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ORIGINAL ARTICLE

An integrated parameter optimization system for MIMO plastic injection molding using soft computing

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Abstract This study proposes an integrated optimization system to find out the optimal parameter settings of multi-input multi-output (MIMO) plastic injection molding (PIM) process. The system is divided into two stages. In the first stage, the Taguchi method and analysis of variance (ANOVA) are employed to perform the experimental work, calculate the signal-to-noise (S/N) ratio, and determine the initial process parameters. The back-propagation neural network (BPNN) is employed to construct an S/N ratio predictor and a quality predictor. The S/N ratio predictor and genetic algorithms (GA) are integrated to search for the first optimal parameter combination. The purpose of this stage is to reduce the process variance. In the second stage, the quality predictor is combined with particle swarm optimization (PSO) to find the final optimal parameters. The quality characteristics, product length and warpage, are dedicated to finding the optimal process parameters. After the numerical analysis, the optimal parameters can meet the lowest variance and the product quality requirements simultaneously. Experimental results show that the proposed optimization system can not only satisfy the quality specification but also improve stability of the PIM process.

Keywords PIM · Taguchi method · ANOVA · BPNN · GA · PSO

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1 Introduction

In today's world, plastic injection molding (PIM) process is one of the most important methods for producing plastic components. Historically, many engineers and experienced operators have regarded the PIM as a simple manufacturing process without many dedicated manufacturing adjustments required. However, PIM is actually one of the complex manufacturing processes, and the quality of products depends on material selection, mold design, and determination of process parameter settings. Optimizing parameter settings is an extremely critical issue requiring prompt and effective solutions from the manufacturing industry, especially when searching for the global optimal process parameter settings. Thus, the determination of the optimal process parameter settings is recognized as one of the most crucial steps in plastic injection molding for improving the multi-input multi-output (MIMO) quality of PIM products.

Every product, however, has its own process parameter settings created by engineers relying on experience and trial and error, resulting in time-consuming repetitive testing. The Taguchi method using the signal-to-noise (S/N) ratio is frequently employed for finding the initial process parameter settings. Lin [1] employed cutting parameters to examine the effectiveness of the Taguchi technique with regard to multiple performance characteristics. Yang et al. [2] employed the Taguchi method to arrange 16 experimental runs using melting temperature, injection velocity, and injection pressure as process control factors. Contour distortions were utilized as the product's quality. Altan [3] employed the Taguchi method, experimental design, and analysis of variance (ANOVA) to determine minimum shrinkage in injection moldings and to find the significant process factors of product quality. Fei et al. [4] employed the Taguchi technique and ANOVA to find out the effect of injection molding process parameters and optimal settings. Öktem [5] used the Taguchi method to arrange the experimental work, and a series of Moldflow analysis had been performed. ANOVA was employed to search for which of the process parameters are statistically important. However, the Taguchi method can only determine the best set of specified factor level combinations that are the discrete setting values. An improper process parameter setting can induce many defective products and lower product quality during the PIM process.

To deal with these problems, many researchers have investigated optimization of the PIM process by using computer-aided engineering (CAE) simulations [6–11]. The neural network or the general regression model has been selected to build up the relationships between the input process parameters and output responses [12–17]. Subsequently, the prediction model can be combined with related optimization theories to resolve the optimum process parameters. Shi et al. [18] presented an improved hybrid strategy for optimizing a plastic injection molding process. Numerical simulation software, genetic algorithms (GA), and back-propagation neural network (BPNN) were employed to optimize process parameters. Costly numerical calculations were avoided by creating a BPNN quality predictor. Ozcelik and Erzurumlu [19] used CAE and response surface methodology to develop two regression models and to describe the relationship between the input variables and responses. After initial parameter settings are obtained using response surface methodology (RSM) then the final optimization of parameter settings will be found using simulated annealing optimization. Kurtaran and Erzurumlu [20] integrated finite element analysis, design of experiment (DOE) method, response surface methodology (RSM), and GA to effectively optimize warpage of thin-shell plastic parts. In considering product warpage, ANOVA was used to determine the most significant process parameters. Optimum values for those process parameters can be determined through a predictive response surface model in conjunction with GA. Zhao et al. [21] proposed optimization of PIM process parameters using a finite difference method, evolutionary algorithms, fast strip analysis (FSA), and particle swarm optimization (PSO). Chen et al. [22] studied optimization of process parameters using DOE, RSM, and GA. In the first stage, significant PIM process parameters were determined by ANOVA and DOE screening experiments via CAE simulations. Then, the optimal process parameter settings were obtained by integrating regression models with GA. However, there is an error existing in the setting value of control parameters due to interference from an injection molding process's inner and outer noise neglected by CAE simulations.

