Determination of Ranged Sets of Design Specifications by Incorporating Design Space Heterogeneity

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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 method is developed for obtaining a ranged set of design specifications that meets design criteria while incorporating design space heterogeneity, meaning some areas in the design attribute space are more achievable than the others. There are two notable features of the proposed method. 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 design criteria. 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 influence of potential design alternatives on overall achievability. The proposed approach enhances the ability of a design system to adapt to evolving design knowledge as well as unexpected changes. The proposed method is demonstrated by a numerical example and the design of a domestic blender.

Keywords: design specification, flexibility, design attribute, heterogeneity, ranged set of targets

Nomenclature

a_j/$\mathbf{A}$	potential design alternative/ set of potential design alternatives
$D(\mathbf{y})$	aggregated influence function
$E_{\mathbf{s}}$	design flexibility over a subregion **s** in a design attribute space
$\mathbf{F}$	single or multiple design criteria
$I_j(\mathbf{y})$	influence function of a design alternative a_j
$\mathbf{T}$	ranged set of design targets (specifications)
$\mathbf{x}$/X	design variables/design variable space
$\mathbf{y}$/Ω	design attributes/ design attribute space
$\boldsymbol{\alpha}$	acceptable threshold(s) on design criteria

1 Introduction

Engineering design is an iterative process that involves the transformation of design requirements into descriptions of design alternatives. In target-driven design (Kim et al. 2003a, Kim et al. 2003b), 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 (Ge et al. 2005).

Because knowledge of a design artifact is limited before the design is fully realized, it is not a trivial task to determine targets for multiple design attributes to meet design criteria while considering achievability via downstream design activities. There are several challenges. First, in the early design stages, detailed evaluation models are not yet available. Information about what a system can achieve is usually limited and abstract (Pacheco et al. 2003, Wood and Agogino 2005, Huang et al. 2005a). The process of target setting is similar in this way to a conceptual design process. Second, target setting for multiple performance attributes is usually not a simple combination of the most desirable values of individual attributes. The design attribute space is *heterogeneous* in the sense that some areas are more achievable than the others. Third, due to the dynamic nature of the design process, changes in the 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 (Sobek II and Ward 1996, Sobek II and Ward 1999, Ford and Sobek II 2005). 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 (Sobek II and Ward 1999). 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 (Simpson et al. 1998, Chen and Yuan 1999, Olewnik et al. 2004), and does not consider the design space heterogeneity.

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 (Cooper et al. 2006) and the analytical target cascading methods (Kim et al. 2003a, Kim et al. 2003b) 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 (Michelena et al. 2003). Chen et al. (1997) 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 space heterogeneity was not considered in their problem formulation. Above methods for target setting either assume that design concepts are fully described or completely ignore design space heterogeneity.

The research objective of this work is to develop a new and efficient method for obtaining a ranged set of design specifications that meets the design criteria and provides the maximum design flexibility while incorporating the *design space heterogeneity*, which is defined as the extent to which some areas in a design attribute space are more achievable than the others. The premise is that in the early stages of a design process, even though design concepts (alternatives) are not fully developed, estimates of their achievable performance attributes 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. The proposed method consists of two steps. In Step 1, a design attribute space is decomposed into subregions based on how well they meet the design criteria. The quantization algorithm (Nguyen and Skowron 1995) based on rough set theory (Pawlak 1982) 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 potential achievability retrieved from the influence of potential design concepts. The proposed approach enhances the ability of the system to adapt to evolving design knowledge as well as unexpected changes. The method is applicable for setting targets on performance attributes at various stages in a design process. In this article, the focus is 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. The proposed method for identifying flexible design specifications is presented in Sec. 3. The implementation of the developed 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 effort that may involve multiple disciplines and specialty groups, both technical and non-technical. Some terms that are used throughout this paper are defined here. Most of these definitions are consistent with those provided in Messac and Chen, 2002.

