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Optimal Parameter Selection in Gas-Assisted Injection Molding : A Comparison of Neural Network Models and the Taguchi Method

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ABSTRACT

A statistical Taguchi approach and a backpropagation neural network model were utilized to evaluate the effect of various parameters and to determine the optimal parameter setup values in a gas-assisted injection molding process. In the application of the Taguchi approach, an L18 orthogonal array was used to collect the observations. The same data set was utilized to construct a neural network model and to determine if the utilization of a neural network would provide improved generalization capability over the statistical method. The effect of the learning rate and the number of hidden nodes on the efficiency of the neural network learning algorithm was extensively studied to identify the learning rate and the number of hidden nodes that resulted in the best network performance. In addition, to verify the generalization capability of neural model, eight different parameter setups, not all included in the full factorial design, were constructed for network testing. The results show that the neural network has a higher chance than the Taguchi experimental design approach of finding the optimal parameter setup.

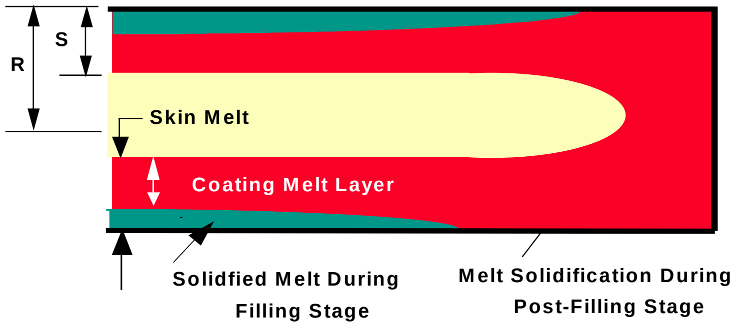
Keywords: Gas-Assisted Injection Molding, Taguchi Method, Orthogonal Array, Artificial Neural Network, Backpropagation Learning Algorithm

I. INTRODUCTION

Gas-assisted injection molding is one of the innovative multicomponent injection molding processes developed in the recent years. The mold is first partially filled with a polymer melt followed by the injection of inert gas through a nozzle or other designed locations in the mold cavity (Rush, 1989; Schwartz, L.W., 1986). During the primary gas penetration period, the injected gas hollows out the melt core and pushes the melt to fill the mold cavity. During the post-filling stage, the gas continues to penetrate as a result of melt shrinkage and exerts uniform pressure on the molded part until the part is sufficiently solidified and ejected. This innovative technology can substantially reduce operating expenses in terms of reduction in material cost, in clamp tonnage, and in cycle time.

Several new processing parameters which must be closely controlled are introduced even thought gas-assisted injection provides many advantages. In order to describe the polymer melt flow in thin cavities and find the optimal values for the impact variables, a simulation model based on the Hele-Shaw type of flow was developed nearly a decade ago. These simulations provide acceptable forecastings from the engineering application perspective. The appearance of gas-assisted injection molding requires a new model that can handle both gas and melt flows in thin parts laid out with gas channels. Numerical simulation is one possible way to establish a general model or empirical formula describing the thickness variation of skin melt existing between the gas/melt interface and the cavity wall (Figure 1) as a function of processing parameters, melt properties and/or flow geometry (Chen, et.al, 1996; Turng, 1992). But the correlation of skin melt thickness to all contributing parameters by a mathematical model is quite a complicated issue. Theoretical and experimental investigations on bubble/liquid displacement in a tube were previously reported (Bretherton, 1960; Cox, 1962; Kolb, et. al, 1991; Reinelt, et. al, 1985; Shah, 1991; Taylor, 1960). The investigations showed that surface tension at the liquid/bubble interface plays an important role in determining the interface shape of the bubble nose as well as the coating film thickness. Also, the thickness ratio of coating film approaches a limiting value at higher capillary numbers. For gas penetration within the polymer melt, the correlation of skin melt thickness variation with capillary number or other processing parameters is far more complicated than those reported for different types of molding. Recent experiments studying the effect of melt temperature mold temperature, gas delay time as well as gas pressure on skin melt thickness variation were reported by several researchers (Burton, et. al, 1994; Chen, et. al, 1995; Findeisen, 1994).

