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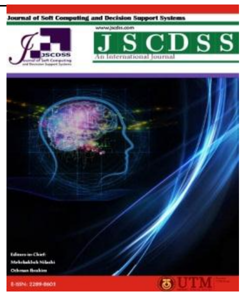

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Warpage Prediction in Injection Molding Using Artificial Neural Network

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Abstract

Finding optimal parameters setting which produce minimum warpage value in injection molding always a big challenging. The traditional method which based on trial and error and workers knowledge and experiences required a lot of time and costs. Artificial Neural Network (ANN) is a modelling technique which has been used widely in many areas. In this study, ANN is used as modelling technique in predicting the optimal parameters setting that lead to minimum warpage value in injection molding. As the results, ANN model successfully improves the warpage value by 0.02% compare to experiment result with 39.68°C for cooling temperature, 2.183s for injection time , 97.43% for V/P switchover and 39.07°C for mold temperature.

Keywords: Warpage, Injection molding, Artificial Neural Network

1. Introduction

Injection molding is a popular method for producing complex plastic part and suitable for mass production. It has been used widely in various field of economy (Li et al., 2009). Injection molding has several advantages such as has the ability to produce complicated geometries product shape and excellent accuracy of product in single production step, short cycle time and very long mold life, has the ability to produce excellent quality product, light weight, high production rate and low cost and it is an economic method to produce mass production (Chen & Liu, 1999; Goodship, 2004; Koh & Lee, 2002; Oktem et al., 2007; Stanek et al., 2011).

In injection molding, there are six steps involved which are (Drobny, 2014; Rosato et al., 2000):

i. **Start plastication.** The plastic material is feed into hopper and transfer into barrel. In this step, the plastic material will be melted and the screw will be spin along with melted plastic material and transfer it in front of screw tip called screw chamber.
ii. **End plastication.** The screw will stop when enough plastic material in screw chamber.
iii. **Mold closing.** The mold clamp is closing.
iv. **Start injection.** The screw move forward and push the melted plastic material in mold cavity. In this step, the screw did not spin.
v. **End injection.** The mold consists of hot melted plastic material being cooled from melt temperature. In this step, the plastication in step (i) is making preparation for the next injection.
vi. **Molding ejection.** The mold will be open and finishing plastic product can be ejecting after go through the cooling procedure. The injection molding steps is end. New injection can start from step (ii).

During injection molding process, defects of the product which affect the quality such as warpage may occur. Warpage is the non-desired shaped which produce after the plastic product ejected from the mold. One of the methods to overcome this problem is by selecting the optimal parameters in injection molding which can minimize the warpage value (Shi et al., 2013).

Traditionally, selection of combination parameters in injection molding is based on trial and error and workers knowledge and experiences (Cheng et al., 2013). These methods required a lot of time and costs. Moreover, inexperienced workers may undergo difficulty in selecting optimal parameters. Artificial Neural Network (ANN) is one of promising technique in finding the optimal parameters which lead to minimum warpage value. ANN has the ability to represent almost every function that maps an input to an output. This means that even the difficult nonlinear problems can be solved by using ANN. In addition, compared to conventional approaches ANN is more successful and fast in learning from examples.

This paper discusses the implementation of ANN in finding the combination of optimal parameters setting in minimizing the warpage value in injection molding. Hence the objectives of this paper are:

i. To estimate minimum warpage value in injection molding using ANN technique.
ii. To estimate optimal parameters setting namely cooling temperature, injection time, V/P switchover and mold temperature that lead to minimum warpage value in injection molding using ANN technique.

2. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) was inspired from biological system of human brain. ANN has been widely used in signal processing, telecommunication, financial, industry, business, science and others. ANN has been choosing to use as prediction and modelling in recent decades (Akbari et al., 2015; Azlan et al., 2010; Nilashi et al., 2014; Nilashi et al., 2015; Prihasto et al., 2014). The basic flow of ANN method is as shown in Fig. 1.

