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Determination of Optimal Manufacturing Parameters for Injection Mold by Inverse Model Basing on MANFIS

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ABSTRACT

Since plastic products are with the features as light, anticorrosive and low cost etc., that are generally used in several of tools or components. Consequently, the requirements on the quality and effectiveness in production are increasingly serious. However, there are many factors affecting the yield rate of injection products such as material characteristic, mold design, and manufacturing parameters etc. involved with injection machine and the whole manufacturing process. Traditionally, these factors can only be designed and adjusted by many times of trial-and-error tests. It is not only waste of time and resource, but also lack of methodology for referring. Although there are some methods as Taguchi method or neural network etc. proposed for serving and optimizing this problem, they are still insufficient for the needs. For the reasons, a method for determining the optimal parameters by the inverse model of manufacturing platform is proposed in this paper. Through the integration of inverse model basing on MANFIS and Taguchi method, inversely, the optimal manufacturing parameters can be found by using the product requirements. The effectiveness and feasibility of this proposal is confirmed through numerical studies on a real case example.

***Keywords**: Optimal Manufacturing Parameter, Injection Mold, Multiple Adaptive Network Based Fuzzy Inference System (Manfis), Taguchi Method*

1. Introduction

Recently for the surge in the prices of fuel and raw materials like steel or iron, plastic goods used in industries and everyday life are taking the place of metal ones. Generally, since those products combined by pieces of parts required higher precision and smoothness, the demands on quality and efficiency of production become higher than before. In order to level up the yield rate of made-up articles, the manufacturing process should be improved for the required of different goods [1]. Nowadays, for coping with the diversifying demands of present markets, developed countries in industry have been introducing the technologies of computer-integrated manufacture (CIM) as CAE/CAD/CAM to get competitive advantages [2–3]. That is, for the manufacturing process of an industrial product with completed design, first, its prototype is designed by the original concept. Next, through computer-aided design (CAD) tool complete the initial design. Third, by the analysis technology of computer-aided engineering (CAE) to test and modify the design. Finally, depending on the better design, automotive production can be done by computer-aided manufacture (CAM).

Before concurrent engineering attracting much attention, the technologies of computer-aided engineering analysis were seldom used to estimate designing faults by manufacturers in advance. Where, mold design and manufacturing process should be modified through many times of trial-and-error tests [4–6]. It not only wastes time and cost but also makes such experiences became more difficult in teaching or accumulating. Besides, under the situation of different product required or new materials, the awkward problems as one more times of teaching experience and molding can not be avoided. Sometimes part of business chances may be losing for it.

The most helpful function of CAE is to carry out simulation analysis of prototype design by computers [6]. By which, all possible problems and faults occurring in manufacturing and design stages can be found in advance. It is convenient to diagnose and modify designed before product manufacture for reducing cost and time, and leveling up quality. However, even though those modern computer-aided technologies as mentioned above play an important role in manufacture, the subject of how to determine optimal manufacturing parameters for extremely matching product required still exists [7–24]. Although there are a lot of methods such as statistical regression calculation, neural network model and genetic algorithm, grey relational analysis, and fuzzy theory etc. proposed for optimizing parameters [25–30], lacking of methodology and integration. For it, a concept for building the inverse model of manufacturing platforms by multiple adaptive network fuzzy inference system (MANFIS) is proposed. Through data self-organized and deductive reasoning mechanisms of MANFIS, the optimal manufacturing parameters corresponding to product required can be found. In this paper, the blade of a small-scale wind power generator is selected as a real case studying on injection mold. Through the simulation results by computer-aided analysis software Moldex3D, the appropriateness and effectiveness of the proposal can be confirmed.

2. Solution Design and Problem Statement

2.1 Solution Description

The main purpose of this study is to determine the optimal manufacturing parameters for injection mold. According to the literatures mentioned above know that the manufacturing parameters of injection mold are highly interdependent. That is, the whole system should be considered while part of parameters is undertaken to modify. Here, a method for finding out the optimal parameters is proposed. Figure 1 shows the executing flow of the method. First, since there are always a lot of manufacturing parameters as well as controllable factors existing, in order to realize which ones are the key factors and reduce time and flows in computation, a less number of important factors with more controllability can be extracted through the calculation of Taguchi method. Next, instead of all possible experimental combinations to simulator, the orthogonal arrays basing on those important factors are developed. In addition, for the results found by Taguchi method are unique, and possibly trapping in local optimum, a decimal-fraction random matrix as the numerical stirring is introduced into the orthogonal arrays for wider-range simulation. Finally, by using the simulated results such as warpage displacement or volumetric shrinkage etc. along with the corresponded orthogonal arrays, the proposed inverse model can be built through MANFIS.

