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GLOBAL PRODUCT DESIGN OPTIMIZATION STRATEGIES BASED ON SIMPLIFICATION OF PRODUCT CHARACTERISTICS

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ABSTRACT
The utility and validity of the "simplification" concept in product optimization are discussed and product design optimization methodologies based on this concept are proposed. First, the roles and significance of simplification processes are clarified. Product design optimization methods based on simplification strategies are then constructed, which feature three dedicated types of simplification that are applied to (1) characteristics, (2) structural models used for analyses, and (3) design variables. Pertinent characteristics are transformed into simpler characteristics and/or decomposed into simpler characteristics to enable the construction of optimization strategies based on these simplifications. Hierarchical optimization procedures for obtaining global optimum product designs are constructed, each of which is formulated using corresponding simplified structural models and a reduced number of design variables in the multiobjective optimization problems. The proposed methods are described using applied examples pertaining to machine products.

Keywords: product design optimization, simplification, hierarchical optimization, multiobjective optimization

1 INTRODUCTION
This paper discusses the utility and validity of the concept of "simplification" in product optimization, and proposes a product design optimization methodology and practical procedures based on this simplification concept. In today's product manufacturing environment, where highly competitive product development is taken for granted, a wide range of factors such as product performances, product qualities, and operational and manufacturing costs must be considered when designing and producing machine products. Ultimately, many product characteristics must be concurrently evaluated so that the requirement factors for product designs can be satisfied to the highest degree possible. To accomplish these tasks, it is essential that system optimization methods be constructed and then effectively used, rather than simply attempt to optimize certain machine elements or specific characteristics. Unfortunately, obtaining globally optimal design solutions through optimizations that include a large number of related factors is far from easy.

To enable optimization methods to be effectively applied to practical product design systems, sophisticated optimization strategies are required. Various approaches based on simplification or approximation methods [1-6] and uses of surrogate models [7-10] have been proposed for system design optimizations, and decomposition methods for system optimization problems have been actively studied. Optimization methods based on the decomposition concept generally employ hierarchical optimization procedures. Many kinds of methodologies have been proposed to accomplish such procedures, but decomposition of the design variables or design fields is the most widely used [11-18]. The goal of these system optimization methodologies is generally to efficiently obtain optimum solutions using minimal computational time.

In usual hierarchical design optimization methods, the main focus when constructing hierarchical procedures is upon design variables or design fields. Other approaches have also been proposed, where hierarchical design optimization methodologies based on clarification among related characteristics include objective and constraint functions [19-22].

In this paper, to expand the utility of the hierarchical optimization methodologies, simplification strategies are classified and explicitly incorporated in product design optimization methodologies. Representative performance characteristics for machine products are first presented, the features of the characteristics and the relationships among the characteristics are examined, and the factors that make comprehensive system optimizations difficult are clarified. Next, with the goal of effectively conducting product optimizations in mind, simplification concepts are introduced and the roles and significance of simplification processes are clarified. Then, product design optimization methods based on simplification strategies are constructed, featuring three dedicated types of simplification applied to (1) characteristics, (2) structural models used for analyses, and (3) design variables. Pertinent characteristics are transformed into simpler characteristics and/or decomposed into simpler characteristics to enable the construction of optimization strategies based on these simplifications. The simplified characteristics to be evaluated facilitate the construction of structural models that are as simple as possible and incorporate the required design variables.

The methodologies proposed in this paper aim to (1) obtain the global optimum solution even in design circumstances that include many local optimum solutions, and (2) enable useful examination of the obtained solutions.

The proposed methods are demonstrated using several applied product model examples and the obtained results are compared with those provided by conventional optimization procedures. Finally, the validity and applicability of the proposed hierarchical optimization procedures for practical product designs are discussed.

2 SIGNIFICANCE OF SIMPLIFICATION PROCESSES IN PRODUCT DESIGN OPTIMIZATIONS AND FUNDAMENTAL STRATEGIES FOR PRODUCT OPTIMIZATIONS

2.1 Performance characteristics for machine products

Machine products have functions that are designed to accomplish specific tasks, jobs that are performed by the movement and operation of certain parts of the machine. During design, the operational accuracies and the time taken to complete specific jobs are evaluated so that overall efficiency of the product can be considered. Here, the accuracy and efficiency are concurrently evaluated and higher values of both are generally more preferable, while it is desirable to minimize the operational energy used to accomplish the desired jobs that the product is designed to carry out. The product manufacturing cost is always to be minimized in actual manufacturing.

