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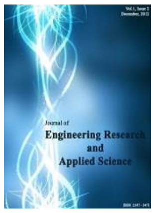

Optimization of plastic injection process using optimization techniques

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Abstract

In this study, Moldflow analysis performed in accordance with the set of design of experiment by using statistical experimental design methods for optimization of injection parameters. In order to evaluate the results, firstly finite element analysis was applied with Moldflow. Secondly, in finding optimum values, Finite Element Analysis, Response Surface Methodology and Genetic Algorithm are integrated. To achieve efficient and effective integration, a computer program is written. Evaluated which method gives more accurate results by comparing to results being obtained by different optimization method in the final phase. From this study it is observed that process parameters improve injection significantly. Application of optimization method also improves further injection characteristics of plastic parts.

Keywords: Plastic injection parameters, genetic algorithm, response surface methodology, finite element analysis.

1. Introduction

The injection molding process is currently one of the most popular methods used in the industry for production from plastic raw materials. High production rate, relatively short molding cycle, low waste rate, smooth surface and the possibility to produce complex geometries are the main factors that make the process attractive. A good mold design and optimum process parameter value are the main factors of productivity, quality and product cost. Plastic injection simulation, experimental design methods, artificial intelligence applications are frequently used tools. By using these tools alone, it is very unlikely that many factors affecting the process can be improved simultaneously and the desired optimum result is achieved. On the other hand, a certain systematic is required in order to use all these tools correctly. There are many studies on optimizing the plastic injection process. The effect of injection parameters on shrinkage was investigated. The relationship between inputs and outputs was examined using Taguchi Method and variance analysis tools. Melt temperature, injection pressure, ironing pressure and ironing time effects are the injection parameters examined [1]. An attempt was made to provide the minimum draw amount of a container made of polymer material with process parameter optimization. For this, Taguchi Experiment Design method and variance analysis (ANOVA) were used. The signal / noise ratio was used to determine the effects of parameters on shrinkage [2]. In the study conducted to determine the most suitable process parameters affecting the dimensional shrinkage resulting from the pressing of a DVD-ROM front cover by plastic injection, a series of moldflow flow analysis was done with the injection parameters planned according to the L27 orthogonal experimental design. The signal / noise ratio has been used to provide minimum shrinkage. The effect of each parameter on shrinkage was determined by ANOVA. An injection press and experiment set were used to verify the most appropriate parameter values found by the Taguchi method [3]. Taguchi experiment design method and ANOVA (Variance analysis) were used to optimize melt temperature, injection pressure and cooling time parameters. For this purpose, firstly, the tea tray from polycarbonate raw material was produced with different melt temperature, cooling time and injection pressure values. Tensile strength testing of each workpiece obtained was carried out. By evaluating the obtained results with analysis of variance, optimum process parameters were determined [4]. Numerical simulations are used to investigate the effect of recycled Polypropylene raw material on the warping of rheological properties. Capillary and rotation rheometers were used to obtain the rheological curves of the mixes at high and low shear rate. With the experimental results, the Cross WLF model and Moldflow flow simulation were used to predict distortion. With Monte Carlo simulation, distortion values and tolerance values for robust design were determined [5]. The effects of the

