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Optimization of Plastic Speed Meter Housing for Automobiles: Injection Molding Simulation, Taguchi Method and Machine Learning

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Abstract: *The plastic speed meter housing for automobiles requires accurate parts and assembly to inform the driver of their exact speed. For accurate assembly, the molded speed meter should have a minimize amount of deformation. In this study, to obtain injection molding conditions that minimize the deformation of the speed meter, the main molding conditions that cause the deformation of the speed meter were identified using the Taguchi method. By combining the confirmed molding conditions, 150 data sets were created, and machine learning was conducted using the data set. The model with the best accuracy learned through machine learning was the Linear Regression model. The results of this Linear Regression model were then validated with test data. The optimal injection molding conditions were derived by inputting 5000 molding conditions data into the learned Linear Regression model. Injection molding analysis was performed using the derived injection molding conditions, and the amount of deformation was reduced by about 6.4% compared to the case where current molding conditions were applied. The optimal molding conditions obtained by machine learning were applied to actcual molding. The amount of deformation of the mold amount of the molded speed meter housing was smaller than the amount of deformation predicted in the machine learning model.*

Keywords: *injection molding simulation, Taguchi method, machine learning, Linear Regression, plastic speed meter housing*

1. Introduction

The number of plastic molded products manufactured by injection molding is steadily increasing. Injection molding has advantages including the ability to form light weight, complex shapes with a single process, and no secondary processing such as painting is required. Because of these advantages, plastic molding is currently used in products throughout society. In addition, plastic materials with improved properties can be used to replace metals. The use of precision mechanical components precision is also increasing [1,2].

In particular, the use of plastic parts for automobiles continues to increase with efforts to lighten weight [3,4]. Typically, the front and rear bumpers on the exterior of car are made of plastic. The car's interior includes instrument panels and door trim [5,6]. In addition, precise parts are used as components in the motor that helps the door glass rise and fall, and also as an absorption pipe cover for engine gas. Plastic parts are gradually replacing other small metal parts. This is only possible when the dimensional accuracy of the plastic molded product is ensured.

Many studies are being conducted to improve the dimensional accuracy of plastic parts, and in particular, using an industrial engineering approach. Han et al. reported a study applying the Taguchi method to develop a plastic airbag housing to protect passengers in the passenger seat of a car. In the study, the main factors affecting the deformation of the airbag housing were identified and optimized using molding simulations and applied to the development of the injection mold [7]. Hentati et al. studied using molding experiments and experimental designs investigate whether the injection pressure of PC/ABS molded products is a molding factor with the greatest influence on the shear stress of the molded product [8]. AlKaabneh et al. introduced an Analytical Hierarchical Process (AHP) to establish optimal

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injection conditions. Verification after AHP was performed using FEM, experimental planning method, ANOVA, etc [9]. Park et al. conducted foam molding experiments and DOE to obtain optimal molding by easing the spring back of the door trim while manufacturing the large door trim of the car. The results of the study proved the effectiveness of the new foam molding system [10]. Based on the 6-sigma approach, Lo et al. conducted research to improve the quality of precision injection molding lenses based on definition, measurement, analysis, improvement, and control (DMAIC) procedures. In the process, the Taguchi experimental planning method was performed to find the optimal molding conditions [11]. Tsai et al. reported that they created a model to predict the shape of plastic lenses using Artificial Neural Network (ANN) and Response Surface Methodology (RSM), one of the optimization techniques. In our study, the process window established by ANN was more accurate RSM [12]. Trotta et al. proposed an experimental procedure to find the optimal molding conditions optimal microinjection molding using the Central Composite Design for the flash and weight characteristics of the molded product [13].

This study focused on minimizing deformation of the plastic speed meter housing, in which parts are assembled to inform the driver of the speed of the car. Factors affecting deformation were derived using the Taguchi method to determine the optimal molding conditions to minimize deformation of the speed meter housing. A data set was generated by combining the molding conditions derived using the Taguchi method, and then machine learning was conducted. The optimal model was selected from among several machine learning models. The prediction accuracy of the selected model was also verified with test data. For the verified model, a big data set was created by combining the previously obtained molding conditions, and the optimal molding conditions were derived by applying them to the selected model. In addition, the whole experiment in this study was conducted using an injection molding analysis program that can provide economical, fast and objective data before actual mold design and manufacturing [14]. Figure 1 is a flowchart summarizing the process of this study.