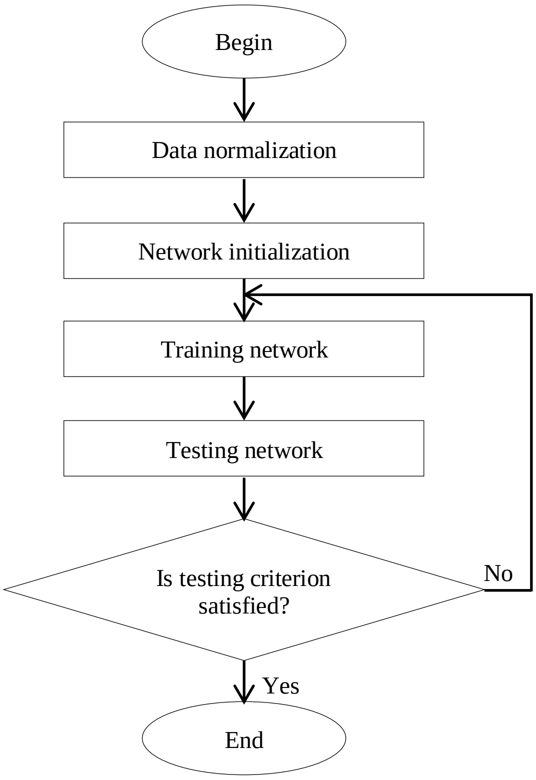

Fig. 1. Basic ANN Flow.

From Fig. 1, firstly, the initial data will undergo normalization process. Then, the network is initialized which include the selection of data ratio between training and testing phase, selection of network structure, selection of transfer function and selection of performance measure. After that, the network will continue to training phase and then testing phase. If the testing criterion is satisfied, the flow will end. If not, same procedure will be done from training to testing until the desired result is obtained.

3. Case Study

This study used the experiment data from Moldflow by Guo et al. (2012). The researchers select the automotive interior trim product as shown in Fig. 2 as research model which has 260mm x 450mm x 70mm dimensions and used polypropylene copolymer from Moldflow as product material.

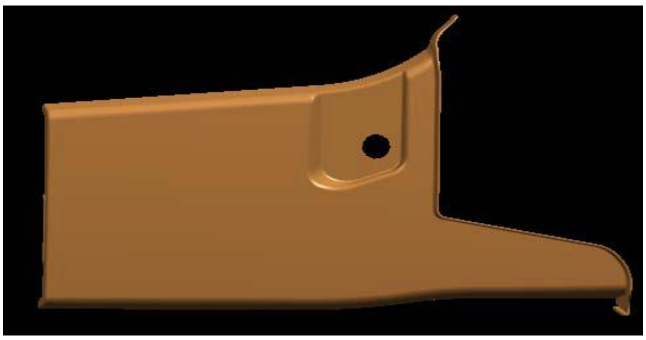

Fig. 2. The Automotive Interior Trim Product (Guo et al., 2012)

Four parameters involve in this study which are cooling temperature (T_{cool}), injection time (t_{inject}), V/P switch over (V/P) and mold temperature (T_{mold}). Table 1 shows the levels for each parameter.

Table 1
Level of Parameters.

Code Level	T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)
-1	20	1.8	97	20
-0.5	25	1.9	97.5	25
0	30	2.0	98	30
0.5	35	2.1	98.5	35
1	40	2.2	99	40

4. Estimation Minimum Warpage Value using ANN

Since the data from case study is quite small, this study used method suggested by Manjunath and Krishna (2012) to generate 200 dataset. More data is necessary to produce better result and avoid overfitting. To generate 200 dataset, the value of parameters is generated within the range of parameters and the mathematical model in Eq. (1) is required to produce predicted warpage value.

$$W = 4.09888 - (0.11621)T_{cool} - (0.12179)t_{inject} + (0.00587)V/P - (0.00387)T_{mold} - (0.02497)T_{cool}^{2} - (0.00509)t_{inject}^{2} - (0.01734)V/P^{2} - (0.00772)T_{mold}^{2} - (0.04706)T_{cool}\, t_{inject} + (0.00419)\, T_{cool}V/P - (0.00106)T_{cool}T_{mold} + (0.01294)t_{inject}V/P - (0.00106)\, t_{inject}T_{mold} - (0.00056)\, V/PT_{mold} \quad (1)$$

This study used MATLAB ANN toolbox in implementation of warpage prediction using ANN. Feedforward multilayer perception with back propagation learning algorithm (BPNN) is use as network model since it is most applied by researchers.