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selected injection parameters of the Led Lamp body on the shrinkage amount were investigated. For this, Taguchi experiment design method was used. As a result, it was understood that the selected parameters effectively reduced the amount of pull. There was a 3.82% difference between the optimum predicted value and the validated value [6]. Using the Taguchi approach, the effects of injection molding variables on the depression effect were investigated. Using the Taguchi approach, the amount of debris associated with optimum parameter settings was obtained. The amount of sediment obtained by verification attempts was compared with the predicted amount of sediment and the results were observed to be compatible. The results show that the Taguchi approach can be successfully used to estimate the amount of precipitation with various combinations of process parameters [8]. A program has been developed that calculates the cost of plastic injection mold manufacturing. First of all, an interface was created in which mold material, type of plastic material to be produced, injection molding machine features, standard mold elements, and geometrical features of the part to be produced are entered. The program is calculated as the sum of raw material cost, design cost, labor cost and machining cost according to these parameters. An experimental study was carried out on the plastic elbow piece to test the program effectiveness [10]. Optimization of distortion in plastic injection molding was investigated using contrast analysis, artificial neural networks and genetic algorithm. As is known, plastic injection molding includes plastic preparation, injection, ironing, cooling, removal of parts and control applications during the process [11]. The effect of injection parameters on shrinkage in seven different types of plastic materials has been systematically examined. As a result of the examination, it was determined that the holding pressure is the most critical parameter. Melt temperature has slightly less effect. Injection speed and mold temperature affect the drawing value relatively less [12]. In order to determine the balance between energy consumption and product quality, as well as to determine which variables and the process can be optimized, the car fender injection molding process has been researched. In order to solve multi-surface optimization problems, YYM was applied and process parameters were optimized by using non-dominated sequencing GA. In the problem-solving procedure, the combination of CIS integration tools was used to reduce the cost and time of calculation [13]. The process of new product commissioning in the plastic injection process takes considerable time. Firms that can shorten this process have significant advantages in competition, while firms that cannot shorten this period may face the risk of losing customers. The new product, which is one of the most important processes in the automotive supplier industry companies using the plastic injection method, has been made to shorten the commissioning process and to reduce material, machine usage and labor costs. Artificial Neural Networks (ANN) and Expert System (US), one of the artificial intelligence techniques, were used in the study [14]. Effective in the production of plastic parts using the Taguchi method; Different product design, number of inlets, inlet dimensions and runner design parameters are used to minimize distortion in the product. Product design, number of inlets, inlet dimensions, runner design were used as control parameters, and the test pattern was designed and manufactured. After the mold manufacturing, production was made by plastic injection method using the mold produced to obtain the distortion values. Polypropylene (PP) Petoplen MH220 was used as plastic material. The Taguchi method based on three-level experimental design was used in the mold design phase and using the distortion values. Taguchi's orthogonal array was used to find the optimum levels of control parameters affecting S / N ratio and ANOVA distortion. Verification test results with optimum levels of control parameters have shown that the Taguchi Method is an appropriate method of reducing distortions in the plastic injection molding process [15]. The parameters of the optimization injection molding process are very important to increase efficiency. In process optimization, parameters should work at optimum levels for acceptable performance. The experimental design of the Taguchi orthogonal array was used for optimization. PP material was used as a plastic material group [16]. Injection parameters were tried to be determined by the effect of distortion. The distortion value of a circular plastic part was tried to be estimated. In this way, it is predicted that process parameters can be adjusted without the need for trial production. ANN model is used to achieve this goal. Some of the Moldflow analysis results using different process parameters were used for training of ANN model. In the second step, another data group was used to determine the amount of distortion estimation error. The results were found to be 0,997 for R-square (sum of squares) ANN training and 0,995 for test data [17].

In this study, Moldflow analysis performed in accordance with the set of design of experiment by using statistical experimental design methods for optimization of injection parameters. In order to evaluate the results, firstly finite element analysis was applied with Moldflow. Secondly, in finding optimum values, Finite Element Analysis, Response Surface Methodology and Genetic Algorithm are integrated. To achieve efficient and effective integration, a computer program is written. Evaluated which method gives more accurate results by comparing to results being obtained by different optimization method in the final phase. From this study it is observed that process parameters improve injection significantly. Application of optimization method also improves further injection characteristics of plastic parts.

2.Materials and method

In this study, the top panel covering part used in the refrigerator was chosen. This piece is a visual piece that was first noticed by the customer. For this reason, quality defects such as depression, distortion, junction trail are definitely undesirable. This piece is printed from POLYFLAM RIPP 3625 CS1 material produced by A Shulman GMBH from PP material group. Figure 1 shows the 3D model of the part designed with the Siemens NX10 program. The part is an example of a typical thin-walled part design. There is a rib structure added in the middle for strength.

