[1.] Oluwole Abiodun RAIMI

OPTIMIZATION–BASED MULTI–CRITERIA INJECTION MOLDING PROCESS DECISION MAKING FOR THIN–PICTURE FRAME POLYSTYRENE PART USING METAMODELING AND PLACKETT–BURMAN DESIGN: A SIMULATION APPROACH

[1.] School of Mechanical Engineering, Chonnam National University, 77 Yongbong–ro, Buk–gu, Gwangju 61186, REPUBLIC OF KOREA

Abstract: Warpage defects are flaws that are mostly found in injection molded parts. The development of multi–decision criteria using combined metamodels integrated into the TOPSIS approach was investigated in this work. Four processing parameters were used for the simulation analysis of thin–picture frame polystyrene material based on the Plackett–Burman design: melting temperature, mold temperature, packing pressure, and packing time. The following metamodels were considered in the simulation study: artificial neural network, support vector machine, and linear regression model. Compared to the Taguchi method of smaller is better signal–to–noise ratio by selecting optimal processing conditions, the simulation results revealed that the combined metamodels integrated into the TOPSIS technique show satisfactory performance, agreement, and effectiveness. This study's novel approach will assist manufacturers in developing a robust strategy for minimizing a target variable or response using multiple metamodels that can potentially be integrated or optimized as one for decision–making.
Keywords: Optimization, Multi–criteria injection molding process, TOPSIS, Metamodeling, Plackett–Burman design

1. INTRODUCTION

The concept of multi–criteria decision–making has become extremely important in the manufacturing industry. The approach may differ depending on the manufacturing industry, but the final goal is finding an optimal solution to avoid defects in manufactured products. TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) is the multi–criteria decision technique used in the study to optimize the warpage defect of the molded part using the metamodeling of some selected algorithms. The TOPSIS decision approach can be used to choose the best optimal solution in an experimental or numerical study to make optimum selection (Lim et al., 2021). Furthermore, some investigations have demonstrated the usefulness of multi–criteria ideas by establishing a higher performance in terms of selection ranking of a particular sample of study (Devaraj et al., 2021; Hasanzadeh, Azdast, et al., 2022; Hasanzadeh, Mojaver, et al., 2022; Mojaver et al., 2022).

On the other hand, the study investigates the multi–criteria decision concept on an injection–molded portion of a thin–picture frame manufactured from polystyrene polymer material using a simulation approach with warpage defect as the goal variable. Many studies have been conducted in injection molding to determine the best way to control some defects in molded products. To achieve the highest mechanical properties and lowest volumetric shrinkage of the molded part, (Öktem & Shinde, 2021) concentrated on determining an optimal solution for polyethylene and polypropylene polymer material using a multi–objective optimization approach with ANOVA and regression analysis. By optimizing the warpage in the Z–direction of injection molded parts, (C. Li et al., 2022) employed a multi–objective optimization approach based on IFOA–GRNN–NSGA–II and evaluated the optimal solution using the entropy TOPSIS method. The need to achieve high product quality, (Zhou et al., 2021) employed multi–objective optimization techniques in plastic injection molding for minimizing warpage through a proposed differential sensitivity fusion method. In understanding the effect of injection molding simulation parameters on shrinkage and warpage of bone screw, (Ayun et al., 2022) employed the Taguchi approach through particle swarm optimization to determine the optimal responses for polylactic acid and polyglycolic acid materials. In showing the simulation development of injection–molded automobile instrument parts, (Ramesh et al., 2021) employed Taguchi orthogonal design and particle swarm optimization to measure shrinkage volume rate and warpage amount rate.

Similarly, (Wang et al., 2021) used gray correlation degree and the Taguchi approach through an orthogonal array to analyze the optimal solution for an injection–molded plastic back door car panel. To minimize the warpage deformation, (Cao et al., 2022) employed an adaptive network–based fuzzy inference system and genetic algorithm to optimize the injection molded automobile audio shell part for economical and effective manufacturing methods. In experimentally investigating the quality of an injection molded micro–filter part, (Shiroud Heidari et al., 2022) optimized the simulation injection molding process to minimize the shrinkage of the part quality using regression analysis. To reduce the transparent parts warpage of multi–cavity parts, (S. Li et al., 2021) employed an optimization technique combining orthogonal experiment, kriging model, and an optimization algorithm in the investigation. Applying response surface methodology and particle swarm optimization methods, (Roslan et al., 2021) optimize the shrinkage defect on thick plate molded parts using virgin and recycled low–density polyethylene materials. In characterizing the non–linear shrinkage of a small

