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WARPAGE PREDICTION IN PLASTIC INJECTION MOLDED PART USING ARTIFICIAL NEURAL NETWORK*

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Abstract– The main objective of this paper is to predict the warpage of a circular injection molded part based on different processing parameters. The selected part is used as spacers in automotive, transmission, and industrial power generation industries. The second goal is facilitating the setup of injection molding machine without (any) need for trial and error and reducing the setup time. To meet these objectives, an artificial neural network (ANN) model was presented. This model is capable of warpage prediction of injection molded plastic parts based on variable process parameters. Under different settings, the process was simulated by Moldflow and the warpage of the part was obtained. Initially, the effects of the melt temperature, holding pressure and the mold temperature on warpage were numerically analyzed. In the second step, a group of data that had been obtained from analysis results was used for training the ANN model. Also, another group of data was applied for testing the amount of ANN model prediction error. Finally, maximum error of ANN prediction was determined. The results show that the R-Squared value for data used for training of ANN is 0.997 and for the test data, is 0.995.

Keywords– Plastic injection molding, warpage, artificial neural network

1. INTRODUCTION

It would be difficult to imagine the modern world without plastics. Today, plastics are an integral part of everyone's life. Properties of the plastic materials such as high strength to weight ratio, the volume to price ratio, corrosion resistance, ease and speed of production have resulted in an ever-increasing use of them. Nowadays, in new part designs, plastics are used not only as a material for producing parts but also as alternative material for the metal alloys [1].

Injection molding with its excellent dimensional tolerance is one of the most common methods in mass production of plastic parts. Generally, injection molded plastic parts do not need any finishing or secondary operations [2]. This process consists of four stages that include melting, injection, holding and cooling [3]. Process parameters, plastic material properties and product design criteria are the basic factors in determining the final product quality.

Warpage of the molded plastic parts is one of the most important problems in injection molding process. Warped parts may not be functional or visually acceptable. Different shear rate profiles along the cross-section of part cause differences in orientation and these phenomena affect the shrinkage. Therefore, there will be variation in shrinkage in the part. Warpage occurs due to the non-uniform shear rate and temperature distribution in part material. Imbalance of shrinkage in any section of a part will produce a net force that could warp it. The stiffness of the part and the shrinkage imbalance level determine the warpage

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amount. If the part is too stiff to allow deflection, residual stresses will be created in the part that may cause problems later in its life [4]. If the shrinkage of a material is completely isotropic with respect to thickness, flow direction and distance, and packing pressure plastic parts will not warp. Asymmetric shrinkage and unequal contraction in the different directions cause warpage. Moreover, process parameters such as melt temperature and holding pressure have an effect on the rate of shrinkage in the different directions [5, 6]. Thus, different melt temperature and holding pressure will affect the warpage amount of the part. Non-uniform shrinkage in different directions could be determined using the material pressure-volume-temperature (PVT) relation diagrams [7].

Temperature-based warpage is caused by anisotropic cooling distribution in the cavity [8]. Low thermal conductivity of the plastic materials is one of the major factors in anisotropic cooling across the part thickness. Moreover, the lower thermal conductivity means that the plastic inside the barrel is melted over a long period. In addition, the molten plastic will require more time to solidify inside the mold cavity. Low thermal conductivity makes it hard to provide a uniform cooling profile across the part thickness and anywhere in the part body. In practice, variations in the melt temperature and melt pressure from one point to another in other cavity do not allow a steady-state condition to be established to produce parts with repeatable quality [9]. For the polymers, the thermal conductivity varies with temperature, degree of crystallinity and level of orientation.

Many researches have been carried out to analyze the relationships between process parameters and warpage of the plastic parts and decreasing the warpage [10-13]. In addition to the studies which focus on the relationship between the processing parameters and warpage, many researchers have proposed optimization methods for minimizing the warpage of the injection molded parts [10, 14]. Simplex algorithm [14], artificial neural network (ANN) [3, 15-19], genetic algorithm [9, 16, 20], Taguchi experimental design method [21] and fuzzy [22, 23] are the most preferred optimization methods found in the literature.

In two different studies, Min and Postawa presented models for creating a relationship between the melt pressure and part dimensions [24, 25]. In injection molding process, several processing parameters and setting conditions have a non-linear influence on the quality of the final part. Due to the nonlinear relationship between the processing parameters and the part quality indicators, it is difficult to estimate the quality parameters accurately using mathematical models [26-28].

