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ORIGINAL ARTICLE

An integrated parameter optimization system for MISO plastic injection molding

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Abstract This paper presents the development of a parameter optimization system that integrates mold flow analysis, the Taguchi method, analysis of variance (ANOVA), back-propagation neural networks (BPNNs), genetic algorithms (GAs), and the Davidon–Fletcher–Powell (DFP) method to generate optimal process parameter settings for multiple-input single-output plastic injection molding. In the computer-aided engineering simulations, Moldex3D software was employed to determine the preliminary process parameter settings. For process parameter optimization, an L_{25} orthogonal array experiment was conducted to arrange the number of experimental runs. The injection time, velocity pressure switch position, packing pressure, and injection velocity were employed as process control parameters, with product weight as the target quality. The significant process parameters influencing the product weight and the signal to noise (S/N) ratio were determined using experimental data based on the ANOVA method. Experimental data from the Taguchi method were used to train and test the BPNNs. Then, the BPNN was combined with the DFP method and the GAs to determine the final optimal parameter settings. Three confirmation experiments were performed to verify the effectiveness of the proposed system. Experimental results show that the proposed system not only avoids shortcomings inherent in the commonly used Taguchi method but also produced significant quality and cost advantages.

Keywords Parameter optimization · Mold flow analysis · Taguchi method · ANOVA · GAs · DFP · Plastic injection molding

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1 Introduction

Determination of optimal process parameter settings is critical work that has a direct and dramatic influence on product quality and costs. In industry, trial-and-error processes and the Taguchi method are frequently employed to determine the initial process parameter settings for injection molding. The Taguchi optimization methodology uses the signal to noise (S/N) ratio approach to determine the initial process parameter settings. In previous studies, many researchers used the Taguchi method to determine the initial process parameter settings for an injection molding process. Tseng [1] determined statistically significant parameters, including effects from multiple interactions of the selected factors, through an analysis of variance (ANOVA) and the *F* test. Lin [2] examined the effectiveness of the Taguchi technique with regard to multiple performance characteristics by employing cutting parameters. Shiou and Chen [3] examined optimal process parameters related to a Taguchi orthogonal array in the finishing operation of freeform surface plastic injection molding. Ghani et al. [4] described a Taguchi optimization methodology for finding a combination of milling parameters using the S/N ratio approach and ANOVA. Yang et al. [5] employed an orthogonal array experiment to arrange 16 experimental runs. Melting temperature, injection speed, and injection pressure were adopted as the process control factors, and contour distortions were utilized as the quality index. However, the Taguchi method can only find the best set of specified process parameter level combinations which are discrete setting values of the process parameters. Application of the conventional Taguchi method is unreasonable when the variable of a process parameter is continuous, and it cannot help engineers obtain optimal initial process parameter setting results [6]. An unsuitable process parameter setting can cause many defective products and unstable product quality during the injection molding process. Therefore, efficient analytical methodologies and tools are necessary to efficiently and rapidly analyze process parameters and control product quality.

To deal with these problems, many researchers of injection molding processes have investigated the application of artificial neural networks (ANNs) on quality predictions [7–12]. The main reason for using ANNs is that neural networks have the ability to learn arbitrary nonlinear mappings between noisy sets of input and output data. When the quality predictor is precise, the quality controller can adjust the controllable parameters closer to the target values of the injection molding process, and an efficient model can be obtained. In finding the optimal parameter settings of injection molding processes, ANNs are frequently combined with genetic algorithms (GAs) [13, 14]. Ozcelik and Erzurumlu [13] employed an ANN model to validate the predictive capability and then interfaced with an effective GA to find optimum process parameter values. The most important parameters were determined using mold flow analytical results based on the ANOVA method. Upon optimization, it was seen that the genetic algorithm reduced the warpage that appeared in the initial samples. Shi et al. [14] presented an improved hybrid strategy for optimizing a plastic injection molding process. Numerical software simulation, a GA, and a back-propagation neural network (BPNN) were fused to optimize process parameters. Costly numerical calculations were avoided by creating an approximate model that used a BPNN. Kurtaran and Erzurumlu [15] integrated finite-element (FE) analysis, design of experimental method, response surface methodology, and a GA to effectively optimize warpage of thin-shell plastic parts. In considering product warpage, an ANOVA-based FE analysis can determine the most significant process parameters. Optimum values for those process parameters can be determined through a predictive response surface model in conjunction with a GA. The above approaches used computer-aided engineering (CAE) simulations with an optimization technique that can determine the optimal process parameter settings for injection molding. The main problem with previous studies was that CAE simulations are not practical since the molding environments create other noises to the part quality; besides, the controllability, repeatability, and the precision of molding machines provide more noises that contribute to part quality in real molding. These noises are not considered in the optimization processes using CAE simulations. To resolve such problems, Chen et al. [16] integrated the Taguchi method, BPNNs, GAs, and engineering optimization concepts to optimize process parameters. A real-world plastic injection molding (PIM) experiment was performed, and an L_{25} orthogonal array experiment was conducted to arrange the number of experimental runs. Experimental data from the Taguchi method were used to train and test the BPNN. Then, the BPNN was combined with GA to determine final optimal parameter settings. Their research results indicated that the BPNN–GA approach can effectively help engineers determine optimal process parameter settings. However, Chen et al. [16] used a standard testing slug; in the present study, we used a real-world housing piece which is better related to actual manufacturing experiences. In addition, the proposed parameter optimization system integrates mold flow analysis, the Taguchi method, ANOVA, BPNNs, GAs, and the DFP method to generate optimal process parameter settings for multiple-input single-output (MISO) plastic injection molding. The final optimal process parameter settings obtained from the proposed system should be more reliable and practical.