In this paper, as representative performance characteristics, the accuracy, the efficiency, the operational energy, and the product manufacturing cost are all considered.

Each original performance characteristic is usually very complicated, since it is expressed as compounds or additions of various other component characteristics. The optimum design solutions for each of the original performance characteristics are generally different from each other, meaning that such performance characteristics have conflicting interrelationships, which is a proximate cause of the difficulty of obtaining globally optimal solutions.

To clarify the interrelationships among characteristics, they are examined so that their expression and composition, as well as their dynamic behaviour and mathematical expression, can all be succinctly expressed in the context of the optimization problem at hand. For example, machine accuracies are often expressed by static and/or dynamic displacements at specific points that are determined according to the objective of specific jobs. Similarly, static rigidities can be used to evaluate the static displacements, and dynamic rigidities used when evaluating the dynamic displacements. In general, machine products can be classified into those where static rigidities alone are evaluated, and those where dynamic rigidities are also evaluated. Since machine products carry out their jobs by the movement and operation of various parts, it is usually necessary to evaluate and optimize dynamic rigidities as well as static rigidities.

Figure 1 shows an example of the frequency response at a specific point of the machine (the cutting point in the case of machine tools, the end-effector point in the case of industrial robots, etc.). The receptance frequency response is expressed as follows:

$$r(\omega) = \frac{X}{F}(\omega) = \sum_{m=1}^{\infty}\left[\frac{f_m}{1-(\frac{\omega}{\omega_m})^2 + 2j(\frac{\omega}{\omega_m})\varsigma_m}\right] \qquad (1)$$

The static rigidity k_s is obtained using the reciprocal of the static compliance f_s, while the dynamic rigidity k_d is obtained using the reciprocal of the maximum receptance value $r_{\max}$ over the whole frequency range.

When the frequency ω is set to 0 in equation (1), the following simple relationship between f_s and modal flexibility f_m is established.

$$f_s = \sum_{m=1}^{\infty} f_m \qquad (2)$$

Both f_s and f_m have positive values. The modal flexibility f_m $(m = 1,2,...,\infty)$ expresses the distributed magnitude of the static compliance f_s for each natural mode. Equation (2) indicates that minimizing the static compliance f_s, which is equivalent to maximizing the static rigidity, reduces the modal flexibility at the natural mode where the modal flexibility value is highest.

In machine structures, vibration damping is most pronounced at joint interfaces, be they bolted or sliding. The consequences of damping effects can generally be controlled by carrying out detailed adjustments of joint parameters during the detailed design stage. When structural member rigidities are maximized, increasing the damping effects at the joints becomes easier [19]. The damping ratio ζ_m has a different value at each natural mode. The material damping ratios and the damping ratios for machine elements or parts vary according to the material properties, shapes and other parameters, however the damping ratios for the machine structure as a whole, despite the inclusion of many joints, often has a specific value or lies within a rather narrow range of values. Such values are often defined by experimental studies, and here, the damping ratio is given as a specific constant value of ς for the initial stages of the design optimization.

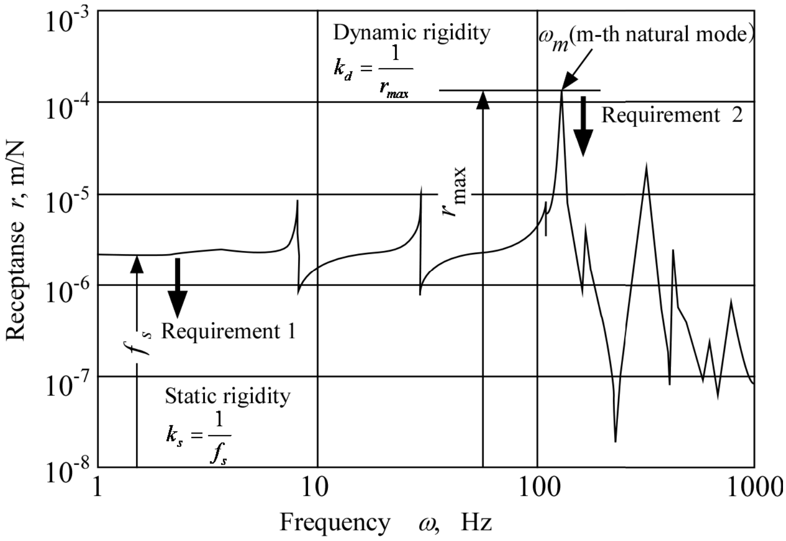

Figure 1. An example of frequency response at the cutting point of a machine-tool model

The dynamic rigidity k_d is approximately expressed by the static rigidity k_s and the damping ratio ς as follows:

$$k_d = \frac{1}{r_{\max}} \cong \frac{2\zeta}{af_s} = \frac{2k_s\zeta}{a} \qquad (3)$$

where a is assumed to be a constant value, such as 0.7.