ANN is a very useful method for prediction of linear and nonlinear systems. It has been widely used in many areas, such as control, data compression, forecasting, optimization, pattern recognition, classification, speech, vision, etc. The use of the ANNs for modeling and prediction purposes has become increasingly popular during the last decades [29]. In various studies, the neural network algorithm was used to establish a more accurate model for processing parameters and product quality that could estimate the product quality parameters more accurately. To determine the optimum values of process parameters, an ANN model was presented [16, 29, 30]. Sheleshnejhad and Taghizadeh presented a neural network model with 3-3-1 architecture. The model was designed to predict the fine length of the molded parts based on the cavity pressure profile [15]. Changyu et al. in 2007 used a combination of artificial neural networks and genetic algorithms to optimize the injection molding process parameters [16]. Ning and Lau have proposed neural network model for dimensional control of the molded parts based on the inverse process model [29].

To ensure the quality of plastic parts, the importance of part design and mold design in the initial stage of product development and process conditions during the final production process should be considered. However, the most economical one, is changing the process parameters systematically for the optimal process conditions [31]. The presence of an ANN model will facilitate the injection molding machine primary setup; the reason is that ANN could omit all trial-and-error activities and will prevent wasting of plastic material in a trial-and-error process. In addition, this would reduce machine stop time.

Other studies found in the literature reported that the most effective process parameters on warpage are the packing pressure and the melt temperature [31, 32]. In simulation of plastic injection molding process, computer aided engineering software (CAE) is presented. One of the specialized and applicable software(s) used in this field, is the Moldflow Plastic Insight. To simulate the injection molding process, this software was used in several studies [10, 21, 33, 34].

In this study, in the first step, warpage of circular plastic part was determined by computer-aided simulation according to various process parameters. Then effects of the process parameters on the part warpage were investigated. Finally, to predict product warpage by means of different simulation results, a neural network model was created and then the amount of ANN model prediction error was determined.

2. MATERIALS AND METHODS

The selected part for this research is a circular disc whose drawing and schematic 3D-view is shown in Fig. 1a and 1b. Parts with similar geometry are used as trust washers, shims, U-flanges and spacers in automotive, transmission, and industrial power generation. The reason for choosing this geometry as a part is that the form tolerances of such parts are important because of their function. Low Density Poly Ethylene (LDPE) with "M-201; Asia Poly" commercial name, was selected as a polymer material for simulation of the plastic injection molding process. Properties of this plastic are shown in Table 1 [35]. Finite element analysis results were obtained by Moldflow Plastics Insight (MPI) software. Gate was located on the parting line and outer diameter of the part as shown in Fig. 2.

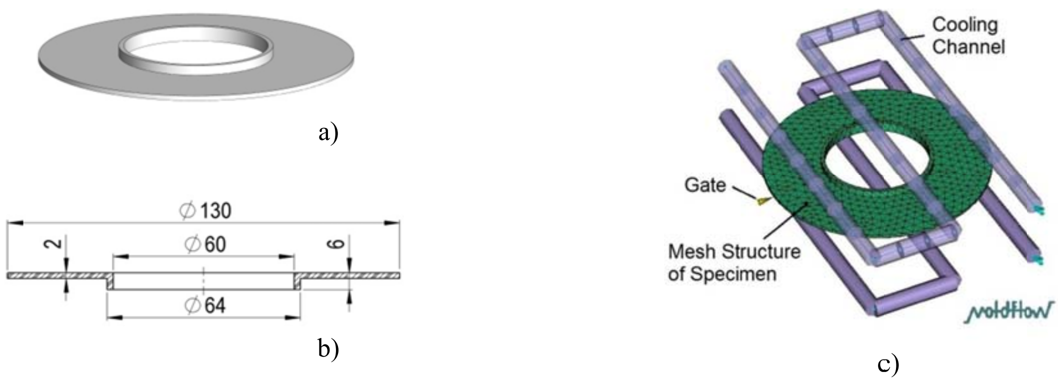

Fig. 1. a) Schematic 3D-view of the part. b) Drawing of the part. c) Finite Element model of the part, cooling channels and position of the gate