Previously, researchers showed that product weight is a critical quality attribute, and a good indicator of manufacturing process stability for plastic injection molding. Yang and Gao [17] revealed that product weight is an important quality index for injection-molded products because the product weight has a closer relation to other quality properties (e.g., surface properties and mechanical properties) and particularly dimensional properties (e.g., dimensions and thickness). They also claimed that the performance of a manufacturing process and its quality control can be monitored through product weight. Kamal et al. [18] showed that the control of injection-molded product weight is of great commercial interest and can produce great value for production management. Since injection molding is commonly used in the production of plastic housing components, product weight is a feasible single quality characteristic that can be used for product quality control of plastic housing components.

Process parameter settings for plastic injection molding critically influence the quality of the molded products. An unsuitable process parameter setting inevitably causes a multitude of production problems: long lead times, many rejects, and substandard moldings. The negative impact on efficiency raises costs and reduces competitiveness. This research develops a process parameter optimization system to help manufacturers make rapid, efficient, preproduction setups for MISO plastic injection molding. The focus of this study was molded housing components, with attention to a particularly telling quality characteristic: weight. The optimization system proposed herein includes two stages. In the first stage, mold flow analysis was used to obtain preliminary process parameter settings. In the second stage, the Taguchi method with ANOVA was applied to determine optimal initial process parameter settings, and a BPNN was applied to build up the prediction model. Then, the BPNN was individually combined with the DFP method and with a GA to search for the final optimal process parameter settings. Three confirmation experiments were performed to verify the effectiveness of the final optimal process parameter settings. The final optimal process parameter settings are not limited to discrete values as in the Taguchi method and can determine settings for production that not only approach the target value of the selected quality characteristic more closely but also with less variation.

2 Optimization methodologies

The optimization methodologies including BPNNs, GAs, and the DFP method are briefly introduced as follows.

2.1 Back-propagation neural networks

Many researchers have mentioned that BPNNs have the advantage of fast response and high learning accuracy [19–23]. A BPNN consists of an input layer, one or more hidden layers, and an output layer. The parameters for a BPNN include: the number of hidden layers, the number of hidden neurons, the learning rate, momentum, etc. All of these parameters have significant impacts on the performance of a neural network. In this research, the steepest descent method was used to find the weight and bias change and minimize the cost function. The activation function is a hyperbolic tangent function. In network learning, input data and output results are used to adjust the weight and bias values of the network. The more detailed the input training classification is and the greater the amount of learning information provided, the better the output will conform to the expected result. Since the learning and verification of data for the BPNN are limited by the function values, the data must be normalized by the following equation:

$$PN = \frac{P - P_{\min}}{P_{\max} - P_{\min}} \times (D_{\max} - D_{\min}) + D_{\min}; \tag{1}$$

where PN is the normalized data; P is the original data; $P_{\max}$ is the maximum value of the original data; $P_{\min}$ is the minimum value of the original data; $D_{\max}$ is the expected maximum value of the normalized data, and $D_{\min}$ is the expected minimum value of the normalized data. When applying neural networking to the system, the input and output values of the neural network fall in the range of $[D_{\min}, D_{\max}]$.

According to previous studies [24, 25], there are a few conditions for network learning termination: (1) when the root mean square error (RMSE) between the expected value and network output value is reduced to a preset value; (2) when the preset number of learning cycles has been reached; and (3) when cross-validation takes place between the training samples and test data. In this research, the first approach was adopted by gradually increasing the network training time to slowly decrease the RMSE until it was stable and acceptable. The RMSE is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - y_i)^2}; \tag{2}$$

where N, d_i, and y_i are the number of training samples, the actual value for training sample i, and the predicted value of the neural network for training sample i, respectively.

2.2 Genetic algorithms

GAs are a method of searching for optimized factors analogous to Darwin's survival of the fittest and are based on a biological evolution process. The evolution process is random yet guided by a selection mechanism based on the fitness of individual structures. There is a population of a given number of individuals, each of which represents a particular set of defined variables. Fitness is determined by the measurable degree of approach to the ideal. The “fittest” individuals are permitted to “reproduce” through a recombination of their variables, in the hope that their “offspring” will prove to be even better adapted. In addition to the strict probabilities dictated by recombination, a small mutation rate is also factored in. Less-fit individuals are discarded with the subsequent iteration, and each generation progresses toward an optimal solution.