Examination of the related characteristics yields the result that increasing the static rigidity k_s increases the dynamic rigidity k_d.

In light of the above, it is clear that optimization of the static rigidity should have priority over optimization of the dynamic rigidity.

Simpler characteristics such as static rigidities can usually be effectively evaluated using simpler structural models**. Figure 2** is a conceptual diagram of an optimization based on the simplification of product characteristics. The final goal of this product optimization is to obtain optimum design solutions for practical detailed models via an “implementation” process typically composed of multi-step optimizations. In each implementation step, as simple as possible corresponding structural models are used.

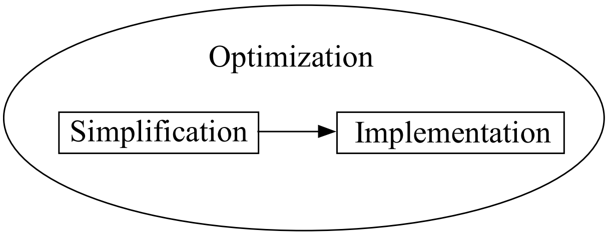

Figure 2. Explanation diagram for optimization based on “simplification” concept

2.2 Roles and significance of simplification concepts in product optimizations

Direct optimizations of product performances that include dynamic characteristics encounter the following difficulties:

(1) Many local optimum solutions are usually present in the design variable space, and obtaining a globally optimal solution is elusive.

(2) It is difficult to deeply examine the obtained solutions and also impossible to judge whether or not the obtained solutions are effective and suitable.

(3) The obtained solutions tend not to facilitate discoveries of better design solutions.

Table 1 shows three simplification objects: (1) characteristics, (2) structural model for analyses, and (3) number of design variables, and their relationship to simplification and implementation. For the “characteristics” simplification object, static characteristics corresponding to the simplification, and dynamic characteristics corresponding to the implementation, are used in the applied example here.

Table 1. Three simplification objects in product optimization

Simplification object	**Simplification**	**Implementation**
Characteristics	Static characteristics	Dynamic characteristics
Structural model for analyses	Simplified or idealized model	Detailed model, practical model
Number of design variables	Small	Larger

Simplification and/or idealization of the product or product design to be optimized must be carried out to accomplish the following two important points:

(1) To achieve a truly global optimum solution for practical design problems having many local optimum solutions.

(2) To obtain more preferable solutions to a simplified or abstracted problem that includes a larger number of alternatives.

2.3 Fundamental strategies of optimization based on simplification concepts

The following are examples of techniques for simplifying an optimization problem that can then satisfy the above points:

(1) A complicated characteristic can be expressed as combination of several simpler characteristics.

(1-1) In machine product designs, evaluations of vibration characteristics are indispensable as explained above, however design optimizations including vibration characteristics usually give results that contain unwanted local optimum solutions in the feasible design space, hence obtaining clearly global optimum solutions to such design optimization problems is elusive. The dynamic rigidity k_d is decomposed into two characteristics, the static rigidity k_s and the damping ratio ζ as explained in section 2.1.

(1-2) The static rigidity k_s is composed of the static rigidity of the structural members k_M and the rigidity of the joints k_J. The rigidity of the structural members k_M has a conflicting relationship with the weight of the structural members W_M, while the rigidity of the joints has a conflicting relationship with the machining cost of the joint contact surfaces. The static rigidity k_s is thus decomposed into the static rigidity of the structural members k_M and the rigidity of the joints k_J.

(1-3) The manufacturing cost for machine products is composed of various kinds of costs, such as material costs, machining costs, welding costs, casting costs, and assembly costs. Decomposition of the total manufacturing cost into specific types of cost prior to optimization is an effective technique for both obtaining optimum solutions and evaluating the results in terms of the influence that each cost has on the total manufacturing cost. Energy use during operation and the structural weight of the machine product are also easily decomposed into various sub-characteristics according to the specific parts that make up the product.

