict the construction cost in the design phase (MOCT 2007). For this reason, individuals who are having public multi-family housing units constructed do not predict the construction costs in the design phase.

The analysis of such existing studies reveals two key issues (Al-Harbi et al. 1994; Arditi and Tokdemir 1999; Attalla and Hegazy 2003; Christain and Pandeya 1997; Dogan et al. 2008; Hegazy and Ayed 1998).

(1) The existing construction cost prediction models mostly predict the construction cost in the feasibility phase.

(2) The existing construction cost prediction models predict only the total construction cost. As such, it is impossible to identify reasons based on the results of the use of such models.

These models that were developed in the previous studies predict the construction cost in the planning phase of construction projects. It is thus difficult to use such models in the design phase because more specific information is required when predicting the construction cost in the design phase than when predicting it in the feasibility phase (Karshenas and Tse 2002). For this reason, there are limitations to the prediction of the construction cost in the design phase using the factors that may allow a user to predict the construction cost in the feasibility phase.

In the design phase, detailed estimates are thus far being made at the stage when the design documents and specifications have been completed (Barrie and Paulson 1992). The design documents and specifications, however, are not completed in the design phase, making it difficult to predict the construction cost on the detailed-estimates level. Models that utilize detailed-level information are thus needed.

Meanwhile, the results of the past researches are so far being used to predict the total construction cost in a construction project, but the problem with this is that it is difficult to predict the cost of the base materials based on the results of such researches. When predicting the construction cost in the design phase, it must be confirmed cost related information as well as construction cost. This is because the design phase is more detailed than the feasibility phase, which makes it possible to predict the specific changes in the construction cost based on the detailed information when predicting the construction cost in the design phase.

In this study, therefore, a cost prediction model for the design phase of the public multi-family housing was developed, based on the design documents and specifications.

1.2 Research Scope and Methodology

As shown in Fig. 1, this paper achieved its goal in four steps:

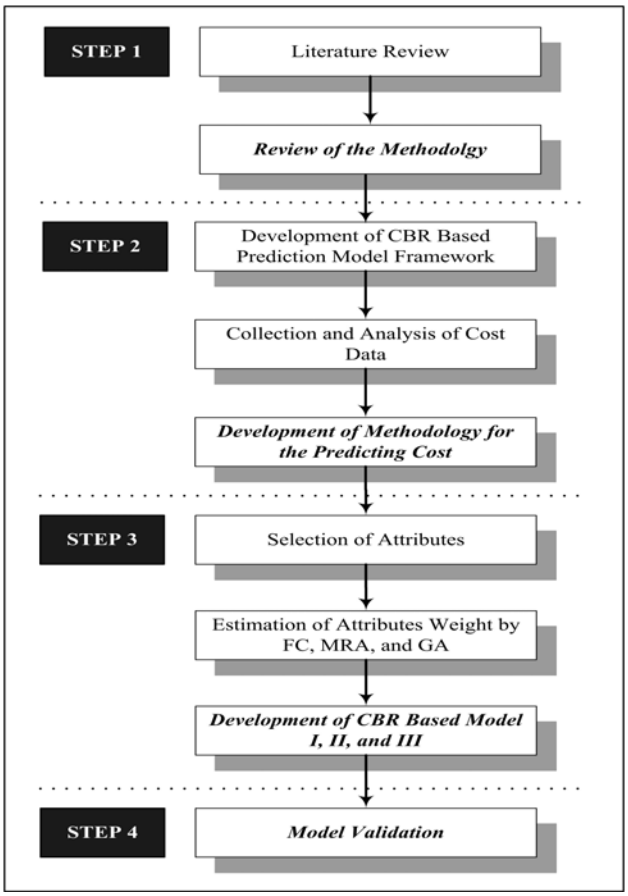

Figure 10. Research framework

In step 1, a variety of cost prediction models were analyzed via preliminary studies. Then the algorithm of case-based reasoning (CBR) and Genetic Algorithm (GA), which were to be applied to the proposed model, was reviewed.