Another alternative methodology to explore the relationship between parameters and to find the optimal setup values is the Taguchi approach to experimental design. The utilization of the Taguchi method of experimental design to estimate the optimal settings for the parameters in the gas-assisted injection molding process was recently addressed by Hsu (1995). Similar explorations have been done by many researchers (Hunter, 1985; Kackar, 1985; Nair, 1992; Pignatiello, 1988; Pignatiello, et. al, 1991-1992; Wild, et. al, 1991). A brief description of this approach and the results are presented in this research. The best parameter setup among the full factorial design combinations can be successfully identified by applying the Taguchi method, however the optimal parameter values in the complete region (i.e. not within the full factorial design combinations) can not be guaranteed (Pignatiello, 1988).



$$\text{Skin melt ratio} = \frac{S}{R}$$

$$\text{Hollowed core ratio} = \frac{R - S}{R}$$

Figure 1. Schematic of Gas Penetration Along a Gaswise Direction

To overcome this shortcoming, a neural network approach for planning the designed experiment is proposed. The generalization capability of the neural model is expected to provide a good forecast of the experimental result. A neural network based on the training data set used in the Taguchi analyses was constructed. Several extra experiments that were not included in the full factorial design combinations were collected and used to test the constructed network model. The results show that the neural network performed well and has a higher opportunity that the Taguchi technique to find the optimal parameter setup. In addition, the strong functional mapping capability of the neural network model provides a more effective experimental design methodology by combining neural networks and traditional experimental design methods.

II. THE UTILIZATION OF TAGUCHI METHOD

Gas-assisted injection technology provides advantages in the molding process. But it also introduces several new parameters which make the process more complicated. The Taguchi method was used to determine optimal setting values in the molding process as proposed by Hsu (1995). The settings of impact variables are first chosen to optimize the performance measure and, then, the factors found to have no influence on the performance measure are utilized to adjust the results (Hunter, 1985). Shah (1991) has applied this approach and used an *L8* orthogonal array to explore a new product. But because the parameter level is restricted to two in the *L8* orthogonal array and nonlinear characteristics exists among the parameters in the gas-assisted injection molding process, the *L18* orthogonal array was utilized in this case to provide the sufficient degrees of freedom (Hsu, 1995). In the Hsu works, a computer aided engineering (CAE) package was developed to identify the impact parameters in the gas-assisted injection molding process and eight controllable factors were found. These factors were: (A) mold temperature--the temperature at which the mold is set, (B) melt temperature--the temperature at which melting occurs, (C) injection speed--the injection velocity of the assisted gas, (D) gas injection time--the length of time that the gas is injected, (E) gas pressure--the amount of gas pressure used in the process, (F) gas distance-the length of distance that the gas gets through, (G) gas delay time--the length of time that the gas is delayed in the process and (H) constant pressure time--the length of time that the constant pressure is used. All of these factors have 3 levels except the mold temperature (2 levels). The levels of each factor studied in Hsu experiment are reproduced in Table 1.

Table 1. Levels of Factors Studied in the Experiment

		Levels		
Letter	Factor	Low	Medium	High
A	Mold Temperature (^{0}C)	40		60
B	Melt Temperature (^{0}C)	230	240	250
C	Injection Speed (%)	50	60	70
D	Gas Injection Time (Sec)	1.0	1.5	2.0
E	Gas Pressure (Bar)	90	110	130
F	Gas Distance (mm)	64	65	66
G	Gas Delay Time (Sec)	0.0	0.5	1.0
H	Constant Pressure Time (Sec)	0	3	6

The Taguchi *L18* orthogonal array was used as the inner array to design the data collection plan as shown in Table 2. There is only one response variable (Y), calculated on 5 observations at each of the 18 inner array experimental design points. The signal to noise ratio (Z) was used as the response of interest (see Table 3). This response (Z) is calculated over the 5 points in the outer array. Since the objective is to make the gas penetration period as long as possible, that is, we want the length of the gas channel as small as possible, Z is calculated as (Kackar, 1985).

$$Z = -10\log(\sum y_i^{\,2} / n) \qquad \textbf{(1)}$$

where y_i is the random sample from the distribution of Y which is the performance characteristic and $n=5$ is the number of observations.

Table 2. The Used L18 Orthogonal Array and the Corresponding Data

1	2	3	4	5	6	7	8						
A	B	C	D	E	F	G	H	y_1	y_2	y_3	y_4	y_5	$\bar{y}$
1	1	1	1	1	1	1	1	42	40	57	68	74	56.3
1	1	2	2	2	2	2	2	71	76	74	74	75	74.2
1	1	3	3	3	3	3	3	84	80	83	80	82	81.9
1	2	1	1	2	2	3	3	37	29	34	38	41	35.5
1	2	2	2	3	3	1	1	117	115	121	123	116	118.5
1	2	3	3	1	1	2	2	37	36	36	39	36	36.7
1	3	1	2	1	3	2	3	85	87	88	93	90	88.4
1	3	2	3	2	1	3	1	28	26	24	25	29	26.3
1	3	3	1	3	2	1	2	84	79	84	79	73	79.8
2	1	1	3	3	2	2	1	74	84	64	69	65	71.2
2	1	2	1	1	3	3	2	84	87	95	88	94	89.6
2	1	3	2	2	1	1	3	71	68	68	70	65	68.6
2	2	1	2	3	1	3	2	25	24	25	28	24	25.2
2	2	2	3	1	2	1	3	88	88	89	90	79	86.8
2	2	3	1	2	3	2	1	114	124	125	117	118	119.6
2	3	1	3	2	3	1	2	106	106	104	99	107	104.4
2	3	2	1	3	1	2	3	31	41	43	36	40	38.3
2	3	3	2	1	2	3	1	60	53	58	51	61	56.4

