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DESIGN PROCESS ASSESSMENT IN GLOBALLY COMPETITIVE PRODUCT DEVELOPMENT

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Abstract

Globalization of industry and the manufacturing environment is spurring intensification of international competition in the designing products. This inevitably causes the changes in the style and characteristics of design activities. We have already proposed a methodology for quantitative estimation of design load and efficiency in our previous work.

In this paper, we survey the design processes for professional-use devices and discuss recent design process innovation by introducing an index to measure the efficiency of design optimization. This progress is explained as the transition of design type from "fulfilling the design requirements" to "searching for the optimum design solution." For the latter design type, rational decision making at the early design stages is particularly important for achieving the optimum design solution efficiently. In this context, finally, the influence of uncertainty in decision making on design time is quantitatively evaluated by treating it as a probability density function, in conjunction with the proposed estimation methodology. We name the quantitative approach shown in this paper "Design Process Assessment," and we aim to systematize it in order to analyze and optimize design processes based on rational indices.

Keywords: Shannon's entropy, Taguchi Method, D-efficiency, Analytic Hierarchy Process, Design Process Assessment

1. Introduction

Recently, advances in the performance of personal computers have been remarkable. Simultaneously, low-priced CAE tools have also been introduced that are user-friendly not only for CAE specialists but also for designers or CAE novices. In view of these developments, the rational and optimized usage of CAE tools is crucial for efficient product development.

In accordance with this progress of the CAE environment, design support methodologies and tools are being actively studied. Design for X [1], which is a system of strategic design techniques, and Six Sigma^{TM} [2] are well-known examples of such methodologies.

In addition, design methods and tools to perform CAE simulation according to optimization algorithms [3] are also entering widespread use.

As described above, design and development processes in actual design fields are improving steadily through the following two steps:

1. Spread of CAD/CAE
2. Spread of design optimization methods/tools

However, it is difficult to apply these tools and methods efficiently based on quantitative indices.

To address this subject, we have proposed an evaluation method based on information engineering techniques to relate the total design period and probabilities of correct decisions of design variables and alternatives [4]. As a result, the reduction of design period by the improvement of probability was evaluated quantitatively at every design stage.

Consequently, designers can efficiently improve their design processes. We introduce these results briefly in section 2.
In this paper, in analyzing design processes, we focus on how design processes have been improved in the past several years. Through this analysis, in section 3 we aim to clarify how design support methods affect the design period and how they change the style of design activities.
In this evolution of design processes, it is also difficult to discuss the improvement of design processes in terms of a concrete index. To address this issue, we adopt an index called "D-efficiency" which represents the coverage and efficiency of searching in the design variable space and discuss the relation between this index and progress of design efficiency.
In regard to the background of the recent evolution of design processes, we explain the transition of design process by taxonomical analysis of design types in section 4.
Finally, we also show the importance of rational decision making for efficient product development by treating uncertainty as a probability density function.

2. Previous work – Approach for quantitative estimation of design load and efficiency

The design task is a process to reduce the ambiguity of the total system of decision making with regard to design alternatives and parameters. In this context, we proposed a methodology to measure load and efficiency of design [4] by introducing one of the basic information theories, namely, the formula of Shannon's entropy [5], and derived a simple expression for quantitative estimation of design complexities.

2.1 Theoretical basis

Shannon's entropy is an index used to measure uncertainty of discrete random variables. The entropy is defined from probability distribution of variables by Shannon's formula (eq. 2.1).

$$H(p) = -\sum_{i=1}^{n} p_i \cdot \log_2 p_i \qquad (2.1)$$

H is called Shannon's entropy of information and its unit is *bit*. p_i (*i*: natural number between 1 and *n*) is the probability distributions that satisfy:

$$\sum_{i=1}^{n} p_i = 1$$

In the context of design processes, the probability distribution exists at the choice of design alternatives. If designers have *n* number of alternatives, and do not have any information regarding which one to choose, the probability of selection of each alternative equals 1/*n*, and its entropy is maximized.
However, once information is obtained, for example, results of experiments and/or computer simulations, designers can choose one of the alternatives more confidently, and as a result, the probability distribution changes to an uneven one. This reduces the entropy.

2.2 Expression of branching structure of design processes

We classified branches in design processes into two types (See the lower right of Figure 1):

- Alternatives: The branch for selection of one alternative.
- Modules: The set of design units to be processed independently and/or in parallel.

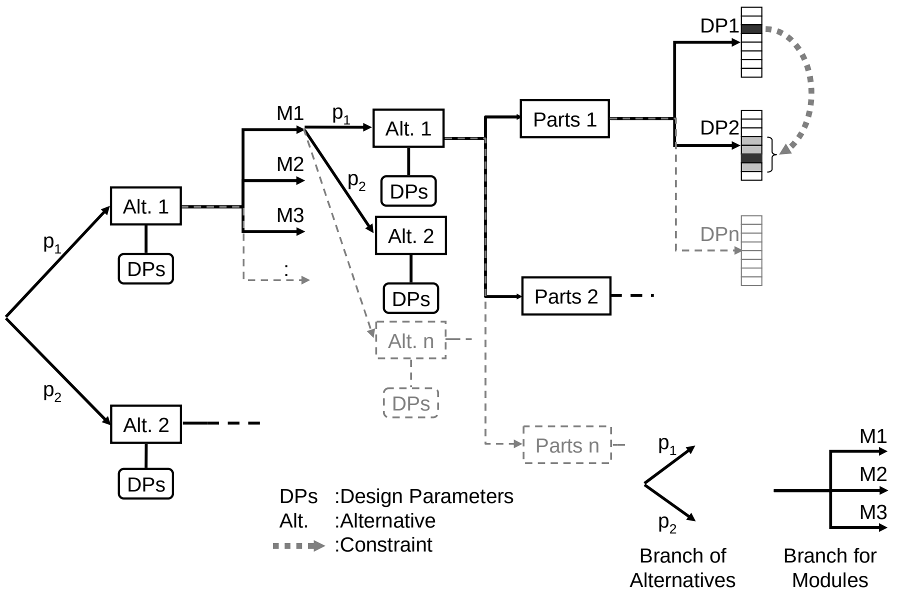


Figure 1. Expression of branching structure of design process

By composing these two branch types, complex branching structures of actual design processes can be expressed as shown in Figure 1. Where, p_1, p_2 means the probabilities assigned for alternatives, "DPs" means the design parameters to be determined at each alternative, and M_1 - M_3 means modules.

