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CONCURRENT ENGINEERING: Research and Applications

A Flexible and Robust Approach for Preliminary Engineering Design Based on Designer's Preference

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Abstract: This study proposes a new set-based design approach for preliminary engineering design that intrinsically contains various sources of uncertainties. The goal is to achieve design flexibility and robustness while capturing designer's preference. The proposed design approach includes three computational methods: (1) *set representation method* to specify the varying degree of desirability of a ranged set of design solutions and performance requirements, thereby enabling the manipulation of uncertain design solutions and requirements based on designer's preference structure; (2) *set propagation method* to obtain performance possibilities achievable by uncertain design solutions, thus exploring a broader design possibilities; (3) *set narrowing method* to generate a ranged set of feasible solutions (i.e., robust and flexible solution set) instead of single point solution that satisfies changing sets of performance requirements by eliminating infeasible and inferior subsets of solutions, thus allowing designs to be readily adapted to changing conditions. Finally, the proposed design approach is illustrated with a successful implementation of real industrial design problem (i.e., vehicle side-door structure design) in the simulation-based design environment.

Key Words: set-based design, robust and flexible design, preference, uncertainty, multiobjective design optimization.

1. Introduction

The traditional design practice often regards the engineering design as the iterative process. That is, it quickly develops a 'single solution', critiques it based on multiobjective criteria, and then iteratively moves to some other points until it reaches a satisfactory solution point [1]. It often uses single values to represent quantities (i.e., design solutions and requirements) describing engineering systems. For example, it usually forces designers to pick precise numbers to specify performance requirements, such as the use of the minimum level of a performance, in which only a single design solution is sought [2]. However, the precise value assignments do not include information about uncertainty, and a single-point solution provides limited information about the full range of possible designs under consideration [3]. At the early phase, a large design space needs to be explored to get a set of feasible design solutions instead of a single-point solution for the later detailed design stages [4]. Developing a set of design solutions also provides design flexibility by allowing designs to be readily adapted to changing conditions [2].

In the engineering design field, there have been rigorous research efforts for handling uncertainties or incorporating set-based (not single point) engineering quantities. Wood and Antonsson [5] propose a *fuzzy set-based approach*, called method of imprecision (MoI), for the manipulation of imprecise design information through the specification of preferences on design and performance variables. MoI uses preference functions to represent the designer's desire to use particular values for design parameters, and employs the fuzzy weighted average (FWA) algorithm [6] to propagate uncertainties through engineering equations. Using a preference function is more expressive than using intervals alone in that they can represent a combination of preference and possibility in calculations. Although the FWA algorithm solves the well-known overestimation problem of conventional decomposed fuzzy mappings [7]

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using the combinatorial interval analysis, it also causes another kind of overestimation problem, due to the use of conventional interval arithmetic that does not consider the causal relationships among variables [8,9]. As a result, MoI produces a wider solution than it should be.

Finch and Ward [8,9] proposes an *interval set-based approach* that solves the overestimation problem of conventional interval arithmetic by developing the Quantified Relations (QRs) and interval propagation theorem (IPT). However, it cannot explicitly express the degree of desirability (i.e., preference) of designer, and thus generate only bounds on the membership of feasible sets of design variations.

Probability distributions are often used to describe variations resulting from stochastic processes. Chen and Yuan [2] propose a *probabilistic-based approach* for achieving design flexibility. Here, the design flexibility is provided by allowing designers to specify a ranged set of design solutions and requirements, and developing a range of design solutions (not single-point solution) that meets those design requirements. However, it is not allowed to specify the varying degree of preference of a ranged set of design solutions. In addition, as in most probabilistic-based approaches, its probabilistic representation for design solutions is limited to normal curve, and thus cannot incorporate various shapes of preference.

In addition to individual problems of aforementioned approaches, there is a common problem in evaluating uncertainties. Even though they differ in the types of uncertainties under consideration, and their representation and propagation, a common feature is the use of the variations (i.e., range or set) of design solutions and performance requirements, with (or without) expressing different degrees of designer's preference. When the deviations of design solutions are considered, the resulting performance will correspondingly vary within a range. Therefore, a design metric is required to measure the goodness of the resulting performance variations with respect to a ranged set of performance requirements.

Based on these observations, this study proposes a new set-based design approach for preliminary engineering design problems with uncertain parameters. This approach incorporates designer's *preference* (i.e., design intent) in describing designs, and achieves design *flexibility* and *robustness* under various sources of uncertainties. This approach makes it possible to represent uncertain design solutions and uncertain performance requirements by allowing designers to specify the *varying degree of desirability* (or satisfaction) of both a ranged set of design solutions and a ranged set of performance requirements, based on their preferences. For achieving design flexibility, this approach also develops a ranged set of feasible solutions that satisfy changing sets of performance requirements, through *set propagation* from design variables to performance variables and *set narrowing* to eliminate infeasible or inferior subsets of solutions. Then, a *new design metric* is developed to measure the level of design preference and robustness simultaneously.

