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ORIGINAL ARTICLE

A decision support method for product conceptual design considering product lifecycle factors and resource constraints

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Abstract In general, it is difficult to select a satisfactory product concept because the information in the early stage of design process is subjective, qualitative, and even uncertain to design engineers. The correlations among engineering characteristics for a product concept also increase the complexity of conceptual design. Moreover, it becomes important to consider not only customer requirements but also product lifecycle requirements. In spite of these problems, the resources that can be allocated in the product development are limited so that a company should select the most satisfactory product concept within its available resources. Therefore, it is useful to develop a new method for efficiently supporting conceptual design under this complex design environment. To this end, this study proposes a decision support method with extended house of quality (HOQ). With the proposed method, the best product concept and the associated investment allocation can be decided concurrently under consideration of product lifecycle factors and resource constraints. As a mathematical model combined with the extended HOQ, a mixed integer nonlinear programming model is defined and three heuristic search algorithms are developed. To show the usefulness of the proposed algorithms, a case study and computational experiments are introduced.

Keywords Conceptual design · QFD · Product lifecycle requirement · Resource constraint · Heuristic search method

1 Introduction

In recent years, customer requirements on products become individualized and are dynamically changing since it is easy for customers to get information on products from various channels such as commercial advertisements and internet [1]. Customers use gathered information in evaluating, comparing, and selecting products for purchase. Therefore, it is important for companies to generate products which can maximize the satisfaction of customer requirements in a timely manner. However, the product development process consists of many activities and complex co-operations among several departments of a company. Moreover, due to various reasons such as increasing interests on environmental problems and government regulations for recycling and reusing, considering product lifecycle factors on product design as well as customer requirements is increasingly more important than in the past. To deal with these situations, a company should have the ability to develop a product that meets not only customer requirements but also product lifecycle requirements from the early steps of product development. As a result, product lifecycle constraints combined with customer requirements should be considered at the product conceptual design phase. However, it is not easy to select satisfactory product

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concepts because the information in the early stage of product development process is subjective, qualitative, and even uncertain to design engineers. Therefore, several methods to support effective product conceptual design have been proposed. One of them is the quality function deployment (QFD) method [2]. The QFD is a well-known method to combine customer requirements and product characteristics at the initial stage of product conceptual design. This method has received considerable attention in the previous literature as a useful method for conceptual design because of its several merits [3].

However, as of yet, only a few QFD works have considered product lifecycle requirements into the process of QFD in spite of its importance. Furthermore, the previous QFD works have the limitations from our viewpoint. Although some QFD studies have dealt with end-of-life issues, they are still primitive [4]. Moreover, despite the intuitive and straightforward characteristics of the original QFD, it is still limited in terms of considering quantitative correlations among engineering characteristics. Even though some engineering characteristics have a positive or negative effect on each other, the original QFD method oversimplifies this correlation in the prioritization of engineering characteristics.

In addition to this, the resource constraint is also another important factor of conceptual design because there is usually limited resource capacity in product conceptual design. Since it is inefficient to try all possible design alternatives with limited resources, a company should select and focus on the best product concept which will be invested. Hence, the resource constraints for the development of a product concept should be also dealt with during the product conceptual design phase. Although some previous works had an interest in these issues, there have been only a few works proposing decision support methods to resolve the conflicts or trade-offs occurred due to complex relations between engineering characteristics and product lifecycle requirements under resource constraints.

To cope with these limitations, this study deals with developing a new method for supporting product conceptual design considering product lifecycle requirements and resource constraints in addition to customer requirements. The problem dealt in this study is to select the engineering characteristics of a product concept and concurrently to decide the amount of investment allocations for implementing the engineering characteristics, in order to maximize the overall satisfaction of product concept design. It considers complex correlations among engineering characteristics. The problem also considers the constraints related to resource and product lifecycle requirements. In addition, it deals with various types of relations between the degree of design quality and investment cost for each engineering characteristic. To handle the above things, two combined techniques are used; an extended house of quality (HOQ) and a mixed integer nonlinear programming (MINLP) model. At the first step, the customer and product lifecycle requirements with resource constraints are integrated into an extended HOQ so as to consider both of them concurrently. Then, in the next step, the problem is formulated as a MINLP model derived from the result of the extended HOQ. The selection of engineering characteristics can be expressed as an integer programming model and the investment cost can be formulated as linear, nonlinear, and step functions depending on the types of engineering characteristics. To resolve the MINLP model, new heuristic search algorithms are proposed. To show the effectiveness of the proposed algorithms, a case study is introduced with computational experiments.

The rest of this study is organized as follows: Section 2 looks into relevant previous works and discusses their limitations. Section 3 addresses product lifecycle requirements and proposes a framework for an extended HOQ. In section 4, an MINLP model is defined, and heuristic search algorithms are proposed to resolve the problem in section 5. Section 6 introduces a case study to exemplify the proposed algorithms and computational experiments to show their usefulness. Finally, Section 7 presents the summary of this study with discussion and further research topics.

2 Previous works

The QFD method is a well-known tool for supporting product conceptual design, which was developed by a Japanese company [2]. The QFD is defined as "an overall concept that provides a means of translating customer requirements into the appropriate technical requirements for each stage of product development and production (i.e., marketing strategies, planning, product design and engineering, prototype evaluation, production process development, production, and sales)." [5]. Since the QFD is a well-known method, this study does not address the basics of QFD. For more details on QFD, see Akao [2], Martin et al. [6] and Chan and Wu [3].

There have been a large number of works applying QFD into various domains. Some works combined QFD and operations research methods considering resource constraints. For example, Wasserman [7] developed a mathematical model to prioritize design requirements in the QFD method considering cost constraints as resource constraints. The model was a 0–1 integer linear programming formulation of the knapsack problem. The model connected the required engineering characteristics (ECs), their cost, and their contribution to the final product quality in order to optimize the investment on a product. Park and Kim [8] improved this model by adding the relationships between

ECs. They proposed a mathematical model for selecting an optimal set of engineering characteristics. They calculated the priority of engineering characteristics using the analytic hierarchy process (AHP) method. They then proposed a quadratic integer programming model using the priority for selecting the optimal set of ECs. The model could reflect reality better and as a result allowed better utilization of resources. Bode and Fung [9] improved Wasserman's model differently by relaxing the 0–1 restriction on variable assignment; they got an integer-relaxed knapsack problem. According to this model, the relationship between investment and its resulting quality is linear between zero and the maximum quality, and any additional investment does not improve the quality of the EC. Moreover, Fung et al. [10] presented a new methodology for design resource optimization in QFD planning using nonlinear programming. They mathematically formulated the costs for achieving certain degrees of design targets with reference to the attributes relationship and correlation in an HOQ. The concepts of actual attainments and planned attainments for technical attributes, primary costs, actual costs, and planned costs for various technical attributes are adopted in the fuzzy cost function for solving resource allocation problems. Fung et al. [11] dealt with an operational QFD planning problem considering resource allocation. In the problem, the objective is to decide the best attainment of technical attributes in order to maximize overall customer satisfaction. The technical and resources constraints, including limited design budgets, were incorporated in the problem. They formulated the problem as a linear programming model and proposed a heuristics-combined simplex method. Recently, Reich and Levy [12] used the nonlinear programming technique for the resource allocation of product development under resource constraints. Their model used a realistic cost function and provided global optimality. In addition, Lai et al. [13] proposed an approach integrating dynamic programming into the product design process with QFD. In the approach, limited resources are allocated to technical attributes using dynamic programming. They assumed that the value of each technical attribute could be determined according to the resources allocated to them. Yung et al. [14] developed a function deployment method to find the compromise between customer requirements and design resources. An AHP was used to prioritize the requirements while a linear programming (LP) optimization method was used to determine the feasible solution of the design variables within limited resources.

On the other hand, there have been a few research works that tried to integrate lifecycle factors into the original QFD. For example, Störnebel and Tammler [15] incorporated environmental requirements into traditional QFD matrices, i.e. HOQ. Cristofari et al. [16] developed the Green QFD (GQFD), in which lifecycle assessment (LCA) and the QFD were combined to evaluate different product concepts. Moreover, Zhang et al. [4] proposed the GQFD-II to design and manufacture sustainable products that meet customer requirements, cost less and are environmentally sound. They integrated LCA, lifecycle cost, and QFD into one efficient tool, and deployed customers, environmental, and cost requirements throughout the product development process. Rahimi and Weidner [17] proposed a product design methodology for incorporating environmental considerations into the product design process, based on integration of the DfE “environmentally responsible product assessment matrix”| into HOQ. To this end, a new sequence of HOQ was devised based on multi-objective utility theory. Kuo [18] developed GQFD using six product lifecycle phases such as raw material, manufacturing, assembly and disassembly, transportation, consumer usage, and disposal. In addition, Cagno and Trucco [19] proposed the Integrated Green QFD focusing on integration of quality and environmental requirements, based on the simplified LCA model called “Matrix approach” and an Enhanced QFD. Kobayashi [20] presented a methodology and a software tool to establish an ecodesign concept of a product and its lifecycle by assigning appropriate lifecycle options to the components of the product. To this end, they used QFD and lifecycle assessment data. Recently, Lei et al. [21] described the extended quality function deployment in lifecycle design (LCD). They defined the structure of the extended QFD for LCD. They also proposed the method to choose and adjust HOQ depending on different target products.

In addition, there are some research works on considering lifecycle factors into deciding or generating product concepts. For example, Borg et al. [22] developed a knowledge-intensive computer aided design framework, called FORSEE, in order to efficiently foresee several lifecycle aspects during design concept synthesis. Yu et al. [23] also developed a multi-objective optimization method based on EcoDesign method [24, 25] in order to propose the lifecycle design for variety correspondent to customers' requirements. They considered the fuzzy set to quantify and transform incomplete and ambiguous information when determining the values of parameters for modeling product lifecycle. Moreover, Wanyama et al. [26] surveyed computer tools or methods for design for the environment, environmentally conscious design and manufacturing, and lifecycle engineering, which simulate flows in a lifecycle and optimize them. In addition, Wimmer et al. [25] presented guidelines for implementing EcoDesign in a company. They included LCA tools and methods as to how to integrate environmental considerations into product design and development.

