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DETERMINATION OF RANGED SETS OF DESIGN SPECIFICATIONS BY INCORPORATING HETEROGENEOUS DESIGN CAPABILITY INFORMATION

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ABSTRACT

Setting design specifications (targets) is a critical task in the early stages of a design process. Flexible targets can accommodate uncertainty and changes in design by postponing design commitments and preserving design freedom. In this work, a new and efficient method for obtaining a ranged set of design specifications that meets the overall design goal while incorporating heterogeneous design capability information is developed. Our proposed method involves two important aspects. First, a quantization algorithm based on rough set theory is used to decompose a design attribute space into subregions based on how well they meet the overall design goal. Second, a new design flexibility measure is used as a metric to select the most desired "target region" based on both the size of the region and the design capability information retrieved from potential design concepts. Our approach captures heterogeneous design capability information in the design attribute space and enhances the ability to adapt to evolving design knowledge as well as unexpected changes. The proposed method is much more efficient than conventional optimization algorithms for solving such problems. The proposed method is demonstrated by a numerical example and the design of a domestic blender.

KEYWORDS

target-driven, design specification, flexibility, design capability, heterogeneity, ranged set of targets

NOMENCLATURE

- a_i potential design alternative
- $D(\mathbf{y})$ density function of design capability
- $E_\mathbf{s}$ design flexibility over a region **s** in design attribute space
- $\mathbf{F}$ single design objective or multiple design criteria used to express overall design goal
- $I_i(\mathbf{y})$ influence function of design capability provided by a design alternative a_i
- $\mathbf{T}$ ranged set of design targets (specifications)
- $\mathbf{y}$ design attributes
- $\boldsymbol{\alpha}$ acceptable threshold on overall design goal
- Ω design attribute space

1 INTRODUCTION

Engineering design is an iterative process that involves the transformation of design requirements into descriptions of design alternatives. In target-driven design [1,2], design requirements are often provided in the form of design specifications that consist of target values of multiple design attributes. These high-level specifications serve as a starting point and are cascaded to guide disciplinary activities at the lower subsystem and component levels. Determining realistic design specifications (targets) is a critical task, especially in the early design stages [3].

Due to limited knowledge of a design artifact before it is fully realized, it is not a trivial task to simultaneously determine targets for multiple design attributes to address the overall goal of the design while considering design capabilities. *Design capability* is defined here as the design performance that is expected to be achieved via downstream design activities. There are several challenges. First, in the early design stages, detailed evaluation models are not yet available. There is limited and abstract information about what a system can achieve [4–6]. The process of target setting is similar in this way to a conceptual design process. Second, target setting for multiple attributes is usually not a simple combination of the most desirable values of individual attributes. Considering that not all combinations of attribute values are feasible, design

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capability information is *heterogeneous* in the attribute space. Third, due to the dynamic nature of the design process, changes in design and production environment are often not predictable. Starting with a single preferred design concept or with a single target value often leads to expensive iterations.

To accommodate uncertainty and changes in design, *flexible* targets (or a ranged set of targets) are desired to preserve design freedom by postponing design commitments. Any design whose performance falls within the specification range is acceptable. Setting a ranged set of targets reduces premature design commitments caused by lack of information. On the other hand, with flexibility in design targets, more design options can be explored. Setting a ranged set of targets is consistent with the principles of "set-based concurrent engineering", which asserts that reasoning and communicating about sets of ideas is preferable to working with one idea at a time [7–9]. The "Second Toyota Paradox" demonstrated that preserving design freedom actually improves both the efficiency (time to market) and the effectiveness (quality) of the design process [8]. Different measures of design flexibility have been proposed in the literature. However, in most of the existing work, design flexibility is represented solely by the size of a target range [10–12], and does not consider the heterogeneous design capability information.

Even though flexible design specifications are desirable, the search for a target region remains a computational challenge. Many existing methods for setting design specifications provide a point-based target (represented by a single target value) for each design attribute. The analytical target setting [13] and the analytical target cascading [1,2] methods identify point-based design specifications through optimization of multilevel hierarchical systems, which requires complete descriptions of design concepts and analytical design models at each design level to capture downstream design capabilities [14]. Chen *et al*. [15] applied the robust design concept to determine flexible top-level design specifications by treating targets as design variables and considering the "noise" associated with them. However, design capabilities associated with later design stages are not considered in their problem formulation. In conclusion, existing methods for target setting either assume that design concepts are fully described or completely ignore downstream design capability information and its heterogeneity.

The research objective of this work is to develop a new and efficient method for obtaining a ranged set of design specifications that meet the overall design goal and provide the maximum design flexibility while incorporating heterogeneous design capability information. The premise of our work is that in the early stages of a design process, even though design concepts (alternatives) are not fully developed, estimates of their achievable performance (design capability) can be obtained in the design attribute space. The achievable performance of potential design alternatives in the attribute space forms the basis for assessing design flexibility. Our proposed method consists of two steps. In Step 1, a design attribute space is decomposed into subregions based on how well they meet the overall design goal. The quantization algorithm [16] based on rough set theory [17] is applied here for space decomposition. In Step 2, a most desired target region (a ranged set of targets) is identified as either one or a combination of several subregions obtained in Step 1. A flexibility measure is developed and used as the metric for selecting the best target region based on the information of design capability retrieved from potential design concepts. Our approach captures the heterogeneous design capability in the design attribute space and enhances the ability of the system to adapt to evolving design knowledge as well as unexpected changes. The method is applicable at various stages in a design process. In this article, we focus on its applications in the early design stages.

The organization of the article is as follows. Terms used throughout the article are defined in Sec. 2. Our proposed method for identifying flexible design specifications is presented in Sec. 3. The implementation of our method is illustrated first by a numerical example in Sec. 4.1, and then in Sec. 4.2 by application to the design of a domestic blender. Conclusions are presented in Sec. 5.

2 DEFINITIONS AND TERMINOLOGY

In this work, engineering design is considered as a collaborative design effort that may involve multiple disciplines and specialty groups, both technical and non-technical. Here we define a few terms that are used throughout this paper.