(2) Characteristic factors that only exercise minor effects can be disregarded.

(2-1) The static rigidity k_s at the cutting point is determined by the rigidities of the structural members and joints 1 through 5, collectively termed the static force loop. On the other hand, the structural members, elements, and joints outside the static force loop have no influence on the static rigidity at the cutting point. When the static rigidity is evaluated, structural members, joints, and elements that have only a minor influence on the static rigidity should be excluded from consideration.

(2-2) A system having numerous degrees of freedom is transformed into a system with only one degree of freedom. The dynamic rigidity k_d at the cutting point is the reciprocal of the magnitude of the maximum receptance value $r_{\max}$. The modal flexibility at the natural mode almost always has the largest value among the various natural modes across the entire frequency range, so the system being considered in terms of its vibration can be approximately modelled as a single degree-of-freedom system.

(3) When two characteristics have a dominant/subordinate relationship, the dominant characteristic should be determined before determining the subordinate characteristic.

When optimization or minimization of characteristic f_A dominates the optimization or minimization of characteristic f_B, characteristic f_A should be processed first, independently of and prior to the processing of characteristic f_B. That is, simultaneous optimization of characteristics f_A and f_B is not appropriate in this case, since doing so would require significantly more computation time and yield ineffective solutions. Thus, not only is concurrent optimization is not always recommendable, but sequential optimization procedures are usually simpler than concurrent optimization procedures.

Among the rigidity of the structural members and the rigidity of the joints, determination of the rigidity of the structural members is dominant with respect to determination of the rigidity of the joints. This implies that the following optimization procedure can be used to optimize the static and dynamic rigidities:

(a) The structure of the product model is optimized under the condition that the joints are rigid and the structural member design solutions are used as initial design solutions in succeeding optimizations.
(b) Then, the spring stiffnesses of the joints are optimized after the contact surface shapes have been determined according to the cross-sectional dimensions of the structural members.
(c) Finally, all structural member and joint design variables, including the damping coefficients for the joints, are optimized by evaluating the dynamic rigidity of the whole structure.

(4) The value of a specific characteristic can be fixed as a constant value that is approximately obtained from experience or prior experiment.

Damping characteristics and appropriate magnitudes for product structures can seldom be clearly specified at during design stages, but the magnitudes for the structure as a whole can often be experimentally given. In such cases, setting a specific value for the damping ratio ζ is often reasonable.

3 METHODOLOGIES FOR PRODUCT OPTIMIZATION BASED ON SIMPLIFICATION OF PRODUCT CHARACTERISTICS

3.1 Procedures of optimization

The proposed optimization methodologies have the following features:

(1) The optimization procedures based on "simplification" concepts have hierarchical stages.
(2) Since optimizations at each stage have conflicting characteristics, multiobjective optimization methods are used.

Simplified characteristics are arranged as a hierarchical structure and each simplified characteristic contains conflicting characteristics. Multiobjective problems are solved as a series of optimizations carried out at each hierarchical level. The optimization procedure begins at the level of the simplest characteristics and the results, in the form of Pareto optimum solutions, are then transferred to the next hierarchical level. Ultimately, Pareto optimum solutions for the original product performances at the highest hierarchical level are obtained. The methods for transferring Pareto optimum solutions to successive optimization stages are the same as those used in a previous paper [20].

3.2 Practical procedures with applied examples

Practical procedures are explained with applied examples. **Figure 3** shows a framework model of a machine tool composed of structural members and joints. The performance characteristics to be considered are the static and dynamic rigidities at the cutting point and the manufacturing cost of the machine tool. The static rigidity k_s is the reciprocal of the static compliance f_s between points A and B at the cutting point, which is obtained as X/F where X is the relative displacement between A and B, and F is the cutting force at points A and B. The dynamic rigidity k_d, i.e., the reciprocal of the maximum receptance value $r_{\max}$ of the frequency response curve, is obtained from the frequency response curve.

