Technology Introduction

Utilization of CAE for Model-Based Development

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1 Introduction

Model-based design (MBD) is a method of developing an embedded software system that effectively uses model-based simulation to reduce development time and improve software quality. As MBD has recently been applied to wider fields including mechanical engineering (strength, vibration, motion, etc.), the term MBD is often used to refer to "on-the-desk" development using computer aided engineering (CAE) [1]. By taking the latter sense, this paper introduces MBD as methodology of efficiently promoting "on-the-desk" development. Industry has a long history of using CAE as a front-loading approach to address problems as early as in the upstream stage of product development. A publication [2] defines the term "design" as "to come up with an idea for a new product with a target quality, fabricate new elements of the product, and combine them to be an integral product," and further "to establish theoretical grounds of the design, prepare many alternatives and efficient assessment methods, and select the best option with active and human design reviews (DRs)."

In relation to "establish[ing] theoretical grounds of the design," easy-to-use physical modeling tools have emerged and been widely used with the dramatic advancement of CAE software technology. To "prepare many alternatives and efficient assessment methods," automation and rationalization of assessments are needed for the earlier selection of excellent ideas. Assessment automation will increase the time and frequency of thinking to come up with ideas while assessment rationalization will allow designers to have the mental capacity to notice a failure in advance [3].

Practicing these in the upstream stage of product development will help efficiently promote MBD in mechanical engineering. As one of the methodologies, the following sections describe the parametric CAE method using parameter design by introducing specific cases:

2 Parameter Design

2.1 Functionality Assessment

First of all, this section discusses how a technology works from the viewpoint of "establishing theoretical grounds of the design." The verb "works" can be replaced by "functions." For example, the function of a hydraulic pump is to input a driving force from outside and to discharge high-pressure oil at a high flow rate. For a mechanical product, the function can be generally represented by energy conversion. A hydraulic pump converts driving energy (revolving speed x torque) into hydraulic energy (discharge pressure x flow rate).

Once a product is shipped to market, it is used under a variety of conditions. A product free of problems at the time of shipment may experience failure or an abnormality when subjected to many different conditions including improper use by the user, adverse temperature/humidity conditions, and deterioration over time. Quality may be defined as stability of the function(s) of a product under various service conditions.

A reliability test for determining the quality of a product usually requires a long period of time. One of the approaches to complete such a reliability test in a short time is a functionality assessment. For a functionality assessment, functions of a target product are measured under the worst conditions reflecting possible various usages of the product in the market area, and then stability of the functions is assessed. As an index of stability assessment, the signal to noise (SN) ratio is used. The SN ratio refers to the ratio between the signal and noise originally used in information engineering and can be defined as "signal/noise." The signal represents the average of signals when subjected to two or more worst conditions, while the noise represents the standard deviation (variation). Using the common logarithm, the SN ratio can be expressed by:

SN ratio = 20 log (average / standard deviation) [db]

The antilogarithm is the inverse of the coefficient of variation.

As an example of a functionality assessment, Table 1 shows the results of an efficiency test on two types of hydraulic pumps A and B when subjected to two levels of worst conditions: low and high temperatures. Both pumps have identical average performance, but the pump A, having a higher SN ratio, shows higher stability.

Table 1 Example of SN ratio calculation

Pump	Worst conditions		Average	Standard deviation	SN ratio [db]
	Low temp.	High temp.			
A	0.88	0.92	0.90	0.028	30.1
B	0.85	0.95	0.90	0.071	22.1

2.2 Parameter Design and Its Procedure

Next is discussion about "prepar[ing] many alternatives and efficient assessment methods." The parameter design is an approach to determine the design conditions with high stability by implementing a functionality assessment with variable combinations of multiple design parameters. In the example shown in Table 1, two levels of worst conditions have been set against two types of pumps, which means that four experimental runs in total need to be performed. In addition, a number of parameters should be discussed during product development. It is also recommended to apply as many worst conditions as possible with considerations given to actual usage in the market area. If the product were to be tested under all the combinations of conditions, a huge number of experimental runs would be needed. For this reason, the concept of parameter design was established as an approach to substantially reducing the number of experimental runs by applying the concept of experimental design. In parameter design, an orthogonal array is used to reduce the number of experimental runs. As an example, an L18 orthogonal array is shown in Fig. 1:

Experimental run # / Column #	Design parameter (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

Fig. 1 L18 (2^1 x 3^7) orthogonal array

In this orthogonal array, up to eight design parameters can be analyzed through 18 runs of testing with an arrangement of 1 factor at 2 levels and 7 factors at 3 levels. Besides the L18 orthogonal array, various orthogonal arrays including L36 and L54 can be used according to the number of design parameters to be analyzed.