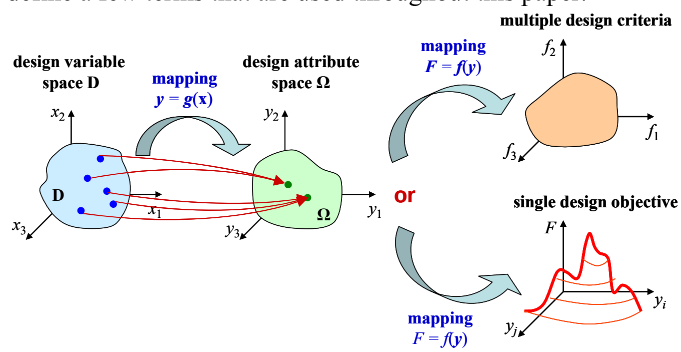


Figure 1 Mappings between different spaces

<u>Design Attribute Space</u>

Design attributes provide quantitative measures of design performance, which are mapped from design options in the design variable (**x**) space D, as shown in Fig. 1. Suppose that a system has *m* design attributes, denoted by a vector **y**= $[y_1, y_2, ..., y_m]$. The space of all possible values of **y** is called the *design attribute space*, denoted as Ω. It should be noted that one point in the design attribute space Ω may correspond to multiple design options in the design variable space D.

<u>Potential Design Alternatives</u>

In the early stages of design, design concepts may not be fully developed, therefore, design descriptions are not fully available in the design variable space D. In this work, design alternatives are described by values of estimated design performance (design attributes **y**). A point *a* in the attribute space Ω is called a *potential design alternative*. Multiple design options in D that correspond to the same point in Ω are considered as distinct alternatives. In a design attribute space, the total set of *n* potential design alternatives is denoted $A = \{a_1, a_2, ..., a_n\}$. We use the word "potential" because design changes may occur and the final design performance may deviate from that estimated in the early stages.

<u>Overall Design Goal and Acceptable Threshold</u>

The overall design goal represents designers' objective or goal for the design. As shown in Fig. 1, the design goal can be either a single design objective (e.g., maximizing profit) or multiple design criteria (e.g., minimizing weight, minimizing production cost, and maximizing efficiency), denoted by a vector $\mathbf{F}$. In this work, the term "objective" is differentiated from "criteria". The former refers to a *single* design objective which may be a function of multiple design attributes. If a single objective function is not available, the overall design goal $\mathbf{F}$ is a vector containing multiple design criteria, each of which is likewise a function of one or more design attributes.

In general, there is a mapping between the design objective/criteria $\mathbf{F}$ and the design attributes $\mathbf{y}$, stated by a (set of) function(s) $\mathbf{f}$, as shown in Eq. (1).

$$\mathbf{F} = \mathbf{f}(\mathbf{y}). \tag{1}$$

The acceptable threshold ($\boldsymbol{\alpha}$) on the overall design goal represents the minimum performance requirement for the design of a system. The acceptable threshold is set by designers on the single design objective or the multiple design criteria by imposing threshold values (e.g., $F>\alpha$ or $F<\alpha$) or by specifying desired ranges (e.g., $\alpha^{L}<F<\alpha^{U}$). It should be noted that threshold values are set in the early stages of design to facilitate concept exploration; these value are not necessarily the same as the desired system performance for the final design.

Ranged Set of Design Targets (Specifications)

In the proposed method, targets for design attributes $\mathbf{y}$ are identified as design specifications to guide further engineering development. In this work, a ranged set of design targets $\mathbf{T}_i$ for an attribute y_i is represented by an interval, as shown in Eq. (2).

$$\mathbf{T}_i = \left\{T : T \in \left[T_i^{L}, T_i^{U}\right]\right\},\ i=1,2,\ldots,m. \tag{2}$$

The set of targets for all m design attributes $\mathbf{y}$ is represented by $\mathbf{T}=\{\mathbf{T}_1,\mathbf{T}_2, \ldots,\mathbf{T}_m\}$. This set forms a "target region" in a multi-dimensional attribute space.

Heterogeneous Distribution of Design Capability Information

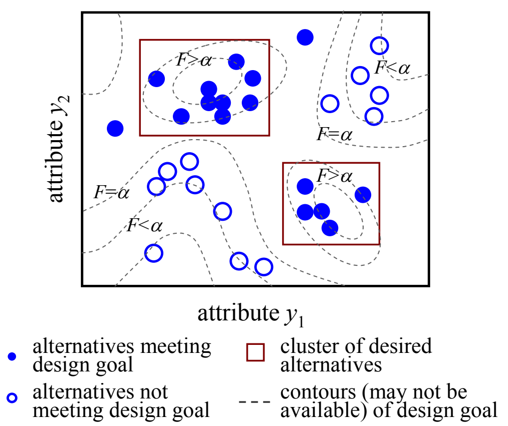


Figure 2 Heterogeneous distribution of design alternatives in the design attribute space Ω

As shown in Fig. 2, potential design alternatives generated in the attribute space Ω usually are not distributed uniformly due to physical restrictions [18], tradeoffs among design attributes, and coupling among various design aspects that address multidisciplinary needs [5]. In addition, the mappings between design variables and attributes are usually not one-to-one, as shown in Fig. 1. This heterogeneous distribution of design alternatives in the attribute space demonstrates a heterogeneous distribution of design capability; this needs to be taken into account when measuring the design flexibility for choosing the best target region.

Design Flexibility over a Target Region

When design flexibility is represented solely by the extent of a target range, a large target range will appear advantageous, but if it contains an unachievable part it may provide little benefit. In this work, a new measure of design flexibility is developed to consider the size of the region as well as the heterogeneous design capability provided by potential design alternatives. Details of the design flexibility metric are presented in Sec. 3.4.

3 METHOD FOR OBTAINING FLEXIBLE DESIGN SPECIFICATIONS

3.1 Problem Description

The problem of identifying flexible design specifications is stated as follows: *Given a finite number of potential design alternatives (represented in design attribute space) and the overall design goal (a single design objective or multiple design criteria) with acceptable threshold, obtain a ranged set of design targets of performance attributes that meets the overall design goal and maximizes the design flexibility.*

Given acceptable threshold $\boldsymbol{\alpha}$ on a single design objective or multiple design criteria $\mathbf{F}$, a set of design alternatives A, **find** a ranged set of targets $\mathbf{T}$, **to maximize** design flexibility over $\mathbf{T}$, **such that** acceptable threshold $\boldsymbol{\alpha}$ is met over $\mathbf{T}$.

