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Decision making support for designers at the early design stage regarding narrowing down the range values of design variables

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Abstract

This study presents a search method for a solution space that aligns with a designer's design intent. The proposed method uses multiobjective optimization to determine the size of the narrowed solution space and the weakness of the constraint relationships between the design variables. The suitability of the proposed method is tested by applying it to the design problem of an electric motor for an EV, aiming to provide designers with solution spaces that offer a high degree of freedom in the later design stages and that have weaker constraint relationships among the design variables.

Keywords: *decision making, visualisation, simulation-based design, set-based design, early design phase*

1. Introduction

Customer needs for products have become more sophisticated and diverse in recent years, with the environmental and resource constraints associated with the SDGs being markedly radicalized. As the customer needs for products increase and constraints become stricter, product development becomes more complex. Concern has also been raised regarding the increasing amount of design rework, which contributes to issues such as higher costs and longer design times. This highlights the need to develop a method that supports designers' decision making and reduces design rework in the early design stages when various uncertainties including aleatory uncertainty, epistemic uncertainty, uncertainty in the decision of other designers, changes in environmental conditions, and numerical uncertainty (Inoue et al., 2013).

1.1. Set-based design

Many studies have proposed set-based design methods (Sobek and Liker, 1996; Sobek and Liker, 1999; Ward and Cristiano, 1995) to support decision making in the early design stages. This method considers preceding uncertain design information as ranges to derive common sets that simultaneously satisfy multiobjective performance, suggesting its ability to determine range solutions while handling uncertainty in the early design stages. In addition, the preference set-based design (PSD) method (Inoue et al., 2010; Inoue et al., 2013) was proposed to support the designer's design intent in the early design stage by implementing the concept of the set-based design method. The PSD derives range solutions that satisfy the designer's design intent by defining preference function for the design variables and required performance criteria to deal with the abovementioned uncertainties, especially epistemic uncertainty. Despite this method's presumption of independent relationships between design variables, actual product design may involve constraint relationships that limit the levels of design variables relative to one another. Furthermore, an appropriate order for determining the design variable levels must be defined because they cannot be decided concurrently owing to the constraint relationships among the design variables. The inappropriateness of the order reduces the degrees of freedom in the design and eliminates range solutions, resulting in design rework.

1.2. Constraint relationships and design-priority order

Kuroyanagi (2021) determined the ranges of required performance by defining their desirability as preference functions and expressed the constraint relationships among design variables under the limiting conditions of the required performance as a network. They also derived a design-priority order that maximizes the degrees of freedom in later design stages by analysing the constraint relationships among the design variables. This method allowed for the definition of a decision order for the values of the design variables while considering the constraint relationships between them. Notably, narrowing the range values of design variables as a design solution space while considering the constraint relationships among the design variables is imperative; however, conventional methods have rarely addressed this, and the development of the method remains unmet. Therefore, establishment of a technique to reduce the range values of the design variables as a solution space by following the constraint relationships among the design variables is desired.

1.3. Research aims

This study presents a method for searching for a solution space that aligns with the designer's design intention by connecting the narrowing method based on set-based design with the constraint analysis. To illustrate the constraint relationships among design variables, a network visually expresses them corresponding to design variable levels was established. Moreover, two-objective optimization regarding the size of the narrowed solution space and the weakness of the constraint relationships was implemented according to design-priority order. This realizes the effective narrowing dealt with the uncertainties and the design rework by exploring larger solution spaces with weaker constraints. Additionally, the proposed method visualizes the networks in a narrowed solution space that reflects the designer's intention and guides the designer's decision making when narrowing the range values of design variables in the early design stages.

2. Proposed method

This section describes the overall process of the proposed method for narrowing the range values of the design variables. Figure 1 shows the process flow, with the details of each process provided in each section.

2.1. Derivation of the design solution space

Similar to Kuroyanagi's (2021) approach, this study used simulation and metamodeling to generate comprehensive design solutions to analyze the entire design space. The product's components and elements that characterize the units were interpreted as design variables, and parameters representing the product's performance were considered as objective variables. For the simulation, a physical simulation was employed, and when the number of variables increased and the computation became extremely slow, metamodeling was used. The goal of metamodeling is to replicate a more detailed design space via an approximation. This reduces the time and financial expenses by enabling the acquisition of adequate design solutions with a minimal number of trials. The combinations of design variable levels satisfying all performance constraints are defined as design solutions. The design solution space is the result of integrating all design solutions. In this study, design solutions were extracted from the output results of the simulation and metamodeling.