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module of plastic gears, (He & Wu, 2021) proposed a practical numerical approach to optimize the dimensional deviation of the parts. In exploring the automobile lock parts using computer–aided engineering simulation performance analysis, (Huang et al., 2021) employed intelligent modeling of different injection molding process parameters to analyze the warpage's influence on the auto locks' development. In finding optimum process parameters for high–quality end products with minimum defect possibility, (Moayyedian et al., 2018) employed artificial neural network and Taguchi techniques through finite element analysis of a thin–walled polypropylene part to minimize the shrinkage and warpage defects. To obtain high–quality plastic finished products, (Maslarova & Krus, 2021) employed particle swarm optimization algorithm which is improved through back propagation neural network to minimize the warpage and shrinkage defects on a display panel product parts characterized by large size and thin thickness.

Furthermore, to the author's knowledge, no study has merged a set of metamodels to optimize warpage defects in molded parts using a multi–criteria decision technique. The simulation study combined certain metamodels using a metamodeling approach and developed a decision criterion utilizing the TOPSIS technique for the optimum process condition with minimal warpage defects, and this establishes the study's purpose and uniqueness.

2. METHOD AND NUMERICAL APPROACH

— Method

The investigation study used polystyrene (STRON™ 678D) polymer material, a general–purpose type for the simulation study. The primary purpose of the polymer selection is because of its typical application in the area of the household, kitchenware, and package application. For the simulation study, a thin–picture frame molded part made from polystyrene polymer material was used for the investigation, as shown in Figure 1, to determine the minimum warpage conditions based on the selected processing parameters.

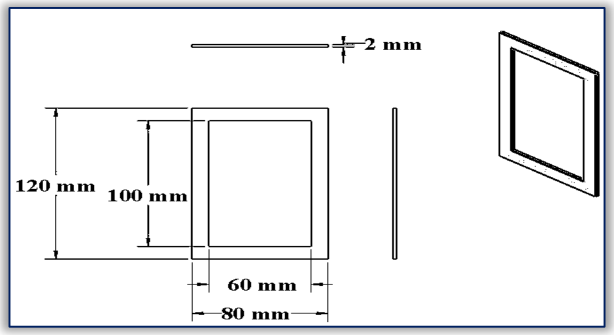

Figure 1. Schematic diagram of the thin–picture frame molded part used for this study

Table 1. Two levels and corresponding values of parameters

Level	Processing Parameters			
	Melting temperature (°C)	Mold temperature (°C)	Packing pressure (MPa)	Packing time (s)
1	200 (–1)	40 (–1)	80 (–1)	5 (–1)
2	240 (+1)	60 (+1)	100 (	10 (+1)

Table 2. Plackett–Burman design and the corresponding simulation warpage values

Runs	Melting temperature (°C)	Mold temperature (°C)	Packing pressure (MPa)	Packing time (s)	Warpage (mm)
1	–1	1	–1	1	0.0425
2	1	–1	1	1	0.1990
3	–1	1	–1	–1	0.4030
4	1	–1	1	–1	0.1100
5	1	1	1	–1	0.3910
6	1	–1	–1	–1	0.2690
7	–1	–1	1	1	0.2780
8	–1	–1	1	–1	0.0895
9	–1	–1	1	1	0.2780
10	–1	1	–1	1	0.0425
11	–1	1	1	–1	0.3560
12	1	1	–1	–1	0.5000
13	–1	1	1	1	0.2210
14	–1	–1	–1	–1	0.1690
15	–1	1	1	–1	0.3560
16	1	1	–1	1	0.1020
17	–1	–1	–1	–1	0.1690
18	1	1	1	1	0.1570
19	1	–1	–1	1	0.0771
20	–1	–1	–1	1	0.0704
21	1	1	–1	–1	0.5000
22	1	–1	1	–1	0.1100
23	1	1	1	1	0.1570
24	1	–1	–1	1	0.0771

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Four processing parameters, which are melting temperature, mold temperature, packing pressure, and packing time at two–level conditions, as shown in Table 1, were employed to simulate the molded part using a commercial software package known as Moldex3D R14.0.