Figure 3 Problem of obtaining flexible design specifications on design attributes

Although the problem statement in Fig. 3 very much follows the format of an optimization problem, it is difficult to solve using conventional optimization algorithms. First, searching for an interval of solutions in optimization is computationally much more challenging and numerically less stable than searching for a point solution. Second, as will be discussed in greater detail in Sec. 3.4, evaluations of the design flexibility metric and its derivatives are computationally expensive. Applying derivative-based optimization techniques is therefore not feasible. Third, when candidate design alternatives form disjoint desirable subregions in Ω, optimization often terminates prematurely and returns a sub-optimal region of flexible targets. Information on the capability of alternatives to meet the overall design goal cannot be easily incorporated.

3.2 Overall Procedure

A general procedure for setting flexible design targets is illustrated by the flowchart in Fig. 4. Before applying our method, as many design concepts as possible are generated through conceptualization, searching databases of past designs and design catalogues, benchmarking, and computational methods such as simulation or sampling [19]. The feasible design concepts are represented in the *design attribute space* Ω as a set of potential design alternatives *A*. Values of the single design objective or multiple criteria are evaluated for all potential design alternatives. Satisfaction of the pre-specified acceptable threshold for the overall design goal is also checked.

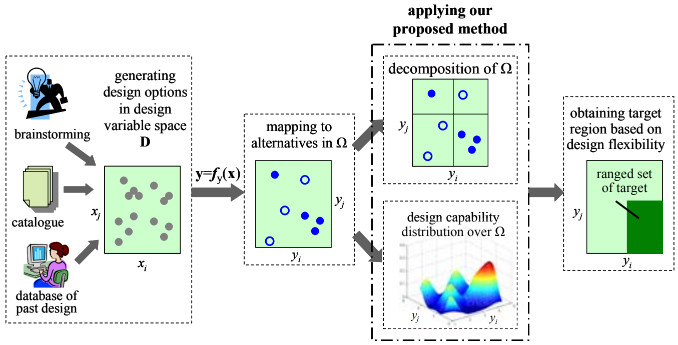


Figure 4 Setting design specifications based on both overall design goal and heterogeneous design capability

As illustrated in Fig. 4, our method contains two major steps.

Step 1: Given the acceptable threshold on the overall design goal and a set of potential design alternatives, the attribute space Ω is decomposed into subregions to differentiate those design alternatives that meet the overall design goal from those that do not. The MD-heuristic quantization algorithm [16] is adopted as an efficient method to find a minimum number of partitions along axes of design attributes for the decomposition of the attribute space. Among the subregions thus obtained, those meeting the overall design goal are referred to as *candidate target regions*. Even though all candidate target regions could be selected to guide the downstream design, in this work, we assume that a range of targets is preferred for each individual design attribute. In that case, the final target region takes the form of a hypercube, which can be either a single candidate region or a combination of several adjacent candidate regions. More details of the use of the quantization algorithm are provided in Sec. 3.3.

Step 2: To obtain a ranged set of targets for each design attribute, the final target region is determined based on the design flexibility evaluated over all candidate target regions. Each potential design alternative provides information about design capability over the design attribute space, modeled by an influence function as presented in detail in Sec. 3.4. The heterogeneous distribution of the overall capability information obtained from all potential design alternatives is modeled by a density function that is the aggregation of all influence functions. As illustrated in Fig. 4, the peaks of the capability distribution correspond to the attribute values that have a large chance to be realized through downstream design activities. The valleys indicate either a relatively small chance to be realized or little capability information available over those areas. Based on the density function obtained, a metric that measures the design flexibility over candidate target regions is used to obtain the most desirable target region that corresponds to as many peaks of the capability distribution as possible. As with set-based concurrent engineering [7–9], downstream design commitments can only be made within assigned ranges.

3.3 Attribute Space Decomposition Based on Rough Set Theory

To identify a ranged set of targets, subregions in an attribute space that meet the overall design goal must first be obtained. This is done using a quantization algorithm based on rough set theory. Before introducing details of the quantization algorithm [16], we first introduce some key concepts associated with rough set theory [17].

Rough set theory, also referred to as rough sets, was developed by Pawlak [17] to abstract information, such as knowledge rules, from available data. Efforts have been made to apply rough sets to engineering design, such as in aesthetic design [20], in design optimization to improve the efficiency of finding a global optimum [21], and in design concepts analysis to detect design inadequacy [22]. Detailed introduction to rough sets can be found in Pawlak [17,23] and Komorowski *et al* [24]. Here, we leave out the mathematical background and highlight the use of rough set theory to identify subregions that meet an overall design goal. The *potential design alternatives* and *design attributes* defined in this work correspond to the *objects* and *conditional attributes* in rough sets, respectively. An index d is defined as

$$d = \begin{cases} 0, & \text{threshold on the overall design goal is not met} \\ 1, & \text{threshold on the overall design goal is met} \end{cases}, \quad (3)$$

Based on rough set theory, a quantization (also called discretization) problem of a continuous real value attribute y is to divide its value range into a finite number of intervals through a set of cuts along y called a *partition* [16]. The partition identified is not necessarily unique. The MD-heuristic quantization algorithm [16,25] is an efficient method to obtain a set of cuts on a minimum number of attributes. As a result, a number of subregions in Ω are identified such that the subregions containing design alternatives with d=1 are differentiated from those containing the alternatives with d=0.

The implementation of the quantization method for attribute space decomposition is described as follows. Suppose that a finite number of potential design alternatives are available in a design attribute space Ω, usually not uniformly distributed. As shown in Fig. 5, the alternatives meeting the overall design goal are denoted as solid dots while others as circles. Each solid dot and circle are considered as a pair. For example, if there are 16 solid dots and 13 circles, as shown in Fig. 5, there are in total 16×13=208 pairs. The MD-heuristic algorithm is applied to find a minimum number of cuts along design attributes to discern all pairs of alternatives with different values of the index d. Correspondingly, the entire range of each attribute is divided into a finite number of intervals. As illustrated in Fig. 6, the two cuts along attribute y_1 and one along y_2 decompose the attribute space into six subregions, such that the alternatives with d=1 and those with d=0 are not contained in the same subregion. If the number of cuts obtained by the quantization along an attribute y_i is equal to k_i, i=1,2,…,m, then the total number of subregions obtained is $\prod_{i=1}^{m}(k_i+1)$.