GAs consist of four main stages: evaluation, selection, crossover, and mutation [26]. The evaluation procedure measures the fitness of each individual solution in the population and assigns it a relative value based on the defining optimization (or search) criteria. Typically, in a nonlinear programming scenario, this measure reflects the objective value of the given model. The selection procedure randomly selects individuals of the current population to develop the next generation. Various alternative methods have been proposed, but all follow the idea that the fittest have a greater chance of survival. The crossover procedure takes two selected individuals and combines them about a crossover point thereby creating two new individuals. Simple reproduction can also occur which replicates a single individual into the new population. The mutation procedure randomly modifies the genes of an individual subject by a small mutation factor, introducing further randomness into the population.

2.3 Davidon–Fletcher–Powell method

Fletcher and Powell [27] revised Davidon's variable metric method and proposed the DFP method. The DFP method is an improved alternative to Newton's method, which is too costly for many applications. The DFP method is often called the quasi-Newton method. In the DFP method, it is not necessary for practitioners to actually evaluate the Hessian matrix as they must for the Newton method. The DFP method uses a symmetrical, positive, definite $\mathbf{M}_{n\times n}$ matrix as an estimate for the inverse Hessian matrix of Newton's method. For any given initial starting value vector of parameter variables, the $\mathbf{M}^{(k)}$ matrix will converge to the inverse Hessian matrix after k iterative computations. Consequently, the DFP method has advantages of faster convergence and less computation than Newton's method when applied to nonlinear optimization problems. The iteration process of the DFP method is given as follows after analysis defined an objective function, $f(X)$ [26].

Step 1 Set initial values $X^{(0)}$; decide a convergence parameter, ε; let the initial symmetric positive matrix, $\mathbf{M}^{(0)}$, be the identity matrix, $\mathbf{I}$; compute the gradient vector as

$$C^{(0)} = \nabla f\left(X^{(0)}\right). \tag{3}$$

Step 2 Compute the norm of the gradient vector as $\left\|C^{(k)}\right\|$. If $\left\|C^{(k)}\right\|\langle\varepsilon$, then stop the iteration process. If not, the iteration process continues. k is the number of iterations.

Step 3 Calculate the search direction of k iterations:

$$D^{(k)} = -M^{(k)}C^{(k)}. \tag{4}$$

Step 4 Calculate the optimum step size $\alpha_k=\alpha$. Any one-dimensional search procedure can be used to minimize $f\left(X^{(k)}+\alpha D^{(k)}\right)$ and obtain the α value.

Step 5 Update the design variables as

$$X^{(k+1)} = X^{(k)} + \alpha_k D^{(k)}. \tag{5}$$

Step 6 Update the symmetric positive matrix $\mathbf{M}^{(k)}$ as follows:

$$M^{(k+1)} = M^{(k)} + N^{(k)} + O^{(k)}; \tag{6}$$

where

$$N^{(k)} = \frac{S^{(k)}S^{(k)^T}}{\left(S^{(k)}\cdot Y^{(k)}\right)}, \tag{7}$$

$$O^{(k)} = \frac{-Z^{(k)}Z^{(k)^T}}{\left(Y^{(k)}\cdot Z^{(k)}\right)}, \tag{8}$$

$$S^{(k)} = \alpha_k D^{(k)} \quad \text{(the change in design of } k \text{ iterations)}, \tag{9}$$

$$Y^{(k)} = C^{(k+1)} - C^{(k)} (\text{the change} \in \text{ gradient of } k \text{ iterations}), \tag{10}$$

$$C^{(k+1)} = \nabla f\left(X^{(k+1)}\right), \tag{11}$$

$$Z^{(k)} = M^{(k)}Y^{(k)}, \tag{12}$$

and superscript T denotes transposition of a matrix.

Step 7 Set $k=k+1$ and go to step 2.

3 Parameter optimization system for MISO plastic injection molding processes

This section presents the process parameter optimization system for MISO PIM under four process control factors and one response. The proposed optimization system integrates mold flow analysis, the Taguchi method, ANOVA, BPNNs, GAs, and the DFP method. The product is a plastic injection-molded push-button housing component. The injection time (IT), velocity pressure switch position (VP), packing pressure (PP), and injection velocity (IV) were selected as process control factors. Product weight was selected as the only response for the case study. The proposed optimization system herein has two stages. In the CAE simulations, the preliminary process parameter settings were determined using a mold flow analysis. In the process parameter optimization, the Taguchi method was used to arrange an L_{25} orthogonal array experiment and reduce the number of set test cycles. Subsequently, the S/N ratio and ANOVA were used to determine the initial process parameter settings that have minimal sensitivity to noise with consideration of the major quality characteristic. The experimental data of the Taguchi method were used to effectively train and test the BPNN that finely maps the relationship between the input process control factors and the output response. Then, the BPNN was individually combined with the DFP method and GAs to determine the final optimal parameter settings. Finally, three confirmation experiments were performed to confirm the effectiveness of the final optimal process parameter settings. The statistical averages, standard deviations, and process capability indices were compared in order to judge the best approach for determining the final optimal process parameter settings. The flow chart of the proposed parameter optimization system is shown in Fig. 1. The procedures of the proposed system consisted of two stages and are given as follows.