Entropies on branches of modules are simply summed, and entropies on branches of alternatives are calculated following eq. 2.1. Entropy of multilayer branching structure can be calculated recursively by eq. 2.2.

$$H_l = H(p_{l,1}, \cdots, p_{l,n_l}) + \sum_{j=1}^{n_l} p_{l,j} \cdot H_{l+1,j} \qquad (2.2)$$

Where, l is the number of layer levels counted from top level. $H_{l+1,j}$ is the entropy of j th alternative on the l +1 th level.

n_l is the number of alternatives belonging to the objective branch on level l. The first member of right side of eq. 2.2 is the entropy of the probability distribution $(p_{l,1}, \cdots, p_{l,n_l})$ calculated from eq. 2.1.

Eq. 2.2 is important from the viewpoint of practicality and utilized later for evaluation of design period in section 5.2.

We also introduce the "assumption of symmetry" to the branch where the complete structure of all alternatives is unknown. Namely, we assume that if one alternative has been chosen on a certain branch, other (uninvestigated) alternatives would have the same degree of complexity. Of course, this assumption is not necessarily true in actual design stages. However, from the standpoint of statistical analysis of design activities, we think this assumption is rational. Owing to this assumption, if a completed design process is investigated and one final set of alternatives and design parameters are analyzed, the total entropy of design processes can be roughly estimated.

2.3 Conversion of entropy into time or cost

As the final step of practical application of information theory to evaluation of the design process, time constant k and cost constant k_c are introduced as shown below.

$$T = k \cdot 2^H \qquad (2.3)$$

$$C = k_c \cdot 2^H \qquad (2.4)$$

Where, T is the time needed to process design task and C is the cost to process design task. Here, we name 2^H "equivalent number of alternatives." By these two equations, we assume that design period or cost is proportional to the scale or complexity of design process. k or k_c is the constant of proportionality between time or cost and equivalent number of alternatives, respectively. In the case where alternatives have different k, average of k is represented by $\bar{k}$. Then, T_{total} can be expressed simply as shown in eq. 2.5.

$$T_{total} = \bar{k} \cdot 2^{H_{total}} \qquad (2.5)$$

Where, "*total*" is the suffix for total value of each variable.
Next, H' is defined from eq. 2.3 as follows.

$$H' = \log_2 T = \log_2 k \cdot 2^H = H + \log_2 k \qquad (2.6)$$

By assuming H' also follows eq. 2.2, $\bar{k}$ is derived from eq. 2.5 and 2.6 as follows:

$$\bar{k} = \frac{T_{total}}{2^{H_{total}}} = \frac{2^{H'_{total}}}{2^{H_{total}}} = \frac{2^{H(p_1, \cdots, p_n) + \sum_{i=1}^{n}(p_i \cdot H_i')}}{2^{H(p_1, \cdots, p_n) + \sum_{i=1}^{n}(p_i \cdot H_i)}} = \frac{2^{\sum_{i=1}^{n}(p_i \cdot (H_i + \log_2 k_i))}}{2^{\sum_{i=1}^{n}(p_i \cdot H_i)}}$$

$$= 2^{\sum_{i=1}^{n} \log_2 k_i^{p_i}} = \prod_{i=1}^{n} \left(k_i^{p_i} \right) \qquad (2.7)$$

Where, n is the total number of alternatives on the target branch. $\bar{k}$ possesses the meaning as an index of the overall efficiency of an target branch.

2.4 Results of quantitative analysis of actual design processes

Actual design processes were analyzed by the methodology explained above. Firstly, the branching structure consisting of several design stages was investigated. Then, number of alternatives, their probability distributions, and minimum design time to process each stage were also examined. Such information was modeled and analyzed using spreadsheet as shown in Figure 2. With this model, the appropriateness of introducing certain design support methods/tools or priority of design stages to be improved can be determined rationally on quantitative grounds. In many cases, variation of probability distribution in upper design stages leads to more variation in design time or cost.

Moreover, the imaginary minimum (= best) total design time can be derived by setting 100% probability to one convincing alternative on all branches. The maximum (= worst) total design time can also be derived by setting the perfectly even (namely, the least confident and the most ambiguous) probability distribution to the alternatives. These benchmark results are

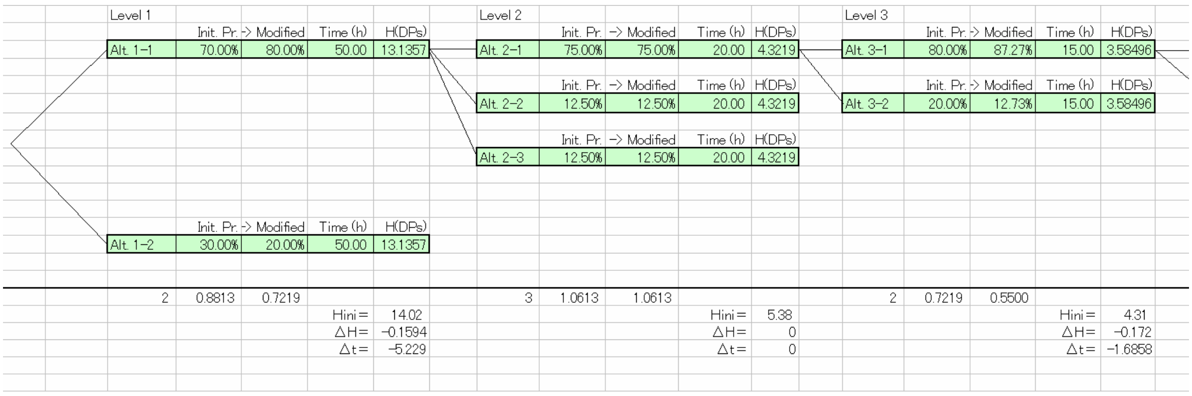


Figure 2. Example of actual design process (partial view)