As discussed above, although a lot of works have been done, there are still some limitations. Firstly, there is still a need for a systematic methodology that effectively considers overall aspects of product lifecycle during the early stage of product design. Although several heuristics and frameworks or methods including QFD have been proposed, most of them only focus on a specific aspect of lifecycle, e.g., environmental issue, disassembly, maintenance, and so on. In particular, in the research of QFD, there is the lack of decision support method that considers product lifecycle requirements as well as customer requirements, simultaneously dealing with resource allocation to maximize the product design satisfaction. The original QFD focuses on translating only customer voices into engineering characteristics of a product at the conceptual design phase. It does not consider other voices of lifecycle phases. Although a few publications have considered some lifecycle factors (e.g., environmental factors) into the original QFD, there are no clear methods to analyze the relations between lifecycle requirements and engineering characteristics. Previous guidelines are sometimes too abstract for design engineers to know what to do while designing their products [27]. To consider the environmental impacts of alternative engineering characteristics and indispensible engineering characteristics, QFD models should support for representing alternative and indispensable engineering characteristics. Secondly, in conceptual design, several design requirements should be considered together under resource constraints. Here, resources indicate the number of human resources or the number of software licenses available to implement engineering characteristics. In general, the more the investment for engineering characteristics increases, the more the satisfaction on product design increases. However, the investment budget of a company is limited. Moreover, resources that are able to simultaneously participate in the conceptual design activities are restricted. In addition, some product lifecycle requirements may restrict available kinds of engineering characteristics. Thus, these constraints should be considered to determine the appropriate investment cost for the implementation of engineering characteristics in the conceptual design. Although the QFD is a good tool to get prioritized engineering characteristics considering customer requirements in a simple manner, it is limited in prioritizing engineering characteristics considering the constraints mentioned above. Although some previous QFD works dealt with several resource allocation problems, they are limited in terms of considering product lifecycle requirements and efficiently distributing investment costs. Since product design engineers have to face the increasingly difficult task of assessing various interactions between customer requirements and lifecycle requirements under limited resources, an enhanced ability is required to resolve conflicts and trade-offs among numerous design requirements.

3 Product lifecycle requirements and extended HOQ

Since the 1960s, in response to the rising recognition of the potential dangers of products and production to mankind and the planet, the focus on the product lifecycle has steadily increased [28]. In general, a product lifecycle can be defined as a series of stages through which a product passes during its life time (see Fig. 1 of Kiritsis et al. [29]). CIMdata [30] defined the overall product lifecycle as composed of three major interacting lifecycles: product definition, production definition, and operational support. As of today, its scope becomes extended. As a result, the product lifecycle can be divided into three main phases: beginning of life (BOL), middle of life (MOL), and end of life (EOL) [31]. Each lifecycle phase includes several lifecycle activities (Fig. 1). The BOL phase consists of design and production activities. The MOL phase has distribution and maintenance activities while the EOL phase includes EOL product recovery and disposal activities. Depending on the lifecycle phase and its activities, there will be several lifecycle requirements. Alting and Legarth [32] introduced the design strategies for each

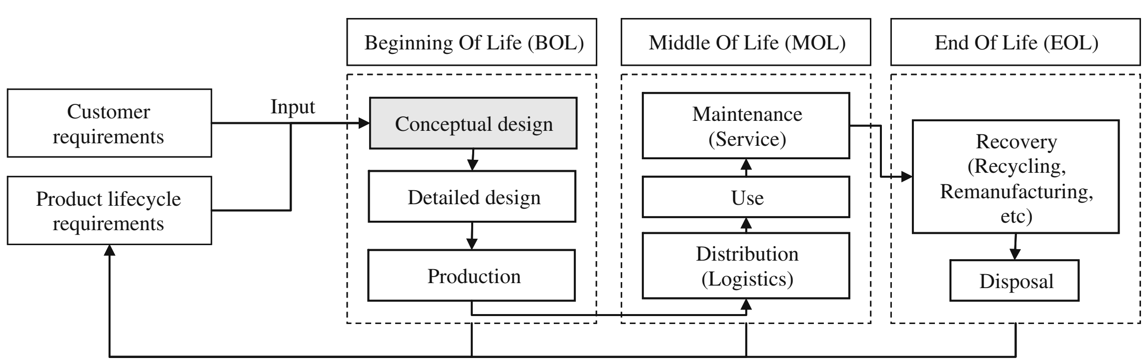


Fig. 1 Product lifecycle and conceptual design

Table 1 Examples of product lifecycle requirements

Product lifecycle phase		Examples of lifecycle requirements
BOL	Design	Design requirements related to the technical restrictions in production
	Production	Design requirements for ease of assembly
		Design requirements for ease of disassembly
		Design requirements for environmental consciousness
		Design requirements for reliability
		Design requirements for health and safety
MOL	Usage	Design requirements related to normal usage conditions
		Design requirements related to usage environment
	Maintenance	Design requirements related to warranty conditions
		Design requirements related to warranty period
		Design requirements for ease of maintenance
EOL	EOL product recovery	Design requirements related to product deregistration process
		Design requirements for product reuse
		Design requirements for product recycle
		Design requirements related to environmental restrictions
		Design requirements for ease of disassembly
		Design requirements related to take-back policy

lifecycle phase most often pursued in product design. Table 1 shows the examples of product lifecycle requirements for each lifecycle phase and activities [33–37]. Each product lifecycle phase can have several lifecycle options related to its activities from lifecycle requirements. For example, in the EOL phase, there can be several options related to the EOL product recovery activity such as recycling, remanufacturing, and so on [38]. Some products should be designed for reuse, while some products are designed for disposal without reuse. At the beginning of product conceptual design, design engineers should decide which lifecycle options will be applied into a product concept, and which lifecycle requirements related to these options should be considered in the product concept generation. Product lifecycle requirements are performed by engineering characteristics that have complex relationships. Depending on product lifecycle requirements, some engineering characteristics should be prioritized or unselected in the product concept. For example, if there is a lifecycle requirement related to specific materials that should be recycled by government regulations, some engineering characteristics related to material selection should be prioritized and others should be unselected. Hence, engineers should consider the relationship between product lifecycle requirements and engineering characteristics in the product conceptual design, in addition to the relations between customer requirements and engineering characteristics.

To consider the information on product lifecycle requirements as well as customer requirements together, this study uses an extended HOQ as shown in Fig. 2. It basically follows the ordinary HOQ that contains customer requirements, engineering characteristics, importance rate of customer requirements, relationships between customer requirements and engineering characteristics, and correlations among engineering characteristics. In addition to

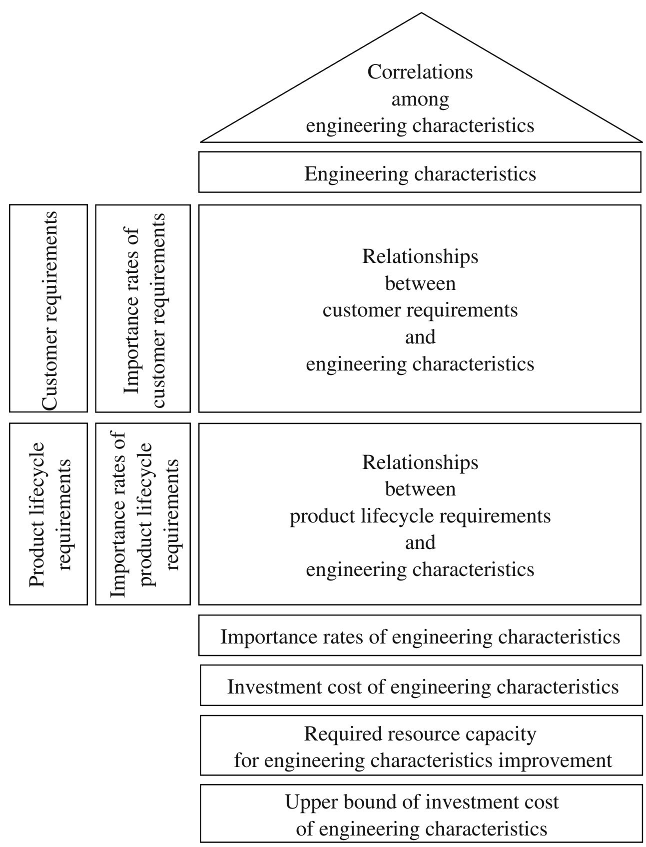


Fig. 2 Template of extended HOQ

them, it has the information on required investment cost, required resource capacity, and the upper bound of investment cost. The additional part of the extended HOQ is implemented to select engineering characteristics and allocate investment costs. The roof of the extended HOQ represents the correlations among engineering characteristics. In the product conceptual design, some correlations sometimes tend to be incompatible with each other in deciding the priorities of engineering characteristics. For example, a product conceptual designer considers the following three kinds of engineering characteristics for the design of a product part: weight, strength, and hardness. If the hardness of a part increases, its strength also increases as a positive effect. However, it may lead to an increase of its weight which may be a negative effect. This kind of feature in the conceptual design is represented in the roof of the extended HOQ. In this study, the correlations among engineering characteristics are considered to reevaluate the importance rates of engineering characteristics.

To build the extended HOQ, customer requirements can be collected from various channels. For example, direct methods that ask customers their requirements, such as relevant surveys, market research, and interviews, can be used although they cost and are time-consuming. In addition to the direct methods, throughout the indirect methods such as analyzing customer claims or product failure reports, customer requirements can be obtained. However, regardless of the type of the methods, the most important thing is how to truly extract the customer requirements from the various sources, which is beyond the scope of this study.

The product lifecycle requirements are decided by product lifecycle activities selected for the product lifecycle strategy. The product lifecycle strategy can be affected by the internal policy of a company, outer regulation such as government law, or customer requirements. Sometimes, technical and cost issues influence the decision about the product lifecycle strategy. After the decision on product lifecycle activities according to a product lifecycle strategy, several product lifecycle options which are related to the product lifecycle activities should be selected. Until so far, it is not easy for design engineers to think of several product lifecycle options at the early design stage. However, recently, with the development of information systems for product development process such as product data management and product lifecycle management system, at the early stages of design, lots of information including not only legal requirements but also other requirements associated to whole product lifecycle, can be systematically provided to product design engineers, which helps engineers think of several product lifecycle options at the early design stage.

The selected options are described in the product lifecycle requirements part in the extended HOQ. The selection of options will be formulated as constraints of MINLP in the next step. The selection of engineering characteristics related to the lifecycle requirement options and the allocation of investment for the selected engineering characteristics are settled at the same time by the MINLP solution. The investment cost of engineering characteristics, the required resource capacity for the engineering characteristics improvement, and the upper bound of investment cost of engineering characteristics are calculated by engineers considering the capacity of the company. These parts are also formulated as constraints in the MINLP. The importance rate of engineering characteristics from the result of the extended HOQ is included in the objective function of MINLP.

