퍼지-신경망을 이용한 미성형 사출제품의 최적해결에 관한 연구

A Study on Optimal Solution of Short Shot Using Fuzzy Logic Based Neural Network(FNN)

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ABSTRACT

In injection molding, short shot is one of the frequent and fatal defects. Experts of injection molding usually adjust process conditions such as injection time, mold temperature, and melt temperature because it is the most economic way in time and cost. However it is a difficult task to find appropriate process conditions for troubleshooting of short shot as injection molding process is a highly nonlinear system and process conditions are coupled. In this paper, a fuzzy neural network(FNN) has been applied to injection molding process to shorten troubleshooting time of short shot. Based on melt temperature and fill time, a reasonable initial mold temperature is recommended by the FNN, and then the mold temperature is inputted to injection molding process. Depending on injection molding result, specifically the insufficient quantity of an injection molded part, an appropriate mold temperature is recommend repeatedly through the FNN

Keywords : FNN, Injection Molding, Short Shot, Filling Analysis, Process Conditions, Fuzzy

I. Introduction

Injection molding is a process by which plastic pellets or powders are melted and pressurized into a cavity to form a complex three-dimensional part in a single operation [1]. Among the variety of quality problems with injection molded plastic parts, short shot has top priority[2,3]. Problematic short shots occur when the polymer melt cannot fill the entire cavity most commonly at thin sections or extremities. Once short shot has occurred, the cause should be found and probable remedies for the problem should be done immediately. As the first remedy, experts of injection molding might try to adjust process conditions such as temperature, pressure, and injection time based on their empirical knowledge because it is a convenient and economic way to solve the problem. But it is not an easy task to determine appropriate process conditions because process conditions are highly coupled, or they affect each other.

Fuzzy rule base stores the empirical knowledge of the experts and inference engine has the capability of simulating human decision making by performing approximate reasoning[4]. But fuzzy logic algorithm has a problem in acquiring the fuzzy rules and tuning the membership functions because it doesn't have much learning capability[5,6]. Therefore, a fuzzy neural network(FNN) has been applied to injection molding so that troubleshooting time of short shot can be reduced by finding an appropriate mold temperature as soon as possible. To evaluate the FNN, a cell phone flip has been selected as a model for the application and then computer simulations with a CAE software named C-MOLD[7] have been performed.

II. Application of FNN to Injection Molding

In general, experts of injection molding process adjust the mold temperature to solve short shot by trial and error, which is very demanding in time and cost, and even harder for non-experts to carry out as it depends on empirical knowledge. A FNN has been applied to injection molding process to reduce troubleshooting time of short shot by finding an appropriate increment of the mold temperature quickly. Figure 1 shows the architecture of the FNN application to injection molding process. In Figure 1, e is the insufficient quantity of the injection molded part after filling simulation.

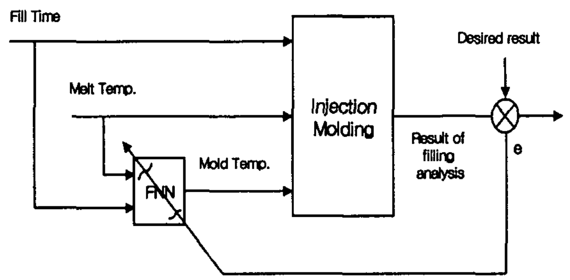

Figure 1 Schematic diagram of fuzzy logic algorithm application to injection molding

To speed up learning, an effective strategy has been proposed. The learning of the FNN was executed in two stages as follows.

First stage

The FNN has been trained with the mold temperature data which was obtained from the pre-performed simulation results conducted by Golden Section Search method. The data have become the target mold temperature. In this stage, fill time and melt temperature was taken into consideration.

Second stage

In the second stage, the learning was performed in direction of reduction of error which is the percentage of the insufficient quantity of an injection molded part. The speed of the learning in this stage was considerably improved since the FNN has been trained in the first stage to generate reasonable mold temperature.

Figure 2 shows the configuration of the proposed FNN which is a feedforward architecture with five layers.