Table 3. Summary Statistics for the Data in Table 2

1	2	3	4	5	6	7	8		
A	B	C	D	E	F	G	H	$\sum_i y_i^2$	Z
1	1	1	1	1	1	1	1	16787	-35.3
1	1	2	2	2	2	2	2	27558	-37.4
1	1	3	3	3	3	3	3	33521	-38.3
1	2	1	1	2	2	3	3	6390	-31.1
1	2	2	2	3	3	1	1	70233	-41.5
1	2	3	3	1	1	2	2	6750	-31.3
1	3	1	2	1	3	2	3	39144	-38.9
1	3	2	3	2	1	3	1	3470	-28.4
1	3	3	1	3	2	1	2	31943	-38.1
2	1	1	3	3	2	2	1	25605	-37.1
2	1	2	1	1	3	3	2	40264	-39.1
2	1	3	2	2	1	1	3	23545	-36.7
2	2	1	2	3	1	3	2	3197	-28.1
2	2	2	3	1	2	1	3	37760	-38.8
2	2	3	1	2	3	2	1	71627	-41.6
2	3	1	3	2	3	1	2	54499	-40.4

2	3	2	1	3	1	2	3	7433	-31.7
2	3	3	2	1	2	3	1	15995	-35.1

The analysis of variance for the response Z is shown in Table 4.

Table 4. Analysis of Variance for the Response Z

Source	SS	df	SSE	F	p-value
A	3.664	1	3.664	9.493	1.08
B	14.154	2	7.077	10.335	4.40
C	8.648	2	4.324	11.203	2.59
D	1.004	2	0.502	1.301	0.08
E	1.305	2	0.652	1.690	0.18
F	194.144	2	97.072	251.482	63.51
G	78.858	2	39.429	102.148	25.65
H	1.932	2	0.966	2.503	0.38
Error	0.773	2	0.386		
Total	304.477	17	17.911		

In the analysis of variance, Hsu observed that F, G, B, C and A are much significant than the other factors respectively. In terms of reviewing the estimates of each effect, the optimal selection of all these factors to minimize Z is A1B2C1D3E3F1G3H2. The detailed description of the analysis can be found in Hsu (1995).

Further experimentation was conducted to determine whether the combination of setup values identified by the Taguchi method was optimal within the experiment. Observations under the A1B2C1D3E3F1G3H2 factor setups were collected. The results are summarized in Table 5. It is observed that the chosen optimal combination did give a Z smaller than all the other factor combination of levels, verifying that the Taguchi method identified the optimal setup within the experiment.

Table 5. Collected Observations Under the A1B2C1D3E3F1G3H2 Factor Setup

A	B	C	D	E	F	G	H	y_1	y_2	y_3	y_4	y_5	$\bar{y}$
1	2	1	3	3	1	3	2	17	19	20	20	17	18.6

Although the Taguchi method successfully provided some insights into the explored parameter regions, several papers have appeared in the recent statistical literature that have focused on some particular shortcoming or technical flaw that has been found with one or more of the tactics of Taguchi (Box, et.al, 1988; Nair, 1992; Pignatiello, et. al, 1991-1992). In 1991-1992, Pignatiello pointed out that parameter design in the

Taguchi method is used to find the region of the design parameters where the performance variability is minimized about a customer-specified target. This is similar to locate the point or areas on the face of a golf club or tennis racket that yields optimal performance. This location is often known as the *sweet spot* of the club or racket but its global optimality can not be guaranteed.

To solve the problems caused by the application of Taguchi methods, neural network theory was used to find the optimal parameter values in the entire region. A neural network is a parallel system of interconnected processing elements that are based on neurobiological models. The network processes information by a dynamic response of the processing elements and their connections to external inputs (Casdagli, 1989). Because of its nonparametric nature, neural network theory has increasingly found use in modeling manufacturing processes. Neural networks are considered for use in offering an alternative approach for forecasting the performance measure under different parameter value combinations.

III. NEURAL NETWORKS

A neural network is a massively parallel system comprised of highly interconnected, interacting processing elements, or units, that are based on neurobiological models (Rumelhart, et.al, 1986). Neural networks process information through the interactions of a large number of simple processing elements or units, also known as neurons. Knowledge is not stored within individual processing units, but is represented by the strength between units (Rumelhart, et. al, 1986). Each piece of knowledge is a pattern of activity spread among many processing elements, and each processing element can be involved in the partial representation of many pieces of information.

Neural networks can be classified into two different categories, feedforward networks and feedback networks (Rumelhart, et. al, 1986). The feedback networks contain neurons that are connected to themselves, enabling a neuron to influence other neurons and itself. Examples of this type of network are Kohonen self-organizing network and the Hopfield network. Neurons in feedforward networks (as shown in Figure 2) take inputs only from the previous layer and send outputs only to the next layer. The ADALINE and backpropagation neural network are two typical examples of this kind of network.