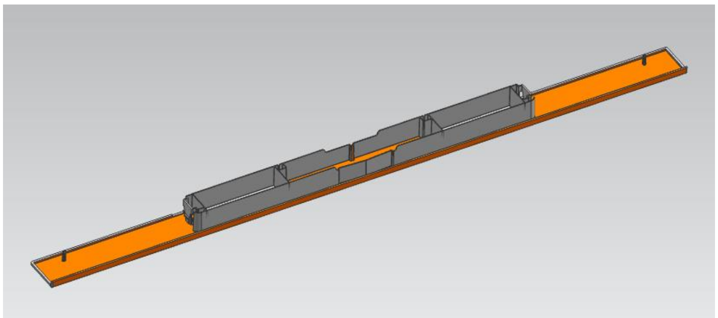

Figure 1. Three-dimensional model designed in Siemens NX10 program.

While choosing materials during design, the properties expected from mechanical, thermal and optical secret parts are evaluated in the light of this information provided by the raw material supplier. In this study, the material properties shown in Table 1 were used.

Table 1. Material Properties.

Density in Liquid State g/cm³	1,23
Density in Solid State g/cm³	1,37
Elastic Modulus, Perpercidular direction MPa	2822
Elastic Modulus, Paralel direction MPa	2387
Poisson rate, Perpercidular direction	0,375
Poisson rate, Paralel direction	0,389
Shear Modulus MPa	907
Ejection temperature C°	122

Moldflow Synergy 2018.1 version was used in the analysis studies. Part and mold design was realized with Siemens NX10 software. The model shown in Figure 2 consists of approximately 127.000 triangular elements and 63.479 connection knot elements created with the Dual domain mesh technique.

The aspect ratio, which is one of the main factors indicating mesh quality, is slightly higher than the desired value for multiplication and cooling analysis with 11.49, but 1.68 and min. 1.16 values are quite ideal.

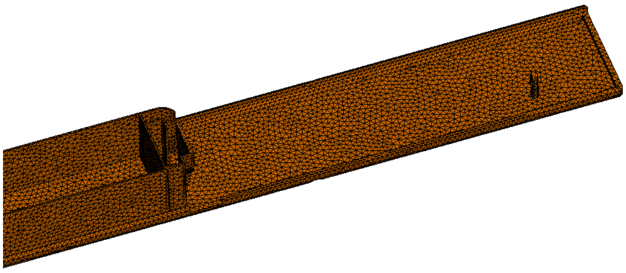

Figure 2. Finite element model created in Autodesk Moldflow Plastic Synergy18.1 program.

In the next stage, hot and cold runner systems were created. Runners are modeled with beam elements in the Autodesk Moldflow Plastic Synergy library. Figure 3 shows the general view of the runner model. The gating elements seen in red are hot runner and the gating elements seen in green are cold runner inlets.

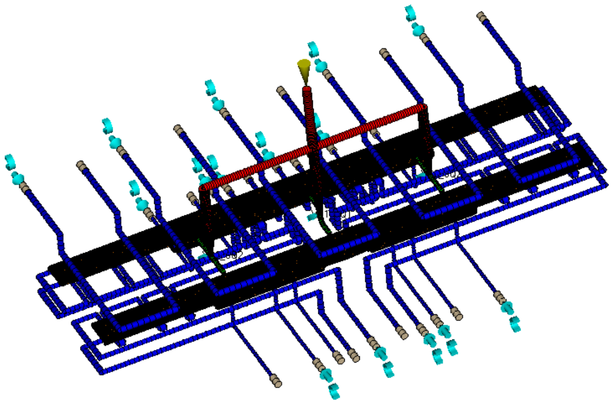

Figure 3. Finite element model created in Autodesk Moldflow Synergy program.

Determination (adjustment) of process parameters by trial and error requires many computationally costly finite element simulations. A more effective approach is to adopt an appropriate optimization methodology. In optimization methodology, desired injection criterion is expressed as objective(s) and constraint function(s) in terms of process parameters. These functions are then solved to find optimum parameter values by a numerical optimization method.

