Interval Estimation of Construction Cost
Using Case-Based Reasoning and Genetic Algorithms

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Abstract
During a construction project, the cost of progress is the most important factor affecting the profitability of the project. It would be beneficial to the contractor to have prior knowledge concerning the cost of progress of a project. This study uses case-based reasoning (CBR) to predict the cost of progress in order to develop appropriate strategies. This study also investigates genetic algorithms (GAs) for weight generation and applies them to a real project case. To achieve the objective, quantitative data have been collected from real completed construction projects. The proposed prediction system, namely EVAS-CBR-GAs, was then performed on the identified influential variables. The results show that the presented methodology can consistently reduce errors and potentially be useful for owners and contractors in the early financial planning stage. Recognizing this need, the author has developed a comprehensive system for planning and controlling the cost of contractor progress.

Keywords: case-based reasoning; cash flow; estimation; genetic algorithms

1. Introduction
For many years, the construction industry has suffered a proportionally higher bankruptcy rate than other industries (Statistics Korea, 2011). Some of the major causes of bankruptcy are inadequate cash resources and failure to convince creditors that this inadequacy is only temporary. Thus, contractors did not pay much attention to the problem of their cost of progress associated with implementing project work. Still, construction companies typically focus on budget planning during the early project stage. By doing so, they ignore the impact of engineering cost changes and information updates made during construction. However, when a construction project is in progress, it would be beneficial for the contractor to have prior knowledge of the cost of progress. Normally, the forecast of project expenditure cost is produced during the early estimating and tendering stages. The expenditure cost flow then forms the basis for forecasting project cash flow. Accordingly, accurate cost of progress forecasting is essential at the early stages. Accurate cost of progress forecasting provides contractors with the capital requirements, the amount of interest that needs to be paid to support an overdraft and the evaluation of different life cycle strategies.

Contractors can use cost of progress forecasting methods to improve their financial position and reduce the risk of bankruptcy, which threatens so many construction companies. There has been a large amount of work in the field of mathematical and statistical modeling of cost of progress forecasts. Current methods of predicting cash flow have significant weaknesses (Boussabaine and Kaka, 1996; Boussabaine and Elhag, 1998; Tam and Fang, 1999; Kim et al., 2004). In most current practices the accuracy of cash flow forecasting is largely dependent on the past experience of the estimator performing the forecast. For this reason a consistent forecast cannot be guaranteed, as there is no binding mechanism to relate the present case to any past patterns (Boussabaine and Kaka, 1996; Boussabaine and Elhag, 1998). Previous studies of the accuracy of cost expenditure forecasting at the early stages concluded that the level of accuracy was not acceptable (Kim et al., 2004). Most of the previous models mentioned are based on regression techniques where the "best fit" is sought. This approach is not appropriate when describing non-linear relationships, which are multidimensional, consisting of a multiple input and output problem (Tam and Fang, 1999). Additionally, the vast majority of project progress cost models are based on the use of S-curves to forecast project expenditure cost flow. In truth, the variables that determine the shape of S-curves are very

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difficult to quantify and may not lend themselves to curve fitting. In addition, the thousands of sub-projects involved make it impossible to individually examine and construct an S-curve for each sub-project. Finally, S-curves constructed from actual cumulative progress are not smooth and are often highly uneven.

Many scholars have tried to develop artificial intelligence (AI) models to address various practical problems (Hegazy, 2002). The application of an artificial neural networks (ANNs) approach is currently considered an alternative approach to control project costs. Accordingly, this study furthers existing work in the use of ANNs. However, ANNs can lose their effectiveness when the patterns are very complicated or noisy, ill-defined knowledge representation and problem structuring, and training trapped in local minima (Chao and Chien, 2010). Thus, this study offers a case-based reasoning (CBR) system that overcomes these limitations by separating the mathematical component. Despite its superiority, application of CBR in cost of construction progress is still very limited.