Table 1. Recommended process parameters for LDPE

Names of polymer	Trade name	Melt temperature (°C)	Mold temperature (°C)	Ejection temperature (°C)	Thermal conductivity (W/m-°C)	Specific heat (J/kg-°C)
Low Density Poly Ethylene	M-201 : Asia Poly	180-280	20-70	80	0.31	3400

3. FINITE ELEMENT ANALYSIS (FEA)

In this study, according to recommended process parameters of selected material (LDPE), recommended melt temperature values for LDPE vary from 180 to 280 °C, and permissible mold temperature values vary from 20 to 70 °C. For simulations, five levels of melt temperature (280, 255, 230, 205 and 180°C), three levels of holding pressure (90, 75 and 60% of maximum injection pressure (IP)) and three levels for mold temperature (70, 45 and 20°C) were considered. As mentioned above, holding pressure (HP) was considered as a percentage of the maximum injection pressure (IP).

For simulation, the CAD model was imported to MPI and meshed before analyzing. A three-node element was selected for meshing the part. The mesh type is a fusion surface mesh. The numbers of nodes are 1174, the numbers of triangular elements are 2204, average aspect ratio of triangle elements is 1.6801 and maximum aspect ratio of triangle elements is 3.5959. The percentage of matched elements in the Fusion mesh is a key factor in determining the quality of the mesh, and that should be at least 85 [36]. In this research, the Match ratio is equal to 97%, which shows that the quality of mesh is acceptable. As shown in Fig. 1c, in order to cool the mold, there are three cooling channels with diameters of 10mm in each side of the mold. The distance of cooling channels from mold surface is 15 mm and centre distance between adjacent cooling channels is 55 mm.

By using full factorial experiment design method, combinations of mentioned levels were created. The total number of possible combinations or settings is 45. In this paper, simulations, which were done under the mentioned setting (45 setting), were named “Training Simulations”. By applying this setting, the simulated results were used for training ANN. Numbering of each test was performed based on the levels of each parameter. These values dictate the level of each factor: conventionally, 1 for the lowest level, 2 for the second and 3 for the third and 4 for the fourth level. For example, in test T-423, digit 4 indicates fourth level of melt temperature (280 ºC), digit 2 indicates the second level of Holding pressure (75% of IP), and digit 3 indicates the third level of mold temperature (70 ºC).

Table 2. Settings for Training Simulation and related results

Test No.	Process setting			Simulated part warpage (mm)	Test No.	Process setting			Simulated part warpage (mm)
	Melt temp. (°C)	Holding pressure (%)	Mold temp. (°C)			Melt temp. (°C)	Holding pressure (%)	Mold temp. (°C)	
T-533	280	90	70	1.351	T-321	230	75	20	1.294
T-532	280	90	45	1.368	T-313	230	60	70	1.517
T-531	280	90	20	1.343	T-312	230	60	45	1.517
T-523	280	75	70	1.500	T-311	230	60	20	1.499
T-522	280	75	45	1.514	T-233	205	90	70	0.888
T-521	280	75	20	1.491	T-232	205	90	45	0.893
T-513	280	60	70	1.632	T-231	205	90	20	0.848
T-512	280	60	45	1.642	T-223	205	75	70	1.185
T-511	280	60	20	1.623	T-222	205	75	45	1.181
T-433	255	90	70	1.241	T-221	205	75	20	1.146
T-432	255	90	45	1.232	T-213	205	60	70	1.439
T-431	255	90	20	1.229	T-212	205	60	45	1.433
T-423	255	75	70	1.455	T-211	205	60	20	1.411
T-422	255	75	45	1.464	T-133	180	90	70	0.527
T-421	255	75	20	1.450	T-132	180	90	45	0.789
T-413	255	60	70	1.556	T-131	180	90	20	0.896
T-412	255	60	45	1.564	T-123	180	75	70	0.961
T-411	255	60	20	1.555	T-122	180	75	45	0.989
T-333	230	90	70	1.083	T-121	180	75	20	0.981
T-332	230	90	45	1.100	T-113	180	60	70	1.310
T-331	230	90	20	1.065	T-112	180	60	45	1.328
T-323	230	75	70	1.314	T-111	180	60	20	1.328
T-322	230	75	45	1.320					

Table 2 shows the settings for different simulations and related results. The results of “Training Simulations” were used for training ANN model. Because of this, there should be another data for testing the created ANN model. Therefore, other simulations with random setting were carried out. In this paper, simulations done under random setting, were named “Testing Simulations". By applying the Test Simulations, the created ANN model can be tested. Test Simulations with random setting were carried out and so the relevant warpage was determined. These results are used for distinguishing ANN model errors to estimate the part warpage.

