AN INTEGRATED MULTI-OBJECTIVE OPTIMIZATION MODEL FOR SOLVING THE CONSTRUCTION TIME-COST TRADE-OFF PROBLEM

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Abstract. As construction projects become larger and more diversified, various factors such as time, cost, quality, environment, and safety that need to be considered make it very difficult to make the final decision. This study was conducted to develop an integrated Multi-Objective Optimization (iMOO) model that provides the optimal solution set based on the concept of the *Pareto front*, through the following six steps: (1) problem statement; (2) definition of the optimization objectives; (3) establishment of the data structure; (4) standardization of the optimization objectives; (5) definition of the fitness function; and (6) introduction of the genetic algorithm. To evaluate the robustness and reliability of the proposed iMOO model, a case study on the construction time-cost trade-off problem was analyzed in terms of effectiveness and efficiency. The results of this study can be used: (1) to assess more than two optimization objectives, such as the initial investment cost, operation and maintenance cost, and CO_2 emission trading cost; (2) to take advantage of the weights as the real meanings; (3) to evaluate the four types of fitness functions; and (4) to expand into other areas such as the indoor air quality, materials, and energy use.

Keywords: multi-objective optimization, pareto front, non-dominated solution, fitness function, construction management.

Introduction

The Construction Management Association of America (CMAA) defines Construction Management (CM) as a professional service that applies effective management techniques to control various standards, such as the time, cost, quality, environment, and safety, under a series of processes from the project planning phases to operation and maintenance phase. CM is defined as a management system created for the successful performance of a project from the owner's viewpoint (Henderickson, Au 1989; CMAA 1999; Unnikrishnan *et al.* 2009).

Various complex and large-scale projects such as super-high-rise buildings, green buildings, super-long-span bridges, u-city projects, and urban regeneration projects have recently emerged. In the early stage of a project, it is important to recognize the role of a construction manager or contractor in effective and reliable management of a project. For instance, a super-high-rise building project requires careful review of new techniques or methods in terms of structural and construction engineering. Based on the review, a plan should be established to engage appropriate labor and equipment. Such decision-making ultimately affects the time, cost, and quality, among other factors, of a project, and thus, determines the outcome of the project as the final decision. The larger the project scales, the more varied factors for consideration are generated. This makes it very difficult to make the final decision. It becomes increasingly difficult to review all possible combinations of factors for the best decisions, which leads to obstacles in obtaining reliability. To solve this problem, experts should be involved or a sophisticated decision support system should be developed (Pagnoni 1990; Adeli, Hung 1995; Adeli, Sarma 2006).

As the delivery methods (i.e. the design and build, best-value contract, management contract, prime contracting, build-operate-transfer, partnering, etc.) are diversified, the target standards on project performance (i.e. the time, cost, quality, environment, etc.) likewise become diversified based on the characteristics of a project (Zheng *et al.* 2004; Ammar 2011). For instance, the best-value contract grants a higher value to quality than to time and cost (Ansell *et al.* 2009; Lam *et al.* 2009; Asmar *et al.* 2010; Sullivan 2011). LEED certification projects give priority to the environmental standards. Nevertheless, while meeting the construction contract time, there should be no increase in the cost or a reduction in quality (Hegazy 1999; Hegazy, Ersahin 2001; Rogoža *et al.* 2006).

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This study was conducted to develop an integrated multi-objective optimization (iMOO) model capable of comprehensively analyzing various standards that are traditionally considered in the construction industry, such as time and cost, and of determining an optimal solution according to the following procedure: (1) through an extensive literature review, a preliminary analysis was conducted on various methodologies applied in the past (i.e. heuristic, mathematical programming, and genetic algorithms) and the limitations of these methodologies were analyzed; and (2) by solving these limitations, a model with improved flexibility or applicability and usability was developed that can be applied to various areas related to multi-objective optimization. Two criteria were used to assess the robustness and reliability of the proposed iMOO model: effectiveness in terms of the quality of the generated optimal solution set; and efficiency in terms of computational time.

1. Conventional multi-objective optimization techniques

There have been several studies on multi-objective optimization, and various methodologies have been implemented, including heuristics, mathematical programming, and genetic algorithms.