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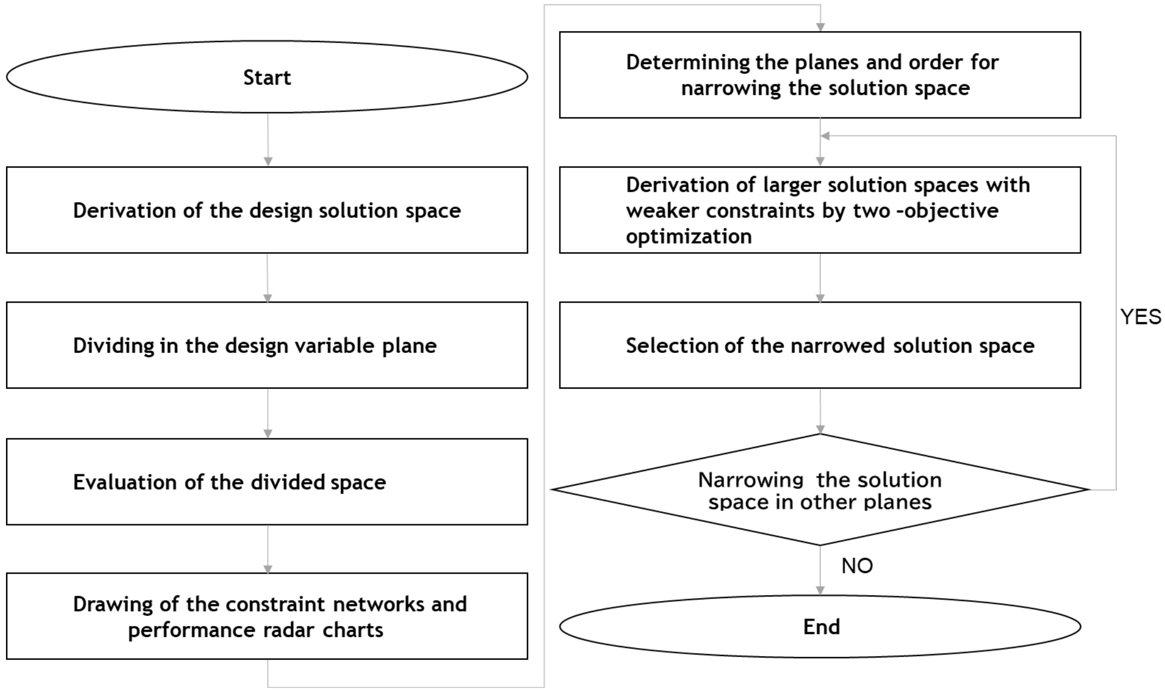

Figure 1. Process flow of the proposed method

2.2. Dividing in the design variable plane

This study focuses on a specific two-design-variable plane of the target design solution space, aiming to quantitatively narrow down the range of values of the design variables for each axis of the planes according to the designer's design intent. For the two selected variables, the plane area was partitioned by binning it into an arbitrary number of divisions. This number was determined based on the number of design variable levels. It was derived using the determination method for the class width of histograms to prevent the amount of data in the divided spaces from being excessively small when the design variables do not take levels. For example, when a system has 4 design variables and they have 5 levels respectively, 12 planes are derived from ${}_4C_2$, and each of them is partitioned into 25 sections. In this study, the divisions in a plane and data points in the partitioned areas were defined as divided spaces.

2.3. Evaluation of the divided space

Because this study's inputs were the simulation results from the initial design stage, the design variable levels may change in the later stages. Hence, the relationships among the design variables are suitable for evaluating the divided space criteria owing to their insignificant fluctuations, regardless of the design stage. Therefore, the constraint relationships between the design variables in the design solution of each divided space were expressed as a network, and the relationship between two specific design variables in the spaces was evaluated using the bivariate distribution concentration described in Section 2.3.1. In addition, the performance achieved by the design variables in the divided spaces was visualized using radar charts.