Stage I Determine the preliminary process parameter settings via mold flow analysis.

- Step 1 Identify the simulation parameters and quality characteristics.
- Step 2 Perform the mold flow analysis to obtain the preliminary process parameter settings. Moldex3D software was used for the mold flow analysis.

Stage II Determine the final optimal process parameter settings via the Taguchi method, ANOVA, BPNN, the DFP method, and GAs.

- Step 1 Identify the feasible quality response as the target requirement of the experiment. The response must be confirmed to have significant influences on the final product quality.
- Step 2 Determine the feasible control parameters and levels that influence the performance of the quality characteristic. The number of control parameters which should be included in the experiment and the number of levels for each parameter can be decided using experience, preliminary studies, or brainstorming.
- Step 3 Select an appropriate orthogonal array for arranging the experiment and acquiring the experimental treatments.
- Step 4 Perform experiments for each treatment and collect the performance measurements of the responses.

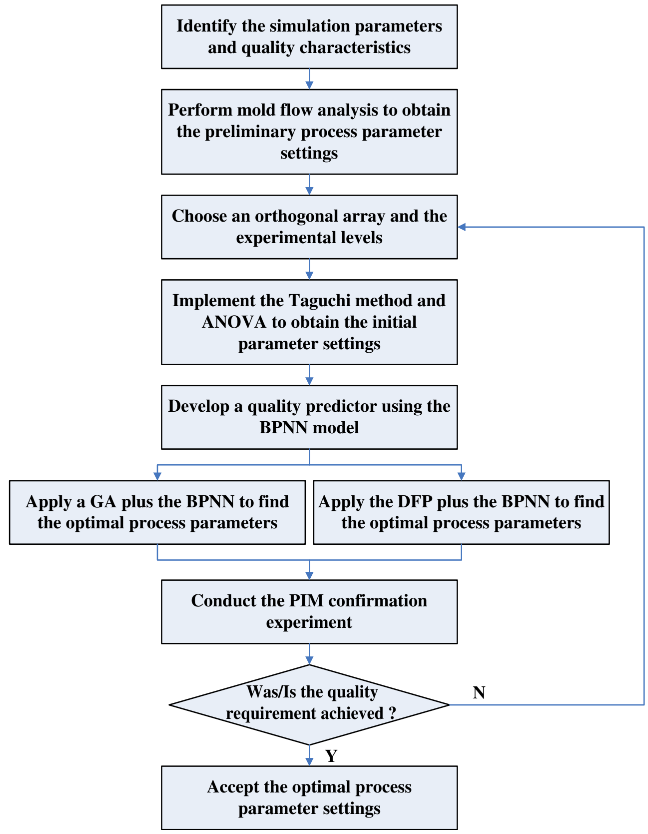

Fig. 1 The flow chart of the proposed parameter optimization system

- Step 5 Select an appropriate formulation for the S/N ratio and calculate the S/N ratio for each response under different treatments of the orthogonal array. The S/N ratio has three types: nominal-the-best, larger-the-better, and smaller-the-better.
- Step 6 Implement the S/N ratio and ANOVA method to determine the initial parameter settings.

