Optimization of Resin Molding Process by Functional Evaluation Method Focusing on Melting Energy Related to Resin Filling Characteristics

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Abstract: In recent years, along with the increasing demand for plastic products and the deepening of academics, mass production, weight reduction, and higher precision are progressing. In the field of design development and production technology, there is an increasing need for analysis technology related to resin flow and behavior in order to solve problems related to quality assurance such as molding defects and product strength. Especially in the resin molding process, it is an important issue to create a quality function that applies the analysis of complex multidimensional information because of the high degree of freedom in product shape and mold structure. In order to solve the quality issues regarding the strength and dimensional stability of resin materials, it is effective to apply the “Functionality Evaluation Method” in robust design which is an analytical evaluation method. In this study, we focus on the function of managing the resin filling density in the mold (the input/output relationship of the melting energy related to the resin filling characteristics) for the optimization of resin strength and dimensional stability. We propose a functional evaluation method with the ideal function of stabilizing the resin filling density based on the original definition of material mechanics. As a result of verification of the proposed method, it was clarified that it is extremely important to make the resin filling density in the mold uniform to stabilize the strength of the resin injection molded product.

Keywords: Resin Molding Process, Resin Filling Characteristics, Robust Design, Functional Evaluation Method, Energetic S/N ratio,

1. Introduction

In recent years, the automobile industry has been actively promoting environmental measures even more than ever before, and as a part of this activity, the improvement of fuel efficiency by reducing the weight of parts is being promoted. As an example of this, resin-made steel pulleys for automobiles are being actively used. European automobile manufacturers are promoting the use of resin for pulleys for power steering and idler pulleys. In particular, the plasticization rate of the transmission pulley used in drive transmission parts around the engine has reached about 30% (Fig. 1). However, Japanese automobile manufacturers have a low plasticization rate of pulleys of 5 to 6%, and future growth is expected. Plasticization is the replacement of steel parts with resin, the purpose of which is to reduce weight and reduce costs. The resin pulleys currently in practical use cannot be said to have sufficient characteristics as substitutes for steel pulleys in terms of strength and dimensional stability [1]~[3].

Figure 1: Plasticization rate of parts around automobile.

In the engineering process, products whose quality has been stabilized to the limit of theoretical values are easily affected by variations in conditions. As a result, the trade-off of “increasing defect rate and decreasing process capability” develops [4] [5].

In this paper, we apply a functional evaluation method with the ideal function of stabilizing the resin filling density in the mold. It is clarified that homogenizing the resin filling density in the mold is extremely important for optimizing the resin pulley strength.

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Figure 2: Main structure and model of injection molding machine.

2. Overview of resin injection molding process

There are several types of resin molding methods depending on the purpose, but in this research, we approach the optimization of the injection molding method suitable for the mass production method of resin pulleys. The injection molding method is a method of obtaining a molded product by injecting a heated and melted material into a mold, cooling and solidifying the material. It is suitable for mass production of products with complicated shapes and is a major field of molding processing.

Injection molding is one of the molding methods using a mold. This is a processing method that heats and melts a material such as synthetic resin (plastic), sends it to a mold, and then cools it to form the desired part.

Figure 2 shows the main structure and model of the injection molding machine. As shown in Fig. 3 the injection molding process is roughly divided into 6 steps: (1) mold clamping, (2) injection, (3) pressure retention, (4) cooling, (5) mold opening, and (6) product removal. Specifically, first, pelletized resin is put into a hopper which is a material feeding port. The pellets are warmed in the cylinder and become liquid, ready for injection. The material sent out from the nozzle of the injection section passes through a pipe line called a sprue in the mold, and further flows into a mold-

ing section through a branched runner. After the material has cooled and solidified, the mold opens and the molded product is discharged to the outside. Through this process, continuous production becomes possible [6]~[9].

The injection molding machine is divided into a mold clamping unit and an injection unit. The mold clamping unit has a mold opening/closing function and uses a toggle type. The injection unit heats and melts the resin and injects it into the mold. Rotate the screw to collect the resin charged from the hopper at the front of the screw and then inject it.

The injection speed of the screw is controlled when the resin is flowing, and the pressure is controlled after the resin is filled. The switching from speed control to pressure control is set to switch when a certain screw position or injection pressure is reached [10]~[12].

In practice, it is often the case that a plurality of molded products are manufactured at the same time by a single injection molding, so it is important that the molten material uniformly flows into all parts. Therefore, it is necessary to devise the shape of the mold such that the runners have the same length for designing.