In step 2, the framework of the CBR-based prediction model was developed. For this, historical cost data were collected and analyzed. Then, based on the results of the analysis, a construction cost prediction methodology was developed.

In step 3, the attributes that were to be applied as the input data of the cost prediction model was selected. Then, the attribute weights were selected via feature counting (FC), Multi Regression Analysis (MRA), and Genetic Algorithm (GA). Based on these, three prediction models were developed via attribute weight calculation method.

In step 4, for verification, the three prediction models that were developed in step 3 were applied to real cases.

2. STEP 1: PRELIMINARY STUDY

2.1 Previous Studies

Interviews, questionnaire surveys, sample analysis, Regression Analyses (RA), Artificial Neural Networks (ANN), and CBR methods were used as construction cost prediction models in the previous studies.

However, it is difficult to ensure objectivity and validity even in the prediction of the construction cost, when gathering data through interviews, questionnaire surveys, and sample analyses in the design phase. In RA, it is difficult to cope with the changes in time (Ferry and Brandon 1984). As for ANN, the inference process has not been sufficiently explained, and there is no direct or approximate method for designing network structures and for setting up parameters (Hegagy and Moselhi 1994).

In the meantime, as a result of the prediction of the results of the RA, ANN, and CBR, it was determined that the proposed model based on CBR is the best one (Arditi and Tokdemir 1999).

As can be seen in the aforementioned contents, in predicting the construction cost, it would be best to use CBR. Thus, in this study, the CBR method was used to predict the construction cost of public multi-family housing.

2.2 Case-Based Reasoning (CBR)

CBR is a method that was developed for design, planning, and decision making. It is also used to extract the most similar case and to work out new problems. Fig. 2 shows CBR Process. CBR is generally composed of four steps (Kim et al. 2004), namely Retrieve, Reuse, Revise, and Retain.