2.3.1. Evaluation index

In this study, the bivariate distribution concentration developed by Kuroyanagi (2021) was used to evaluate divided space. This index signifies the degree to which the available levels of the two-design variables are restricted to satisfy all the constraints given to the objective variables and is calculated using Equation (1). "Con" is the symbol of concentration. A high bivariate distribution concentration indicates a strict constraint relationship between the design variables. The essential indicator of the index, the constraint satisfaction rate, is calculated using Equation (2).

$$Con(\mathrm{R})_{\alpha,\beta} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(max\left(\mathrm{S}(\alpha,\beta)_{n,m}\right)-\mathrm{S}(\alpha,\beta)_{n,m}\right)}{NM-1} \tag{1}$$

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$$S(\alpha,\beta)_{n,m} = \frac{n(\{p \in P(R) | p_{\alpha} = \alpha_n \wedge p_{\beta} = \beta_m\})}{n(P(-))/NM} \quad (2),$$

where N and M denote the number of levels of design variables α and β for a given set of constraints R, and $S(\alpha,\beta)_{n,m}$ means the constraint satisfaction rate when the design variable levels α and β are n and m. P (-) and P(R) respectively imply all simulated sample points and the set of sample points satisfying the constraint R, and p_{α} and p_{β} are the level values of the design variables α and β at the sample points.

2.3.2. Constraint network

The indexes in Section 2.3.1 are visualized as a constraint network. Figure 2 shows that the constraint network comprises design variable x_1, x_2 and x_3 at each node, for which their size expresses the range value of the design solution in the divided space. The color of the nodes and the thickness of the edges individually represent the univariate distribution concentration, indicating the degree of concentration of the potential design variable levels and the bivariate distribution concentration. The visualized constraint network provides characteristics of the design solution space. For example, the larger the node, the wider the range of available design solutions; the darker the color of the node, the more concentrated the design solution is at particular design variable levels; and the thicker the edge, the stronger the constraint relationships between the design variables.

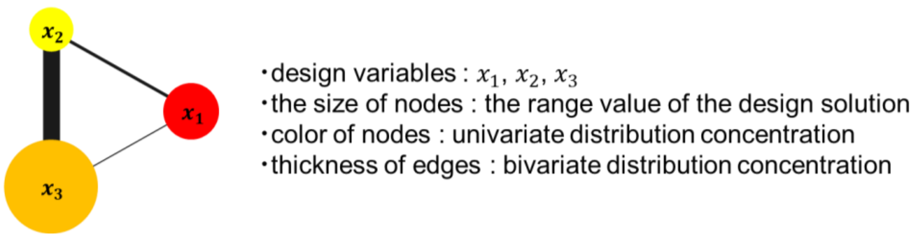

Figure 2. Constraint network

2.3.3. Drawing of the constraint networks and performance radar charts

By drawing constraint networks and performance radar charts for each divided space, designers are guided to narrow down the range values of the design variables. The visualized graphs are placed on the design variable planes mentioned at the beginning of the process, and the axes of the planes are the selected design variables. Constraint networks and performance radar charts were constructed for each area of the corresponding divided space.

2.4. Determining the planes and order for narrowing the solution space

The number of drawn planes is ${}_nC_2$ in total when the number of design variables is n. However, if all planes are employed to narrow the range values of the design variables, they are repeatedly filtered and excessively narrowed. Therefore, the planes to be referred to and their orders should be settled.

In the method of Kuroyanagi (2021), $Constraint_{\alpha\to\beta}$, the constraint force, which signifies the degree of restriction for the available levels of design variable β when design variable α takes a certain level, is derived using Equation (3). Moreover, $Priority_{\alpha\to\beta}$, the relationships of priority, which implies that the design variable α should be prioritized over the design variable β, is calculated using Equation (4) with the forward and reverse constraint forces.

$$Constraint_{\alpha\to\beta} = \frac{\sum_n^N \sum_m^M (\max(S(\alpha_n)_m) - S(\alpha_n)_m)}{N(M-1)} \quad (3)$$

$$Priority_{\alpha\to\beta} = \frac{Constraint_{\beta\to\alpha}}{Constraint_{\alpha\to\beta}} \quad (4)$$

The matrix of design–priority relationships is considered a parameter design structure matrix (DSM) (Browning, 2001), which is rearranged using the partitioning method, where the order of the row labels is the design order based on the priority relationships. The planes of two adjacent design variables in the

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row labels of the DSM derived using this method are the planes to be utilized in the narrowing and referred based on the design–priority order.

