S7-3

OPTIMIZING QUALITY AND COST OF METAL CURTAIN WALL USING MULTI-OBJECTIVE GENETIC ALGORITHM AND QUALITY FUNCTION DEPLOYMENT

Tae-Kyung Lim[1], Chang-Baek Son[2], Jae-Jin Son[3] and Dong-Eun Lee[3]

[1] Graduate student, Kyungpook National University, School of Architecture & Civil Engineering
Daegu, KOREA

[2] Associate professor, Semyung University, Department of Architectural Engineering
Chungbuk, KOREA

[3] Research professor, Kyungwoon University, Department of Architectural Engineering
Gumi, KOREA

[3] (Corresponding) Assistant professor, Kyungpook National University, School of Architecture & Civil Engineering, Daegu, KOREA.
Correspond to dolee@knu.ac.kr

ABSTRACT: This paper presents a tool called Quality-Cost optimization system (QCOS), which integrates Multi-Objective Genetic Algorithm (MOGA) and Quality Function Deployment (QFD), for tradeoff between quality and cost of the unitized metal curtain-wall unit. A construction owner as the external customer pursues to maximize the quality of the curtain-wall unit. However, the contractor as the internal customer pursues to minimize the cost involved in designing, manufacturing and installing the curtain-wall unit. It is crucial for project manager to find the tradeoff point which satisfies the conflicting interests pursued by the both parties. The system would be beneficial to establish a quality plan satisfying the both parties. Survey questionnaires were administered to the construction owner who has an experience of curtain-wall project, the architects who are the independent assessor, and the contractors who were involved in curtain-wall design and installation. The Customer Requirements (CRs) and their importance weights, the relationship between CRs and Technical Attributes (TAs) consisting of a curtain-wall unit, and the cost ratios of each components consisting curtain-wall unit are obtained from the three groups mentioned previously. The data obtained from the surveys were used as the QFD input to compute the Owner Satisfaction (OS) and Contractor Satisfaction (CS). MOGA is applied to optimize resource allocation under limited budget when multi-objectives, OS and CS, are pursued at the same time. The deterministic multi-objective optimization method using MOGA and QFD is extended to stochastic model to better deal with the uncertainties of QFD input and the variability of QFD output. A case study demonstrates the system and verifies the system conformance.

Keywords: Building Envelop, Curtain-wall, Quality Function Deployment (QFD), Cost, Quality, Optimization, Multi-objective Genetic Algorith

1. INTRODUCTION

1.1 Background

Curtain wall is an exterior cladding system which establishes a building envelope and determines the aesthetic appearance of it [1]. Particularly, curtain wall is a critical operation in tall building construction because it accounts for 10 to 15% of total construction cost. Therefore, optimizing the quality and cost of design alternatives provides an opportunity to save cost effectively. However, selecting the optimum design alternative of curtain wall unit is not only involved in multi performance variables but also is a decision making attributed by multi project participants who have conflicting interests. Generally, construction owner and contractor have conflicting interests relative to quality and cost in the delivery of a project. Construction owner aims to maximize the quality of the constructed facility by making the contractor to input as much cost as possible into the actual production within (or over) the contract amount. On the contrary, the contractor aims to maximize her satisfaction to the unit cost by minimizing the production cost of curtain wall unit, that is, by maximizing their profit. In this way, the interests of owner and contractor relative to the expense input to production are always conflicting. In addition, the budget of curtain wall unit is actually constrained by the unit price bounded by contract estimate which is part of a contract document. The cost ratio combination assigning the budget to components consisting of a curtain wall unit (hereafter, components), leads to a unique design alternative. There are many design alternatives because many sets of cost combination exist. Therefore, the optimum design alternative is the one having a cost combination maximizing the construction owner's satisfaction (OS) and contractor's satisfaction (CS) all at once out of these many design alternatives.

An automated system, which identifies the cost ratio combination achieving the optimum trade-off between quality and cost of components, supports a decision making involved with multi-attributes and multi-participants. This combinational optimization tool trade-off the conflicting interests contributed by project participants and to consider the constraints attributed by contract.

Existing QFD method mainly is used to quantify the customer satisfaction by identifying customer requirements (CRs), technical attributes (TAs) and their relationship without considering financial condition. Thus, King et al. [2] addresses the necessity to incorporate a cost analysis into QFD process. The goal of a cost integrated QFD is to maximize customer satisfaction subject to cost and other organizational constraints [3]. In addition, Bode and Fung [4] insists that existing QFD applications are technically one-sided, because they only aim to maximize quality performance and neglect that an enterprise is usually an economic entity which is demanded t o tradeoff between quality and cost. In this way, existing QFD researches do not consider that the actual costs which can be allocated to each TAs are constrained [3,4,5].