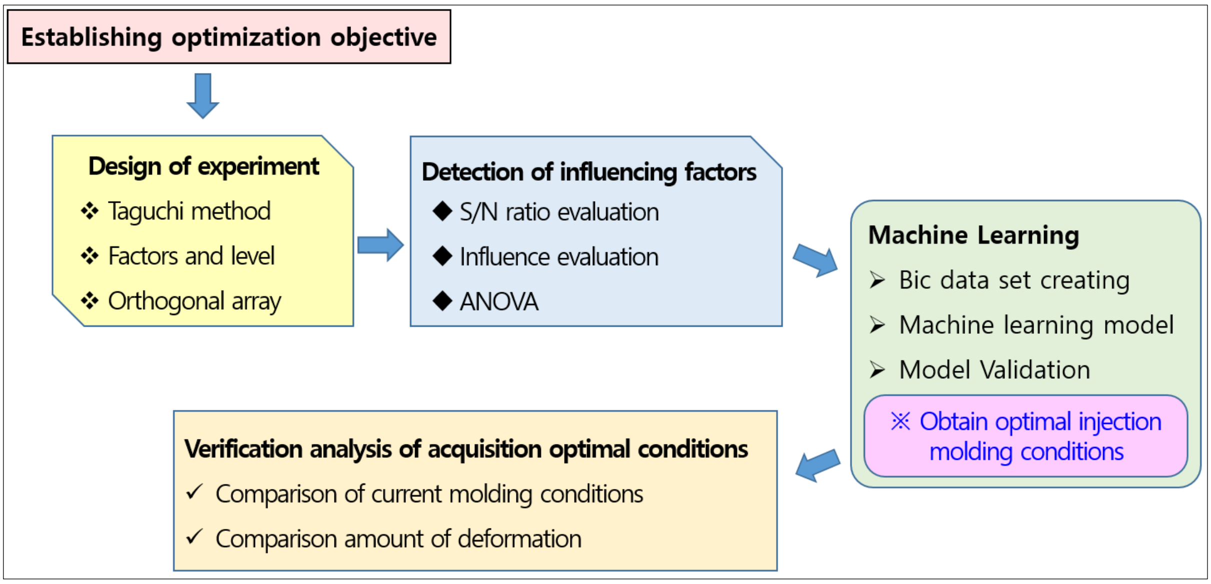

Figure 1. Flowchart summarizing the process of the study

2. Materials and methods

2.1. Plastic speed meter housing and materials

The part used in the study is a plastic speed meter housing for automobiles, which is assembled at the back of instrument panel inside the car. The housing includes components that move the speed meter bar indicating the speed of the car. To stably assemble these magnetic speedometers, a plastic speed meter housing with minimal deformation should be used. However, speed meter housing that is currently injection-molded often has a deformation amount that exceeds the standard.

The speed meter housing was originally built using a metal plate. However, with the trend of lightening automobiles, it is currently manufactured by injection molding methods using plastic. Figure 2 is a 3D model of the speed meter housing used in this study. Figure 3 shows the size of the housing, which is approximately 75×35×3 to 6 (mm). The left and right sides are asymmetric due to the structure of the speed meter housing molding. In addition, because the central part of the molding is locally thick, uneven shrinkage may occur after molding.

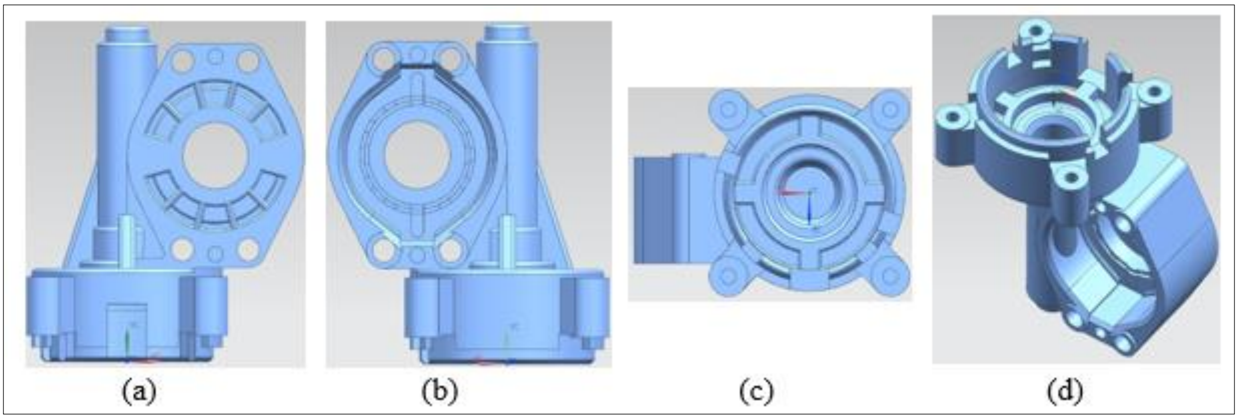

Figure 2. Plastic speed meter housing 3D model: (a) Front side (b) Back side (c) Right side (d) Isometric view