2.5. Derivation of larger solution spaces with weaker constraints by two-objective optimization

By performing a two-objective optimization of the size of the narrowed solution space and the weakness of the constraint relationships between the design variables for each selected plane in the order determined based on the DSM of the design–priority relationships, the multiple optimized solution spaces are plotted on the Pareto frontier. This enables the selection of a large solution space with weak constraint relationships between the design variables.

2.5.1. Size of the narrowed solution space and weakness of constraint relationships between design variables

A wide range of values for each design variable realizes a high degree of design freedom in the later stages of the process, which enhances the attainability to deal with design changes and adjustments between different departments as the design process progresses. In this study, the area of the narrowed solution space on the two-design variable plane is calculated as the size of the solution space for which each design variable is refined. Designers can keep the design margins wide until the later stages of the process by exploring the narrowed solution space has large area. The average value derived by dividing the sum of the bivariate distribution concentrations of each constraint network by the size of the narrowed solution space is referred to as the weakness of the constraint relationships between the design variables in the solution space.

Figure 3 shows a conceptual diagram of the size of the narrowed solution space and the weakness of the constraint relationships between the design variables in this study. The graph describes how the design variables x_1 and x_2 are narrowed down to 1 and 2 levels, and 2 and 3 levels, respectively. The reason for narrowing the shape of a rectangle is to realize a state in which the number of solutions does not differ among any design variable level because the entire solution space takes the shape of a hyper-rectangle.

According to the third level of the design variable x_1 in Figure 3, all the constraint networks have thick network edges; that is, the values of the bivariate distribution concentration are high. In other words, these solutions are undesirable for designers because they have strict constraint relationships between the design variables. However, the wider the narrowed solution space, the more design solutions with strong constraint relationships among the design variables that may be included in the solution space. Consequently, the size of the narrowed solution space and weakness of the constraint relationships between the design variables have a trade-off relationship. Therefore, optimization for both and Pareto analysis were conducted to search for solution spaces that reflect the designer'’s design intent.

2.5.2. Search for a narrowing pattern that simultaneously satisfies the wide design space and the weak constraints among design variables

Two-objective optimization was performed to maximize the narrowed solution space area and minimize the average value of the sum of the bivariate distribution concentrations within the solution space. In this study, NSGA-II (Deb et al., 2002), a multiobjective genetic algorithm, was utilized to perform two-objective optimization for each of the two-design-variable planes based on the design–priority order derived in Section 2.4. This leads to a search for narrowed large solution spaces: the range values of each design variable are wide, and the constraint relationships between the design variables are weak simultaneously.

Regarding the optimization of the second and subsequent planes in order, optimization was conducted by reflecting the results of the narrowing of the planes that have been previously optimized. In other words, the information on the design variables that were already narrowed down was transferred to narrow the range values of the design variables in the subsequent planes.