To solve the above-mentioned problems, Deng et al. [23] adopted the Taguchi orthogonal arrays to calculate the S/N ratios and to find an initial combination of process parameters. Regression analysis and the Davidon-Fletcher-Powell method were used to determine the optimal process parameter settings of plastic injection molding under single quality characteristic considerations. Chen et al. [24] integrated the Taguchi method, BPNN, and GA to optimize the MIMO process parameters. A real-world plastic in molding experiment was performed. A BPNN quality predictor was established and combined with GA to find the other optimal parameter settings. The experimental results show that the optimization approach can effectively help engineers determine optimal process parameter settings. Xu et al. [25] presented a parameter optimization system for the MIMO plastic injection molding process by using the Taguchi method, BPNN, and particle swarm optimization (PSO). Yang et al. [26] studied variations of mechanical properties in the injection molding process. The experimental materials used were the blending of short glass fiber (SGF) and polytetrafluoroethylene (PTFE)-reinforced polycarbonate composites. An optimization approach integrating back-propagation neural networks, genetic algorithms, and simulated annealing was proposed to search for the optimal mixture ratio.

According to the previous studies, parameter optimization of the injection molding process can be classified into three categories: (1) the Taguchi method in the realistic injection experiment, (2) numerical simulations in experiments by applying the CAE simulation software with DOE and optimization methodologies, and (3) realistic injection experiments along with the neural network or the regression model to develop a quality predictor with the optimization algorithms integrated to find the optimal process parameters. In the first, the Taguchi method can only determine the best set of specified factor level combinations that are the discrete setting values. In the second category, CAE simulations are not practical since the injection molding process's inner and outer noises are neglected. In the third category, the stability of the injection molding process is neglected, which fails to optimize both the product's quality and stability. Thus, this study proposes the two-stage optimization system to optimize process parameters in the PIM. The system is divided into two stages. The purpose of the first stage is to reduce the process variance, and the second stage is to reach the quality specification. Thus, the proposed parameter optimization system not only effectively increases the process stability but also meets the quality specification.

2 Design of the optimization system

This study proposes an integrated optimization system for the MIMO plastic injection molding process under five control factors and two quality responses. Injection pressure, injection velocity, melt temperature, packing pressure, and packing time are selected as process control parameters, while warpage and length are employed as the quality responses. The proposed system integrates the Taguchi method, BPNN, ANOVA, GA, and PSO to obtain the optimal process parameter settings. The system is divided into two stages. In the first

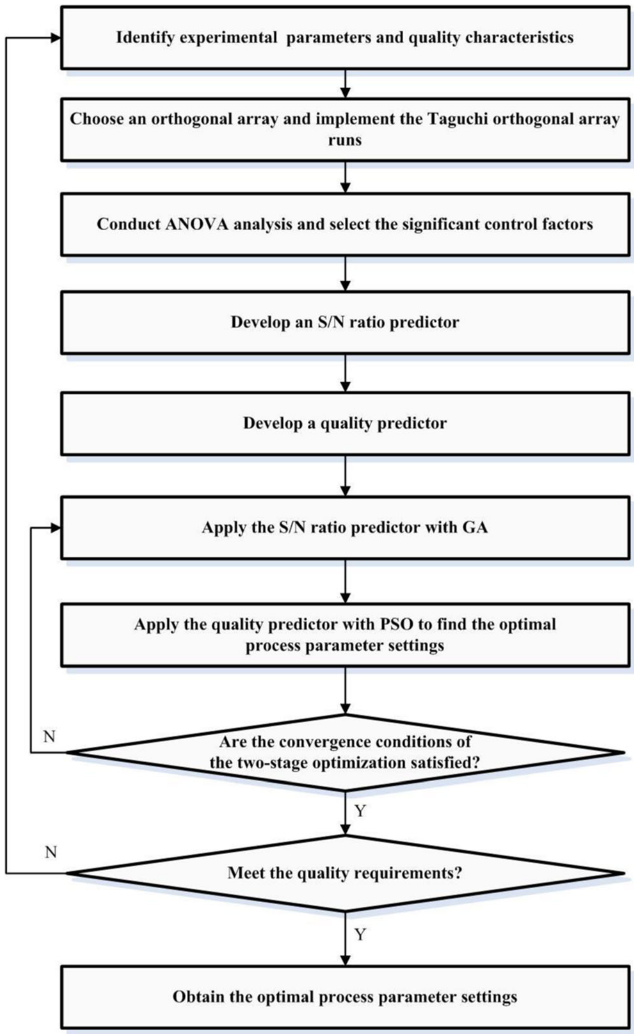

Fig. 1 Flowchart of the proposed optimization system

stage, the Taguchi method is used to perform the $L_{25}(5^6)$ experiment and to calculate the S/N ratio. Subsequently, the experimental data with ANOVA is employed to determine the initial process parameter settings that have minimal sensitivity to noise with the consideration for the major quality characteristic. The BPNN is used to construct an S/N ratio predictor and a quality predictor. The S/N ratio predictor is combined with GA to generate the first optimal parameter combination.