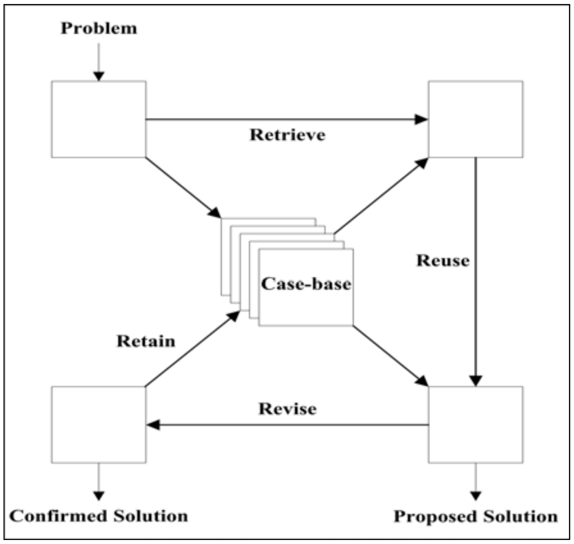

Figure 11. CBR Process

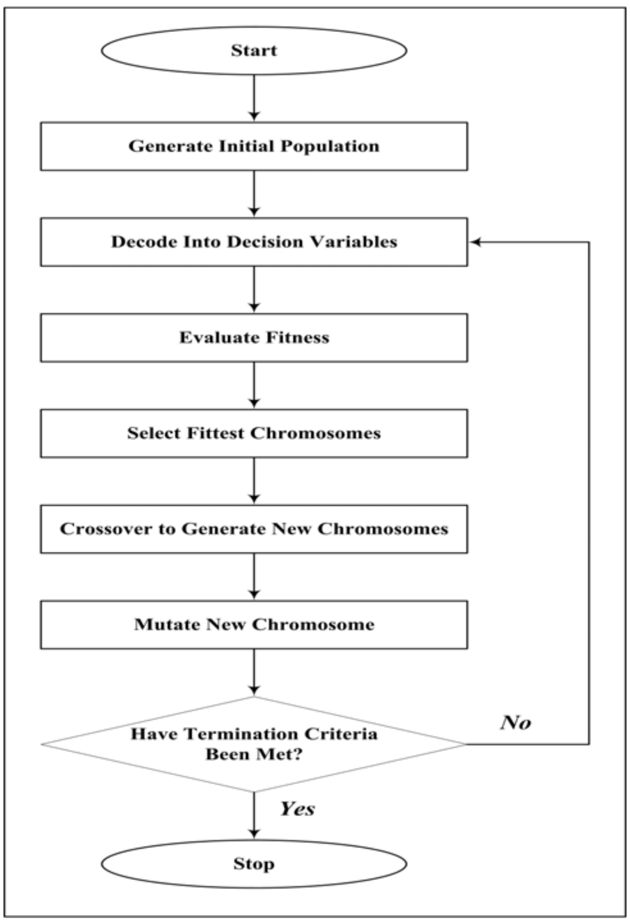

Figure 12. GA Process

(1) Retrieve: In this step, the cases that are most similar to the problems to be solved among the ones that have been experienced are identified.

(2) Reuse: In this step, new problems are solved using scanned cases.

(3) Revise: In this step, the scanned cases are corrected in case new problems are not solved based on such scanned cases.

(4) Retain: In this step, new problems are solved and saved in a case base.

For case extraction via CBR, to extract the case that is most similar to the attribute obtained from a database, the similarity function is used. Similarity functions are used to express how similar property values are to one another (Dogan et al. 2008).

Similarity can be decided via several methods. The most useful among these involves the weighted sum of the attribute distance method. The attribute similarity between j and k is estimated via Eq. (1) (Karim and Adeli 2003).

$$Similarity(A_i^j, A_i^k) = \frac{\min(|v_i^j|, |v_i^k|)}{\max(|v_i^j|, |v_i^k|)} \quad (1)$$

Where A_i^j = ith attribute value representation in case and v_i^j = value (A_i^j) $\neq 0$.

Eq. (1) computes similarity as the ratio of the minimum value to maximum value, which ranges from greater than 0 to 1.

The similarity operations are commutative (i.e., $Similarity(A_i^j, A_i^k) = Similarity(A_i^k, A_i^j)$). If the attribute is text, the similarity between texts is defined by the following Eq. (2);

IF (v_i^j appears in v_i^k) OR (v_i^k appears in v_i^j) THEN

$$Similarity(A_i^j, A_i^k) = 1 \quad \text{ELSE} = 0 \quad (2)$$

2.3 Genetic Algorithm (GA)

Genetic Algorithm (GA) is search algorithm that is the mechanic of natural section and natural genetics, as shown in Fig. 3 (Goldberg 1989, Mohan 1997). GA has been used to optimize attribute weight of the CBR models (Dogan et al. 2006).

In this method, the results are obtained in three steps (1) Reproduction, (2) Crossover, and (3) Mutation, which are applied with the attribute weight.

(1) Reproduction: It is the information stored in chromosome with higher fitness value to survive into the next generation. Fig. 4 shows the example of chromosome structure (Feng and Burns 1997).

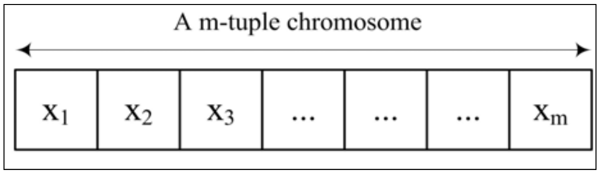

Figure 13. Example of Chromosome Structure

(2) Crossover: It is a superior genetic operator that produces new designs in the optimization process. The crossover creates variations in the solutions population by producing new solution chromosomes that consist of parts taken from selected parent chromosomes. Fig. 5 shows the example of crossover.