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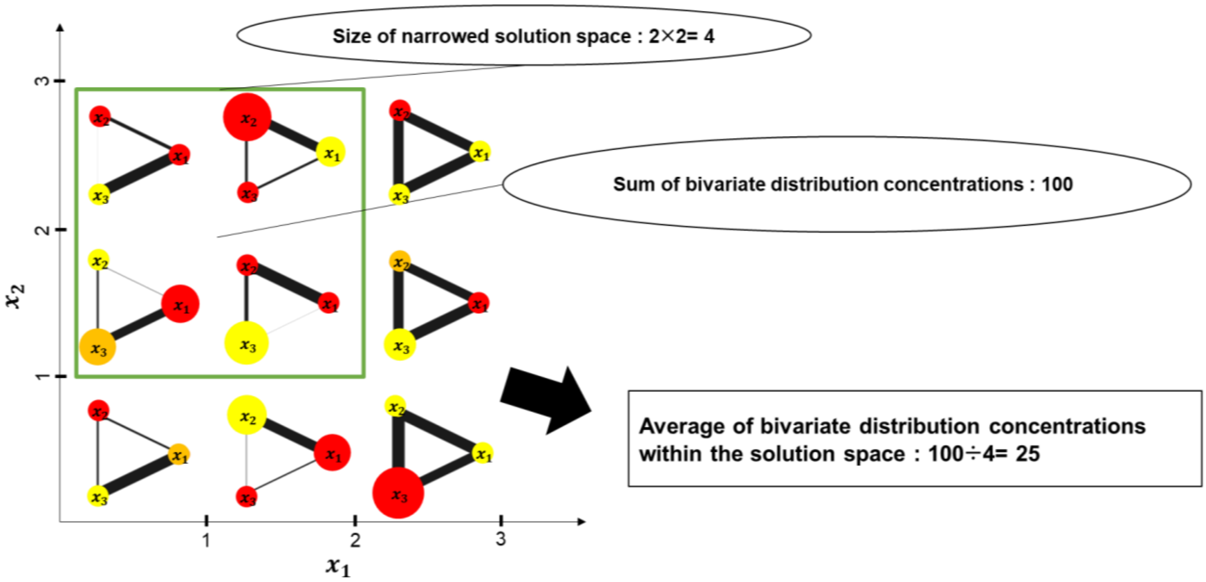

Figure 3. Conceptual diagram of the refinement of the range values of design variables in the 2-design variable plane (green: solution space after refinement)

2.6. Selection of the narrowed solution space

The solution spaces for which the size of the narrowed solution space and the weakness of the constraint relationships between the design variables are optimized are shown in the Pareto charts generated by the two-objective optimization described in Section 2.5. The designer selects a solution space based on the design intent. For instance, selecting a narrowed solution space with a large area on the Pareto frontier is desirable if increasing the degrees of freedom in the later stages of the design process is the primary aim. However, a solution space with weak constraint relationships between design variables, that is, a solution space with a smaller average value of the sum of bivariate distribution concentrations on the Pareto frontier, should be selected when the attainability of design, such as less design rework, is prioritized. The methods in Sections 2.5 and 2.6 are applied once to every plane determined in Section 2.4 to narrow the range of values of all design variables.

3. Application example: Application to a functional model of an electric motor for an EV

In this study, a functional model of an electric motor for an EV was chosen to illustrate the effectiveness of the proposed method. Table 1 presents the parameters of the applied functional model. The data for this model were normalized after extracting the design solution space to satisfy the constraints.

3.1. Two-design variable planes are divided

As an example, the case of dividing on the plane comprising the determined reduction ratio and the battery voltage was examined. The battery voltage was divided by the number of levels, because it was the design variable that took levels. However, as the determined reduction ratio lacked stationary levels, it was divided by 10 in this application example to arrange each divided space, including approximately 100 samples. Figure 4 shows that every divided space has a design solution for the determined reduction ratio and battery voltage plane when it is divided.

3.2. Evaluation of each divided space

Constraint networks and performance radar charts were calculated for each of the divided spaces. Figure 4(a) illustrates the constraint networks and Figure 4(b) shows the performance radar charts for each divided space on the determined reduction ratio and battery voltage plane. Designers can comprehend the design solutions contained within the narrowed solution space with these graphs when they narrow

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the range values of the design variables. In addition, the graphs provide approximate design characteristics to designers by visualizing the constraint relationships between the design variables and performance trends.

Table 1. Number of levels of target and design variable

Type of variables	Name of variables	Unit	Levels
Design variables	M.G. stator O.D.	mm	7
	M.G. loading thickness	mm	9
	M.G. turns	-	5
	Battery voltage	V	11
	Determined reduction ratio	-	Not leveling
Objective variables	System max. output	kW	Larger-is-better
	Axle shaft max. torque	Nm	Larger-is-better
	Combined electricity consumption	kWh/100km	Smaller-is-better
	Capacity requirement	kWh	Smaller-is-better
	Battery volume	L	Smaller-is-better
	Power unit volume	L	Smaller-is-better