The extended HOQ has differences from ordinary HOQ in that it includes additional information such as the product lifecycle requirements and resource constraints. The selection of engineering characteristics is solved not only by the extended HOQ but also by the combined MINLP. Hence, the result of the extended HOQ becomes an input to the modeling of MINLP in the next step. In addition, the MINLP solves the investment allocation for engineering characteristics as well as the selection of engineering characteristics.

4 Problem definition

Before problem definition, note that this study assumes the followings:

1. Engineering characteristics for customer requirements and product lifecycle requirements on a certain product are given.
2. The values of all parameters except ρ_i, ρ_j^r, and $\rho_k^{'}$, are given.
3. Investment cost for each engineering characteristic indicates the cost for implementing the engineering characteristic, in association with the use of resource and material. It has values in the range (0, 10).
4. The product design satisfaction depends on the degree of design qualities for engineering characteristics, and has concave, linear, or convex type of dependence over the investment cost.
5. The degree of design quality for each engineering characteristic has values in the range (0, 1).

The assumptions (1–3) as to the values of parameters used in QFD are based on the idea that domain experts can fix the appropriate values of the parameters from their experiences and knowledge. The assumption (4) implies that the product design satisfaction is mainly affected by the degree of design qualities for engineering characteristics although there may be other factors to decide the product design satisfaction. Regarding the design quality of an engineering characteristic over investment cost, it is assumed that there are three types of relations between the degree of design qualities for engineering characteristics and investment cost: concave, linear, and convex. Although there could be more complex relations, in this study, these three types are considered into our problem because they are basic types of relations. More complex types of relations can be considered as the future research issue. In addition, without any loss of generality, the degree of design quality is set into the range (0, 1) as mentioned in the assumption (5).

4.1 Mixed integer nonlinear programming model

Based on assumptions and with the result of the extended HOQ, our problem can be formulated as a MINLP as follows. For the notations used in the MINLP, please refer to Appendix 1.

$$\text{Max } f\left(x_i; x_j^r; x_k^{'}\right) = \sum_{i=1}^{i_n} \rho_i \cdot g_{x_i}(x_i) + \sum_{r=1}^{r_n}\sum_{j=1}^{j_r} \rho_j^r \cdot g_{x_j^r}\left(x_j^r\right) + \sum_{k=1}^{k_n} \rho_k^{'} \cdot g_{x_k^{'}}\left(x_k^{'}\right) \quad (1)$$

Subject to

$$\sum_{i=1}^{i_n} \delta_i x_i + \sum_{r=1}^{r_n}\sum_{j=1}^{j_r} \delta_j^r x_j^r + \sum_{k=1}^{k_n} \delta_k^{'} x_k^{'} \leq \delta \quad (2)$$

$$\sum_{i=1}^{i_n} \lambda_{it} y_i + \sum_{r=1}^{r_n}\sum_{j=1}^{j_r} \lambda_{jt}^r y_j^r + \sum_{k=1}^{k_n} \lambda_{kt}^{'} y_k^{'} \leq \lambda_t \quad (3)$$

for $t = 1, \ldots, t_n$

$$x_i \leq M \cdot y_i \text{ for } i = 1, \ldots, i_n \quad (4)$$

$$x_j^r \leq M \cdot y_j^r \text{ for } j = 1, \ldots, j_r \text{ and } r = 1, \ldots, r_n \quad (5)$$

$$x_k^{'} \leq M \cdot y_k^{'} \text{ for } k = 1, \ldots, k_n \quad (6)$$

$$x_k^{'} \geq y_k^{'} \text{ for } k = 1, \ldots, k_n \quad (7)$$

$$L_{x_i} \leq x_i \leq U_{x_i} \text{ for } i = 1, \ldots, i_n \quad (8)$$

$$L_{x_j^r} \leq x_j^r \leq U_{x_j^r} \text{ for } j = 1, \ldots, j_r \text{ and } r = 1, \ldots, r_n \quad (9)$$

$$L_{x_k^{'}} \leq x_k^{'} \leq U_{x_k^{'}} \text{ for } k = 1, \ldots, k_n \quad (10)$$

$$\sum_{j=1}^{j_r} y_j^r = 1 \text{ for } r = 1, \ldots, r_n \quad (11)$$

$$y_i \in \{0, 1\} \text{ for } i = 1, \ldots, i_n \quad (12)$$

$$y_j^r \in \{0, 1\} \text{ for } j = 1, \ldots, j_r \text{ and } r = 1, \ldots, r_n \quad (13)$$

$$y_k^{'} \in \{1\} \text{ for } k = 1, \ldots, k_n \quad (14)$$

4.1.1 Objective function and decision variables

The objective of MINLP is to maximize the satisfaction of product concept design under investment budget, resource, and product lifecycle constraints. The decision variables in the MINLP are the suitable engineering characteristics and the amount of investment costs required for implementing the engineering characteristics, which can maximize the overall satisfaction. The selection on engineering characteristics is decided by the amount of investment cost. For example, in case the investment cost of a certain engineering characteristic is zero, it means that this engineering characteristic is not selected because it is more effective in the viewpoint of increasing overall satisfaction. The overall satisfaction of product concept design can be calculated by the multiplication of the modified importance rates of engineering characteristics and their design qualities which have been determined by the design quality functions ($g_x(x)$) over investment costs. The modified importance rate of engineering characteristics can be calculated considering three factors. The first factor is the relationship between customer requirements and engineering characteristics. The second factor is the one between product lifecycle requirements and engineering characteristics. The last factor is the correlations among engineering characteristics. Formula (15) shows a traditional method to calculate the importance rate of each engineering characteristic without considering the correlations among engineering characteristics [39].

$$p_i = \sum_{c=1}^{c_n} w_c R_{ci}, p_j^r = \sum_{r=1}^{r_n} w_r R_j^r, p_k' = \sum_{k=1}^{k_n} w_k R_k' \qquad (15)$$

An engineering characteristic can have positive or negative effects on other engineering characteristics. The engineering characteristic which has a high positive effect on others should have a higher priority. To deal with this feature, this study considers the correlations among engineering characteristics into calculating the modified importance rate of engineering characteristics. There have been some previous works in applying correlations among engineering characteristics into their importance rates. One popular method is to consider the linear multiplication between correlation value and importance rate of engineering characteristics. For example, Chan and Wu [39] mentioned this method in their QFD framework. During the HOQ building procedure, they used Khoo and Ho's [40] proposal which modified the importance rate with a linear multiplication. In addition, Liu [41] applied the correlation of engineering characteristics into the modification of important rate in the same way. In this study, the same method is used as explained below [39].

$$\text{importance rate of engineering characteristic} = \sum \left(\text{initial importance rate of engineering characteristic} \times \text{value of correlation between the engineering characteristic and other engineering characteristic}\right)$$

To calculate this, Q matrix is built. It represents the correlations among engineering characteristics. The diagonal of Q has a value, 1. The upper triangle of Q is symmetrical to its lower triangle.

$$Q = \begin{bmatrix} \sigma_{11} \ldots \sigma_{1s_n} \\ \vdots \quad \ddots \quad \vdots \\ \sigma_{s_n 1} \ldots \sigma_{s_n s_n} \end{bmatrix} \qquad (16)$$

The p_i, p_j^r, and p_k' can also be described in a matrix form by the following matrix P.

$$P = \left[p_i p_j^r p_k'\right]^T \qquad (17)$$

Then, from formula (16) and (17), the modified importance rate matrix (P') considering the correlations among engineering characteristics can be calculated with the formula (18).

$$P' = \left[\rho_i \rho_j^r \rho_k'\right]^T = Q \cdot P \qquad (18)$$

Then, as can be seen in formula (1), the objective function can be calculated by the multiplication of the modified importance rates, ρ_i, ρ_j^r, and ρ_k', and the degree of design qualities, $g_x(x)$, $x \in \left\{x_i, x_j^r, x_k'\right\}$. In formula (1), there are three kinds of decision variables: x_i, x_j^r, and x_k'. The variable x_i represents the amount of investment cost of engineering characteristic i related to customer requirements. The variable x_j^r is the one related to product lifecycle requirement r. The x_k' is a variable for an indispensable engineering characteristic k needed to satisfy product lifecycle requirements or customer requirements.

4.1.2 Relation between investment cost and design quality

The relation between investment cost and design quality of an engineering characteristic can be linear, concave, or convex. In this study, the relation of the degree of design quality $g_x(x)$ with the corresponding investment cost is defined as the following function:

$$g_x(x) = \frac{1}{u}\ln\left(1 + \frac{x}{10}\cdot e^u - \frac{x}{10}\right), 0 \leq x \leq 10, \text{where } u \text{ is the shape parameter.}$$

If there are field data for the relation between investment cost and design qualities of an engineering characteristic, u can be obtained by statistical regression analysis. Figure 3 depicts three types of relations depending on the value of u. It is assumed that the investment cost has a value in the range (0, 10) and the degree of design quality has a value in (0, 1). Figure 3 shows that the degree of design quality,

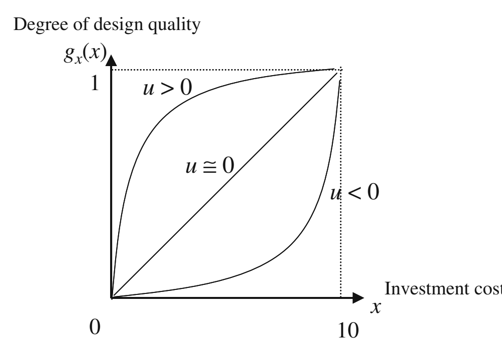


Fig. 3 Degree of design quality over investment cost

$g_x(x)$, starts from the zero value and converges to 1 as the investment cost increases up to the upper bound of investment cost. If $u>0$, then $g_x(x)$ is a concave function in $x \in (0, 10)$. It represents the case that the degree of design quality increases rapidly at the beginning as the investment cost is increasing, but the rate of quality improvement decreases afterward. If $u<0$, then $g_x(x)$ is a convex function. It represents the case that the degree of design quality increases slowly at the beginning and the rate increases afterward. Note that the function is approximately linear when $u \cong 0$. With the proposed function, several relations between investment cost and degree of design quality can be considered in the problem.

4.1.3 Investment budget constraint

To represent an investment budget limitation, the inequality (2) is defined. This inequality means that the total investment for implementing engineering characteristics cannot exceed the total budget limit. We assume that the investment cost of each engineering characteristic should not surpass the upper bound of investment cost for the engineering characteristic, because too much investment cost has little effect on the improvement of customer satisfaction [9]. Therefore, the upper bound of investment is added as formulae (8–10). Note that the engineering characteristics, $x_k^{'}$, should have at least one investment cost unit because it is the engineering characteristic that is necessarily considered.