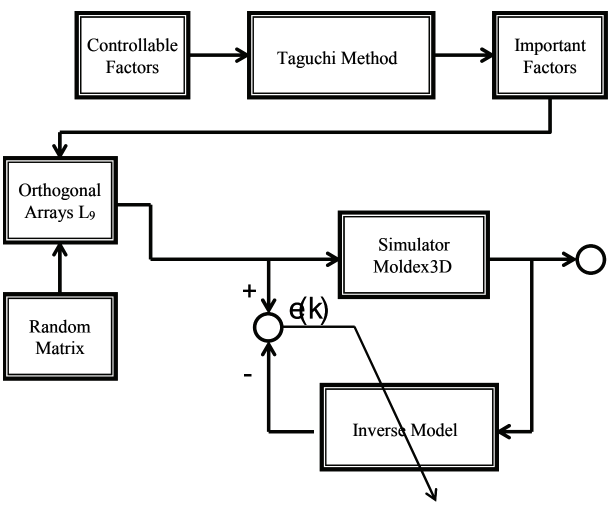


Figure 1. Flow of proposed method

2.2 Real Case Selection

The real case selected for confirming the proposed method is the manufacturing design of a blade for a small-scale wind power generator. Since the blades are the key part of such generators for their generation efficiency and cost, the weight, smoothness, surface friction, physical stress, and twisting angles etc. of them are required seriously in manufacture. In addition, instead of FRP which is denounced by its environmental pollution, the material ABS_NovodurP2GHV_1 is adopted to study. Here, through the analysis of momentum theory and blade element model, the geometric data of the blade is determined as shown in Figure 2. Moreover, the hot and cooling distributions by one-point injection and four groups of cooling runners are shown in Figure 3.

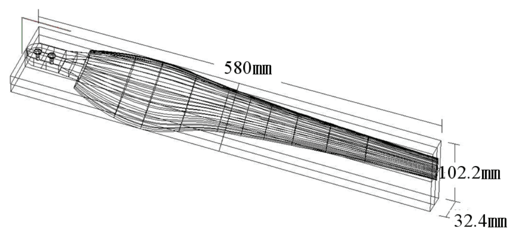


Figure 2. Studying case designed by 3D's flow

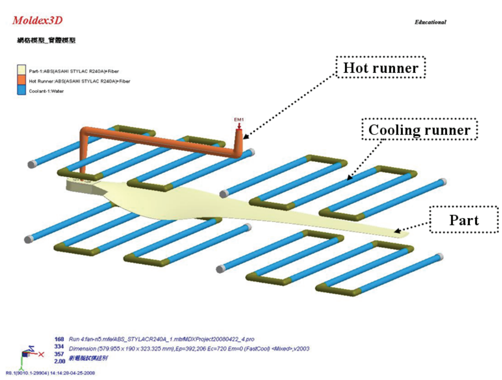


Figure 3. Distribution of hot runner and cooling runner

3. Numerical Studies

Since the initial controllable factors are always selected by the product required. Through the analysis of fish bone diagram shown in Figure 4 and the consideration of required product strength, there are eight factors selected such as fiber percentage of material, material temperature, injection pressure, holding time, holding pressure, mold temperature, cooling time, and filling time.

3.1 Selection of Important Factors by Taguchi Method

Two major tools used in the Taguchi method are the orthogonal arrays and the signal-to-noise ratio. Additional details and application of Taguchi method can be found in the books presented by Phadke [31], Montgomery [32], and Park [33]. In this paper, three- level orthogonal arrays are used. The design parameters and the levels chosen for the Taguchi experiments are listed in Table1. Continuously, a L_{18} (3^8) orthogonal arrays with eight columns and eighteen rows can be developed as shown in Table 2. Each design parameter has three levels assigned to each column of the arrays. The eighteen rows represent the eighteen experiments to be conducted.