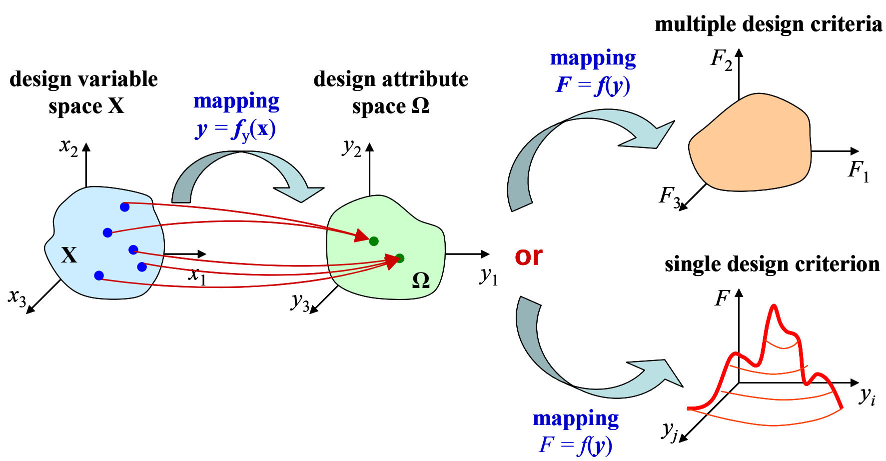

Figure 1 Mapping between different spaces

<u>Design Attribute Space</u>

Design attributes provide quantitative measures of design performance and are mapped from design options in the design variable (**x**) space X, as shown in Figure 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 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 X.

Potential Design Alternatives

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 X. In this work, design alternatives are described by values of estimated design performance expressed as design attributes **y**. A point *a* in the attribute space Ω is called a *potential design alternative*. Multiple design options in X 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 $A = \{a_1, a_2, ..., a_n\}$. The word "potential" is used here because design changes may occur and the final design performance may deviate from the estimated performance.

Design Criteria and Acceptable Threshold

As shown in Figure 1, the overall goal of design can be represented by either a single design criterion (e.g., maximizing profit), a scalar, or multiple design criteria (e.g., minimizing weight, minimizing production cost, and maximizing efficiency), denoted by a vector **F**. The single design criterion can be viewed as a special case of the latter.

In general, there is a mapping between the design criteria **F** and the design attributes **y**, given by a (set of) function(s) **f**, as shown in Equation (1).

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

The acceptable threshold ($\boldsymbol{\alpha}$) on design criteria represents the minimum performance requirement. The acceptable threshold is set by designers for each design criterion (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 often set based on the minimum design expectation in the early stages of design to facilitate concept exploration.

<u>Ranged Set of Design Targets (Specifications)</u>

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 Equation (2).

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

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.

<u>Design Space Heterogeneity</u>

As shown in Figure 2, potential design alternatives generated in the attribute space Ω usually are not distributed uniformly due to physical restrictions (Klein et al. 2003), tradeoffs among design attributes, and coupling among various design aspects that address multidisciplinary needs (Wood and Agogino 2005). In addition, the mappings between design variables and attributes are usually not one-to-one, as shown in Figure 1. The non-uniform distribution of design alternatives and their influence suggest that some areas in an attribute space are more achievable than the others. Such design space heterogeneity must be taken into account when measuring the design flexibility for choosing the best target region.

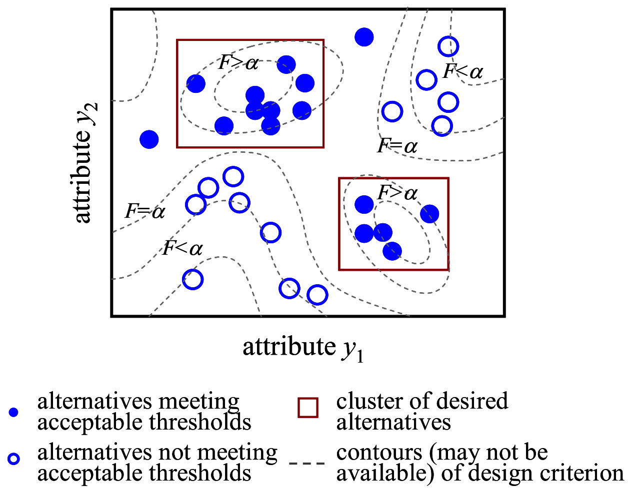

Figure 2 Heterogeneous design attribute space Ω

<u>Design Flexibility over a Target Region</u>

When design flexibility is represented solely by the extent of a target range, a large target range will appear advantageous, but if most parts of it are unachievable it may provide little benefit. In this work, a new measure of design flexibility is developed to consider the size of the desired region in the attribute space as well as the potential achievability retrieved from the influence of 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 design criteria with acceptable thresholds, obtain a ranged set of design targets of performance attributes that meets design criteria and maximizes the design flexibility.*

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

Figure 3 Problem of obtaining flexible design specifications on design attributes

Although the problem statement in Figure 3 follows the format of an optimization problem, it is difficult to solve using conventional gradient-based 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, the flexibility metric involves integration, and thus evaluations of the design flexibility metric and its derivatives are computationally expensive and numerically unstable. Applying derivative-based optimization techniques therefore may not be feasible. Third, when candidate design alternatives form disjoint desirable regions in Ω, optimization often terminates prematurely and returns a sub-optimal region of flexible targets. The heterogeneous character of the design attribute space cannot be easily incorporated.