4.1.4 Resource capacity constraint

The inequality (3) shows a resource capacity constraint, which indicates that the total required resource capacity for the implementation of engineering characteristics should not exceed the resource capacity limit for the development of the product concept. For example, the limits on man power and the number of software licenses are kinds of resource capacity limits. Unlike the investment budget constraint, the total resource capacity should be calculated by summing the minimum necessary amount of resource capacity for each engineering characteristic that has a positive x value. For this, dummy binary variables are defined: y_i, y_j^r, and $y_k^{'}$. If x_i and x_j^r are positive, y_i and y_j^r have value 1, respectively. Formulae (4–7) and (12–14) are used to make y_i, y_j^r, and $y_k^{'}$ binary variables.

4.1.5 Product lifecycle requirement constraint

A product can have various lifecycle requirements depending on the options of production, maintenance, end-of-life, and so on, which leads to the selection of several alternative engineering characteristics. Selecting one engineering characteristic among several ones can be expressed by the formula (11). From this formula, only one engineering characteristic is selected among competitive ones. In addition, there is a case that some engineering characteristics should be necessarily selected and invested upon. For example, the improvement of product material should be considered to satisfy the regulation for environment. For this purpose, the formula (7) is needed. The satisfaction of formula (7) makes sure that the indispensable engineering characteristics are invested. The formula (8–10) defines the minimum amount of investment cost. These two kinds of formulae ((7) and (11)) are made to consider product lifecycle requirements in selecting engineering characteristics.

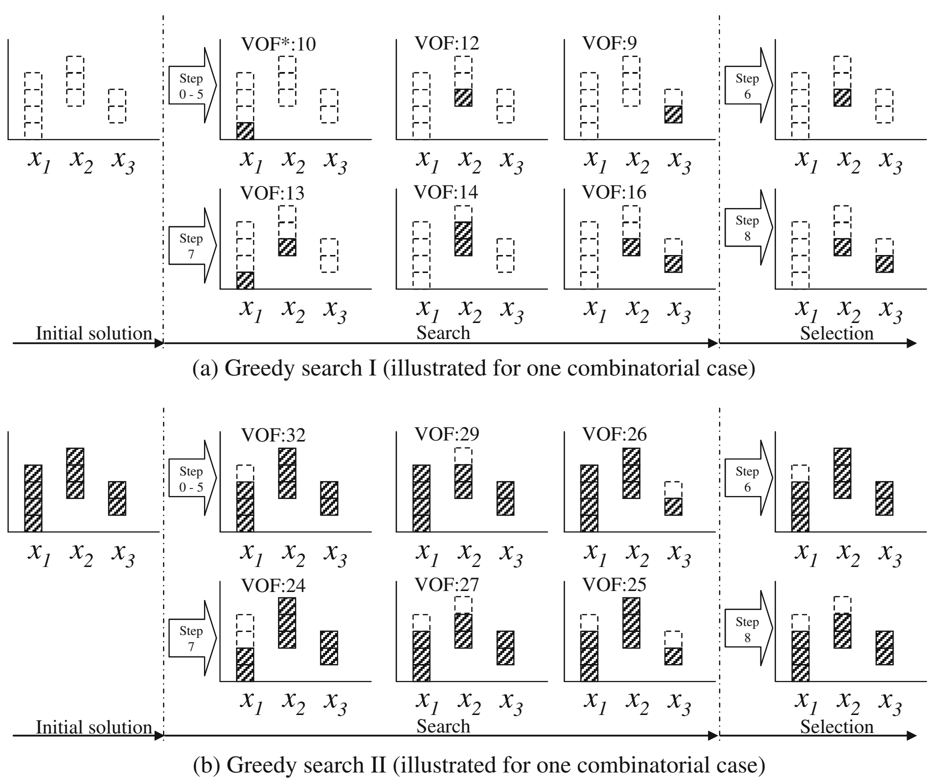
5 Solution approach for MINLP

The proposed problem can be expressed by a MINLP model. The MINLP model refers to mathematical programming with continuous and discrete variables, and nonlinearities in the objective function and/or constraints [42]. MINLP models are much more difficult than both mixed integer linear programming and nonlinear programming models. Many engineering design problems can be formulated as MINLP models, since they involve the selection of a configuration or topology (which components should be included in the design) as well as design parameters of those components, i.e. size, weight, and so on [43]. The MINLP problem is known as a theoretically difficult problem (NP-complete). To solve MINLP models, various solution methods have been developed since the early 1980s: Outer approximation methods, branch-and-bound, extended cutting plane methods, and generalized bender's decomposition. Although theoretical algorithms solving MINLP problem have been around for a while, the practical implementation of such concepts is much more difficult because of several reasons such as memory limitations and efficient numerical linear algebra routines [42]. Depending on product types and product characteristics, in product conceptual design, many engineering characteristics (e.g., dozens of engineering characteristics) can be involved. Thus, it requires solution methods for large-sized problems, which makes applying general known techniques difficult. Considering much efforts and time to solve the NP-complete problem with the theoretical algorithms, heuristic methods considering problem characteristics may provide good solutions for the MINLP problem in a reasonable time. To this end, this study proposes heuristic search algorithms. Because with only a single search method it is not enough to provide good solutions for resolving our problem, all three search methods are developed for resolving our problem, which results in three heuristic algorithms. Two algorithms are based on greedy search methods. The greedy search method is normally fast and useful because it often gives good approximations to the optimum. Another search algorithm is based on a two-phase approach considering the characteristics of the proposed MINLP problem. The two-phase method is developed to make up for the low quality of solutions of greedy search methods that might exist.

For the three heuristic search algorithms, several combinatorial cases regarding lifecycle requirements, i.e., several combinations of x_j^r, are considered. Since many lifecycle requirements consider only one engineering characteristic among several possibilities, it can be divided into several combinatorial cases. For example, if there are two lifecycle requirements (*A* and *B*) and each lifecycle requirement has two relevant engineering characteristics (e.g., a_1 and a_2) and three ones (e.g., b_1, b_2, and b_3), respectively, then six combinatorial cases can be considered, i.e. (a_1, b_1), (a_1, b_2), (a_1, b_3), (a_2, b_1), (a_2, b_2), and (a_3, b_3). For all combinatorial cases, three search algorithms are applied independently.

5.1 Greedy search *I* algorithm

The greedy search *I* algorithm explores solutions starting from the initial solution which is set to the minimum investment costs for all engineering characteristics at a combinatorial case of x_j^r. If the initial solution satisfies the budget constraint and resource constraints, this solution is set as an incumbent solution. Otherwise, the minimum investment cost is assigned for the next combinatorial case and the feasibility is checked until an incumbent solution is found. After the incumbent solution is found, for each engineering characteristic, 0.1 is added up to its investment cost and its objective function value is calculated; 0.1 is one of a hundred scales for the range of investment cost, which is the reasonable unit for searching. Then the engineering characteristic which gives the highest value of objective function without violating the budget constraint and resource constraints is selected. For the selected engineering characteristic, 0.1 is added up to its investment cost, and this is set as a new incumbent solution. This improvement procedure is repeated until there is no feasible solution to increase the objective value. For all combinatorial cases of x_j^r, the above procedure is repeated and the best solution is found among



* VOF: the value of objective function

(a) Greedy search *I* algorithm repeats searching steps as far as the budget requirement and resource requirements are satisfied.

(b) Greedy search *II* algorithm repeats searching steps until the budget requirement and resource requirements are satisfied.

Fig. 4 Greedy search *I* and greedy search *II* algorithms them. Figure 4a shows the procedure graphically. The detailed procedure is as follows.

Step 0. Initialize a solution.

Let X denote a solution vector, $X = \left(x_i, x_j^r, x_k^{'}\right)$. Then, assign the minimum amount of investment cost into all engineering characteristics x_i, x_j^r, and $x_k^{'}$ for one combinatorial case of x_j^r.

Step 1. Check the feasibility of the solution.

If the budget constraint and resource constraints are satisfied for the initialized solution vector, set the solution vector as the current incumbent solution vector X and go to step 2. Otherwise, repeat step 0 for the other combinatorial case of x_j^r.

Step 2. Calculate its objective function value.

For the incumbent solution vector X, calculate the value of objective function.

Step 3. Increase the investment costs of engineering characteristics.

For each engineering characteristic of the incumbent solution vector X, add up 0.1 to its investment cost, respectively, and set the updated incumbent solution vector X as tentative solution vector X_s, s=1,..., s_n. Here, X_s indicates that the solution vector of which the sth element in the X has been increased.

Step 4. Check the feasibilities of tentative solutions X_s.

For all tentative solution vectors X_s, check the budget constraint and resource constraints.

Step 5. Calculate the objective value of the feasible tentative solution.

For all feasible tentative solution vectors X_s, calculate the values of objective functions.

Step 6. Select the best tentative solution.

Select the feasible tentative solution vector X_s^* which shows the highest value of objective function. If the objective value of X_s^* is better than that of X, let X_s^* as the new incumbent solution X.

Step 7. Improve the incumbent solution.

Repeat steps 3–6 until there is no tentative solution vector X_s^* which gives a better solution than the incumbent solution vector X does.

Step 8. Repeat whole steps 0–7 for all combinatorial cases of x_j^r and select the best solution among them.

5.2 Greedy search *II* algorithm

Contrary to the greedy search *I* algorithm, the greedy search *II* algorithm starts from the maximum investment costs for all engineering characteristics at each combinatorial case of x_j^r. Thus, at the beginning of search, it does not consider the feasibility of solutions, and reduces the amounts of investment costs until the feasible solution is found. Except them, all procedures are very similar to the greedy search *I* algorithm. At first, for each combinatorial case of x_j^r, greedy search *II* algorithm assigns the maximum values of investment cost into all engineering characteristics and set this as an initial incumbent solution. From the initial incumbent solution, it generates several alternative solutions. To this end, for each engineering characteristic, it removes 0.1 from its investment cost, and then calculates the value of the objective function. Among all alternatives, it selects the solution which gives the highest value of objective function. It sets this solution as a new incumbent solution. This removal procedure is repeated until the incumbent solution satisfies the feasibility of the solution, i.e. satisfying the budget constraint and resource constraints. The best solution can be found by repeating this overall procedure for all combinatorial cases of x_j^r. Figure 4b shows the procedure graphically. The detailed procedure is as follows.

Step 0. Initialize a solution.

Let X denote a solution vector, $X = \left(x_i, x_j^r, x_k^{'}\right)$. Then, assign the maximum amount of investment cost into all engineering characteristics x_i, x_j^r, and $x_k^{'}$ for one combinatorial case of x_j^r.

Step 1. Decrease the investment costs of engineering characteristics.