Since the assessing indices are the warpage displacements and volumetric shrinkages in three dimensions as x, y, and z axes, respectively, through the computations of simulator Moldex3D all indices corresponding to all experimental combinations in L_{18} (3^8) orthogonal arrays can be found. By substituting these indices into Equations

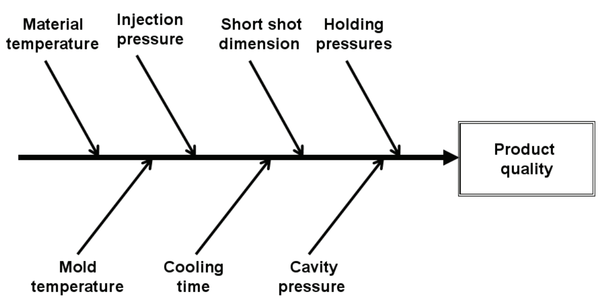


Figure 4. Fish bone diagram for factor analysis

Table 1. Eight controllable factors with three levels

level / factor	1	2	3
A. (%) percentage of fiber contents	20	16	
B. (℃) material temperature	210	225	240
C.(MPa) injection pressure	90	105	120
D. (S) holding time	2	4	6
E. (MPa) holding pressure	63	73.5	84
F. (℃) mold temperature	50	70	87
G. (S) cooling time	10	20	30
H. (S) filling time	2.3	3.65	5

1 to 3, the important factors and optimal combination for Taguchi method can be extracted and found by assessing the quality characteristic (in Figure 5) and signal-to-noise ratio (in Figure 6). By above results realized that the factors with more controllability as mold temperature, material temperature, injection pressure, and holding time are selected as the important factors.

$$\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{1}$$

$$S = \sqrt{\frac{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2}{n-1}} \tag{2}$$

$$S/N = -10 \quad log \frac{S^2}{\bar{y}^2} \tag{3}$$

3.2 Collection of Training Data Sets

For training the inverse model to be with more comprehensively deductive reasoning, all possible combinations basing on the changes of four important factors should be collected in general. However, it would be a cumbersome task for experiment or computation. For the main advantages of orthogonal arrays including experimental plan simplification and feasibility of studying interaction effects among the different parameters, a L_9 (3^4) orthogonal arrays developing with three levels (Table 3) from above four important factors is built as shown in Table 4. Moreover, for more detailed numerical data, a random matrix (Table 5) as well as a stirring is introduced into the L_9 (3^4) orthogonal arrays. Table 6 shows the input-output training data sets through the computation of simulator Moldex3D.

Table 2. L_{18} (3^8) orthogonal arrays

Exp	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

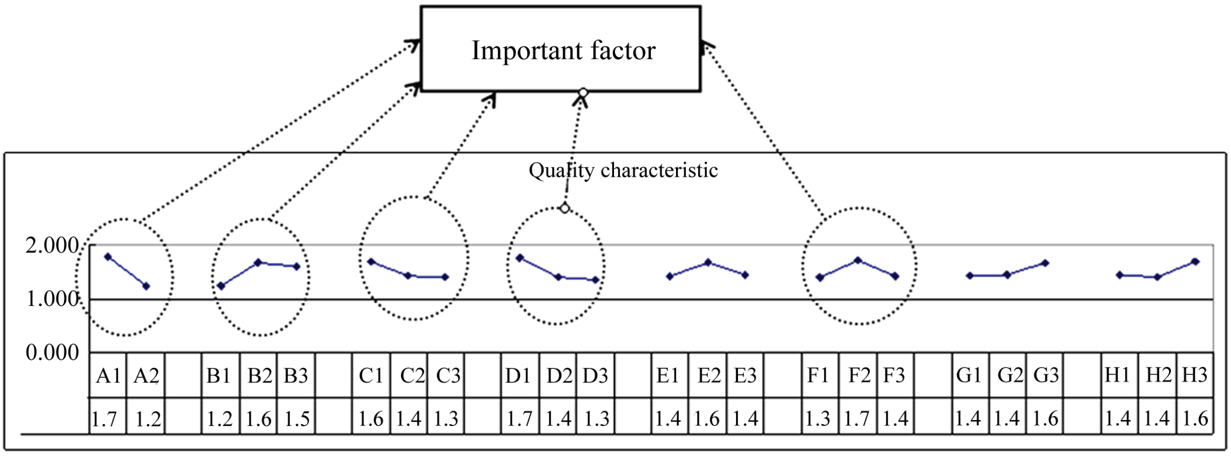


Figure 5. Quality characteristic (2、B1、C3、D3、E1、F1、G1、H2)