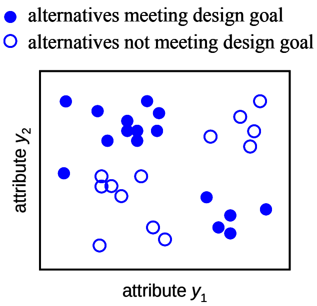


Figure 5 Design alternatives in attribute space

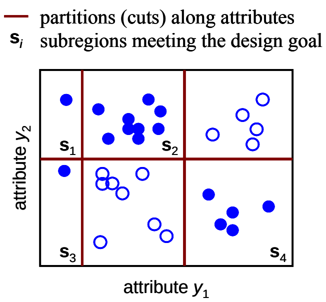


Figure 6 Decomposition of the attribute space

Among all subregions obtained, those meeting the overall design goal are considered as *candidate target regions* and denoted $\mathbf{s}_i$. As observed from Fig. 6, different candidate target regions have different sizes and contain different numbers of potential design alternatives. Intuitively, the more potential alternatives contained in a subregion, the larger the chance to find a feasible design within that subregion through the development in later design stages. Because our interest is to set a target range for each design attribute, the final target region must be a rectangular area in Ω (it cannot be "L-shaped"). This can be either a single candidate target region $\mathbf{s}_i$ or a combination of adjacent regions ($\mathbf{s}_1$ and $\mathbf{s}_2$ or $\mathbf{s}_1$ and $\mathbf{s}_3$ in Fig. 6), determined based on the design flexibility metric.

3.4 Metric for Accessing Design Flexibility

Before presenting the proposed metric of design flexibility, the concept of density function is introduced to model the heterogeneous distribution of design capability. The basic idea is similar to that in Farhang-Mehr and Azarm [26], where the density function is used for assessing the quality of a solution set obtained from multi-objective optimization. Each design alternative provides some design capability information over its neighborhood in the attribute space, modeled by an influence function. The total available information of design capability is the accumulated information provided by all alternatives, modeled by a density function over the attribute space. Based on the density function, a metric of design flexibility over a subregion in Ω is developed based on which the final target region is determined.

Influence Function

In general, an influence function provides the influence of one point over other points in a space [26]. In this work, given that the downstream design activities are capable of realizing a potential design alternative a_i, an influence function indicates the opportunity to achieve other neighboring points in the attribute space under the design and production conditions similar to those associated with a_i. An influence function needs to be created for each alternative. Influence functions may take different forms for different alternatives, and are determined using information provided by discipline designers about their willingness to deviate from a potential design alternative to reach other points in Ω. Mathematically, an influence function can be any nonnegative piecewise continuous function whose value is the largest at a_i and changes with the distance from a_i. Influence functions in a one-dimensional space are illustrated in Fig. 7. Influence functions act as kernels to a density function.

Density Function

Given that all potential alternatives are generated independently and considered equally important, the simplest form of a density function is the summation of all influence functions as

$$\tilde{D}(\mathbf{y}) = \sum_i I_i(\mathbf{y}), \tag{4}$$

where $I_i(\mathbf{y})$ is the influence function for the alternative a_i, i=1,2,…,n. A density function can take other forms that accumulate the capability information provided by each alternative. A density function indicates the uncertainty in the capability of a system to find a feasible design at which the attribute values $\mathbf{y}$ are realized.

In this work, the scaled density function $D(\mathbf{y})$ in Eq. (5) is used, obtained by dividing Eq. (4) by the total volume over Ω underneath the hypersurface of $\tilde{D}(\mathbf{y})$ in Eq. (4).

$$D(\mathbf{y}) = \frac{\sum_i I_i(\mathbf{y})}{\int_\Omega \left[\sum_i I_i(\mathbf{y})\right] d\mathbf{y}}. \tag{5}$$

Note that Eq. (5) provides a normalized density function $D(\mathbf{y})$ so that $\int_\Omega D(\mathbf{y}) d\mathbf{y} = 1$. After this normalization, the density function $D(\mathbf{y})$ over Ω can be used in a manner similar to a joint probability density function (PDF) to capture the uncertainty in the design capability to realize a point in Ω. The aggregation of influence functions at design alternatives to a one-dimensional density function is illustrated in Fig. 8. $D(\mathbf{y})$ is usually a hypersurface in Ω with multiple modes.

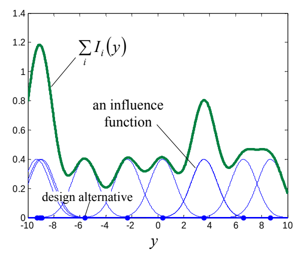


Figure 7 Illustration of influence functions

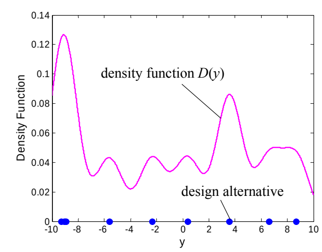
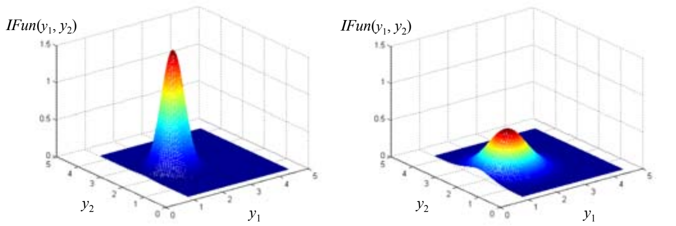


Figure 8 Illustration of a density function

Impact of Influence Function Forms

The forms of influence functions may have a significant impact on the density function and consequently on the final target region obtained. Two forms of influence functions are compared in Fig. 9. The "narrow" influence function in Fig. 9(a) indicates that designers are not willing or allowed to negotiate and modify the design and production conditions associated with a specific design alternative. A "wide" influence function in Fig. 9(b) indicates that designers may have more design freedom and resources. For the set of potential alternatives shown in Fig. 10, the density functions corresponding to these two forms of influence functions are compared in Fig. 11. Each peak in a density function indicates a cluster of potential design alternatives. For simplicity, the form of the influence function is chosen to be the same for all points.