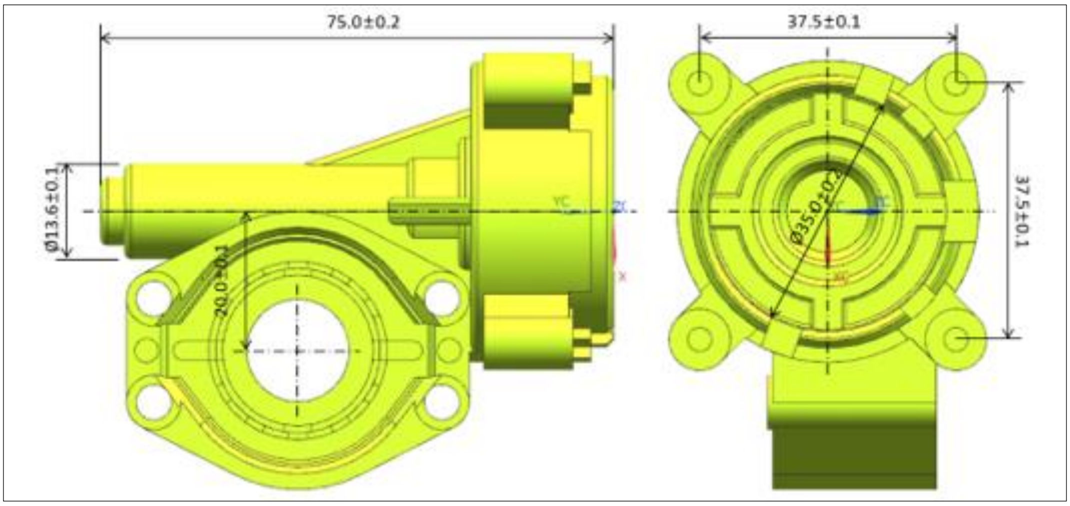

Figure 3. 3-D geometry and dimensions of the speed meter housing

Zytel FE5382 BK276 provided by Dupont was used as the plastic used in the housing. This plastic contains 33% glass fiber to improve its mechanical properties. Table 1 shows the mechanical properties of the plastics used.

Table 1. Mechanical properties of Zytel FE5382 BK276

Property	Unit	Value
Density	g/cm^3	1.32
Tensile strength	MPa	150
Tensile modulus	GPa	8.0
Poisson’ ratio	-	0.38
Izod impact strength	kJ/m^2	11.0
Shrinkage rate	%	0.21
Glass filler	%	33

2.2. Injection molding analysis

The speed meter housing part being molded has a problem, in that sometimes it cannot bet accurately assembled because intermittent deformation occurs outside standard. This makes it necessary to objectively digitize the amount of deformation of the speed meter housing molded under the current injection molding conditions, by conducting an injection molding analysis.

Table 2 shows the injection molding conditions applied when molding the current speed meter housing. This molding condition was based on the molding of similar products in the past, the recommended molding conditions of resin manufacturers, and the conditions obtained from test injection molding. The injection molding analysis of the speed meter housing used Autodesk's Moldflow [15, 16]. Figure 4 shows the analysis model used for the injection molding analysis. A cold sprue was employed and there was a Ø6 runner and a rectangular side gate with a size of 6*3*1.5(mm). A Ø8 diameter coolant channel for cooling the mold was used. A Ø14 baffle cooling channel was applied to cool the side surface and the lower surface circular part. The mesh of the analysis model consisted of 1,227,547 3D tetra elements.

Table 2. Current injection molding conditions

Injection molding condition	Unit	Value
1. Melt temperature	℃	290
2. Filling time	s	1.6
3. Holding pressure	MPa	25
4. Holding time	s	5
5. Cooling time	s	40
6. Coolant temperature	℃	70
7. Velocity/pressure switch-over (%)	%	98

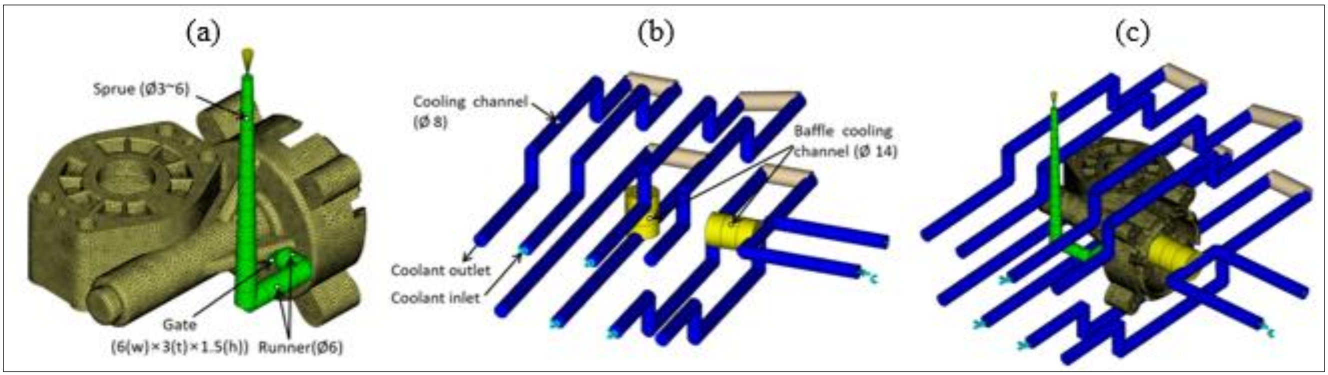

Figure 4. Analysis model: (a) housing with flow channel (b) cooling channel (c) FEM model

Figure 5 shows the deformation of the molded housing product when the current molding conditions in Table 2 were applied. The maximum deformation occurred around the screw holes at the bottom of the molded article used to assemble the housing. The maximum deformation value was 0.596 mm. The amount of deformation of these injection molded products need to be minimized as much as possible.