The rest of the article is organized as follows. Section 2 overviews the proposed design approach. In Section 3, the proposed design approach is illustrated with the successful implementation of a real industrial problem (i.e., vehicle side-door structure design). Section 4 concludes the article.

2. The Proposed Design Approach

2.1 Set Representation Method (SRM)

For the set-valued assignments to design or performance variables, two types of assignments can in general be considered: *continuous set* and *discrete set*. Although an intuitive and qualitative method has been proposed to represent the designer's preference structure on the discrete set [10], this study confines the scope of the discussion to the continuous set.

To incorporate the designer's preference structure into design solutions or performance requirements, a new engineering quantity, called 'quantified preference number' (QPN) is proposed. The QPNs for design solutions and performance requirements are here called the *design QPN* and *performance QPN*, respectively. As shown in Figure 1(a) and (b), consider an interval set-valued design variable X_i, $i = 1, 2, \ldots, m$, defined on the real line R, and denote an element of X_i by x. Then, the design QPN $\tilde{X}_i$ is defined by:

$$\tilde{X}_i = Q\bar{X}_i, \tag{1}$$

where

$$Q \in \{\forall, \exists\}, \text{ and} \tag{2}$$

$$\bar{X}_i = \{(x, p_i(x)) | x \in X_i, p_i(x) : x \to [0, 1]\}. \tag{3}$$

Instead of using pure intervals, the design QPN uses an interval set and a preference function ($p_i(x)$) on the interval set. Any shapes of preference function are allowed to express the designer's preference structure. By employing the concept of QRs [8,9], the design QPN is further quantified by preceding it with a logic quantifier (Q). Therefore, the design QPN is a more expressive representation for specifying individual design solutions. For example, designers may require that the full variety of interval sets assigned into some design variables should be taken into account because