1.2 Objectives

This study aims to develop an automated system that optimizes the OS and CS relative to the quality and cost of a curtain wall design. The research activities are consisted of two folds. First, the House of Quality (HoQ) computing OS and CS was modeled. Second, an automated system implementing the HoQ was developed. The system integrates conventional QFD and multi-objective genetic algorithm (MOGA). It provides an optimization tool identifying the optimal trade-off point yielding to maximum OS and CS. The Quality-Cost Optimization System (QCOS) is designed to complement the deficiencies of existing QFD system, which are as discussed in previous sections. QCOS automatically quantifies the OS and CS all at once and identifies the optimal trade-off between them, provides what is the optimal combination of cost allocation to the curtain wall components within the allowable budget. In addition, it provides a decision-maker with the extent of the variance of the project participants' satisfaction changes when the allowable budget is calibrated.

2. Literature Survey

2.1 Current state of QFD researches Considering Cost Dimension

Most of the existing QFD models do not take the resource constrained situation into account in product designing [6]. After Wasserman [3] proposes a QFD model which computes the priorities of Technical Attributes (TAs) using the equation in the following parenthesis (*Priorities of TAs = Technical Importance* (w_k)*/Cost Index* (c_k)) and allocates the limited budget to respective TAs in proportion to the priorities, Bode and Fung [4] advanced the Wasserman's model. Bode and Fung's model [4] allocates the primary costs, which should be input to produce the components of a product under designing and are mutually exclusive without considering the correlation between TAs, to the TAs in proportion to the priorities of TAs, then, converts the primary costs into actual costs by considering the correlation between TAs. These and other researchers [3,4] integrate an approach, which allocates a budget in proportion to the priorities of TAs, into the traditional QFD. However, this approach is limited in that some of the TAs having lower priority is not committed with enough cost allocation to attain design target due to the resource constraints. To complement the discrepancies discussed previously, Fung et al. [6] suggests a model that integrates a resource optimization method into existing QFD using Genetic Algorithm (GA). It searches the combination of cost allocation ratios maximizing the customer satisfaction within the limited budget, introduces the concepts of planned attainment (y_i) and actual attainment (x_i) of TAs into QFD to quantify the level of customer satisfaction, introduces the concept of target attainment (i.e., satisfaction threshold, $\theta_0 = 0.45$) to assure that the actual attainments of all TAs always achieve more than a specific cut-line, and searches the combination of planned attainments maximizing the customer satisfaction defined in the following parenthesis ($OS = \sum w^*_i y_i$) while all actual attainments are over the target attainment.

2.2 Current state of QFD researches Considering Optimization

Existing QFD researches are applied to prioritize the TAs of a product which maximizes customer satisfaction. However, a product design process is involved in multi-participants (e.g., construction owners and contractors) having complicated objectives (e.g., minimizing budget, maximizing product quality, and minimizing technical difficulty, etc) in practices. Therefore, several studies accept that it is desirable to integrate a method which trade-off among these objectives into existing QFD.

Wasserman [3] introduced linear programming into QFD to find the optimal budget allocation which achieves maximum customer satisfaction. Park and Kim [7] employed integer programming to compute the priority of TAs, which maximize the customer satisfaction, incorporating the limited operational resources. In addition, the improvement of customer satisfaction in proportion to the budget increment was analyzed using sensitivity analysis. Tang et al. [5] and Fung et al. [6] integrated Genetic Algorithm into QFD to identify optimal budget allocation which maximize customer satisfaction and enterprise satisfaction all at once. Karsak et al. [8] proposed the fuzzy multiple objectives decision making model that enables to prioritize TAs which maximizes both attainment and extendibility of TAs and minimizes technical difficulty while considering budget constraint. Through the discussed researches, it is found that the previous QFD models are not arrived at a maturity in that an automated system which integrates multi-objective optimization algorithm into QFD is not available.

3. Methodology

Detailed explanations of QFD method into which financial dimension is integrated are provided in other publications (e.g., [3,5,6]). This section is consisted of two folds. First, the detailed steps by which the HoQ computing the OS and CS relative to curtain wall design is modeled are presented. Second, the steps by which MOGA are applied to find an optimal trade-off between the OS and CS with the HoQ.