Evolutionary (global) optimization algorithms can be used to find an optimal solution to the problem in Figure 3. However, global search algorithms typically require hundreds or even thousands of iterations for convergence. Even though "the optimal" solution is not guaranteed, the proposed method is expected to work more efficiently than global search algorithms because the number of function evaluations required is at most $\prod_{i=1}^{m}(k_i+1)$

where k_i is the number of partitions along the i^{th} attribute. More details are presented in Section 3.3.

3.2 Overall Procedure

A general procedure for setting flexible design targets is illustrated by the flowchart in Figure 4. Before applying the proposed 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, sampling (Huang et al. 2005b), and Constraint Programming (Lottaz et al. 1999, Lottaz et al. 2000, Yannou et al. 2003, Yannou et al. 2005). The feasible design concepts are represented in the *design attribute space* Ω as a set of potential design alternatives A. Values of design criteria are estimated for all potential design alternatives. Satisfaction of the pre-specified acceptable threshold for the design criteria is also checked. It should be noted that in the early design stage design concepts are not yet fully developed and only the estimations of design attribute values are provided.

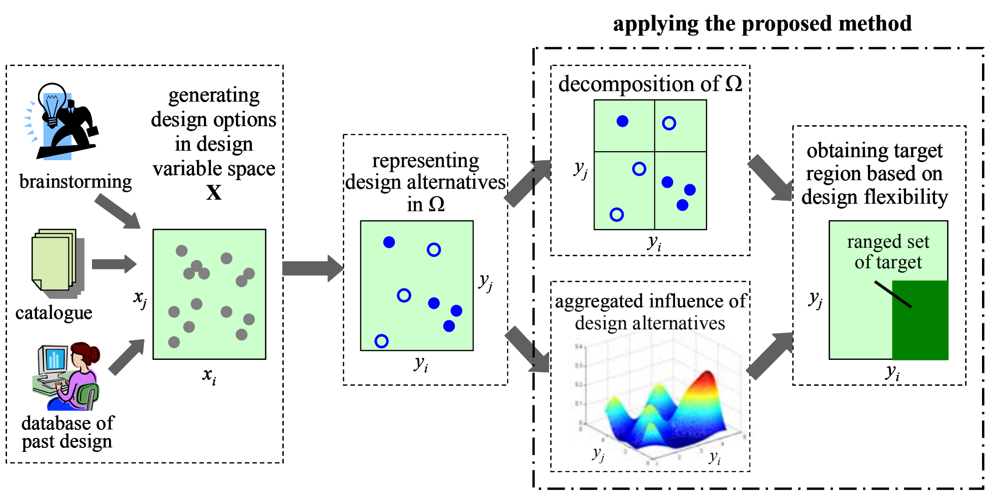

Figure 4 A general procedure for setting flexible design specifications

As illustrated in Figure 4, the proposed method contains two major steps:

Step 1: Given the acceptable thresholds on design criteria and a set of potential design alternatives, the attribute space Ω is decomposed into subregions to differentiate those design alternatives that meet the thresholds from those that do not. The MD-heuristic quantization algorithm (Nguyen and Skowron 1995) is adopted as an efficient means 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 thresholds are referred to as *candidate target regions.* Even though all candidate regions could be selected as the final target region to guide the downstream design, in this work, it is assumed 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 its influence on achieving other points over the design attribute space, modeled by an influence function as presented in detail in Sec. 3.4. The overall influence information retrieved from all potential alternatives, modeled by an aggregated influence function, indicates the potential achievability of points in an attribute space. As illustrated in Figure 4, the peaks of the aggregated influence function correspond to the attribute values that have a relatively large chance to be realized through downstream design activities. The valleys indicate either a relatively small chance to be realized or little information available over those areas. Based on the aggregated influence function obtained, a metric that measures the design flexibility integrated over candidate target regions is used to obtain the most desirable target region. As with set-based concurrent engineering (Sobek II and Ward 1996, Sobek II and Ward 1999, Ford and Sobek II 2005), 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 acceptable thresholds must first be obtained. This is done using a quantization algorithm based on rough set theory. Before introducing details of the quantization algorithm, some key concepts associated with rough set theory (Pawlak 1982) are introduced first.