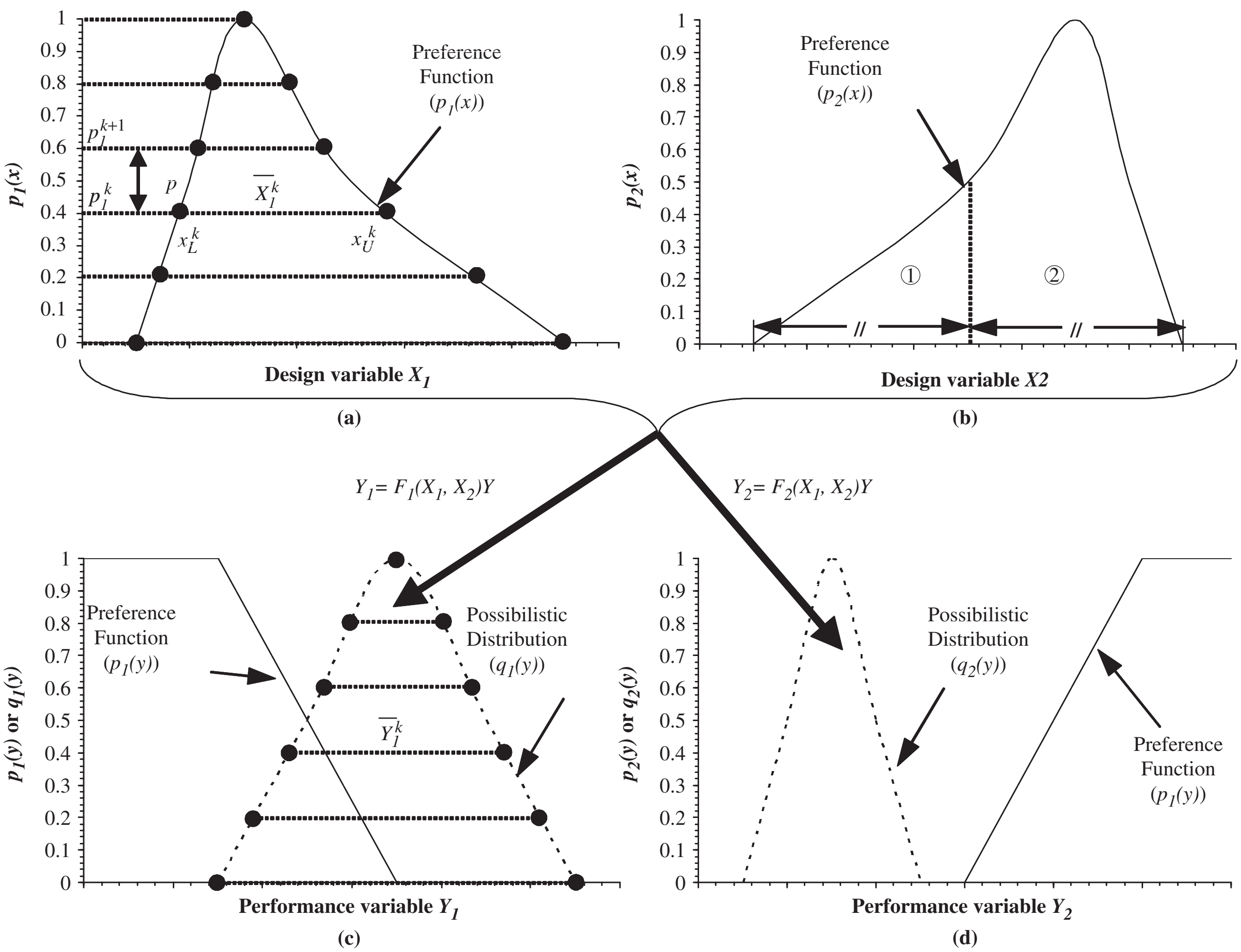

Figure 1. Overview of the proposed design approach.

those variables cannot be directly controlled by them. In this case, the design QPN is universally quantified. On the contrary, interval sets controlled by designers may be expected to be adjusted to some desired performances within their lower and upper bounds. Then, the design QPN is existentially quantified.

As shown in Figure 1(c) and (d), the performance QPN for specifying the performance requirement of a performance variable Y_j, $j = 1, 2, \ldots, n$, by denoting its element by y can be also defined by a similar form to the design QPN:

$$\tilde{Y}_j = Q\overline{Y}_j, \tag{4}$$

where

$$\overline{Y}_j = \{(y, p_j(y)) | y \in Y_j, p_j(y) : y \rightarrow [0, 1]\}. \tag{5}$$

Like the design QPN, any shapes of preference function ($p_j(y)$) are allowed to express the designer's preference structure, as well as the traditional specifications, such as *the-larger-the-better*, *the center-the-better*, and *the-smaller-the-better*. The performance QPN is also useful to represent both design constraint and goal. The interval set at the preference level of 0 can be the *hard* constraint which must be met in order for the designs to be feasible, while the interval set at the preference level of 1 is the *soft* goal that designers would like to meet.

In this manner, the set representation method (SRM) captures the designer's preference and provides the design flexibility by allowing the designer to specify a ranged set (i.e., interval) and its controllability of both design solutions and performance requirements with a varying degree of desirability (i.e., preference function).

2.2 Set Propagation Method (SPM)

As shown in Figure 1, once (input) design QPNs and (output) performance QPNs are specified, the set propagation method (SPM) is used to obtain possibilistic distributions of performances achievable by design QPNs through input–output relationships (e.g., F_1 and

F_2 in Figure 1). The proposed SPM is similar to the FWA algorithm [6] of decomposing a fuzzy number into a number of α-cuts, $\alpha \in [0, 1]$, for which arithmetical operations can be defined using the interval arithmetic. However, the major differences of proposed SPM are its capabilities to handle the causal relationship among design and performance variables, and to remove overestimation effects of conventional fuzzy arithmetic by employing IPT [8,9]. The underlying idea of IPT is that the designer must assume worst-case values for uncontrollable variables and best-case values for controllable variables. For example, in the worst case scenario that all design QPNs are universally quantified, it is assumed that all variations of system performance may occur simultaneously in the worst possible combinations of design variables. A more detailed description on IPT is given in [8,9], and is not repeated here.

Consider design QPNs $\tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_m$ as design solutions (i.e., alternatives) assigned into design variables $X_1, X_2, \ldots, X_m$, and performance QPNs $\tilde{Y}_1, \tilde{Y}_2, \ldots, \tilde{Y}_n$ as performance requirements defined on performance variables $Y_1, Y_2, \ldots, Y_n$, respectively. Suppose design variables $X_1, X_2, \ldots, X_m$ are related to a performance variable Y_j by the mapping $Y_j = F_j(X_1, X_2, \ldots, X_m)$. Then, the SPM solution to possibilistic distribution $\tilde{Y}'_j$ achievable by design QPNs can be obtained by the following steps:

1. Decompose the range of the ordinate (i.e., $p_i(x)$-axis) [0, 1] into a finite number of l segments, equally spaced by $\Delta p_i = \max(p_i(x))/l$ (see Figure 1(a)).
2. For each preference level p_i^k $(k = 0, 1, \ldots, l,$ $p_i^k = p_i^{k-1} + \Delta p_i$, and $p_i^0 = 0)$, find the corresponding intervals for design QPNs $\tilde{X}_i$, denoted by $\overline{X}_i^k = [x_L^k, x_U^k]$. Here, the subscripts L and U indicate the lower and upper bounds of the interval.
3. Apply IPT to obtain the correct (not overestimated) output interval $\overline{Y}_j^k$ of possibilistic distribution $\tilde{Y}'_j$ at the preference level p_j^k. Owing to the IPT, instead of evaluating the function F_j by giving 2^m combinations for the 2m bounding values of $\overline{X}_i^k$, the SPM needs only two combinations according to the logic quantifier of performance QPN $\tilde{Y}_j$, thus significantly reducing computation.
4. Repeat the above step for other preference levels to obtain additional intervals of $\tilde{Y}'_j$.
5. Recompose the intervals obtained from the above step.