However, due to the characteristics of injection molding, it is quite difficult to reduce the deformation of products and there is a limit to reducing the amount of deformation of the molded product by adjusting the molding conditions in once manufactured molds. Moreover, if the mold is modified to reduce the deformation of the molded product, it is necessary to re-work the cavity in which the molded product is made. This requires additional mold modification costs and time, which is the most avoidable situation in the mold manufacturing process. Therefore, the most ideal mold manufacturing process is to conduct a thorough injection molding analysis, combine the results with mold design, and proceed with mold manufacturing.

In this study, the current injection molding conditions can be optimized without reprocessing the mold to reduce the amount of deformation of the product, thereby reducing mold manufacturing costs and reducing working time.

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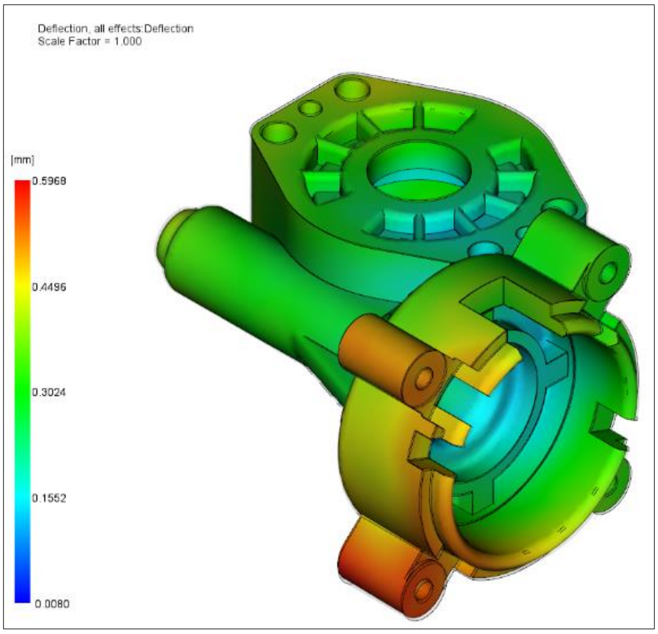

Figure 5. Max. deformation of the speed meter housing fabricated with current injection molding conditions

2.3. Design of the experiment

First of all, the Taguchi method, one of the optimization techniques, was used to determine the molding factors that affect deformation. The Taguchi method can identify factors that affect the final result from a small number of experiments, and has the ability to optimize such factors [17-19]. The main factors to be applied in the Taguchi method are melt temperature, fill time, velocity/pressure switch-over, holding time, holding pressure, coolant temperature and cooling time. Table 3 shows the factors and levels. Each factor consisted of three levels.

Table 3. Factors and levels

Factor	Level		
	1	**2**	**3**
H. Melt temperature (℃)	270	280	290
I. Holding time (s)	3	5	7
J. Holding pressure (MPa)	27	30	33
K. Coolant temperature (℃)	50	60	70
L. Cooling time (s)	45	50	55
M. Filling time (s)	1.5	1.8	2.1
N. Velocity/pressure switch-over (%)	95	97	99

A total of 2187 experiments should be conducted for an experiment that includes all seven main factors and 3 levels, but using the Taguchi method, the main factors that affect deformation can be identified by conducting a total of 27 experiments. Table 4 is an L27 (3^7) orthogonal array table that summarizes a total of 27 experiments. For example, the orthogonal array Table 1 experiment is a combination of melt temperature 270℃, holding time 3 s, holding pressure 27MPa, coolant temperature 50℃, fill time 1.5 s, and velocity/pressure switch-over 95%.

Table 4. L27 orthogonal array

No.	H	I	J	K	L	M	N
1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2
3	1	1	1	1	3	3	3

4	1	2	2	2	1	1	1
5	1	2	2	2	2	2	2
6	1	2	2	2	3	3	3
7	1	3	3	3	1	1	1
8	1	3	3	3	2	2	2
9	1	3	3	3	3	3	3
10	2	1	2	3	1	2	3
11	2	1	2	3	2	3	1
12	2	1	2	3	3	1	2
13	2	2	3	1	1	2	3
14	2	2	3	1	2	3	1
15	2	2	3	1	3	1	2
16	2	3	1	2	1	2	3
17	2	3	1	2	2	3	1
18	2	3	1	2	3	1	2
19	3	1	3	2	1	3	2
20	3	1	3	2	2	1	3
21	3	1	3	2	3	2	1
22	3	2	1	3	1	3	2
23	3	2	1	3	2	1	3
24	3	2	1	3	3	2	1
25	3	3	2	1	1	3	2
26	3	3	2	1	2	1	3
27	3	3	2	1	3	2	1

The experiment was conducted based on the orthogonal array table in Table 4. The results of the amount of deformation in each experiment were analyzed using the S/N ratio (signal-to-noise ratio). The smaller the amount of deformation of the molded product, the better. This corresponds to the SB(smaller the better) of the Taguchi method. The formula used to calculate the S/N ratio of the SB is shown in Equation (1) below. Units are dB.

$$\mathrm{SN} = -10log_{10}\sum_{i=1}^{n}\frac{y_i^2}{n} \quad (1)$$

N : Number of experiments by level for each factor
y_i : Amount of deformation for each experiment

Table 5 summarizes the maximum amount of deformation and the SN ratio of the speed meter housing identified in the experiment. The smaller the deformation amount, the larger the SN ratio value. The statistical processing program Minitab 2020 was used to calculate the SN ratio.