As shown in Figure 2, the neural net consists of a number of nodes or neurons connected by links. The nodes in the neural network can be divided into three layers: the input layer, the output layer, and one or more hidden layers. The nodes in the input layer receive input signals from an

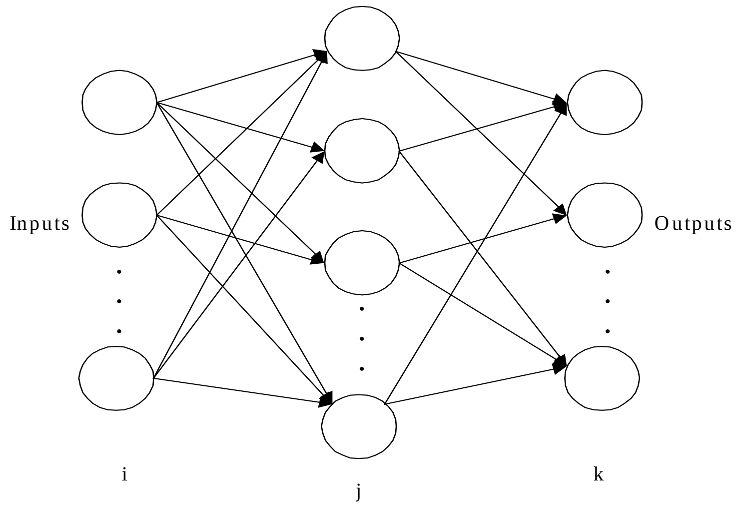


Figure 2. A Backpropagation Neural Network

external source and the nodes in the output layer provide the target output signals.

The output of each neuron in the input layer is the same as the input to that neuron. For each neuron *j* in the hidden layer and neuron *k* in the output layer, the net inputs are given by

$$net_j = \sum_i w_{ji} * o_i \quad \text{and} \tag{2}$$

$$net_k = \sum_j w_{kj} * o_j \tag{3}$$

where *i (j)* is a neuron in the previous layer, o_i (o_j) is the output of node *i (j)* and w_{ji} (w_{kj}) is the connection weight from neuron *i (j)* to neuron *j (k)*. The neuron outputs are given by

$$o_i = net_i \tag{4}$$

$$o_j = \frac{1}{1 + \exp - (net_j + \theta_j)} = f_j(net_j, \theta_j) \tag{5}$$

$$o_k = \frac{1}{1+\exp-(net_k+\theta_k)} = f_k(net_k, \theta_k) \tag{6}$$

where net_j (net_k) is the input signal from the external source to the node j (k) in the input layer and θ_j (θ_k) is a bias. The transformation function shown in Eqs. 5 and 6 is called sigmoild function and is the one utilized most commonly to date. And it is used in this research.

The generalized delta rule is the conventional technique used to derive the connection weights of the feedforward network (Rumelhart, et. al, 1986). Initially, a set of random numbers are assigned to the connection weights. Then for a presentation of a pattern p with target output vector $t_p=[t_{p1}, t_{p2},..., t_{pM}]^T$, the sum of squared error to be minimized is given by

$$E_p = \frac{1}{2}\sum_{j=1}^{M}(t_{pj} - o_{pj})^2 \tag{7}$$

where M is the number of output nodes. By minimizing the error E_p using the technique of gradient descent, the connection weights can be updated by using the following equations (Rumelhart, et. al, 1986) as

$$\Delta w_{ji}(p) = \eta\delta_{pj}o_{pi} + \alpha\Delta w_{ji}(p-1) \tag{8}$$

where for output nodes

$$\delta_{pj} = (t_{pj} - o_{pj})o_{pj}(1-o_{pj}) \tag{9}$$

and for other nodes

$$\delta_{pj} = (\sum_k \delta_{pk} * w_{kj})o_{pj}(1-o_{pj}). \tag{10}$$

Note that the learning rate η affects the network's generalization and the learning speed to a great extent. The overall training (learning) process for the network using the gradient descent technique is summarized in Figure 3. In this research, the initial values of the connection weights are randomly generalized from an uniform distribution U(-1,1).

Initialize the weights between layers, w_{ji} and w_{kj} ;

for *m=1* to output layer iteration number or error criterion **do**

decrease the adjusting rate for w_{ji} and w_{kj} gradually;
for *n=1* to training sample size **do**
calculate the output for each hidden node;
calculate the output for each output node;
accumulate the difference between actual and target outputs;
calculate the modified gradient for w_{kj};
calculate the modified gradient for w_{ji};
modify w_{kj};
modify w_{ji};
end
end

Figure 3. Training Process for Networks

IV. Neural Network Model Development

An artificial neural network was used to forecast the performance measure under different parameter value combinations. The neural network simulator NETS, developed by NASA (Baffes, et. al, 1989), was used to develop the networks. NETS was implemented on a PC with Pentium 75 MHz CPU. It is a C based simulator that provides a system for developing various neural network configurations using the generalized delta backpropagation learning algorithm. The network investigated in this paper is illustrated in Figure 4.