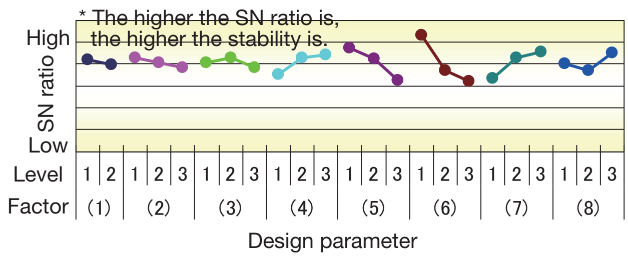


Fig. 2 Factorial effect diagram of SN ratio

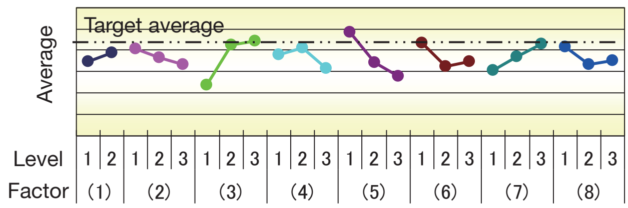


Fig. 3 Factorial effect diagram of average

Design parameters are assigned to an orthogonal array, and experimental runs are carried out under the worst conditions. As in the example of Table 1, the SN ratio of each row is calculated with an experimental run # in the array. The results are statistically processed and the factorial effect for each design parameter is calculated. The results are plotted as shown in Fig. 2. Similarly, the average is calculated and the results are plotted as shown in Fig. 3. From these two figures, a combination of design parameters that is high in stability (high SN ratio) and meets the average target (optimization) is selected.

Note that the optimal value selected from the factorial effect diagrams is the one that has been mathematically estimated from the test results of only some combinations in the orthogonal array. Therefore, it is important to carry out experimental runs by using actual combinations to verify the estimation accuracy. This is called a verification test. If there is no difference between estimation and verification, it can be determined that the testing has been properly done. If there is a difference between the two, it should be determined that the process to evaluate the stability of functionality has a problem. Many of the factors that lower the estimation accuracy involve interaction of output values among the design parameters. If interaction takes place, the output level of specific combinations may be affected, leading to difficulty in adjustment. Good design is based on the idea that individual design parameters reflecting the design concept each exert an effect independent of the output value.

Table 2 Eight steps of parameter design

(1) Select themes - Define the purpose and project scope
(2) Define the functions and create a calculation model
(3) Establish a worst condition strategy
(4) Set up design parameters and assign them to an orthogonal array
(5) Collect data by actual machine testing or CAE calculation
(6) Analyze data using SN ratio
(7) Carry out optimization, estimation, and conformation run
(8) Develop (and document) an action plan

Table 2 shows the parameter design procedure. For more information about the calculation for statistical processing, refer to the reference [4].

3 Examples of Application

Electromagnetic proportional pressure-reducing valves used in the hydraulic system of construction equipment use proportional solenoids. To develop inexpensive high-performance products meeting the market needs, it was necessary to reduce the design man-hours and prevent rework in the development phase. Accordingly, we applied the parameter design and parametric CAE methods to design a proportional solenoid with stabler attraction characteristics. This case is introduced in the following:

(1) Select themes - Define the purpose and project scope

The proportional solenoids are required to:

① have a flat stroke-attraction characteristic;

② have a proportional current-attraction characteristic; and

③ deliver these characteristics stably in actual applications.

Now determine the design conditions that satisfy these requirements at the same time.

(2) Define the functions and create a calculation model

(3) Establish a worst condition strategy

We have given a functional definition of the proportional solenoid as a device to generate an attraction force proportional to the current (Fig. 4).