In all of the simulations, coolant temperatures are considered 15 °C lower than mold surface temperature. Furthermore, water velocity of the cooling channels was set to 10 lit/min.

4. EFFECTS OF PROCESSING PARAMETERS ON WARPAGE

In the second step, effects of process parameters on warpage of part were investigated. By using the “Training Simulations” data, influence of each process parameter on warpage was investigated. Then, by combination of these parameters, the process was simulated with Moldflow Plastic Insight. Other molding parameters such as Injection time to fill (2 sec.), Holding time duration (10 sec.) and Cooling Time (18 sec.) were considered as fixed. The total amount of warpage in each simulation is given in Table 2.

The results show that creation of a specific relation between the selected process parameters and the amount of warpage is difficult. Hence, to predict the total warpage, creating an ANN model is necessary. By putting data into the created ANN model, the amount of warpage can be predicted.

Table 2 shows the amount of warpage in “Training Simulations”. Maximum amount of warpage takes place in the simulation test number T-512 that is equal to 1.642 mm, in which the melt temperature is 280°C, holding pressure is 60% of IP, and mold temperature is 45°C. Minimum amount of warpage takes place in simulation test number T-133 which is equal to 0.527 mm, with the melt temperature of 180 °C, holding pressure of 90% of IP, and mold temperature of 70°C.

5. ARTIFICIAL NEURAL NETWORKS AND APPLICATION

An artificial neural network model has several layers namely, first layer, hidden layer and last layer. The first layer is input layer, and the last one is the output layer. The input layer consists of all the input factors. The hidden layers process all data from the input layer. In the following step, the next hidden layer computes the output vector, and then this output vector is processed in the last layer (output layer) to create the final result. The hidden and output layers have a transfer function. In this paper, Fermi's function is used as a transfer function whose output lies between 0 and 1. Fermi's function was used as a transfer function in ANN models in previous researches [37, 38]. It is given in Eq. (1).

$$\mathrm{F} = \frac{1}{\left(1+\exp\left(-4\,(\mathrm{Z}-0.5)\right)\right)} \tag{1}$$

where, Z is the weighted sum of the inputs, and is calculated in equation 2.

$$\mathrm{Z} = \sum_{i=1}^{n} \mathrm{I_i} \times \mathrm{w_i} \tag{2}$$

where, I is the input and w is the weight.

In a neural network, the first important stage is the training step. In the training step, an input is introduced to the network accompanied by the desired output. Initially, the weights were set randomly. Since the output may not be what is expected, the weights may need to be altered. During the training phase, random weights are changed by the back-propagation algorithm to produce a satisfactory level of performance. Back Propagation algorithm is a learning technique that adjusts weights in neural network by propagating weight changes backward from the output to the input neurons [5]. The goal of the back-propagation training algorithm is to minimize the global error. After training, the weights contain meaningful information, whereas before training, they were random and had no meaning. When a satisfactory level of the performance is reached, the training will stop. Then the network uses these weights to make decisions.

In this paper, to evaluate model performance, absolute fraction of variance (R-Squared (R^2)) was computed from the results produced by the ANN model. R-Squared measures the proportion of the variation around the mean. R-square is 1 if the model fits perfectly. In addition, R-square of 0 indicates that the fit is no better than the simple mean model. R-Squared (R^2) defined by Eq. (3):

$$R^2 = 1\text{-}\left(\frac{\sum_i (T_i\text{-}O_i)^2}{\sum_i (O_i)^2}\right) \tag{3}$$

where, T is target value, O is output value.

To ensure that the statistical distribution of values for each net input and output are roughly uniform, the inputs and output data should be normalized. The input and output data are normalized in the (0, 1) range with the Eq. (4). To train ANN model, all the Training Simulation data were normalized. Normalized data of “Training Simulations” are listed in Table 3.

$$V_N = 0.1 + 0.8 \times \left(\frac{V_R - V_{min}}{V_{max} - V_{min}}\right) \tag{4}$$

where, V_{min}, and V_{max} are the minimum and maximum of related data respectively. V_R is real data obtained from simulation tests, and V_N is normalized value of V_R.