Injection molding is a processing technique suitable for mass production. However, in order to produce a highly

Figure 3: Injection molding.

accurate molded product, it is necessary to extract various processing parameter conditions such as resin material selection accuracy, mold processing accuracy, and temperature and speed at which the material is injected.

3. Analysis of resin filling characteristics by “Functional Evaluation Method”

In this chapter, we apply the functional evaluation method of parameter design which is the core method of “Robust design” to approach the stabilization of the resin filling density focusing on the input/output relationship of the melting energy.

3.1 Overview of Robust design Figure 4 shows the concept of robust design in quality engineering. The concept of improving technology to bring it closer to what it should be is called robust design. Robust means stability in quality engineering. Parameter design is one of the central methods of robust design, and is a method for evaluating functionality and determining system parameter values.

Parameters are design constants and components of the system and are selected as control factors in parameter design experiments. In the combination of system parameters, robustness is improved by deliberately generating variations by noise factors and optimizing the level of strong control factors that can counter the variations [13] [14].

In parameter design, it is important to understand the target function of the system. The objective function refers to the role that the system should play, and the quality characteristics are divided into the following four types. By taking up the objective function, the design information can be utilized in other similar systems, and the versatility of the technology is expanded [15] [16].

- (a) Preferably small characteristics (nonnegative and smaller the better)
- (b) Preferably large characteristics (nonnegative and larger the better)
- (c) Preferably target characteristics (with target value)
- (d) Dynamic characteristics (I/O correlation, output stability)

Figure 4: Robust design.

The purpose of this research is to stabilize the filling density of output against the processing conditions of input in injection molding.

The evaluation procedure for robust design is shown in Fig. 5. In robust design, start by clarifying the functions of the system. We define it as an ideal function of the input (signal factor) and output (characteristic value) of the system. In order to realize the ideal function, the experiment is performed efficiently using the orthogonal table, and the effect of each control factor is grasped by the SN ratio, sensitivity, and slope β . After that, the optimum conditions and comparison conditions are determined from the factor-effect diagram, and the average of each process is obtained to estimate the magnitude of improvement.

Finally, a confirmation experiment is performed to verify the reproducibility of the optimum condition gain.

3.2 Functional evaluation method and ideal function setting

The ideal function of many system technologies is that the output changes linearly with respect to the input. The total output characteristic value (total work) of the system must be proportional to energy or work. Especially in the injection molding process, there are melting energy required to obtain resin strength and dimensional accuracy, and loss energy that affects productivity. In robust design, a “Functional evaluation method” that defines the functionality based on energy conversion and quickly evaluates its stability is important [17]. In this research, we focus on the fact that the ideal function that represents the input-output relationship has a linear relationship with energy conversion.

Figure 6 shows a cross-sectional view of the molded resin

Figure 5: Robust design procedure.

Figure 6: Pulley sectional view.

pulley component. The quality issue is that cracks occur in the R part indicated by the red circle due to insufficient mechanical strength and stress concentration. In this example, regarding the optimization of resin strength, the relational expression between the allowable stress of the resin material and the material density is newly defined as follows based on material mechanics considerations.

Allowable stress: σ

$$\sigma = M/Z = K \cdot \rho \quad (1)$$

M : Moment of force Z : Section modulus
 K : Proportional factor ρ : Resin filling density

The physical quantity in Eq. 1 is regarded as constant for the dimension and shape [L] and the processing time [T], and is replaced with a unit of dimension.

Since the moment of force $M = [ML^2T^{-2}]$ and the section

Figure 7: Relations of ideal function.

modulus $Z = [L^3]$, It can be defined as

$$\sigma = \frac{[ML^2T^{-2}]}{[L^3]} = [L^2T^{-2}][ML^{-3}] = K \cdot \rho.$$

The allowable stress, which is an index of resin strength, is determined by the section modulus and the moment of force. Therefore, if the dimension and shape of the material and the processing time are constant, as shown in Eq. 1, the linear proportional (linear equation) to the allowable stress σ and the material density ρ with a proportional constant K . It can be defined as a relationship. Based on this definition, it can be estimated that stabilizing the degree of variation in the resin filling density ρ is highly effective in optimizing the resin strength.