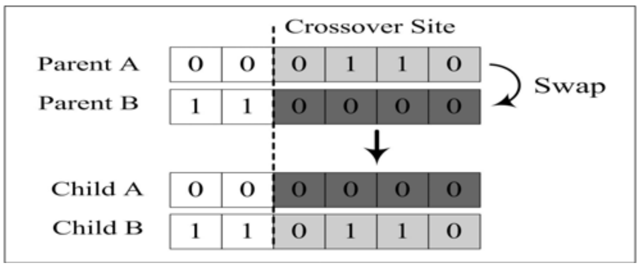

Figure 14. Example of Crossover

(3) Mutation: It is simply changes from 1 to 0 or vice versa. With P_m (i.e., Mutation rate, a rate to randomly alter one or more genes of a selected chromosome), the value of chromosome is changed. Fig. 6 shows the example of mutation.

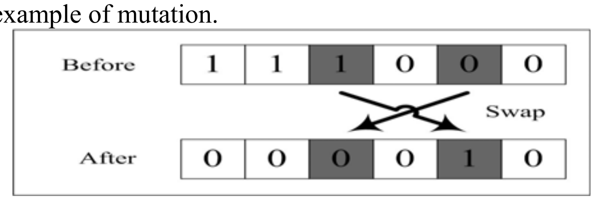

Figure 15. Example of Mutation

3. STEP 2: DEVELOPMENT OF METHODLOGY FOR PREDICTING COST USING CBR

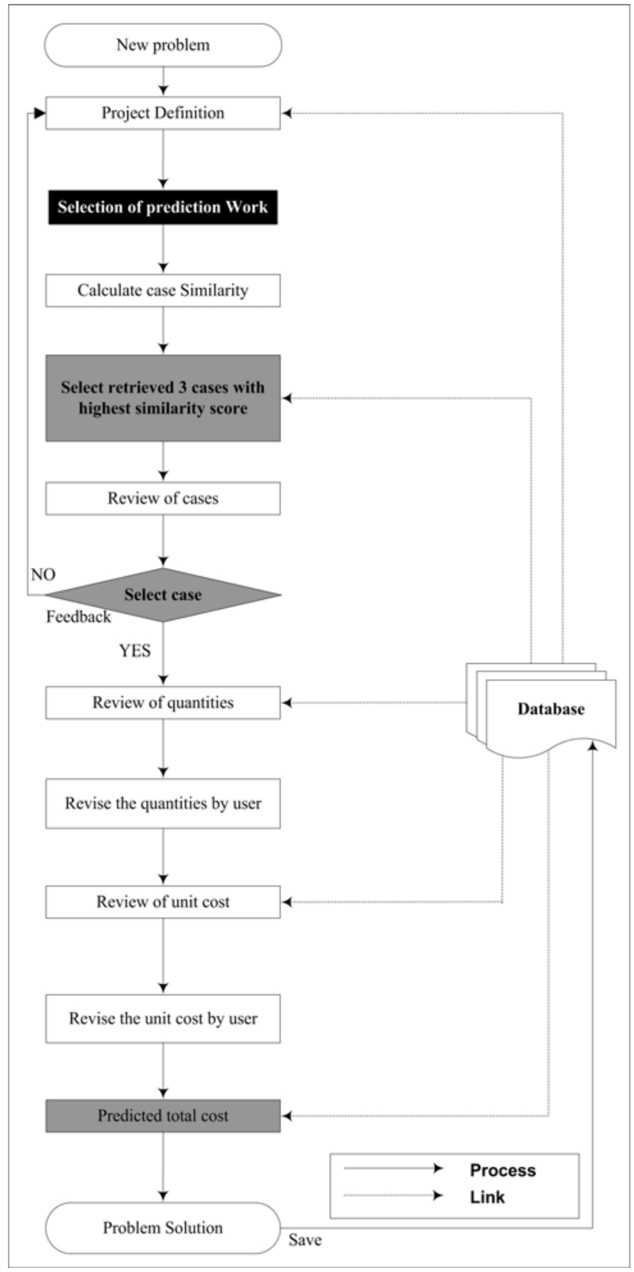

Figure 16. Framework of Prediction Model

3.1 Framework of Prediction Model

The bill of quantities for public multi-family housing units in Korea has been used as an important means for estimating the cost. As it is possible to figure out the bill of quantities, however, it is impossible to forecast the cost using such in cases when the design has not been completed. If the existing bill of quantities for a public multi-family housing project has been started, however, it is possible to forecast the cost with high accuracy in the design phase.