Fig. 2 The push-button housing and runner system

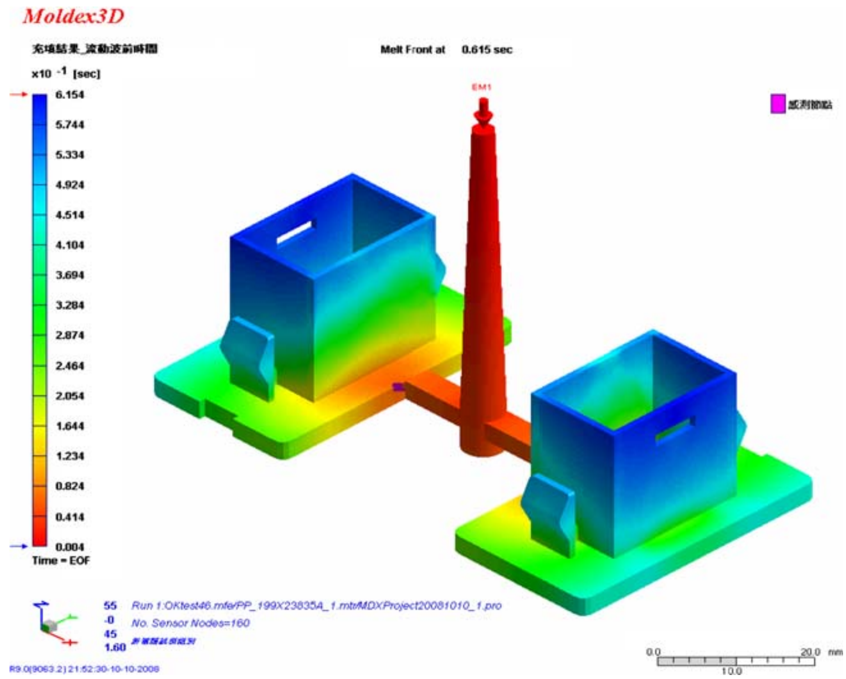

Fig. 3 Simulation result at the end of filling

Step 7 Build a BPNN quality predictor that will finely map the relationship between the input process control parameters and the output response.

Step 8 Formulate the objective function of the DFP method and the fitness function of the GA with ranges of the process parameters.

Step 9 Determine the final optimal process parameter settings via soft computing. The DFP method and GA are individually coupled with the BPNN model to yield two optimal solutions.

Step 10 Conduct three confirmation experiments.

3.1 Experimental equipment and illustrative example

In this study, the experimental material used was polypropylene. The injection molding machine was a Nissei ES-400. The product in this illustrative example was a plastic injection-molded push-button housing piece shown in Fig. 2. Product weight was selected as the only quality response. This study used a Mettler AE-100 electronic balance to measure the product weight to an accuracy of 0.5 mg.

3.2 CAE simulations

The CAE simulations of the plastic part were carried out to identify the preliminary process parameter settings. The ranges of the parameters were set based on the material processing guide for the selected polypropylene. Simulations of the plastic part were performed to validate the processing windows using Moldex3D software. Simulation results indicated that the plastic part could be successfully filled with good weight repetitiveness inside the processing window. Figure 3 shows the simulation result at the end of filling with the molding parameter values shown in Table 1.

Table 1 Processing parameters employed in Moldex3D analysis

Control parameters	Value
Injection time	1.5 s
Velocity pressure switch position	7.9 mm
Packing pressure	45 MPa
Injection velocity	46 mm/s
Melt temperature	250°C
Mold temperature	50°C
Injection pressure	175 MPa

Table 2 Product parameter setting ranges

Control parameters	Setting ranges
Injection time	1.3~1.7 s
Velocity pressure switch position	7.5~8.3 mm
Packing pressure	35~55 MPa
Injection velocity	40~52 mm/s

Table 3 Control factors and settings of the various levels

Variable notation	Control factors	Level				
		1	2	3	4	5
A	Injection time	1.3	1.4	1.5	1.6	1.7
B	Velocity pressure switch position	7.5	7.7	7.9	8.1	8.3
C	Packing pressure	35	40	45	50	55
D	Injection velocity	40	43	46	49	52

3.3 Implementation of the Taguchi method and BPNN quality predictor

The Taguchi method normally selects an appropriate formulation of the S/N ratio and calculates the S/N ratio for each treatment. There are three types of S/N ratios: nominal-the-best, larger-the-better, and smaller-the-better. Most engineers choose the highest S/N ratio treatment as the preliminary optimal initial process parameter setting. In this study, product weight was selected as the only response for a plastic injection-molded standard since it is easily monitored online, and weight is a critical quality attribute [17, 18]. The weight of the plastic injection-molded push-button housing piece was a nominal-the-best-type response. Prior to this research, the molder found that parts weighing 10.58 g had good and acceptable dimensions and mechanical qualities. So the target value of the push-button housing piece was set to 10.58 g, and the formula of the nominal-the-best is given as follows:

$$S/N = -10 \times \log\left(\frac{\sum_{i=1}^{n}(y_i - m)^2}{n}\right)$$
$$= -10 \times \log\left((\bar{y} - m)^2 + S^2\right); \quad (13)$$

where y_i is the response value of a specific treatment under i replications; n is the number of replications; $\bar{y}$ is the average of all y_i values; m is the target value, and S is the standard

Table 4 Experimental treatments, response statistics, and the signal to noise (S/N) ratio