To optimize the resin strength, the ideal function shown in Fig. 7 is set from the function of controlling the resin filling density in the mold (input/output relationship of melting energy related to resin filling property) and the material mechanical definition. The main purpose of applying the “Functional evaluation method” is to extract parameter levels that make the fusion energy parameter and the stable function of the filling density closer to the ideal state and reduce variations and fluctuations. The difference from the ideal state can be considered as some kind of energy loss.

In other words, the function of injection molding is consumed other than the intended output, and as a result, the stability of the filling density is affected. The effectiveness of the ideal function, in which the input is used as the parameter (control factor) of the molding processing conditions related to the melting energy during resin flow and the resin filling density as the output is the characteristic value is verified [18].

3.3 Energetic S/N ratio The conventional SN ratio, which is used in parameter design and represents the scale of variation, may change depending on the size (range) of the input signal and the number of data, and the technician should keep this in mind when acquiring data. There is a problem of having to analyze. The idea of the SN ratio is to evaluate the variation and non-linearity from the ideal functional state ($y = \beta M$) by considering it as poor functional stability.

Table 1: Data form.

		Input signal M				
		M_1	M_2	M_3	$\cdots$	M_k
Noise factor N	N_1	y_{11}	y_{12}	y_{13}	$\cdots$	y_{1k}
	N_2	y_{21}	y_{22}	y_{23}	$\cdots$	y_{2k}
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	N_n	y_{n1}	y_{n2}	y_{n3}	$\cdots$	y_{nk}

The “Energetic S/N ratio” adopted in this study is a new SN ratio announced in June 2008 by a research member of the Kansai Quality Engineering Society which is a certified regional study group of the Quality Engineering Society [13]. Since all technologies involve the conversion and transfer of energy, an energy perspective is important in technological development and evaluation of their technical levels.

Energetic S/N ratio is a technical quality evaluation measure (measurement) based on how various energies are used. Technical quality means that more energy input to the system can be stably used for the purpose (output) forever [21]. In the ideal functional state of injection molding, energy is decomposed into effective components (S_β) and harmful components (S_N), and the energetic S/N ratio is calculated by the ratio of these. In the calculation of the energetic S/N ratio, it can be expressed in decibel value as 10 times the common logarithm like the conventional type SN ratio.

The basic calculation formula of the energetic S/N ratio (η_E) is shown below. As shown in Table 1, it is assumed that the output noise y_{ij} at the noise factor level i ($i = 1, 2, \dots, n$) and the signal factor level j ($j = 1, 2, \dots, k$) is obtained.

(a) Total variation component S_T

This is the sum of the squares of nk pieces of data y_{ij} and shows the variation from $y = 0$.

$$S_T = \sum_{i=1}^n \sum_{j=1}^k y_{ij}^2 \quad (2)$$

(b) Average slope size β_{N0}

For some dynamic characteristics of the input signal, the slope of the noise factor N_i level β_{Ni} is obtained by considering the effective component as the average slope.

$$\beta_{Ni} = \frac{\sum_{j=1}^k M_j y_{ij}}{\sum_{j=1}^k M_j^2} = \frac{L_{Ni}}{r} \quad (3)$$

Here,

r : Effective divisor, L_{Ni} : Linear format

$$r \equiv \sum_{j=1}^k M_j^2 \quad (4)$$

$$L_{Ni} \equiv \sum_{j=1}^k M_j y_{ij} \quad (5)$$

The sum of squares of the signal, which is the denominator of β in Eq. 3, is called the effective divisor r , and the sum of products of the numerator signal and output is called the linear form L_{Ni} . From the slope β_{Ni} for each noise factor level, the average slope β_{N0} is given by the following equation.

$$\beta_{N0} = \frac{\sum_{i=1}^n \beta_{Ni}}{n} \quad (6)$$

(c) Average slope fluctuation (active ingredient) S_β

The variation of the average slope is expressed as the sum of squares of the size $y = \beta_{N0}M$.

$$\begin{aligned} S_\beta &= n \sum_{j=1}^k (\beta_{N0} M_j)^2 \\ &= n \beta_{N0}^2 \sum_{j=1}^k (M_j)^2 = n r \beta_{N0}^2 \end{aligned} \quad (7)$$

(d) Harmful component S_N

The harmful component represents the variation of the difference between each data and the proportional equation of the average slope, and is obtained by subtracting the effective component from the total variation component.

$$S_N = \sum_{i=1}^n \sum_{j=1}^k (y_{ij} - \beta_{N0} M_j)^2 = S_T - S_\beta \quad (8)$$