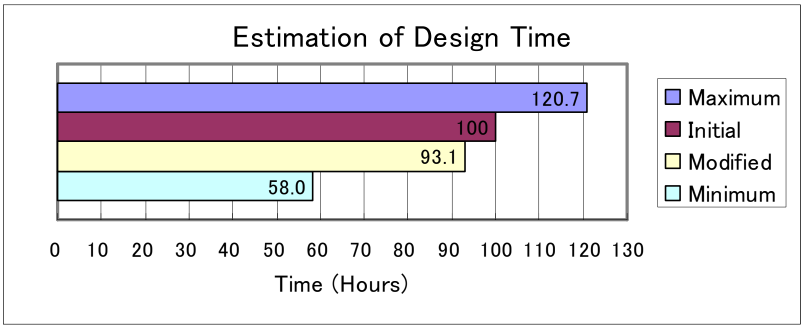


Figure 3. Benchmarking of design time (Values are fictional.)

shown in Figure 3. As shown in this graph, the effect or impact of the design information against the design time is quantitatively estimated by the proposed methodology.

3. Transition of characteristics and efficiency in design processes

In this section, we proceed to the further analysis of the design processes, focusing on how design processes have been improved in the past several years. Through this observational study, we aim to clarify whether design support methods can actually reduce the design time and how they change the style of design activities.

3.1 Target design projects

We investigated three actual design projects concerning the cooling systems of professional-use devices performed in 1998, 2002 and 2004. There were the trade-off constraints among the main function, size and heat generation. This means designers have to deal with the multi objective optimization problems. In the design department investigated in the present work, various appropriate design support methods including the Taguchi method were eagerly introduced aiming to improve the design efficiency in this target period.

3.2 Effects of the Taguchi method on design time

The design processes we examined have evolved through the following three steps:

Step 1. In Project 1 in 1998, designers surveyed design parameters according to the order of their importance until design requirements were fulfilled.

Step 2. In Project 2 in 2002, the Taguchi method was introduced for efficient parameter surveys covering many design variables simultaneously.

Step 3. In Project 3 in 2004, a commercial optimization engine was utilized to investigate the relation between the key parameter and the main function.

In this evolution of design processes, it is difficult to measure the extent to which the design processes are improved quantitatively. To approach this problem, we estimated the expected design time if the Taguchi method had been introduced in Step 1.

3.2.1 Trial calculation 1

In the first trial calculation, we estimated the design time if the Taguchi method had been introduced in Project 1. To fit the actual combination of parameter levels used in Project 1 as closely as possible, original orthogonal arrays $L16(2^{15})$ and $L18(2^1 \times 3^7)$ are modified into $L16(4^2 \times 2^4)$ and $L18(2^3 \times 3^3)$ respectively, by combining rows or introducing dummy levels. Recently in this design department, selection has tended to favor $L18$ rather than $L16$ in similar cases, since $L18$ disperses interaction effects to other rows. Total design times are calculated by eq. 3.1 with parameters and conditions listed in Table 1 and Table 2.

$$T_{total} = T_i + T_m \cdot N_m + T_F \cdot N_F + T_s \cdot N_s \qquad (3.1)$$

Table 1. Conditions for trial calculation

Legend	Description	Average time (hrs.)
T_i	Time needed to make 3D model first	3.00
T_m	Time needed to modify 3D model	0.60
T_F	Time needed to construct FEM model from 3D model	3.42
T_s	Time needed to solve an FEM simulation case	2.05

Table 2. Construction of design processes

Legend	Description	Actual	*L*16	*L*18
N_m	Number of times to modify 3D model	4	7	11
N_F	Number of times to construct FEM model from 3D model	5	8	12
N_s	Number of times of FEM simulation	22	16	18
T_{total}	Total design time (hrs.)	67.6	67.3	87.5

The points of results are listed below:

- With *L*16, designers can obtain the information of factorial effects among variables in nearly the same time (67.3hrs.) as the actual design time (67.6hrs.).
- However, with *L*18, design time is prolonged by about 20 hrs. In this case, there is a trade-off relation between design time and richness of obtained design information.

3.2.2 Trial calculation 2

Secondly, we estimated the design time if the Taguchi method had not been used in Project 2. As an imaginary comparative condition, we assumed designers would have used the *single factor experiment*, which is a common method if the Taguchi method is not used.

In a single factor experiment, all control factors are independently optimized in sequence in order of importance, with all other parameters fixed. In fact, the parameter survey conducted at Project 1 followed almost the same procedure. Conditions are listed in Table 3, and Constructions of design processes are shown in Table 4. Total design times are calculated by eq. 3.2. Note that one verification analysis was added for the cases with the Taguchi method.