As shown in Fig. 11, density functions over the same set of potential alternatives may be quite different for different influence functions. The density function in Fig. 11(a) corresponding to the "narrow" influence function has multiple peaks of similar heights. The density function in Fig. 11(b) corresponding to the "wide" influence function has one peak that stands above all others. The highest peak indicates the area where designs have the largest chance to be achieved.



a) A "narrow" influence function **b) A "wide" influence function**

Figure 9 Two forms of influence functions

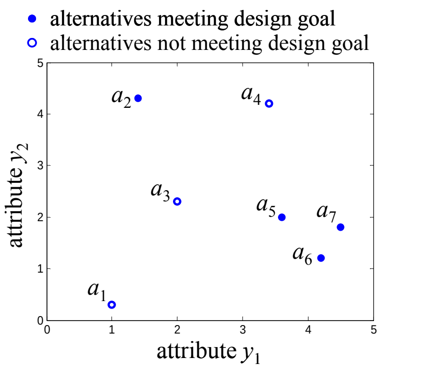
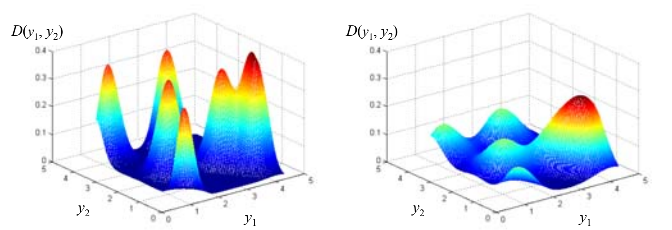


Figure 10 Potential design alternatives



a) Density function corresponding to Fig. 9.a) **b) Density function corresponding to Fig. 9.b)**

Figure 11 Impact of forms of influence functions

Proposed Metric of Design Flexibility

Based on Eq. (5), a metric of design flexibility over a target region **T** is proposed as

$$E_{\mathbf{T}} = \int_{\mathbf{T}} D(\mathbf{y})d\mathbf{y}\,, \tag{6}$$

where $D(\mathbf{y})$ is the density function in Eq. (5). Since $\int_{\Omega} D(\mathbf{y})d\mathbf{y} = 1$, the flexibility measured in Eq. (6) is a scalar between 0 and 1, indicating the accumulated potential of the system to achieve points in the target region **T** considering the uncertainty associated with a design process. A higher value of $E_{\mathbf{T}}$ therefore indicates greater flexibility of a system to achieve points over the region **T** of acceptable design attribute values**.** Peaks of a density function often occur around clusters of potential design alternatives. Also, for a given set of design alternatives, the larger the integration region, the larger the flexibility, because $D(\mathbf{y})$ is non-negative everywhere in Ω.

The evaluation of Eq. (6) can be expressed as

$$E_{\mathbf{T}} = \int_{\mathbf{T}} \frac{\sum_i I_i(\mathbf{y})}{\sum_i \left[\int_{\Omega} I_i(\mathbf{y})d\mathbf{y}\right]} d\mathbf{y} = \frac{\sum_i \int_{\mathbf{T}} I_i(\mathbf{y})d\mathbf{y}}{\sum_i \left[\int_{\Omega} I_i(\mathbf{y})d\mathbf{y}\right]}\,, \tag{7}$$

which involves multivariate integration. Particularly, when influence functions take the forms of PDFs and the volume under each influence function over Ω is approximately 1, Eq. (7) can be simplified as

$$E_{\mathbf{T}} \approx \left[\sum_{i=1}^{n} \int_{\mathbf{T}} I_i(\mathbf{y})d\mathbf{y}\right] \Big/ n\,, \tag{8}$$

where n is the total number of potential design alternatives. This simplification significantly reduces the computational cost for numerical integration.

4 EXAMPLES

4.1 Illustration of the Proposed Method with a Numerical Example

Two design attributes, y_1 and y_2, are considered in the numerical problem. The attribute space is defined as $\Omega = \{(y_1, y_2): -10 \le y_i \le 10,\ i = 1, 2.\}$. The overall design goal is stated by a single design objective, $F = 0.01\left[(y_1 - 2)^2 + y_2\right]$. The acceptable threshold is set as $F \geq 0.3$.

Ten design options are generated randomly in the design variable space $\mathbf{x}=\{x_1, x_2, x_3\} \in$ D. Two kriging models are given that map the options in D to y_1 and y_2, respectively. The two design attributes are evaluated at all ten design options as listed in Table 1. Before applying the quantization algorithm from Nguyen and Skowron [16], all potential alternatives are checked for *indiscernibility* with respect to each attribute. The indiscernibility check helps reduce the complexity of a quantization problem. In this example, it is noted that a_3 $ind(y_1)$ a_4, and a_2 $ind(y_1)$ a_9 $ind(y_1)$ a_{10}. Therefore, a_3 and a_4 can be considered as the same with respect to y_1. The same treatment is applied to (a_2, a_9, a_{10}) with respect to y_1.