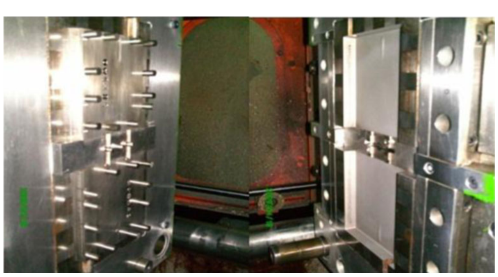

Fig. 2 Experimental mold

This optimization methodology can significantly reduce variance of the PIM process. In the second stage, a BPNN quality predictor is along with PSO to find the final optimal parameter settings. The quality characteristics, product length and warpage, are dedicated to finding the final optimal process parameter settings for the best quality specification. The significant control factors of optimization process influencing the product quality and S/N ratio are determined using experimental data based on ANOVA. In the numerical computation, the optimal parameter combination in the first stage is taken as the initial values for PSO searching conditions in the second stage. After the second stage optimization, the optimal parameters obtained should be able to meet the lowest variance and the product quality requirements simultaneously. If not, the two-stage iteration procedure must be repeated. Finally, three confirmation experiments are performed to verify the effectiveness of final optimal process parameter settings. Flowchart of the proposed optimization system is shown in Fig. 1.

2.1 Experimental equipment

For this investigation, the experimental material used is PA-765 fire-proof plastic material. The injection molding machine is a Victor Taichung Vs-100. The device to measure length is Mitutoyo digital slide caliper with the measuring range up to 300 mm with a precision of 0.01 mm, and the device to measure warpage is PEACOCK PC-1L lever indicator with a precision of 0.01 mm. The mold features as two cavities in one mold. The experimental mold was installed on the injection molding machine as shown in Fig. 2. The illustrative example shows two ADSL modems as shown in Fig. 3. The specifications and measuring positions of two quality characteristics, length and warpage, are shown in Fig. 4. The measuring sample is selected from modem I, which has been marked “1” in the back. The positions to measure the warpage are along a straight line with a distance of 1 cm from the cover edge and at the same side as measuring the length. Warpage is the highest distance measured along a straight line. Target length is 124 mm.

2.2 Implementation of the Taguchi method and ANOVA

Chen et al. [22] studied optimization of process parameters using DOE, RSM, and GA. The experimental mold is the same as this study. Significant PIM process parameters were determined by ANOVA and DOE screening experiments via the CAE simulations, in which the significant parameters were melt temperature, injection velocity, injection pressure, packing pressure, and packing time. Therefore, this research applies the $L_{25}(5^6)$ orthogonal array to assign five factors into rows. Melt temperature (MT), injection velocity (IV), injection pressure (IP), packing pressure (PP), and packing time (PT) are control factors and are assigned to variable A, B, C, D, and E, respectively. Table 1 shows the five process control

Fig. 3 Illustrated component

Table 1 Product parameter setting range

Control parameters	Setting range
Melt temperature	195~203 °C
Injection velocity	30~38 mm/s
Injection pressure	60~68 MPa
Packing pressure	50~58 MPa
Packing time	1~2.2 s

factors and parameter setting range. Experimental control factors and the setting of level are shown in Table 2. There are in total 25 treatments with different level combinations of five factors. Five replications are taken to increase analytical data amount. In total, 125 data samples are collected. In addition, the experimental data of five new combinations randomly generated within the levels of the orthogonal array are used to test the quality predictor and S/N predictor. During the collection of samples, ten shots of each treatment are made before the actual sample collecting started to ensure that the injection molding process is stable. Since the responses of the experiment are warpage and length, the target product length is 124 mm, and the nominal-the-best is applied to calculate S/N ratio for each treatment. In addition, the company's production consulting team has concluded that the target warpage must be less than 0.25 mm and the smaller-the-better is applied to calculate S/N ratio for each treatment. The nominal-the-best and the smaller-the-better are defined as the following:

Nominal-the-best:

$$S/N = -10\log\frac{\sum_{i=1}^{n}(y_i-m)^2}{n} = -10\log\left[(\bar{y}-m)^2 + S_n^2\right] \quad (1)$$

Smaller-the-better:

$$S/N = -10\log\frac{\sum_{i=1}^{n}y_i^2}{n} = -10\log\left[\bar{y}^2 + S_n^2\right] \quad (2)$$