Table 3. Conditions for trial calculation

Legend	Description	Average time (hrs.)
T_a	Time needed to make analysis model	1.59
T_c	Time needed to define analysis condition	0.135
T_s	Time needed to solve an FEM simulation case	0.05

Table 4. Construction of design processes

Legend	Description	Actual (*L*36*2)	*L*36*1	Single factor experiment
N_a	Number of times to make analysis model	37	37	14
N_c	Number of times to define analysis condition	74	37	20
N_s	Number of times of FEM simulation	74	37	33
T_{total}	Total design time (hrs.)	72.4	65.5	26.6

$$T_{total} = T_a \cdot N_a + T_c \cdot N_c + T_s \cdot N_s \quad (3.2)$$

The results unexpectedly show that design time with the Taguchi method (72.4hrs) is much longer than that with the single factor experiment (26.6hrs). Even if repetition is not applied to the Taguchi method, the reduction in total design time is slight (65.5hrs)(see Table 4).
This is because total design time mainly depends on the time needed to make analysis models, and with the Taguchi method, the number of analysis models necessary (N) increases exponentially and easily reach the maximum number (L) by following eq. 3.3:

$$N = \begin{cases} \prod_l (l^{n_l}) & (\prod_l (l^{n_l}) \leq L) \\ L & (\prod_l (l^{n_l}) > L) \end{cases} \tag{3.3}$$

Where, L is size of orthogonal array, l is number of levels, and n_l is number of parameters which have l levels. For example, if a model has four parameters which have three levels on L36, N reaches the maximum number (L=36) easily as calculated below:

$$l^{n_l} = 3^4 = 81 \geq 36$$

These results show the blind spot and provide instructive lessons in applying the Taguchi method or Design of Experiments (DOE). These methods are indubitably useful and powerful for exploring and optimizing many design parameters efficiently. However, as we showed, prior estimation is important. If estimation time is much longer than for the conventional single factor experiment, some measures might be recommended such as reduction the number or levels of design parameters, or division of large orthogonal arrays into smaller ones.

3.3 Approach to quantitative evaluation of design efficiency

As shown in the preceding section, sometimes there are trade-off relations between design time and richness of obtained design information. This causes difficulty for designers in judging whether a certain method or tool should be introduced.
To address this problem, we consider the possibility of applying an index called "D-efficiency (D_{eff})"[5] to measure the efficiency of designing.

3.3.1 Introduction of D-efficiency

Originally, D_{eff} was defined as the criterion that results in minimizing the generalized variance of the matrix of coordinates of experiment points, and is often used to optimize the experiment set for the response surface method (RSM). D_{eff} is derived as follows.
Firstly, the regression equation is defined as eq. 3.4.

$$\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\varepsilon} \tag{3.4}$$

$$\mathbf{y} = \begin{Bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{Bmatrix} \qquad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \qquad \boldsymbol{\beta} = \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{Bmatrix} \qquad \boldsymbol{\varepsilon} = \begin{Bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{Bmatrix}$$

Where, $\mathbf{X}$ is matrix of the normalized coordinates of experiment points, k is the number of dimensions, and n is the number of experiment points.
Then D_{eff} is defined by eq. 3.5, as the criterion to minimize the regression error of eq. 3.4.

$$D_{eff} = \frac{\left(Det\left[\mathbf{X}^{\mathrm{T}}\mathbf{X}\right]\right)^{1/p}}{n} \tag{3.5}$$

Where, p is number of unknown regression coefficients.
As shown in the definition of D_{eff} by eq. 3.5, it is based on the generalized variance of $\mathbf{X}$ and

the geometric meaning of $Det\left[\mathbf{X}^{\mathrm{T}}\mathbf{X}\right]$ is the p-dimensional volume of matrix $\mathbf{X}^{\mathrm{T}}\mathbf{X}$. D_{eff} takes a value between 0 and 1, and the larger the value D_{eff} takes, the better is the orthogonality of the coordinates set. D_{eff} expresses the unbiasedness of the experiment points.

Therefore, the experiment points with high D_{eff} value are expected to have high probability and efficiency to reach the optimum design solution especially in high-dimensional search space. These characteristics of D_{eff} are considered to be appropriate for application as the index of efficiency of searching.

In this context, we compare D_{eff} of design cases of Project 2 shown in section 3.2.2.

3.4 Comparison of D_{eff} among design processes

As a calculation assumption, each set of experiment points is to be fitted to response surface from second-order Chebyshev polynomials. The results are shown in Table 5.

Table 5. Construction of D_{eff} in Project 2

Description	D_{eff}
With the Taguchi method (*L*36)(Actual)	0.53
Single factor experiment (Imaginary)	0.073

These results show that D_{eff} of single factor experiment is much worse than that with the Taguchi method. This means that the searching efficiency of single factor experiment is much worse than that of the Taguchi method, and consequently, has high risk of not reaching a better solution. In this manner, designers can evaluate the efficiency of searching by D_{eff} relatively or qualitatively.

However, the relation of the absolute value of D_{eff} to the quality of the induced solution is still a subject of research. In addition, if there is a complete correlation between a certain two parameters, D_{eff} becomes zero. It is inconsistent with the actual validity of experiment points and a designer's subjective sense. In such case, some measures, e.g. reduction of redundant parameters, should be applied.

Taking these issues into consideration, we will continue with a more broadly based investigation with a view to elucidating the design efficiency.

4. Innovation of design process and maturity of market

In section 3, we showed that the improvement of the efficiency to reach the optimum design solution is more noticeable than the reduction of the design period in the recent transition of design processes we investigated. One reason for this was the difference in design circumstances between Project 1 and 2. In 1998, when Project 1 was proceeding, global competition in the market for the present device was less fierce than that in 2002, when Project 2 was proceeding.

In regard to the background of this evolution of design processes, we assume that the paradigm in designing globally competitive products was shifting from "fulfilling the design requirements" to "searching for the optimum design solution." In the following sections, we try to explain this qualitative innovation in design processes by a taxonomical approach.

4.1 "Fulfilling the design requirements" type design

We start by considering the relation between types of design style and maturity of product as listed below.

- "Fulfilling the design requirements" type designs mainly exist in product fields where the requirements for specifications are not severe because there are few competitors, or the products are protected for some reasons, e.g. exclusive technologies, core competence, or non-technological regulations such as protective trade.