(e) Energetic S/N ratio η_E

$$\eta_E = 10 \log \left(\frac{S_\beta}{S_T - S_\beta} \right) = 10 \log \left(\frac{S_\beta}{S_N} \right) [\text{db}] \quad (9)$$

(f) Sensitivity S_E

The sensitivity when evaluating not only the energetic S/N ratio but also the effective output magnitude is expressed in decibel values, where the square of the average slope magnitude β_{N0} is 10 times the common logarithm.

$$S_E = 10 \log \beta_{N0}^2 [\text{db}] \quad (10)$$

3.4 Level table and determination of various factors

In this section, the optimization of the processing conditions is verified by “Dynamic characteristics evaluation (Energetic S/N ratio)” with the objective function of stabilizing the fusion energy parameter and the filling density in injection molding. The dynamic characteristic is a characteristic that examines the output by changing the input, and is a method of evaluating the condition that minimizes the two-dimensional variation of the input and the output in the combination of various factors.

It is desirable that the input and output signals have a proportional relationship even under various usage conditions and environments, and more robust improvement effects can

Table 2: Control factors.

Symbol	Control factors	Level 1	Level 2	Level 3
A	Gate width(mm)	0.5	0.8	-
B	Mold temperature(°C)	165	175	185
C	Resin temperature(°C)	96	102	108
D	Measurement level(mm)	103	105	107
E	Retention pressure(Mpa)	35	45	55
F	Screw rotational speed(rpm)	490	510	530
G	Bush temperature(°C)	165	185	205
H	Virtual factor	e1	e2	e3

Table 3: Noise factors.

Noise factors	N1	N2
Mold type	No.1Die	No.2Die

Table 4: Signal factors.

Signal factors	M1	M2	M3
Injection pressure(Mpa)	4.0	8.0	12.0

be obtained in terms of reproducibility, precedence, and ver-satility. Various factors and level tables in this study are shown in Table 2, Table 3 and Table 4.

The control factors are injection molding processing conditions resin inlet gate width (Gate width: A), actual temperature control mold temperature (Mold temperature: B), injection cylinder temperature setting resin temperature (Resin temperature: C), Measurement level of volume required for injection (Measurement level: D), Retention pressure to prevent resin backflow (Retention pressure: E), Screw rotational speed during molding (Screw rotational speed: F), Preheat temperature of bearing bush (Bush tem-

perature: G), Virtual factor: H are assigned to each level.

The noise factors are two types of dies (No.1 Die and No.2 Die) used to process the same product. The signal factors (injection pressure; 4MPa, 8MPa, 12MPa) are set as an input. The reason for setting the signal factor to the injection pressure is that a high injection pressure must be applied to fill the molten resin to the end of the cavity. In the mold, the flow resistance increases as the filling progresses, and injection pressure is applied so that the resin flows by overcoming this resistance to ensure the filling property of the resin.

3.5 Allocation of “Orthogonal table” and experimental results

Create an “Orthogonal table” which is a statistical tool for making an experimental design, based on the level table.

Table 5 shows the allocation of the orthogonal table and the experimental results. This table shows L18 orthogonal table experimental data (filling density; kg/m^3) with control factors (A to H) on the inside, and signal factors (M1, M2, M3) and noise factors (N1, N2) on the outside.

In parameter design, mixed orthogonal tables (L12, L18, etc.) are often used for the inner allocation, and only the

Table 5: L18 orthogonal table and experimental data.