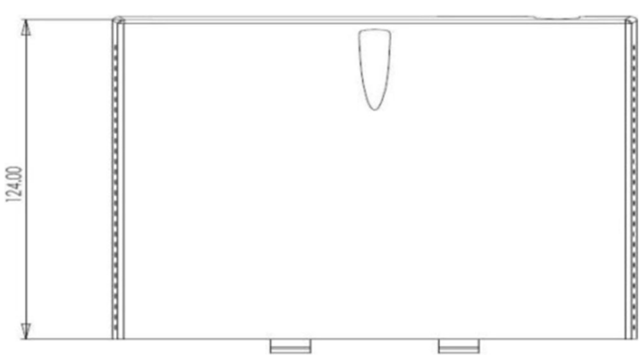

Fig. 4 Sample's external for measurement of length and warpage

where y_i is the response value of a specific treatment under i replications, m is the target value, n is the number of replications, $\bar{y}$ is the average of all y_i values, and S_n is the standard deviation (DOF=n) of all y_i values. From the experimental treatments, average and standard deviation of each treatment with five replications and the S/N ratio of two quality characteristics, length and warpage, are shown in Tables 3 and 4. Table 5 shows the process parameter combinations of highest S/N ratio under different responses. Table 6 shows the ANOVA results of length and indicates that D is significant. Table 7 also reveals that D and E are significant for warpage. Therefore, the control factors in the optimization of the product quality model could only employ packing pressure and packing time. According to the process parameter combinations of highest S/N ratio under different responses in Table 5 and the ANOVA results in Tables 6 and 7, the initial process parameter settings obtained from the Taguchi method and ANOVA are melt temperature=197, injection velocity=36, injection pressure=65, packing pressure=52, and packing time=1.6.

2.3 Hybrid $BPNN_{SN}$-GA search approach

In the first stage, the hybrid S/N ratio predictor ($BPNN_{SN}$)-GA search approach is adopted to yield the first optimal process parameter settings. Melt temperature (MT), injection velocity (IV), injection pressure (IP), packing pressure (PP), and packing time (PT) are

Table 2 Control factors and settings of the various levels

Variable	Control factor	Levels				
		1	2	3	4	5
A	Melt temperature (°C)	195	197	199	201	203
B	Injection velocity (mm/s)	30	32	34	36	38
C	Injection pressure (MPa)	60	62	64	66	68
D	Packing pressure (MPa)	50	52	54	56	58
E	Packing time (s)	1	1.3	1.6	1.9	2.2

Table 3 Experimental treatments, response statistics, and S/N ratio (length)

Treatment	Control factor					Length					Average	Standard deviation	S/N ratio
	A	B	C	D	E	1	2	3	4	5			
1	195	30	60	50	1.0	123.90	123.90	123.91	123.94	123.94	123.92	0.0251	22.04
2	195	32	62	52	1.3	123.96	123.95	123.95	123.97	123.94	123.95	0.0117	26.07
3	195	34	64	54	1.6	123.99	124.00	124.00	123.99	123.97	123.99	0.0164	33.05
4	195	36	66	56	1.9	124.05	124.04	124.04	124.05	124.03	124.04	0.0151	28.04
5	195	38	68	58	2.2	124.12	124.12	124.11	124.10	124.11	124.11	0.0117	19.25
6	197	30	62	54	1.9	123.98	123.99	123.99	123.97	124.00	123.99	0.0105	34.75
7	197	32	64	56	2.2	124.04	124.04	124.02	124.04	124.07	124.04	0.0163	26.69
8	197	34	66	58	1.0	124.05	124.06	124.08	124.06	124.06	124.06	0.0133	24.46
9	197	36	68	50	1.3	123.93	123.95	123.97	123.97	123.95	123.95	0.0204	25.11
10	197	38	60	52	1.6	124.00	123.99	123.95	123.94	123.91	123.96	0.0333	25.25
11	199	30	64	58	1.3	124.04	124.03	124.06	124.07	124.05	124.05	0.0163	25.07
12	199	32	66	50	1.6	123.97	124.01	123.99	124.00	123.96	123.99	0.0397	26.24
13	199	34	68	52	1.9	124.01	124.00	123.98	123.97	123.96	123.98	0.0210	30.76
14	199	36	60	54	2.2	123.95	123.98	123.96	123.96	123.95	123.96	0.0137	28.15
15	199	38	62	56	1.0	124.01	123.98	123.95	123.97	123.99	123.98	0.0204	30.53
16	201	30	66	52	2.2	123.94	123.93	123.95	123.94	123.96	123.94	0.0105	25.04
17	201	32	68	54	1.0	123.93	123.93	123.96	123.95	123.94	123.94	0.0138	24.93
18	201	34	60	56	1.3	124.03	124.02	124.02	124.01	124.01	124.02	0.0089	33.19
19	201	36	62	58	1.6	124.11	124.14	124.11	124.16	124.13	124.13	0.0250	18.00
20	201	38	64	50	1.9	123.92	123.98	123.96	123.96	123.94	123.95	0.0210	25.32
21	203	30	68	56	1.6	124.08	124.09	124.08	124.08	124.09	124.08	0.0075	21.72
22	203	32	60	58	1.9	124.11	124.13	124.12	124.12	124.09	124.11	0.0137	18.85
23	203	34	62	50	2.2	123.95	123.92	123.99	123.96	123.95	123.95	0.0232	25.42
24	203	36	64	52	1.0	123.98	123.93	123.98	123.94	123.94	123.95	0.0217	26.03
25	203	38	66	54	1.3	124.05	124.05	124.03	124.04	124.05	124.04	0.0103	26.41
26	202	31	65	56	1.5	124.11	124.12	124.12	124.11	124.10	124.11	0.0075	19.00
27	202	38	60	50	1.5	123.96	123.93	123.98	123.94	123.94	123.95	0.0271	24.90
28	196	38	67	52	1.9	123.97	123.95	123.96	124.00	124.00	123.98	0.0207	29.97
29	202	34	67	50	2.0	124.00	123.96	123.98	123.97	123.99	123.98	0.0141	32.22
30	200	36	65	51	1.2	123.91	123.95	123.93	123.93	123.95	123.93	0.0152	23.39

