Modeling and Prediction of Warpage in Plastic Injection Molded Parts Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract
***This* study focuses on applying Adaptive Neuro Fuzzy Inference System (ANFIS) to model and predict the effect of injection molding process parameters, used to produce mobile coverage, on the coverage warpage. The control factors were the mold temperature (MT), packing time (Pt), packing pressure (PP) and cooling time (Ct) in the packing stage. The warpage was analyzed as performance indices. To validate the prediction model, the MAPE error and the Nash Sutcliffe model were utilized. Their values were 3.17% and 86.6% respectively which indicated that the model is accurate and reliable.**

Keywords*: *Modeling and prediction, injection molding process, warpage, Adaptive neuro-fuzzy inference system

I. INTRODUCTION

The four main properties of plastic materials that make plastic materials one of the most important materials are high strength to weight ratio, the volume to price ratio, corrosion resistance, ease and speed of production. Injection molding process is the main manufacturing process use to manufacturing plastic material. This process is classified as net shape process because there is no need four subsequent process.[1].

The main four steps of injection molding process are melting, injection, holding and cooling. The success of the injection molding process could be evaluated based on the warpage of the molded plastic parts. [2].

The main inputs parameters that cause the appearance of the warpage are the non-uniform shear rate and the temperature distribution in the processed material part. Moreover, imbalance of shrinkage in any section of the injected part leads to a net force that could warp it. Some previous studies have investigated and analyze the relationships between the input process parameters and warpage of the plastic parts to decrease the warpage as an output process parameter. [3-5].

For injection molding process, it was concluded that, the input process parameters have a non-linear effect on the quality of the part produced, therefore, mathematical models were introduced to predict the effects of this input parameter on the quality of the product. [6, 7].

It was also reported that the most crucial input process parameters of injection molding processes, that affect the warpage, are the packing pressure and the melting temperature. [8, 9].

Another study investigated the effect of melt temperature , mold temperature, inject speed, and packing pressure on the warpage. In this study the used a simulation software namely computer aided design, simulate the injection molding process [10, 11].

A recurrent neural network was also utilized to investigate the effect of input process parameters in injection molding namely, melt temperature, mold temperature, packing pressure packing time and cooling time on the warpage of the product part prediction. Finite element analysis software Moldflow was used to simulate the injection molding process and to collect data for training and testing the model produced using recurrent neural network. The designed neural network acutely predicts the warpage. [15].

Artificial Neural Network (ANN) was utilized to model the injection molding process. In this process, the input process parameters were cooling temperature, injection times, V/P switchover rates and mold temperature. The output process parameter was the warpage. It was concluded that the ANN model successfully reduces warpage by 0.02 percent when compared to the experimental result. The optimal values of the cooling temperature, injection molding, V/P switchover rates and mold temperature were 39.68°C, 2.183s, 97.43 % and 39.07°C respectively. [16].

The adaptive network based fuzzy inference system (ANFIS) and genetic algorithm (GA) were utilized to model and optimize the injection molding process parameters**.** These two approaches have successfully overcome the complexity of producing the slender, cantilevered, and thin-walled plastic parts using injection molding process and reduced the warpage 88.25 %. Therefore, its highly recommended to implement these two approaches to predict the warpage and identify the optimal process parameters. [17].

The radial basis function (RBF) coupled with the k-fold cross validation technique were implemented to model and optimize the process parameters in plastic injection molding for minimizing the volumetric shrinkage and warpage. In this study, a multi-objective design optimization method based on a radial basis function (RBF) model was utilized to minimize both the volumetric shrinkage and warpage of hip liners to produce injection-molded biomedical part. The hip liners included an ultrahigh molecular weight polyethylene (UHMWPE) liner and UHMWPE reinforced with a nano-hydroxyapatite (nHA) liner. The shrinkage and warpage values of the hip liners generated by simulation was utilized in injection molding process by using Autodesk Moldflow. To identify and develop the approximate function between the input process parameters namely, the mold temperature, melt temperature, injection time, packing time, packing pressure, coolant temperature, and type of liner with the output process parameters namely shrinkage and warpage, the result of this study showed that, the importance of adding nHA to get more accrue dimensional stability. The model was checked and validated using the k-fold cross validation approach. The model specified the optimal process conditions to achieve the minimum shrinkage value and warpage simultaneously. [18].

Fuzzy logic (FL) technic, as a type of Artificial intelligence (AI), was used to develop accurate models for investigating the processing parameters and estimate the product quality of injection molding process. However, there is still a need to adjust the setup of injection molding machine without any need for trial and error approach , to reduce the setup time and improve the injection molding process. This paper presents an Adaptive Neuro-Fuzzy Inference System (ANFIS) model, as a type of Artificial intelligence (AI), to meet these objectives.