The primary aim of this study was to develop a CBR system to assist contractors in forecasting, planning and controlling the cost of progress. However, the scope of this study is limited to forecast expenditure cost, part of cash flow management. The accuracy of estimates from the progress matching method is unstable in a project's beginning stage because estimating is based entirely on the fitted historical cases. These are similar in progress to the project, but just for that short period of time. Their progress may differ at later stages of the project. To counter this instability and improve accuracy, the authors propose incorporating the previously mentioned CBR system into the estimation process by integrating genetic algorithms (GAs) into the progress matching method. Thus, incorporating prediction uncertainty into deterministic forecasts can improve the reliability and credibility of the system outputs.

2. Model for Cash Flow Management

Many models from different industrial sectors have been developed for cash flow management (Golden et al., 1979; Malburg, 1992). A smaller number of publications have addressed the needs of the construction industry. The need for simple and fast techniques in cash flow forecasting has been acknowledged in previous studies (Kaka and Ammar, 1996; Malik, 1996) and, cash flow forecasting models have been developed. These models tend to follow the same concept and mechanism.

Over the years, many alternative ways of determining S-curves have been studied, along with various mathematical formulas for generalizing cumulative project progress as a function of time (Navon, 1996; Kaka and Lewis, 2003). Studies on the accuracy of traditional cash flow models based on ideal S-curves have demonstrated a need for further work in this area. Previous studies have investigated numerous issues related to cash flow in construction. Barbosa and Pimentel (2004) constructed a linear programming model for cash flow management for the Brazilian construction industry. Barraza et al. (2000) introduced a stochastic S-curve as an alternative to the deterministic S-curve that generated the most likely budget and duration values. Park et al. (2005) adopted moving weights of cost categories in a variable budget while constructing a cash flow forecasting model, and applied realistic data to examine model accuracy. Blyth and Kaka (2006) produced an individual S-curve for a particular project using a multiple linear regression model based on 50 projects and 20 criteria. Suhanic (1986) addressed the use of the banana envelope to show the integration of project resources with the project schedule stated as early and late dates. The S-curve is based on combinations of historical projects and is popularly formed by third, fourth, or fifth degree polynomials (Kaka and Ammar, 1996). These models usually involve a complicated procedure and a large number of variables.

ANN models have also been proposed for forecasting project progress and its cash flow. Chao and Chien (2007) proposed an ANN model for estimating S-curves using a cubic polynomial for fitting S-curves. The results provided better accuracy than the regression and average curve methods. Bousabaine and KaKa (2009) and Boussabaine et al. (1998) proposed a method for forecasting project progress and cash flow at a set interval of every tenth of project time without using an S-curve formula. Despite the relative success of many applications, companies in the construction industry still face difficulties in implementing procedures for cash flow management.

3. Methodology

Fig. 1. Hybrid Structure of a CBR-GAs

The reasoning behind the proposed system is presented in Fig.1. Data that incorporate all the input variables, which were selected by interviewing fifteen experts with over five years of field experience, are required. When potential input variables were identified, the weight of each variable was optimized by GAs, and strategies for data collection established.
In addition, an appropriate CBR system was developed and validated, and preliminary testing of a developed system was carried out, using a relatively small number of data sets. In order to use GAs to generate weights, one of the cases in the input case-based library was removed. For the purpose of developing a CBR system, a new Excel Visual Basic Application System (EVAS) was selected.

### 4. Case-Based Reasoning

CBR is not a computerized tool that imitates the analogical reasoning of human brains in problem solving (Ardit and Tokdemir, 1999). The principle of CBR is based on the assumption that similar problems have similar solutions. According to Riesbeck and Schank (1998), CBR solves problems by capturing previous experiences and matching the important features of new problems with those of old cases that have been successfully solved. The main source of knowledge in CBR is the case that can be reused even if it only partially matches the problem in hand (Riesbeck and Schank, 1989). Especially, CBR can deal efficiently with both numeric and nominal data, and can handle effectively cases that have incomplete data or variable data structures (Morcous et al., 2002). Furthermore, CBR has powerful learning capabilities that do not require time-consuming training and testing operations (Riesbeck and Schank, 1989).