Whatever the nature of a construction project is, however, if its representative specifications are induced and the construction cost is accurately estimated based on more items, the accuracy will not increase largely (PSA

1987). Especially, in the process of predicting the cost, the law of triviality is created, and the case when a cost with high accuracy may not be predicted (Ahuja and Campbell 1986).

Thus, in the case of predicting the construction cost based on quantities, focusing on those items whose cost is highly weighed, it is possible to develop a model that would allow a user to predict the construction cost in a simple way, maintaining accuracy and efficiency.

Based on the aforementioned premise, in this study, the quantity was extracted for the prediction of the construction cost of public multi-family housing projects via the CBR method, and the construction cost was predicted, reflecting the cost in the recent period. The model for predicting the construction cost was developed in the process of analyzing the date of the collection of data regarding multi-family housing projects, selecting an item with a highly weighted cost, and extracting each input formation property and weight.

Fig. 7 shows the process for the proposed model for predicting the construction cost of a multi-family housing project based on CBR.

(1) Project Definition: In this step, project information is inputted, and the inputted information is used as an input material required for the extraction of similar cases.

(2) Prediction Scope Selection: In this step, the work whose cost will be predicted (i.e., building, civil, mechanical, electronic and telecommunication, landscaping work) is selected.

(3) Similar Case Extraction: If the project information and a predicting scope are set up, similar cases are extracted in this step based on such information.

(4) Quantity Information and Correction: If similar cases are selected, it is possible to extract the quantity of the said cases in this step. Then a user can control the quantity that will suit the features of the project.

(5) Cost Information Correction: If the quantity information is decided, the cost in accordance with the said quantity can be extracted in this step, and a correction may be made as the case may be.

(6) Total Construction Cost Prediction: In this step, the user checks the predicted construction cost.

3.2 Data Collection and Analysis

In this study, the data regarding 80 construction projects were collected, to be used as data for the development of a prediction model. Then, to forecast an item whose cost is weighed highly, the collected cases were analyzed.

The results of the analysis are as shown in Fig. 8. Especially building construction cost reached 67.88% of the total construction cost.

In the building construction cost, reinforcement concrete work reached 41.81% of the building construction cost. In addition, glazing work (i.e., 10.21%), finishing work (i.e., 9.10%), furniture work (i.e., 6.91%), temporary work (i.e., 5.09%), metal work (i.e., 4.10%), and foundation work (i.e., 3.87%) reached 81.09% of the building construction cost including 24 works, as shown in Fig. 9.