Rough set theory, also referred to as rough sets, was developed by Pawlak (1982) 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 (Yanagisawa and Fukuda 2003), in design optimization to improve the efficiency of finding a global optimum (Shang and Wang 2004), and in design concepts analysis to detect design inadequacy (Alisantoso et al. 2005). Detailed introductions to rough sets and their mathematical background can be found in Pawlak (1982 and 1991) and Komorowski et al. (1998). The brief discussion here highlights the use of rough set theory to identify subregions that meet design criteria. The *potential design alternatives* and *design attributes* defined in this work correspond to the *objects* and *conditional attributes* in rough sets, respectively. A decision attribute d is defined in this article as

$$d = \begin{cases} 0, & \text{thresholds on design attributes are not met} \\ 1, & \text{thresholds on design attributes are met} \end{cases} \tag{3}$$

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* (Nguyen and Skowron 1995). The partition identified is not necessarily unique. The MD-heuristic quantization algorithm (Nguyen and Skowron 1995, Nguyen 1998) is an efficient method for obtaining 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 quantization method for attribute space decomposition is implemented as follows. Suppose that a finite number of potential design alternatives are available in a design attribute space Ω, usually not evenly distributed. As shown in Figure 5, the alternatives meeting the acceptable threshold are denoted as solid dots while those that do not are denoted as circles. Each solid dot and circle are considered as a pair of objects with different decision values (Shan and Wang, 2004), which can be regarded as an edge in a complete bipartite graph. For example, if there are 16 solid dots and 13 circles, as shown in Figure 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 Figure 6, the two cuts along attribute y_1 and the one along y_2 decompose the attribute space into six subregions, such that no subregion contains both alternatives with d=1 and alternatives with d=0. 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 $\prod_{i=1}^{m}(k_i+1)$. Using the MD-heuristic algorithm for attribute space decomposition is quite efficient as the algorithm uses simple matrix operations, such as row and column elimination. The heuristic algorithm can therefore handle a large number of design attributes.

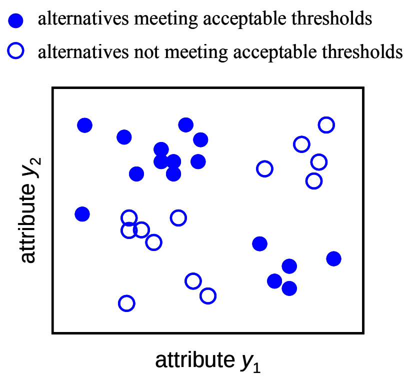

Figure 5 Design alternatives generated

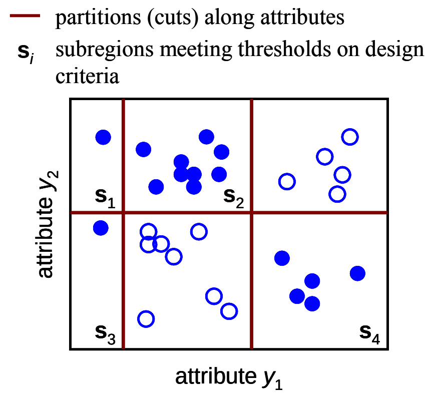

Figure 6 Decomposition of the attribute space

Among all subregions obtained, those meeting the thresholds of design criteria are considered as *candidate target regions* and denoted as $\mathbf{s}$. Because the interest of this article is to set a target range for each design attribute, the final target region must be a rectangular area in Ω (for example, it cannot be "L-shaped"). This can be either a single candidate target region $\mathbf{s}_k$ or a combination of adjacent regions ($\mathbf{s}_1$ and $\mathbf{s}_2$ or $\mathbf{s}_1$ and $\mathbf{s}_3$ in Figure 6), determined based on the design flexibility metric.

3.4 Metric for Assessing Design Flexibility

As observed from Figure 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 an achievable design through development in later design stages. However, the final target region cannot be solely determined based on the number of potential alternatives contained or on the dispersion of potential alternatives. The potential of achieving neighboring points of a design alternative should also be taken into consideration. The number of potential design alternatives is limited, especially at the early design stages. The attribute space is not fully explored before the end of a design process. The final target region may contain some "empty" area in the attribute space. An "empty" area is not necessarily unachievable, it has not yet been explored. The achievability of the "empty" area needs to be considered. Different potential alternatives may indicate different information about the achievability of a neighborhood. The above considerations are addressed by the design flexibility metric proposed in this work, which leaves room for design innovation and provides flexibility to accommodate changes in later design process.