First, using heuristic methods, previous studies hoped to solve the Time-Cost Trade-off Problem (TCTP). Based on the rule of thumb, this methodology may provide a good result, but it cannot guarantee that the result would always be the optimal solution. Additionally, since the result is not presented in terms of the range of possible solutions, this methodology is inappropriate for use in analyzing various scenarios, such as in Fondahl's method, Prager's structural model, Moshlhi's structural stiffness method, and Siemens's effective cost slope model (Fondahl 1961; Prager 1963; Siemens 1971; Moselhi 1993).

Second, some methodologies, such as linear programming and integer programming, hoped to solve TCTP by applying mathematical programming methods. While linear programming may be appropriate in determining the existence of a linear time-cost relationship, it is limited in determining the existence of a discrete time-cost relationship. To solve this problem, integer programming was introduced (Liu *et al.* 1995; Burns *et al.* 1996). Integer programming, however, requires too much time and effort to model a large number of activities or complex relationships. Many studies have pointed out the disadvantages of heuristics and mathematical methods, the most serious of which is that they are not appropriate for dealing with more than one objective.

Third, to solve this issue, several studies have defined the trade-off among management indices as multi-objective optimization problems and introduced genetic algorithms (Goldberg 1989; Adeli, Cheng 1993; Li, Love 1997; Elbeltagi *et al.* 2005; Ng, Zhang 2006; Chen, Weng 2009). Feng *et al.* (1997) introduced the concept of multi-objective optimization to optimize the time and cost at the same time. However, this approach uses the convex hull concept, which is also used in linear programming and thus has a limitation in providing the actual optimal solution. Gen and Cheng (2000) hoped to solve TCTP using the adaptive weight approach (AWA), but they were only able to produce an optimal solution when several assumptions were satisfied. Zheng *et al.* (2004) aimed to solve TCTP using the modified adaptive weight approach, which improved the disadvantages of AWA. Zheng *et al.* (2005a) and Zheng and Ng (2005b) also proposed the range of possible solutions by introducing the concept of Pareto ranking and niche formation.

Fourth, aside from TCTP, several studies have considered the quality, environment, and productivity at the same time (Hsieh, Liu 2004; Balling *et al.* 2004; Huang *et al.* 2009; Jiang *et al.* 2011; Liu *et al.* 2012; Simanaviciene *et al.* 2012). El-Rayes and Kandil (2005) tried to solve the time-cost-quality trade-off problem in highway construction. Marseguerra *et al.* (2004) and Martorell *et al.* (2005) applied the concept of multi-optimization using genetic algorithms to solve the optimization problem on the technical specifications and maintenance activities in nuclear power plants. Carvalho *et al.* (2012) conducted a study to assess the economic and environmental aspects on a trigeneration system.

2. Motivation from previous studies

Through an extensive literature reviews with regards to the multi-optimization, the limitations of the methodologies applied to the existing research were identified. At the same time, the advantages of these methodologies were determined. Based on the results, this study aims to develop more intuitive, simplified, applicable and flexible model (i.e. research team named it "iMOO model") to solve the multi-optimization problems. The following are several motivations for developing the iMOO model:

- The iMOO model should guarantee that the results would always be the optimal solution, which could not be achieved using heuristic method.
- The iMOO model should be simplified to minimize the time and effort spent to model a large number of activities or complex relationship, which could not be achieved using linear and integer programming.
- The iMOO model should provide an optimal solution set based on the concept of the *Pareto front*. Accordingly, the reliability on the final results should be improved (refer to Figs 1 and 2).
- The iMOO model should have improved flexibility or applicability depending on the problem statement and should be able to easily handle more than two optimization objectives (refer to Fig. 3).
- The iMOO model should have improved usability by simplifying the complicated processes and equations shown in previous studies (Feng *et al.* 1997; Goldberg 1989; Li, Love 1997; Gen, Cheng 2000; Zheng *et al.* 2004, 2005a; Zheng, Ng 2005b) (refer to Section 3, "Model implementation").

– The iMOO model adopts two criteria for improving the performance of the models proposed in previous studies: (1) effectiveness in terms of the quality of the generated optimal solution set; and (2) efficiency in terms of computational time (refer to Section 4, "Model application").