Table 3. Normalized data of “Training Simulations” and resulted warpage

Test No.	Melt temp.	Holding pressure	Mold temp.	Part warpage (T_i)	Warpage predicted by ANN (O_i)	Test No.	Melt temp.	Holding pressure	Mold temp.	Part warpage (T_i)	Warpage predicted by ANN (O_i)
T-533	0.9	0.9	0.9	0.6911	0.6917	T-321	0.5	0.5	0.1	0.6502	0.6518
T-532	0.9	0.9	0.5	0.7033	0.6887	T-313	0.5	0.1	0.9	0.8103	0.8127
T-531	0.9	0.9	0.1	0.6854	0.6864	T-312	0.5	0.1	0.5	0.8103	0.8053
T-523	0.9	0.5	0.9	0.7981	0.8042	T-311	0.5	0.1	0.1	0.7974	0.8003
T-522	0.9	0.5	0.5	0.8081	0.7989	T-233	0.3	0.9	0.9	0.3587	0.3585
T-521	0.9	0.5	0.1	0.7916	0.7943	T-232	0.3	0.9	0.5	0.3622	0.3617
T-513	0.9	0.1	0.9	0.8928	0.8917	T-231	0.3	0.9	0.1	0.3300	0.3259
T-512	0.9	0.1	0.5	0.9000	0.8902	T-223	0.3	0.5	0.9	0.5720	0.5703
T-511	0.9	0.1	0.1	0.8864	0.8881	T-222	0.3	0.5	0.5	0.5691	0.5731
T-433	0.7	0.9	0.9	0.6117	0.6117	T-221	0.3	0.5	0.1	0.5440	0.5421
T-432	0.7	0.9	0.5	0.6091	0.6091	T-213	0.3	0.1	0.9	0.7543	0.7561
T-431	0.7	0.9	0.1	0.6015	0.6015	T-212	0.3	0.1	0.5	0.7500	0.7496
T-423	0.7	0.5	0.9	0.8209	0.8209	T-211	0.3	0.1	0.1	0.7342	0.7430
T-422	0.7	0.5	0.5	0.8153	0.8153	T-133	0.1	0.9	0.9	0.1000	0.1103
T-421	0.7	0.5	0.1	0.8103	0.8103	T-132	0.1	0.9	0.5	0.2878	0.2957
T-413	0.7	0.1	0.9	0.9599	0.9599	T-131	0.1	0.9	0.1	0.3643	0.3670
T-412	0.7	0.1	0.5	0.9505	0.9505	T-123	0.1	0.5	0.9	0.4111	0.4071
T-411	0.7	0.1	0.1	0.9404	0.9404	T-122	0.1	0.5	0.5	0.4316	0.4316
T-333	0.5	0.9	0.9	0.4988	0.5024	T-121	0.1	0.5	0.1	0.4256	0.4268
T-332	0.5	0.9	0.5	0.5110	0.5081	T-113	0.1	0.1	0.9	0.6617	0.6692
T-331	0.5	0.9	0.1	0.4859	0.4864	T-112	0.1	0.1	0.5	0.6746	0.6666
T-323	0.5	0.5	0.9	0.6646	0.6749	T-111	0.1	0.1	0.1	0.6746	0.6767
T-322	0.5	0.5	0.5	0.6689	0.6693						

Several different architectures of ANN model were created in Pythia software in order to reach best performance. Finally, ANN model with a 3-5-3-1 architecture was selected and is shown in Fig. 2. In other words, the created ANN has three inputs and five neurons in the first hidden layer, three neurons in the second hidden layer and one neuron in last layer or output layer. Inputs for the ANN are plastic melt temperature, holding pressure and mold temperature. Output layer has only one neuron that represents the warpage.