Influence Function

Foundational to assessing the design flexibility is the determination of the influence function at each potential design alternative. As described in Hinneburg and Keim (1998) as well as in Farhang-Mehr and Azarm (2003), an influence function provides the influence of one point over other points in a space. In this work, an influence function $I_j(\mathbf{y})$ is defined over the attribute space Ω as a function whose value takes its maximum at a potential design alternative a_j and decreases with the distance from a_j. Given that the downstream design activities are capable of realizing a potential design alternative a_j, an influence function is used to indicate the achievability of other neighboring points in the attribute space under design and production conditions similar to those associated with a_j. Influence functions need to be defined for each potential alternative. The forms of influence functions are often determined by designers based on subjective evaluations. Mathematically, an influence function can be any nonnegative piecewise continuous function, such as a square wave, Gaussian, etc. (Hinneburg and Keim 1998, Farhang-

Mehr and Azarm 2003). Examples in a one-dimensional space are illustrated in Figure 7. Different forms of influence function may apply for distinct alternatives.

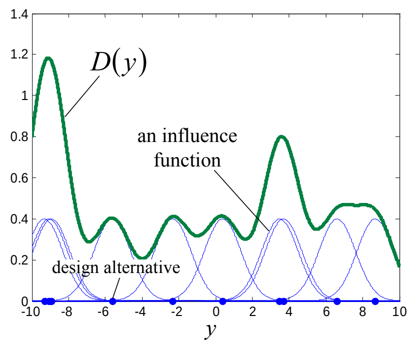

Figure 7 An aggregated influence function formed by a summation of influence functions

Aggregated Influence Function

An aggregated influence function is defined as the aggregation of influence functions of all potential design alternatives *over the whole design attribute space*. Given that all potential alternatives are generated independently and considered equally important, the simplest form of this aggregation is a summation:

$$D(\mathbf{y}) = \sum_j I_j(\mathbf{y}) \tag{4}$$

where $I_j(\mathbf{y})$ is the influence function for the alternative a_j, j=1,2,…,n, and n is the total number of potential alternatives. The aggregation function may take other forms that accumulate the influence provided by each potential alternative. The aggregation of influence functions associated with multiple design alternatives to a one-dimensional aggregated influence function is illustrated in Figure 7. $D(\mathbf{y})$ is usually a hypersurface in Ω. In this work, Equation (4) provides a relative, heuristic measure of the achievability at the settings of the attribute values $\mathbf{y}$.

Proposed Metric of Design Flexibility

Based on Equation (4), a metric of design flexibility is assessed *over a target region* **T** as

$$E_{\mathbf{T}} = \int_{\mathbf{T}} D(\mathbf{y}) d\mathbf{y} \tag{5}$$

where $D(\mathbf{y})$ is the aggregated influence function defined in Equation (4). The flexibility measured in Equation (5) indicates the overall, accumulated potential of the system to achieve points in the target region **T** considering the opportunity to achieve neighboring points associated with potential design alternatives. A higher value of $E_{\mathbf{T}}$ therefore indicates greater flexibility of a system to achieve points over the region **T.** Peaks of $D(\mathbf{y})$ 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 Equation (5) for the simplest case represented by Equation (4) can be expressed as

$$E_{\mathbf{T}} = \int_{\mathbf{T}} \sum_{j} I_j(\mathbf{y}) d\mathbf{y} = \sum_{j} \int_{\mathbf{T}} I_j(\mathbf{y}) d\mathbf{y} \tag{6}$$

which involves multivariate integration. The expression is more complicated if the aggregation of influence functions into $D(\mathbf{y})$ is not a simple summation.

It should be noted that the design flexibility defined above is a relative metric for selecting the final target region. E_{T} depends on the distribution of potential design alternatives both inside and outside the target region **T**, forms of the individual influence functions, and the form (Equation 4) chosen to aggregate the influence functions. These factors together represent designers' knowledge about a design system and a design process. Hence, the flexibility cannot be solely determined by the number of potential design alternatives included in the target region. For example, a region **T** containing relatively few potential alternatives may still be preferred if there are alternatives around it with a large influence value on points inside T. As further illustrated by Equation (7),

$$E_{\mathbf{T}} = \sum_{j=1}^{n} \int_{\mathbf{T}} I_j(\mathbf{y}) d\mathbf{y} = \sum_{j_1=1}^{n_1} \int_{\mathbf{T}} I_{j_1}(\mathbf{y}) d\mathbf{y} + \sum_{j_2=1}^{n_2} \int_{\mathbf{T}} I_{j_2}(\mathbf{y}) d\mathbf{y} \tag{7}$$

where n_1 is the number of alternatives within the target region **T**, n_2 is the number of alternatives outside **T**, and n is the total number of potential alternatives. The design flexibility over a region **T** incorporates not only the influence of potential alternatives within the region, but also the aggregated influence of alternatives outside **T**.