In addition, the study employed Plackett–Burman (PB) design for 24 simulation runs in the investigation, as shown in Table 2. PB design is an effective technique for selecting the significant parameters among sizeable number of operating parameters that affect controlling the warpage defects using minimum simulation trials. The prime motive behind the study is to develop a metamodeling approach to determine the optimum processing parameters to minimize warpage defects.

— Numerical Approach

The study employed three different metamodels, which are artificial neural network (ANN), support vector machine (SVM), and regression model (REM). The ANN is based on Levenberg Marquardt algorithm for two different transfer functions (Tansig and Logsig) which are denoted as $(\mathrm{ANN})_{\mathrm{tansg}}$ and $(\mathrm{ANN})_{\mathrm{logsg}}$ respectively. Also, the SVM is based on two different algorithm which is cubic gaussian and medium gaussian, denoted as $(\mathrm{SVM})_{\mathrm{cg}}$ and $(\mathrm{SVM})_{\mathrm{mg}}$ respectively. The regression model is also based on two different model which are linear interaction $(\mathrm{REM})_{\mathrm{LI}}$ and stepwise linear $(\mathrm{REM})_{\mathrm{SL}}$ respectively. The selected metamodels were surrogated through the TOPSIS technique to determine the optimum parameters requirement to minimize warpage defects. The TOPSIS approach involves the following procedure:

$$\text{weight attribute} = w_{ij} = \frac{x_{ij}}{n_{ij}} \tag{1}$$

where n_{ij} the number of estimated metamodel samples.

$$\text{normalize the decision matrix} = r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}} \tag{2}$$

$$\text{compute weighted decision matrix} = v_{ij} = w_{ij} r_{ij} \tag{3}$$

Compute the ideal (positive and negative) alternatives:

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\} \tag{4}$$

where $v_j^+ = \max_i v_{ij}$ among the estimated metamodels and $v_j^+ = \min_i v_{ij}$ among the estimated metamodels.

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} \tag{5}$$

where $v_j^- = \min_i v_{ij}$ among the estimated metamodels and $v_j^+ = \max_i v_{ij}$ among the estimated metamodels.

Compute the separation measures of each alternative based on the ranking:

$$S_i^+ = \sqrt{\textstyle\sum_j (v_{ij} - v_j^+)^2}; \; S_i^- = \sqrt{\textstyle\sum_j (v_{ij} - v_j^-)^2} \tag{6}$$

Compute the relative closeness to the ideal solution:

$$R_i = \frac{S_i^+}{S_i^+ + S_i^-} \tag{7}$$

3. RESULTS AND DISCUSSION

The metamodels were statistically examined to determine their effectiveness and acceptability for integration into the TOPSIS multi–criteria decision for optimal selection of processing parameters that can minimize warpage defects. Table 3 shows that there is a good correlation relationship between the processing parameters and the warpage defects, as evidenced by the R^2 value larger than 50% between the studied metamodels. This demonstrated the metamodels' usefulness in establishing a surrogate using the TOPSIS multi–criteria decision technique.

Table 3. Statistical value of the metamodels showing correlation relationship of the parameters

Metamodels	Types	R^2	MSE	RMSE
Artificial neural network (ANN)	Tansig function $(\mathrm{ANN})_{\mathrm{tansg}}$	0.9809	0.000067	0.008185
	Logsig function $(\mathrm{ANN})_{\mathrm{logsg}}$	0.9999	0.008723	0.093397
Support Vector Machine (SVM)	Cubic Gaussian SVM $(\mathrm{SVM})_{\mathrm{cg}}$	0.9368	0.006127	0.078273
	Medium Gaussian SVM $(\mathrm{SVM})_{\mathrm{mg}}$	0.9974	0.005862	0.076565
Linear Regression	Linear interaction $(\mathrm{REM}_{\mathrm{LI}})$	0.9961	0.000390	0.01976
	Stepwise linear $(\mathrm{REM}_{\mathrm{SL}})$	0.9955	0.000143	0.011967

In addition, Table 4, which shows the weight attributes of the metamodels, is estimated using equation (1). Table 5, which shows the weight decision matrix and the ideal alternative values of the metamodels, is estimated using equations (2), (3), (4), and (5) respectively. Also, Table 6, 7, and 8, which shows the separation measure of each alternative and the relative closeness to the optimum conditions from the metamodels, were estimated using equation (6) and (7), respectively.