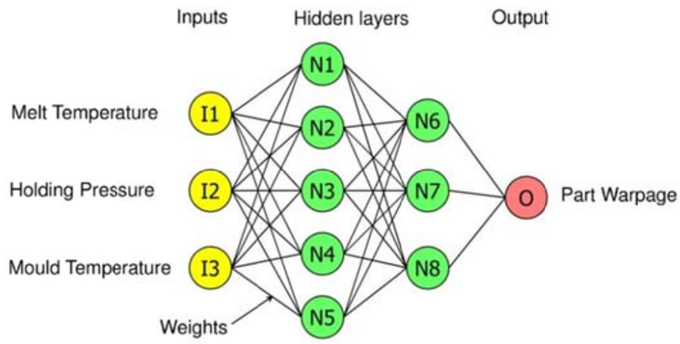

Fig. 2. Architecture of created ANN model

The formula of the first hidden layer with five neurons is given in Eq. (5) and the formula of the second hidden layer with three neurons is given in Eq. (6). The formula of the output layer with one neuron is given in Eq. (7). If injection parameters are known, with these equations, the amount of warpage could be calculated.

$$N_j = \frac{1}{\left(1+\exp\left(-4\times(I_1\times w_{11}+I_2\times w_{12}+I_3\times w_{13}-0.5)\right)\right)}, \text{ (for j=1 to 5)} \tag{5}$$

$$N_j = \frac{1}{\left(1+\exp\left(-4\times(N_1\times w_{21}+N_2\times w_{22}+N_3\times w_{23}+N_4\times w_{24}+N_5\times w_{25}-0.5)\right)\right)}, \text{ (for j=6 to 8)} \tag{6}$$

$$O = \frac{1}{\left(1+\exp\left(-4\times(N_6\times w_{31}+N_7\times w_{32}+N_8\times w_{33}-0.5)\right)\right)} \tag{7}$$

where, I_1, I_2, and I_3 are normalized value of melt temperature, holding pressure and mold temperature respectively and w is the weight for each neuron.

Weights of each neuron are listed in Table 4. For example, according to Table 4, for calculating N_2, w_{13} (the weight for I_3) is equal to -0.015087 and to calculate N_7, w_{23} (the weight for N_3) is equal to 2.788553. To calculate O, w_{33} (the weight for N_8) is equal to -1.319948. N_1 to N_5 are the output values of first hidden layer and N_6 to N_8 are the output values of second hidden layer and O is the final output.

As mentioned previously, the results of "Training Simulations" were used for training of ANN model and results of Testing Simulation were used for distinguishing ANN model errors in warpage estimation. Settings and results of Testing Simulations are listed in Table 5. Outputs of ANN model are in (0, 1) range. To obtain the actual values of predicted warpage, all the results were re-normalized by equation 8. Re-normalized values are listed in Table 5.

Table 4. Weight of each neuron in the ANN model

	First Layer					Second Layer			Output Layer
Weight	N1	N2	N3	N4	N5	N6	N7	N8	O
W1	2.899414	0.596148	-2.335289	0.587112	-2.543607	-0.972153	0.361672	-1.122330	0.977077
W2	-1.073932	-0.424527	1.062468	-0.722455	1.321112	0.532098	1.652928	-0.022480	0.948488
W3	4.553558	-0.015087	-1.594293	0.061561	-0.183996	-0.700208	2.788553	-1.695445	-1.319948
W4						2.229601	1.578676	1.203406	
W5						0.624063	0.027321	2.163266	

Table 5. Results of Testing Simulation and predicted warpage by ANN and amount of error

Test No.	Melt Temp. (ºC)	Holding Pressure (% of IP)	Mold Temp. (ºC)	Simulated Warpage (mm)	Warpage Predicted by ANN (mm)	Error (%)	Test No.	Melt Temp. (ºC)	Holding Pressure (% of IP)	Mold Temp. (ºC)	Simulated Warpage (mm)	Warpage Predicted by ANN (mm)	Error (%)
T1	270	80	50	1.440	1.435	-0.347	T11	215	76	38	1.212	1.223	0.908
T2	270	70	40	1.527	1.519	-0.524	T12	203	67	49	1.314	1.312	-0.152
T3	260	65	60	1.557	1.552	-0.321	T13	190	72	62	1.129	1.150	1.860
T4	260	78	35	1.417	1.418	0.071	T14	192	81	47	0.958	0.981	2.401
T5	260	85	65	1.328	1.323	-0.377	T15	198	75	23	1.102	1.138	3.267
T6	250	77	48	1.396	1.392	-0.287	T16	210	70	40	1.289	1.297	0.621
T7	245	82	25	1.280	1.283	0.234	T17	266	65	69	1.561	1.575	0.897
T8	240	80	56	1.312	1.292	-1.524	T18	205	78	51	1.134	1.138	0.353
T9	213	90	28	1.050	1.078	2.667	T19	191	73	63	1.115	1.139	2.152
T10	220	82	59	1.162	1.147	-1.291							