The objective functions are the maximum receptance value and the machine's manufacturing cost C_T, each of which should be minimized. The formulation of $r_{\max}$ is simplified as shown in equation 3. Then, the characteristic of the maximum receptance value $r_{\max}$ is decomposed into two characteristics, namely, the static compliance f_s and the damping ratio ς. The manufacturing cost C_T is decomposed into the material cost C_M of the structural members and the machining cost C_J of the joints

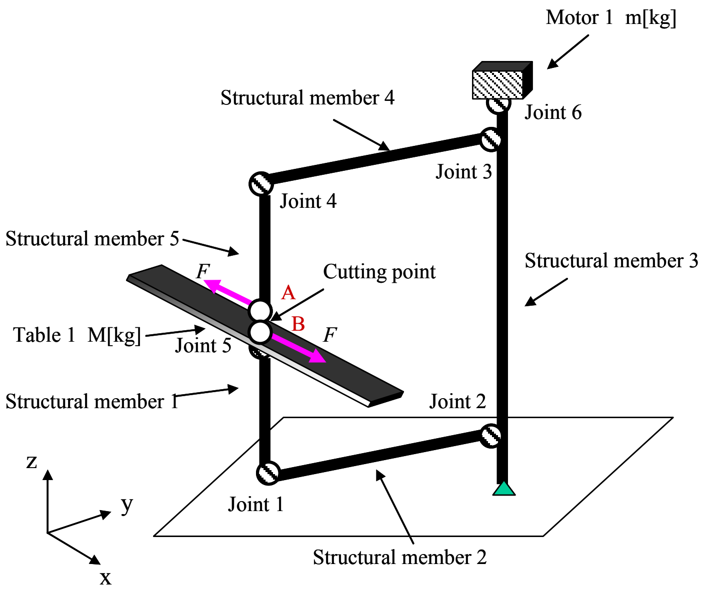

Figure 3. Framework model of a milling machine

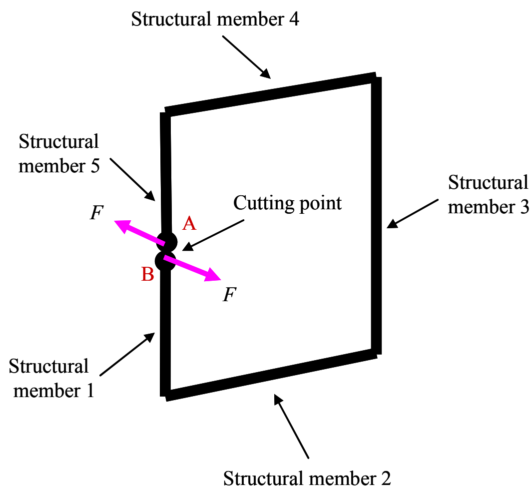

Figure 4. Structural model of the static force loop

The optimization procedures carried out during the hierarchical multiobjective optimization are as follows:

Step 1: The multiobjective optimization problem for the static rigidity k_M and the total structural weight W_s of the structural members on the static force loop is solved and a Pareto optimum solution set of cross-sectional dimensions is obtained. The structural model used for the structural analysis is shown in **Figure4**, where only structural members on the static force loop are indicated, and each joint is treated as a rigid joint for the purposes of simplicity. The design variables are the cross-sectional dimensions of each structural member.

Step 2: The Pareto optimum solution line between the static rigidity k_M of the structural members and the material cost C_M of the structural members is obtained. The material cost C_M is calculated by multiplying the material cost per unit weight by W_s.

Step 3: The multiobjective optimization problem is solved for the total joint rigidities k_J on the static force loop and the machining cost C_J of the joints. The structural model used for the structural analysis is shown in **Figure 4**, where each joint is now treated as a flexible joint modelled as a spring, and the maximum surface roughness of the contact surface is included in the design variables. The results of the cross-sectional dimensions obtained in Step 1 are used as initial design variables. In this optimization, the relationships between the surface roughness $R_{\max}$ and the machining cost C_u per unit contact surface, shown in **Figure 5**, are used, where three kinds of machining methods, namely, milling, grinding, and super finishing, are considered. The joint rigidities are calculated according to their surface roughness values and contact surface areas.

Step 4: The multiobjective optimization problem is solved for the static compliance f_s (the reciprocal of the static rigidity k_s) and the total manufacturing cost C_T of the structural members on the static force loop, which is the sum of the material cost C_M and the machining cost C_J of the joints, and a Pareto optimum solution set is obtained.