Table 5. Deformation values and S/N ratio

No.	Deflection	S/N ratio(dB)
1	0.5817	4.706
2	0.5828	4.690
3	0.5840	4.672
4	0.5727	4.841
5	0.5673	4.924
6	0.5733	4.832

7	0.5609	5.022
8	0.5686	4.904
9	0.5744	4.816
10	0.5957	4.499
11	0.5900	4.583
12	0.5929	4.540
13	0.5735	4.829
14	0.5677	4.918
15	0.5710	4.867
16	0.5869	4.629
17	0.5801	4.730
18	0.5809	4.718
19	0.5922	4.551
20	0.6015	4.415
21	0.5943	4.520
22	0.5948	4.513
23	0.5953	4.505
24	0.5974	4.475
25	0.5765	4.784
26	0.5698	4.886
27	0.5747	4.811

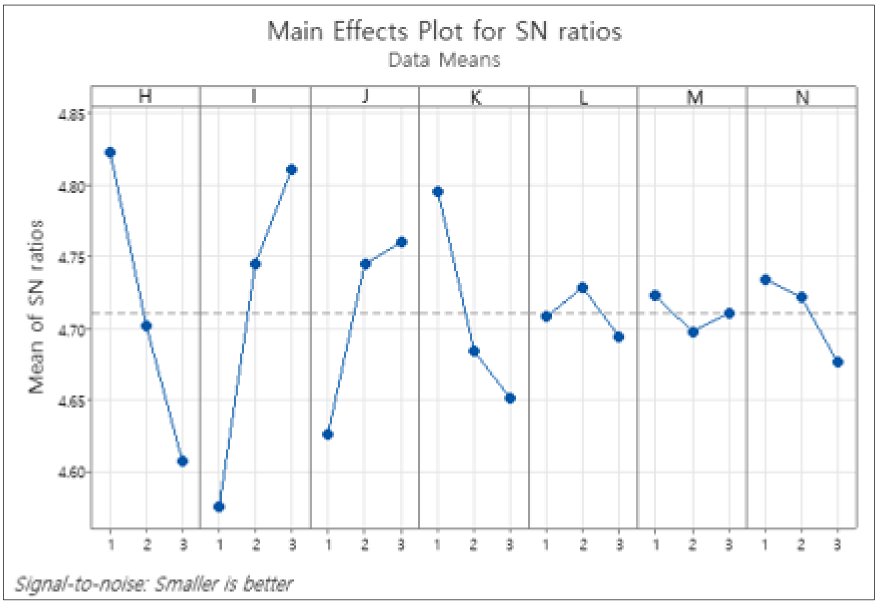

Figure 6. Main effects plot for SN ratios

Figure 6 shows the main effects of factors on the SN ratio for the amount of deformation in table 5. This means that the change in slope in the main effect diagram is large and the factor with a large difference has a great influence on the change in the amount of deformation. Additionally, table 6 shows the SN ratio by level of main factors. The delta value shows the difference between the maximum and minimum SN ratio of the main factors by level. The rank was assigned based on the order of delta values. The larger the delta value, the greater the change in the SN ratio for each level of factor, so the higher the ranking factor, and the greater the amount of deformation.

The order of molding conditions that greatly affect the deformation of the molded product is the holding time (I), the melt temperature (H), the coolant temperature (K), the holding pressure (J), the cooling time (L), and the fill time (M). Among the molding conditions, the main factor that affects the deformation of the molded product can be determined by the SN ratio value. In addition, ANOVA was performed to understand the relative effect [20]. The results of the ANOVA are shown in Table 7. According to ANOVA the results, if the significance level was set at 5%, the factors affecting the deformation of the molded product were melt temperature (H), holding time (I), holding pressure (J), and coolant temperature (K) [21].