$$V_R = V_{min} + V_N\left(V_{max}\text{-}V_{min}\right) \quad (8)$$

where, V_{min}, and V_{max} are the minimum and maximum of data respectively. V_N is normalized value that was obtained from ANN model prediction, and V_R is the real value of V_N.

To determine the accuracy of ANN model for each test, the predictive system error was calculated by Eq. (9) and the error results are given in Table 5. To evaluate the total accuracy of the ANN model, R-Squared (R^2) was used. R-Squared of data used for training of ANN model is equal to 0.997. This shows that ANN model fits perfectly, and its performance in training data is satisfactory. Then R-Squared was calculated for Testing Simulations. R-Squared for data that were not used in the training phase of ANN model is equal to 0.995 as shown in Fig. 3. This shows that the performance of ANN model is also satisfactory for random data that were not trained. Comparison of the simulated warpage with the ANN results is graphically shown in Fig. 3.

$$\text{Error} = \frac{\text{Predicted value-Simulated value}}{\text{Simulated value}} \times 100\% \quad (9)$$

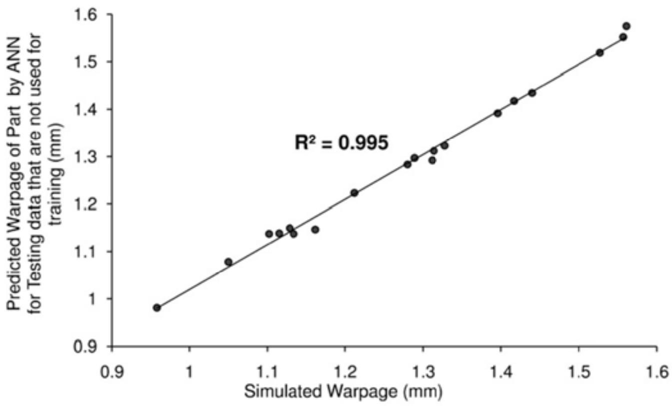

Fig. 3. Comparison of the simulated warpage and predicted warpage by ANN model for testing data not used for training.

6. RESULTS AND DISCUSSION

According to the warpage simulation results, it is determined that melt temperature and holding pressure are more effective parameters than the mold temperature. Figure 4 helps us to get a better view of the simultaneous influence of melt temperature and holding pressure in total warpage. As shown in Fig. 4, with an increase in the melt temperature, the warpage increases. For example, in four simulation tests (test numbers 433, 333, 231 and 133), the mold temperature and holding pressure were held constant but melt temperatures were 280, 230, 205 and 180 and related warpage amounts were 1.351, 1.083, 0.888 and 0.527mm respectively. With an increase in holding pressure, the warpage decreases. For example, in three simulation tests (test numbers 233, 223 and 213), the mold temperature and melt temperature were held constant but holding pressures were 90, 75 and 60% of IP and related warpage amounts were 0.888, 1.185 and 1.439 mm respectively. In Figs. 4, 5 and 6 the straight lines with filled circle represent the simulation results, and the dashed lines with unfilled circle represent the ANN model predicted results.

In Fig. 5, simultaneous effects of melt temperature and mold temperature on the warpage amount at constant holding pressure (75% of IP) are shown. In Fig. 6, simultaneous effects of holding pressure and mold temperature on the warpage amount at constant melt temperature (230°C) are shown. As shown in Figs. 5 and 6, when the melt temperature and holding pressure are constant with a change in mold temperature, no significant change is observed in the amount of warpage. Therefore, one can say that the mold temperature has the least influence on warpage than the other two parameters. Briefly, melt temperature and holding pressure are the most effective parameters on the warpage of the part. As is observed, there is not a linear relationship between the process parameters and the part warpage. Therefore, using an ANN model could be useful, and it can make a relationship between such nonlinear problems.