In the case of the panel forming, the optimization problem is defined as below:

Find Process Parameters:

Fill Time (tf), Fill Pressure (Pf), Holding Time (th), Holding Pressure (Ph), Melt Temperature (Tme),Mold Temperature (Tmo), Cooling Time (tc) (1)

To Minimiz Objective Function:

Warpage (3)

Subjected to Constraints:

Warpage ≤ Warpage_limit (4)

Cycling Time ≤ Cycling Time limit (5)

Within Parameter Ranges:

70 MPa ≤ Fill Pressure (Pf) ≤ 90 MPa (6)

2 sn ≤ Fill Time (tf) ≤ 7 sn (7)

6 sn ≤ Holding Time (th) ≤ 10 sn (8)

60 MPa ≤ Holding Pressure (Ph) ≤ 80 Mpa (9)

290° ≤ Melt Temperature (Tme) ≤ 310° (10)

110° ≤ Mold Temperature (Tmo) ≤ 130° (11)

Ranges process parameters have been selected based on the recommended values from A Shulman GMBH company.

3.Results

In order to minimize warpage in the plastic injection process, according to the feedback from the manufacturer, the warpage values from the points specified in the specification were measured in a three-dimensional measuring device (CMM) and the values were verified with the values from the finite element analysis. Measurement points for warpage is shown in Figure 4. The compared results are given in Table 2.

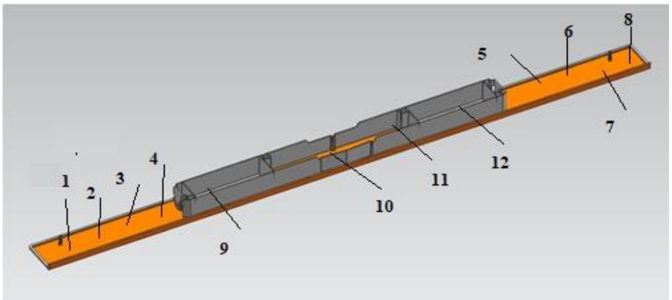

Figure 4. Measurement points

Table 2. Comparision of CMM measurement and FEM results for warpage

Measurement No	CMM Measurement (mm)	FEM Results (mm)
1	1.252	1.102
2	1.345	1.306
3	1.692	1.605
4	1.942	1.802
5	1.214	1.210
6	1.774	1.684
7	2.604	2.549
8	1.157	1.079
9	1.792	1.739
10	1.685	1.579
11	1.718	1.716
12	1.318	1.285

To solve the optimization problem effectively, a Genetic Algorithm (GA) program has been developed and coupled with the RSM based analytical models of warpage to find a global optimum.

In the solution of the optimization problem given in Equations 1-11, objective and constraint functions that come from computationally costly FEAs are evaluated many times. This can make the solution process inefficient. A more effective solution strategy is to replace the objective and constraint functions with corresponding simpler analytical functions using RSM before the solution process. RSM is defined as a model building technique based on statistical design of experiment and least square error fitting [18]. RSM creates a polynomial function, f, for the available data set as following:

$$f = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \ldots\ldots \qquad (11)$$

Where a_0, a_i and a_{ij} are tuning coefficients and n is the number of parameters (i.e. process parameters). The polynomial models generated by RSM are often referred to as Response Surface (RS) models in the literature. To cerate RS models, a computer program has been written in this study. The program has the capability of creating RS polynomials up to 10^{th} order if sufficient data exist. All cross terms in the models can be taken into account. RS models can also be generated in terms of inverse of parameters. That is, x_i can be replaced as $\frac{1}{x_i}$ (i.e. inversely) in RS model if desired. In creating the RS models, FEA results based on D-optimal experimental design method is utilized. Statistical three-level full factorial experimental design is employed as the basis for D-optimality [18]. To create a quadratic response surface model (n+1)/(n+2)/2 number of analysis results are required where n is the the number of design parameters. In the literature 50% more points than required are recommended for the improvement of the prediction accuracy of the model [18]. For 6 design parameters 40 FEAs as shown in Table 3 are conducted in this study. Injection process parameters in Table 3 are selected utilizing D-optimal experimental design method.

