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Modelling and Prediction of Responses in the IC Process using Artificial Neural Networks

Sarojrani Pattnaik and Mihir Kumar Sutar
Dept. of Mechanical Engg,Veer Surendra Sai University of Technology,
Burla, Odisha, India

ABSTRACT

In this study, an artificial neural network model has been developed to predict the characteristics of the disposable wax patterns used in the investment casting process (IC). The selected process parameters were the injection temperature, injection pressure, die temperature and injection time. The responses were the linear shrinkage and surface roughness of the wax patterns. The experiments have been performed as per Taguchi's L18 Orthogonal array. A feed-forward back propagation neural network has been built using 13 randomly chosen experimental data and the remaining 5 data were used for testing the accuracy of the built model. It was found that the mean absolute percentage error between the actual and the predicted results of the responses was less than 15% in all cases, which shows that the model has been well built.

KEYWORDS

Artificial Neural Network; Taguchi Method; Casting; Linear Shrinkage; Surface Roughness

1. INTRODUCTION

Now a day's, most of the manufacturing processes are being modelled using artificial intelligence (AI) techniques. The main purpose of AI is to simulate the human activities in order to predict the desired output. Artificial neural network (ANN), fuzzy logic (FL), etc., are some of the basic areas of AI. ANN models have been successfully used as predictor tools because it can accommodate unrestricted number of parameters for a more precise prediction of responses [1-2].

Yang developed a Taguchi-ANN model for predicting the resistivity and transmittance in semiconducting transparent thin films [3]. It was found that initial neural network was not so effective in predicting the responses accurately owing to poor network training. However, the rectified network led to refined global predictions. Yang et al [4] also constructed a Taguchi-ANN based model to forecast CO_2 laser cutting experiments and they found that the predicted results agreed well with that of the experimental ones. The strength of woven fabric used in upholstery industry was modelled successfully using ANN by Zeydan [5]. The data were taken from a jacquard woven fabric factory. This modelling analysis helped to reduce the waste or scrap ratio so that production planning could be more efficient.

Zheng et al [6] used ANN model to predict the surface defects namely, hot cracking, cold

Shut, misrun and die sticking in die-casting process. The process parameters were pouring temperature, mould temperature and injection velocity. It was established that the trained ANN had grand predictability. Moreover, the trained ANN model was further used as an objective function to optimize the die-casting process. The determined optimal process parameters were used for experimentation which led to satisfactory surface quality characteristics of the cast part. Markopoulos et al [7] developed an ANN model for predicting the surface roughness of the machined steel surface by Electrical Discharge Machining (EDM) process. The model was trained using the EDM experimental data on steel grades. The input parameters selected were pulse current, pulse duration and processed material. The results showed that the developed ANN model could agreeably forecast the surface roughness of machined parts by EDM process.

Investment casting (IC) process also known as lost wax process is extensively employed for producing ferrous and non-ferrous intricately shaped parts. It generally involves a disposable wax pattern by injecting semi-

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liquid wax into a metallic die, building a ceramic shell by dipping the wax pattern into a slurry, dewaxing the shell and casting the molten metal into the resultant cavity [8, 9]. Now a day's, IC industries are under tremendous pressure to enhance their economic performance constantly to meet the competitive environment worldwide with outstanding quality. The accuracy of the wax patterns directly influences the quality of the casting [10, 11]. The wax patterns should possess least shrinkage (LS) and surface roughness (SR). It has been found from the literature survey that ANN model could accurately predict the responses in different streams of manufacturing. The present study focuses on studying the viability of ANN model in the field of IC process. Thus, a back propagation ANN (BPNN) model has been developed on the basis of experimental data to predict the LS and SR of the wax patterns of the IC process, for a given set of injection process parameters.

2. EXPERIMENTAL DETAILS

The injection process parameters such as injection temperature, injection pressure, die temperature and injection time were selected to visualize their effect on linear shrinkage and surface roughness of the wax patterns made by the IC process. The process parameters, their designed symbols and range are given in Table 1. L_{18} OA was chosen for conducting the experiments. Three wax patterns were prepared each time and the average values of LS and SR were recorded. The prepared wax patterns as per L_{18} OA are shown in Fig. 1. The results are furnished in Table 2.

Table 1. Process parameters and their values at different levels

Symbol	Process parameters	Range	Unit	Level 1	Level 2	Level 3
A	Injection temperature	70-80	^{0}C	70	75	80
B	Injection pressure	0.5-0.7	kg/cm^2	0.5	0.6	0.7
C	Die temperature	35-45	^{0}C	35	40	45
D	Injection time	25-30	Sec	25	30	35