– The iMOO model realizes an optimization algorithm using a genetic algorithm.

Figures 1 and 2 show the concept of the *Pareto front* (i.e. non-dominated set) and the optimal solution set, respectively (Chen and Weng 2009). As shown in Figure 1, the alternatives for the *Pareto front* were not superior to the other alternatives in terms of both of two optimization objectives (i.e. Z_A and Z_B, which represent the time, cost, quality, environment, etc.). The *Pareto front* signifies a set of alternatives whose superiority cannot be easily determined.

Figure 2 explains Areas (1)–(4), which are compartmentalized based on *Alternative α*. First, all alternatives in Area (1) are superior to the *Alternative α* in terms of both two optimization objectives, Z_A and Z_B (i.e. the area that *Alternative α* is dominated by). Moreover, within Area (1), the set of alternatives whose superiority cannot be easily determined is called the optimal solution set. Second, Areas (2) and (3), compared to *Alternative α*, signify indifferent areas in which one of the two optimization objectives is superior and the other is inferior. Third, all alternatives in Area (4) are inferior to the *Alternative α* in terms of both of two optimization objectives, Z_A and Z_B (i.e. the area that *Alternative α* dominates).

The proposed iMOO model presents the process of producing the optimal solution set based on the two concepts explained in Figures 1 and 2 – the *Pareto front* and the optimal solution set. This approach can also be applied identically to more than two objectives. Figure 3 conceptually shows three optimization objectives (for which it was assumed that an index is better when Z_A and Z_B are smaller and when Z_C is larger). This shows that the proposed iMOO model can be easily expanded to multiple dimensions.
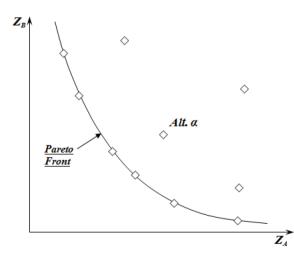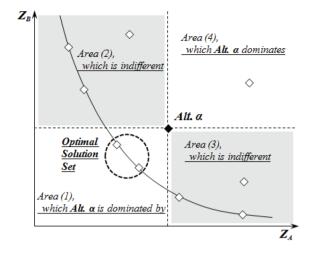

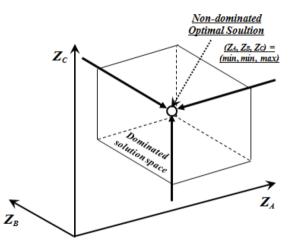Fig. 2. Non-dominated area and the optimal solution set

Fig. 3. Non-dominated optimal solution in the three-objective space

3. Model implementation

Based on the motivations for this study that were explained in Section 2, "Motivation from the previous studies", the following core engine of the iMOO model was developed.

The values of the optimization objectives, which are defined by the characteristics of a project, should be standardized. First, the maximum extreme point (Z^+) and the minimum extreme point (Z^-), i.e. the two extreme points within the whole criteria space, can be found using Eqns (1) and (2) suggested by Gen and Cheng (2000). Moreover, the hyperplane, which is used to find the optimal solution set, can be established based on the two extreme points (here, it was assumed that an index is better when Z_A and Z_B are smaller) (refer to Fig. 4):

$$Z^+ = \left\{ Z_A^{\max}, Z_B^{\max} \right\}; \tag{1}$$

$$Z^- = \left\{ Z_A^{\min}, Z_B^{\min} \right\}, \tag{2}$$

Fig. 1. Pareto front in the two-objective space

where: Z^+ is the maximum extreme point; Z^- is the minimum extreme point; $Z_A^{\max}$ and $Z_B^{\max}$ are the maximum value for the optimization objectives of A and B, respectively; and $Z_A^{\min}$ and $Z_B^{\min}$ are the minimum value for the optimization objectives of A and B, respectively.

Second, all points within the whole criteria space should be standardized using Eqns (3) and (4):

$$S_A = \frac{Z_A - Z_A^{\min}}{Z_A^{\max} - Z_A^{\min}}; \tag{3}$$

$$S_B = \frac{Z_B - Z_B^{\min}}{Z_B^{\max} - Z_B^{\min}}, \tag{4}$$

where: S_A is the standardized value for the Z_A; and S_B is the standardized value for the Z_B.