For each engineering characteristic of the solution vector X, decrease 0.1 to its investment cost, respectively, and set the updated solution vector X as tentative solution vector X_s, s=1,..., s_n. Here, X_s indicates that the solution vector of which the sth element in the X has been decreased.

Step 2. Check the feasibilities of tentative solutions X_s.

For all tentative solution vectors X_s, check the budget constraint and resource constraints.

Step 3. Calculate the objective value of the feasible tentative solution.

For all feasible tentative solution vectors X_s, calculate the values of objective functions. If there is no feasible X_s, then go to Step 1 again.

Step 4. Select the best tentative solution.

Select the feasible tentative solution vector X_s^* which shows the highest value of objective function.

Step 5. Repeat whole steps 1-4 for all combinatorial cases of x_j^r and select the best solution among them.

5.3 Net search algorithm

The net search algorithm (NSA) tries to efficiently explore the solution space where the objective function seems to have its highest value. For this, the NSA uses a two-phased approach. In the first phase, instead of searching the whole solution space, the NSA briefly explores the solution space that has a high potential of identifying good solutions by considering integer solutions at first. In the second phase, it extensively searches the selected solution space. Since the considering problem deals with both integer and real numbers, it is impossible to search all solution spaces in a reasonable computation time. Hence, for finding initial solutions, the NSA reduces the searching area from the real number solution space to the discrete integer solution space for saving computational time. Then, for each solution vector (X*) within the integer solution space, the NSA calculates the value of its objective function to compare with those of its neighbors that indicate the integer solution vectors for which the Euclidean distance is a certain integer from X*. If the value of its objective function is higher than those of its neighborhoods, the NSA sets this solution vector as an initial solution vector. By repeating this procedure for every solution vector within the integer solution space, several initial solution vectors can be gotten in the first phase. In the second phase, the NSA intensively navigates the solution space around the initial solution vectors to find the best solution. Since the objective function in the problem is continuous, according to the extreme value theorem [44], there must be a solution vector which has the maximum value of its objective function within the confined solution spaces of its neighborhoods. To find the solution vector, the NSA searches the confined solution space that indicates a real number solution space generated by splitting the interval between an initial solution and its neighborhoods in a certain grid. For each alternative solution vector within the confined solution space, the NSA calculates the value of its objective function, and finds the solution vector which gives the highest value of objective function among all alternative solutions. Eventually, the best solution vector can be found by repeating this procedure for all initial solutions. The concept of NSA is depicted in Fig. 5, and the more detailed procedure of the NSA algorithm is given below.

Phase 1. Finding initial solution vectors that have high potentials

Step 0. Define solution vectors.

Let $X_\alpha = \left(x_i, x_j^r, x_k^{'}\right)$, α=1,..., be solution vectors. Depending on the combination of values of x_i, x_j^r, x', there are lots of solution vectors.

Step 1. Check the feasibilities of X_α's and calculate the values of the objective function of all feasible X_α's.

- (a) Check the feasibility of X_α in terms of budget and resource constraints.
- (b) Calculate the values of objective function of all feasible X_α's.

Step 2. Find initial solution vectors.

- (a) For each feasible X_α, if the objective function value of X_α is better than those of neighborhoods that indicate the integer solution vectors of which the Euclidean distance is a certain integer (ζ) from the X_α, then put X_α into a set of initial solution vectors, I_β.
- (b) Repeat (a) for all feasible X_α's. If there are no initial solutions vectors, then put the defined number of solution vectors, X_α, which have the higher value of objective function in decreasing order.

Phase 2. Searching the best solution around the initial solution vectors

Step 3. For each initial solution vector, set the confined solution space.

- (a) For each initial solution vector, I_β, define the confined solution space that indicates a real number solution space generated by splitting the interval between an initial solution and its neighborhoods in a certain grid (ζ/10).
- (b) Generate alternative solution vectors and denote them as $X_\alpha^{'}$.
- (c) Set the initial incumbent solution vector and its objective function value to be a zero vector and zero, respectively.

Step 4. For all $X_\alpha^{'}$'s, check feasibility and calculate the value of objective function.

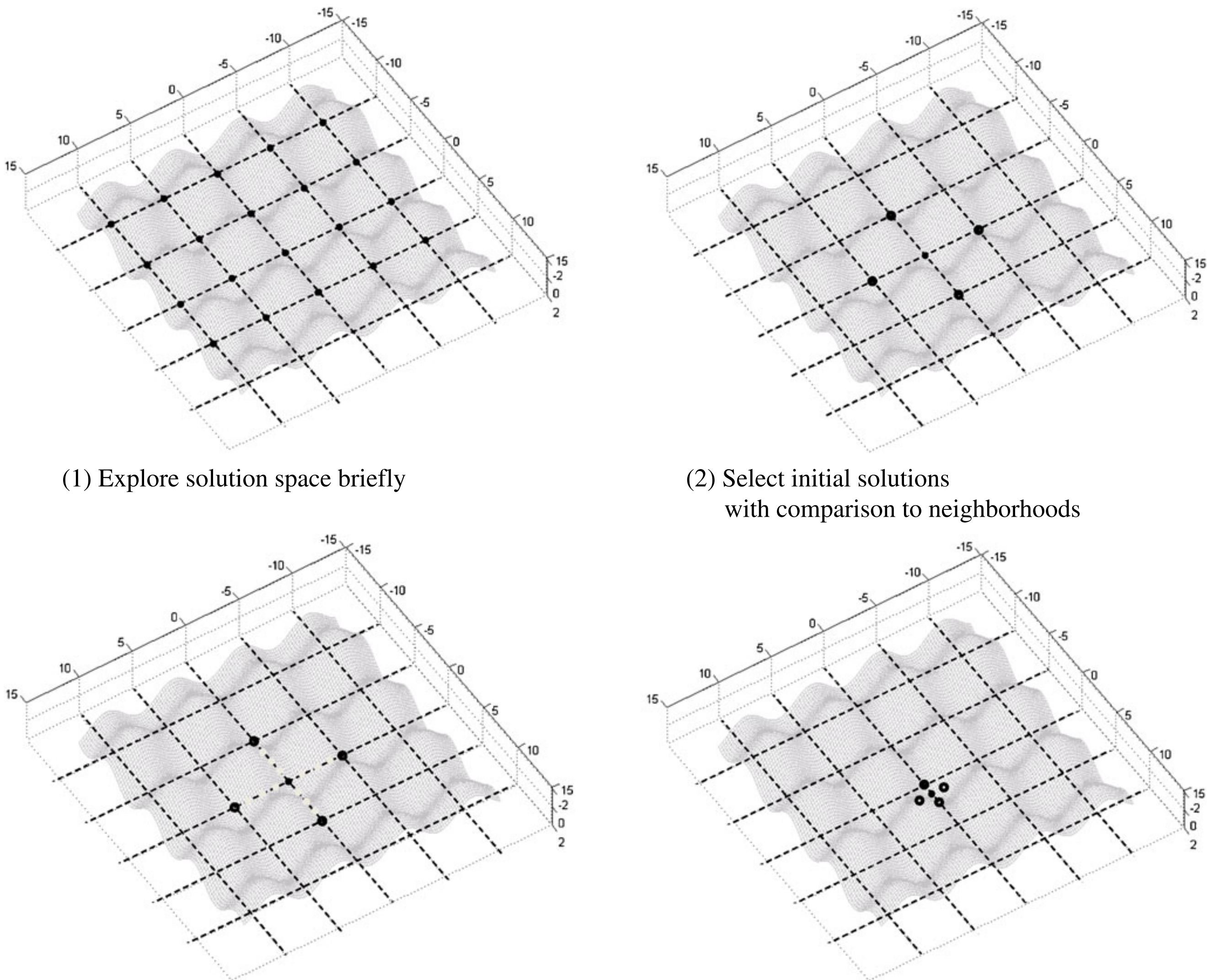
- (a) Check the feasibility of $X_\alpha^{'}$'s in terms of budget and resource constraints.
- (b) Calculate the values of objective function.

Step 5. Find an incumbent solution.

- (a) Select the best alternative solution vector and compare its objective value with that of the current incumbent solution.
- (b) If the objective value of the best alternative solution vector is better than that of the current incumbent solution, set the best alternative solution as a new incumbent solution.

Step 6. Repeat Step 3–5 for all initial solution vectors.

Step 7. Set the current incumbent solution as the best final solution.



(1) Explore solution space briefly

(2) Select initial solutions with comparison to neighborhoods

(3) Search around initial solutions

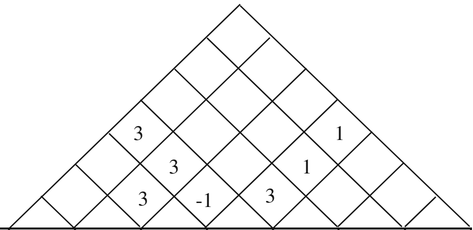
(4) Repeat step (1)-(3) for reduced solution space

Fig. 5 Concept of net search algorithm (in the case of two variables)

6 Case study and computational experiments

In this section, to show the usefulness of the proposed approach, a case study and computational experiments based on generated examples are introduced. The example of the case study is generated based on the conceptual design of a locomotive wheel and related components of boogie. The considered locomotive is made by a Swiss locomotive company. Figure 6 shows the extended HOQ for a locomotive wheel and related components, which has four customer requirements, two product lifecycle requirements, seven engineering characteristics, relations between customer/product lifecycle requirements and engineering characteristics, and correlations among engineering characteristics. This extended HOQ is a reduced version of the design for X transformation matrix provided by that company. In this matrix, key performance indicators for product design are defined, which can be considered engineering characteristics: boogie type (motor, e.g., trailer, single axle), concept of primary suspension (e.g., longitude, lateral stiffness), concept of secondary suspension (e.g., coil, air, spring), brake type (e.g., tread, disc, rail brake), applied wheel/rail friction coefficient, brake concept (e.g., friction brake, electro brake, hydro-dynamic brake), wheel profile, wheel material, and so on. As an output, design knowledge for reliability, availability, maintainability, lifecycle cost, safety, and environment are defined. Also the relationship between input and output is described.