It should be noted that the design flexibility defined above provides only a relative measure, with no physical interpretation, for comparing the design flexibility over multiple potential subregions when choosing the final target region.

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 $\Omega = \{(y_1, y_2) : -10 \le y_i \le 10, i = 1,2\}$. There is a single design criterion, $F = 0.01\left[(y_1 - 2)^2 + y_2\right]$. The acceptable threshold is set as $F \geq 0.3$.

Ten design options $\mathbf{x}=\{x_1, x_2, x_3\}$ are considered. The corresponding values of design attributes y_1 and y_2 are listed in Table 1. Before applying the quantization algorithm, all potential alternatives are checked for *indiscernibility* with respect to each attribute (Nguyen and Skowron 1995, Nguyen 1998). Indiscernible alternatives a_i and a_j with respect to an attribute y can be regarded as a single point in the quantization for the attribute, denoted as a_i *ind*(y) a_j. 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, and a_{10} with respect to y_1.

Table 1 Potential design alternatives generated

	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: <u>Attribute Space Decomposition</u>

The potential design alternatives in Table 1 are plotted in Figure 8. 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 decomposes the attribute space into subregions such that the two alternatives in each pair are separated.

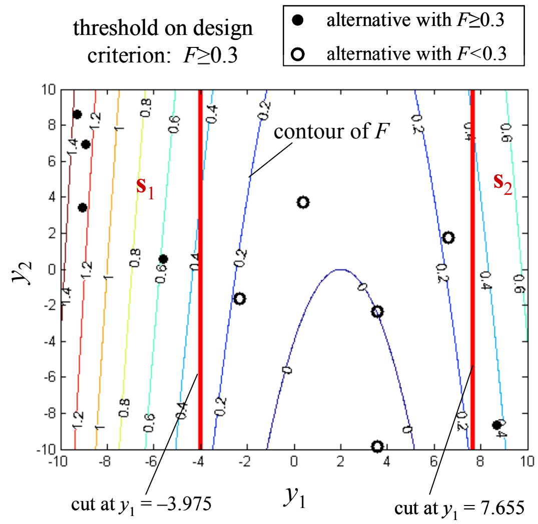

Figure 8 Candidate target regions obtained using the quantization algorithm

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 Figure 8. Correspondingly, two candidate regions $\mathbf{s}_1$ and $\mathbf{s}_2$ are obtained, as listed in Table 2. Both correspond to F≥0.3. From the contours of the design criterion F plotted in Figure 8, it is noted 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≥0.3.

Table 2 Candidate target regions with F≥0.3

		$\mathbf{s}_1$	$\mathbf{s}_2$
Candidate regions	y_1	[–10, –3.975]	[7.655, 10]
	y_2	[–10, 10]	[–10, 10]
# of a_j included with F≥0.3		4	1
Flexibility, E_{sk}		3.4107	0.8578

The quantization results also provide information about 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 Equation (5). For simplicity, the influence functions are chosen to be bivariate Gaussian PDFs:

$$I_j(\mathbf{y}) = \frac{1}{2\pi\left|\mathbf{\Sigma}_j\right|^{1/2}} \cdot \exp\left[-\frac{1}{2}\left(\boldsymbol{\mu}_j - \mathbf{y}\right)^{\mathrm{T}} \mathbf{\Sigma}_j^{-1}\left(\boldsymbol{\mu}_j - \mathbf{y}\right)\right],\ j=1,2,\ldots,10 \tag{8}$$

where $\boldsymbol{\mu}_j$ is the location of the alternative a_j, and $\mathbf{\Sigma}_j$ is a covariance matrix, assumed to be a two-by-two identity matrix. $D(\mathbf{y})$ is obtained using Equation (4), 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, 3.4107. 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 the visual interpretations. As observed from Figure 8, $\mathbf{s}_1$ 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 a non-uniform distribution of potential alternatives in the heterogeneous design attribute space. For example, a larger jug capacity requires larger motor power to provide enough torque to handle ingredients in the container. With more 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

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

$$\text{Profit} = \text{Demand} \cdot \text{Price} - \text{Cost} \tag{9}$$

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.

$$\text{Demand} = \text{Market Share} \cdot \text{Market Size} \tag{10}$$

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 (Wassenaar and Chen 2003).