3.1 HoQ integrating Cost Dimension

This section introduces the detail steps by which cost dimension is integrated into the HoQ for selecting optimal curtain wall design alternative. The HoQ integrating cost dimension has five different feature comparative to the existing HoQ [3,4,6]. First, the HoQ defines the construction owner requirements (ORs) and TAs (i.e., curtain wall components) provided by the contractor. Second, it facilitates collecting and processing QFD input data. Third, it encourages using the positive or negative correlations among the TAs defined in the roof of the HoQ. Fourth, it computes the OS and CS all at once. Fifth, it presents both the information relative to achievement (i.e., the planned achievement and the actual achievement degrees) and the information relative to cost (i.e., the primary cost, the actual cost, and the planned cost) in the HoQ. Figure 1 shows the HoQ for selecting optimal curtain wall design alternative. The definition of QFD input variables and the data processing to obtain QFD output data of the HoQ are presented in detail as below;

● Column ①: The Owner Requirements (ORs) – The information in column ① is the construction owner requirements involved in a metal curtain wall for tall building. The 10 dimensions, which are 'Thermal Performance', 'Moisture Protection', 'Visual', 'Sound', 'Safety', 'Maintenance Access', 'health and Indoor Air Quality', 'Durability and Service Life Expectancy', 'Maintainability and Repair-ability' , and 'Sustain-ability' (adapted from WBDG [9])

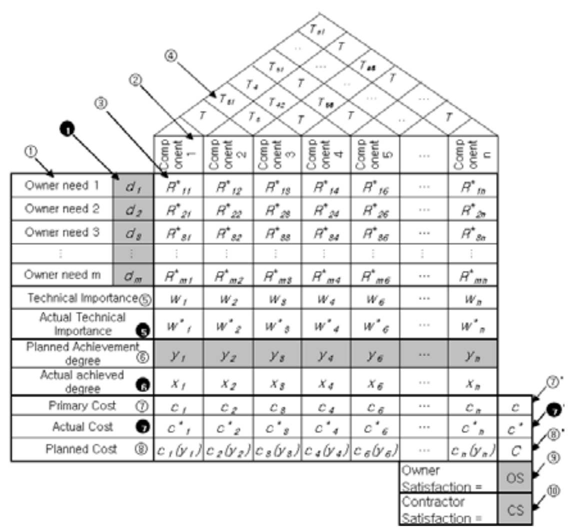

Figure 1. The HoQ integrating cost dimension

● Column ❶: includes the relative importance weights of the 10 ORs (d_i). They were reported by construction owners in a questionnaire survey on a 9-point Likert scale where 1 is 'not important', and 9 'extremely important'. Then, the weights were normalized using the mean value of the survey data.

● Row ②: includes 12 TAs (i.e., components of a curtain wall unit). They represent the engineering components with which a curtain wall unit is expected to meet the ORs. The 12 components include 'Vision Glass', 'Spandrel Glass', 'Aluminum Frames', 'Back pan', 'Gaskets', 'Seals', 'Glazing Setting Blocks', 'Splice Sleeve', 'Exterior Cover', 'Fire Safe Insulation', 'Index Clip', and 'Anchor Accessory' (adapted from WBDG [9]). They were categorized as cost account to assign the budget committed.

● Matrix ③: represents the strength of the relationship (R^*_{ij}) between the ORs (column ①) and the TAs (row ②). This information was obtained from architects who have an extensive experience of a curtain wall project by means of a survey instrument on a 9-point Likert scale where 1 is 'no relation', and 9 'perfect (one-on-one) relation'. Then, the weights were normalized using the mean value of the survey data.

● Matrix ④: represents the correlation (T_{ij}) between the TAs (row ②). This information was obtained from contractor, who has an extensive experience in dealing with manufacturing, delivering and installing the curtain wall, by means of a survey instrument on a 5-point Likert scale.

● Row ⑤: represents the normalized importance weight (w_i) of TAs. It represents the priority of each curtain wall component. They are calculated by Eq.1.

$$w_j = \sum_{i=1}^{m} d_i \, R^*_{ij}, \, j = 1,2,...,n. \tag{1}$$

Where, R^*_{ij} is obtained by normalizing R_{ij} matrix.

● Row ❺: represents the actual importance (w^*_i) of the TAs. They are calculated according to Eq.2.

$$w^*_j = \sum_{k=1}^{m} w_j T_{kj}, \, j = 1,2,...,n. \tag{2}$$

● Row ⑥: represents the planned achievement degree (y_i) of the TAs. They are the design targets set to be fulfilled under the assumption that there are no dependency among TAs. The sets of planned achievement degree are the decision variables of the two objective functions, i.e., the functions of the OS and CS.