![Fig.2. Case-Based Reasoning Cycle](image)

Aamodt and Plaza (2002) call the top level task of CBR problem solving and learning from experience which directly matches two phases, maintenance and application, as shown in Fig.2. In the application phase, CBR searches the case based library for stored problems that are similar to the given one and retrieves them. The next, CBR assesses the similarity of the retrieved problems and selects the solution of the best-matched problem. Third, CBR adapts this solution for the differences between the given problem and the retrieved problem. The adapted solution is then, presented to the decision-maker as the final solution of the given problem. The maintenance phase in the original CBR cycle consists of the retention step alone. During this phase the revised solution is stored in the case based library. The indexing structures to the newly added case are also adapted. If no new case was constructed existing indexing structures are modified to improve the similarity assessment (Morcous et al., 2002).

In the six-Re processes, changes initiated from outside of the CBR can be modeled easily: (1) Retrieve the most similar cases from stored previous cases; (2) Reuse the retrieved cases to attempt to solve the problem; (3) Revise the proposed solution if necessary; (4) Retain the new solution as a part of a new case; (5) Review the results from applying the solution; and (6) Restore the case into the case base library. This cyclical process will make the base increasingly broad and useful for estimation regarding future projects.

### 5. Genetic Algorithms

GAs are particularly suitable for multi-variable optimization problems with an objective function subject to numerous hard and soft constraints. GAs perform the search process in four phases: initialization, selection, crossover, and mutation (Aamodt and Plaza, 1994; Davis, 1991). Thus, GAs first create a population of possible solutions to the problem. GAs seek to solve optimization problems using the methods of selection, specifically survival of the fittest (Tam and Fang, 1999). Individuals in the population are then allowed to randomly breed, which is called crossover and mutation operation, until the fittest offspring is generated (Wong and Tan, 1994; Holland, 1992).

The central idea of the combination of GAs and the EVAS-CBR system is that CBR transfers the burden of knowledge assignment of the indexing and retrieving process to the searching and learning capabilities of evolutionary algorithms to increase the overall effectiveness of the system.

### 6. Description of Data

The system must be affected by using collected information data. The first stage in producing the EVAS-CBR-GAs system required gathering data from sample cases of matching progress. These data were required to be of similar project type and duration. Typically, in such systems, previous case projects are collected and retrieved according to some attributes. The proper formula parameters for a case-based library are used to produce a standard matching progress as the basis for prediction for a new project classified in the same category. To illustrate the development of a system for estimating matching progress, data on the nature and actual progress of 56 building projects in South Korea completed in 2000-2010 were collected. From these data, five projects were discarded because of their unusual delays, resulting in a usable set of 51
projects. The case representation is shown in Table 1.

### Table 1. Case Representation

| Description                  | Type of variable | Remarks                   |
|------------------------------|------------------|---------------------------|
| Duration                     | Numeric (months) | Max. = 41, Min. = 19     |
| No. of floors                 | Numeric (stories)| Max. = 50, Min. = 16      |
| No. of parking spaces        | Numeric (places) | Max. = 1,690, Min. = 90   |
| Year                         | Numeric (years)  | Max. = 2010, Min. = 2000  |
| Floor area ratio             | (%)              | Max. = 275, Min. = 15     |
| Building coverage ratio (%)  | (%)              | Max. = 69, Min. = 15      |
| Total area (m²)              |                  | Max. = 22,421, Min. = 573 |
| Type of building             | Nominal          | Apartment, Office,        |
| Location                     | Nominal          | Commercial building,      |
| Form system                  | Nominal          | Ganged, Conventional wall,|
| Roof                         | Nominal          | Jump, Slip               |
| Foundation                   | Nominal          | Mat, PHC-Pile, Wall       |
| Superstructure               | Nominal          | SRC, RC                  |
| Substructure                 | Nominal          | SRC, RC                  |
| Retaining wall               | Nominal          | H-Pile+E/A, Slurry wall,  |
| External wall                | Nominal          | AL panel, Water paint,    |
| Internal wall                | Nominal          | Granite, Stainless,       |
| Ceiling                      | Nominal          | Gypsum board, Sound       |
| Floor                        | Nominal          | OA, Laminates, Vinyl,     |
| Output                       | Numeric (costs)  | Max. = 13,415, Min. = 491|

### Time Standardization

After construction begins, actual progress is periodically measured and recorded. It is proposed to match the progress data that become available over time, especially early on in a project to retrieve similar cases for providing a subsequent estimate of project progress.