Finally, denoting an element of $\tilde{Y}'_j$ by y and its *possibilistic function* by $q_j(y)$, the possibilistic distribution $\tilde{Y}'_j$ can be defined by:

$$\tilde{Y}'_j = \{(y, q_j(y)) | y \in Y_j, q_j(y) : y \to [0, 1]\}. \quad (6)$$

2.3 Set Narrowing Method (SNM)

By using the SPM, the designer can obtain output possibilistic distributions of performances achievable by input design QPNs. On the one hand, input QPNs may sometimes produce undesirable output performances so that they do not have intersections with one or more performance QPNs. As shown in Figure 1(d), the possibilistic distribution of performance variable Y_2 is outside the performance QPN. Then, initial design QPNs need to be modified to make all possibilistic distributions have overlapping regions with all performance QPNs.

On the other hand, when all possibilistic distributions have overlapping regions with all performance QPNs (e.g., Figure 1(c)), the designer knows that there exist feasible solutions within initial design QPNs. However, if the possibilistic distribution is not the subset of performance QPN, there also exist infeasible solutions that produce performances outside the performance QPN. That is, a fraction of possibilistic distribution exists outside the performance QPN. Then, the set narrowing method (SNM) is used to narrow initial design QPNs by eliminating infeasible or inferior design solutions.

2.3.1 *GENERATION OF COMBINATIONS OF DESIGN SUBSETS*

The SNM first generates combinations of subsets of design QPNs by employing design of experiment (DoE) techniques. While in most researches DoE techniques are used to sample different design *points*, the SNM samples different design *sets*. As shown in Figure 1(b), all design QPNs are partitioned into two or more levels, where each has the same width of interval at the preference level of 0. Figure 1(b) shows the example of subsets (i.e., sub-regions ① and ②) of design QPN partitioned into two levels. After generating combinations of those subsets of all design QPNs by selecting a DoE technique (e.g., full factorial design, fractional factorial design, central composite design, space filling design, orthogonal arrays, etc. [11]), the SNM calculates possibilistic distribution by each combination using the SPM.

2.3.2 *DESIGN METRIC FOR DESIGN PREFERENCE AND ROBUSTNESS EVALUATION*

Then, combinations of which possibilistic distributions have overlapping regions with all performance QPNs are only regarded as feasible designs, which will be used for further consideration. However, if two or more feasible combinations still remain, a design metric is required to select a more optimal one than others. For this purpose, the SNM employs the design preference index (DPI) to measure the goodness of performances [2]. Mathematically, the DPI is defined as the expected preference function value of design performance within the range of possibilistic distribution with the following form:

$$\mathrm{DPI}(\tilde{Y}'_j) = E[p_j(y)] = \int_{y_L^0}^{y_U^0} p_j(y) q_j(y) \mathrm{d}y. \tag{7}$$

Although the DPI is a good design metric to evaluate the performance expressed by the form of distribution (i.e., possibilistic distribution) with respect to the varying degree of preference (i.e., performance QPN), it often makes incorrect measures due to the incapability of measuring design robustness. As shown in Figure 2, suppose a performance QPN, $\tilde{Y}_1$, as the performance requirement, and two possibilistic distributions, $\tilde{Y}_1^{1'}$ and $\tilde{Y}_1^{2'}$, achievable by two combinations of subsets of design QPNs. Then, the DPI provides similar results between two designs, because $\tilde{Y}_1^{1'}$ and $\tilde{Y}_1^{2'}$ have similar overlapping regions with $\tilde{Y}_1$. However, from the viewpoint of design robustness (i.e., minimizing variations in response caused by variations in noise or control factors), $\tilde{Y}_1^{1'}$ is more robust than $\tilde{Y}_1^{2'}$, because $\tilde{Y}_1^{1'}$ contains the smaller variation.