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Table 4. Weight attributes of the metamodels

x_{ij}						
ANN_{tansg}	ANN_{logsg}	SVM_{cg}	SVM_{mg}	REM_{LI}	REM_{SL}	w_{ij}
0.0438	0.0265	0.0438	0.0440	0.0977	0.0624	0.0515
0.1956	0.1830	0.1991	0.1991	0.2021	0.2027	0.1972
0.3935	0.3870	0.4015	0.4013	0.3381	0.3855	0.3871
0.1093	0.0940	0.1108	0.1109	0.1427	0.1229	0.1144
0.3819	0.3750	0.3896	0.3894	0.3301	0.3747	0.3760
0.2635	0.2530	0.2686	0.2685	0.2487	0.2654	0.2624
0.2723	0.2620	0.2775	0.2774	0.2547	0.2735	0.2708
0.0894	0.0735	0.0904	0.0906	0.1290	0.1045	0.0953
0.2723	0.2620	0.2775	0.2774	0.2547	0.2735	0.2708
0.0438	0.0265	0.0438	0.0440	0.0977	0.0624	0.0515
0.3479	0.3400	0.3549	0.3547	0.3068	0.3434	0.3434
0.4876	0.4840	0.4978	0.4974	0.4028	0.4724	0.4774
0.2170	0.2050	0.2209	0.2209	0.2167	0.2224	0.2177
0.1665	0.1530	0.1693	0.1694	0.1821	0.1758	0.1693
0.3479	0.3400	0.3549	0.3547	0.3068	0.3434	0.3434
0.1015	0.0860	0.1029	0.1030	0.1374	0.1157	0.1069
0.1665	0.1530	0.1693	0.1694	0.1821	0.1758	0.1693
0.1549	0.1410	0.1574	0.1575	0.1741	0.1650	0.1581
0.0774	0.0611	0.0782	0.0783	0.1208	0.0934	0.0838
0.0709	0.0544	0.0715	0.0717	0.1163	0.0874	0.0775
0.4876	0.4840	0.4978	0.4974	0.4028	0.4724	0.4774
0.1093	0.0940	0.1108	0.1109	0.1427	0.1229	0.1144
0.1549	0.1410	0.1574	0.1575	0.1741	0.1650	0.1581
0.0774	0.0611	0.0782	0.0783	0.1208	0.0934	0.0838

Table 5. Weight decision matrix and the ideal alternative values of the metamodels

$v_{ij} = w_{ij} r_{ij}$						v_n^+	v_n^-
0.0160	0.0097	0.0160	0.0161	0.0357	0.0228	0.0357	0.0097
0.0714	0.0668	0.0727	0.0727	0.0738	0.0740	0.0740	0.0668
0.1437	0.1413	0.1466	0.1465	0.1234	0.1407	0.1466	0.1234
0.0399	0.0343	0.0405	0.0405	0.0521	0.0449	0.0521	0.0343
0.1394	0.1369	0.1422	0.1422	0.1205	0.1368	0.1422	0.1205
0.0962	0.0924	0.0981	0.0980	0.0908	0.0969	0.0981	0.0908
0.0994	0.0957	0.1013	0.1013	0.0930	0.0998	0.1013	0.0930
0.0326	0.0268	0.0330	0.0331	0.0471	0.0382	0.0471	0.0268
0.0994	0.0957	0.1013	0.1013	0.0930	0.0998	0.1013	0.0930
0.0160	0.0097	0.0160	0.0161	0.0357	0.0228	0.0357	0.0097
0.1270	0.1241	0.1296	0.1295	0.1120	0.1254	0.1296	0.1120
0.1780	0.1767	0.1817	0.1816	0.1470	0.1725	0.1817	0.1470
0.0792	0.0748	0.0807	0.0807	0.0791	0.0812	0.0812	0.0748
0.0608	0.0559	0.0618	0.0618	0.0665	0.0642	0.0665	0.0559
0.1270	0.1241	0.1296	0.1295	0.1120	0.1254	0.1296	0.1120
0.0371	0.0314	0.0376	0.0376	0.0502	0.0423	0.0502	0.0314
0.0608	0.0559	0.0618	0.0618	0.0665	0.0642	0.0665	0.0559
0.0565	0.0515	0.0575	0.0575	0.0635	0.0603	0.0635	0.0515
0.0283	0.0223	0.0285	0.0286	0.0441	0.0341	0.0441	0.0223
0.0259	0.0199	0.0261	0.0262	0.0425	0.0319	0.0425	0.0199
0.1780	0.1767	0.1817	0.1816	0.1470	0.1725	0.1817	0.1470
0.0399	0.0343	0.0405	0.0405	0.0521	0.0449	0.0521	0.0343
0.0565	0.0515	0.0575	0.0575	0.0635	0.0603	0.0635	0.0515
0.0283	0.0223	0.0285	0.0286	0.0441	0.0341	0.0223	0.0441