Data Normalization in this study is based on normalize equation in Eq. (2).

$$x_N = 0.1 + 0.8 \times \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (2)$$

where x_N is parameter value after normalized, parameter value before normalize, $\min(x_i)$ is minimum of parameter value and $\max(x_i)$ is maximum parameter value.

Normalized parameters values are used as the inputs, and normalized warpage values are used as the target in the modelling process.

The data are divided randomly into three sections namely training sample, validate sample and testing sample in 85:5:10 ratios.

ANN consists of several layers which include input layer, hidden layer and output layer in the network structure. Each layer consists of neurons or nodes. In network structure, nodes in input layer usually consist of variables of the problem, while nodes in output layer consists the target of the problem. These nodes are connected to each other using communication links to form a network. These links consist of weights which carry information used by the network to solve a problem. The nodes in input layer received information from external. The nodes in hidden layer received information from input nodes in input layer and transfer the information to output nodes in output layer. The output nodes in output layer consists the solution of the problem. In this study, the input variables are the four parameters namely T_{cool}, t_{inject}, V/P and T_{mold} while the output variable is warpage of plastic part in injection molding.

For network structure, the selection of hidden layer is based on trial and error and this study using one hidden layers. The selection of hidden nodes in the hidden layer is based on guideline by Zhang et al. (1998). Thus the network structures are 4-2-1, 4-4-1, 4-8-1, and 4-9-1.

Logsig and *purelin* are use as transfer function while *trainlm* and *learngdm* are use as training function and learning function respectively. MSE is use as performance function since it is most applied by researchers.

5. Results and Discussion

ANN model 4-8-1 was selected as the best ANN model for modelling the automotive interior trim product since it has the lowest warpage value (3.7752mm), lowest MSE value (0.0000003) and highest correlation value (0.9999) compared to other three models. Fig. 3 shows network structure for ANN model 4-8-1.

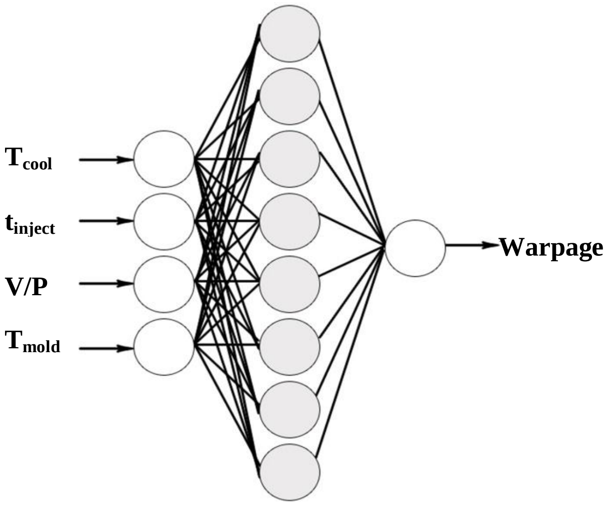

Fig. 3. Network Structure for ANN Model 4-8-1

Table 2 shows the comparison result between experiment from case study and ANN model.

Table 2
Comparison Result between Experiment and ANN Model.

	T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)	Warpage (mm)
Experiment	40	2.0	98	30	3.7760
ANN Model	39.68	2.183	97.43	39.07	3.7752

From Table 2, ANN model successfully improves the warpage value by 0.02% compare to experiment result with 39.68°C for T_{cool}, 2.183s for t_{inject} , 97.43% for V/P and 39.07°C for T_{mold}.

6. Conclusion

This study has discusses on the implementation of ANN in predicting the minimum warpage value in injection molding. Four parameters namely T_{cool}, t_{inject}, V/P and T_{mold} is used as input nodes in input layers and warpage used as output nodes in output layers. The result shows that ANN successfully minimized warpage value by 0.02% compare to experiment result.

For future work, this study recommends using others soft computing technique such as Genetic Algorithm (GA), Fuzzy Logic (FL), swarm intelligent and others in finding the optimal parameters setting which lead to minimum warpage value in injection molding. Additionally, this study also recommends using multi-objective optimization which consists of more than one defect such as weld line, sink mark, shrinkage and others in order to produce a high quality product.

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