#### Table 2. The Value of Building Cost Index

| Year  | Building Cost Index | Converted Value |
|-------|---------------------|-----------------|
| 2000  | 78.5                | 1.27389         |
| 2001  | 79.8                | 1.25313         |
| 2002  | 81.6                | 1.22549         |
| 2003  | 90.1                | 1.10988         |
| 2004  | 95.4                | 1.04822         |
| 2005  | 100.0               | 1.00000         |
| 2006  | 101.1               | 0.98912         |
| 2007  | 104.0               | 0.96154         |
| 2008  | 111.0               | 0.90090         |
| 2009  | 126.6               | 0.78989         |
| 2010  | 127.1               | 0.78678         |

First, the data collected for developing EVAS-CBR-GAs have diverse characteristics and differences, such as when and where the projects were constructed. Such differences may have caused low accuracy in the prediction results (Han et al., 1997; Kim and Kang, 2003; Kim et al., 2005). For improving accuracy and system fidelity, it was necessary to ensure consistency by standardizing the data. This study converted the cost data of all the cases from February 2005 using the building cost index (BCI) of the Korea Institute of Construction Technology (KICT). The BCI of South Korea, which is announced monthly, was used for the cost adjustments. Then, Eq. (1) is fitted to the standardized actual progress data of each project. The BCI to the conversion was official statistical data prepared to estimate the price fluctuation of input resources by assuming 100.0 as the price of a direct construction cost input in a project at a certain point in time (KICT, 2011).

The index of standard reference time

\[ \text{Adjusted BCI} = \frac{100 \text{BCI}}{\text{Targeting time}} \]  

The index of targeting time

\[ L(c_x) = \sum_{j=1}^{100} \prod_{i=1}^{100} \left( \frac{c_x - c_i}{c_j - c_i} \right) \]  

### Weight Optimization

"Weight" indicates how much attention should be paid to each variable during the matching process in a CBR cycle (Kolodner, 1992). It reflects the importance of that variable relative to other cases. It was found that weight is the main variable in predicting the project cost (Kolodner, 1992; Arditi and Tokdemir, 1999; Chua et al., 2001; Luu et al., 2005; An et al., 2007. The determination of an appropriate variable weighting method is a major issue for effective case retrieval and indexing in a CBR cycle (Park and Han, 2002; Ahn et al., 2005). The major issue in CBR is retrieving not just a similar past case but a usefully similar case. For this reason, the integration of domain knowledge into the case-retrieving and indexing process is highly recommended when developing an EVAS-CBR-GAs system. This section utilizes a hybrid approach using GAs in the case-based retrieval process.
in an attempt to improve the overall cost accuracy. Furthermore, GAs are equivalent to attribute weights. They also consider the uncertainty of human judgment and recognize relative importance among variables. These values represent the contribution of different variables in predicting the solution (Kolodner, 1992). If this hybrid is carried out well, a CBR system can prove more economical and improve estimating. It can operate more accurately or cost less, and EVAS-CBR-GAs will be have a better understanding of the effects of CFs interaction and variation during developed the system working process.

GeneHunter software was used to find the optimum weights. For the controlling parameters, research should be based on Hegazy and Ayed (1998). That is, the population size is generally determined by the size of the problem. This study uses 50 population sizes (see ① in Fig.3.). The crossover and mutation rates are changed to prevent the output from falling into the local optima (Evolver, 1995; Hegazy and Ayed, 1998; GeneHunter, 1998). Crossover combines subsets of promising solutions by exchanging some of their parts. Mutation slightly perturbs the recombined solutions to explore their immediate neighborhood. Most commonly used crossover operators combine pairs of promising solutions. One of the most common mutation operators for binary strings is the bit-flip mutation, in which each bit is modified (flipped) with the same probability. The crossover rate is 0.9 and the mutation rate is 0.01 (see ② in Fig.3.). Stopping condition is selected after 100 trials (see ③ in Fig.3.). Weights generated by GeneHunter were manually plugged into the EVAS-CBR-GAs system. Each weight was assigned to an attribute for case-based retrieval, representing the importance of each variable. These weights enable retrieval of the most similar process plans based on an effective similarity function in the proposed application area. The optimal weight of each variable is shown in Fig.4.