selected as process control factors. Warpage and length are employed as the quality responses. Furthermore, the experimental data of the Taguchi method are used for effectively training and testing BPNN quality predictor ($BPNN_{PQ}$) and S/N ratio predictor ($BPNN_{SN}$) that finely map the relationship between the input control factors and output responses. The steepest descent method is used to minimize the cost function to perform stable results. The activation function is a sigmoid function. The architecture of BPNN is shown in Fig. 5.

The training performance (RMSE) of $BPNN_{SN}$ is up to 0.007, and the testing performance amounts to 0.035. Two S/N ratios for length and warpage are selected as the target values in the Taguchi experimental data. In the quality predictor, length and warpage are selected as the output values. The training performance (RMSE) of $BPNN_{PQ}$ is up to 0.0065, and the testing performance amounts to 0.0228. Then, $BPNN_{SN}$ is employed as an S/N ratio predictor combined with GA to search for the first optimal process parameters. To identify optimal process parameters of the hybrid $BPNN_{SN}$-GA search approach, the fitness function of GA is given as follows:

$$
\begin{aligned}
&Min \quad F_1(X) = (y_{o1}-34.75)^2 + (y_{o2}-16.65)^2 \\
&s.t \\
&\quad 196 \le x_1 \le 198 \quad 30 \le x_2 \le 37 \\
&\quad 61 \le x_3 \le 68 \qquad 50 \le x_4 \le 55 \\
&\quad 1.15 \le x_5 \le 2.05
\end{aligned}
$$

Table 4 Experimental treatments, response statistics, and S/N ratio (warpage)