From the locomotive manufacturer viewpoint, main customer requirements on the wheel and related components are to let the wheel have high reliability, availability, and safety with low price because these



		Engineering characteristics / Weight	Wheel profile	Suspension type	Part modularity	Part price	Break type	Wheel material *A*	Wheel material *B*
Customer requirements	High reliability	4	3	3			3	3	3
	High availability	4	3	3	5		3	3	3
	High safety	5	3	1			5	3	3
	Low price	3	3	1	3	5			
Product lifecycle requirements	Easy maintenance	3			5				
	Material recycle regulation	4		3				5	5
Importance rates of engineering characteristics			48	44	44	15	49	59	59
Required investment costs of engineering characteristics			3	5	2	1	5	6	3
Required resource capacity for engineering characteristics improvement			4	5	1	2	4	4	4
Upper bound of investment cost for engineering characteristics			3	5	3	5	7	6	4

Fig. 6 Extended HOQ for a locomotive wheel

characteristics are critical issues in operating the locomotive. In addition to them, from the lifecycle viewpoint, it is important to design components considering easy maintenance under keeping material recycle regulation. As the result, there are two product lifecycle requirements to be considered: easy maintenance and material recycle regulation. For the "easy maintenance" lifecycle requirement, there are some lifecycle options such as part modularity, design for disassembly, and so on. For the "material recycle regulation" requirement, some lifecycle options can be considered: replacement with other parts or reconsideration of material used in the product. To meet the "easy maintenance" lifecycle requirement, in this study, improving the "part modularity" is considered. To keep the "material recycle regulation," changing "suspension type" and "material type (material *A* and material *B*)" are considered.

These requirements are complicatedly related with engineering characteristics as shown in the HOQ matrix of Fig. 6. To measure the degree of the relationship between customer/lifecycle requirements and engineering characteristics, in this study, a (1, 3, 5) rating scale [45] is used: weak (1), medium (3), and strong (5). For representing the correlation among engineering characteristics, a (−3, −1, 1, 3) rating scale [45, 46] is also used: strong negative (-3), weak negative (−1), weak positive (1), and strong positive (3). Although the final results may be varied depending on rating scales, this effect is not much in our problem as the results of small tests. Note that the analysis of the effects of various rating scales on the solutions is beyond the scope of this study.

In addition to the complex relation, because of limited resource capacity and investment cost, it is required to think over which engineering characteristic should be more importantly considered. To this end, the modified importance rate is calculated for each engineering characteristic with formulae (16–18) as follows:

$$Q = \begin{bmatrix} \sigma_{11} \cdots \sigma_{1s_n} \\ \vdots \quad \ddots \quad \vdots \\ \sigma_{s_n 1} \cdots \sigma_{s_n s_n} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 3 & 0 & 0 & 0 \\ 0 & 1 & 3 & 3 & 0 & 0 & 0 \\ 0 & 3 & 1 & -1 & 0 & 0 & 0 \\ 3 & 3 & -1 & 1 & 3 & 1 & 1 \\ 0 & 0 & 0 & 3 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix},$$

$$P' = \begin{bmatrix} 1 & 0 & 0 & 3 & 0 & 0 & 0 \\ 0 & 1 & 3 & 3 & 0 & 0 & 0 \\ 0 & 3 & 1 & -1 & 0 & 0 & 0 \\ 3 & 3 & -1 & 1 & 3 & 1 & 1 \\ 0 & 0 & 0 & 3 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 48 \\ 44 \\ 44 \\ 15 \\ 49 \\ 59 \\ 59 \end{bmatrix} = \begin{bmatrix} 93 \\ 221 \\ 161 \\ 512 \\ 94 \\ 74 \\ 74 \end{bmatrix}$$

$$p_1(\text{wheel profile}) = 4\cdot 3 + 4\cdot 3 + 5\cdot 3 + 3\cdot 3$$
$$= 48 \rightarrow \rho_1 = 93$$
$$p_1^{'}(\text{suspension type}) = 4\cdot 3 + 4\cdot 3 + 5\cdot 1 + 3\cdot 1 + 4\cdot 3$$
$$= 44 \rightarrow \rho_1^{'} = 221$$
$$p_2^{'}(\text{part modularity}) = 4\cdot 5 + 3\cdot 3 + 3\cdot 5 = 44 \rightarrow \rho_2^{'}$$
$$= 161$$
$$p_2(\text{part price}) = 3\cdot 5 = 15 \rightarrow \rho_2 = 512$$
$$p_3(\text{break type}) = 4\cdot 3 + 4\cdot 3 + 5\cdot 5 = 49 \rightarrow \rho_3 = 94$$
$$p_1^1(\text{wheel material A}) = 4\cdot 3 + 4\cdot 3 + 5\cdot 3 + 4\cdot 5$$
$$= 59 \rightarrow \rho_1^1 = 74$$
$$p_2^1(\text{wheel material B}) = 4\cdot 3 + 4\cdot 3 + 5\cdot 3 + 4\cdot 5$$
$$= 59 \rightarrow \rho_2^1 = 74$$

In the above, Q is obtained from the correlations among engineering characteristics at Fig. 6 (see the roof of HOQ at Fig. 6). The importance rates of engineering characteristics are calculated by the multiplication of the weights of requirements and the rating scale as to the degree of relations between requirements and engineering characteristics. As shown in the matrix of HOQ at Fig. 6, the engineering characteristics related to customer requirements having no relation with product lifecycle requirements are: (1) wheel profile, (2) part price, and (3) break type. The engineering characteristics having relation with product lifecycle requirements are (1) wheel material A, (2) wheel material B, (3) suspension type, and (4) part modularity. Among them, the alternative engineering characteristics are "wheel material A" and "wheel material B" because only one of both can be considered for product design. The indispensable engineering characteristics are "suspension type" and "part modularity".

The investment cost and resource capacity are generated based on the interviews with engineers of the locomotive company. The resource capacity is represented by the multiplication of unit amount such as money, people, software license, and so on. To decide the best amount of investment costs of engineering characteristics under resource capacity and investment cost constraint, a mixed integer nonlinear programming model can be formulated as below. In this formulation, M is set to 1,000,000 and the values in constraints are randomly generated.

$$\text{Max} \quad 93\cdot g_{x_1}(x_1) + 512\cdot g_{x_2}(x_2) + 94\cdot g_{x_3}(x_3) + 74\cdot g_{x_1^1}(x_1^1) + 74\cdot g_{x_2^1}(x_2^1) + 221\cdot g_{x_1^{'}}\left(x_1^{'}\right) + 161\cdot g_{x_2^{'}}\left(x_2^{'}\right)$$

Subject to

$$3x_1 + x_2 + 5x_3 + 6x_1^1 + 3x_2^1 + 5x_1^{'} + 2x_2^{'} \leq 40$$
$$4y_1 + 2y_2 + 4y_3 + 4y_1^1 + 4y_2^1 + 5y_1^{'} + y_2^{'} \leq 30$$
$$x_1 \leq 1,000,000\cdot y_1$$
$$x_2 \leq 1,000,000\cdot y_2$$
$$x_3 \leq 1,000,000\cdot y_3$$
$$x_1^1 \leq 1,000,000\cdot y_1^1$$
$$x_2^1 \leq 1,000,000\cdot y_2^1$$
$$x_1^{'} \leq 1,000,000\cdot y_1^{'}$$
$$x_2^{'} \leq 1,000,000\cdot y_2^{'}$$
$$x_1 \geq y_1,\ x_2 \geq y_2,\ x_3 \geq y_3,\ x_1^1 \geq y_1^1,\ x_2^1 \geq y_2^1,\ x_1^{'} \geq y_1^{'},\ x_2^{'} \geq y_2^{'}$$
$$0 \leq x_1 \leq 3,\ 0 \leq x_2 \leq 5,\ 0 \leq x_3 \leq 7$$
$$0 \leq x_1^1 \leq 6,\ 0 \leq x_2^1 \leq 4$$
$$1 \leq x_1^{'} \leq 5,\ 1 \leq x_2^{'} \leq 3$$
$$y_1^1 + y_2^1 = 1$$
$$y_1^1,\ y_2^1 \in \{0, 1\}$$

where x_1 (wheel profile), x_2 (part price), x_3 (break type), $x_1^{'}$ (suspension type), $x_2^{'}$ (part modulation), x_1^1 (wheel material A), and x_2^1 (wheel material B)

Here, the shape parameters (u) of $g_x(x)$'s in the objective function are generated as follows: 0.000006, −0.000002, 4.3, 0.000006, −0.000001, 8, and −9.1, respectively. To solve this problem, the NSA is applied and the following result is obtained.

Overall satisfaction: 4,574.13

$$x_1 = 3.0,\ x_2 = 5.0,\ x_3 = 0.0,\ x_1^1 = 0.0,\ x_2^1 = 4.0,$$
$$x_1^{'} = 1.6,\ x_2^{'} = 3.0,$$

According to the search result, the investment cost of x_1 (wheel profile), x_2 (part price), x_2^1 (wheel material B), $x_1^{'}$ (suspension type), and $x_2^{'}$ (part modularity) should be 3.0, 5.0, 3.0, 1.6, and 3.0 units, respectively. Here the investment cost for part price can be interpreted as the part management cost in order to negotiate reasonable part price with suppliers. The overall satisfaction with these investments is 4,574.13. $x_1^{'}$ (suspension type), $x_2^{'}$ (part modulation), x_1^1 (wheel material A), and x_2^1 (wheel material B) are decision variables related to product lifecycle requirements. $x_1^{'}$ (suspension type) and $x_2^{'}$ (part modulation) are indispensable variables and should be necessarily considered in product conceptual design. Therefore, at least, a 1.0 unit cost (the lower bound value of the amount of investment cost for these indispensable engineering characteristics) should be invested for the improvement of the suspension type and part modularity, respectively. The solution says that 1.6 and 3.0 unit costs should be invested from the MINLP solution result for maximizing the overall satisfaction of product concept design. x_1^1 and x_2^1 are alternative decision variables of which only one can be invested by the product lifecycle constraint. According to the solution, x_2^1 (wheel material B) is selected and invested as much as 4.0 units.

To compare the above results with those of the case that does not consider the correlations among engineering characteristics, the same test is done with the importance rate "P" (i.e. without considering the correlations among engineering characteristics) instead of the modified importance rate "P''". The obtained results in this case are as follows: the overall satisfaction is 848.91 and the decision variables are x_1=3.0, x_2=5.0, x_3=0.6, $x_1^1 = 0.0$, $x_2^1 = 4.0$, $x_1^{'} = 1.0$, $x_2^{'} = 3.0$. This result shows that x_3 (break type) has investment cost compared with the result by the modified importance rate. The investment cost of $x_1^{'}$ (suspension type) is less than that of the modified importance rate case. These differences may lead to inappropriate resource allocations on product development because the above results do not consider the correlations among engineering characteristics.

To compare the performance of the proposed heuristic search algorithms, computational experiments are done with 230 problems (for small-sized) and 490 problems (for large-sized) randomly generated. The extended HOQ and parameter values are generated randomly with values as described in the following generation rules. Here, let $R(a, b)$ denote the random value between a and b.