As the original values for the optimization objectives of A and B are converted into standardized values between 0 and 1, several advantages can be obtained:

– The effect from the non-identical unit between the optimization objectives of A and B that are applied to the fitness function can be removed in advance.

– Gen and Cheng (2000) did not solve the problem of a zero division scenario. Zheng *et al.* (2005a) and Zheng and Ng (2005b) attempted to solve this issue using several stages of processes, complicated equations, and random number τ (between 0 and 1). This study could solve this problem using a simplified process called the standardization of optimization objectives.

– By simplifying the optimization process and equation, this study offers flexibility – i.e. it can easily access various applied problems.

– According to the project characteristics and the owner's requirements, the weight value of the optimization objectives can be applied. Gen and Cheng (2000), Zheng *et al.* (2005a) and Zheng and Ng (2005b) also used a weighed value, but since their process did not have a stage where the optimization objectives were standardized, the weighed value cannot be a weighed value in its purest sense.

– The model can help facilitate understanding and solve the problems on more than two optimization objectives through the multi-dimensional concept.

As shown in Figure 5, the model consists of four types of fitness functions. Based on the characteristics of the optimization objectives that were defined according to the project characteristics, an appropriate fitness function can be selected. A concrete example was explained in Section 4 "*Model Application*". As mentioned, all points can be standardized using Eqns (3) and (4) (refer to Fig. 5). A weight value can be found through the significance evaluation of each optimization objective. In this study, the weighted Euclidean distance, as shown in Eqn (5), was used:

$$wEd_{x,b} = \sqrt{\sum_{i=1}^{n} w_i \times (x_i - b_i)^2}, 0 \prec w_i \prec 1 \, and \sum_{i=i}^{n} w_i = 1, \tag{5}$$

where: $wEd_{x,b}$ is the weighted Euclidean distance between x and b; x_i is the value of the i-th measure for the particular data; b_i is the corresponding benchmark value (0 or 1) for the value of x_i; and w_i is the weight value for the i-th measure.

There are many methods for calculating the weight value (e.g. AHP based on interviews with specialists, the will of the decision-maker, or statistical methods, etc.), but these methods were not considered in this study. Four types of fitness functions are as follows:

(1) In case of minimizing the value for the optimization objective of A, and minimizing the value for the optimization objective of B:

Fitness Function (i)

$$= \sqrt{W_A \times (S_A - 0)^2 + W_B \times (S_B - 0)^2}, \tag{6}$$

where: the optimization process is continued until the *Fitness Function (i)* meets the minimum value; W_A is the relative weight defined by the final decision-maker for minimizing the value of the optimization objective of A; and W_B is the relative weight defined by the final decision-maker for minimizing the value of the optimization objective of B. For instance, if the optimization objectives of A and B are time and cost, respectively, the
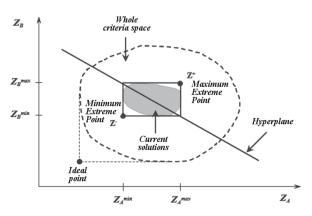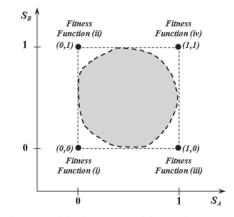

Fig. 4. Two extreme points and the hyperplane

Fig. 5. Concept of the four types of fitness functions

two variables are optimized if they are both closer to the minimum value.

(2) In case of minimizing the value for the optimization objective of *A*, while maximizing the value for the optimization objective of *B*:

$$\text{Fitness Function } (ii) = \sqrt{W_A \times (S_A - 0)^2 + W_B \times (1 - S_B)^2}, \quad (7)$$

where: for instance, if the optimization objectives of *A* and *B* are cost and quality, respectively, the optimization objective of *A* (cost) is optimized if it is closer to the minimum value, whereas the optimization objective of *B* (quality) is optimized if it is closer to the maximum value.