- In this situation, the single factor experiment can be an advantageous strategy to fulfill the design requirement in shorter design period as analyzed in section 3.2.2.
- Consequently, design solutions can take diverse forms reflecting designers' discretion, taste, etc. These statuses are often found in the early, immature period of product history.
- In the state of "fulfilling the design requirements" type design, "natural selection" in the market proceeds quite slowly, or the distribution of market share is stable or an oligopoly exists.

4.2 "Searching for the optimum design solution" type design

However, as a market matures, selection and standardization progress. In this latter phase, "searching for the optimum design solution" type design becomes more important for survival.

The features and characteristics of this type of design are listed below.

- For the products in this phase, the basic functions and prices have large weight.
- Objective functions mostly converge on cost or basic functions (e.g., CPU, HDD, size and weight for mobile computers, fuel efficiency for automobiles).
- Because of these characteristics, development of high value-added products with distinctive features becomes difficult.
- Since requirements for basic functions do not have clear limits, competition among competitors intensifies.
- Consequently, "searching for the optimum design solution" type design, i.e. the design with the Taguchi method or multi objective optimization methods, sometimes, with some search algorithms, etc., becomes indispensable.
- As a result, design solutions become relatively similar unless any breakthrough technologies are introduced.

4.3 Mechanism of design process innovation

By classifying design processes into two types as shown in section 4.1 and 4.2, the difference of design processes in Project 1 and 2 becomes more explicable. In this section, we proceed to a consideration of the circumstances in which the transition of design processes is accelerated. Christensen[7] explains the cause of disruptive innovation in the market with Figure 4.

At point 1 in Figure 4, product performance by conventional technology exceeds the requirements of the high-end market. Manufacturers relying on conventional technology ignore the rise of new technology because the market for it is still smaller than theirs at this

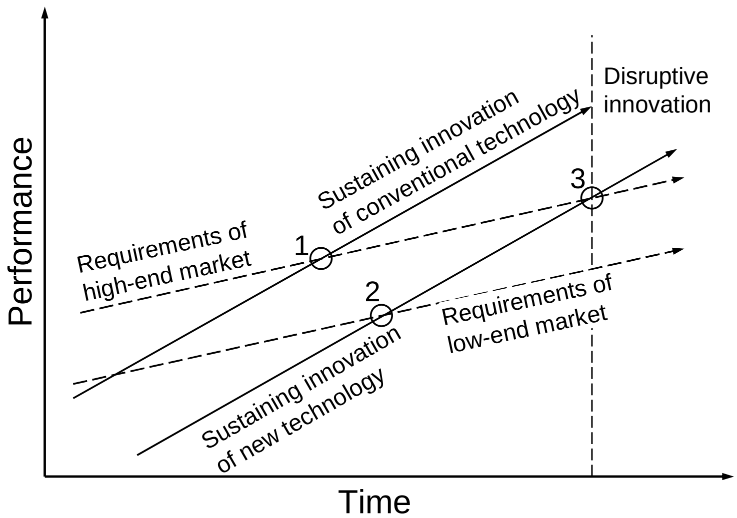


Figure 4. Mechanism of disruptive innovation (cited from Christensen[7], modified by the authors)

point.
However, when the level of new technology exceeds the requirements of the low-end market at point 2, the market for new technology grows explosively.
Finally, once new technology exceeds even the requirements of the high-end market, disruptive innovation with drastic transition from conventional technology to new technology occurs at point 3. Christensen pointed out such disruptive innovation has been observed in many product domains such as hard disc drives (several times), automobiles, steel, home appliances, semiconductor devices, etc.
In addition to Christensen's view of the performance transition of technologies, we point out the role of customers' perceptions of the cost-performance ratio as another cause of disruptive innovations. Figure 5 shows the typical transition patterns of technologies in contrast with cost-performance ratios. Three slanting solid lines show the customers' requirements concerning the cost-performance ratio in phase 1 to 3, respectively. From phase 1 to 3, conventional technology progresses from 1c to 3c and new technology progresses from 1n to 3n correspondingly.
At phase 1, the cost-performance ratio realized by new technology is relatively lower than that by conventional technology, and the market for new technology is smaller than that for conventional technology. Thus, the products based on conventional technology maintain a high price.
However, with the lapse of time, the cost-performance ratio of new technology catches up with that of conventional technology in phase 2 and finally surpasses it in phase 3.
Once the cost-performance ratio is reversed in phase 3, the disruptive innovation breaks out.
Since the cost-performance ratio usually improves in proportion to the expansion of the market, phase 1 to 3 in Figure 5 generally correspond to point 1 to 3 in Figure 4 respectively.
Of course, this transition dose not necessarily fit all the cases. For example, if progress of the cost-performance ratio of new technology does not exceed that of conventional technology as shown by 3n' in Figure 5, the superiority of conventional technology in the market could continue.
Furthermore, customers' perceptions of the cost-performance ratio are sometimes nonlinear as shown by the dotted line for phase 3. This nonlinearity could arise because customers sometimes place a "premium" on high-performance products. However, in many cases, it may delay the outbreak of disruptive innovation only for a certain period.
Why are successful possessors of conventional technology so often defeated by newcomers despite being aware of the rise of new, promising technologies? Christensen enumerated