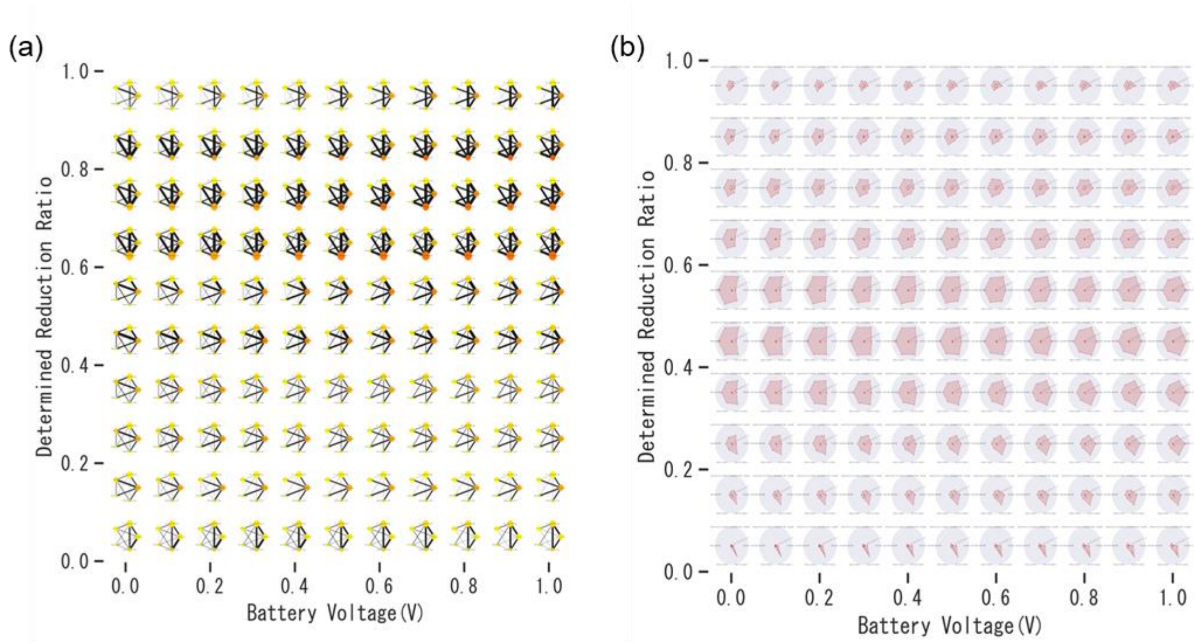

Figure 4. (a) Constraint networks; (b) Performance radar charts for each divided space on the determined reduction ratio-battery voltage plane

3.3. Determination of the two-design variable planes and order for narrowing

In this application example, a total of 10 planes were drawn because there were five design variables. The planes used for narrowing down the range values of the design variables were selected, and the order of the planes was derived based on the design–priority order described in Section 2.4. Table 2 presents the DSM showing the design–priority order in this examination. The numbers in the matrix are the values of the design–priority relationships calculated using Equation (4).

From Table 2, the design–priority order in this examination is the order of the row labels, and the determined reduction ratio–M.G. stator O.D., M.G. stator O.D.–M.G. turns, M.G. turns–battery voltage, and battery voltage–M.G. loading thickness planes, shown in bold, are referenced to narrow down the range values of the design variables.

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Table 2. DSM of design-priority relationships sorted by the partitioning method

	Determined reduction ratio	M.G. stator O.D. (mm)	M.G. turns	Battery voltage (V)	M.G. loading thickness (mm)
Determined reduction ratio	1	**1.18**	4.50	5.83	2.40
M.G. stator O.D. (mm)	0.849	1	**1.19**	1.38	1.69
M.G. turns	0.222	0.837	1	**1.17**	1.87
Battery voltage (V)	0.172	0.735	0.854	1	**1.55**
M.G. loading thickness (mm)	0.417	0.590	0.534	0.645	1

3.4. Two-objective optimization results based on the narrowed solution space's size and weakness of constraint relationships between design variables

For the selected planes, optimization was performed with the two objectives of maximizing the size of the narrowed solution space and minimizing the average value of the sum of bivariate distribution concentrations in the space. Figure 5 shows a Pareto chart of the battery voltage and the M.G. loading thickness plane. Each point on the Pareto frontier corresponds to a narrow solution space. Designers can select a solution space based on their design intent. In this examination, the largest solution space was selected, assuming that the highest priority was to increase the degrees of freedom in the later stages of the design process.