Table 1 Potential design alternatives

	x_1	x_2	x_3	y_1	y_2	F
a_1	0.20	8.95	195.01	-5.62	0.59	0.5865
a_2	-0.12	7.44	123.11	-9.06	3.42	1.2574
a_3	1.30	3.62	160.68	3.58	-9.85	-0.0735
a_4	-1.67	4.20	148.60	3.59	-2.33	0.0020
a_5	0.63	9.22	189.13	8.69	-8.66	0.3610
a_6	1.10	2.25	176.21	-2.33	-1.65	0.1710
a_7	0.93	10.91	145.65	0.39	3.74	0.0633
a_8	0.78	9.84	101.85	6.62	1.78	0.2312
a_9	0.24	2.89	182.14	-9.31	8.61	1.3653
a_{10}	0.88	5.67	144.47	-8.93	6.92	1.3638

Step 1: Attribute Space Decomposition

The potential design alternatives in Table 1 are plotted in Fig. 12. In total, there are five potential alternatives with $F \geq 0.3$ (illustrated by solid dots) and five with $F<0.3$ (illustrated by circles). A *pair of alternatives* consists of one satisfactory alternative and one with $F<0.3$. In total, there are twenty-five pairs of alternatives. The MD-heuristic quantization algorithm is applied to identify a minimum number of partitions along attributes to separate all pairs of alternatives. In other words, the algorithm decomposes the attribute space into subregions such that the two alternatives in each pair are separated. Detailed descriptions on the MD-heuristic quantization algorithm can be found in Nguyen and Skowron [16], Nguyen [25], and Shan and Wang [21].

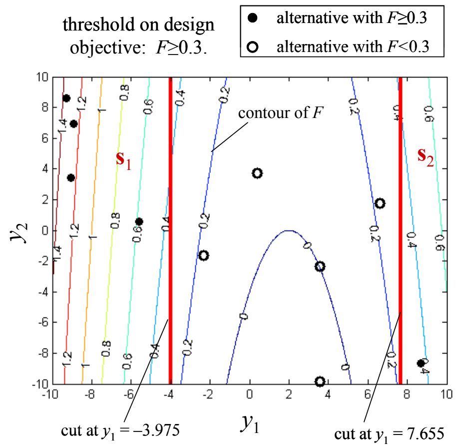


Figure 12 Candidate target regions obtained using the quantization algorithm

Applying the quantization algorithm, cuts are obtained at y_1=–3.795 (discerning twenty pairs of alternatives) and at y_1=7.655 (discerning five pairs). For this example, only two cuts are needed, both along y_1; no cut is needed along the y_2 axis, as shown in Fig. 12. Correspondingly, two candidate regions $\mathbf{s}_1$ and $\mathbf{s}_2$ are obtained, as listed in Table 2. They both correspond to $F\geq0.3$. From the contours of the design objective F plotted in Fig. 12, we note that the two cuts obtained are located between the contour curves of F=0.2 and F=0.4. This demonstrates that candidate subregions $\mathbf{s}_1$ and $\mathbf{s}_2$ do meet the acceptable threshold on F, i.e., $F\geq0.3$.

Table 2 Candidate target regions with $F\geq0.3$

		$\mathbf{s}_1$	$\mathbf{s}_2$
Candidate regions	y_1	[–10, –3.975]	[7.655, 10]
	y_2	[–10, 10]	[–10, 10]
# of a_i included with $F\geq0.3$		4	1
Flexibility, E_{si}		0.3303	0.0597

The quantization results also provide the sensitivity of the ability to meet the acceptable threshold on F to each design attribute. Because no cut is needed along y_2, it indicates that whether the acceptable threshold on F can be met or not is not sensitive to values of y_2. The MD-heuristic algorithm is computationally very efficient because the attribute space decomposition is conducted by simple matrix operations, such as row and column eliminations.

Step 2: Determination of the Ranged Set of Targets Based on Design Flexibility

In this example, it is assumed that the final target region is desired to be a hypercube. Since the two candidate regions $\mathbf{s}_1$ and $\mathbf{s}_2$ are disjoint from each other, the choice between $\mathbf{s}_1$ and $\mathbf{s}_2$ is made based on the design flexibility metric in Eq. (6). The influence functions are chosen to be bivariate normal PDFs:

$$I_i(\mathbf{y}) = \frac{1}{2\pi|\boldsymbol{\Sigma}_i|^{1/2}} \cdot \exp\left[-\frac{1}{2}(\boldsymbol{\mu}_i - \mathbf{y})^{\mathrm{T}} \boldsymbol{\Sigma}_i^{-1} (\boldsymbol{\mu}_i - \mathbf{y})\right],\ i=1,2,\ldots,10, \tag{9}$$

where $\boldsymbol{\mu}_i$ is the location of the alternative a_i, and $\boldsymbol{\Sigma}_i$ is a covariance matrix, assumed to be a two-by-two identity matrix. The density function is obtained using Eq. (5), aggregating the influence functions of all ten potential alternatives.

The design flexibility values obtained over $\mathbf{s}_1$ and $\mathbf{s}_2$ are listed in the last row in Table 2. It can be seen that $\mathbf{s}_1$ has the larger flexibility value, 0.3303. Therefore, the subregion $\mathbf{s}_1$ is chosen as the final target region, and the ranged set of design specifications is given by the intervals [–10, –3.975] for y_1 and [–10, 10] for y_2. For this example, choosing $\mathbf{s}_1$ as the final target region based on the flexibility metric is consistent with our visual interpretations. As observed from Fig. 12, $\mathbf{s}_1$ contains more potential alternatives and has a larger size than $\mathbf{s}_2$.

4.2 Design of a Domestic Blender

The major function of domestic blenders is to blend ingredients completely, smoothly, and quickly, under various speed settings and with different amounts of ingredients in the container. A mapping between customers' interests and the attributes used in a blender design is illustrated in Table 3. Based on how strongly attributes are related to customers' interests, four key attributes of a blender are identified as the *motor power*, the *jug capacity*, the *allowable speed levels*, and the *retail price*. The first three are engineering attributes, each associated with a particular subsystem of the blender, i.e., the base (including the motor), the container (including the jug and the lid), and the speed control devices, respectively. The targets set for these attributes will serve as the starting point for subsystem design.

Table 3 Relations between customer interests and design attributes of a blender

Attributes / Customer interests	**Motor Power**	**Jug Capacity**	**Speed Levels**	**Price**	Warranty	Weight	Size	Noise	Sealing	Jug Material	Blade material
Construction						√	√				
Complete mixture	√	√	√								√
Fast blending	√	√	√								√
No leakage									√		
Ease of use			√								
Comfort of use		√				√	√	√		√	
Ease of cleaning											
Reliability					√						
Price				√							

Interrelations among the four attributes lead to heterogeneous design capability in the design attribute space. For example, a larger jug capacity requires larger motor power to provide enough torque to handle ingredients in the container. With a large power, a blender can fulfill its job at relatively low speed settings and handle tough ingredients, such as frozen fruits.