● Row ❻: The actual achievement degrees (x_i) are calculated by using the planned achievement degree (y_i) of TAs and the correlation between the TAs (T_{ij}) according to Eq. 3.

$$x_j = y_j + \sum_{k \neq j} T_{kj} y_k = \sum_{k=1}^{n} T_{kj} y_k \tag{3}$$

● Row ⑦: represents the primary cost (c_i) of TAs. They are the cost required to deliver each of the TAs completely under the assumption that there are no dependencies among curtain wall components. The cost information was collected by survey questionnaires administered to the curtain wall design and estimation experts.

● Row ⑦*: represents the summation (c) of the primary costs of TAs.

● Row ❼: represents the actual costs (c^*_i) of TAs. These costs are calculated using the information, i.e., the achievement degrees of neighbor components involved in the specific component and the technical dependency, according to Eq.4.

$$. c^*_j = c_j (1 - \sum_{k \neq j} T_{kj} y_k) \tag{4}$$

● Row ❼* : represents the summation (c^*) of actual costs of TAs (c^*_i). It is the total adjusted primary costs which are obtained by adjusting the primary cost assigned to a specific component according to the technical dependency among the curtain wall components.

● Row ⑧: represents the planned costs ($C_j(x_j)$) calculated using the actual costs (c^*_i) and the actual achievement degrees (x_i) according to Eq. 5. This costs are the cost demanded to produce a specific component in practice.

$$C_j(x_j) = c^*_j x_j = c_j (1 - \sum_{k \neq j} T_{kj} y_k)(y_j + T_{kj} y_k) \tag{5}$$

● Cell ⑧* : represents the sum of planned costs of all components which is the budget(B) demanded to produce a curtain wall unit.

● Cell ⑨: represents the owner satisfaction (OS). It is obtained from the objective function formulated using the normalized importance weight of TAs (w_i) and the actual achievement degree (x_i) according to Eq. 6.

$$OS = \sum_{j=1}^{n} w_j x_j = \sum_{j=1}^{n} w^*_j y_j \tag{6}$$

● Cell ⑩: represents the contractor satisfaction (CS) computed according to Eq.7. It is obtained from the objective function which depends on the unit cost of a curtain wall unit shown in Cell ⑧*.

$$CS = \begin{cases} 1 & C \leq C_0 \\ (1-\alpha_0)\left(\dfrac{B-C}{B-C_0}\right)^r + \alpha_0 & C_0 < C \leq B \\ 0 & C > B \end{cases} \tag{7}$$

Where, C : total planned cost, C_0 : minimum planned cost , B : allowable budget, α_0 : satisfaction with total budget committed, r : coefficient of curve shape.

3.2 Multi-objective Genetic Algorithm

MOGA is integrated into the QFD model described previously to search an optimal solution which tradeoffs between quality and cost. Given several conflicting objective functions, MOGA finds Pareto optimal solution which maximally satisfies all at once. Pareto optimal solution is the most dominant and best solution out of the non-dominant solutions produced by the conflicting objective functions [10].

The HoQ automatically calculates QFD output data such as actual achievement degree, planned cost, OS and CS, when planned achievement degrees (y_j) of TAs are set as a design target. However, the HoQ does not have optimization capability to trade-offs the conflicting interests of the two participants, the HoQ computes the OS and CS. Therefore, MOGA is integrated into the HoQ to find the optimal solution by trading-off the conflicting interests.

3.2.1 Defining the Objective Functions

Selecting the optimal curtain wall design alternative is involved in maximizing the two objective functions such as OS and CS (refer to Eq.6 and 7) all at once according to Eq. 8.

$$\text{Max}\{\text{OS, CS}\} \tag{8}$$

$$s.t. \quad \alpha_0 \le OS \le 1, \qquad \alpha_0 \le CS \le 1$$

3.2.2 Defining the Constrains

The QCOS produces the data of QFD output variables such as such as actual achievement degrees and the planned costs in the middle of the QFD computation. These QFD output variables (Hereafter, QFD In-process variable) are returned to the QFD to calculate other QFD output variables such as OS, CS, and the total planned cost (B). In selecting an optimal design alternative (i.e., optimal solution), various constrains, which are project specific and bounded by contract, exist similar to the follows; First, the actual achievement degrees (x_j) of TAs should be achieved over a certain levels (e.g., [5]). Second, the budget (B) assigned to a curtain wall unit is bounded to a certain value (e.g., 500$/unit). The performance to search optimum solution is affected by setting the range of output data of the QFD In-process variables.

3.2.3 MOGA Implementation

Applying MOGA to selecting optimal curtain wall design alternative was conducted in four steps. First, the QFD input data were imported and the GA options were initialized. Second, the fitness of OS and CS was calculated using the sets of the planned achievement degrees, that is, decision variables. Third, the fittest individual was identified over successive generations. Fourth, QFD output data were analyzed. The method described below was coded into an automated system by using MATLAB programming. The algorithm of QCOS is presented in Figure 2 with detailed descriptions as follows.