(3) In case of maximizing the value for the optimization objective of *A*, while minimizing the value for the optimization objective of *B*:

$$\text{Fitness Function } (iii) = \sqrt{W_A \times (1 - S_A)^2 + W_B \times (S_B - 0)^2}, \quad (8)$$

where: for instance, if the optimization objectives of *A* and *B* are sustainability and cost, respectively, the optimization objective of *A* (sustainability) is optimized if it is closer to the maximum value, whereas the optimization objective of *B* (cost) is optimized if it is closer to the minimum value.

(4) In case of maximizing the value for the optimization objective of *A*, and maximizing the value for the optimization objective of *B*:

$$\text{Fitness Function } (iv) = \sqrt{W_A \times (1 - S_A)^2 + W_B \times (1 - S_B)^2}, \quad (9)$$

where: for instance, if the optimization objectives of *A* and *B* are productivity and safety, respectively, two variables are optimized if they are both closer to the maximum value.

The iMOO model can solve all possible problems with four types of fitness functions (refer to Fig. 5). Moreover, the iMOO model can solve the problems on more than two optimization objectives through the multi-dimensional concept (refer to Fig. 3).

(5) In case of minimizing the value for the optimization objectives of *A* and *B*, and maximizing the value for the optimization objective of *C*:

Fitness Function (v)

$$= \sqrt{W_A \times (S_A - 0)^2 + W_B \times (S_B - 0)^2 + W_C \times (1 - S_C)^2}, \quad (10)$$

where: for instance, if the optimization objectives of *A*, *B*, and *C* are cost, time, and environment, respectively, the optimization objectives of *A* (cost) and *B* (time) are optimized if they are closer to the minimum value, while the optimization objective of *C* (environment) is optimized if it is closer to the maximum value.

4. Model application

The iMOO model proposed in this study was developed as a computer-aided program based on the following six-

phase process: (1) problem statement; (2) definition of the optimization objectives; (3) establishment of the data structure; (4) standardization of the optimization objectives; (5) definition of the fitness function; and (6) introduction of the genetic algorithm. To evaluate the robustness and reliability of the proposed iMOO model, a case study on the construction TCTP was analyzed in terms of effectiveness and efficiency. In order to illustrate the concept of the proposed iMOO model more easily as well as to evaluate the robustness and reliability of the iMOO model more clearly, the case study used in Liu *et al.* (1995) and Zheng *et al.* (2005b) was applied to the iMOO model in this study.

4.1. Problem statement

In a construction project, the indices that the owner or the project manager is most interested in are the time, cost, quality, and environment. These indices have a trade-off relationship since there are so many considerations in construction project, i.e. construction materials, construction methods, equipment, labors, etc. For instance, applying new technology to reduce the project time or improve the external appearance or the residential environment increases the project cost. If the budget is insufficient, it is difficult to undertake measures to reduce time or improve the quality. Accordingly, a reasonable method for determining the optimal solution is required to solve such a trade-off relationship while satisfying the limited budget, contract period, and minimum quality requirements.

4.2. Definition of optimization objectives

Traditionally, it is project time and cost that are most strongly bound by a trade-off relationship in construction project. Once design alternatives or construction methods that satisfy the minimum requirements of owner are selected, project manager reviews them in terms of the time and cost and then makes the final decision. Thus, in this study, the time and cost are defined as the optimization objectives in performing the model application. The two objectives can be calculated using Eqs (11) and (12):

$$\text{Project Time} = \sum_{i=1}^{l} T_i^n, \quad (11)$$

where: T_i^n is the duration of activity (*i*) on the critical path using resource utilization (*n*) and *l* is the number of activities. To establish the critical path in the activity network, the critical path method is used to calculate the activity time and flow.

$$\text{Project Cost} = \sum_{i=1}^{l} \left[M_i^n + \left(T_i^n \times R_i^n \right) \right], \quad (12)$$

where: M_i^n is the direct cost of activity (*i*) using resource utilization (*n*); T_i^n is the time of activity (*i*) using resource utilization (*n*); R_i^n is the daily cost rate in \$/day using resource utilization (*n*); and *l* is the number of activities.