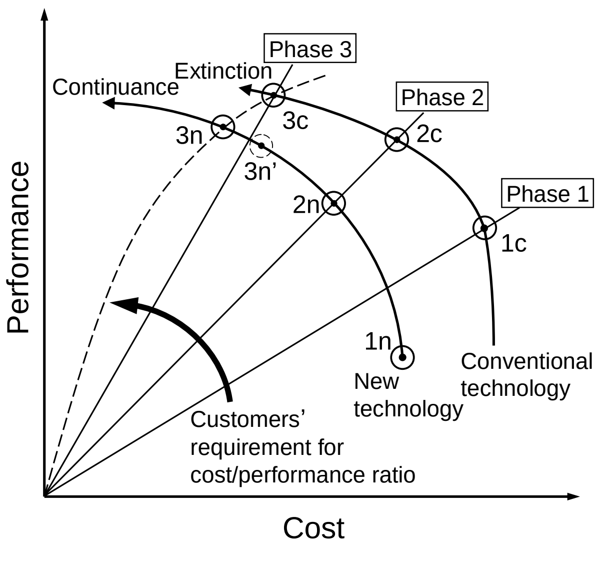


Figure 5. Innovation of technology and cost-performance ratio

several reasons, e.g. being misled by their main customers' requirements, difficulty of early entry by stable and successful companies into new, low-profit markets. Christensen argues that when a conventional company pursues growth based on new technologies, the establishment of a new vehicle to conduct the business, such as an independent unit or company, is often a shortcut to success. Although that may be a radical solution, it is always difficult for designers to execute a timely shift to new technology in competitive markets.
This leads us to the discussion of the importance of decision making in the next section.

5. Evaluation of ambiguity and uncertainty on decision making

As explained in the previous section, transition from conventional technology to new technology sometimes erupts dramatically and disruptively. These characteristics and the nature of technology transition exacerbate the difficulty and risk in decision making by designers. They often have to make difficult decisions, such as whether to adopt new technology or conventional technology, considering complicated design constraints in a limited period. Consequently, such decisions inevitably involve anxiety, ambiguity or uncertainty. A bad decision made in the early stages of designing can have an immense influence on design time and cost.
To address this problem, in this section we also apply our methodology for quantitative estimation of design load explained in section 2. Combined with decision making techniques, application of the present methodology is extended for management of risk caused by ambiguity involved in designers' decisions.

5.1 Scenario of alternative selection

To discuss the ambiguity of decision making in the design process, we introduce a scenario designers typically face. Although it is an imaginary one, it is based on an actual design case we investigated in Section 3. In this scenario, we suppose that designers have three alternatives for the device design discussed in section 3 as shown below.

- Alternative #1: Adoption of new technology
- Alternative #2: Improvement of conventional technology
- Alternative #3: Improvement of cost performance

To cope with improvement of both the main feature and miniaturization of the body of the present device, introduction of recent innovative technology seems to be advantageous. However, as is usual in such a case, there is a certain risk in adopting new, inexperienced technology (e.g., difficulty of design, unexpected side effects). In this case, we assume the management of heat generation would be a difficult issue.
Improvement of conventional technology would be the least disruptive strategy. However, drastic improvement of performance and miniaturization could not be expected.
The third alternative is improvement of cost performance by pursuing reduction of cost for both parts and manufacturing processes without sacrificing performance of current model. It is assumed that this is easier to accomplish than the first or second alternative.
In this situation, designers have to consider the advantages and disadvantages of each alternative from various perspectives. Some of the features of alternatives usually have trade-off relations, and priorities or weights for the features may differ according to circumstances.
In such complicated circumstances, appropriate use of decision making techniques could help designers settle and organize their thoughts regarding alternative selection in an orderly fashion and reduce the risk of backtracking in the design process.
In the next section, we discuss the effects of decision making techniques in design scenes.

5.2 Application and effect of decision making techniques

Firstly, referring to Wynne's classification of uncertainty [8], we tentatively redefine three terms regarding decision making as shown in Table 6.

Table 6. Tentative definition of terms regarding decision making

Term	Definition
Ambiguity	Extent of unclearness of primary factors affects decision.
Uncertainty	Extent of unclearness of probability of each primary factor.
Preference	Intensity of preference for certain alternative.

In following sections, we use these terms distinctively according to Table 6.
In this section, we take up the Analytic Hierarchy Process (AHP)[9] as an example of decision making techniques used in design processes. Since the main subject of this section is to discuss generally the nature of decision making by human designers, we do not limit the objective decision making techniques to AHP.
AHP was developed by Thomas Saaty in 1971. It is widely known and recently has been used in various fields. AHP consists of the following three steps.

- STEP 1: Problem is analyzed into hierarchical structure (Figure 6).
- STEP 2: Elements or alternatives are compared in a pairwise manner with the scale shown in Table 7.
- STEP 3: Weights between top goal and elements, or elements and alternatives are derived from the results of pairwise comparisons by matrix operations. The results are summed up to get the overall priority of each alternative.

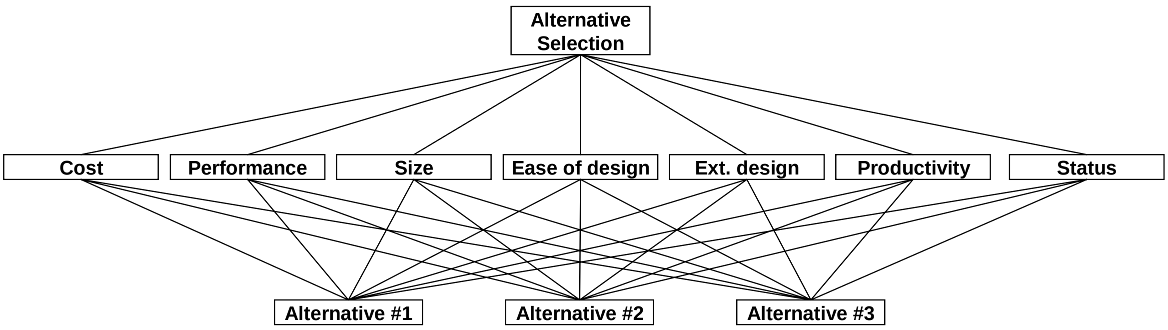


Figure 6. Example of hierarchical decision structure

Table 7. Scale for pairwise comparisons

Numerical values	Definition
1	Equal importance
3	Weak importance
5	Strong importance
7	Very strong importance
9	Absolute importance