Treatment	Control factor					Warpage					Average	Standard deviation	S/N ratio
	A	B	C	D	E	1	2	3	4	5			
1	195	30	60	50	1.0	0.19	0.17	0.18	0.17	0.15	0.172	0.0175	15.01
2	195	32	62	52	1.3	0.17	0.19	0.22	0.20	0.22	0.200	0.0190	13.94
3	195	34	64	54	1.6	0.29	0.31	0.33	0.32	0.33	0.316	0.0163	10.07
4	195	36	66	56	1.9	0.41	0.38	0.39	0.41	0.39	0.396	0.0137	8.10
5	195	38	68	58	2.2	0.39	0.42	0.41	0.40	0.41	0.406	0.0121	7.88
6	197	30	62	54	1.9	0.33	0.31	0.32	0.33	0.35	0.328	0.0175	9.79
7	197	32	64	56	2.2	0.47	0.46	0.46	0.48	0.45	0.464	0.0172	6.77
8	197	34	66	58	1.0	0.28	0.26	0.29	0.27	0.28	0.276	0.0147	11.31
9	197	36	68	50	1.3	0.16	0.15	0.14	0.15	0.13	0.146	0.0103	16.65
10	197	38	60	52	1.6	0.27	0.25	0.23	0.22	0.23	0.240	0.0197	12.49
11	199	30	64	58	1.3	0.34	0.38	0.38	0.39	0.37	0.372	0.0175	8.55
12	199	32	66	50	1.6	0.20	0.18	0.19	0.18	0.17	0.184	0.0141	14.87
13	199	34	68	52	1.9	0.35	0.34	0.32	0.31	0.33	0.330	0.0187	9.75
14	199	36	60	54	2.2	0.36	0.38	0.40	0.36	0.37	0.374	0.0151	8.55
15	199	38	62	56	1.0	0.26	0.25	0.25	0.26	0.28	0.260	0.0117	11.75
16	201	30	66	52	2.2	0.33	0.34	0.35	0.33	0.34	0.338	0.0117	9.32
17	201	32	68	54	1.0	0.20	0.22	0.21	0.22	0.21	0.212	0.0117	13.61
18	201	34	60	56	1.3	0.37	0.33	0.32	0.33	0.32	0.334	0.0197	9.44
19	201	36	62	58	1.6	0.38	0.35	0.36	0.37	0.34	0.360	0.0147	8.91
20	201	38	64	50	1.9	0.23	0.21	0.22	0.20	0.22	0.216	0.0103	13.27
21	203	30	68	56	1.6	0.40	0.38	0.36	0.36	0.38	0.376	0.0183	8.59
22	203	32	60	58	1.9	0.43	0.42	0.41	0.42	0.42	0.420	0.0103	7.60
23	203	34	62	50	2.2	0.27	0.28	0.27	0.24	0.25	0.262	0.0197	11.79
24	203	36	64	52	1.0	0.19	0.18	0.19	0.21	0.17	0.188	0.0137	14.56
25	203	38	66	54	1.3	0.31	0.30	0.29	0.30	0.28	0.296	0.0147	10.69
26	202	31	65	56	1.5	0.39	0.37	0.38	0.39	0.37	0.380	0.0121	8.41
27	202	38	60	50	1.5	0.21	0.20	0.21	0.19	0.18	0.198	0.0242	14.13
28	196	38	67	52	1.9	0.29	0.31	0.30	0.31	0.30	0.302	0.0151	10.41
29	202	34	67	50	2.0	0.29	0.33	0.27	0.28	0.30	0.294	0.0228	10.66
30	200	36	65	51	1.2	0.20	0.19	0.22	0.19	0.18	0.196	0.0172	14.19

where melt temperature, injection velocity, injection pressure, packing pressure, and packing time are control parameters and assign to variable $X=[x_1, x_2, x_3, x_4, x_5]$, respectively. y_{o1} and y_{o2} are the output S/N ratios of $BPNN_{SN}$. y_{o1} is for length and y_{o2} is for warpage. Two highest S/N ratios of length and warpage, 34.75 and 16.65, respectively, are set to the target values.

2.4 Hybrid $BPNN_{PQ}$-PSO search approach

In the second stage, $BPNN_{PQ}$ is combined with PSO to search for the final optimal process parameter settings. The optimal parameter combination in the first stage is taken as the initial values. According to the ANOVA results in Section 2.2, the control factors in the optimization model only em-

Table 5 The process parameter settings of highest S/N ratio under different responses

Parameter variable	A	B	C	D	E	Highest S/N ratio for length	Highest S/N ratio for warpage
Parameter combination	197	30	62	54	1.9	34.75	/
	197	36	68	50	1.3	/	16.65

Table 6 ANOVA for product length

Source of variance	DOF	Seq SS	Adj SS	Adj MS	F	p value
A	4	0.0048127	0.0048127	0.0012032	1.30	0.404
B	4	0.0003771	0.0003771	0.0000943	0.10	0.976
C	4	0.0013971	0.0013971	0.0003493	0.38	0.817
D	4	0.0695149	0.0695149	0.0173787	18.72	0.007
E	4	0.0073449	0.0073449	0.0018362	1.98	0.262
Error	4	0.0037127	0.0037127	0.0009282		
Total	24	0.0871593				

Table 7 ANOVA for product warpage

Source of variance	DOF	Seq SS	Adj SS	Adj MS	F	p value
A	4	0.000994	0.000994	0.000248	0.23	0.909
B	4	0.003596	0.003596	0.000899	0.83	0.569
C	4	0.003155	0.003155	0.000789	0.73	0.617
D	4	0.104525	0.104525	0.026131	24.13	0.005
E	4	0.064735	0.064735	0.016184	14.94	0.011
Error	4	0.004332	0.004332	0.001083		
Total	24	0.0181336				