4.3. Establishment of the data structure

In order to derive the optimal solution for the aforementioned optimization objectives, the basic information on each variable should be determined and their relationship should be established. Figure 6 shows the seven activities and their relationship in the case used in Liu *et al.* (1995) and Zheng and Ng (2005b). Table 1 shows the description of the case study, i.e. activities and their relationship, construction methods applicable for each activities and their duration and direct cost. Generally, if the duration of the project increases, the indirect cost may increase even if the direct cost is reduced. This relationship leads to an increase in the total cost. In order to define such a relationship, as determined by Zheng and Ng (2005b), the indirect cost was set at $500/day in this study.

4.4. Standardization of optimization objectives

The heuristic method was used to calculate the maximum extreme point (Z^+) and the minimum extreme point (Z^-), i.e. the two extreme points within the whole criteria space. Since the goal was to minimize both two-optimization objectives in the case, the maximum extreme point (Z^+) based on Eqn (1) became the most undesirable point and the minimum extreme point (Z^-) based on Eqn (2) became the ideal point:

- Ideal point: Z^- (time, cost) = (60, 143,000);
- Most undesirable point: Z^+ (time, cost) = (105, 203, 200).

The values are located on the original coordinate axis (refer to Fig. 4). To define the fitness function and derive the optimal solution, a new coordinate axis between 0 and 1 should be created through the standardization process for these values using Eqns (3) and (4) (refer to Fig. 5).

4.5. Definition of the fitness function

As illustrated in Section 4.4 "*Standardization of optimization objectives*", the goal was to minimize both two-optimization objectives. Accordingly, the *Fitness Function* (*i*) presented in Eqn (6) was used. The ideal point corresponded to (0, 0) on the standardized coordinate axis (refer to Fig. 5). As a result, the combination at which the *Fitness Function* (*i*) had the minimum value is the optimal solution.

4.6. Introduction of the genetic algorithm

A genetic algorithm (GA) was used as a search algorithm for determining the optimal solution of the fitness

Table 1. Description of the case study

Activity description	Activity number	Precedent activity		Construction methods	Duration (days)	Direct cost ($)
Site preparation	1	–	1	Crew 1 + Equipment 1	14	23,000
			2	Crew 2 + Equipment 2	20	18,000
			3	Crew 3 + Equipment 3	24	12,000
Forms and rebar	2	1	1	Method 1	15	3,000
			2	Method 2	18	2,400
			3	Method 3	20	1,800
			4	Method 4	23	1,500
			5	Method 5	25	1,000
Excavation	3	1	1	Equipment 1	15	4,500
			2	Equipment 2	22	4,000
			3	Equipment 3	33	3,200
Precast concrete girder	4	1	1	Method 1	12	45,000
			2	Method 2	16	35,000
			3	Method 3	20	30,000
Pour foundation and piers	5	2, 3	1	Method 1	22	20,000
			2	Method 2	24	17,500
			3	Method 3	28	15,000
			4	Method 4	30	10,000
Deliver PC girders	6	4	1	Railroad	14	40,000
			2	Truck	18	32,000
			3	Barge	24	18,000
Erect girders	7	5, 6	1	Crane 1 + Crew 1	9	30,000
			2	Crane 2 + Crew 2	15	24,000
			3	Crane 3 + Crew 4	18	22,000

function. In a GA, the decision variables that affect the optimization objectives are defined as chromosomes. Such chromosomes consist of various genes. In this study, each gene in the chromosome signified each activity in the network defined in Figure 6.

As shown in Figure 7, the number on each gene signified the construction method that performed each activity (refer to Table 1). The result value of fitness function was calculated by applying the properties (i.e. time and cost) of the construction method. Additional information on the fundamentals of multi-objective optimization and GA can be found in the related references (Certa *et al.* 2011; Elbehairy *et al.* 2006; Elegbede, Adjallah 2003; Geem 2010; Kandil *et al.* 2010; Konak *et al.* 2006; Moradi *et al.* 2011; Sayin, Kouvelis 2005; Šešok, Belevicius 2008; Šešok *et al.* 2010; Šostak, Vakrinien 2011; Venskus *et al.* 2010). In this study, a software program called '*OptQuest*' (an optimization tool that runs with a software program called '*Crystal Ball*') was used to introduce the GA.