No.	Weight (g) Y_1	Weight (g) Y_2	Weight (g) Y_3	Weight (g) Y_4	Weight (g) Y_5	Average weight (g)	Standard deviation	S/N ratio
1	10.4959	10.4915	10.5003	10.4817	10.4942	10.4927	0.0069	21.15
2	10.5188	10.5184	10.5221	10.5172	10.5190	10.5191	0.0018	24.30
3	10.5534	10.5479	10.5568	10.5523	10.5529	10.5526	0.0031	31.20
4	10.5755	10.5741	10.57	10.5792	10.5757	10.5763	0.0019	47.62
5	10.5984	10.598	10.5938	10.5950	10.5910	10.5952	0.0030	36.16
6	10.5585	10.5599	10.552	10.5540	10.5500	10.5548	0.0042	31.87
7	10.5773	10.5800	10.5791	10.5731	10.5800	10.5779	0.0029	48.91
8	10.6002	10.6039	10.6029	10.6037	10.6035	10.6028	0.0015	32.80
9	10.5855	10.5789	10.5756	10.5851	10.5854	10.5821	0.0045	45.95
10	10.4853	10.4863	10.4439	10.5066	10.4976	10.4839	0.0240	20.09
11	10.6018	10.6008	10.6026	10.6036	10.6023	10.6022	0.0010	33.05
12	10.5925	10.5883	10.5852	10.5914	10.5851	10.5885	0.0034	40.75
13	10.6113	10.6140	10.6161	10.6161	10.6167	10.6148	0.0022	29.14
14	10.5379	10.5300	10.5383	10.5410	10.5452	10.5384	0.0055	27.55
15	10.5687	10.5722	10.5653	10.5711	10.5710	10.5696	0.0027	39.41
16	10.6168	10.6205	10.6153	10.6197	10.6226	10.6189	0.0029	28.15
17	10.6362	10.6335	10.6368	10.6349	10.6363	10.6355	0.0013	25.10
18	10.5646	10.5668	10.5651	10.5660	10.5665	10.5658	0.0009	36.93
19	10.5877	10.6011	10.5955	10.5925	10.5914	10.5936	0.0050	36.75
20	10.583	10.5782	10.5863	10.5853	10.5831	10.5831	0.0031	47.01
21	10.6596	10.6546	10.6603	10.6560	10.6562	10.6573	0.0024	22.22
22	10.5847	10.5840	10.5913	10.5785	10.5853	10.5847	0.0045	43.62
23	10.5892	10.5829	10.5787	10.5881	10.5768	10.5831	0.0055	43.95
24	10.6155	10.6189	10.6078	10.6158	10.6136	10.6143	0.0041	29.22
25	10.6368	10.6328	10.6352	10.6404	10.6369	10.6364	0.0027	24.96

deviation of all y_i values. This research applied an $L_{25}(5^6)$ orthogonal array to assign four factors to the rows, with IT (from the beginning of injection to completion of packing), VP, PP, and IV assigned to rows A, B, C, and D, respectively. Table 2 shows the four process control factors and parameter setting ranges. Table 3 shows the control parameters and settings of the various levels. There were 25 treatments in total with different level combinations of the four factors. Five replications were taken to increase the amount of analytical data, in order to increase the sensitivity of the statistical analysis. In total, 125 sample data points were collected. During the collection of samples, ten shots of each treatment were made before the official sample collecting job began to ensure that the injection molding process was operating stably. Since the response of the experiment was the weight of the injection-molded plastic housing piece and the company's production consulting team had concluded that the target product weight was 10.58 g with a tolerance of 0.048 g, nominal-the-best was applied to calculate the S/N ratio for each treatment. From the experimental treatments, response statistics, and the S/N ratio, the response average and standard deviation of each treatment with five replications and the S/N ratio were obtained. Experimental treatments, response statistics, and the S/N ratio are shown in Table 4. The initial optimal process parameters that had the highest S/N ratio were determined from the factor levels. The value of the S/N ratio for each factor under different levels is shown in Table 5. Table 6 shows the ANOVA results of the product weight and indicates that all four control factors were significant in terms of product weight. Table 7 reveals that the influences of the four factors on the S/N ratio were insignificant. Treatment no. 7 ($A_2B_2C_3D_4$) in Table 4 had the highest S/N ratio and was employed as the possible initial optimal process parameter settings. Therefore, the optimal initial process parameter settings were an IT of 1.4 s, a VP of 7.7 mm, a PP of 45 MPa, and an IV of 49 mm/s. Furthermore, the experimental data of the Taguchi method were used to effectively train and test the BPNN quality predictor that was used to finely map the relationship between the input process control factors and output responses. The network performance was obtained by calculating the RMSE. The RMSE was 0.00108 for the test BPNN. Comparisons between the target and predicted values are shown in Fig. 4.

