Using an Artificial Neural Network to Model and Predict Tensile Tests for the Injection Molding Process

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Abstract

This study focuses on applying artificial neural network (ANN) to model and predict the effect of injection molding process parameters, use, on the tensile test. The control factors were the melt temperature, packing pressure and injection pressure. The tensile test was analyzed as performance and quality indices. To validate the prediction model, the MAPE error and the Nash Sutcliffe model were utilized. Their values were 8.16% and 98.3% respectively which indicated that the model is accurate and reliable.

Keywords: Modeling and prediction, injection molding process, tensile test, artificial neural network (ANN).

الملخص

تركز هذه الدراسة على تطبيق الشبكات العصبية الاصطناعية لنمذجة وتوقع تأثير معايير عملية قولبة الحقن، مثل الاستخدام، على اختبار الشد. وشملت عوامل التحكم درجة حرارة المصهور، وضغط التعبئة، وضغط الحقن. وتم تحليل اختبار الشد كمؤشرات للأداء والجودة. وللتحقق من صحة نموذج التوقع، تم استخدام متوسط الخطأ المطلق النسبي (MAPE)ونموذج (NSE). وقد بلغت قيمتاهما 8.16% و98.3% على التوالي، مما يشير إلى دقة وموثوقية النموذج.

الكلمات المفتاحية: النمذجة والتنبؤ، عملية قولبة الحقن، اختبار الشد، الشبكة العصبية الاصطناعية (ANN).

1-Introduction

Injection molding is a comprehensive production process for producing plastic products with high strength and low cost. In this process, raw material is injected into a mold and solidified under pressure and cooling. Dong et al (2014) reviewed various control parameters and optimization strategies to increase production in plastic injection molding. Kramar et al (2010) proposed a slow expert method to determine the mechanical properties of injection molded metal parts that were optimized using particle swarm optimization. Masato et al (2017) studied the effect of injection molding processing parameters on the dimensional accuracy of polymer composites with the aim of reducing shrinkage and improving accuracy. Olyaei et al (2016) investigated the shrinkage and deformation of UHMWPE thigh liners reinforced with nanohydroxyapatite by injection molding. Azdest et al. (2019) with the aim of optimizing the errors in injection molding through volumetric shrinkage analysis using the response surface method. Finally, Goyal et al. (2020) used the feedback mesh method to distinguish important and irrelevant parameters in advanced engineering, highlighting the challenge of creating accurate components. The reactive surface method was used to develop a detailed model to examine the process parameters and estimate the product quality of the injection molding process. However, there is always a need to adjust the settings of the coating machine without trial and error to reduce setup time and improve the injection process. This paper presents an artificial neural network (ANN) model as a form of artificial intelligence (AI) to achieve these goals. Materials and methods This study was conducted based on previously published studies. This paper presents an Artificial Neural Network (ANN) model, as a type of Artificial intelligence (AI), to meet these objectives.

2- Methodology

This study was conducted in accordance with earlier suggested and published research Goyal et al. (2020). For the current experimental effort, polypropylene (PP) material and a standard specimen in the shape of a double are employed. The selected process parameters and their levels are presented in Table1. The actual data are shown in Table2, as they were obtained from a previous published study Goyal et al. (2020).

Table 1. Range and level of process parameters

Parameters	Levels		
	-1	0	+1
Melt Temp (C^o)	190	220	250
Packing Pressure (psi)	50	90	130
Injection Pressure (psi)	80	120	160

Table 2. Design of experimental matrix and experimental results

Melt Temp (C^o)	Packing Pressure (psi)	Injection Pressure (psi)	Tensile Test
190	50	80	41.88
250	130	80	10.61
250	50	160	16.34
190	130	160	25.87
220	90	120	35.31
220	90	120	22.55
250	50	80	11.9
190	130	80	27.67
190	50	160	22.81
250	130	160	6.9
220	90	120	25.1
220	90	120	23.88
188.37	90	120	17.27
251.63	90	120	3.25
220	48.37	120	24.76
220	131.63	120	16.82
220	90	78.37	16.44
220	90	161.63	17.38
220	90	120	21.88
220	90	120	18.29

3-Results and Discussion

The actual values of the tensile test obtained by the experimental and the predicted values of the warpage predicted using ANN are compared and shown in Table 3.