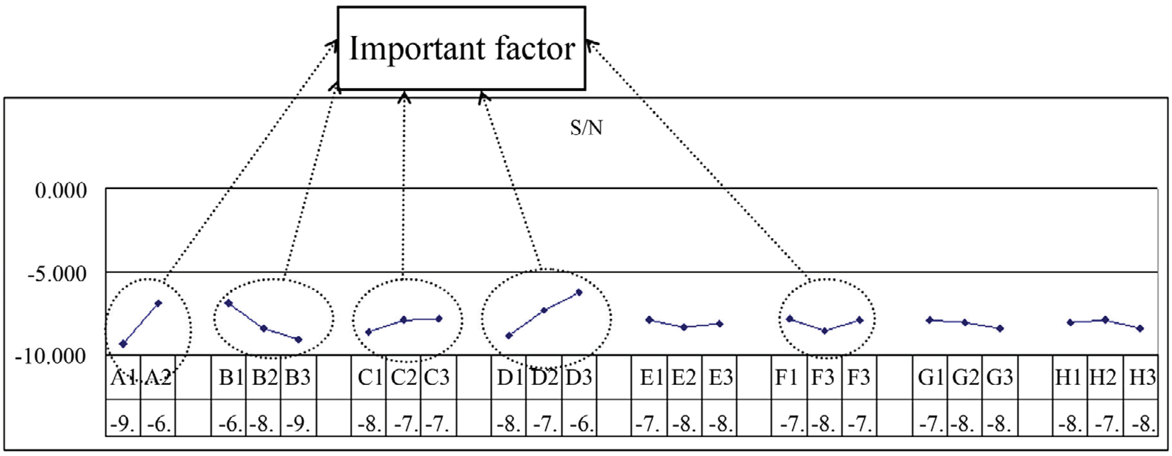


Figure 6. S/N ratio (A2、B1、C3、D3、E1、F1、G1、H2)

Table 3. Four important factors with three levels

level / factor	1	2	3
B. (℃) material temperature	220	240	260
C.(MPa) injection pressure	110	120	130
D. (S) holding time	4	6	8
F. (℃) mold temperature	45	50	55

Table 4. L_9 (3^4) orthogonal arrays

Exp	B	C	D	F
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 5. Random matrix example

0.95	0.2311	0.6068	0.486
0.891	0.7621	0.4565	0.0185
0.821	0.4447	0.6154	0.7919
0.922	0.7382	0.1763	0.4057
0.935	0.9169	0.4103	0.8937
0.058	0.3529	0.8132	0.0099
0.139	0.2028	0.1987	0.6038
0.272	0.1988	0.0153	0.7468
0.445	0.9318	0.466	0.4187

3.3 Inverse Model

The proposed inverse model for finding out the optimal manufacturing parameters corresponding to product required is built by MANFIS (in Figure 7), which is an extension of ANFIS to produce multiple real responses of the target system. The number of ANFIS is equal to the number n of responses. ANFIS is a fuzzy inference

Table 6. Training data sets for MANFIS

exp	B	C	D	F	X	Y	Z	V
1	220.9	110.2	4.6	45.4	0.402	0.053	-0.129	4.14
2	220.8	120.7	6.4	50.0	0.581	0.058	-0.109	3.962
3	220.8	130.4	8.6	55.7	0.302	0.132	-0.038	3.774
4	240.9	110.7	6.1	55.4	0.326	0.017	-0.083	4.774
5	240.9	120.9	8.4	45.8	0.358	0.004	-0.106	4.568
6	240.0	130.3	4.8	50.0	0.577	-0.041	-0.137	4.888
7	260.1	110.2	8.1	50.6	0.305	0.028	-0.166	5.32
8	260.2	120.2	4.0	55.7	0.483	-0.068	-0.238	5.796
9	260.4	130.9	6.4	45.4	0.69	0.096	-0.131	5.515