7. Description of the System

In order to evaluate the accuracy of matching progress estimates obtained from the above presented progress matching method, Fig.5. shows the main system menu of the developed system. This menu contains five different system modules sequenced in the order that should be followed. The system interface follows the basic process used to construct a CBR application. Buttons are provided for the system browser facility and for running a loaded application. Buttons on the left of the interface provide easy entry into the five modules used to build the application.

This stage of the CBR system allows the decision-maker to add new case data directly into the database. After clicking the New Case button, the decision-maker enters the required case into the appropriate case-based library. The New Case button is used to create the basic definition of a case and to define the variables for that case. A case consists of a set of variables that best describe the attributes of a prior experience. For example, the information required in the new case can be divided into six main types: year, location, number of floors, general information, construction technique, and cost by sixteen trades information as shown in Fig.6.

A weight estimating process for each variable that minimizes estimating errors using GAs is shown in Fig.4. Cases that are similar to the new cases were retrieved from the case-based library in order to
estimate the cash flow of the new cases. To retrieve similar cases, the following process is used. First, the similarity score (SS) is calculated in order to determine if each case in the case-based library is actually similar to the new cases. The SS is calculated by multiplying the SS of each variable for a case of the case-based library by weight and then summing all of them. Weights of the retrieved cases are calculated by the similarity weight of the retrieved similar case. The weighted average of the cash flow cost from the retrieved cases is then used as the estimated cash flow cost for the new case.

The above procedure will be successful as long as adequate similar past projects are found and retrieved from the case-based library and as long as they turn out to be the same as those that actually occur.

8. Results

Collected cases are used to illustrate the method and evaluate its accuracy. Five test cases are used to demonstrate the process by which project cost of progress is produced, refined, and then rearranged to reflect the broader objectives of the contractor. Table 3 and Fig.7 summarize the results from the five test cases. In order to evaluate the accuracy of expenditure cost estimates obtained from the above presented progress matching method. Two error measures are used to measure the accuracy of the results in terms of closeness of fit as well as to provide a basis for system performance evaluation later: mean absolute error rate (MAER) and Cronbach’s alpha.

Table 3. Results of the EVAS-CBR-GAs

| Time          | Case 1  | Case 2  | Case 3  | Case 4  | Case 5  |
|---------------|---------|---------|---------|---------|---------|
|               | Error rate (%) | Cum. Error rate (%) | Error rate (%) | Cum. Error rate (%) | Error rate (%) | Cum. Error rate (%) | Error rate (%) | Cum. Error rate (%) | Error rate (%) | Cum. Error rate (%) |
| 0% to 10%     | 12.89   | 12.89   | 10.90   | 10.90   | 7.55    | 7.55    | 12.59   | 12.59   | 4.73    | 4.73    |
| 11% to 20%    | 9.15    | 11.02   | 11.81   | 11.35   | 1.65    | 4.60    | 6.73    | 9.66    | 4.25    | 4.49    |
| 21% to 30%    | 9.90    | 10.65   | 13.99   | 12.23   | 2.53    | 3.91    | 6.30    | 8.54    | 1.71    | 3.56    |
| 31% to 40%    | 7.89    | 9.96    | 13.60   | 12.57   | 2.10    | 3.46    | 5.03    | 7.66    | 0.90    | 2.90    |
| 41% to 50%    | 11.05   | 10.18   | 12.04   | 12.46   | 1.42    | 3.05    | 4.05    | 6.94    | 1.21    | 2.56    |
| 51% to 60%    | 9.76    | 10.11   | 12.26   | 12.43   | 1.81    | 2.84    | 2.94    | 6.27    | 1.23    | 2.34    |
| 61% to 70%    | 10.14   | 10.11   | 12.42   | 12.43   | 1.28    | 2.62    | 3.45    | 5.87    | 1.16    | 2.17    |
| 71% to 80%    | 9.73    | 10.06   | 12.40   | 12.43   | 2.34    | 2.59    | 5.30    | 5.80    | 1.58    | 2.10    |
| 81% to 90%    | 11.10   | 10.18   | 11.97   | 12.37   | 1.26    | 2.44    | 3.06    | 5.49    | 1.33    | 2.01    |
| 91% to 100%   | 10.14   | 10.18   | 11.41   | 12.28   | 1.44    | 2.34    | 2.81    | 5.23    | 1.84    | 1.99    |

\[ MAER = \frac{1}{n} \sum_{i=1}^{n} \frac{c_e - c_a}{c_a} \times 100 \]  