Table 6. Result of S/N ratio for each factor

		Level			Delta	Rank
		1	2	3		
S/N ratio	H	4.823	4.702	4.607	0.216	2
	I	4.575	4.745	4.811	0.236	1
	J	4.626	4.745	4.760	0.134	4
	K	4.796	4.684	4.651	0.145	3
	L	4.708	4.728	4.695	0.034	6
	M	4.722	4.698	4.711	0.025	7
	N	4.734	4.721	4.676	0.058	5

Table 7. ANOVA result

Factors	DF	Adj SS	Adj MS	F	P
H	2	0.211805	0.105903	39.13	0.000
I	2	0.266601	0.133301	49.26	0.000
J	2	0.096514	0.048257	17.83	0.000
K	2	0.103695	0.051848	19.16	0.000
L	2	0.005148	0.002574	0.95	0.414
M	2	0.002718	0.001359	0.50	0.617
N	2	0.016738	0.008369	3.09	0.083
error	12	0.032475	0.002706		
Total	26	0.735694			

3. Results and discussions

3.1. Machine learning

The injection molding factors that affect the deformation of the speed meter housing were identified using the Taguchi method. Machine learning was conducted to obtain a model that predicts the exact amount of deformation for the level of identified factors, and to obtain injection molding conditions that would minimize the amount of deformation. The identified factors and levels are shown in Table 8.

150 data sets for machine learning were prepared by combining the factors and levels in Table 8. In other words, 150 molding conditions were planned by combining the injection molding conditions in Table 8. Data for the injection molding conditions L81(3^4) were generated through complete factor design, and 69 were generated by combining the injection conditions within the level range in Table 8. Table 9 shows the conditions of 150 experiments used to secure a data set for machine learning.

Table 8. Factors and levels of injection molding analysis for machine learning

Factor	**Level**		
	1	**2**	**3**
A. Melt temperature (℃)	270	280	290
B. Holding time(s)	3	5	7
C. Holding pressure (MPa)	27	30	33
D. Coolant temperature (℃)	50	60	70

Machine learning was conducted using the data set obtained from 150 experiments. Machine learning used Orange 3, a drag and drop program that can be easily used without coding. Figure 7 shows the process built to learn and evaluate various artificial intelligence models using Orange 3 [22].

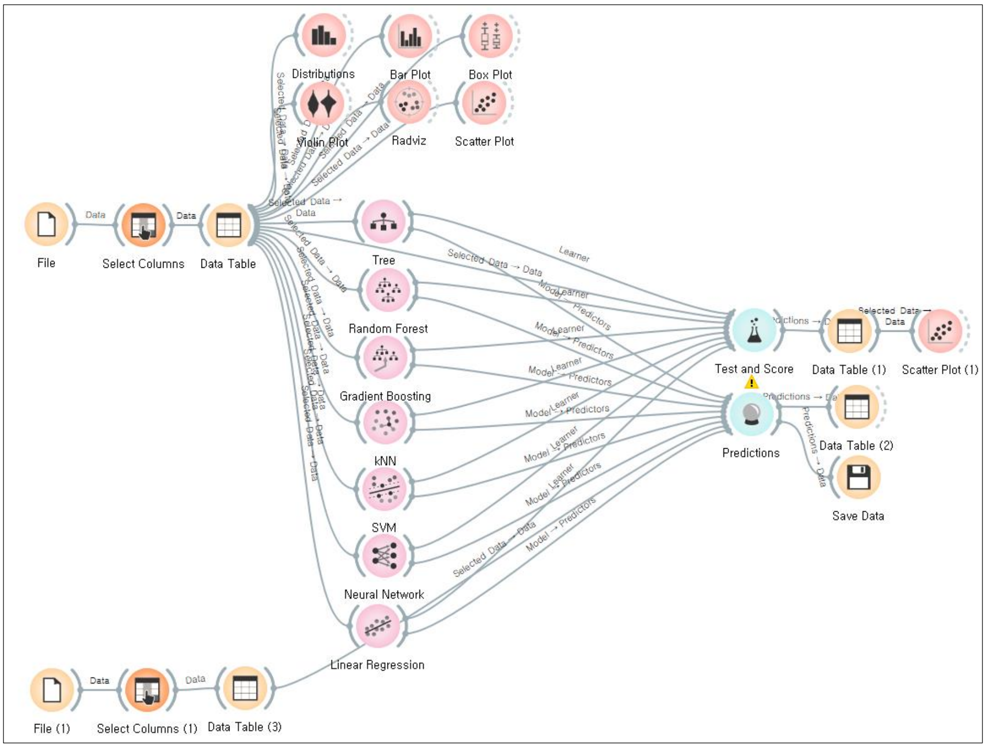

Figure 7. Machine learning process with Orange 3

Table 9. Experimental conditions and amount of deformation for securing data set

No.	A	B	C	D	Deformation
1	270	3	27	50	0.5833
2	270	3	27	60	0.5828
3	270	3	27	70	0.5884
4	270	3	30	50	0.5812
5	270	3	30	60	0.5800
6	270	3	30	70	0.5858
7	270	3	33	50	0.5751
8	270	3	33	60	0.5738
9	270	3	33	70	0.5791
10	270	5	27	50	0.5664
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
140	282	4.8	29	50	0.5728
141	279	3.3	27.9	56	0.5885
142	288	6.7	31.5	67	0.5877
143	278	4.8	28	65	0.5856
144	280	4.2	31.5	53	0.5757
145	275	5.5	28.5	61	0.5720
146	286	6.0	28.5	59	0.5836
147	279	4.0	27.5	69	0.5929
148	286	3.5	33	64	0.5887
149	277	5.5	27.5	53.5	0.5801
150	288	6.5	28.8	58.5	0.5810

First of all, the process used data analysis widgets such as descriptive statistics and violin plots to confirm that there were no outliers or missing values in the data set. After that, models predicting the amount of deformation were learned using the 150 learning data. The learned models were Random Forest [23], SVM (support vector machine) [24], Decision Tree [25], kNN (K-Nearest Neighbor) [26], Linear Regression [27], ANN (artificial neural network) [28], etc. The performance evaluation indicators used were mean square error (MSE), mean square root error (RMSE), mean absolute error (MEA), and R^2. Among them, the closer the value of MSE, RMSE, and MEA approaches 0, the better the prediction performance. The closer the value of R^2 approaches 1, the better the prediction performance [29].