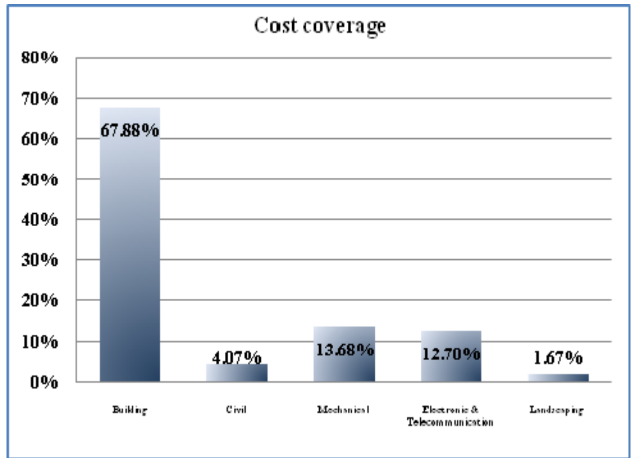

Figure 17. Cost Coverage

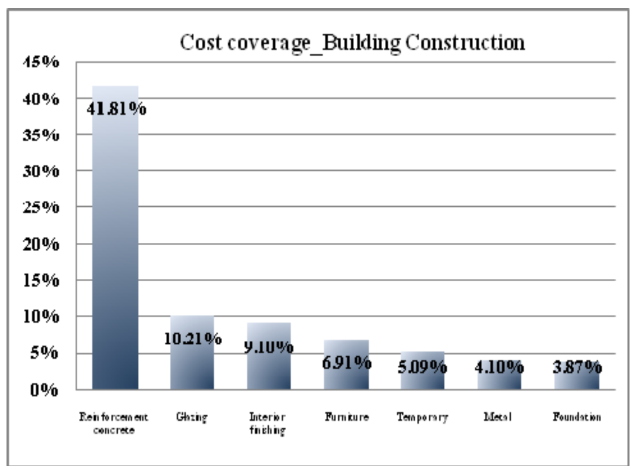

Figure 18. Coverage of the Building Construction

Civil, Mechanical, Electronic & Telecommunication, and Landscaping construction consist of an exceedingly great number of items. In addition, each of such items lacks influence, and there is a limit to the selection of items with a high cost. Thus, Civil, Mechanical, Electronic & Telecommunication, and Landscaping construction, the construction cost per unit area was applied.

Based on the results of the data analysis that was conducted in this study, Building construction was selected as an item with a high cost, and for those items with low cost, rates was applied.

3.3 Methodology of Predicting cost

Based on the construction and other data that were collected in this study, the construction cost method was divided into three methods, as shown in Table 1.

(1) Quantity Information Base: This method is used to extract the quantity of similar cases via CBR, and to predict the construction cost, reflecting the recent construction cost. The items that can be applied to this method are reinforcement concrete, glazing, interior finishing, furniture, temporary, metal, and foundation works.

Table 5. Methodology of Predicting cost

Construction	Work	Application
Building	Reinforcement concrete	Quantity information base
	Glazing	
	Interior Finishing	
	Furniture	
	Temporary	
	Metal	
	Foundation	
	Others	Rate base
Civil		Unit cost (won/m^2) base
Mechanical		
Electronic & Telecommunication		
Landscaping		

(2) Rate Base: This method is for the calculation of the cost of each item by multiplying the predicted construction cost by rate based on the items that do not correspond to the applied works (1). For example, the construction cost based on (1) reached 81.09%. Thus, 18.91% of the rest of the construction costs can be predicted via the rate (predicted construction cost: 81.09% = other costs: 18.91%). In other words, the rest of the construction costs can be estimated by multiplying the predicted construction cost by 0.2332 (others cost =

predicted construction cost ×18.91%/81.09%).

(3) Unit Cost (won/m^2) Base: The construction cost based on the unit cost was reflected from Civil, Mechanical, Electronic & Telecommunication, and Landscaping construction, with the exception only of building construction, which was applied in (1) and (2). If a similar case is extracted via CBR, the construction cost is estimated by multiplying the exclusive area by the unit cost of a similar case (e.g., for landscape construction, landscape area is applied). In this case, the historical cost data in a database were reflected from a past period. As such, for the prediction of the construction time, the Construction Cost Index applied in Korea must be used.

Based on the analysis results, the gathered data regarding the selected 80 cost data were included in a database. Of the building construction, the work based on quantities includes the quantities information plus the database. In addition, the unit cost based construction (i.e., Civil, Mechanical, Electronic & Telecommunication, and Landscaping) include the unit cost.

4. STEP 3: DEVELOPMENT OF CBR BASED PREDICTION I, II, and III

4.1 Selection of Attributes

To select the attributes, (1) the design and document of the collected data, and the bill of quantities, were analyzed to select the factors affecting the cost, and (2) for the selected factors, the correlation analysis and multicollinearity were reviewed, and the attributes of the model were derived.

(1) The design, including the bill of quantities, was analyzed after dividing it into building, civil, mechanical, Electronic and telecommunication, and landscaping works. It was found in such analysis that, for example, even if the housing units are apartments with the same gross floor area, the quantity changes according to the type of households, number of households, number of floors, lot area, building area, gross floor area, building coverage, and floor space index. The construction cost also changes.