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Table 6. Separation measure of each metamodel alternatives at S_i^+

$S_i^+ = (v_{ij} - v_n^+)^2$						$\sum S_i^+$	$\sqrt{S_i^+}$
0.000387283	0.000676266	0.000387138	0.000384264	0	0.000166093	0.002001044	0.044733031
6.62265E–06	5.16176E–05	1.69412E–06	1.67925E–06	4.93717E–08	0	6.1663E–05	0.007852578
8.55295E–06	2.81036E–05	0	6.75025E–09	0.00053616	3.42031E–05	0.000607027	0.024637911
0.000148917	0.000316449	0.000135776	0.000134751	0	5.22928E–05	0.000788185	0.028074634
7.99378E–06	2.84675E–05	0	5.92749E–09	0.000472174	2.94606E–05	0.000538102	0.02319703
3.38178E–06	3.23006E–05	0	5.96914E–10	5.23652E–05	1.3267E–06	8.93749E–05	0.009453829
3.65526E–06	3.20096E–05	0	8.01404E–10	6.89822E–05	2.15285E–06	0.000106801	0.010334441
0.000209514	0.000411491	0.000198528	0.00019704	0	8.01005E–05	0.001096673	0.033116056
3.65526E–06	3.20096E–05	0	8.01404E–10	6.89822E–05	2.15285E–06	0.000106801	0.010334441
0.000387283	0.000676266	0.000387138	0.000384264	0	0.000166093	0.002001044	0.044733031
6.47082E–06	2.95424E–05	0	3.83309E–09	0.000308764	1.76489E–05	0.00036243	0.019037602
1.37669E–05	2.52476E–05	0	1.53631E–08	0.001202592	8.55266E–05	0.001327149	0.036430053
3.92282E–06	4.03319E–05	2.81443E–07	2.8544E–07	4.2628E–06	0	4.90844E–05	0.007006024
3.21729E–05	0.00011261	2.15601E–05	2.13873E–05	0	5.24521E–06	0.000192975	0.013891557
6.47082E–06	2.95424E–05	0	3.83309E–09	0.000308764	1.76489E–05	0.00036243	0.019037602
0.000171314	0.00035202	0.000158827	0.000157632	0	6.24315E–05	0.000902225	0.030037053
3.21729E–05	0.00011261	2.15601E–05	2.13873E–05	0	5.24521E–06	0.000192975	0.013891557
4.90064E–05	0.000145723	3.68309E–05	3.65423E–05	0	1.08585E–05	0.000278961	0.016702114
0.000251064	0.000474858	0.000242135	0.000240326	0	9.97339E–05	0.001308118	0.036167912
0.000275118	0.000511044	0.00026754	0.000265544	0	0.000111256	0.001430501	0.03782196
1.37669E–05	2.52476E–05	0	1.53631E–08	0.001202592	8.55266E–05	0.001327149	0.036430053
0.000148917	0.000316449	0.000135776	0.000134751	0	5.22928E–05	0.000788185	0.028074634
4.90064E–05	0.000145723	3.68309E–05	3.65423E–05	0	1.08585E–05	0.000278961	0.016702114
3.53576E–05	0	3.88196E–05	3.95487E–05	0.000474858	0.000139347	0.000727931	0.026980199