Therefore, a new measure of uncertainty, called precision and stability index (PSI), is developed to evaluate the design robustness. To date, a number of measures of fuzziness have been proposed, including Shannon's entropy measure [12], γ-*level* measure [5], and so on. However, it is found that those measures of uncertainty often fail to make correct measures according to the shape and height of membership function [10,13]. On the contrary, the proposed PSI consistently produces reasonable measures, regardless of the height and shape of membership function (i.e., preference function in this study). The complete comparison between the proposed PSI and other measures is given in [10]. The PSI is defined by modifying the Shannon's entropy measure as:

$$\mathrm{PSI}(\tilde{X}_i) = C \sum_{x}^{|\overline{X}_i^0|} \mathrm{PS}(p_i(x)), \tag{8}$$

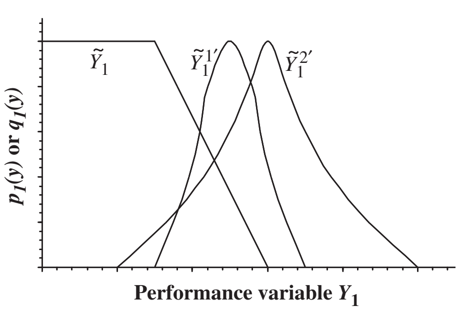

Figure 2. Measuring the goodness of designs.

where

$$C = \frac{|\overline{X}_i^0|}{\text{area}\,(\tilde{X}_i)}, \text{ and} \tag{9}$$

$$\mathrm{PS}(p_i(x)) = \begin{cases} p_i(x)\ln(p_i(x)) & \\ \quad +(1-p_i(x))\ln(1-p_i(x)) & \text{if } 0 < p_i(x) < 0.5 \text{ or } 0.5 < p_i(x) < 1 \\ \quad -\ln(0.5), & \\ -\ln(0.5) & \text{if } p_i(x) = 0 \text{ or } p_i(x) = 1 \\ 0 & \text{if } p_i(x) = 0.5. \end{cases} \tag{10}$$

Here, C is a correction factor to make correct measures about the subnormal fuzzy numbers [13]. $|\overline{X}_i^0|$ is the width of interval at the preference level of 0 (i.e., the length of support) and area $(\tilde{X}_i)$ is the area of QPN. The PSI is an inverse type of Shannon's entropy function with the correction factor. While the Shannon's entropy measure and γ-level measure evaluate how much of membership function is close to 0.5 (i.e., the 'steepness' of the bounding curves for the membership function) and 1.0 (i.e., the 'spread' of the membership function), respectively, the PSI measures the values centered on both $p_i = 0.0$ and $p_i = 1.0$, indicating the spreads of preference function (near 0.0 and 1.0). That is, the more values of preference function close to 0.0 and 1.0, the larger the PSI values. Therefore, the smaller the PSI value, the less the uncertainty.

Finally, a new design metric, called 'preference and robustness index' (PRI), is developed to simultaneously measure design preference and robustness, by combining the DPI with the PSI:

$$\mathrm{PRI}(\tilde{Y}_j^{r\prime}) = \underbrace{\left(\mathrm{DPI}(\tilde{Y}_j^{r\prime}) / \max_{c=1,\ldots r\ldots,s} (\mathrm{DPI}(\tilde{Y}'_{j^c}))\right)}_{\mathrm{NDPI}} \times \underbrace{\left(\min_{c=1,\ldots r\ldots,s} (\mathrm{PSI}(\tilde{Y}'_{j^c})) / \mathrm{PSI}(\tilde{Y}'_{j^r})\right)}_{\mathrm{NPSI}}. \tag{11}$$

where the NDPI and NPSI indicate the normalized DPI and normalized PSI, respectively. To provide the relative goodness among possibilistic distributions $\tilde{Y}'_{j^c}$ $(c = 1, \ldots, r, \ldots, s)$ resulting from all combinations with respect to a performance variable Y_j, the DPI and PSI of the possibilistic distribution $\tilde{Y}_j^{r\prime}$ by the rth combination are first normalized with respect to the maximum of all DPI values and the minimum of all PSI values, respectively. In particular, since the smaller PSI value implies the better robustness, the PSI is normalized to allow the smaller PSI value to contribute more to the PRI value.

Next, since the designer generally considers more than one performance variable, the PRIs for multiple performances need to be aggregated, what is called 'aggregated PRI' (APRI), to provide the goodness of each design with respect to all performances. For this purpose, the SNM uses a family of parameterized aggregation functions for multi-objective decision making problem, based on the weighted root-mean-power [14]:

$$\mathrm{APRI}_q((\mathrm{PRI}_1, \omega_1), \ldots, (\mathrm{PRI}_n, \omega_n)) = \left(\frac{\omega_1(\mathrm{PRI}_1)^q + \cdots + \omega_n(\mathrm{PRI}_n)^q}{\omega_1 + \cdots + \omega_n}\right). \tag{12}$$

When varying the parameter q by $-\infty$, -1, 0, 1, 2, and $+\infty$, the Expression (12) respectively corresponds to the following well-known weighted averaging operations: min, harmonic mean, geometric mean, arithmetic mean, quadratic mean, and max. These averaging operators accommodate all cases of compensation, from non-compensating (min) to super-compensating (max) with different degrees of compensation.