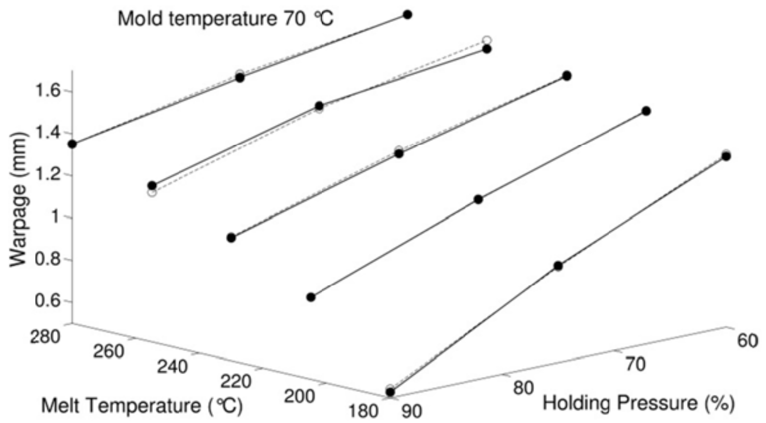

Fig. 4. Comparison of the simulation and predicted results of ANN model based on the various melt temperatures and holding pressures at constant mold temperature, 70 ºC

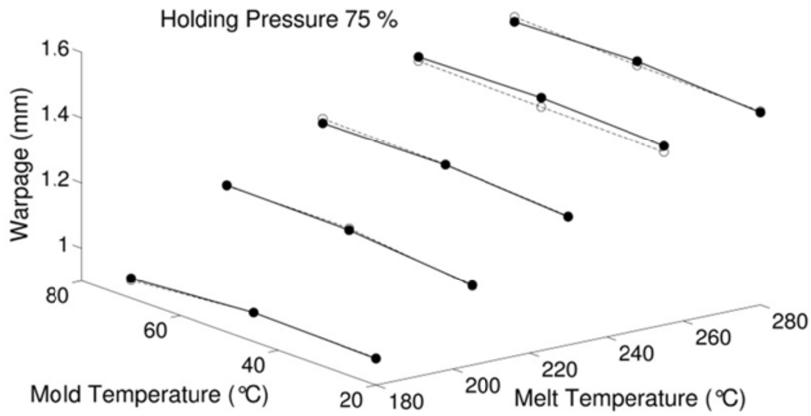

Fig. 5. Comparison of the Simulation and predicted results of ANN based on the melt temperature and mold temperature in constant holding pressure, 75 % of IP

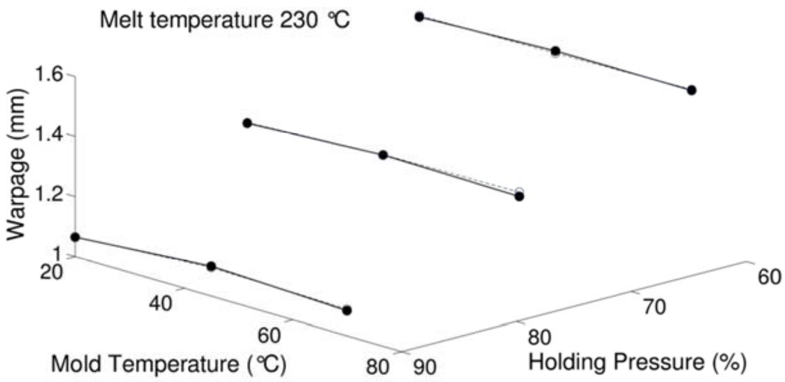

Fig. 6. Comparison of the simulation and predicted results of ANN based on the holding pressure and mold temperature in constant melt temperature, 230 ºC

7. CONCLUSION

Process simulation with different settings including melting temperature, holding pressure and mold temperature, was carried out and the result of each simulation was recorded. Then the effects of process parameters on the part warpage were investigated. The results showed that holding pressure and melt temperature have the most and mold temperature has the least effect on the part warpage. Subsequently, an ANN model was created based on results of the first group of process simulation. Performance of the created ANN model was satisfactory. Results of the second group of simulation were used for testing the ANN model, whose performance was also satisfactory. The results of validation and comparative study indicate that the ANN model-based estimation technique for part warpage is more suitable. This study confirms the ability of the ANN model to predict the part warpage.

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