(2) The factor that was derived via the first method can be applied as an attribute affecting the construction cost. As collinearity, however, can be problematic in each factor, correlation analysis was conducted, and the factor where VIF is higher than 10 was excluded via multicollinearity diagnosis (Myers 1990).

Table 2 shows the arrangement of the attributes by work, based on the above method.

Table 6. Attribute

Construction	Attribute	
Building	type of households	number of Elevator
	number of households	Gross floor area
Civil	Lot area	number of buildings
	Building Area	
Mechanical	Lot area	number of buildings
	number of households	
Electronic & Telecommunication	Lot area	number of buildings
	number of households	
Landscaping	Building Area	Landscaping area

For building construction, type of households, number of households, number of elevators, and gross floor area were applied as attributes. Then the attributes of civil (i.e., lot area, building area, and number of buildings), mechanical (i.e., lot area, number of households, and number of buildings), electronic & telecommunication work (i.e., lot area, number of households, and number of buildings), and landscaping (i.e., building area and landscaping area) were derived.

4.2 Estimation Attribute Weight by Feature Counting (FC), Multi Regression Analysis (MRA), and Genetic Algorithm (GA)

To determine each attribute weight, it is very important to determine the degree of similarity of the attributes. There are several methods for determining each attribute weight, but it is estimated using Feature Counting (FC), Multi Regression Analysis (MRA), and Genetic Algorithm (GA) (Dogan et al.2006).

(1) Estimation attribute weight by FC: The attribute weight determined via this method is assumed to be 1, and the degrees of importance of the attributes are assumed by the method to be equal.

(2) Estimation attribute weight by MRA: In this method, the absolute β value among the regression coefficients derived via MRA is applied with the attribute's weight. In this study, the attribute's weight was derived using the SPSS 12.0 software.

(3) Estimation attribute weight by GA: In this study, the Evolver 4.0 for Excel software was used, and each attribute's weight was derived through 10,000-time simulation.

Table 3 shows the arrangement of the attribute weights that were derived via the above three methods.

Table 7. Attribute Weight by FC, MRA, and GA

Construction	Attribute	Attribute Weight		
		FC	MRA	GA
Building	type of households	1	0.042	0.709
	number of households	1	0.065	0.477
	number of Elevator	1	0.040	0.549
	Gross floor area	1	1.024	0.111
Civil	Lot area	1	0.738	0.021
	Building Area	1	0.738	0.928
	number of buildings	1	0.842	0.144
Mechanical	Lot area	1	0.649	0.181
	number of households	1	0.208	0.928
	number of buildings	1	0.115	0.037
Electronic & Telecommunication	Lot area	1	0.774	0.781
	number of households	1	0.112	0.581
	number of buildings	1	0.826	0.499
Landscaping	Building Area	1	0.294	0.021
	Landscaping area	1	0.613	0.849

At the early stage, to develop a model for predicting the construction cost, the cost dates were collected and analyzed. Then the attributes were used as input information for a model, and each weight was decided. In this study, the three prediction models were defined as follows, in accordance with the method that was used to determine the attribute weight:

(1) Model I: Prediction Model using FC
(2) Model II: Prediction Model using MRA
(3) Model III: Prediction Model using GA

The accuracy of the aforementioned three models was confirmed via model validation.

5. STEP 4: MODEL VALIADATION

To confirm the accuracy of the three models that were developed at an early stage, S projects, which have not been used for a database, were individually, applied to models I, II, and III. To analyze their pure forecasting accuracy, the quantity was not corrected, as shown in Fig. 10.

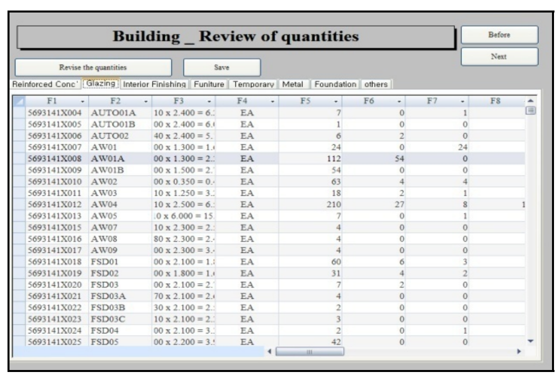

Figure 19. Quantity Information and Correction

Table 4 shows a summary of the results of the verification of model III. As can be seen in the table, the predicted cost was forecasted to be 29,312,464,432 won, and the error rate reached 2.44%.