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 $100,000) is represented by two design criteria: maximize market share and minimize production cost, stated as

$$\mathbf{F} = \{(\text{PC}, \text{MS}): \text{PC} \leq \$20, \text{MS} > 16\%\} \tag{11}$$

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:

$$\mathbf{y} = [\text{MP}, \text{JC}, \text{SL}, \text{P}] \tag{12}$$

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***, is a single design criterion that is to maximize profit. Again, the profit should at least exceed the threshold $100,000. Targets are to be set for five design attributes:

$$\mathbf{y} = [\mathrm{MP}, \mathrm{JC}, \mathrm{SL}, \mathrm{P}, \mathrm{PC}] \tag{13}$$

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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 alternatives is first obtained. After design and manufacturing feasibility assessment, in total, twenty potential design alternatives are identified, as listed in Table 4. Values of the production cost, market share, and profit are estimated for each alternative. Although quantitative values are shown in Table 4, it should be noted that the proposed method can also handle discrete and qualitative attributes. For example, in early design stages, the attribute price (P) can be set as low, medium, or high. For the first scenario, there are seven out of twenty 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 Equation (8) with μ_i as the location of an alternative and the diagonal entries in Σ_i assumed to be 30% of μ_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

Index of alternative	Motor power (w)	Jug capacity (oz)	Speed levels	Price ($)	Production cost per unit ($)	Market share (%)	Profit ($)
1	350	36	8	18.9	11.54	13.60	5.80e+4
2	350	48	2	20.15	13.23	15.40	6.30e+4
3	375	48	10	23.76	14.60	19.23	1.11e+5
4	390	40	∞[1]	26.23	20.75	14.82	5.31e+4
5	400	56	8	28.35	18.79	18.43	1.12e+5
6	400	32	3	21.56	11.92	13.72	8.05e+4
7	400	40	12	25.39	13.16	20.76	1.46e+5
8	400	48	7	26.05	15.09	18.81	1.32e+5
9	400	50	10	26.71	16.26	18.69	1.29e+5
10	425	48	5	27.64	16.04	16.74	1.23e+5
11	450	40	3	27.61	14.72	16.58	1.17e+5
12	450	50	18	31.67	23.23	14.33	7.25e+4
13	475	42	6	30.2	16.90	14.95	1.27e+5
14	500	40	5	31.46	18.76	13.86	1.01e+5
15	500	44	20	36.2	24.98	10.49	7.03e+4
16	500	48	12	33.18	20.83	13.71	1.06e+5
17	500	54	2	33.29	21.92	12.97	9.02e+4
18	525	58	7	34.46	26.27	9.12	4.92e+4
29	550	42	3	34.28	22.07	10.32	7.92e+4
20	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 Equation (11), 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

$$\mathbf{T} = \{350\text{w} \leq MP \leq 600\text{w};\ 32\text{oz} \leq JC \leq 58\text{oz};\ 2 \leq SL \leq 15;\ \$22.66 \leq P \leq \$29.275\} \qquad (14)$$

All seven potential alternatives that meet both design criteria are included in the target region **T**. The design flexibility over **T** is 3.5552.

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

Ranged Set of Targets in Scenario Two

In the second scenario, based on the profit criterion, 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 criteria for desired profit (see Figure 9 and Table 5).

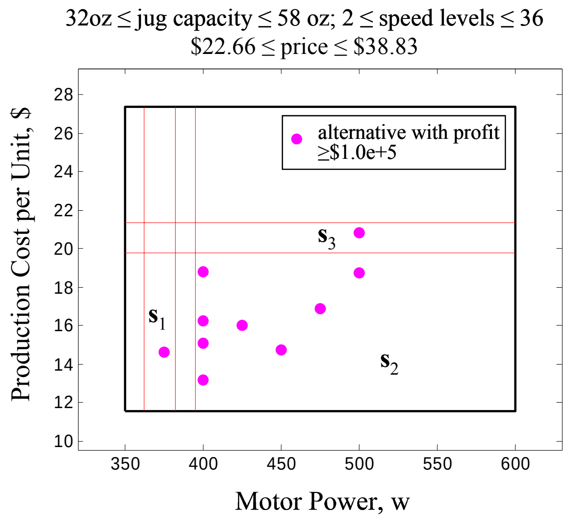

Figure 9 Three candidate target regions obtained in the second scenario

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

	s_1	s_2	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_j contained with profit ≥$100,000	1	8	1
Flexibility, E_{sk}	0.0051	0.0807	0.0240