Table 7. Separation measure of each metamodel alternatives at S_i^-

$S_i^- = (v_{ij} - v_n^-)^2$						$\sum S_i^-$	$\sqrt{S_i^-}$
4.00135E–05	0	4.00601E–05	4.09916E–05	0.000676266	0.000172066	0.000969398	0.031135157
2.12621E–05	0	3.46092E–05	3.46766E–05	4.84742E–05	5.16176E–05	0.00019064	0.013807232
0.000409277	0.00031876	0.00053616	0.000532362	0	0.000299525	0.002096085	0.045783016
3.1202E–05	0	3.76594E–05	3.82022E–05	0.000316449	0.000111464	0.000534976	0.023129558
0.000357295	0.000268766	0.000472174	0.000468834	0	0.000265749	0.001832819	0.042811434
2.91321E–05	2.41187E–06	5.23652E–05	5.20122E–05	0	3.70219E–05	0.000172943	0.013150791
4.08791E–05	7.01112E–06	6.89822E–05	6.85127E–05	0	4.67622E–05	0.000232147	0.015236383
3.37634E–05	0	3.8381E–05	3.90393E–05	0.000411491	0.00012849	0.000651164	0.025517923
4.08791E–05	7.01112E–06	6.89822E–05	6.85127E–05	0	4.67622E–05	0.000232147	0.015236383
4.00135E–05	0	4.00601E–05	4.09916E–05	0.000676266	0.000172066	0.000969398	0.031135157
0.000225838	0.000147292	0.000308764	0.000306592	0	0.000178774	0.001167261	0.034165201
0.000959019	0.000879343	0.001202592	0.001194011	0	0.000646703	0.004881668	0.069868935
1.9098E–05	0	3.3875E–05	3.38314E–05	1.83705E–05	4.03319E–05	0.000145507	0.012062621
2.44003E–05	0	3.5623E–05	3.58459E–05	0.00011261	6.9248E–05	0.000277727	0.016665147
0.000225838	0.000147292	0.000308764	0.000306592	0	0.000178774	0.001167261	0.034165201
3.21886E–05	0	3.79399E–05	3.85275E–05	0.00035202	0.000117958	0.000578634	0.024054811
2.44003E–05	0	3.5623E–05	3.58459E–05	0.00011261	6.9248E–05	0.000277727	0.016665147
2.57161E–05	0	3.60326E–05	3.63191E–05	0.000145723	7.70241E–05	0.000320814	0.017911291
3.53576E–05	0	3.88196E–05	3.95487E–05	0.000474858	0.000139347	0.000727931	0.026980199
3.62357E–05	0	3.9058E–05	3.98258E–05	0.000511044	0.000145407	0.00077157	0.027777151
0.000959019	0.000879343	0.001202592	0.001194011	0	0.000646703	0.004881668	0.069868935
3.1202E–05	0	3.76594E–05	3.82022E–05	0.000316449	0.000111464	0.000534976	0.023129558
2.57161E–05	0	3.60326E–05	3.63191E–05	0.000145723	7.70241E–05	0.000320814	0.017911291
0.000251064	0.000474858	0.000242135	0.000240326	0	9.97339E–05	0.001308118	0.036167912

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According to Table 8, the relative closeness of the optimum conditions from the metamodels of each of the simulated investigated samples revealed that the optimum processing conditions that minimize the warpage of a thin–picture frame polystyrene is ranked one at a percentage of 58.96 percent (0.5896) with the processing parameters as melting temperature at 200°C, mold temperature at 60°C, packing pressure at 80 MPa, and packing time at 10 s.

Furthermore, the results were validated using the Taguchi technique's smaller is better signal ratio to see if the optimum processing parameters from the metamodeling TOPSIS technique exhibit a similar agreement. As shown in Figure 2, they were in good agreement, establishing a satisfactory performance of the novel approach for minimizing warpage when one or more metamodels are applied.

Table 8. The relative closeness to the optimum conditions from the metamodels

Sample	$\frac{S_i^+}{S_i^+ + S_i^-}$	Ranking	Sample	$\frac{S_i^+}{S_i^+ + S_i^-}$	Ranking
1	0.5896	1	13	0.3674	17
2	0.3625	18	14	0.4546	11
3	0.3499	22	15	0.3578	20
4	0.5483	7	16	0.5553	6
5	0.3514	21	17	0.4546	12
6	0.4182	14	18	0.4825	9
7	0.4041	15	19	0.5727	4
8	0.5648	5	20	0.5766	3
9	0.4041	16	21	0.3427	24
10	0.5896	2	22	0.5483	8
11	0.3578	19	23	0.4825	10
12	0.3427	23	24	0.4273	13