Table 3. The actual and predicted values of the tensile test

Melt Temp (C^o)	Packing Pressure (psi)	Injection Pressure (psi)	Tensile Test	
			Actual	Predicted
190	50	80	41.88	39.22
250	130	80	10.61	10.15
250	50	160	16.34	15.28
190	130	160	25.87	25.85
220	90	120	35.31	35.65
220	90	120	22.55	22.68
250	50	80	11.9	11.79
190	130	80	27.67	28.87
190	50	160	22.81	23.07
250	130	160	6.9	7.44
220	90	120	25.1	25.81

220	90	120	23.88	24.33
188.37	90	120	17.27	16.44
251.63	90	120	3.25	6.26
220	48.37	120	24.76	25.90
220	131.63	120	16.82	15.43
220	90	78.37	16.44	15.92
220	90	161.63	17.38	16.02
220	90	120	21.88	21.85
220	90	120	18.29	17.53

To validate the ANN, the actual values and the predicted values of tensile test is presented based on the mean absolute percentage error (MAPE) value. This value was calculated using equation (1).

$$\textbf{MAPE} = (\Sigma|A-P|/Ani=1) / n * 100\% \qquad (1)$$

where:

A: The actual value for tensile test.

P: The predicted value for tensile test.

n: Number of Experimental.

This value was 8. %, which indicates that the model is having good prediction accuracy. Also, Fig. 1 is introduced to show the comparison between the actual values and the predicted values of tensile test. It can be seen from that, the ANN prediction model can reflect the actual values of the tensile test.

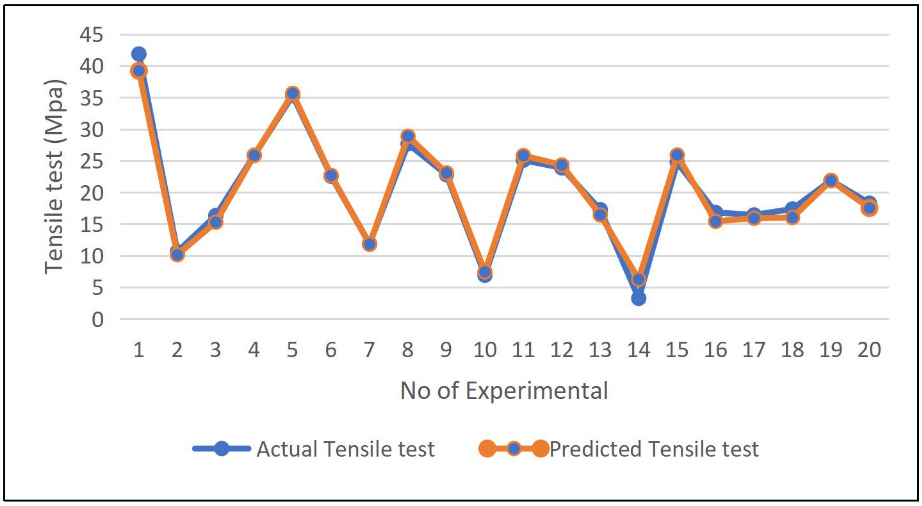

Fig 1. The actual and prediction of tensile test (Mpa)

The Nash-Sutcliffe Efficiency (NSE) was also calculated to evaluate the efficiency of the model by equation (2).

$$\text{NSE} = \Sigma(A-P)^2 / \Sigma(A-A)^2 \qquad (2)$$

Where:

A: Actual value for tensile test.

A: Average actual value for tensile test.

P: Predict a value for tensile test.

The value of the NSE is 98.3%, which also indicates that the model has good efficiency.

4-Conclusion

The present study utilized ANN approach and successfully developed a prediction model that can correlate the effect of melt temperature, packing pressure and injection pressure on tensile test. The accuracy of the developed model was tested by calculating the Nash–Sutcliffe model efficiency coefficient (NSE) and the Mean absolute percentage error (MAPE) the values of both were 98.3% and 8.16% respectively which indicated that the developed model is reliable, accurate and can be successfully be used to predict the tensile test.

5-Refereneces

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