4.2.1 Two Design Scenarios

In this case study, we illustrate how our proposed method can be applied to different design scenarios with differently stated design goals. For a profit-driven company, the ultimate goal is to maximize the profit, computed as the difference between the revenue and cost involved:

$$\text{Profit} = \text{Demand} \cdot \text{Price} - \text{Cost}\,. \quad (10)$$

If the price is a constant, maximizing the profit is equivalent to some combination of maximizing demand and minimizing cost. Demand and cost are both functions of engineering design attributes. The former reflects how customers' preferences change with design and the latter is related to the cost of producing the product. Demand can be derived from the following function.

$$\text{Demand} = \text{Market Share} \cdot \text{Market Size}\,, \quad (11)$$

where the entire market size is considered as a constant and the market share can be estimated as a function of product attributes using market analysis techniques such as Discrete Choice Analysis [27].

Two design scenarios are considered here, both in the early stages of blender design. In the ***first design scenario***, it is assumed that the total market size is unknown and the price has not been determined yet. The goal to maximize the profit (at least larger than \$100,000) is represented by two design criteria: maximize market share and minimize production cost, stated as

$$\mathbf{F} = \{(PC, MS): PC \le \$20, MS > 16\%\}, \quad (12)$$

where PC is the production cost per unit (\$) and MS is the market share, in percentage. The vector **y** contains the four key attributes identified above:

$$\mathbf{y} = [MP, JC, SL, P], \quad (13)$$

where MP is the motor power (watt), JC is the jug capacity (oz), SL is the number of speed levels, and P is the price (\$).

In the ***second scenario***, the overall design goal is stated as a single design objective to maximize profit. The profit should at least exceed the threshold \$100,000. Targets are to be set for five design attributes:

$$\mathbf{y} = [MP, JC, SL, P, PC]. \quad (14)$$

Compared to the list of attributes considered for the first scenario, in the second scenario, PC (Production Cost) is added, a useful target to guide next stage engineering activities.

4.2.2 Method Implementation

A set of blender design concepts is first identified. For each design concept deemed feasible, corresponding attribute values are evaluated. In total, twenty potential design alternatives are obtained, as listed in Table 4. Values of the production cost, market share, and profit are estimated for each alternative. For the first scenario, there are seven potential alternatives that meet the thresholds on both design criteria. In the second scenario, there are ten potential alternatives meeting the threshold on the profit. In both scenarios, it is assumed that influence functions follow the multivariate normal PDF in Eq. (9) with $\boldsymbol{\mu}_i$ as the location of an alternative and the diagonal entries in $\boldsymbol{\Sigma}_i$ assumed to be 30% of $\boldsymbol{\mu}_i$. It should be noted that for both scenarios the final ranged set of targets is assumed to be a single hyperbox, determined based on the design flexibility metric.

Table 4 Potential design alternatives generated

Motor power (w)	Jug capacity (oz)	Speed levels	Price (\$)	Production cost per unit (\$)	Market share (%)	Profit (\$)
350	36	8	18.9	11.54	13.60	5.80e+4
350	48	2	20.15	13.23	15.40	6.30e+4
375	48	10	23.76	14.60	19.23	1.11e+5
390	40	∞[1]	26.23	20.75	14.82	5.31e+4
400	56	8	28.35	18.79	18.43	1.12e+5
400	32	3	21.56	11.92	13.72	8.05e+4
400	40	12	25.39	13.16	20.76	1.46e+5
400	48	7	26.05	15.09	18.81	1.32e+5
400	50	10	26.71	16.26	18.69	1.29e+5
425	48	5	27.64	16.04	16.74	1.23e+5
450	40	3	27.61	14.72	16.58	1.17e+5
450	50	18	31.67	23.23	14.33	7.25e+4
475	42	6	30.2	16.90	14.95	1.27e+5
500	40	5	31.46	18.76	13.86	1.01e+5
500	44	20	36.2	24.98	10.49	7.03e+4
500	48	12	33.18	20.83	13.71	1.06e+5
500	54	2	33.29	21.92	12.97	9.02e+4
525	58	7	34.46	26.27	9.12	4.92e+4
550	42	3	34.28	22.07	10.32	7.92e+4
600	50	5	38.83	27.39	7.02	5.42e+4

Ranged Set of Targets in Scenario One

Based on the two design criteria stated in Eq. (12), a set of partitions in the attribute space is obtained as {P=\$22.66, P=\$29.275, SL=15}, using the MD-heuristic method. There is no partition along motor power and jug capacity. Correspondingly, the attribute space is decomposed into six subregions, of which only one meets both design criteria. This subregion is taken as the final ranged set of targets as

$$\mathbf{T} = \{350\text{w} \le MP \le 600\text{w};\ 32\text{oz} \le JC \le 58\text{oz};\ 2 \le SL \le 15;\ \$22.66 \le P \le \$29.275\}. \quad (15)$$

All seven potential alternatives that meet both design criteria are included in the target region **T**. The design flexibility over **T** is 0.2368.

Ranged Set of Targets in Scenario Two

In the second scenario, based on the single design objective, the set of cuts identified by the quantization method is given by {MP=362.5w, MP=382.5w, MP=395w, P= \$22.66, PC=\$19.77, PC=\$21.375}. There is no partition on the jug capacity and the speed levels, indicating values of these attributes are less critical to the profit meeting the acceptable threshold. In total, the five-dimensional attribute space is divided into twenty-four subregions, among which three meet the goal for desired profit (Fig. 13 and Table 5).

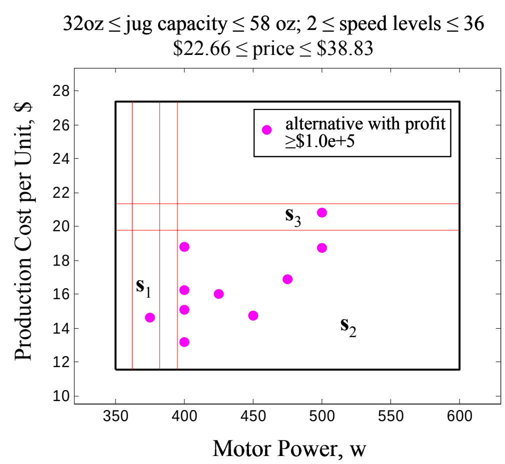


Figure 13 Three candidate target regions obtained in the second scenario

[1] The speed setting "∞" means that any speed within certain range can be reached. The number of speed levels is set to 36 for this case.