Table 5 Response table of the signal to noise (S/N) ratio

Level	A	B	C	D
1	32.092	27.295	29.872	39.769
2	35.929	36.543	35.261	26.183
3	33.985	34.810	37.885	28.142
4	34.793	37.424	34.863	39.025
5	32.801	33.528	31.719	36.482

Table 6 ANOVA for product weight

Source of variance	Sum of squares	Degrees of freedom	Mean square	F_0	p value
A	7.703E−02	4	1.926E−02	375.802	0.000*
B	1.988E−03	4	4.970E−04	9.700	0.000*
C	1.110E−01	4	2.785E−02	543.591	0.000*
D	1.594E−02	4	3.985E−03	77.777	0.000*
Error	5.534E−03	108	5.124E−05		
Total	2.119E−01	124			

*$p \leq 0.0001$

3.4 Hybrid BPNN–DFP and BPNN–GA search approaches to optimize the system

To optimize the process parameter settings of the proposed optimization system, an effective GA was coupled with the BPNN model to yield a global optimal solution. In addition, the DFP method was combined with the BPNN model to produce a local optimal solution. Experimental data of the Taguchi method were used to effectively train and test the BPNN model that finely maps the relationship between the input process control factors and the output response. In this application, the objective function of the DFP method and the fitness function of the GA were minimized by optimizing four independent process parameters, namely, the injection time, velocity pressure switch position, packing pressure, and injection velocity. Product weight was the target quality which was the output value of the BPNN model. The mathematical formulation of the objective function of the DFP method and the fitness function of the GA with the ranges of process parameters were the same and are given as follows [16]:

$$\begin{array}{ll} \text{Min} & F(X) = (y_o - y_t)^2 \\ \text{s.t.} & \\ & \mathrm{LSR}_i \leq x_i \leq \mathrm{USR}_i \quad i = 1, 2, 3 \cdots m \end{array} ; \tag{14}$$

where $X = (x_1, x_2, x_3 \cdots x_m)$ is the process control parameters; y_o is the predicted value (weight); y_t is the target

Table 7 ANOVA for the signal to noise (S/N) ratio

Source of variance	Sum of squares	Degrees of freedom	Mean square	F_0	p value
A	121.771	4	30.443	1.013	0.944
B	129.475	4	32.369	1.078	0.380
C	161.149	4	40.287	1.341	0.587
D	162.766	4	40.691	1.354	0.086
Error	240.323	8	30.040		
Total	815.483	24			

*$p \leq 0.0001$

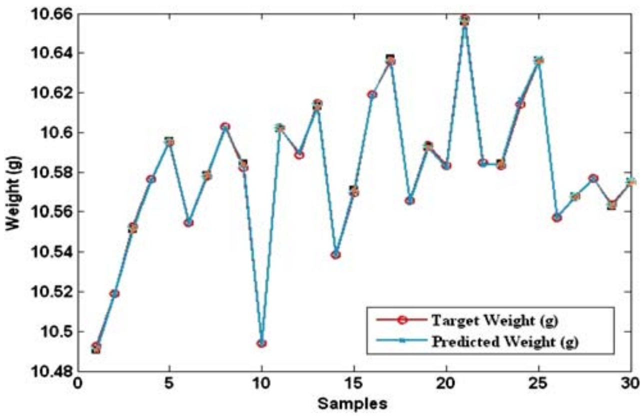

Fig. 4 Comparison between the target and predicted values

value (weight); x_i is the notation of process parameter i, and m is the total number of parameters. LSR_i and USR_i are the lower and upper search ranges of process parameter i, respectively. The method of setting LSR_i and USR_i is given as follows:

$$\mathrm{LSR}_i = \mathrm{PS}_{ni} - \frac{D_i}{2} \qquad \text{and} \tag{15}$$

$$\mathrm{USR}_i = \mathrm{PS}_{ni} + \frac{D_i}{2} \qquad ; \tag{16}$$

where PS_{ni} is the process parameter setting value of parameter i which generates the highest S/N ratio of the response n, and D_i is the factor level's equivalent range of parameter i in the Taguchi experiment. The initial values of parameter variables $X^{(0)}$ for both the hybrid BPNN–DFP search approach and the hybrid BPNN–GA search approach were the preliminary initial process parameter settings obtained from the Taguchi method. Therefore, the initial values of parameter variables $X^{(0)}$ were an injection time of 1.4 s, a velocity pressure switch position of 7.7 mm, a packing of pressure 45 MPa, and an injection velocity of 49 mm/s. According to Eqs. 14, 15, and 16, the search

Table 8 Optimal process parameter settings for both the BPNN–DFP and BPNN–GA approaches

	IT (s)	VP (mm)	PP (MPa)	IV (mm/s)
BPNN–DFP approach	1.39	7.70	44.8	49.0
BPNN–GA approach	1.44	7.68	43.0	48.9

Table 9 Comparisons of quality statistics among the Taguchi, BPNN–DFP, and BPNN–GA approaches

	Average	Standard deviation	C_{pk}
Taguchi approach	10.5739	0.0071	0.585
BPNN–DFP approach	10.5805	0.0035	1.69
BPNN–GA approach	10.5794	0.0021	2.75

ranges of process parameters in the GA or DFP method can be obtained as follows:

$$\begin{aligned} &1.35 \le x_1 \le 1.45, \quad 7.6 \le x_2 \le 7.8, \\ &42.5 \le x_3 \le 47.5, \quad 47.5 \le x_4 \le 50.5. \end{aligned} \tag{17}$$

For this research, a Visual Basic program was developed to effectively determine the final optimal process parameter settings of the illustrative example. The target value of product weight was 10.58 g.