EXP. Number.	Parameter Symbol								M1:4.0		M2:8.0		M3:12.0	
	A	B	C	D	E	F	G	H	N1	N2	N1	N2	N1	N2
1	0.5	165	96	103	35	490	165	e1	0.755	0.771	0.771	0.775	0.785	0.789
2	0.5	165	102	105	45	510	185	e2	0.760	0.773	0.775	0.776	0.786	0.790
3	0.5	165	108	107	55	530	205	e3	0.761	0.771	0.779	0.824	0.805	0.814
4	0.5	175	96	103	45	510	205	e3	0.763	0.770	0.769	0.773	0.779	0.785
5	0.5	175	102	105	55	530	165	e1	0.781	0.798	0.799	0.806	0.811	0.820
6	0.5	175	108	107	35	490	185	e2	0.780	0.795	0.820	0.825	0.829	0.834
7	0.5	185	96	105	35	530	185	e3	0.779	0.791	0.796	0.806	0.812	0.826
8	0.5	185	102	107	45	490	205	e1	0.769	0.781	0.798	0.808	0.825	0.835
9	0.5	185	108	103	55	510	165	e2	0.781	0.799	0.823	0.830	0.829	0.849
10	0.8	165	96	107	55	510	185	e1	0.786	0.802	0.855	0.865	0.864	0.875
11	0.8	165	102	103	35	530	205	e2	0.785	0.811	0.869	0.871	0.872	0.879
12	0.8	165	108	105	45	490	165	e3	0.782	0.795	0.811	0.816	0.822	0.832
13	0.8	175	96	105	55	490	205	e2	0.763	0.781	0.785	0.792	0.795	0.810
14	0.8	175	102	107	35	510	165	e3	0.761	0.779	0.786	0.789	0.791	0.812
15	0.8	175	108	103	45	530	185	e1	0.745	0.769	0.774	0.775	0.780	0.789
16	0.8	185	96	107	45	530	165	e2	0.765	0.782	0.785	0.791	0.796	0.823
17	0.8	185	102	103	55	490	185	e3	0.781	0.798	0.806	0.811	0.821	0.815
18	0.8	185	108	105	35	510	205	e1	0.785	0.821	0.825	0.829	0.835	0.845

Figure 8: Relationship between injection pressure and filling density.

main effects are allocated. The number of experiments is represented by the experiment number on the left side of the orthogonal table. The number of times of this experiment is 18, the upper row in the horizontal direction represents the types of control factors, and the values listed below the lev-

els represent the levels of the control factors. The advantage of using the orthogonal array is the reduction of the number of experiments, and the number of experiments without the orthogonal array is $2^1 \times 3^7 = 4,374$ from the establishment of brute force [19].

Table 6: SN ratio and Sensitivity.

EXP. Number.	Parameter Symbol								Decibel value	
	A	B	C	D	E	F	G	H	SN ratio	Sensitivity
1	0.5	165	96	103	35	490	165	e1	8.10	-21.58
2	0.5	165	102	105	45	510	185	e2	8.06	-21.56
3	0.5	165	108	107	55	530	205	e3	8.34	-21.34
4	0.5	175	96	103	45	510	205	e3	7.99	-21.61
5	0.5	175	102	105	55	530	165	e1	8.11	-21.27
6	0.5	175	108	107	35	490	185	e2	8.34	-21.11
7	0.5	185	96	105	35	530	185	e3	8.22	-21.26
8	0.5	185	102	107	45	490	205	e1	8.50	-21.21
9	0.5	185	108	103	55	510	165	e2	8.40	-21.05
10	0.8	165	96	107	55	510	185	e1	8.72	-20.77
11	0.8	165	102	103	35	530	205	e2	8.73	-20.70
12	0.8	165	108	105	45	490	165	e3	8.27	-21.17
13	0.8	175	96	105	55	490	205	e2	8.18	-21.42
14	0.8	175	102	107	35	510	165	e3	8.19	-21.43
15	0.8	175	108	103	45	530	185	e1	8.15	-21.60
16	0.8	185	96	107	45	530	165	e2	8.25	-21.38
17	0.8	185	102	103	55	490	185	e3	8.14	-21.23
18	0.8	185	108	105	35	510	205	e1	8.24	-21.02
MAX									8.73	-20.70
MIN									7.99	-21.61

Table 7: Calculation process.