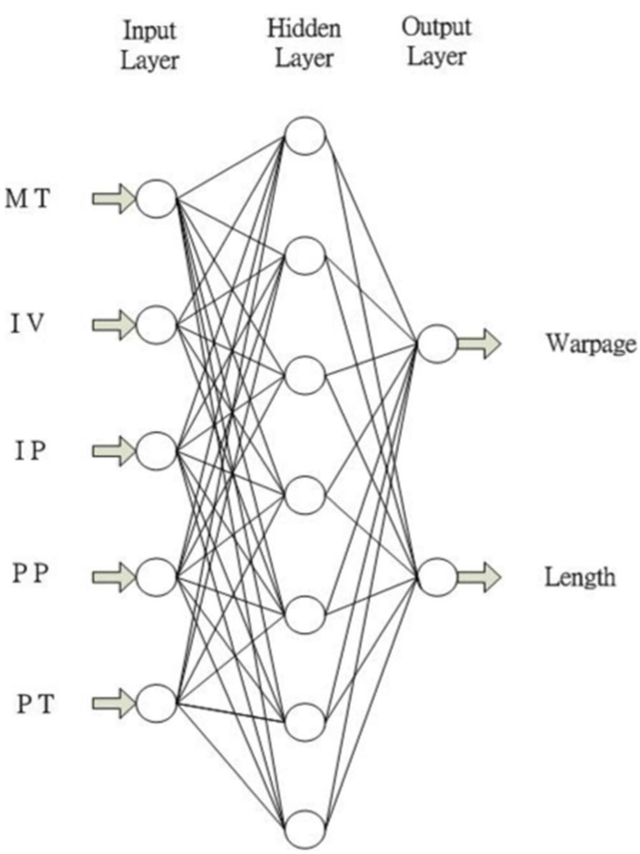

Fig. 5 Architecture of BPNN

ploy packing pressure and packing time. Then, the objective function of the hybrid $BPNN_{PQ}$-PSO search approach is given as follows:

$$\begin{aligned}
&Min \quad F_2(X) = (y_{Lo1} - 124)^2 \\
&Min \quad y_{Wo2} \\
&s.t. \\
&\qquad 50 \leq x_4 \leq 55 \\
&\qquad 1.15 \leq x_5 \leq 2.05
\end{aligned}$$

where x_4 and x_5 are the process control parameters, y_{Lo1} is the predicted length of $BPNN_{PQ}$, and y_{Wo2} is the predicted warpage of $BPNN_{PQ}$.

3 Results and discussion

When the first iteration of the two-stage optimization is completed, the optimal parameters obtained from the numerical analysis should be able to achieve two goals. One is to meet the highest S/N ratio not only for length (34.75) but also for warpage (16.65). The other is to fill the requirements for product quality, which are 124 mm for the length and as small as possible for the warpage. If the optimal parameters do not reach the highest S/N ratio and the product quality requirements, the second

Table 8 Optimal process parameters and machine settings for three confirmation experiments

	Melt temperature	Injection velocity	Injection pressure	Packing pressure	Packing time
Taguchi method	197	36	65	52	1.6
Machine setting	197	36	65	52	1.6
First stage	197.44	34.86	61.13	51.94	1.225
Machine setting	197	35	61	52	1.2
Proposed system	197.44	34.86	61.13	52.018	1.354
Machine setting	197	35	61	52	1.4

Table 9 Comparison of warpage quality statistics

	Average	Standard deviation
Taguchi method	0.2202	0.0080
First stage	0.1545	0.0063
Proposed system	0.1351	0.0041

Table 10 Comparison of length quality statistics

	Average	Standard deviation	C_{pk}
Taguchi method	123.958	0.0152	1.274
First stage	123.969	0.0076	2.592
Proposed system	123.997	0.0111	2.913

iteration of the two-stage optimization must be processed. The optimal parameters gained from the first iteration need to be set for the initial parameter solution of the second iteration. The iteration procedures need to be continued until the results meet the goals. Following the procedure of the two-stage optimization system and executing the numerical computation, three optimal process parameter combinations are obtained, and the results and machine settings are shown in Table 8. To demonstrate the effectiveness of the proposed optimization system, three confirmation experiments are performed. One experiment utilizes preliminary initial process parameter settings obtained from the Taguchi method. The other two experiments utilize the optimal process parameter settings obtained from the first stage and the second stage. Because of the minimum unit of the parameter setting in the plastic injection molding machine, the final optimal process parameter settings are determined after the minimum unit tuning and are shown in Table 8. Each experiment produced 30 product samples in the confirmation experiment. The statistical averages, standard deviations, and process capability indices of all three methods are compared in order to judge the best approach for determining the final