3.3.1. Mode I: Importing QFD input data and initializing GA options

● Step ①: GA repeats steps ② to ⑭ incrementing the mutation rate by a specific interval (e.g., 0.1) with a crossover rate. The best set of crossover and mutation set identified from the experiments was initialized as options to Step ③.

● Step ②: QFD input data are imported from a database which maintains data set collected from expert groups using survey questionnaire. QFD input data are as follows; construction owners' requirements and their relative importance weights, the relationships between construction owners' requirements and curtain wall components; the correlations between the components, and the set of primary costs(or unit costs) of the component.

● Step ③: The options needed to initialize the GA experiments were specified. The GA options include: (1) the length of chromosome (i.e., the number of decision variables); (2) number of generations; (3) population size; (4) crossover rate; (5) mutation rate; and (6) stopping rules. The number of decision variables is defined as 12, because the number of planned achievement degrees is corresponded 12 TAs. Since the GA options effect on the reliability of the GA output data, the number of generations and population size are identified based on the length of chromosome to assure the quality of the solution [10]. In addition, GA stopping criteria were set using the maximum number of generations (e.g., 120) and the cumulative change in the fitness function value (e.g., 1.0e-3) over stall generations.

● Step ④: The random initial population was generated in the first generation. These solutions of initial population represent the set of planned achievement degrees relative to the 12 curtain wall components.

3.3.2. Mode II: Fitness Evaluation

● Step ⑤: A possible solution (S_n) is selected from the initial population generated in step ④.

● Step ⑥: The OS and CS for a possible solution (S_n) in the generation are calculated using the two objective functions shown in Eq. 6 and 7. QCOS utilizes a facility function called "GAMULTIOBJ" available in MATLAB to search an optimal set of planned achievement degrees.

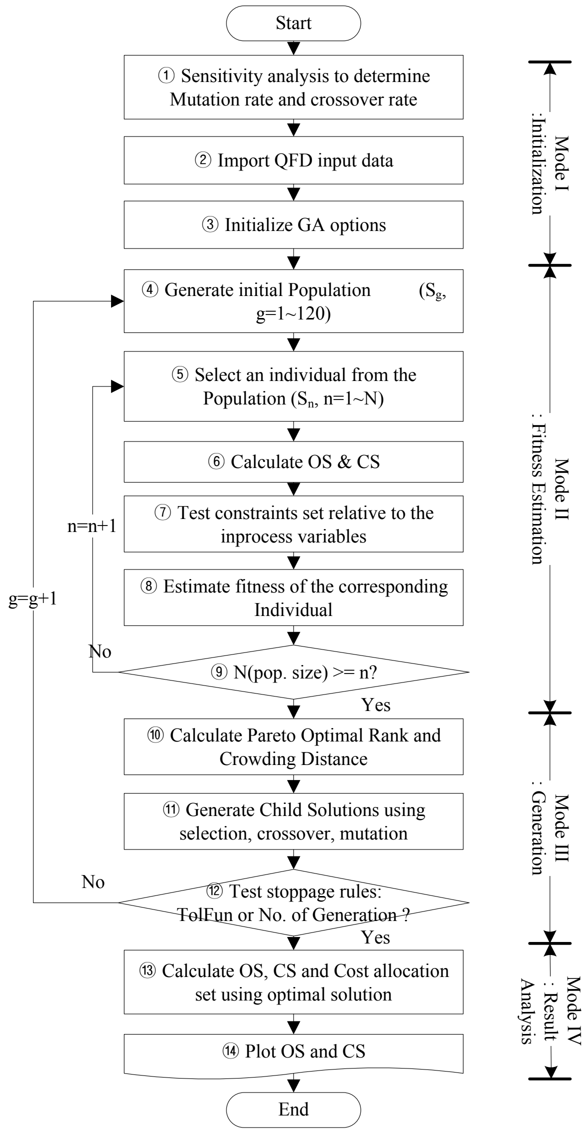

Figure 2. Curtain wall Quality-Cost optimization Algorithm

● Step ⑦: The fitness value of an individual is recalculated only if QFD In-process variable is not free from the constrain involved in, first, the actual attainment (x_i) obtained from QFD computation using the possible solution selected in step ⑤, and second, the planned cost (C_j) of TAs as shown in Fig. 1.

● Step ⑧: This fitness determines the likelihood of survival and reproduction of each solution in successive generations.

● Step ⑨: The algorithm checks if the current number of individual is greater than the number of population size set at the outset in step ③. This step repeats from ⑤ to ⑧ as many as population size defined by based on string size [10].