Finally, the SNM selects a combination of sub-QPNs that has the highest APRI value (i.e., the most preferred and robust combination). The set narrowing process repeats until all possibilistic distributions obtained by the selected combination of sub-QPNs fall within all performance QPNs (i.e., subsets of performance QPNs). In this manner, the SNM selects a feasible and optimal combination of subsets of design QPNs from the design preference and robustness viewpoint.

3. Application to Vehicle Side-Door Structure Design

3.1 Design Problem

In this study, a preliminary design of vehicle side-door structure is chosen to illustrate the quick screening of broad design possibilities using the proposed design approach. A schematic picture of the side-door structure is shown in Figure 3. This design example is confined to the parametric design of main components. For illustrative convenience, five design variables related to thickness are considered including outer panel (X_1), inner-front panel (X_2), inner-rear panel (X_3), frame (X_4), and safety beam (X_5). Three stiffness-related performance variables are considered: residual displacement after the indentation of 0.245 kN on the center of outer panel (Y_1); displacement after longitudinal loading of 0.049 kN on the center of outer panel (Y_2); and displacement after transverse loading of 0.200 kN on the upper part of frame (Y_3). That is, Y_1, Y_2, and Y_3 are performance variables related to the dent resistance, tensional stiffness and torsional stiffness, respectively. In addition, since the side-door structure is subject to extensive loads and high deformation during the crash, it should be designed to be able to absorb more strain energy. Therefore, the energy absorption rate (Y_4) is also considered. In addition to those technical performances, the cost-effective, lightweight, and environment-conscious vehicle design is a very important issue in the automotive industry. Therefore, four non-technical performances are also taken into account, including

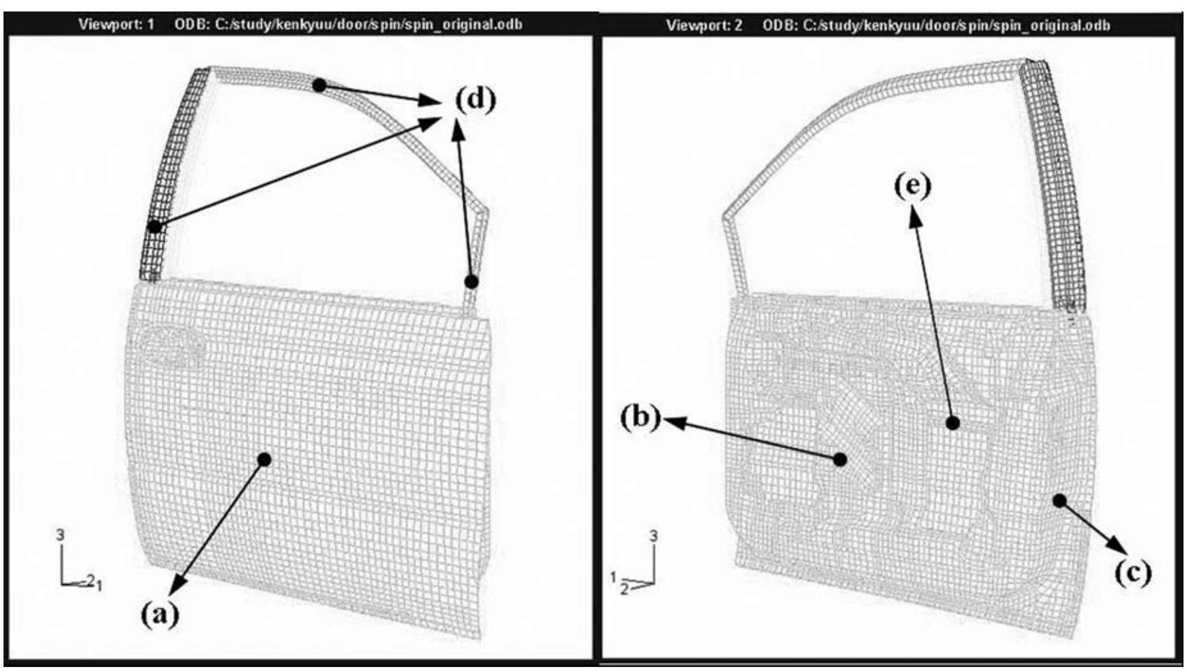

Figure 3. Preliminary parametric design of vehicle side-door structure: (a) outer panel, (b) inner-front panel, (c) inner-rear panel, (d) frame, and (e) safety beam.

manufacturing and assembly cost (Y_5), mass (Y_6), energy consumption rate (Y_7), and CO_2 emission rate (Y_8).

3.2 Construction of Surrogate Models

The computer-based simulation tools such as finite element and computational fluid dynamic analyses are currently used overwhelmingly to simulate the performance of automotive designs. In such a simulation-based design environment, the search for a feasible design space that satisfies the given performance requirements usually involves numerous iterations among several simulation tools. They are computationally expensive and extremely time-consuming, thus limiting the exploration of broad design space and its optimization [4,11]. In addition, these simulation tools are usually used by specialists in individual disciplines and in the later design stages. The fidelity of design analysis is thus low in the early stages [15].