5. Results and discussion

This research aims to develop an iMOO model for solving a multi-objective optimization problem, which determines the optimal solution set based on the concept of the *Pareto front*. Toward this end, this research team introduced the GA as a search algorithm and also simplified the complicated process and equation. Thus, the robustness and reliability of the proposed iMOO model was enhanced in terms of effectiveness and efficiency.

Figure 8 shows the list of 1,000 highly ranked populations generated through the GA in the scatter diagram on the original coordinate axis. The dotted curve at the bottom left of the diagram signify the *Pareto front*. As explained in Section 4.4 "*Standardization of optimization*
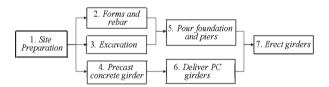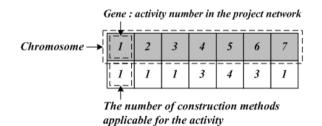
objectives," the coordinate axis should be standardized before the fitness function is defined.

Figure 9 shows the list of the 250 highly ranked populations generated through the GA in the scatter diagram on the standardized coordinate axis. The diagram was transformed into the same scale on the standardized axis. As shown in Figure 9, all 250 highly ranked populations existed near the ideal point (0, 0) based on the longitudinal section and cross-section (compared to Fig. 8). This result showed that the reliability of the proposed iMOO model was improved as the process proceeded.

As shown in Figure 10, the distribution of the 50 highly ranked populations was closer to the ideal point (0, 0) (compared to Fig. 9). This result signifies that the two optimization objectives (time and cost) were being improved at the same time as the process proceeded.

To assess the robustness and reliability of the proposed iMOO model, two criteria were used: (1) effectiveness in terms of the quality of the generated optimal solution set; and (2) efficiency in terms of computational time. Figures 8 to 10 showed that the robustness and reliability of the proposed iMOO model were enhanced.
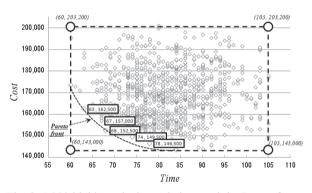

Fig. 8. 1,000 highly ranked populations and the Pareto front in the original coordinate axis

Fig. 6. Activity network of the case study
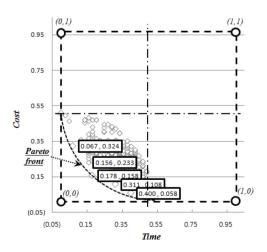

Fig. 7. Description of chromosome

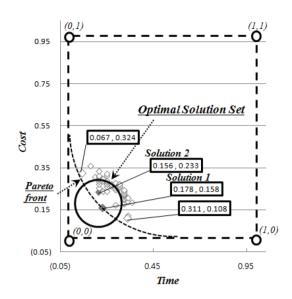Fig. 9. 250 highly ranked populations and the Pareto front in the standardized coordinate axis

Fig. 10. 50 highly ranked populations, the Pareto front, and the optimal solution set in the standardized coordinate axis

First, the effectiveness of the proposed iMOO model was validated from Figures 8, 9, and 10 as follows: (1) the higher the rank of the population was, the more concentrated on the center of the *Pareto front* the population became; and (2) the optimal solution set that was finally generated through the GA (the circle area in Fig. 10) was identical to the results of previous studies (Liu *et al.* 1995; Zheng *et al.* 2005b). Consequently, given the objective of this research that is to develop more intuitive, simplified, applicable and flexible model to solve the multi-objective optimization problem compared to the previous studies (Liu *et al.* 1995; Zheng *et al.* 2005b), it was determined that the effectiveness in terms of the quality of the generated optimal solution set was achieved. Moreover, depending on the decision criteria, the decision-maker can select the more effective one among the optimal solution set. As shown in Figure 10, the two coordinates, *Solution 1 (0.178, 0.158)* and *Solution 2 (0.156, 0.233)*, are standardized values, while the original values are (68, 152,000) and (67, 157,000), respectively. For instance, according to the set level of the value of the loss due to construction delay, the optimal so-
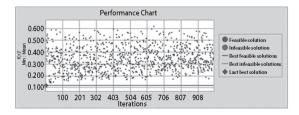
lution can be changed. If the opportunity cost is $500/day, the cost of *Solution 1* is $153,000 (i.e. 152,500 + 500*(68 – 67) = 153,000). Thus, it was determined that *Solution 1* is superior to *Solution 2*. If the decision-maker sets the opportunity cost at $4,500/day or more, depending on the project characteristics, however, the cost of *Solution 1* will exceed $157,000 (i.e. 152,500 + 4,500*(68 – 67) = 157,000). Thus, it was determined that *Solution 2* is superior to *Solution 1*.