X：warpage displacement in x axis
Y：warpage displacement in y axis
Z：warpage displacement in z axis
V：warpage-volumetric shrinkage

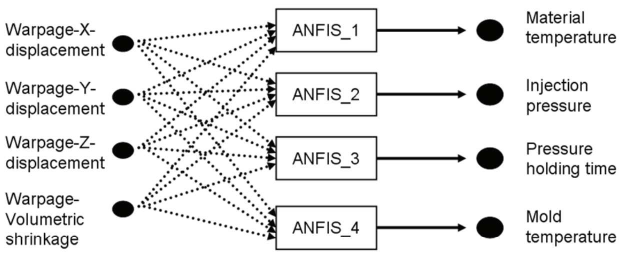


Figure 7. The structure of MANFIS

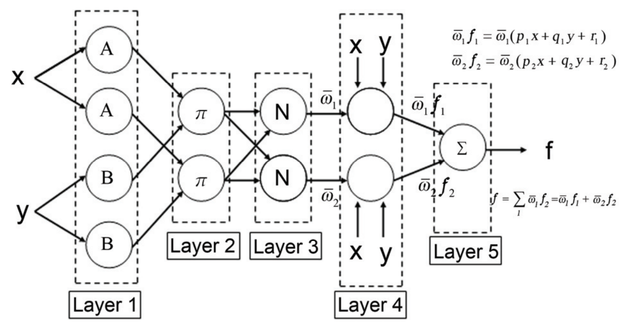


Figure 8. Five-layer structure of ANFIS

system (FIS) implemented in the framework of an adaptive fuzzy neural network. FIS is the process of formulating the mapping from a given input to an output using fuzzy logic.

ANFIS is based on Tagaki-Sugeno FIS. ANFIS generally has two inputs, one output and its rule base contains two fuzzy if-then rules:

Rule l: If x is A_1 and y is B_2 then $f_1 = p_1 + q_1 + r_1$.

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 + q_2 + r_2$.

The five-layered structure of this ANFIS is depicted in Figure 8. The detailed description about it can refer to the studies by R. Jang *et al.* [34–37]. Here, by using the training data sets in Table 6 and through thirty times of training, the errors of the unknown constants in each node of MANFIS have been convergent.

4. Analysis and Discussion

For a complete-trained inverse model that is charac- terized with the inverse function of the simulator Moldex3D as well as manufacturing platform. That is, the manufacturing parameters can be found by the product required inversely. Here, the correlations between two kinds of product required and one manufacturing parameter are shown by 3D mesh diagrams in Figure 9. In addition to identify the reasonable areas for product required, the limits to the four important factors in the real case are set as following; mold temperature: over $40^\circ C$, material temperature: over $210^\circ C$, injection pre- ssure: over 90Mpa, holding time: the smaller warpage the better.

Moreover, for the convenience in observation, the reasonable intervals of each product required are summarized in Table 7.

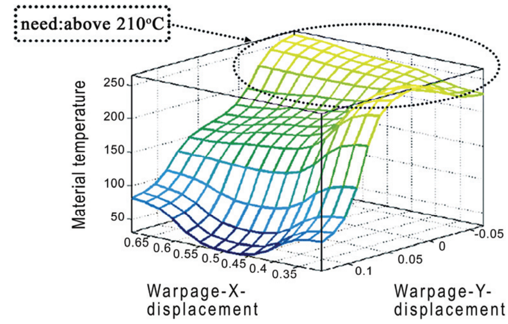
In order to confirm the reliability and preciseness of inverse model, two groups of numerical comparisons are made as shown in Table 8. Here, by comparing with the inputs of inverse model with the outputs of simulator which are corresponding to the outputs of inverse model, the differences between them are tolerably small. This appropriate performance of inverse model also can be observed in Figure 10.