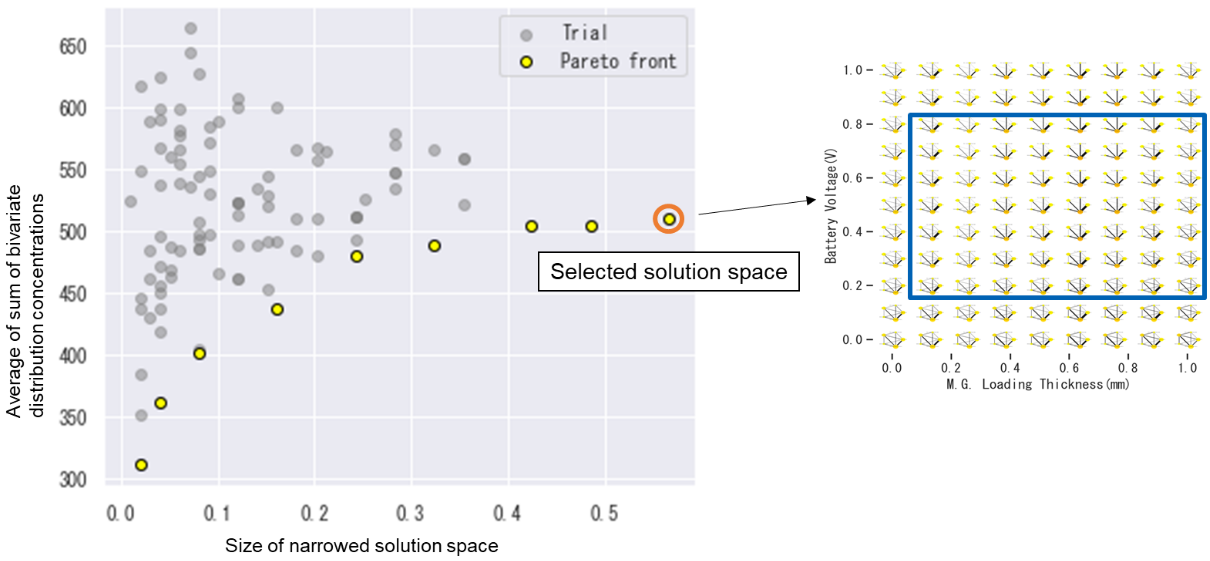

Figure 5. Pareto frontier on the battery voltage-M.G. loading thickness plane

3.5. Results of narrowing the solution spaces

Figure 6 shows the results of the two-objective optimization and selection of narrowed solution spaces for all four planes from the determined reduction ratio–M.G. stator O.D. plane to the battery voltage–M.G. loading thickness plane.

As Figure 6(a) illustrates, the determined reduction ratio and M.G. stator O.D. are finally narrowed down to less than half of their original levels, from 10 to 3 levels and from 7 to 3 levels, respectively, owing to the influence of strict performance constraints. However, in Figures 6(b), (c), and (d), which indicate the slight impact of performance constraints, the design variables that were narrowed down in the plane, M.G. turns, battery voltage, and M.G. loading thickness, are eventually narrowed down from 5 to 4 levels, 11 to 7 levels, and 8 to 7 levels, respectively, remaining more than half of the originally

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existing levels. Moreover, designers can avoid selecting a design solution with a high probability of design rework because the design solutions with extremely strong constraint relationships between the design variables are eliminated by two-objective optimization.