Table 8. Result of Sample Application

Construction	Predicted cost	Actual cost	Accuracy
Building	20,257,542,425	19,800,922,329	97.65%
Civil	855,573,571	1,117,151,396	80.63%
Mechanical	3,817,407,430	3,498,011,265	94.12%
Electronic & Telecommunication	3,320,420,141	3,486,058,456	95.25%
Landscaping	1,131,441,857	1,140,498,862	99.20%

Total cost	**29,312,464,432**	**28,648,427,002**	**97.56%**

Table 4 shows a high error rate in the case of civil work. This is because the indicated unit cost of the actual civil cost was 1,166,942 won/m^2, but the case when the unit cost reached 1,193.990 won/m^2 was extracted as a similar case. The error rate of the total cost reached 2.44%, however, making it possible to check the applicability of a model. In addition, for the database, 80 cases were selected. There was a deviation value, however, in the number of databases according to each work. As such, in some cases, even if the similarity was not high, it was to be extracted as a similar case and was to be applied. Nevertheless, the methodology that was suggested via the aforementioned verification results is efficient for predicting the construction cost in the design phase.

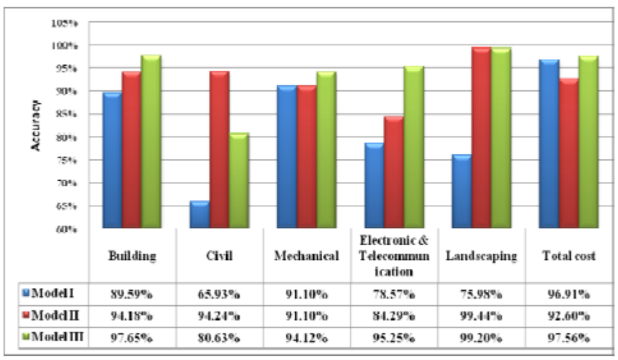

Figure 20. Results of model validation

Fig. 11 shows the verification results: the sums from models I, II, and III. According to Table 5, the accuracy of model I reached 96.91%; that of model II 92.60%; and that of model III 97.56%. These results suggest that the proposed CBR-based construction cost prediction model using GA is the most excellent one.

6. CONCLUSIONS

The existing construction cost prediction models have been often used in the planning stage; as such, they predict only the total construction cost. Thus, there is a limit to their application in the design phase, and there was no way of figuring out the estimation base of the total construction cost.

This study was conducted to develop a prediction model that can be used to predict the construction cost in the step where the design for a public multi-family housing project is being made. In the process of developing such model, a method for predicting the construction cost based on the quantity, and of analyzing the cost data of a public multi-family housing project, was developed. Then, the attributes and weight of each work were estimated. Based on the results, CBR-based models I, II, and III were developed.

The model validation revealed that the proposed models (models I, II, and III) have 96.91%, 92.60%, and 97.56% accuracy, respectively. These results prove that the proposed models are reliable.

As the prediction models that were developed in this study were used to predict the construction cost by work, and as their users can figure out the quantities that can be used in the design phase, it was possible to check the estimation base of the forecasted construction cost. In other words, although it was not applied to the model validation that was done in this study, if a user reviews the quantities and cost information and adjusts them so as to make them suit the features of new projects, the proposed construction cost prediction models are expected to yield more excellent prediction results and to thus be very efficient for cost management in the design phase.

As this study targeted public multi-family housing, it seems to be difficult to be applied to other types of projects immediately. It is thus necessary to conduct other studies with the aim of developing particular types of construction cost prediction models based on the procedures employed in this study.

ACKNOWLEDGEMENT

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