4 Experimental results and discussion

Following the hybrid BPNN–DFP and hybrid BPNN–GA search approaches, the final optimal process settings are shown in Table 8. To demonstrate the effectiveness of the proposed optimization system, this research performed three confirmation experiments. One experiment utilized preliminary initial process parameter settings obtained from the Taguchi method. The other two experiments utilized the final optimal initial process parameter settings obtained from the hybrid BPNN–GA and BPNN–DFP search approaches, respectively. Each experiment produced 30 product samples. The statistical averages, standard deviations, and process capability indices of all three methods were compared in order to judge the best approach for determining the final optimal process parameter settings.

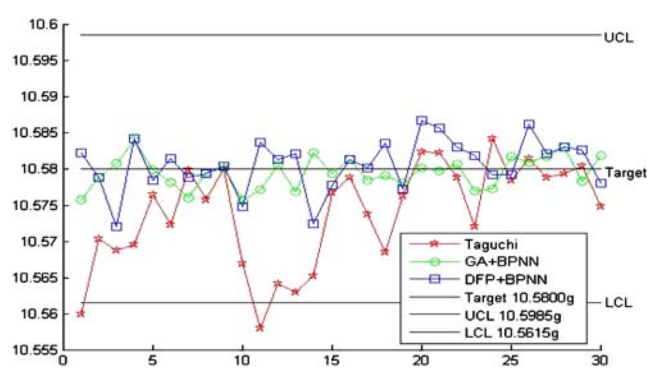

Fig. 5 Comparisons of quality characteristics (weight) among the Taguchi, BPNN–DFP, and BPNN–GA approaches

Comparisons of quality statistics between the Taguchi, BPNN–DFP, and BPNN–GA approaches are shown in Table 9. In addition, comparisons of quality characteristics (weight) between the Taguchi, BPNN–DFP, and BPNN–GA approaches are shown in Fig. 5. According to the experimental results, the standard deviation of the Taguchi approach was 0.0071. That is approximately two times that of the BPNN–DFP approach (0.0035) and 3.5 times that of the BPNN–GA approach (0.0021). In the practical assessment, the process capability index is a major criterion for assessing the ability of a production process to make products that meet specifications. The practical minimum process capability index (C_{pk}) is 1.33 in many manufacturing industries. If the process capability index (C_{pk}) is <1.33, then manufacturers will not achieve a high yield rate and may produce many nonconforming products. Therefore, this research utilized the process capability index as the major criterion for the quality requirement. As the results in Table 9 show, the C_{pk} of Taguchi's approach was 0.585; which is roughly one third that of the BPNN–DFP approach (1.69) and one fifth that of the BPNN–GA approach (2.75). Consequently, the optimal process parameter settings generated by the proposed two approaches definitely produced better performances than the Taguchi method. Experimental results also revealed that the BPNN–GA approach produced the highest C_{pk} value and the best-quality products. The BPNN–DFP approach did not perform quite as well but was still better than the original process parameter calculation method (the Taguchi method). The main reason is that the BPNN–GA approach is a global search methodology for determining an optimal solution, whereas the BPNN–DFP approach is a local search methodology for finding an optimal solution. The Taguchi method can only find the best set of specified process parameter level combinations which comprises discrete setting values of the process parameters. The plastic injection molding industry produces myriad products, and each product has its own optimal machine settings. An unsuitable process parameter setting can cause many defective products and unstable product quality during the injection molding process. In comparing the three methods to arrive at those parameters settings, the BPNN–GA search approach was clearly the best. Therefore, the proposed optimization system is practical and effective for parameter optimization in the plastic injection molding process.

5 Conclusions

Costs of production in plastic injection molding are directly affected by strategies for choosing parameter settings, especially when setting up production runs. Setup strategies have traditionally relied on some combination of skilled trial and error, plus the Taguchi method. These traditional strategies, however, often produce less than optimal results. In seeking to alleviate some of those shortcomings, this research made use of the Taguchi method, adding back-propagation neural networks, genetic algorithms, the Davidon–Fletcher–Powell method, and engineering optimization concepts to determine efficient strategies that optimize both the setup process and product quality. Test results showed that measurably better performance was obtained using a tailored combination of approaches than with the Taguchi method alone. Specifically, the Taguchi method with BPNN plus DFP and BPNN plus GA and statistical techniques optimally predicted process parameter settings for MISO plastic injection molding setup procedures. Application of these simple techniques produced dramatic improvements in productivity by: (1) improving the quality of the parts produced; (2) reducing the number of rejects produced; (3) reducing waste or the regrinding of rejects; (4) reducing inspection times required during production; and (5) improving the scheduling of production. Thus, the proposed system is a feasible and effective method for process parameter optimization of MISO plastic injection molding and can result in significant quality and cost advantages.

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