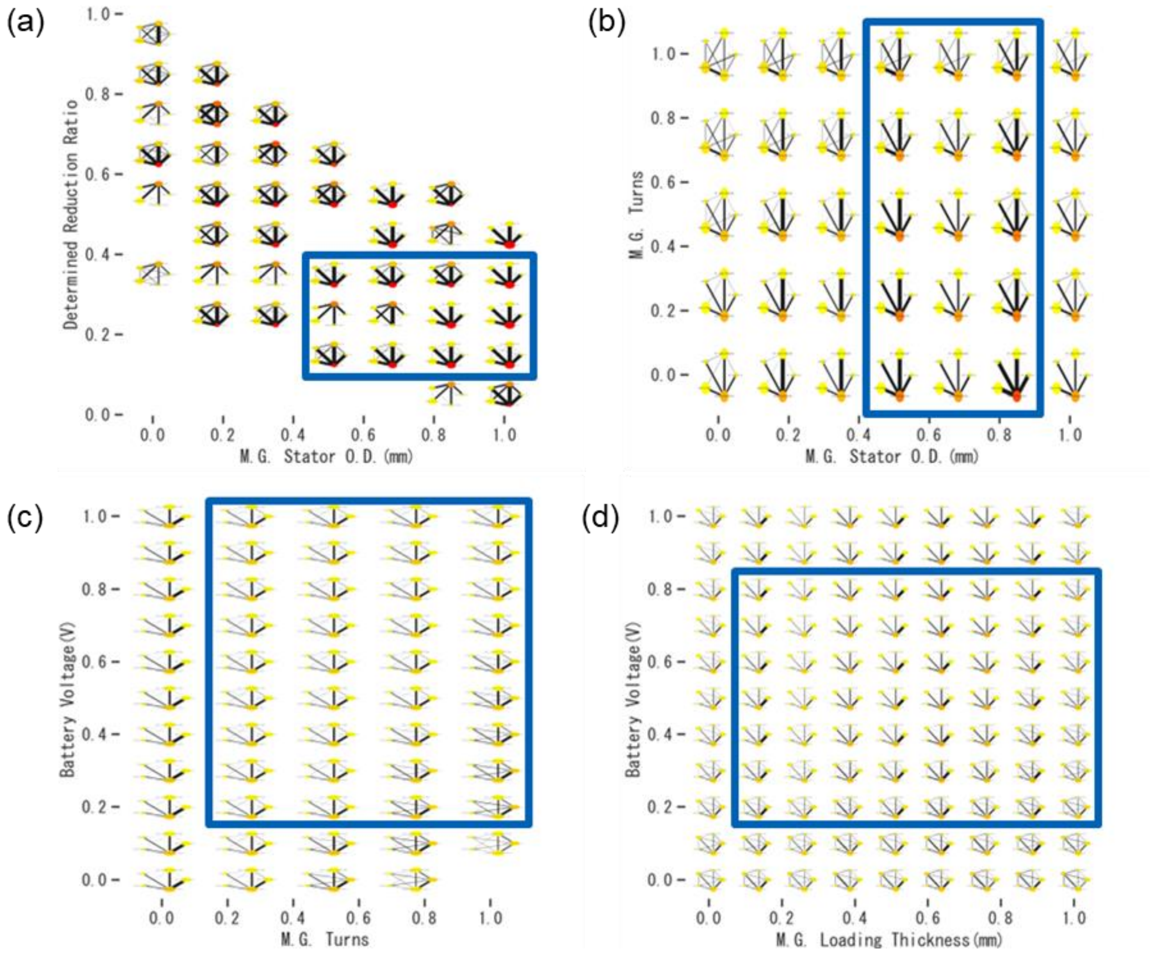

Figure 6. Narrowing results for range values of all design variables: (a) the first plane, (b) the second plane, (c) the third plane, (d) the fourth plane

4. Conclusion

This study proposed a method for searching for a solution space for the design variables in accordance with the designer's design intention in the early stages of the design process. It utilizes a two-objective optimization to maximize the size of the narrowed solution space and minimize the strength of the constraint relationships between the design variables on specific two-design-variable planes on which constraint networks and performance radar charts are drawn. This method enables designers to narrow down the range of values of design variables from the viewpoint of controlling design rework and securing design freedom for the latter stage of the process, considering the constraint relationships among design variables.

While the proposed method narrows down the range values of design variables to search for a solution space with weaker constraint relationships and a higher degree of freedom in the later stages of design, the selected solution space remains unevaluated, relying solely on the designers' judgment. This necessitates further research to develop a quantitative evaluation method for a narrowed solution space.

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