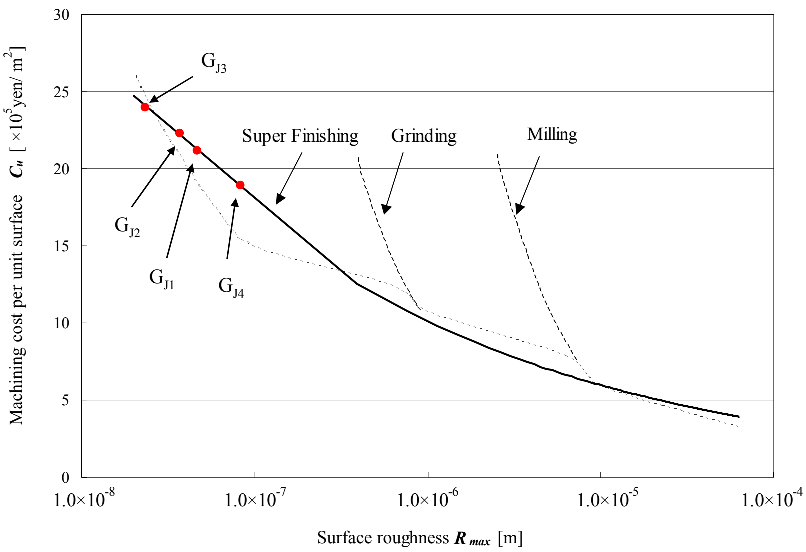

Figure 5. Relations between surface roughness and machining cost per unit contact area

Step 5: The multiobjective optimization problem for the maximum receptance value $r_{\max}$ and the total manufacturing cost C_T is solved and a Pareto optimum solution set is obtained. The structural model now used is shown in **Figure 3**, where each joint is modelled as a flexible joint and the maximum surface roughness of the contact surface is included in the design variables. The results of the cross-sectional dimensions and spring stiffnesses obtained in Step 2 are used as initial design variables.

Figure 6, the Step 1 result, shows the Pareto optimum solution set line between the static rigidity k_M and the total structural weight W_s of the structural members on the static force loop. **Figure 7**, the Step 2 result, shows the Pareto optimum solution set line between the static rigidity k_M and the manufacturing cost C_M of the structural members on the static force loop.

Figure 8, the Step 3 result, shows the Pareto optimum solution set line between the joint rigidity k_J and the machining cost C_J of the joints on the static force loop. And **Fig. 9**, the Step 4 result, shows the Pareto optimum solution set line between the static compliance f_s and the total manufacturing cost C_T