Table 5 Candidate target regions with profit ≥$100,000

	$\mathbf{s}_1$	$\mathbf{s}_2$	$\mathbf{s}_3$
MP (w)	[362.5, 382.5]	[395, 600]	[395, 600]
JC (oz)	[32, 58]	[32, 58]	[32, 58]
SL	[2, 36]	[2, 36]	[2, 36]
Price ($)	[22.66, 38.83]	[22.66, 38.83]	[22.66, 38.83]
PC ($)	[11.54, 19.77]	[11.54, 19.77]	[19.77, 21.375]
# of a_i with profit ≥$100,000	1	8	1
Flexibility, E_{si}	0.00034	0.0055	0.0016

As observed from Table 5, the ten alternatives meeting the profit threshold of $100,000 are included in the three candidate target regions identified. It is noted that the candidate region $\mathbf{s}_2$ contains more potential alternatives and has a larger size than $\mathbf{s}_1$ and $\mathbf{s}_3$. This is verified by evaluating the design flexibility over all three candidate regions. As shown in the last row of Table 5, $\mathbf{s}_2$ has the highest design flexibility, 0.0055. However, the candidate regions $\mathbf{s}_2$ and $\mathbf{s}_3$ are adjacent to each other. The combination of $\mathbf{s}_2$ and $\mathbf{s}_3$ results in a target region with a larger degree of flexibility, expressed as

$$\mathbf{T} = \{395\text{w}\leq \text{MP}\leq 600\text{w};\ 32\text{oz}\leq \text{JC}\leq 58\text{oz};\ 2\leq \text{SL}\leq 36;\ \$22.66\leq \text{P}\leq \$38.83;\ \$11.54\leq \text{PC}\leq \$21.375\}. \quad (16)$$

4.2.3 Observations

The major observations from the blender design problem are summarized as follows. First, comparing the target regions obtained under two design scenarios as shown in Eqs. (15) and (16), the design of a blender as a multicriteria problem tends to identify a target region corresponding to a low price, such as $22.66≤Price≤$29.275 in the first scenario. A wider price range is identified as $22.66≤Price≤$38.83 in the second scenario. This is probably because the impact of price and market size on the profit is not captured in the first scenario, where market share and cost are considered as two separate criteria.

Second, the final target region obtained may be sensitive to the acceptable threshold values assigned (see Table 6). Moreover, with different thresholds, the numbers of potential alternatives that meet the design goal are also different.

Table 6 Impact of design criteria on the target region obtained

		Case 1	Case 2	Case 3
Design criteria		PC<$20 & MS>16%	PC<$20 & MS>18%	PC<$16& MS>16%
T	MP (w)	[350, 600]	[350, 412.5]]	[412.5, 600]
	JC (oz)	[32, 58]	[32, 58]	[32, 58]
	SL	[2, 15]	[2, 15]	[2, 36]
	Price ($)	[22.66, 29.275]	[22.66, 38.83]	[26.14, 27.625]
# of a_i contained		7	5	4

Third, in both scenarios, it is observed in attribute space decomposition that there are attributes along which no partition is needed, such as the jug capacity. This indicates that the ability to meet the threshold for the design goal is insensitive to values of those attributes (and thus to the design of related subsystems). Therefore, the numbers of cuts obtained along design attributes provide relative sensitivity information of meeting the design goal to each design attribute.

5 CONCLUSIONS

In this paper, a new and efficient method is developed that is able to obtain ranged sets of design specifications (targets) that not only meet an overall design goal but also incorporate design capability information. Based on rough set theory, a design attribute space is decomposed to identify candidate regions that meet an acceptable threshold on the design goal. A design flexibility metric is proposed to capture the distribution of design capability and its heterogeneous nature in the attribute space. Our method has the flexibility to be applied to design cases where the overall design goal is stated by either multiple design criteria or a single design objective, as demonstrated by the example of the design of a domestic blender. The major advantages of our proposed method are summarized as follows.

First, with flexible targets, design freedom is preserved in a design process, indicating that more design options can be explored to obtain a design closer to the optimal. A ranged set of design targets also enhances the ability of a system to accommodate unexpected changes in a design process. Furthermore, better coordination among disciplines or specialty groups is expected, which helps reduce the number of iterations in a design process. As a result, both efficiency (time to market) and effectiveness (quality of final design) of a design process can be improved.

Second, our approach is applicable in the early stages of a design process when detailed design models are not yet available. The quantization algorithm used for attribute space decomposition has the flexibility to deal with both quantitative and qualitative values. Our method does not require prior knowledge about the relative importance of different attributes.

Third, the proposed method can be extended to study the sensitivity of the overall design goal with respect to each design attribute. When there is a large number of design attributes, the sensitivity information obtained through attribute space decomposition can be used to identify key attributes. In multidisciplinary design, such sensitivity information can help allocate limited design resources to specialty groups.

Fourth, our method is much more efficient than traditional optimization approaches. With our method, candidate target regions are obtained through simple matrix operations. For the same task of searching for a range of solutions, optimization may terminate prematurely or converge to a sub-optimal region. Optimization approaches can be extremely computationally expensive when multivariate integrations are involved in the evaluations of the flexibility metric and its derivatives.

It should be noted that values of the acceptable threshold on the overall design goal may have a large impact on the final target region obtained. If a threshold is set too high so that few or none of the potential design alternatives pass the threshold, designers should consider whether to explore further for more design concepts or to lower the threshold. Step 1 of our method can be applied repeatedly for this purpose.

Our approach has been demonstrated by design examples in which the design objective and criteria are considered to be deterministic. The same approach can be applied to design under uncertainty by incorporating probabilistic characteristics (e.g., robustness and reliability) into the design goal, which is a subject of our future work.

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