Table 10 shows the performance evaluation of the learned model. Among the learning models, the Linear Regression model had the best prediction performance, and the ANN (artificial neural network) had the worst prediction performance.

Table 10. Results of performance evaluation for models learned

Model	MSE	RMSE	MAE	R^2
kNN	0.000	0.007	0.005	0.449
Decision Tree	0.000	0.006	0.005	0.570
SVM	0.000	0.010	0.008	-0.058
Random Forest	0.000	0.004	0.004	0.774
Artificial Neural Network	0.010	0.100	0.075	-112.968
Linear Regression	0.000	0.004	0.003	0.779

3.2. Validation of machine learning model

10 data were newly constructed to verify of the Linear Regression model with the best prediction of deformation amount. The data were obtained by applying random injection molding conditions based on the Table 8. Table 11 shows the injection molding conditions for 10 verified data and the amount of deformation predicted by the model.

Table 11. 10 experimental conditions for obtaining data to test the learned model

No.	A	B	C	D	Deformation
1	275	4	32	60	0.5693
2	281	6	33	68	0.5781
3	290	5	31	54	0.5811
4	282	7	31	51	0.5776
5	278	3	32	69	0.5899
6	275	7	27	64	0.5823
7	285	7	28	55	0.5783
8	278	6	33	57	0.5759
9	277	5	31	70	0.5814
10	288	7	30	58	0.5846

Among the learning models, the predicted values of the Linear Regression model with the best prediction performance and the ANN model with the worst prediction performance were compared with the plastic experiment values. Figure 8 is a comparison of the predicted value of the Linear Regression model, the predicted value of the ANN model, and the deformed value of the experiment. Analyzing Figure 8 and Table 12, it was confirmed that the predicted value of the Linear Regression model was almost similar to the deformation value of the molding experiment.

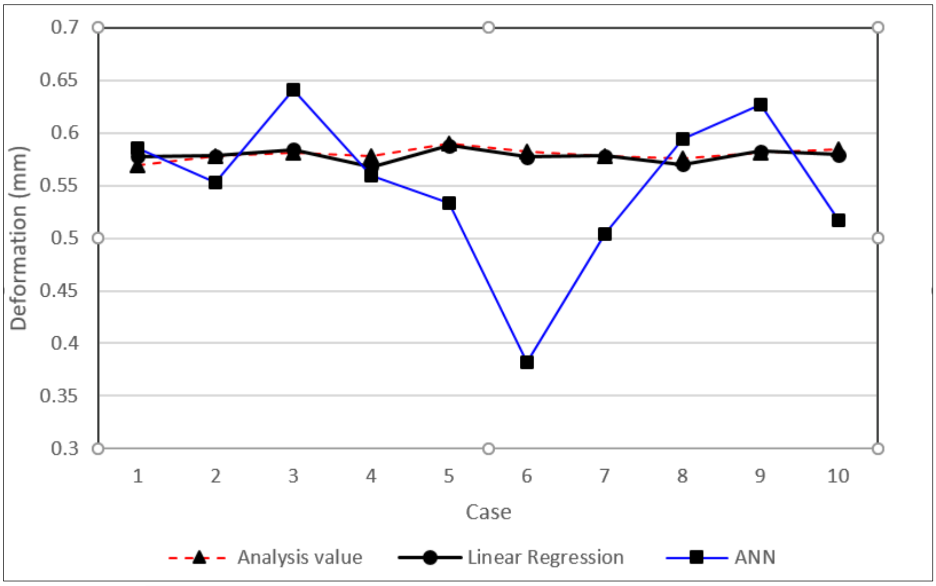

Figure 8. Comparison of the predicted values from the learned models and the deformation value from experiments

Table 12. Comparison of prediction values, analysis value and prediction rate

Case	Analysis value	Linear Regression		ANN	
		Predicted value (mm)	Predicted rate (%)	Predicted value (mm)	Predicted rate (%)
1	0.5693	0.5778	98.52	0.5861	97.13
2	0.5781	0.5784	99.94	0.5530	95.65
3	0.5811	0.5841	99.48	0.6410	90.65
4	0.5776	0.5698	98.64	0.5593	96.83
5	0.5899	0.5882	99.71	0.5329	90.33
6	0.5823	0.5770	99.08	0.3821	65.61
7	0.5783	0.5784	99.98	0.5042	87.18
8	0.5759	0.5704	99.04	0.5938	96.98
9	0.5814	0.5827	99.77	0.6268	92.75
10	0.5846	0.5794	99.11	0.5167	88.38

3.3. Optimal injection molding condition

The optimal injection molding conditions were obtained using the Linear Regression model with the best prediction performance. The molding conditions to be used in the Linear Regression model were based on Table 8. The number of data to be predicted was 5000. 5000 data were obtained using the random function of the Excel program.