2, 4, 6, 8: intermediate values reflecting compromise

Step 1 helps designers to reduce their "*Ambiguity*" by explicitly constructing the elements and their structure relevant to decisions.
We applied these steps to the imaginary scenario described in section 5.1. We assumed that designers ask the simulation department to evaluate the increases in temperature for three alternatives. Then, instead of the actual practice of the designers, we followed the AHP procedure before and after getting the results of simulations. In this imaginary scenario, we assumed that from the simulation results, designers obtain valuable information to guarantee

the design of alternative #1 and become more confident regarding management of the heat increase within the allowable range even with new technology. Consequently, the pairwise scores of "size" and "ease of design" for alternative #1 are improved relatively against alternative #2 and #3. The trial results of AHP are shown in Figure 7. These figures make the degree of designers' preference for alternatives clearer. To express the mental state on decision making, we introduce the probability density function $f(x)$ as defined in eq. 5.1:

$$\int_a^b f(x)dx = \Pr[a \le X \le b] \qquad (5.1)$$

In eq. 5.1, random variable X represents the probability (or confidence) to select a certain alternative and $f(x)$ is assumed to follows beta distribution as defined in eq. 5.2:

$$f(x) = \frac{x^{\lambda_1 - 1}(1-x)^{\lambda_2 - 1}}{B(\lambda_1, \lambda_2)}, \quad (0 < x < 1, \quad \lambda_1 > 0, \quad \lambda_2 > 0) \qquad (5.2)$$

Where, λ_1, λ_2 are free parameters and $B(\lambda_1, \lambda_2)$ is *beta function*. x value to maximize $f(x)$ is put as x_p and obtained by equating the differentiation of eq. 5.2 as zero:

$$x_p = \frac{\lambda_1 - 1}{\lambda_1 + \lambda_2 - 2} \qquad (5.3)$$

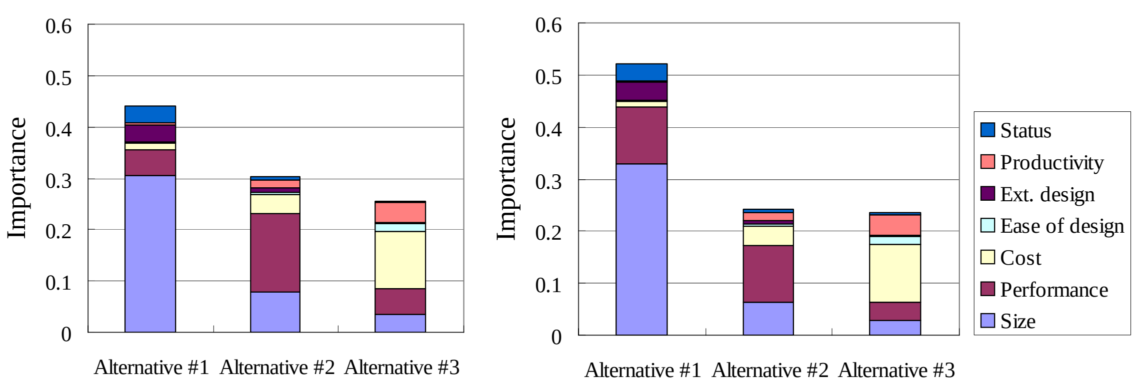
Then, we suppose the three cases shown in Table 8.

Table 8. Three cases of probability densities

Case	AHP	Simulation	Status	x_p	a	b	$\Pr[a \le X \le b]$	λ_1	λ_2	H_c
Case 1	No	No	Initial condition	0.7	0.6	0.8	0.7	15.6	7.2	-1.36
Case 2	Yes	No	Only peak is moved.	0.8	0.7	0.9	0.7	13.8	4.2	-1.37
Case 3	Yes	Yes	Peak moved and peakedness improved.	0.8	0.75	0.85	0.8	84.0	21.8	-2.64

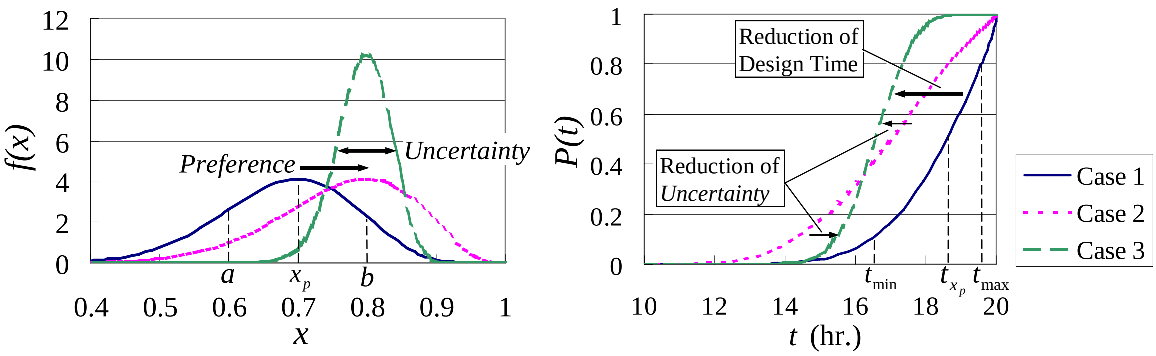
Case 1 is the initial condition. In case 2, only peak (x_p) is improved from 0.7 to 0.8, and peakedness is not improved (70% within error range of ± 0.1). x_p represents the degree of *preference*, and peakedness of the distribution (represented by the range between a and b, and $\Pr[a \le X \le b]$) is related to the *uncertainty* for the peak value. For example, if the results of precise simulation or experiment indicate that two alternatives have nearly equal performances, *preference* stays close to even (x_p=0.5) but *uncertainty* is reduced ($f(x)$ shapes peaked).