3.3.3. Mode III: Population Generation

● Step ⑩: Pareto optimal rank and crowding distance of each solution (s_n) in the parent population (P_g) are calculated [12] Using the Pareto rank and crowding distance, the algorithm always selects the fittest solutions from parent population (S_g) and reused them to generate child population (S_{g+1}).

● Step ⑪: Genetic Algorithm creates child population (S_{g+1}) using dominant solutions obtained from parent population (S_g). It applies selection, crossover, and mutation operators to the dominant solutions [13].

● Step ⑫: The system checks whether the GA experiment passes the maturity test. It checks if the stopping rules set at step ③ are met. If any of the stopping rules is met, the algorithm proceeds to step ⑬, otherwise return to step ④ and continue the algorithm.

3.3.5. Mode IV: Result Analysis

● Step ⑬: Using the best set of crossover and mutation set identified from the sensitivity analysis in Step ①, the optimum solutions converged, i.e., the optimal sets of planned achievement degrees, are found. In addition, the OS, CS, the set of planned cost and total cost are calculated and saved in the computer's memories.

● Step ⑭: Then, the GA output obtained from this experiment is accepted as the optimal global solution. The GA output data calculated in step ⑬ are plotted and the optimal quality-cost trade-off point is identified.

4. Case Study

This case study demonstrates how the system developed by the author tradeoffs between the construction owner satisfaction and the contractor satisfaction all at once and selects an optimal design alternative which allocates allowable budget into the curtain wall components in a way to optimize the quality and cost of the design alternative.

4.1 HoQ input data

QFD input data such as the relative importance weights of construction owner requirements, the relationships between owner requirements(ORs) and curtain wall components(i.e., TAs), the correlations between curtain wall components, and the primary costs of curtain wall components were collected by means of survey questionnaires administered to construction owners, architects, curtain wall design experts, and contractor, respectively.

For example, let us now assume that several constraints are given as follows; The actual achievement degree (x_j) of a component should exceed 45%; the budget of a curtain wall unit is limited to $500/unit; the minimum contractor satisfaction (α_0) when budget is used up is 45%; the minimum budget of a curtain wall unit is $300; and the coefficient of the contractor satisfaction function (r) is 1.

(1) The relative weights among the ORs (d_i) =
[0.17 0.16 0.13 0.13 0.14 0.08 0.08 0.05 0.05 0.02]

(2) The relationships between ORs and TAs (R_{ij}) =

$$\begin{bmatrix} 0.09 & 0.09 & 0.02 & 0.09 & 0.09 & 0.12 & 0.02 & 0.09 & 0.12 & 0.09 & 0.07 & 0.09 \\ 0.07 & 0.02 & 0.02 & 0.22 & 0.22 & 0.00 & 0.07 & 0.12 & 0.07 & 0.00 & 0.07 & 0.10 \\ 0.12 & 0.07 & 0.07 & 0.07 & 0.12 & 0.07 & 0.10 & 0.10 & 0.10 & 0.12 & 0.02 & 0.02 \\ 0.08 & 0.14 & 0.06 & 0.06 & 0.14 & 0.08 & 0.11 & 0.03 & 0.08 & 0.00 & 0.11 & 0.11 \\ 0.15 & 0.12 & 0.03 & 0.03 & 0.03 & 0.03 & 0.12 & 0.15 & 0.09 & 0.09 & 0.15 & 0.03 \\ 0.03 & 0.14 & 0.03 & 0.03 & 0.03 & 0.08 & 0.11 & 0.08 & 0.11 & 0.11 & 0.11 & 0.14 \\ 0.14 & 0.08 & 0.03 & 0.08 & 0.11 & 0.14 & 0.06 & 0.08 & 0.08 & 0.06 & 0.03 & 0.11 \\ 0.08 & 0.08 & 0.08 & 0.13 & 0.03 & 0.11 & 0.11 & 0.13 & 0.11 & 0.03 & 0.05 & 0.08 \\ 0.11 & 0.11 & 0.04 & 0.11 & 0.04 & 0.11 & 0.15 & 0.04 & 0.00 & 0.00 & 0.19 & 0.11 \\ 0.10 & 0.17 & 0.17 & 0.10 & 0.03 & 0.10 & 0.10 & 0.10 & 0.10 & 0.00 & 0.00 & 0.03 \end{bmatrix}$$