Therefore, metamodeling techniques are becoming widely used in today's engineering design to build approximations, often called *surrogate model* or *metamodel*, of expensive computer analysis tools [4,11,15]. For this design problem, the *space filling design* is used to sample a set of design points, because it is the most suitable DoE technique for sampling deterministic computer experiments [11]. For those sample points, the FEM analysis is performed to calculate the technical performances (Y_1–Y_4) using the ABAQUS/Standard and ABAQUS/Explicit (ABAQUS, Inc.), and the DFMA software (Boothroyd Dewhurst, Inc.) and LCA software (Japan Automobile Manufacturers Association, Inc.) are also used for the calculation of non-technical performances (Y_5–Y_8). Then, the response surface methodology (RSM) is adopted to build a surrogate model of actual computer simulations, since it is the most well-established metamodeling technique, probably the easiest to use and provides closed-form equations as the approximation model. Table 1 lists simple surrogate models used in this design problem. Therefore, the variance of performance can be predicted rapidly by using these surrogate models instead of running complex computer simulation tools to all iterations of the solutions.

3.3 Design Example Using the Proposed Design Approach

In this work, the proposed design approach is implemented by developing an add-in program of MS Excel. Using the implemented software, the designer first specifies design and performance QPNs, by directly using MS Excel interface (Figure 4(a)) or initiating a special QPN composer (Figure 4(b)). The relationships between design variables and performance variables (i.e., surrogate models) are also defined. In this example, all design and performance QPNs have linear preference functions, but any shapes of preference function can be specified. Table 2 summarizes the interval sets of design and performance QPNs at the preference levels of 0 and 1. In addition, all design QPNs are now universally quantified, considering the worst case scenario that all variations of design performance may occur simultaneously in the worst possible combinations of design variables.

Second, possibilistic distributions achievable by design QPNs are calculated by the SPM and the result is automatically displayed in a new sheet. Then, the designer checks whether initial design QPNs are feasible by investigating common regions between performance QPNs and possibilistic distributions. In this example, there exist overlapping regions in all performance variables, and thus the designer can predict that there are feasible solutions within initial design QPNs.

Last, a sequence of set narrowing processes is performed to eliminate infeasible and inferior subsets from initial design QPNs, thus resulting in an optimal ranged set of design solutions of which all possible distributions fall within all performance QPNs. The set narrowing process repeats three times in this example. In the set narrowing process, the designer can also specify different weighting factors of performance variables. As listed in Table 3, the narrowing process produces two

Table 1. Surrogate models constructed for vehicle side-door structure design.

	$Y_j = a_0 + a_1 * X_1 + a_2 * X_2 + a_3 * X_3 + a_4 * X_4 + a_5 * X_5$ $(j = 1, \ldots, 8)$					
Performance variable	a_0	a_1	a_2	a_3	a_4	a_5
Y_1	0.5557	−0.3963	−0.0035	−0.0092	−0.0026	−0.0184
Y_2	8.1334	−6.0522	−0.0653	−0.0630	−0.0438	−0.0827
Y_3	49.5977	−1.8881	−2.7523	−15.9911	−2.6830	−1.9747
Y_4	−105.1489	436.6362	101.1238	589.4437	−21.5433	281.8669
Y_5	2706.3000	771.6000	248.2000	799.8000	364.4000	172.5000
Y_6	2.0442	6.0813	1.9083	5.5313	1.6063	0.4625
Y_7	438.4167	1309.3750	410.8333	1191.2500	345.6250	100.0000
Y_8	28.8750	89.0625	28.1250	80.9375	23.5938	6.8750