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, 0.0807. However, the candidate regions $\mathbf{s}_2$ and $\mathbf{s}_3$ are adjacent to each other. The final target region is taken as the *combination* of $\mathbf{s}_2$ and $\mathbf{s}_3$ with a larger degree of flexibility, expressed as

$$\mathbf{T} = \{395\text{w} \le \text{MP} \le 600\text{w};\ 32\text{oz} \le \text{JC} \le 58\text{oz};\ 2 \le \text{SL} \le 36;\ \$22.66 \le \text{P} \le \$38.83;\ \$11.54 \le \text{PC} \le \$21.375\} \quad (15)$$

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 Equations (14) and (15), the design of a blender as a multicriteria problem tended 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). The final target regions obtained are different under different design criteria. Moreover, with different thresholds, the numbers of potential alternatives that meet the design criteria 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_j 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 criteria 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 information on the relative sensitivity of design criteria to each design attribute.

5 Conclusions

In this paper, a new and efficient method is developed that can be used to obtain ranged sets of design specifications (targets) that not only meet design criteria but also incorporate the design space heterogeneity. Based on rough set theory, a design attribute space is decomposed to identify candidate regions that meet the acceptable thresholds on design criteria. A design flexibility metric is proposed to capture the aggregated influence of potential design alternatives on design achievability over a heterogeneous design attribute space. The new method has the flexibility to be applied to design cases where the design requirement is stated by either multiple design criteria or a single design criterion, as demonstrated by the example of the design of a domestic blender. The major advantages of the 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, the developed 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. The proposed 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 design criteria 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, the developed method is expected to be both more effective and more efficient than traditional optimization approaches. With the proposed method, candidate target regions are obtained through simple matrix operations, which can handle a large number of design attributes. 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 design criteria 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 the developed method can be applied repeatedly for this purpose. The choice of the influence function of an individual alternative also has a large impact on design flexibility. Since the proposed design flexibility is a relative measure, normalization of the influence functions at multiple design alternatives needs to be taken into account.

The proposed approach has been demonstrated by design examples in which the design 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 criteria, which is a subject of the future work. Future work will also be devoted to developing efficient techniques for evaluating the design flexibility metric which may involve multivariate integration.

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List of Figures

Table 7. Potential design alternatives generated

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	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

Table 8. Candidate target regions with $F \geq 0.3$

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		$\mathbf{s}_1$	$\mathbf{s}_2$
Candidate regions	y_1	[–10, –3.975]	[7.655, 10]
	y_2	[–10, 10]	[–10, 10]
# of a_j included with $F \geq 0.3$		4	1
Flexibility, $E_{\mathbf{s}k}$		3.4107	0.8578

Table 9 Relations between customer interests and design attributes of a blender

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Customer interests \ Attributes	**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				√							

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Table 10. Potential design alternatives generated

Index of alternative	Motor power (w)	Jug capacity (oz)	Speed levels	Price ($)	Production cost per unit ($)	Market share (%)	Profit ($)
1	350	36	8	18.9	11.54	13.60	5.80e+4
2	350	48	2	20.15	13.23	15.40	6.30e+4
3	375	48	10	23.76	14.60	19.23	1.11e+5
4	390	40	∞[1]	26.23	20.75	14.82	5.31e+4
5	400	56	8	28.35	18.79	18.43	1.12e+5
6	400	32	3	21.56	11.92	13.72	8.05e+4
7	400	40	12	25.39	13.16	20.76	1.46e+5
8	400	48	7	26.05	15.09	18.81	1.32e+5
9	400	50	10	26.71	16.26	18.69	1.29e+5
10	425	48	5	27.64	16.04	16.74	1.23e+5
11	450	40	3	27.61	14.72	16.58	1.17e+5
12	450	50	18	31.67	23.23	14.33	7.25e+4
13	475	42	6	30.2	16.90	14.95	1.27e+5
14	500	40	5	31.46	18.76	13.86	1.01e+5
15	500	44	20	36.2	24.98	10.49	7.03e+4
16	500	48	12	33.18	20.83	13.71	1.06e+5
17	500	54	2	33.29	21.92	12.97	9.02e+4
18	525	58	7	34.46	26.27	9.12	4.92e+4
29	550	42	3	34.28	22.07	10.32	7.92e+4
20	600	50	5	38.83	27.39	7.02	5.42e+4

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

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Table 11. 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_j contained with profit ≥$100,000	1	8	1
Flexibility, E_{sk}	0.0051	0.0807	0.0240

Deleted: 6

Table 12. 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_j contained		7	5	4