(3) The correlations among the TAs (T_{ij}) =

$$\begin{bmatrix} 1.00 & 0.05 & (0.17) & 0.17 & 0.17 & 0.00 & 0.20 & 0.00 & 0.00 & 0.20 & 0.20 & 0.00 \\ 0.05 & 1.00 & 0.00 & 0.00 & 0.00 & 0.10 & 0.00 & 0.03 & 0.00 & 0.10 & 0.00 & 0.03 \\ (0.17) & 0.00 & 1.00 & 0.17 & (0.05) & 0.10 & 0.00 & 0.03 & (0.02) & 0.03 & 0.10 & 0.00 \\ 0.17 & 0.00 & 0.17 & 1.00 & 0.02 & 0.02 & (0.03) & 0.01 & 0.02 & 0.01 & 0.02 & 0.00 \\ 0.17 & 0.00 & (0.05) & 0.02 & 1.00 & 0.10 & 0.03 & 0.03 & 0.00 & 0.10 & (0.05) & 0.05 \\ 0.00 & 0.10 & 0.10 & 0.02 & 0.10 & 1.00 & 0.01 & 0.02 & 0.03 & 0.01 & 0.01 & 0.03 \\ 0.20 & 0.00 & 0.00 & (0.03) & 0.03 & 0.01 & 1.00 & 0.17 & 0.17 & 0.00 & 0.02 & 0.02 \\ 0.00 & 0.03 & 0.03 & 0.01 & 0.03 & 0.02 & 0.17 & 1.00 & 0.02 & 0.01 & (0.03) & 0.03 \\ 0.00 & 0.00 & (0.02) & 0.02 & 0.00 & 0.03 & 0.17 & 0.02 & 1.00 & 0.01 & 0.02 & 0.03 \\ 0.20 & 0.10 & 0.03 & 0.01 & 0.10 & 0.01 & 0.00 & 0.01 & 0.01 & 1.00 & 0.01 & 0.01 \\ 0.20 & 0.00 & 0.10 & 0.02 & (0.05) & 0.01 & 0.02 & (0.03) & 0.02 & 0.01 & 1.00 & 0.01 \\ 0.00 & 0.03 & 0.00 & 0.00 & 0.05 & 0.03 & 0.02 & 0.03 & 0.03 & 0.01 & 0.01 & 1.00 \end{bmatrix}$$

(4) The primary costs of the TAs (C_j) =
[100 40 50 30 60 90 80 30 50 20 30 70]

When there are 12 components of a curtain wall unit and 100 possible values for gene, 100 planned achievement degrees for a component assuming GA computes to two digits after decimal point, the number of planned achievement degrees combination, that is, the possible numbers of planned costs of curtain wall components, is 100^{12} sets. Therefore, a mathematical method to compute all the cases needs is very time consuming. The multi-objective genetic algorithm model was used to search this large space of possible solutions. GA significantly reduces searching time by excluding dominated solutions in the following generations, using the Pareto optimal rank and crowding distance.

4.2 GA experiment with the optimal set of mutation and crossover rates

Table 1 presents the optimal options computed by sensitivity analysis. The GA output data obtained from GA experiment with the optimal options are as follows:

Table 1. GA Parameters set

Parameters	Values
PopulationSize:	72
CrossoverFraction:	0.70
ParetoFraction:	0.50
MutationFraction:	0.20

Fig.3 is the graph plotting the OS and CS in proportion to the cost of a curtain wall unit when the 25 Pareto front solutions were input to QFD input variables. The 25 Pareto optimal solutions were plotted using a two dimensional surface (i.e., satisfaction index and allowable budget) as shown in Fig. 3. The tradeoff points between the OS and CS are located in between 82% and 84%. The corresponding allowable budgets are ranged between \$360 and \$368, respectively. Table 2 provides the 5 Pareto optima out of the 25 optimal solutions for the planned achievement degrees as a curtain wall design alternatives.