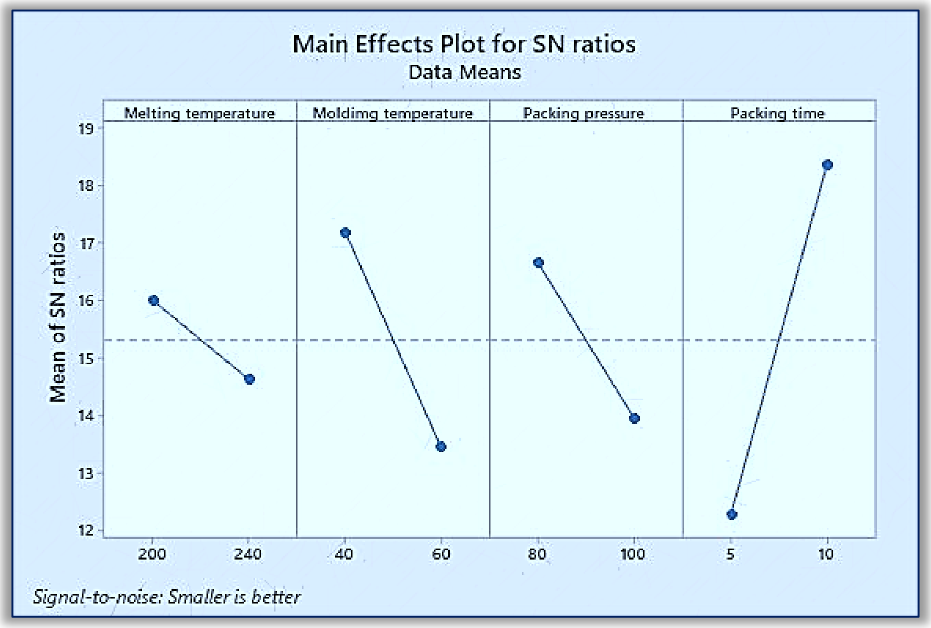

Figure 2. Main effect plot for the SN ratios of the processing parameters in minimizing warpage

4. CONCLUSION

The study developed a novel approach for minimizing warpage defects through metamodeling approach that are surrogated through TOPSIS technique based on a simulation approach. The obtained optimum processing conditions was also verified using the small is better signal ratio from Taguchi technique to establish the agreement of the novelty approach. The verification both shows good agreement which revealed the efficient performance of the established novel method.

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Appendix

x_{ij}^2						$\sum x_{ij}^2$	$\sqrt{\sum x_{ij}^2}$
0.0019	0.0007	0.0019	0.0019	0.0095	0.0039	0.0199	0.1411
0.0383	0.0335	0.0396	0.0397	0.0408	0.0411	0.2330	0.4827
0.1549	0.1498	0.1612	0.1610	0.1143	0.1486	0.8898	0.9433
0.0119	0.0088	0.0123	0.0123	0.0204	0.0151	0.0808	0.2843
0.1458	0.1406	0.1518	0.1516	0.1090	0.1404	0.8393	0.9161
0.0694	0.0640	0.0721	0.0721	0.0619	0.0704	0.4100	0.6403
0.0741	0.0686	0.0770	0.0770	0.0649	0.0748	0.4364	0.6606
0.0080	0.0054	0.0082	0.0082	0.0167	0.0109	0.0574	0.2395
0.0741	0.0686	0.0770	0.0770	0.0649	0.0748	0.4364	0.6606
0.0019	0.0007	0.0019	0.0019	0.0095	0.0039	0.0199	0.1411
0.1210	0.1156	0.1259	0.1258	0.0941	0.1179	0.7004	0.8369
0.2378	0.2343	0.2478	0.2474	0.1622	0.2232	1.3526	1.1630
0.0471	0.0420	0.0488	0.0488	0.0470	0.0495	0.2832	0.5321
0.0277	0.0234	0.0287	0.0287	0.0331	0.0309	0.1726	0.4154
0.1210	0.1156	0.1259	0.1258	0.0941	0.1179	0.7004	0.8369
0.0103	0.0074	0.0106	0.0106	0.0189	0.0134	0.0712	0.2668
0.0277	0.0234	0.0287	0.0287	0.0331	0.0309	0.1726	0.4154
0.0240	0.0199	0.0248	0.0248	0.0303	0.0272	0.1510	0.3886
0.0060	0.0037	0.0061	0.0061	0.0146	0.0087	0.0453	0.2128
0.0050	0.0030	0.0051	0.0051	0.0135	0.0076	0.0394	0.1985
0.2378	0.2343	0.2478	0.2474	0.1622	0.2232	1.3526	1.1630
0.0119	0.0088	0.0123	0.0123	0.0204	0.0151	0.0808	0.2843
0.0240	0.0199	0.0248	0.0248	0.0303	0.0272	0.1510	0.3886
0.0060	0.0037	0.0061	0.0061	0.0146	0.0087	0.0453	0.2128

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