1. The minimum values of engineering characteristics, L_{x_i}, $L_{x_j^r}$, and $L_{x_k^{'}}$ are generated by $R(0, 10)$;
2. The maximum values of engineering characteristics U_{x_i}, $U_{x_j^r}$, and $U_{x_k^{'}}$ are generated by $R(L_{x_i}, 10)$, $R(L_{x_j^r}, 10)$, and $R(L_{x_k^{'}}, 10)$, respectively;
3. The modified importance rates, ρ_i, ρ_j^r, and $\rho_k^{'}$, are generated by $R(0, 100)$;
4. The required costs, δ_i, δ_j^r, and $\delta_k^{'}$, are generated by $R(0, 10)$;
5. The total investment budget δ is generated depending on the number of engineering characteristics with the following formula: $7 \cdot s_n / R(1, 3)$;
6. The minimum required resource capacities, λ_{it}, λ_{jt}^r, and $\lambda_{kt}^{'}$, are generated by $R(0, 10)$;
7. The number of resource types in the resource capacity constraint is generated by $R(1, 3)$;
8. The value of resource capacity of each engineering characteristic is generated by $R(0, 10)$;
9. For the type of $g(x)$, μ is generated from $R(-10, 10)$;
10. The number of engineering characteristics (s_n) is generated as 5, 6, and 7 for small-sized; 10, 20, and 30 for large-sized problems;
11. The number of lifecycle requirements (r_n) is generated by $R(1, 3)$. The number of alternative engineering characteristics related to product lifecycle requirement r (j_r) is generated by $R(1, s_n/3)$ and the combination of x_i, x_j^r, and $x_k^{'}$ is randomly set.

All heuristic search algorithms are coded in C, and computational experiments are done on a personal computer with a Pentium 4 processor operating at 3.2 GHz clock speed. There does not exist any efficient algorithm for finding the optimal solutions of the MINLP. Moreover, it is impossible to find an optimal value through full enumeration in a reasonable time. Hence, in order to evaluate the performance of the three heuristic search algorithms, for the small-sized problems, the three heuristic search algorithms are compared with the full enumeration method that has limited solution space. The full enumeration method searches all discrete solution vectors within the reduced solution space with the interval of 0.1 in the amount of investment cost and finds the solution vector which gives the best solution. For the comparison, a relative performance measure called the relative performance ratio (RPR) is used, which is defined as $(S_B-S)/S_B$ for each problem, where S_B is the best solution obtained by full enumeration and S is the solution value by a heuristic search algorithm.

Table 2 shows the mean and standard deviation of the RPR and computation time, and it describes the performance of three heuristic search algorithms comparing to full enumeration. This comparison shows how well each heuristic search algorithm finds the solution comparing to the best one which is found by the full enumeration method. According to Table 2, the NSA outperforms the greedy search I algorithm and greedy search II algorithm in terms of RPR and computation time. The result of NSA shows a 5% difference from the best one by full enumeration, and gives a better solution than the greedy search I and greedy search II by about 400 times and 15 times, respectively. Also, the NSA shows a reasonable average CPU times which are less than 5 s.

For the large-sized problem, 490 problems are generated considering three levels for the number of engineering characteristics, s_n, (10, 20, and 30), two levels of the number of product lifecycle requirements, r_n, (1 and 2), three levels of the number of engineering characteristics related to product lifecycle requirement r, j_r, (2, 3, and 4).

In Table 3, the RPR and CPU time of three heuristic search algorithms are compared. Here, RPR is defined as $(S_B–S)/S_B$, where S_B is the best solution among the three heuristic solutions and S is the solution value by a heuristic search algorithm, for each problem. Since it is difficult to find an optimal solution for a large-sized problem, the relative performance among three heuristic search algorithms is considered for comparison. According to Table 3, the greedy search I algorithm shows a very poor performance in comparison to the greedy search II algorithm. Since the greedy search I algorithm tries to navigate the solution space as far as feasibility is satisfied, the better search direction may be eliminated by the feasibility check.

Table 2 Performance of heuristic search algorithms for small-sized problems

Number	Number of problem tested	Relative performance ratio (RPR[a])			Average CPU seconds			
		Greedy search I	Greedy search II	NSA	Greedy search I	Greedy search II	NSA	Full enumeration
5	100	0.2631[b] (0.278[c])	0.0733 (0.1148)	0.0029 (0.0090)	0.0009 (0.0037)	0.0016 (0.0047)	4.2900 (5.0265)	30.4962 (72.1399)
6	100	0.2508 (0.2552)	0.0710 (0.0991)	0.0037 (0.0182)	0.1090 (0.0040)	0.2670 (0.0059)	1.0790 (0.0158)	102,304.2020 (3,517.6888)
7	30	0.2294 (0.2518)	0.0771 (0.0983)	0.0051 (0.0191)	0.0374 (0.0055)	0.0911 (0.0073)	1.7965 (0.0193)	20,952.1754 (45,916.0507)
Overall[d]		0.2478 (0.2617)	0.0771 (0.1041)	0.0051 (0.0154)	0.0374 (0.0044)	0.0911 (0.0060)	1.7965 (1.6872)	41,095.6245 (16,501.9589)

[a] RPR=$(S_B–S)/S_B$, S_B: full enumeration solution, S: current algorithm solution

[b] Mean of RPRs

[c] Standard deviation of RPRs

[d] Average over the different computational test

On the contrary, the greedy search *II* algorithm tries to search the solution starting from the best objective value that the solution vector can have regardless of feasibility satisfaction. This is the main reason why the greedy search *I* algorithm gives a poorer performance than the greedy search *II* algorithm does. In the case of the small number of engineering characteristics and low value of ζ, the NSA outperforms the greedy search *II*. However, the difference of performance between the NSA and the greedy search *II* lessens as the number of engineering characteristics and the value of ζ increase. From the viewpoint of the computational complexity of problems, the performances of three heuristic algorithms are not much affected by r_n and j_r. However, the grid value (ζ) of the NSA algorithm affects its computation times as shown in Table 3. For small values of ζ, the NSA did not solve problems in a reasonable time. With $\zeta=3$, it solved problems within a reasonable time. Overall, the NSA requires less than several minutes on a personal computer for solving a problem and shows good performance considering the results compared to the full enumeration method. It is reasonable to solve a design problem in a few minutes since the design problem in real time applications does not require a fast solution approach that should be resolved within a few seconds.

For the product conceptual design, engineering characteristics should be evaluated and prioritized considering resource and investment budget constraints. Moreover, complex correlations among engineering characteristics should be considered in prioritizing them. The proposed MINLP model dealt with them. From the computational result, we could see that the proposed algorithms such as the greedy search *II* and NSA gave good solutions. The proposed approach can guide engineering designers to decide which engineering characteristic should be selected and invested.

7 Discussion and concluding remarks

In general, the product development needs various kinds of efforts from development resources in a company such as engineering staffs, model shop facilities, rapid prototyping equipment, pilot production lines, testing facilities, relevant software licenses, and so on. The company usually carries out several product developments at the same time. However, the company does not always have enough resources so that it may require careful planning and decisions during the early stage of product design. For example, the company may decide in the planning stage what the most important engineering characteristics to be focused are and how much efforts will be adequately assigned for the focused engineering characteristics. To support the decision, in this study, a decision support method with an extended HOQ model has been proposed.

Table 3 Comparison of heuristic search algorithms for large-sized problems

Problem configuration	Number of problem tested	Relative performance ratio (RPR[a])					Average CPU seconds				
		Greedy search I	Greedy search II	NSA			Greedy search I	Greedy search II	NSA		
				$\zeta^{b}=1$	$\zeta=2$	$\zeta=3$			$\zeta=1$	$\zeta=2$	$\zeta=3$
$s_n=10$	250	0.251[c] (0.226[d])	0.066 (0.107)	0.002 (0.010)	0.038 (0.054)	0.084 (0.099)	0.006 (0.008)	0.021 (0.011)	10.042 (44.219)	0.040 (0.090)	0.014 (0.014)
$s_n=20$	120	0.247 (0.171)	0.067 (0.076)	–	0.011 (0.025)	0.062 (0.058)	0.023 (0.032)	0.293 (0.098)	–	183.810 (481.443)	0.503 (0.886)
$s_n=30$	120	0.209 (0.163)	0.048 (0.072)	–	–	0.029 (0.050)	0.029 (0.049)	1.100 (0.233)	–	–	155.64 (456.66)
(1, 2)[e]	90	0.239 (0.187)	0.060 (0.081)	0.001 (0.004)	0.027 (0.044)	0.060 (0.070)	0.006 (0.013	0.178 (0.049)	1.282 (2.465)	38.171 (90.428)	9.523 (23.402)
(1, 3)	90	0.242 (0.171)	0.069 (0.085)	0.003 (0.021)	0.028 (0.049)	0.061 (0.072)	0.011 (0.014)	0.232 (0.061)	2.835 (5.492)	8.835 (18.040)	3.297 (6.547)
(1, 4)	90	0.244 (0.193)	0.057 (0.096)	0.004 (0.025)	0.024 (0.035)	0.054 (0.063)	0.020 (0.026)	0.314 (0.068)	10.332 (40.652)	134.918 (435.020)	10.684 (21.107)
(2, 2)	90	0.228 (0.188)	0.060 (0.073)	0.000 (0.002)	0.019 (0.028)	0.049 (0.061)	0.015 (0.022)	0.330 (0.070)	3.939 (13.871)	84.905 (195.694)	3.234 (5.662)
(2, 3)	90	0.233 (0.193)	0.057 (0.099)	0.000 (0.001)	0.022 (0.034)	0.063 (0.075)	0.030 (0.039)	0.654 (0.218	31.820 (158.62)	110.803 (407.797)	156.481 (611.40)
(2, 4)	40	0.215 (0.169)	0.055 (0.062)	–	0.014 (0.040)	0.050 (0.056)	0.050 (0.090)	1.668 (0.321)	–	347.795 (595.147)	193.642 (370.50)
Overall[f]	490	0.235 (0.185)	0.060 (0.084)	0.002 (0.011)	0.023 (0.038)	0.057 (0.067)	0.020 (0.031)	0.498 (0.120)	–	–	55.114 (161.491)

(–) not available due to computational times

[a] RPR=$(S_B–S)/S_B$, S_B: the best solution among three heuristic solutions, S: current algorithm solution

[b] Distance constant of integer solution vector (see step 2, phase 1 of NSA, section 5.3)

[c] Mean of RPRs

[d] Standard deviation of RPRs

[e] (r_n, j_r)

[f] Average over the different computational test

The method has dealt with selecting engineering characteristics of product conceptual design and deciding the amount of investment cost for implementing the engineering characteristics considering their correlations, with the objective of maximizing the product design satisfaction under investment budget, resource, and product lifecycle requirement constraints. To our knowledge, there has been not much work for it. To consider product lifecycle requirements and other constraints, the ordinary HOQ is extended and is combined with a MINLP model. Note that this study does not focus on proposing a new QFD method but on the decision support method based on the extended QFD, to resolve the problem that other approaches did not deal with. Then, this study has proposed three heuristic search algorithms to solve the MINLP model, and through a case study and computational experiments, it has shown that the combination of the proposed extended HOQ and MINLP formulation provides a good way to select engineering characteristics and allocate the investment on the engineering characteristics. Also, it has provided algorithms to solve MINLP within a reasonable time. Note that selecting engineering characteristics considering not only customer requirements but also lifecycle requirements under complex correlations among engineering characteristics, resource capacity, and budget constraint, and deciding the amount of investment cost of each engineering characteristics are distinguishable points when compared to other QFD methods. This study gives product design engineers a guideline as to how effectively select engineering characteristics. It also provides how efficiently allocate resources under investment budget and resource constraints. In addition it gives us an insight in dealing with the relation between investment cost and the degree of design quality.