EXP. Number.	Slope β	Divisor r	Square sum		$SN \times \beta$	Se	SN'	Antilog		Decibel value	
			ST	$S\beta$				$S\beta/SN'$	$S\beta/r$	SN ratio	Sensitivity
1	0.083	448	3.598	3.116	5.0E-05	0.483	0.483	6.454	7.0E-03	8.10	-21.58
2	0.084	448	3.620	3.131	3.0E-05	0.489	0.489	6.404	7.0E-03	8.06	-21.56
3	0.086	448	3.770	3.288	5.8E-04	0.481	0.482	6.822	7.0E-03	8.34	-21.34
4	0.083	448	3.587	3.095	4.0E-05	0.492	0.492	6.289	7.0E-03	7.99	-21.61
5	0.086	448	3.865	3.348	1.2E-04	0.517	0.517	6.475	7.0E-03	8.11	-21.27
6	0.088	448	3.976	3.468	6.0E-05	0.508	0.508	6.822	8.0E-03	8.34	-21.11
7	0.087	448	3.857	3.352	2.0E-04	0.505	0.505	6.633	7.0E-03	8.22	-21.26
8	0.087	448	3.869	3.390	1.4E-04	0.479	0.479	7.072	8.0E-03	8.50	-21.21
9	0.089	448	4.023	3.515	3.0E-04	0.508	0.508	6.917	8.0E-03	8.40	-21.05
10	0.092	448	4.252	3.749	1.7E-04	0.504	0.504	7.441	8.0E-03	8.72	-21.77
11	0.092	448	4.321	3.810	9.0E-05	0.510	0.510	7.464	9.0E-03	8.73	-21.70
12	0.087	448	3.935	3.425	1.0E-04	0.510	0.510	6.717	8.0E-03	8.27	-21.17
13	0.085	448	3.724	3.232	2.1E-04	0.491	0.492	6.573	7.0E-03	8.18	-21.42
14	0.085	448	3.711	3.223	2.7E-04	0.489	0.489	6.593	7.0E-03	8.19	-21.43
15	0.083	448	3.577	3.102	1.0E-04	0.475	0.475	6.523	7.0E-03	8.15	-21.60
16	0.085	448	3.750	3.261	4.3E-04	0.488	0.488	6.679	7.0E-03	8.25	-21.38
17	0.087	448	3.892	3.375	0.0E+00	0.517	0.517	6.522	8.0E-03	8.14	-21.23
18	0.089	448	4.069	3.539	2.0E-04	0.531	0.531	6.667	8.0E-03	8.24	-21.02

Figure 8 shows the input/output relationship graph of injection pressure (horizontal axis: MPa) and filling density (vertical axis: kg/m^3) for each experiment. From the graph, it can be seen that the relationship between the injection pressure of the input and output and the filling density is a characteristic element that evaluates whether or not there is linearity related to the stabilization of the filling characteristics.

3.6 SN ratio and Sensitivity calculation In parameter design, the SN ratio of dynamic characteristics is used for functional evaluation, and it is ideal that stable output

can be obtained even if there are various errors that affect functional characteristics. To evaluate the functionality, the linearity of the output is examined by changing the input signal. This is the SN ratio of dynamic characteristics. In this experiment, since the ideal functional state is set for the purpose of stabilizing the fusion energy parameter and the filling density in the injection molding process, "Energetic S/N ratio based on zero point proportion" is adopted.

Table 6 shows the SN ratio and sensitivity values from the output data, and Table 7 shows the calculation process of the calculated SN ratio and sensitivity. In functional evalu-

Table 8: Factor effect table.

Factor Symbol	SN ratio Average 8.27			Sensitivity Average -21.26		
	Level1	Level2	Level3	Level	Level2	Level3
Factor effect						
A	0.5	0.8	-	0.5	0.8	-
	8.23	8.32	-	-21.50	-21.35	-
B	165	175	185	165	175	185
	8.37	8.16	8.29	-21.35	-21.57	-21.36
C	96	102	108	96	102	108
	8.24	8.29	8.29	-21.50	-21.40	-21.38
D	103	105	107	103	105	107
	8.25	8.18	8.39	-21.46	-21.45	-21.37
E	35	45	55	35	45	55
	8.30	8.20	8.31	-21.35	-21.59	-21.34
F	490	510	530	490	510	530
	8.25	8.27	8.30	-21.45	-21.41	-21.42
G	165	185	205	165	185	205
	8.22	8.27	8.33	-21.48	-21.42	-21.38
H	e1	e2	e3	e1	e2	e3
	8.30	8.33	8.19	-21.41	-21.37	-21.51

Figure 9: Factor effect diagram of the SN ratio and Sensitivity.

ation, the optimum conditions are obtained by obtaining the SN ratio and sensitivity, and finally determining the presence/absence of effects in the “factorial effect diagram”.

3.7 Analysis of factorial effects Figure 9 shows the SN ratio and sensitivity for each control factor in a factorial effect diagram. The vertical axes in the upper and lower figures represent the SN ratio and sensitivity, respectively, and the horizontal axes represent the factor level. The factor effect table (Table 8) shows the effect of a factor or a combination of factors on the characteristic value, and the diagram that illustrates it is a factor effect diagram.

The significance of this diagram is to extract factors that have a large SN ratio that spreads vertically and have a small effect on output sensitivity, and it can be judged that their level is highly significant in stabilizing the resin filling characteristics.