The optimal molding conditions were obtained by applying 5000 injection molding conditions data to the linear regression model. The optimal conditions predicted by the model were the 3738th, with a resin temperature of 271℃, a holding time of 7s, a holding pressure of 33MPa, and a cooling water temperature of 50℃. The predicted deformation in the linear regression model was 0.5581 mm.

The final injection molding analysis experiment was conducted using the predicted optimal molding conditions. The amount of observed deformation was 0.5578 mm. This was only 0.05% different from the amount of deformation predicted by machine learning. This represents a decrease in deformation of about 6.4% compared to the initial deformation of 0.596mm presented in Section 2.2. Figure 9 shows the results of speed meter deformation analyzed using the predicted optimal molding conditions.

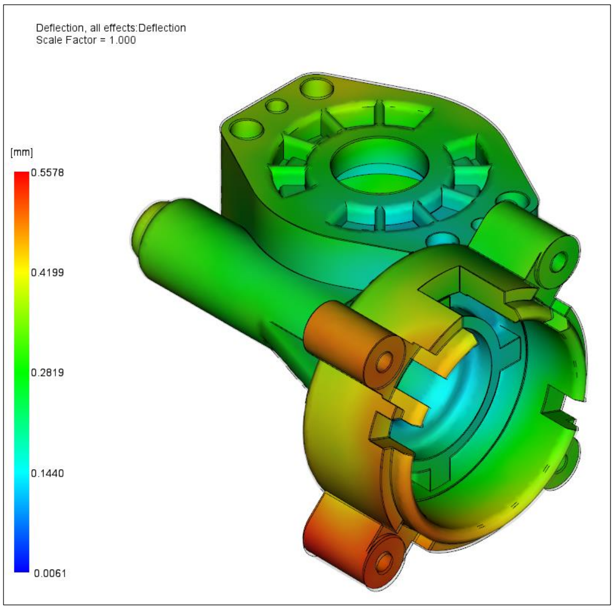

Figure 9. Deformation profile when applying the predicted optimal molding conditions

The optimal injection molding conditions learned through machine learning were applied to the actual injection molding process. To assess the deformation amount of the molded speed meter, a precision 3D scanner was utilized. Figure 10 shows wheel speed meter housing and the 3D scanning process. The 3D scanner used is Breuckmann's SmartSCAN3D, with a measurement accuracy 12 μm.

Figure 10. 3D scanning for checking amount of deformation in wheel speed meter housing

The location where the maximum deformation amount of the actual molded product occurred was the same as in Figure 9. The maximum amount of deformation measured by scanning was 0.521 mm. This is about 0.0368 mm less than the value predicted by the linear regression model learned by machine learning. Although there was a difference of about 6.64% between the predicted value of the learned model and the actual amount of deformation of the molded product, machine learning confirmed the result of reducing the amount of deformation of the molded product.

4. Conclusions

Research was conducted to optimize the deformation of a molded plastic speed meter for automobiles. The main optimization methods used in the study were the Taguchi method and machine learning. The Taguchi method, was used to identify the injection molding factors that affect the deformation of the moldings, and machine learning was conducted by creating a data set for machine learning using the derived factors. The optimal molding conditions were derived using the learned model that best predicted the amount of deformation, and the following conclusions were obtained while verifying the learned model by applying the optimal molding conditions to the actual injection molding.

1. Using the Taguchi method, it was confirmed that the injection molding factors that affect the deformation of the speed meter molded product were melt temperature, holding time, holding pressure, and coolant temperature.
2. Machine learning was conducted using 150 data sets, and the predictive performance of the model developed using machine learning was verified using test data. Among the validated models, the model with the best predictive performance was the linear regression model.
3. The optimal molding conditions were derived by learning 5000 molding conditions data with the learned linear regression model. The predicted optimal molding conditions were a resin temperature of 271°C, a holding time of 7sec, a holding pressure of 33MPa, and a cooling water temperature of 50°C.
4. When the predicted optimal injection molding conditions were applied to the linear regression model, a deformation of 0.5581 mm occurred, which was 0.05% different than the amount of deformation observed in the molding analysis experiment.
5. The deformation results from the simulation applying which used the learned optimal conditions were compared with the deformation observed using current molding conditions. When the optimal molding condition was applied, the deformation amount was reduced by about 6.4% compared to the molding obtained by applying the current molding condition.
6. By applying the optimal injection molding conditions predicted by the learned model to actual injection molding, the amount of deformation of the molded product was measured using 3D scanner. The difference of about 6.6% from the amount of deformation predicted by the learned model was confirmed.

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