As an index of the peakedness of $f(x)$, we propose the use of the entropy for continuous



(a) Initial (b) After simulation

Figure 7. Variation of preferences before (a) and after simulation (b)



(a) Probability density function (b) Cumulative distribution of design time

Figure 8. Variation of probability density (a) and cumulative distribution of design time (b)

random variables ($H_c = -\int_0^1 f(x)\log_2 f(x)dx$). H_c takes negative value, or zero in the worst case ($f(x)$ =const =1). Larger absolute value of H_c represents less *uncertainty* (see Table 8).
The three cases in Table 8 correspond to the scenario shown in section 5.1. Assume alternative #3 had been rejected for some reason and there are two alternatives (#1 and #2) left. Then consider X of eq. 5.1 to be p_1 (probability to select alternative #1) in this case.
From these peaks and deviations shown in Table 8 and eq. 5.2 and 5.3, the probability density functions are determined as shown in Figure 8(a) and represent the following statuses.

1. Before the practice of AHP and simulation, designers do not have enough information to judge, i.e. they are beset by *ambiguity* (Case 1 in Table 8 and Figure 8(a)).
2. Next, after the practice of AHP, elements for judgment become clearer and consequently, the *preference* for alternative #1 is also increased (Case 2 in Table 8 and Figure 8(a)).
3. Finally, simulation results support the advantages of alternative #1 and consequently, *uncertainty* of designers is reduced (Case 3 in Table 8 and Figure 8(a)).

Of course, this scenario is just to explain the meaning of *ambiguity*, *uncertainty* and *preference* distinctively and exaggeratedly. Namely, any information from decision making methods, simulations or experiments could affect *all* of them.
Next, the probability distributions can be converted into the distributions of estimated design time with the methodology applying Shannon's entropy explained in section 2. Assuming that minimum design time for one alternative is 10 (hrs.), estimated distributions of total design time (T_{total}) are calculated by eq. 2.2 as shown in Figure 8(b) and risks to exceed the estimated maximum design time are listed in Table 9. In Figure 8(b), t is variable for T_{total} and $P(t)$ means $\Pr[10 \le T_{total} \le t]$. In Table 9, t_{min}, and t_{max} are minimum and maximum values of T_{total} at $X = b$ and a respectively. t_{x_p} is value of T_{total} at $X = x_p$. $\Pr[T_{total} > t_{\max}]$ means the probability (namely, risk) of exceeding the estimated maximum design time.

Table 9. Estimated distributions of design time (hrs.) and risks of exceeding the estimated maximum design time

Case	t_{min}	t_{x_p}	t_{max}	$\Pr[T_{total} > t_{\max}]$ (%)
Case 1	16.5	18.4	19.6	19.2
Case 2	13.8	16.5	18.4	23.5
Case 3	15.3	16.5	17.5	13.1

These results explain that biasing *preference* shortens the design time (Case 1 to Case 2), and reducing *uncertainty* narrows the range of estimated design time and consequently, reduce the risk of exceeding the estimated maximum design time (Case 2 to Case 3).
In this manner, effects of designers' mental states on design time and risk can be evaluated analytically and quantitatively.

6. Conclusions

In this paper, we analyzed the improvement found in the actual design processes. It was found that introduction of the Taguchi method is not necessarily advantageous for the reduction of design time from the short-term perspective. However, by calculating the D-efficiency, it is shown that the Taguchi method makes it possible to improve the coverage and efficiency of searching in the design variable space. We taxonomically explained this improvement of design processes as transition from “fulfilling the design requirements” type design to “searching for the optimum design solution” type design.

For the latter type design, accurate alternative selection in the early design stages is essential. Accordingly, rational decision making methods, e.g. AHP become important. In this context, we also proposed a statistical estimation methodology to analyze how the *preference* and *uncertainty* regarding designers’ decision making affect the design time and risks.

The results led to an understanding that so far as risk management in the design process is concerned, it is important not only to bias *preference* but also to reduce *uncertainty*.

We name the quantitative approach shown in this paper “Design Process Assessment,” and aim to develop it into a systematic methodology for optimizing the design processes based on objective and quantitative rationales.

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References

[1] Gatenby, D. A., and Foo, G., “Design for X: Key to competitive, profitable markets”, AT&T Technical Journal, 69(3), pp. 2-13, 1990.

[2] Harry, M., Schroeder, R., “Six Sigma - The Breakthrough Management Strategy Revolutionizing The World's Top Corporations -”, Doubleday, 1999.

[3] e.g., http://www.engineous.com/product_iSIGHT.htm

[4] Ozawa, M., Inoue, K., “An approach for quantitative estimation of design load and efficiency”, Proceedings of the Tools and Methods of Competitive Engineering 2004, April, 2004, Lausanne, Switzerland, pp. 811-821, ISBN90-5966-018-8, Millpress, Rotterdam, Netherlands.

[5] Shannon, C. E., 1948, “A mathematical theory of communication”, Bell System Technical Journal, vol. 27, pp. 379-423 and 623-656, July and October.

[6] Atkinson, A.C., Donev, A. N., “Optimum Experimental Designs”, Clarendon Press, 1992.

[7] Christensen, Clayton M, “The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail”, Harvard Business School Press, 1997.

[8] Wynne, B., “Managing Scientific Uncertainty in Public Policy”, background paper to the conference: Biotechnology and Global Governance: Crisis and Opportunity, April 26-28, 2001, Harvard University, Weatherhead Center for International Affairs, Cambridge, MA. USA. (http://www.wcfia.harvard.edu/biotech/wynnepaper1.doc)

[9] Saaty, T., “The Analytic Hierarchy Process”, McGraw-Hill, New York, 1980.

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