The network model consists of 3 layers. The input layer has 8 elements or nodes, each representing an impact parameter identified by the Hsu CAE package. The hidden layer consists of a number of nodes used for computational purposes. The output layer consists of a single node representing the performance measure. The initial number of hidden nodes to test was chosen to be 4, 5, 6, and 7 since there are eight input nodes and only one output node in the neural network model. There is no a commonly accepted method for determining the number of hidden nodes to use in a backpropagation neural network model. Consequently, experimentation and rules of thumb were used to arrive at the numbers to use. Too few hidden nodes limit the generalization capabilities of a network, while too many hidden nodes can result in overtraining or memorization by the network.

An initial evaluation of the learning rate was also conducted. Learning rates of 0.01, 0.05, 0.10, 0.15 and 0.20 were used with the networks. Large step sizes in the learning process can cause the network to oscillate and not accomplish the required minimization of the error term. The root mean square error (RMSE) of the

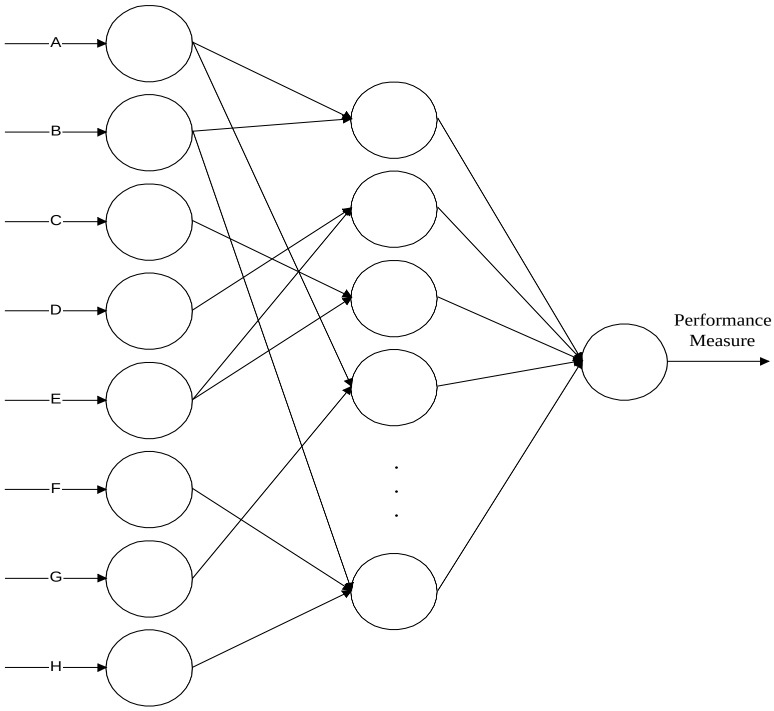


Figure 4. The Utilized Neural Network Topology

predicted performance measure was recorded every 30 epochs or training iterations. Each network was run for 3000 epochs. The minimum RMSE of the performance measure data set was used as the learning rate and the number of hidden nodes selection factor.

V. Performance Measure Forecasting Results

To train the neural networks, the encoded values for the selected parameters and the normalized mean of the five performance measure values (as shown in Table 2) are used as input and output values for neural models. The equation used to normalize the data in this research was shown as Eq. 11.

$$X' = \left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) * 0.90 + 0.05 \tag{11}$$

where X and X' are the raw and normalized values respectively, and X_{max} and X_{min} are the maximum and minuman values of X. The normalized outputs of the average of the performance measure from the *L18* orthogonal array are shown in Figure 5. Eight additional experiments with different factors setup were conducted to collect extra observations for model testing. The complete set of values are summarized in Table 6. It is noted that the optimal values of the controllable factors found by the Taguchi method were also included. The training and testing RMSEs of the neural network model are shown in Table 7 for varying combinations of the number of hidden nodes and learning rates. The convergence criteria used for network training was a mean square error less than or equal to 0.001 or a maximum of 3000 iterations.