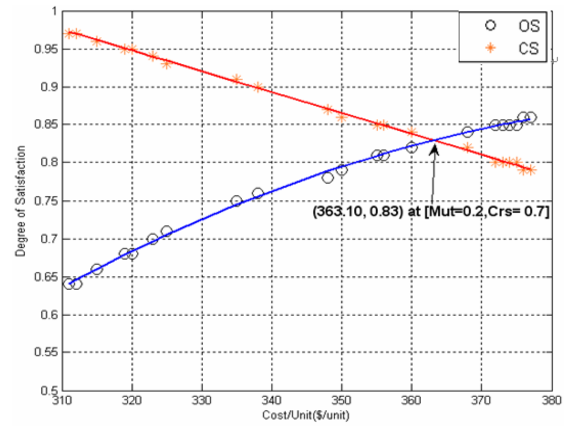

Figure 3. Trade-off between OS and CS

Table 2. Sample Pareto optimal solutions

Pareto Optimal Solutions	OS	CS	Unit Cost
0.35, 0.67, 0.42, 0.71, 0.60, 0.27, 0.51, 0.81, 0.41, 0.75, 0.76, 0.40	0.79	0.86	350
0.38, 0.49, 0.41, 0.65, 0.59, 0.28, 0.58, 0.79, 0.66, 0.76, 0.81, 0.36	0.81	0.85	355
0.38, 0.48, 0.42, 0.75, 0.63, 0.29, 0.58, 0.77, 0.62, 0.76, 0.83, 0.39	0.82	0.84	360
0.39, 0.72, 0.41, 0.67, 0.60, 0.28, 0.57, 0.79, 0.64, 0.74, 0.81, 0.44	0.84	0.82	368
0.33, 0.72, 0.48, 0.74, 0.61, 0.29, 0.56, 0.80, 0.75, 0.75, 0.77, 0.40	0.85	0.80	372

5. Conclusion and Contribution

QCOS implements the HoQ which computes both construction owner satisfaction (OS) and contractor satisfaction (CS) in a curtain wall design phase. It uses Quality Function Deployment (QFD) which facilitates to quantify customer satisfaction. In addition, it computes the optimal tradeoffs both OS and CS all at once by integrating GA that is effective to solve multi-objective optimization problem into the system.

The system performs an automated sensitivity analysis in order to identify the optimal mutation and crossover rates by disclosing the behavior of GA output data by executing the analysis method. These optimal rates are reset to a new GA option. Then, the new Pareto optimal solutions were obtained from the new GA experiment. In this way, the system improves the reliability of GA experiment by complementing the variability of GA output due to random number generation and somewhat arbitrary option setting.

QCOS automatically searches the optimal set of planned achievement degrees (i.e., Pareto optimal solutions) of the curtain wall components which trade-off the OS and CS all at once, provides a decision maker with what is the optimal set of budget allocation to the components, and quantifies the extent of the variance of their satisfactions in proportion to adjusting the budget allocation. QCOS encourages expeditious decision making in design phase, because it has capability to compute the OS and CS all at once. It facilitates to find a tradeoff that lead to the efficient allocation of budget and the improvement of construction quality. The system itself is applicable to select optimal design alternatives of other construction operations. As verified by the case study, one may very rapidly execute the system by integrating the owner requirements and their weights of importance, the architects' expert opinions about the relationship between owner requirements and technical attributes as independent assessor, and the cost information of curtain wall unit obtained from contractors.

REFERENCES

[1] Chew, M.Y.L., Tan, S.S., and Kang, K.H., "A Technical Evaluation for Curtain-wall and Cladding Facades", *Structural Survey*, 22, 210-227, 2004.

[2] King, B., *Better Designs in half the Time: Implementing QFD in America,* Goal/QPC, Methuen, MA, 1987.

[3] Wasserman, G. S., "On how to prioritize design requirements during the QFD planning process", *American Institute of Industrial Engineer,* 25(3), 59-65, 1993.

[4] Bode, J., and Fung, R. Y. K., "Cost Engineering with Quality Function Deployment", *Computers ind. Engrg.,* 35, 587-590, 1998.

[5] Tang, J., Fung, R. Y. K., Xu, B., and Wang, D., "A new approach to quality function deployment planning with financial consideration", *Computers and Operations Research,* 29, 1447-1463, 2002.

[6] Fung, R. Y. K., Tang, J., Tu, Y., and Wang, D., "Product design resources optimization using a non-linear fuzzy quality function deployment model", *Int. J. of Production Research,* 40(3), 585-599, 2002.

[7] Park, T.H., and Kim, K.J., "Determination of an optimal set of design requirements using house of quality", *Journal of Operations Management,* 16, 569-581, 1998.

[8] E.E. Karsak, S. Sozer, and S. E. Alptekin, "Product planning in quality function deployment using a combined analytic network process and goal programming approach", *Computer and Industrial Engineering,* 44, 171-190, 2002.

[9] WBDG, "Building Envelope Design Guide-Curtain Walls",<http://www.wbdg.org/design/env_fenestration_cw.php>.

[10] EI-Rayes, K., and Kandil, A., "Time-Cost-Quality Trade-Off Analysis for Highway construction", *J. of Constr. Eng. Manage.,* 131(4), 477-486, 2005.

[12] Deb, K., *Multiobjective optimization using evolutionary algorithms*, Willey, new York, 2001.

[13] Goldberg, D. E., *Genetic Algorithms in Search, Optimization, and Machine Learning,* Addison Wesley, Reading, Massachusetts, 1989.

S7-4