The proposed approach can be applied in the phase of design conceptualization. During the design conceptualization phase, one or multiple product concepts are generated and evaluated through downstream design phases. When evaluating one or multiple product concepts and freezing the best one in the product development, it is important to consider various aspects. In particular, for technology-intensive products, product concepts are usually iteratively refined. The development team revisits the concepts while assessing actual technology constraints and expected production costs. One of the difficult things in these tasks is recognizing and assessing such trade-offs in a way that optimizes the product development. To set the final product concept, the team must frequently consider optimal trade-offs among alternative engineering characteristics of the product considering several constraints. These product development decisions must usually be made quickly and without complete information, which are formidable tasks. In this context, the QFD is one effective method that is simple but powerful and practical. The proposed approach applies the QFD method and MINLP model to derive the engineering characteristics considering multidisciplinary lifecycle requirements, and to allocate suitable resources considering trade-offs, which leads to reduce the time of product concept development.

However, the proposed approach also has some limitations. Under the severe uncertainties in the conceptual design phase, optimal values for investment cost may not make sense. Sometimes, design guidelines such as EcoDesign or heuristics based on qualitative analysis rather than quantitative ones seem to be more suitable in the early design phase. These design guidelines or heuristics may be good solutions when deciding engineering characteristics or allocating resources because they are more flexible and intuitive than quantitative methods. The proposed approach mainly focuses on the quantitative method, which must be the limitation from that viewpoint. But, the QFD method has not only quantitative but also qualitative aspects so that engineers can apply several heuristics or guidelines in considering the relations between customer voices (lifecycle requirements) and engineering characteristics, and selecting relevant engineering characteristics. Moreover, although qualitative methods in the design processes are important, quantitative methods using mathematics and computers must be also indispensable tools to provide engineers with guidelines. The qualitative approaches do not support whole requirements of product lifecycle, and do not quantitatively evaluate trade-offs in allocating appropriate resources. From these viewpoints, the proposed approach can be meaningful.

Another limitation is that the proposed approach may seem to be regarded as one-shot approach for generating the best product concept. Because the concept development phase of the development process demands more coordination among functions than any other, like the set-based concurrent engineering (CE) strategy of Toyota company [47], generating and keeping several alternatives of product concept for further development and testing rather than early fixing one product concept may be more effective in the complex product development process having various situations. The proposed approach must be the quantitative method for generating one engineering design solution that can be used for a product design concept. This study does not focus on claiming that it is important to select the only one "best" product concept. The proposed approach can be applied to both cases, i.e., not only selecting one product concept but also keeping multiple alternatives concepts like the set-based CE approach. The proposed method can be used in deciding the best resource allocation strategy as well as selecting or generating product concepts for each alternative.

The proposed heuristics algorithms may become stuck within local optimum since the considering problem is nonlinear one. Because of the characteristic of the nonlinear problem, it is not easy to identify whether the solution is local optimum or not. In order to avoid the local optimum, when selecting the initial solution vector, the two-phased search algorithm checks whether the objective value of the initial solution vector is higher than those of its neighborhoods or not, with the parameter (ζ) of the Euclidean distance. However, in the cases of the greedy search algorithms, there is no way to identify the local optimum with the proposed search algorithms. Hence, in order to avoid the possibility to stick to local optimum, the proposed algorithms iteratively search solutions with different initial solutions, and select the best one among them, which might have the possibility to stick to local optimum.

In the end, the following can be overcome by further research works. Firstly, it is necessary to develop a more realistic function which represents an accurate relationship between the degree of design quality and the investment cost over the engineering characteristics, by considering several aspects, e.g., the skill levels of product designers. Secondly, one can develop how to consider the relation between lifecycle requirements and engineering characteristics in detail. Although we tried to show the comparison between the two cases (one considers the interrelations among engineering characteristics and the other does not), one can investigate which other relations between engineering characteristics and lifecycle requirements exist and how to consider the relations into the MINLP. Furthermore, one can analyze how considering the interrelations affect the main result. Thirdly, one can elaborate heuristic search algorithms under more complex and realistic problem situations. Finally, the HOQ combined with the mathematical model can be extended not only in evaluating the importance rates of engineering characteristics but also in combining product failure modes analysis with engineering characteristics.

Appendix

Notations

To describe more clearly the problem considered in the study, the following notations are used.

Indices

- c Index for customer requirement, c=1,...,c_n
- i Index for engineering characteristics related to customer requirements, i=1,...,i_n
- j Index for alternative engineering characteristics related to product lifecycle requirement r, j=1,...,j_r
- k Index for indispensable engineering characteristics which should be considered, in association with customer requirements or product lifecycle requirements, k=1,...,k_n, $\{i\} \cap \{k\} = \emptyset$, $\{j\} \cap \{k\} = \emptyset$
- r Index for product lifecycle requirement, r=1,...,r_n
- s Index for all engineering characteristics, s=1,...,s_n
- t Index for resource constraint type, t=1,...,t_n

Parameters

- c_n Number of customer requirements
- i_n Number of engineering characteristics related to customer requirements
- j_r Number of alternative engineering characteristics related to product lifecycle requirement r
- k_n Number of indispensable engineering characteristics
- r_n Number of product lifecycle requirements
- s_n Number of all engineering characteristics, $s_n = i_n + r_n \cdot j_r + k_n$
- t_n Number of types of resource constraints
- M Arbitrary large number
- p_i Importance rate of engineering characteristic i related to customer requirements having no relation to product lifecycle requirements
- p_j^r Importance rate of alternative engineering characteristic j related to product lifecycle requirement r
- $p_k^{'}$ Importance rate of indispensable engineering characteristic k
- R_{ci} Prioritized weight of engineering characteristic i with respect to customer requirement c, $R_{ci} \in \{1,3,5\}$
- R_j^r Prioritized weight of alternative engineering characteristic j related to product lifecycle requirement r, $R_j^r \in \{1,3,5\}$
- $R_k^{'}$ Prioritized weight of indispensable engineering characteristic k, $R_k^{'} \in \{1,3,5\}$
- w_c Weight of customer requirements c, $w_c \in \{1,2,3,4,5\}$
- w_r Weight of product lifecycle requirements r, $w_r \in \{1,2,3,4,5\}$
- w_k Weight of indispensable customer requirements or product lifecycle requirements, $w_k \in \{1,2,3,4,5\}$
- ρ_i Modified importance rate of engineering characteristic i
- ρ_j^r Modified importance rate of alternative engineering characteristic j related to product lifecycle requirement r
- $\rho_k^{'}$ Modified importance rate of indispensable engineering characteristic k
- $\sigma_{q_1 q_2}$ Correlation between engineering characteristic q_1 and q_2, $q_1 \in \{i,j,k\}$, $q_2 \in \{i,j,k\}$, $\sigma_{q_1 q_2} \in \{-3,-1,1,3\}$
- δ_i Required cost to implement engineering characteristic i

δ_j^r Required cost to implement alternative engineering characteristic j related to product lifecycle requirement r

$\delta_k^{'}$ Required cost to implement indispensable engineering characteristic k

δ Total investment budget

λ_{it} Minimum required resource capacity of type t to implement engineering characteristic i

λ_{jt}^r Minimum required resource capacity of type t to implement alternative engineering characteristic j related to product lifecycle requirement r

$\lambda_{kt}^{'}$ Minimum required resource capacity of type t to implement indispensable engineering characteristic k

λ_t Total available resource capacity of type t for product conceptual design

L_{x_i} Lower bound of investment cost of x_i

$L_{x_j^r}$ Lower bound of investment cost of x_j^r

$L_{x_k^{'}}$ Lower bound of investment cost of $x_k^{'}$

U_{x_i} Upper bound of investment cost of x_i

$U_{x_j^r}$ Upper bound of investment cost of x_j^r

$U_{x_k^{'}}$ Upper bound of investment cost of $x_k^{'}$

Decision variables

x_i Amount of investment cost for engineering characteristic i, $i=1,...,i_n$

x_j^r Amount of investment cost for alternative engineering characteristic j related to product lifecycle requirement r, $j=1,...,j_r$, $r=1,...,r_n$

$x_k^{'}$ Amount of investment cost for the indispensable engineering characteristic k, $k=1,...,k_n$, $\{x_i\} \cap \{x_k^{'}\} = \emptyset$, $\{x_j^r\} \cap \{x_k^{'}\} = \emptyset$

y_i Dummy binary variable to indicate whether engineering characteristic i is selected or not, $i=1,...,i_n$

$$= \begin{cases} 1 & \text{if engineering characteristic } i \text{ is considered} \\ 0 & \text{Otherwise} \end{cases}$$

y_j^r Dummy binary variable for alternative engineering characteristic j which is related to a product lifecycle requirement r, $j=1,...,j_r$, $r=1,...,r_n$

$$= \begin{cases} 1 & \text{if engineering characteristic } j \text{ is considered} \\ 0 & \text{Otherwise} \end{cases}$$

$y_k^{'}$ Dummy binary variable for indispensable engineering characteristic k, $k=1,...,k_n$, $\{y_i\} \cap \{y_k^{'}\} = \emptyset$, $\{y_j^r\} \cap \{y_k^{'}\} = \emptyset$

$$= \begin{cases} 1 & \text{if engineering characteristic } k \text{ is considered} \\ 0 & \text{Otherwise} \end{cases}$$

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