II. MATERIALS AND METHODS

This study was conducted in accordance with earlier suggested and published research [14]. Due to its enhanced mechanical qualities, the Polycarbonate/acrylonitrile Butadiene Styrene (PC/ABS) material was researched. (PC/ABS) plastic is one of the most popular engineering thermoplastics worldwide. Even at low temperatures, this material possesses exceptional strength, stiffness, heat resistance, and impact resistance. Throughout production operations, PC-ABS improves its flow properties and processability while maintaining its dimensional stability. Designers have a lot of latitude when using PC-ABS because it is colorable and printable. The suggested values and input parameter are displayed in Table 1 [14].

TABLE I. INPUT PARAMETERS AND THEIR LEVELS

Symbol	values vary from	Units	-1	0	+1
M_T	Mold temperature	°C	30	50	70
P_t	Packing Time	Sec	0.5	1.5	2.5
Pp	Packing Pressure	MPa	75	125	175
Ct	Cooling Time	Sec	5	7	9

III. ANFIS PREDCTION MODEL

ANFIS utilizes both of the Neural Network and Fuzzy Logic systems to develop a relationship between four inputs namely Mold Temperature (MT), Packing Time (Pt), Packing Pressure (Pp), and Cooling Time (Ct) and one output Y: warpage system parameter. The basic architecture of the ANFIS model is shown in Fig. 1.

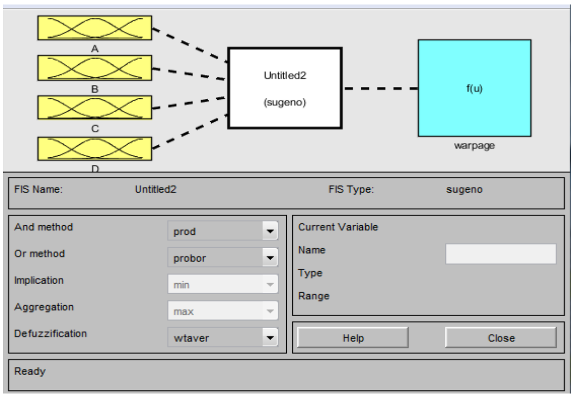

Fig. 1. Four inputs and one output fuzzy inference system for warpage.

The ANFIS model rules was defined by thirty rules. The rules are based on knowledge of predicting warpage as prediction of four inputs are shown in Fig. 2.

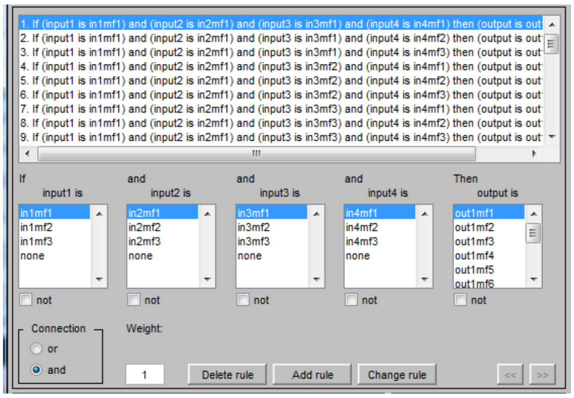

Fig. 2. The rules of membership function to predict warpage

The actual data are shown in Table2, as they were obtained from a previous published study [14]. The data were utilized as a base to measure the accuracy of the developed ANFIS model.

TABLE II. THE EXPERIMENT RUN, AND THE WARPAGE [14]

Run	(M_T) °C	(P_t) Sec	(P_p) MPa	(C_t) Sec	Actual of warpage (mm)
1	50	1.5	75	7	0.136
2	40	1	100	8	0.162
3	40	2	100	6	0.178
4	40	2	100	8	0.181
5	60	1	150	6	0.335
6	60	1	150	8	0.338
7	60	2	150	6	0.365
8	60	2	150	8	0.368
9	50	1.5	175	7	0.417
10	30	1.5	125	7	0.218
11	60	2	100	6	0.221
12	60	2	100	8	0.222

13	50	0.5	125	7	0.227
14	50	1.5	125	5	0.249
15	50	1.5	125	7	0.251
16	50	1.5	125	7	0.251
17	50	1.5	125	7	0.252
18	50	1.5	125	7	0.252
19	50	1.5	125	7	0.252
20	50	1.5	125	9	0.256
21	50	2.5	125	7	0.277
22	40	1	150	6	0.293
23	40	1	150	8	0.296
24	70	1.5	125	7	0.302
25	40	2	150	6	0.324
26	40	2	150	8	0.326
27	60	1	100	6	0.199
28	60	1	100	8	0.202
29	40	1	100	6	0.158
30	50	1.5	125	7	0.252