Table 7. Reasonable intervals for product requirements

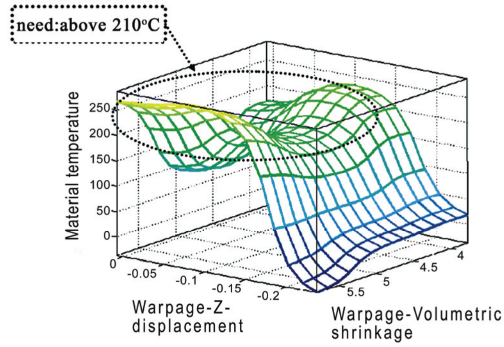
Product required \ factor	B	C	D	F
X(㎜)	0.302~0.65	0.302~0.65	0.302~0.4	0.302~0.5
Y(㎜)	-0.05~0.05	-0.025~0.075	-0.05~0.05	-0.05~0.1
Z(㎜)	-0.15~0.008	-0.175~0.008	-0.1~0.008	-0.15~0.008
V(%)	4	4	4	4

Table 8. Reliability performance of inverse model

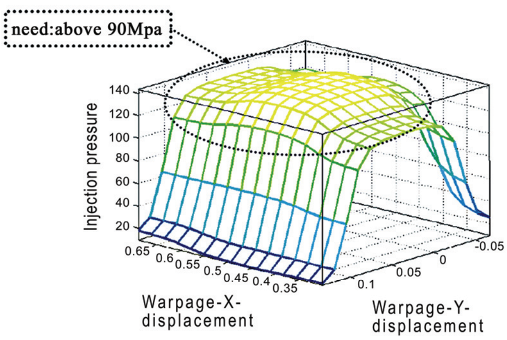
group	Inverse Model								Simulator Moldex3D			
	Input				Output				Output			
	X	Y	Z	V	B	C	D	F	X	Y	Z	V
1	0.302	0.09	0.008	4	220	126	7.26	43.4	0.504	0.012	-0.102	3.851
2	0.302	0.09	-0.07	4	215	108	6.28	57.9	0.346	0.016	-0.028	3.738



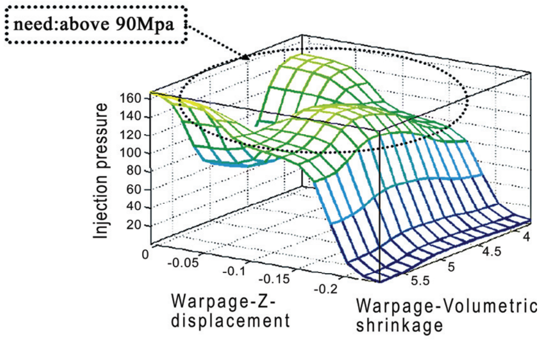
a. warpage-x-displacement and warpagey-displacement to material temperature.



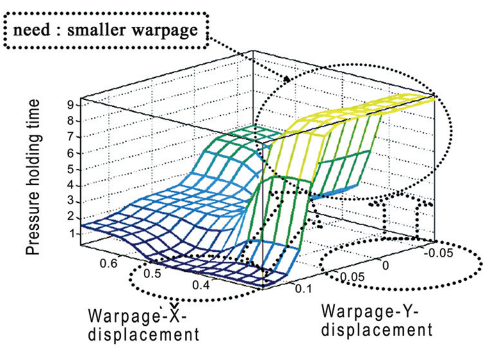
b. warpage-z-displacement and warpage-volumetric-shrinkage to material temperature.



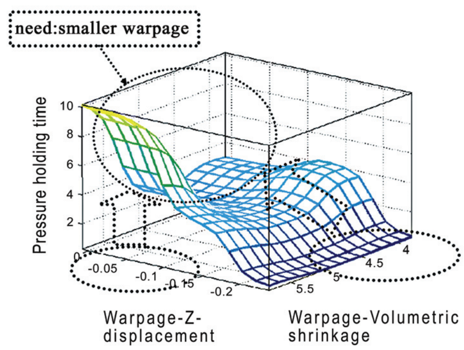
c. warpage-x-displacement and warpage-y-displacement to injection pressure.