Table 3: Combinations of process parameters selected utilizing D-optimal experimental design

Analyses	Fill Pressure (Pf) (MPa)	Holding Pressure (Ph) (MPa)	Holding Time (Th) (sn)	Fill Time (Tf) (sn)	Melt Temperature (Tme) (°)	Mold Temperature (Tmo) (°)	Warpage (mm)	Cycling Time (sn)
1	70	60	8	6	290	110	1.102	30
2	70	60	6	4	310	110	1.306	30
3	90	60	6	4	310	130	1.605	35
4	70	80	6	4	310	120	1.802	50
5	90	80	8	6	310	130	1.210	50
6	70	80	6	4	290	110	1.684	50
7	90	60	8	6	290	130	1.549	35
2	70	80	6	4	310	130	1.079	50
9	70	80	8	6	290	130	1.739	50
3	70	60	8	6	310	130	1.579	30
4	70	60	6	6	290	120	1.716	45
5	70	60	7	5	290	130	1.285	45
6	90	80	8	6	290	110	1.816	50
7	70	80	8	6	310	130	1.826	50
8	90	70	8	6	300	120	1.364	40
9	70	80	8	6	290	110	1.726	50
10	90	80	6	4	300	120	1.879	50
11	90	80	6	4	290	130	1.501	50
12	90	70	6	4	310	110	1.479	40
13	90	60	6	4	290	110	1.311	30
14	90	60	8	3	300	110	1.622	30
15	70	60	6	3	290	130	1.600	45
16	80	70	6	3	300	110	1.506	40
17	80	60	8	3	310	110	1.753	30
18	90	60	7	2	310	120	1.626	30
19	90	80	7	2	310	110	1.648	50
20	90	70	7	2	290	130	1.869	45
21	70	80	8	2	310	110	1.211	50
22	75	80	8	5	310	130	1.415	50
23	80	80	8	5	310	130	1.514	45
24	80	80	9	5	310	130	1.711	50
25	90	80	9	6	310	130	1.321	45
26	70	60	9	6	310	130	1.793	30
27	75	60	9	6	310	130	1.258	30
28	80	60	10	7	310	130	1.188	45
29	80	80	10	7	310	130	1.647	50
30	80	80	10	7	310	130	1.487	50
31	90	80	8	3	310	130	1.625	50
32	70	60	8	3	310	130	1.694	45
33	75	60	8	3	310	130	1.725	45
34	75	60	8	3	300	120	1.635	40
35	80	60	6	4	300	120	1.573	40
36	80	70	6	4	290	130	1.434	50
37	80	70	6	4	290	130	1.187	50
38	90	70	8	5	310	110	1.211	50
39	75	90	6	5	310	110	1.384	45
40	75	90	8	5	300	130	1.228	45

Optimization problem represented by Equations 1-11 is solved for several cases. In each case, optimum process parameters are sought to minimize the specified forming criteria. Multi-objective optimization is applied to minimize warpage value. Optimum injection parameter values found to achieve this purpose are shown in Table 4.

Table 4. Injection process parameters when warpage is minimized at the same time.

	Warpage (mm)	Cycling Time (sn)	Optimum Injection Parameter Values					
			Fill Pressure (Pf) (MPa)	Holding Pressure (Ph) (MPa)	Holding Time (Th) (sn)	Fill Time (Tf) (sn)	Melt Temperature (Tme) (°)	Mold Temperature (Tmo) (°)
GA	1.020	30	70.9	62.8	2.9	7.1	294	114
FEA	1.214	33						

4.Conclusions

In this study, the design methodology of the most appropriate injection process parameters, which are produced for a mass-produced refrigerator, which is caused by the impact of a visual plastic part by pressing the plastic injection process, is proposed. In this proposed methodology, the use of optimization method has been investigated to minimize warpage in plastic parts. The best process parameters were examined with the optimization method. Finite element analysis, response surface methodology, and the power of the genetic algorithm were used to integrate optimum values. Finite element analysis data were performed for the combination of process parameters designed using the D-optimal experimental design method. The models of the warpage result are created by using the surface response methodology that takes advantage of the finite element analysis results. The response surface models are then integrated with an effective genetic algorithm to find optimum process parameter values. Genetic optimization has significantly reduced warpage values. From optimization results, it was seen that injection process parameters of all of them change more effective when optimization criteria is changed. As a result, the optimization methodology proposed in this study can be successfully used to improve and determine the best production conditions in plastic product forming operations.

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