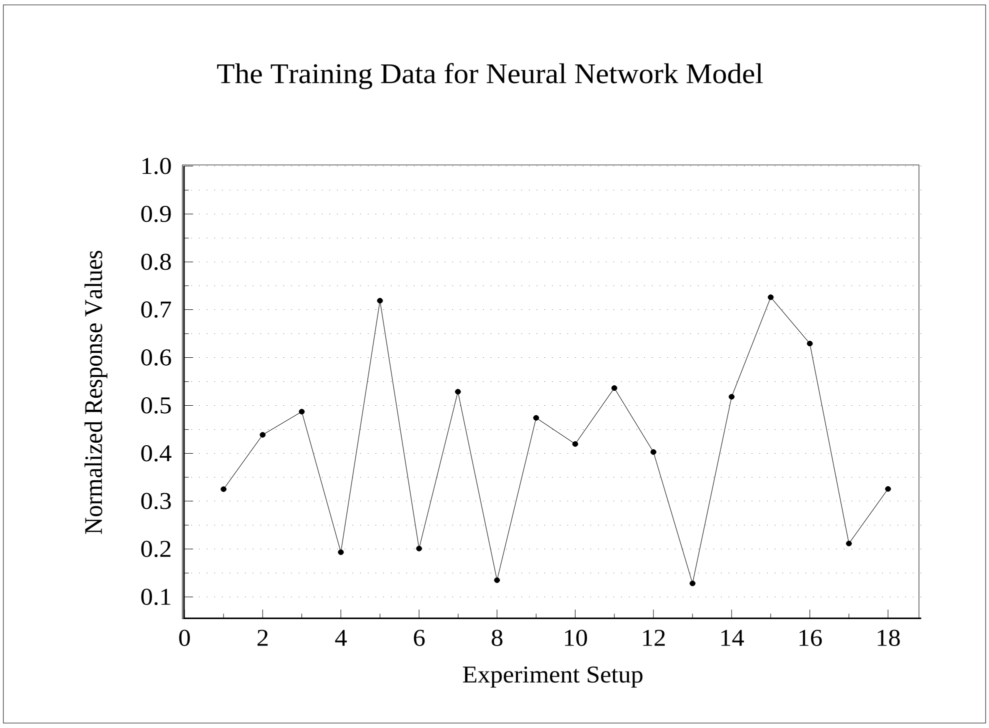


Figure 5. Normalized Training Data Set for Neural Network Model

Table 6. Extra Experiment Combinations Used to Test the Constructed Network

1	2	3	4	5	6	7	8						
A	B	C	D	E	F	G	H	V_1	V_2	V_3	V_4	V_5	$\bar{y}$

50	240	50	2	130	64	1	3	16.9	20.1	20.1	19.1	16.6	18.6
50	250	50	2	90	64	1	6	13.8	19.8	15.8	19.9	17.7	17.4
50	250	60	2	130	64	1	5	16.0	16.3	16.2	15.8	15.6	16.0
46	230	60	1	90	64	.5	5	43.0	44.5	41.9	41.3	45.2	43.2
40	230	60	6	130	66	0	5	155.0	158.6	153.8	154.2	153.1	154.9
46	230	60	1	90	64	1	5	24.0	23.2	25.8	22.6	24.3	24.0
40	250	100	10	130	64	0	5	63.0	65.3	61.5	65.3	60.3	63.1
50	240	50	2	130	63.	1	6	12.8	12.9	12.6	12.6	12.9	12.8

Table 7. The Forecasting Results for Performance Measure

# of Hidden node	Learning Rate	Training	Testing
4	0.01	0.033346	0.187679
	0.05	0.033209	0.182395
	0.10	0.032670	0.145696
	0.15	0.032569	0.125838
	0.20	0.032744	0.172124
5	0.01	0.032505	0.180751
	0.05	0.031885	0.168022
5	**0.10**	**0.031591**	**0.115662**
	0.15	0.032331	0.185167
	0.20	0.032825	0.193978
6	0.01	0.032608	0.140615
	0.05	0.032489	0.130338
	0.10	0.032144	0.142156
	0.15	0.033162	0.140561
	0.20	0.033804	0.143242
7	0.01	0.033951	0.167340
	0.05	0.032897	0.129791
	0.10	0.032030	0.145162
	0.15	0.032295	0.152939
	0.20	0.032516	0.156743

It is observed that the 8-5-1 network with the learning rate of 0.10 provides the best forecasting results for the performance measure with the lowest RMSEs.

The training RMSE of the 8-5-1 network with a 0.10 learning rate are depicted in Figure 6 so that the convergence characteristics of the proposed approach can be evaluated. The excellent convergence characteristic of the proposed approach can be easily observed.

The neural network results for the training data set and testing data set are summarized in Figures 7 and 8. In both figures, the solid line depicts the actual average performance measure in the experiment and dashed line represents the neural network forecasting output for the selected factor combinations. It is noted that the neural network model provides forecasting with high precision (Figure 7). More importantly, Figure 8 illustrates the neural network forecast for the additional experiment combinations shown in Table 6, that were not included in the Taguchi experiment.