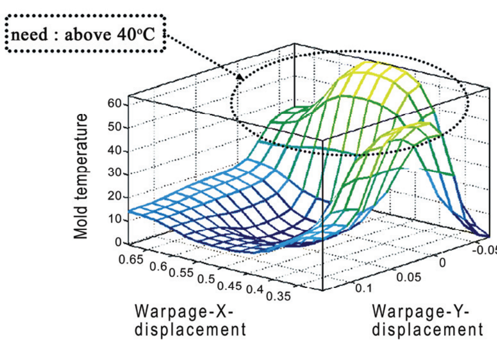
d. warpage-z-displacement and warpage-volumetric-shrinkage to injection pressure.



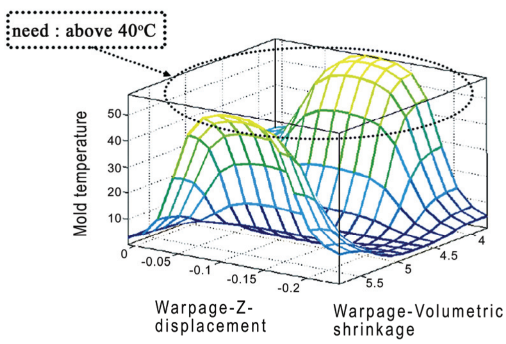
e. warpage-x-displacement and warpage-y-displacement to pressure holding time.



f. warpage-z-displacement and warpage-volumetric-shrinkage to pressure holding time.



g. warpage-x-displacement and warpage-y-displacement to mold temperature.



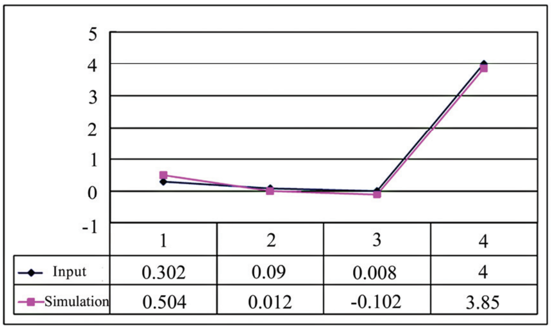
h. warpage-z-displacement and warpage-volumetric-shrinkage to mold temperature.

Figure 9. Correlations between two product requirements and one manufacturing parameter in 3D mesh diagrams

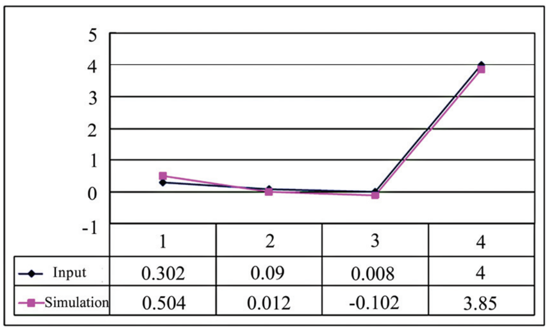
Table 9. Optimized comparisons between Taguchi method and proposed method

factor / method	B	C	D	F
Taguchi method	220℃	130Mpa	8s	55℃
Proposal	215℃℃	108Mpa	6.28s	57.9℃

requirement / method	X	Y	Z	V
Taguchi method	0.46mm	0.09mm	0.008mm	3.79%
Proposal	0.346	0.016	-0.028	3.74%



a. Group 1



b. Group 2

Figure 10. Reliability performance of inverse model by two groups of data

As mentioned above, although it is easy to find out the optimal manufacturing conditions subjected to single quality required by Taguchi method, in the situation of requiring multiple qualities simultaneously, it is difficult to cope with the problem. Besides, for the changing levels of each controllable factor are ambiguous, it is possible to trap the solution in local optimum. The results are shown in Table 9 just can respond above problem. Where, by examining the manufacturing factors and product required found by Taguchi method and the proposed method, respectively, it can be found that the performance of proposed method is better than that done by Taguchi method.

5. Conclusions

For solving the optimal problem in manufacturing design of injection mold, the method basing on the concept of inverse model is proposed in this paper. Through the method, the optimal manufacturing parameters can be found by using the product required inversely. In addition, the effectiveness and appropriateness of the proposal are confirmed by the numerical studies on the real case. Yet the studied results show that the proposed method not only can improve the insufficiencies of Taguchi method but also offers a more précising and concise approach for the optimization of manufacturing design.

6. Acknowledgments

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