In the dynamic characteristic evaluation, it is desirable

that the value of the SN ratio is linearly large, and the optimum conditions are determined based on a comprehensive evaluation comparing the SN ratio and sensitivity factor effect diagrams. The optimum levels in Fig. 9 are the factors in the circled areas; A2 “Gate width (mm): 0.8”, B1 “Mold temperature (°C): 165”, C2 “Resin temperature (°C): 102”, D3 “Measurement level (mm): 107”, E3 “Retention pressure (MPa): 55”, F3 “Screw rotational speed (rpm): 530”, G3 “Bush temperature (°C): 490”, H2 “Virtual factor: e2”. Table 9 shows the combination of the fusion energy parameter and the control factor level that seems to be optimal for obtaining the stabilization of the filling density in the injection molding process.

3.8 Reliability evaluation of L18 orthogonal table experiment As shown in Table 9, the L18 orthogonal table test results were checked for reliability (additivity)

Table 9: Optimal results based on estimate and gain.

Condition	A	B	C	Parameter Symbol					Estimate		Gain	
				D	E	F	G	H	SN ratio	Sensitivity	SN ratio	Sensitivity
Optimal	0.8	165	102	107	55	530	205	e2	8.72	-20.85	0.47	0.49
BM	0.5	165	96	103	35	490	165	e1	8.26	-21.34	-	-

Table 10: Reliability of L18 experiment.

L18 Orthogonal experiment		By inverse estimation	
SN ratio		Reliability check	
Maximum	8.73	Obtained from experiment	8.10
Minimum	7.99	SN ratio of BM estimate	8.26
Difference	0.74		-0.16
10% of difference	0.07	$\geq$	-0.16
Judgment		Reliable	

based on the result that the estimated value of the optimum condition was higher than the benchmark condition (BM) and the gain was secured.

First, the maximum value and the minimum value of the SN ratio obtained in the L18 orthogonal table experiment are obtained. The judgment method can be judged to be reliable if the difference from the SN ratio of the BM condition estimated from the value of 10% of the difference is within 10% from the statistical rule of thumb [20].

Table 10 shows the reliability evaluation results. The optimum condition selected by evaluating the variation of the linear relationship between the injection pressure and the filling density and stabilizing the filling density in the injection molding method is a desirable condition, and it can be judged that the L18 orthogonal array experiment is reliable.

3.9 Evaluation of reproducibility by confirmation experiment

The purpose of the confirmation experiment

is to confirm whether the output is stable even when the time, place, and environment change compared to the orthogonal table experiment. Table 11 shows the evaluation results of the confirmation experiment data. In the confirmation experiment, the SN ratio of the selected optimum condition and BM condition is obtained, and the same two types as in the orthogonal table experiment are performed again to obtain the SN ratio. By comparing the difference between the estimated values of the two and the difference (gain) in the confirmation experiment, the reproducibility of the experiment is examined.

Table 12 shows the reproducibility evaluation results in the confirmation experiment. In parameter design, if the reproducibility of gain is within the range of 70% to 130%, or the gain difference is within $\pm 3\text{db}$, it can be judged that there is reproducibility. In this experimental result, the reproducibility of the gain was 93% and the gain difference

Table 11: Confirmation experimental data and SN ratio/Sensitivity calculation results.

Noise factor	N1			N2								SN ratio	Sensitivity
Signal factor	M1	M2	M3	M1	M2	M3	r	S_T	S_β	S_N	S_β/S_N	η_E	S_E
BM	0.748	0.758	0.756	0.735	0.740	0.738	224	3.34	2.87	0.47	6.10	7.85	-21.94
Optimal	0.779	0.799	0.814	0.780	0.796	0.811	224	3.81	3.31	0.50	6.62	8.21	-21.32

Table 12: Reproducibility of confirmation experiment.

	SN ratio [db]				Sensitivity [db]		
	Estimated	Confirmed	Reproducibility		Estimated	Confirmed	Reproducibility
BM condition	8.26	7.85	95%		-21.51	-22.12	103%
Optimal condition	8.72	8.21	94%		-21.00	-21.48	102%
Gain	0.38	0.36	93%		0.51	0.63	124%
Reproducibility rate (within $\pm 30\%$)	$70\% \leq$	93%	$\leq 130\%$		$70\% \leq$	124%	$\leq 130\%$
Gain difference (within $\pm 3\text{db}$)	0.03	$\leq \pm 3\text{db}$			-0.12	$\leq \pm 3\text{db}$	
Judgment	Reproducible						
Energy loss	36%	1/1.55	(Times)		Reduction		
Density stability	20%	1.24	(Times)		Improvement

Figure 10: Input/output linearity verification.