IV. RESULTS AND DISCUSSION

The actual values of the warpage obtained by the experimental and the predicted values of the warpage predicted using ANFIS are compared and shown in Table 3

TABLE III. THE ACTUAL AND PREDICTED VALUES OF THE WARPAGE

Run	(M_T) °C	(P_t) Sec	(P_p) MPa	(C_t) Sec	Actual of warpage (mm)	Prediction of warpage (mm)
1	50	1.5	75	7	0.136	0.136
2	40	1	100	8	0.162	0.1619997
3	40	2	100	6	0.178	0.178
4	40	2	100	8	0.181	0.181
5	60	1	150	6	0.335	0.335
6	60	1	150	8	0.338	0.338
7	60	2	150	6	0.365	0.365
8	60	2	150	8	0.368	0.368
9	50	1.5	175	7	0.417	0.417
10	30	1.5	125	7	0.218	0.2180003
11	60	2	100	6	0.221	0.221
12	60	2	100	8	0.222	0.222
13	50	0.5	125	7	0.227	0.2270004
14	50	1.5	125	5	0.249	0.2490004
15	50	1.5	125	7	0.251	0.252
16	50	1.5	125	7	0.251	0.252
17	50	1.5	125	7	0.252	0.252
18	50	1.5	125	7	0.252	0.252
19	50	1.5	125	7	0.252	0.252
20	50	1.5	125	9	0.256	0.2560004
21	50	2.5	125	7	0.277	0.2770004
22	40	1	150	6	0.293	0.293
23	40	1	150	8	0.296	0.296
24	70	1.5	125	7	0.302	0.302
25	40	2	150	6	0.324	0.238
26	40	2	150	8	0.326	0.24
27	60	1	100	6	0.199	0.159
28	60	1	100	8	0.202	0.163
29	40	1	100	6	0.158	0.155
30	50	1.5	125	7	0.252	0.252

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

$$\text{MAPE}= \left(\sum_{i=1}^{n} |A - P|/A\right) / \text{n} *100\% \tag{1}$$

where:
A: The actual value for warpage.
P: The predicted value for warpage.
n: Number of Experimental.

This value was 3.17 %, which indicates that the model is having good prediction accuracy. Also, Fig. 3 is introduced to show the comparison between the actual values and the predicted values of warpage. It can be seen from that, the ANFIS prediction model can reflect the actual values of the warpage.

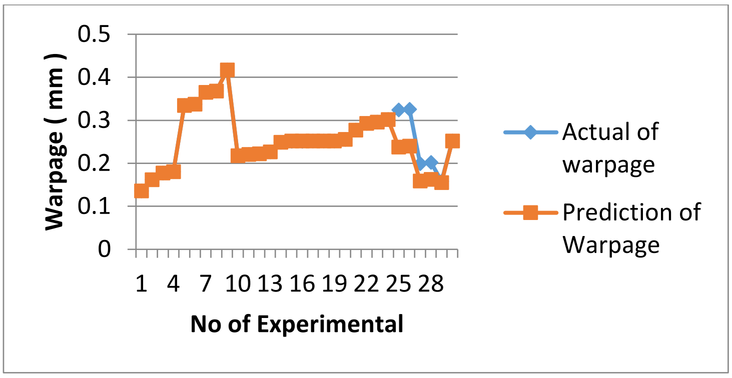

Fig. 3. The actual and prediction of Warpage (mm)

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

$$\text{NSE} = \frac{\sum(A-P)^2}{\sum(A-\bar{A})^2} \tag{2}$$

Where:
A: Actual value for warpage.
$\bar{A}$: Average actual value for warpage.
P: Predict a value for warpage.

The value of the NSE is 86.6%, which also indicates that the model has good efficiency.

This study presents an experimental investigation and introduce ANFIS based modelling during the injection molding process of polycarbonate/ acrylonitrile Butadiene Styrene. The main Finding of this study are as follows:

1- The developed model present MAPE of 3.17%.
2- The developed model ANFIS model is suitable for prediction the effect of the input parameters on the warpage as output parameters.
3- The finding of this study may be useful for the injection molding manufacturing process and for the researches who are interested in this area.

V. CONCLUSION

The present study utilized ANFIS approach and successfully developed a prediction model that can correlate the effect of mold temperature (MT), packing time (Pt), packing pressure (PP) and cooling time (Ct) on warpage of mobile cover. 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 86.6% and 3.17% respectively which indicated that the developed model is reliable, accurate and can be successfully be used to predict the warpage.

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