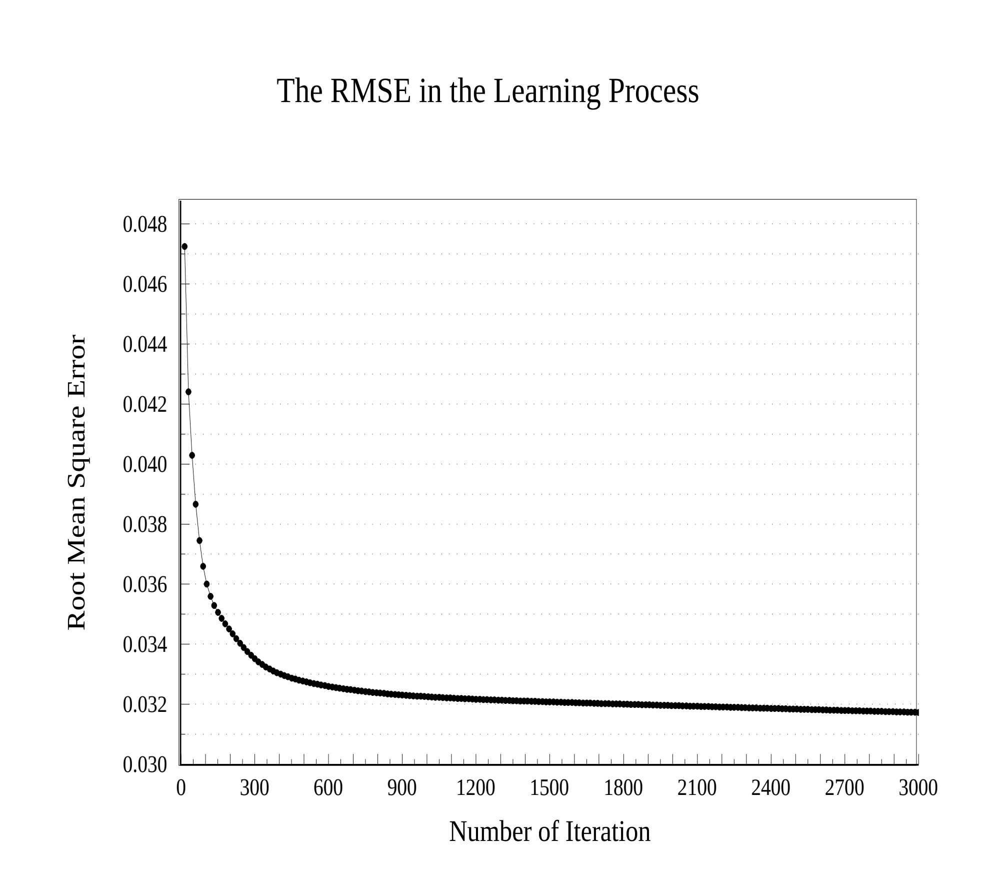


Figure 6. The Training Process for 8-5-1 Network topology with Learning rate = 0.10

The neural network is able to forecast (or estimate) other possible factor combinations. In other words, the strong generalization capability of the network model can be seen. From the figures and table, we know that the optimal parameter setup found by the network (A=50, B=240, C=50, D=2, E=130, F=63.5, G=1, H=6 with $\bar{y}$=12.8) is not same as the one identified by Taguchi method (A=50, B=240, C=50, D=2, E=130, F=64, G=1, H=3 with $\bar{y}$=18.6). The neural network finds a parameter setup that is superior to that determined by the Taguchi method (i.e. the smaller $\bar{y}$ value).

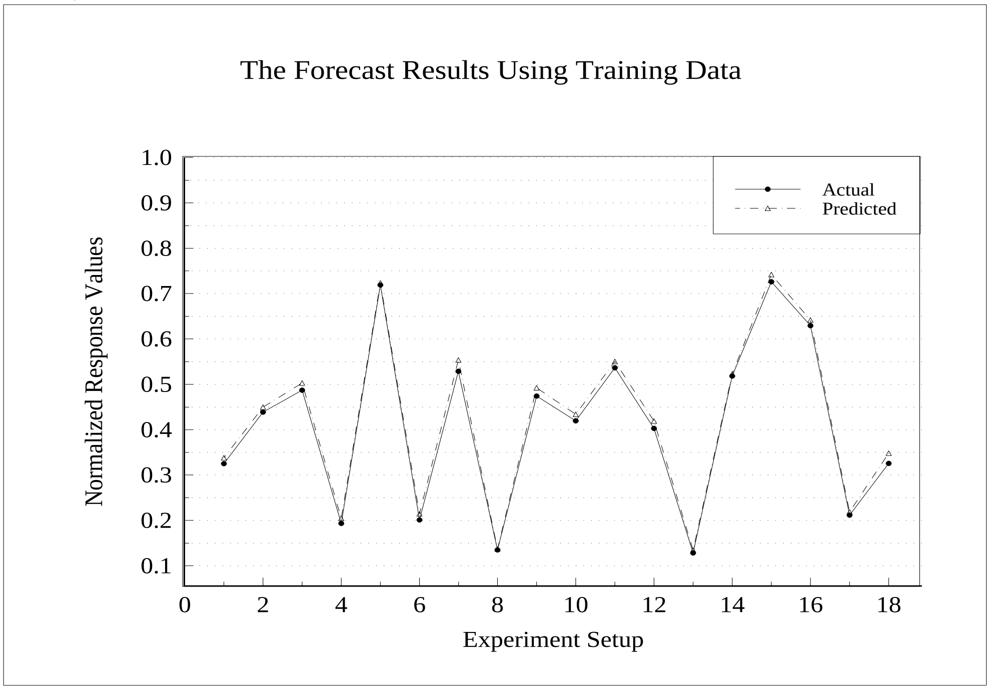


Figure 7. The Testing Results for 8-5-1 Network topology with Learning rate = 0.10 Using Training Data Set