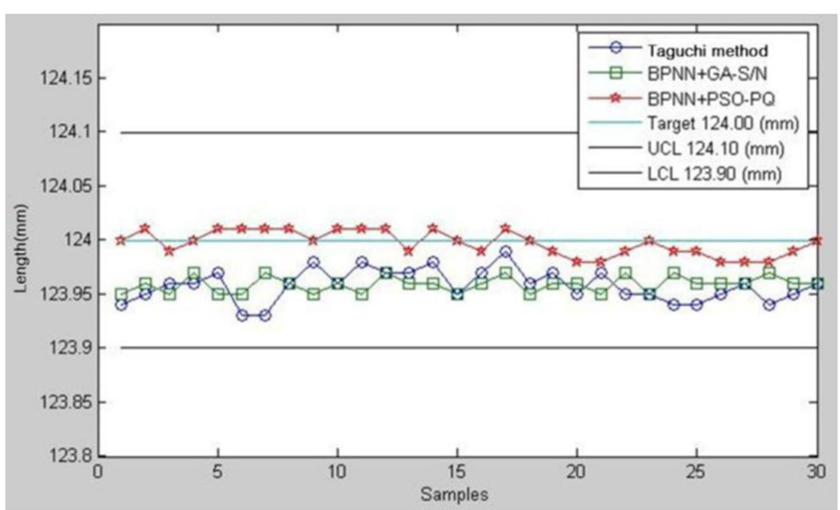

Fig. 6 Comparison of quality characteristics (length) between Taguchi method, first stage and proposed system

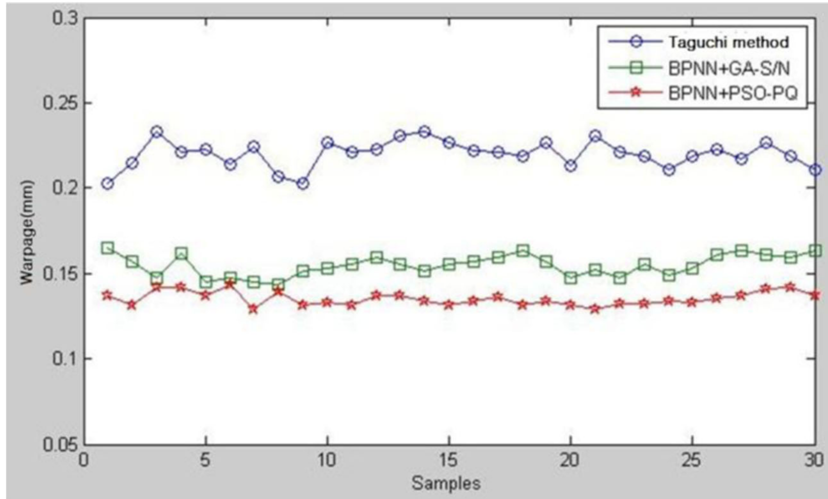

Fig. 7 Comparison of quality characteristics (warpage) between Taguchi method, first stage and proposed system

optimal process parameter settings. Comparisons of quality statistics between the Taguchi method, the first stage and the second stage search approaches are shown in Tables 9 and 10, respectively. In addition, comparisons of quality characteristics (length and warpage) between the Taguchi method, the first stage and the second stage search approaches are shown in Figs. 6 and 7, respectively. According to the experimental results, the standard deviation of the Taguchi method is 0.008, and the standard deviation of the first stage is 0.0063. The Taguchi method approximately two times that of the proposed system (0.0041). In the practical assessment, the process capability index (C_{pk}) is a major criterion for assessing the ability of a production process to make products that meet specifications. The practical minimum process capability index is 1.33 in many manufacturing industries. As the results in Table 10 show, the C_{pk} of Taguchi's approach is 1.274, which is roughly one half that of the first stage (2.592) and the proposed system (2.913). Experimental results also reveal that the two-stage optimization system produced the highest C_{pk} value and the best quality products. Consequently, the final optimal process parameters generated by the proposed two-stage optimization system definitely produced the best performance than the Taguchi method and the first stage approach.

4 Conclusion

Costs of production in plastic injection molding are directly affected by strategies for choosing the suitable parameter settings in different kinds of machines, especially when setting up production runs. The suitable parameter settings have traditionally relied on trial-and-error experiments. These conventional strategies, however, often produce unstable product quality. The application of the Taguchi method cannot help engineers obtain optimal process parameter settings when process parameters are continuous and have a nonlinear relationship. Therefore, this study proposed an integrated optimization system to perform the process parameter optimization for plastic injection products of multiple quality characteristics. After the actual verification, the results show that the two-stage optimization parameter combination for the length C_{pk} value at 2.913 is higher than the Taguchi method optimized parameter C_{pk} value at 1.274. The warping dropped from 0.2202 to 0.1351, which is a 38.6 % decrease, thus indicating that the product quality complies with the specifications and produces the most stable process. Thus, the proposed integrated optimization system is a feasible and effective method for process parameter optimization in MIMO plastic injection molding and can result in significant quality and cost advantages.

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