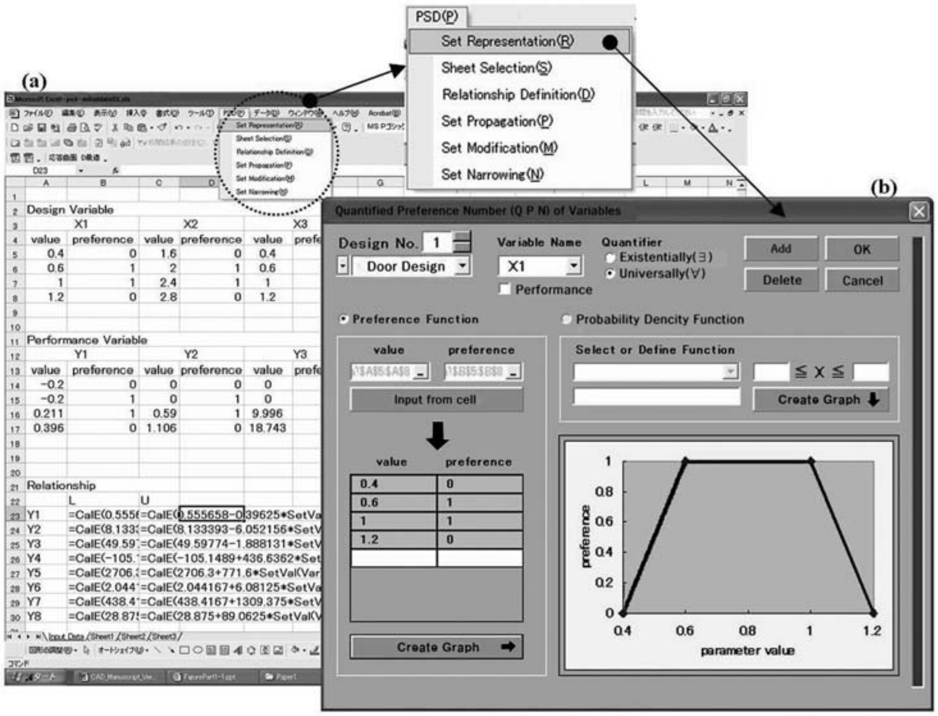

Figure 4. Specification of design and performance QPNs.

Table 2. Specified design and performance QPNs.

QPN	Interval set $p=0$	Interval set $p=1$	Unit
$\tilde{X}_1$	[0.4, 1.2]	[0.6, 1.0]	mm
$\tilde{X}_2$	[1.6, 2.8]	[2.0, 2.4]	mm
$\tilde{X}_3$	[0.4, 1.2]	[0.6, 1.0]	mm
$\tilde{X}_4$	[1.6, 3.2]	[2.0, 2.8]	mm
$\tilde{X}_5$	[3.0, 3.4]	[3.05, 3.35]	mm
$\tilde{Y}_1$	[0, 0.396]	[0, 0.211]	mm
$\tilde{Y}_2$	[0, 1.106]	[0, 0.590]	mm
$\tilde{Y}_3$	[0, 18.743]	[0, 9.996]	mm
$\tilde{Y}_4$	[699, 2400]	[1677.6, 2400]	Nm
$\tilde{Y}_5$	[1000, 8818.011]	[1000, 4702.939]	Yen
$\tilde{Y}_6$	[4, 30.105]	[4, 16.056]	kg
$\tilde{Y}_7$	[1000, 6459]	[1000, 3444.8]	MJ
$\tilde{Y}_8$	[100, 439.5]	[100, 234.4]	kg
–	–	–	–

Table 3. Final ranged sets of design solutions at $p_i = 0$ (a) when technical performances (Y_1–Y_4) are more highly weighted and (b) when non-technical performances (Y_5–Y_8) are more highly weighted.

Design variable	Design solution (a)	Design solution (b)
X_1	[1.10, 1.20]	[1.10, 1.20]
X_2	[1.75, 1.90]	[2.35, 2.50]
X_3	[1.00, 1.10]	[0.60, 0.70]
X_4	[2.80, 3.00]	[1.80, 2.00]
X_5	[3.05, 3.10]	[3.30, 3.35]

different design solutions, when technical performances ($Y_1 - Y_4$) are more highly weighted, and vice versa, during the calculation of APRI. In addition, it is worthwhile to note that the design QPNs with different shapes of preference functions generate different design solutions. That is, the proposed design approach can capture the designers' preferences and reflect their design intents in their design solutions.

4. Conclusions and Future Work

This study presents a new set-based design approach for a multi-objective design problem in the early phase of design. This approach enables design flexibility, robustness, and preference under uncertainty. In order to capture the designer's preference and encode uncertain design solutions and performance requirements, this approach allows the designer to specify the varying degree of desirability (i.e., preference function) of both a ranged set of design solutions (not single-point solution) and a ranged set of performance requirements (not crisp specification). This approach also provides design flexibility by developing ranged sets of robust and preferred solutions (instead of single-point solution) that satisfy uncertain performance requirements based on the new design metric, PRI, thus allowing designs to be readily adapted to changing conditions.

However, there are still several issues to be studied further. First, the present approach assumes linear functions between design and performance variables.

If there is a nonlinear function, the present approach linearizes the nonlinear function by splitting the design variable space in the process of making the metamodels, resulting in a set of linear functions. This shortcoming is caused by the use of IPT. The constraint programming techniques [16] can be considered as an alternative propagation and resolution mechanism of intervals. Second, the metamodeling technique itself is out of scope of the present study. However, the metamodel with fidelity is very important for practical use of the proposed design approach. Therefore, a more suitable metamodeling technique is required, since the RSM is often criticized by its randomness assumption [11]. A good tradeoff of DoE/Metamodel combination should also be made to find the compromise between the metamodel fidelity and the resulting precision of computation [16].

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