Table 13: Process capability index.

BM		Optimal	
Sample	Data	Sample	Data
1	0.765	1	0.761
2	0.765	2	0.760
3	0.764	3	0.760
4	0.763	4	0.759
5	0.760	5	0.760
6	0.759	6	0.763
7	0.760	7	0.756
8	0.764	8	0.760
9	0.754	9	0.758
10	0.767	10	0.759
11	0.762	11	0.762
12	0.760	12	0.759
13	0.756	13	0.762
14	0.759	14	0.762
15	0.765	15	0.761
16	0.761	16	0.759
17	0.765	17	0.765
18	0.762	18	0.762
19	0.765	19	0.761
20	0.763	20	0.760
Average	0.762	Average	0.760
σ	0.003	σ	0.002
C_p	1.00 < 1.33	C_p	1.70 > 1.33
STW.	0.020	STW.	0.020
USL.	0.770	USL.	0.770
LSL.	0.750	LSL.	0.750

was 0.03 db.

Furthermore, the stability improvement rate of the filling density against the BM condition was 20% and the energy loss was reduced by 36%, indicating that the extracted optimum conditions were properly selected and the set ideal functional state was approached.

Figure 10 is a graph comparing the input and output variations and the linear relationship between the optimum condition and the BM condition in the verification experiment. It shows the change in output (filling density) with respect to input (injection pressure), and it is clear that the optimum condition has a stable linear proportional relationship with less variation than the BM condition.

3.10 Process capability evaluation by confirmation experiment

Table 13 shows the evaluation results of the process capability under the comparison condition (BM) and the optimum condition (Optimum) for the resin filling density (standard $0.760 \pm 0.01 \text{ kg/m}^3$) after the injection molding process by the confirmation experiment. The number of samples are $n=20$. “Process capability” is a probability capability that falls within the specifications of the product regarding quality. The “process capability index (C_p)” is used as a measure of the degree of variation in quality characteristics due to process variation, which indicates the stability with respect to the standard range. $C_p \geq 1.00$ is required, and if $C_p \geq 1.33$, it can be judged that the process capability is sufficient.

From the results of Table 13, the process capability is insufficient under the BM condition with $C_p = 1.00 < 1.33$, but under the optimum condition, the process capability is sufficient with $C_p = 1.70 > 1.33$. The C_p data distribution calculated in Table 13 is summarized in the frequency distribution table, and histograms are shown in Fig. 11 and Fig. 12. From the results of the graph, the fluctuation range of the filling density under the optimum condition was reduced compared to the BM condition.

From the results that satisfy the condition of $C_p \geq 1.33$, it can be said that the distribution is close to the normal distribution type (normal type). This indicates that the filling density stability under the selected optimum conditions was improved. C_p was calculated by the following formula.

$$C_p = \frac{USL - LSL}{6\sigma} \quad (11)$$

USL : upper limit standard value

LSL : lower limit standard value

σ : Standard deviation

STW : Standard width

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (12)$$

n : total number of data

x_i : individual data

$\bar{x}$: average value

Figure 11: Histogram of BM.

Figure 12: Histogram of Optimal.

4. Conclusion

In this study, we focused on the function of controlling the resin filling density in the mold (input/output relationship of melting energy related to resin flow) in optimizing resin strength. From the new definition of resin strength based on material mechanical considerations, we applied a functional evaluation method that has the ideal function of stabilizing the resin filling density.

It was clarified that the uniform resin filling density in the mold, which is a management function, is extremely important for stabilizing the resin strength. As a result of research, we achieved 50% reduction in in-process defect rate due to abolition of 100% inspection and defective molding of resin pulleys (cracking/cracking of thin part) by improving process capability of resin filling density which is the current productivity index.

Furthermore, it was verified that the application of the functionality evaluation method, which has the ideal function of stabilizing the resin filling density, brings great knowledge in the optimization of the injection molding process.

As a future research topic, we will focus on the technical basis that the variation of the shape change due to the variation of the shrinkage ratio of the resin in the mold is determined by the response of the mold size and the molded product size, and always has a linear proportional relation-

ship. We plan to set a new ideal function for the relationship between the melting energy related to resin flow and the variation of resin shrinkage in the mold, and to further optimize the strength and dimensional accuracy of parts by the functionality evaluation method [22]~[24].

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