(3)

Where \( c_e \) is the estimated expenditure cost by EVAS-CBR-GAs, \( c_e \) is the collected expenditure cost, \( n \) is the number of sets of test data.

The MAER of cost estimation is then calculated by comparing the estimated expenditure cost with the original cost of the new case. MAER gives a direct measure of the average error in a percentage. Through the repetition of this process for multiple new cases, the expenditure cost of new cases is predicted, and the MAER is calculated. The result for MAER is 6.41% which is calculated by five cases multiplied by 100 time intervals per each case (5 cases×100/time/case = 500 times). The cumulative effects decrease gradually as time proceeds (see Table 3.). However, the MAER in the early rate of progress (0% to 20%) appeared frequently, and during this period to reduce the error rate are able to confirm that an important point. Nevertheless, EVAS-CBR-GAs is an accurate and reliable system. These error rates are smaller than -10% to 15%, which correspond with those presented by the American Association of Cost Engineers (AACE) in the case of the check estimate or bid/tender phase, and with ±10%, correspond with the expected error range in the detailed estimate presented by the Construction Industry Institute (CII). Therefore, the predicted expenditure cost by the system considered to be reliable.

Cronbach’s alpha is used as a measure of the internal consistency or reliability of test results. It is commonly used as a measure of the internal consistency or reliability of a psychometric test score for a sample of examinees. A widely accepted social science cut-off point is that alpha should be .60 or higher for a set of examinees. However, for a sample of examinees, reliability analysis is conducted using Cronbach’s alpha that is calculated by Statistical Package for the Social Sciences (SPSS) 20.0. The result for Cronbach’s alpha is .746. This means that the system developed in this study could control the Cronbach’s alpha of the prediction accuracy and is optimized enough to obtain consistent prediction accuracy.
Equation caption

1. Adjusted BCI (1)

\[ \text{Adjusted BCI} = \frac{100}{1 + \left( \frac{1}{100} \sum_{i=1}^{K} \left( \frac{x_{i} - x_{j}}{x_{j} - x_{i}} \right) \right) \left( \frac{x_{i} - x_{j}}{x_{j} - x_{i}} \right) \sum_{i=1}^{K} c_{i} c_{j} t_{ij} c_{c} L_{cc} t_{cc} } \]

2. \[ \text{Cronbach’s } \alpha = \frac{K}{K-1} \left( 1 - \frac{\sum_{i=1}^{K} \sigma_{Yi}^2}{\sigma_{X}^2} \right) \] (4)

Where \( K \) is the number of components (\( K \)-items or testlets), \( \sigma_{X}^2 \) is the variance of the observed total test scores, \( \sigma_{Yi}^2 \) is the variance of component \( i \) for the current sample.

9. Conclusions

This study highlights the importance of cash flow forecasting and discusses the developed forecasting system for project cost expenditure pattern. This study combines the preliminary cost of progress estimation using hybrid CBR-GAs and subsequent estimation by matching progress. The developed system is an
empirical methodology whose estimate is based on past data and does not depend on a detailed schedule of activity times. In terms of application, whereas the CBR system was intended to predict financing requirements and to get a quick cost of progress forecast before the start of construction, the integration system is intended to forecast progress using actual progress data.

The results show that the presented methodology can consistently reduce errors. Therefore, the system can be used to prepare a preliminary progress estimate at the early stages when only sketchy project information is available.

The main limitations of the system lie with the case based library. First, the case-based library should be created from projects with the same conditions of contract concerning progress measurement, so that case progress records are usable references for the matching progress method. Second, the case-based library should have sufficient cases that cover a variety of projects, so that both the CBR system and its extension and integration model, have better estimation accuracy than present models.

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