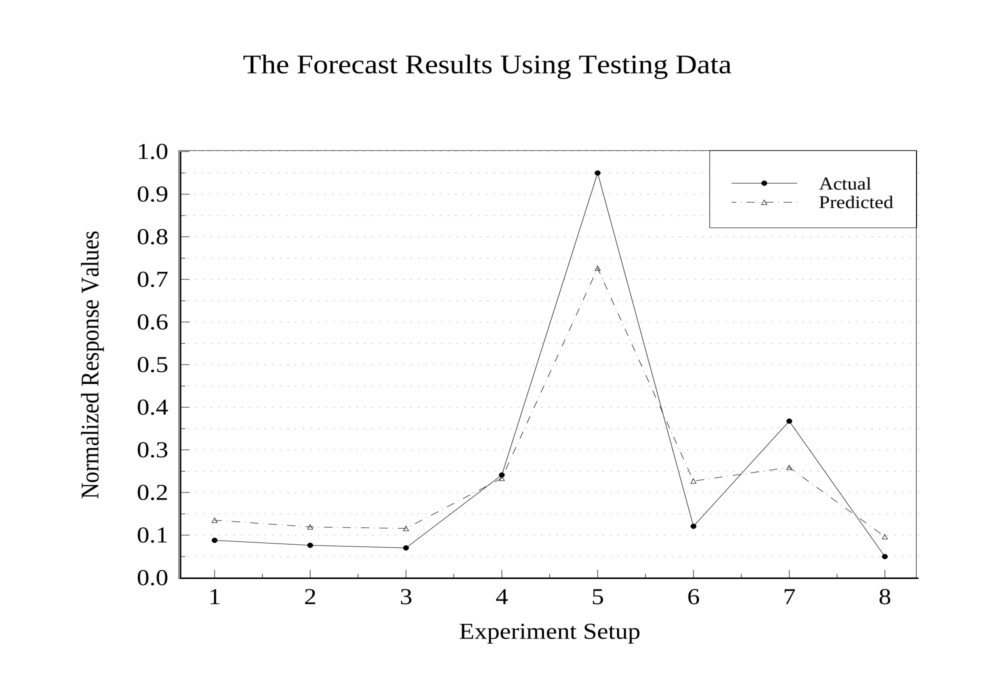


Figure 8. The Testing Results for 8-5-1 Network topology with Learning rate = 0.10 Using Testing Data Set

VI. CONCLUSIONS

A methodology combining the Taguchi method and a neural network was introduced to evaluate the effect of various process parameters and find the optimal parameter setup values in a gas-assisted injection molding process. In the process, an L18 orthogonal array and eight impacted parameters identified by a CAE were used to collect observations in the actual gas-assisted injection molding process by Hsu. These observations were first analyzed by the Taguchi method. Then the same data set was utilized to construct the neural network model to determine if the utilization a neural network would provide improved generalization capability over the statistical method. Eight new parameter setups were constructed for network testing to verify the generalization capability of the neural model. The neural network methodology identified parameter setup values that were superior to those identified by the Taguchi method. Consequently, the results show that the neural network has a higher chance that the Taguchi method of finding the actual optimal parameter setup. In this research, the cope of selected parameters is aimed at quantity variable. For some pratical problems, quality variable is often existed. The parameter space related to discrete variable may be very complicated.

However, the N.N. approach used in this paper also can provide an alternative for solving such problem if an appropriate transformation method can be used to transfor the quality variable to a suitable format.

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應用類神經網路與田口直交法在氣體輔助射出成型製程中參數最佳化選擇之比較

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摘要

在本文中，傳統的田口直交法與倒傳遞類神經網路，被使用來評估且決定在氣體輔助射出成型製程中參數的最佳數值。在田口直交法的應用中，L18 直交表首先被使用來收集實際觀察值。相同的資料集亦被用來建構一適當的類神經網路模式，以比較類神經網路方法是否能較傳統的統計技術，提供出較佳之結果。為能進一步瞭解類神經網路模式的建構程序，針對模式中的學習步伐量及隱藏層的神經元數目有進一步的探討。由研究結果發現，類神經網路模式比傳統的田口直交法，有更高的機會能成的辨識尋找出參數的最佳數值。

關鍵詞彙：射出成型，田口直交法，類神經網路，最佳化