Second, the efficiency of the proposed iMOO model can be validated using the total computational time (shown in Fig. 11). According to the iMOO model developed in this study, the time spent in determining the optimal solution set on a computer [2.8 GHz Intel^R Core^{TM} i5 processor with 6.00 GB (2.96 GB available) of RAM] was only 11 seconds. As shown in Figure 11, the results of the 1,000 simulation runs showed no more improvement in the fitness function. It was determined that efficiency in terms of computational time was achieved.

In conclusion, the proposed iMOO model showed improved effectiveness and efficiency, compared to the results of previous studies (Liu *et al.* 1995; Zheng *et al.* 2005b), indicating that the robustness and reliability of the proposed iMOO model was enhanced.

Conclusions

This study was conducted to develop an iMOO model that can provide the optimal solution set based on the concept of the *Pareto front*, which involves the following six-phase process: (1) problem statement; (2) definition of the optimization objectives; (3) establishment of the data structure; (4) standardization of the optimization objectives; (5) definition of the fitness function; and (6) introduction of the genetic algorithm.

A simple case was verified using the iMOO model that was proposed in this study. The iMOO model is more intuitive, simplified, applicable and flexible one compared to the previous studies. By using simplified process and equations of the iMOO model, the optimal solution can be also found in a real project that has considerably more activities. The results can be summarized as follows.

First, to verify the iMOO model developed in this study, a simple case was used. The case had 4,860 possible combinations (3*5*3*3*4*3*3; refer to the fourth column of "Construction methods" in Table 1). The optimal solution set could be derived within 11 seconds only. It was shown that an optimized approach to develop the iMOO model would be more effective rather than heuristic method and mathematical programming. Since a real project is considerably more complicated, it takes a considerable time to review all possible combinations using the heuristic method, and the result cannot ensure the reliability of the optimal solution. Furthermore, mathematical programming would take too much effort and time to define an extremely complex relationship.

Fig. 11. Optimization summary

Second, in this study, a GA was used to solve a multi-objective optimization problem. Based on the concept of the *Pareto front*, an attempt was made to derive the optimal solution. This study also simplified the complicated process and equation proposed in previous studies and offered a solution that allows the implementation of the meaningful weight value based on the project characteristics and the owner's requirements. However, although there are various methods of calculating the weight value, that was not considered as a main issue in this study. At the same time, compared to the results of previous studies, the proposed iMOO model showed improved effectiveness and efficiency, indicating that the robustness and reliability of the iMOO model was enhanced.

Third, the proposed iMOO model allowed more optimal solutions from the optimal solution set based on the decision criteria of the decision-maker. By analyzing the trade-off relationship between the time and cost (i.e. the indirect cost or the opportunity cost), the final optimal solution can be selected. Furthermore, the iMOO model showed improved flexibility or applicability and usability against the problems on more than two optimization objectives through the multi-dimensional concept (refer to Fig. 3), according to the problem statement.

The iMOO model developed in this study can be used for several objectives in future research: (1) to ensure the usability of the iMOO model, the research team will apply it to a real project that has considerably more activities; (2) to ensure the extendibility of the iMOO model, the research team will apply it to solve the problems on more than two optimization objectives through the multi-dimensional concept; and (3) to ensure the applicability or flexibility of the iMOO model, the research team will apply it to the other research subject such as the optimal selection of new renewable energy system. The results of this study can be used: (1) to assess more than two optimization objectives (i.e. the initial investment cost, operation and maintenance cost, and CO_2 emission trading cost); (2) to take advantage of the weights as the real meanings; (3) to evaluate the four types of fitness functions; and (4) to expand into other areas such as the indoor air quality, materials, and energy use.

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