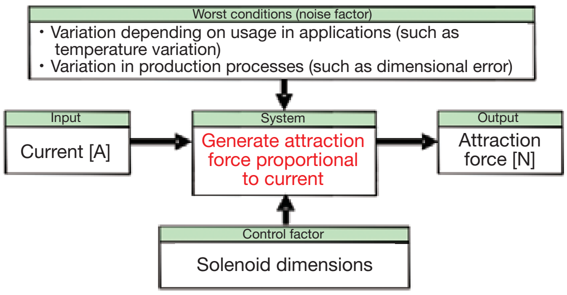
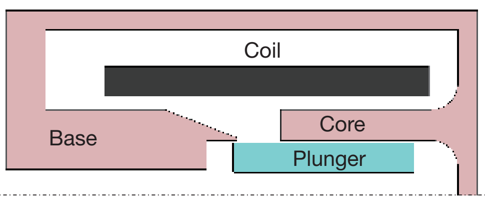


Fig. 4 System chart

For experimental testing, calculation with a CAE model shown in Fig. 5 is carried out. 44 dimensions of this model can be parametrically adjusted for calculation [5]. As a result of engineering discussion, 21 dimensions were selected as design parameters. Since it is not easy with the CAE model to consider product deterioration and wear



* Calculation with 44 variable dimensions is available.

Fig. 5 CAE magnetic field analysis model

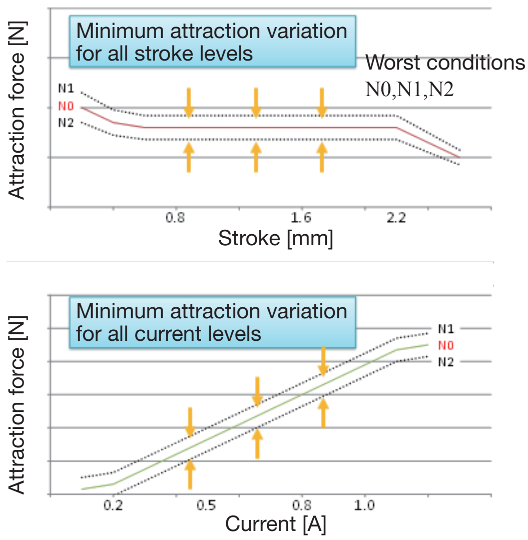


Fig. 6 Characteristics to be stable

during use in applications, the worst conditions have been set to the design parameter tolerance multiplied by a factor [6]. The concept of stabilization of characteristics is shown in Fig. 6.

(4) Set up design parameters and assign them to an orthogonal array

(5) Collect data by actual machine testing or CAE calculation

Since 21 design parameters have been selected, an L54 orthogonal array in which up to 26 factors can be assigned was used. Similarly, 21 worst conditions were assigned to the L54 orthogonal array. The calculation must be repeated for every combination of the design parameters and worst conditions. In total, 2,916 cases (54 x 54 = 2.916) were calculated.

(6) Analyze data using SN ratio

(7) Carry out optimization, estimation and verification test

Statistically process the calculation results and create a factorial effect diagram of each of the three items: SN ratio, magnitude of attraction force, and attraction stability against stroke (Fig. 7). For the design parameters on the horizontal axis, optimal values for three levels are selected so that:

① the attraction variation is small (high SN ratio);

② the magnitude of attraction force is high; and,

③ the attraction force is stable against stroke.

The SN ratio estimation for the optimal condition was 49.9 [db]. The estimation for the reference condition (the initial design condition often used), which had been established for the purpose of comparison, was 44.7 [db]. The difference between the two is 5.2 [db]. The SN ratio is defined by a logarithm and the difference represents the ratio of antilogarithm. 5.2 [db] is equivalent to an approximately 40% decrease in the coefficient of variation. Next, we conducted a verification test (calculation) using actual combinations for the optimal and reference conditions. The results are shown in Table 3:

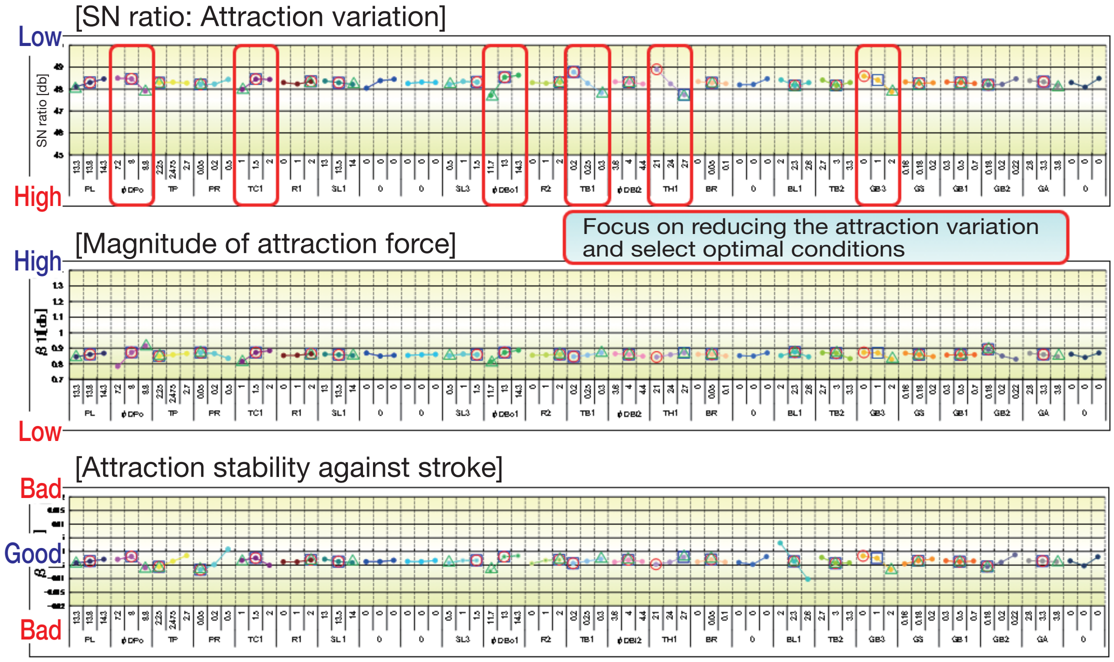


Fig. 7 Factorial effect diagram

Table 3 Results of verification test

	SN ratio [db]	
Condition	Estimation	Verification
Optimal	49.9	48.4
Reference	44.7	45.0
Difference	5.2	3.4

The SN ratio estimation roughly matches the verified results. The difference in verified results between optimal and reference conditions is 3.4 [db], which is equivalent to an approximately 30 [%] decrease in performance variation. The variation reduction for different current levels applied is shown in Fig. 8. The difference between the estimation and verification implies that the selection of design parameters is susceptible to improvement, which remains as a future challenge.

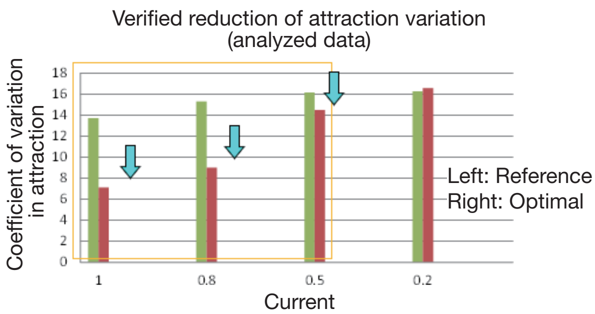


Fig. 8 Reduction of variation in attraction force for different current levels applied

(8) Develop (and document) an action plan

① We have developed a profile with which the performance variation can be reduced by about 30 [%] under the worst conditions in the assumed market.

② We have stablished a magnetic path design method to reduce the performance variation based on a technical analysis of the factorial effect diagram, although it cannot be disclosed because of the proprietary knowhow.

These results will be put into the form of design manuals and effectively used in routine design work.

4 In Closing

The use of parametric CAE using parameter design is effective in increasing the efficiency of MBD in the following points:

① The product functionality can be discussed for stabilization before a problem occurs in the upstream stage of product development.

② A number of design parameters can be adjusted to allow close reviews without making omissions.

③ A well-established procedure can be easily integrated into the development process. For example, the results can be reviewed according to a common method.

In addition, we believe that this approach, as a methodology of pursuing the essence of technologies and allow engineers to be imaginative, can be effectively used to develop young and middle-ranking engineers to be the next-generation of "Monozukuri" manufacturers.

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