Fig. 1: Wax patterns prepared as per L_{18} OA

Trial No.	Process parameters				Mean output response	
	A (^{0}C)	B (kg/cm^2)	C (^{0}C)	D (Sec)	LS (%)	SR (nm)
1	70	0.5	35	25	1.336	61.2493
2	70	0.6	40	30	1.559	60.6582
3	70	0.7	45	35	1.396	60.5465
4	75	0.5	35	30	1.701	61.2482
5	75	0.6	40	35	1.691	59.9147
6	75	0.7	45	25	1.539	61.2028
7	80	0.5	40	35	1.912	60.8133
8	80	0.6	45	25	1.649	60.4927
9	80	0.7	35	30	1.618	60.4976
10	70	0.5	45	30	1.437	60.7588
11	70	0.6	35	35	1.475	61.1992
12	70	0.7	40	25	1.345	61.2634
13	75	0.5	40	25	1.728	60.6931
14	75	0.6	45	30	1.596	59.8024
15	75	0.7	35	35	1.584	61.1063
16	80	0.5	45	35	1.820	60.2059
17	80	0.6	35	25	1.701	59.8116
18	80	0.7	40	30	1.789	59.6923

3. NEURAL NETWORK MODEL

In this study, a typical three-layered feed forward BPNN with an input layer with four input nodes, a hidden layer with nine neurons and an output layer with two output nodes has been considered as shown in Fig. 2. These input and output nodes represent inputs and outputs considered in the process. It was found by trial method that the hidden layer with nine neurons showed least mean square error (MSE). The data presented in Table 2 is normalized using Eq. 1.

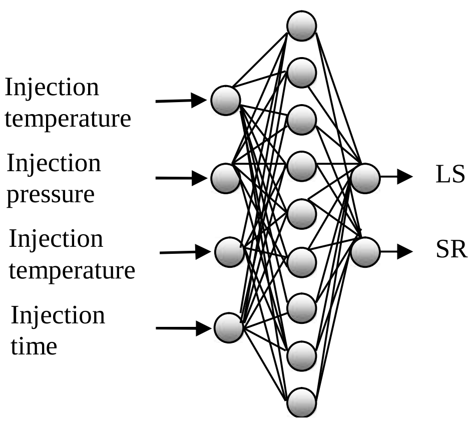

Fig. 2: Back propagation artificial neural network

$$D_{nor} = D_{min} + \frac{V_{orig} - V_{min}}{V_{max} - V_{min}} \left(D_{max} - D_{min} \right) \quad (1)$$

where, D_{nor} denotes the values of the input and output modules after normalization, D_{max} and D_{min} are the fixed maximum and minimum input and output values after data normalization, V_{max} and V_{min} are the maximum and minimum input and output values before normalization, and V_{orig} denotes those input and output values before normalization. The parameters selected for training is shown in Table 3. The training data excluded the experimental run nos. 1, 3, 7, 12 and 16 of the L_{18} OA for testing the model.

Table 3. Parameters selected for training

Input parameters for training	Values
Learning parameter	0.25
Momentum rate	0.7
Number of epochs	10,000
Number of hidden layer	1
Number of hidden layer neurons	9
Number of input layer neuron	4
Number of output layer neuron	2
Error tolerance (goal)	0.00001

In order to get the real world inputs and outputs, the normalized inputs and output are again anti-normalized using Eq. 2.

$$V_{pre} = V_{min} + \frac{\left(V_{nor} - D_{min} \right)\left(V_{max} - V_{min} \right)}{D_{max} - D_{min}} \quad (2)$$

where, V_{pre} and V_{nor} are the actual value and the normalized value of the inputs and the outputs as predicted by the ANN model. The performance of the predictor model is assessed using statistical performance evaluation criteria such as mean absolute percentage error (MAPE).

4. VALIDATION OF THE DEVELOPED MODEL

In order to validate the developed model, the results for LS and SR were predicted by ANN for the remaining data (excluding the training data) which is shown in Table 4. It is seen that the maximum error between the actual and predicted value of responses is found to be less than 15%, which shows that the ANN model is well built to predict the characteristics of the wax patterns.

Table 4. Comparison between actual and the predicted outputs as per ANN method

Sl. No.	Process parameters				LS (%)			SR (nm)		
	A (^{0}C)	B (kg/cm^2)	C (^{0}C)	D (Sec)	Actual	Predicted	MAPE (%)	Actual	Predicted	MAPE (%)
1	70	0.5	35	25	1.336	1.521	13.8	61.2493	59.6860	2.55
2	70	0.7	45	35	1.396	1.468	5.2	60.5465	59.7832	1.26
3	80	0.5	40	35	1.912	1.843	3.6	60.8133	59.5188	2.13
4	70	0.7	40	25	1.345	1.538	14.3	61.2634	60.4137	1.39
5	80	0.5	45	35	1.82	1.910	4.9	60.2059	61.0109	1.34

5. CONCLUSIONS

The present study shows that ANN could accurately predict the responses of the wax patterns which are used in the IC process, as MAPE between the actual and the predicted responses is less than 15% in all cases. It is seen that the prediction accuracy of the surface roughness is higher than that of the linear shrinkage of the wax patterns. However, the prediction capability of the developed model for both the responses is found to be satisfactory. Thus, it shows that ANN modelling can be successfully used in the IC process to predict the final product quality proximately. It would not only reduce the number of non-confirming parts being produced, but also the cost of rejections and reworks.

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