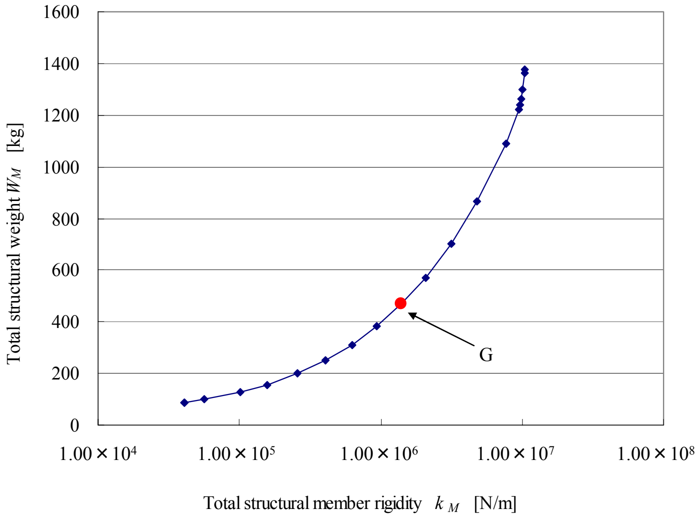

Figure 6. Pareto optimum solution line for Step 1

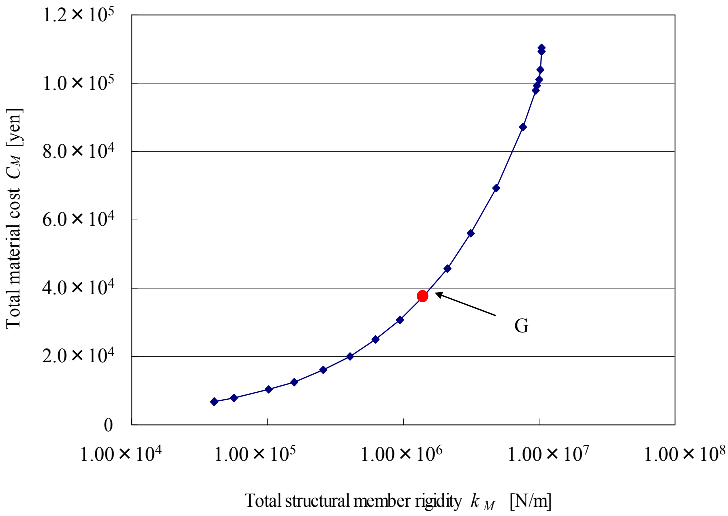

Figure 7. Pareto optimum solution line for Step 2

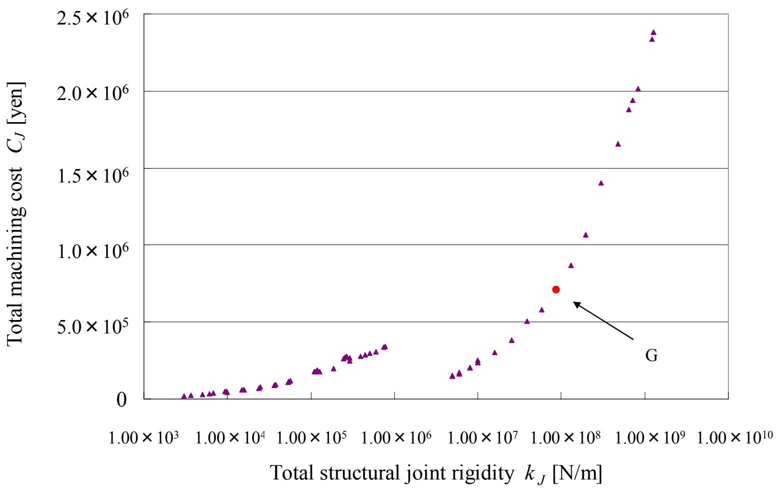

Figure 8. Pareto optimum solution line for Step 3

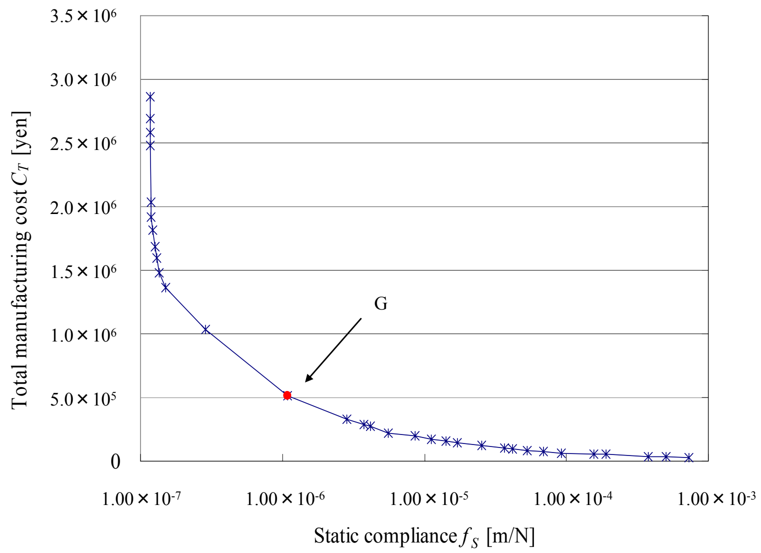

Figure 9. Pareto optimum solution line for Step 4

Figure10, the Step 5 result, shows the Pareto optimum solution set line between the maximum receptance $r_{\max}$ and the total manufacturing cost C_T. To demonstrate the effectiveness of the proposed method, its results are compared with those obtained by a conventional method, where the performance characteristics (objective functions at Step 5) are directly optimized using the feasible direction method but without using the proposed hierarchical optimization procedures. The former are shown with ◆ symbols in **Figure 10**, while the results obtained by the proposed method are shown with ∗ symbols. The Pareto optimum solution line is shown by the thin line, which indicates the optimum solution frontier. The results show that more preferable solutions are more reliably obtained by the proposed method.

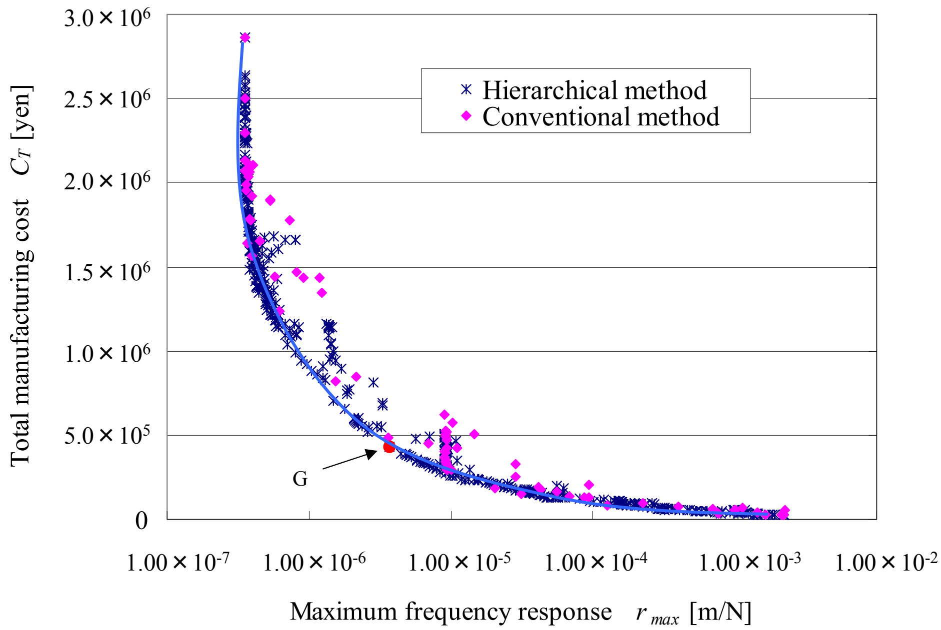

Figure 10. Pareto optimum solutions for Step 5

4 DISCUSSION

The proposed optimization method incorporates the following points:

(1) Optimum solutions can almost always be obtained. Concurrent optimization of multiple characteristics usually yields numerous local optimum solutions, but the optimization process in the

proposed method originates with an initial optimization problem that is usually very simple and includes only a single local optimum solution. Since highly appropriate initial design variables at the succeeding levels can then be used, the final global optimum solution can be more efficiently obtained.

(2) Optimum solutions are first obtained in the form of Pareto optimum solution sets. The design solution most suitable for the specific product requirements being considered can thus be flexibly selected from a useful range of alternative design sets.

(3) The final global optimum solution can be analyzed and understood in terms of the interrelationships between correlated solution points existing in the final and first hierarchical levels, or in intermediate levels. The validity of the obtained design solutions, and their fitness for particular purposes, can therefore be more effectively evaluated. With point G selected on the Pareto optimum solution line in **Figure 10**, corresponding solution points on the Pareto optimum solution lines in **Figure 6** through **Figure 9** are also indicated by points labelled G. At each corresponding point, the detailed values of the design variables and the characteristics can be examined, enabling a deeper understanding of the solution contents. For example, points GsubJx, with x corresponding to the joint number, are shown in **Figure 5** and they indicate the solution's recommended machining method. The design solution corresponding to points G_{J1}, G_{J2}, G_{J3} and G_{J4} for joints 1, 2, 3 and 4, respectively, are illustrated, and it can be seen that super finishing machining is indicated for these particular joints. Furthermore, useful comparisons of several design solutions on the Pareto optimum solution line at the final stage can be conducted by going back to earlier optimization stages, enabling more detailed examinations of the optimum solutions.

(4) Because the relationships between the optimum solution at the final hierarchical level and solutions at the first level are exposed and can be easily understood, examination of the features of characteristics at the first level, which are usually very simple, can often lead to further effective ways of improving these characteristics and, ultimately, the overall fitness of the final product design. That is, the techniques listed in (3) above more effectively support the generation of further ideas for improving tentative design solutions, and facilitate more rapid examination of the resulting improvement levels. For example, it may be potentially beneficial to use a new material for a structural member, and the validity and utility of doing so can be readily evaluated using the Pareto optimum solutions obtained during earlier optimization stages.

5 CONCLUDING REMARKS

This paper proposed product design optimization strategies and procedures based on simplification concepts applied to optimization problems. Fundamental simplification strategies for design optimization were described, and hierarchical optimization procedures based on these simplification strategies were constructed. The results obtained in the provided practical examples show that introducing simplification concepts to product design optimizations makes it easier to obtain globally optimal solutions, deepens the understanding of problem essentials and provides valuable insights concerning optimized results and evaluations of their validity.

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