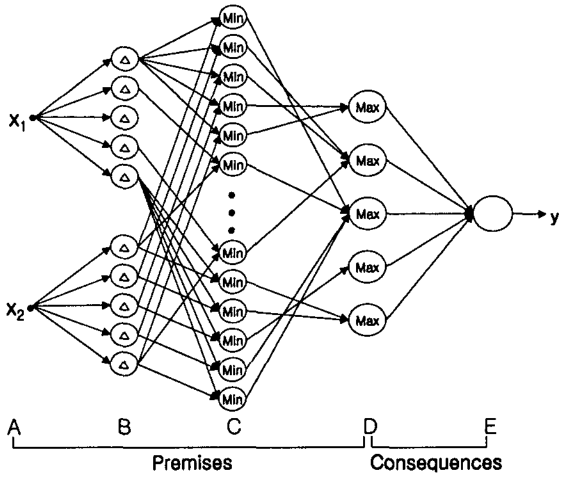

Figure 2 Architecture of the proposed feedforward FNN

In the layer A, x_1 represents fill time and x_2 melt temperature. The second layer B is divided into two groups of neurons. Each neuron in the layer B represents a discrete universe of discourse. Once input data come into the layer B, membership values of each input are calculated in each neuron by Equation (1).

$$F_B = \mu_b = \begin{cases} 1 - \dfrac{x-c}{w_R} & \text{when } c \le x \le c + w_R \\ 1 + \dfrac{x-c}{w_L} & \text{when } c - w_L \le x \le c \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where c , w_R and w_L are nodal values and bounds of the triangle fuzzy numbers. In Equation (1), c , w_R and w_L are initially determined in each fuzzy partition by the membership functions of the inputs shown in Figure 3 and Figure 4.

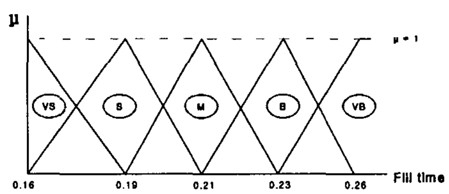

Figure 3 Membership functions of fill time

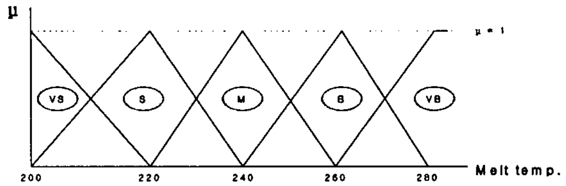

Figure 4 Membership functions of melt temperature

Layer C and layer D play a role as a fuzzy inference specifically Mamdani's MAX-MIN operator. The number of the neurons in the layer C is the number of the fuzzy rules.
And in the layer E, an appropriate mold temperature is acquired by defuzzification. As the defuzzifier to obtain a crisp output, Simplified Center Of Gravity method[8] has been used as follow.

$$y^* = \frac{\sum_{i=1}^{5} \mu_{Di}\, y_i}{\sum_{i=1}^{5} \mu_{Di}} \tag{2}$$

Where y^* is an optimal mold temperature and y_i is a center of each universes of discourse.
The error function can be defined by

$$E = -\frac{(d-y^*)^2}{2} \tag{3}$$

The error signal of the output layer in the FNN is derived as

$$\frac{\partial E}{\partial y^*} = -(d-y^*) \tag{4}$$

,where d is the target mold temperature.
From Equation (2), the derivative of y^* with respect to the output membership value, μ_D, from the layer D is computed accordingly,

$$\frac{\partial y^*}{\partial \mu_{Di}} = \frac{y_i \sum_{i=1}^{5} \mu_{Di}\, y_i - \sum_{i=1}^{5} \mu_{Di}\, y_i}{\left(\sum_{i=1}^{5} \mu_{Di}\right)^2}$$

$$= \frac{1}{\sum_{i=1}^{5} \mu_{Di}} \left[y_i - \frac{\sum_{i=1}^{5} \mu_{Di}\, y_i}{\sum_{i=1}^{5} \mu_{Di}} \right]$$

$$= \frac{1}{\sum_{i=1}^{5} \mu_{Di}} \left[y_i - y^* \right] \tag{5}$$

Following the calculus suggested by Pedrycz[11], the derivatives of the MAX-MIN operation are defined as:

$$\frac{\partial \mu_D}{\partial \mu_C} = \begin{cases} 1 & when \quad \mu_C = \mu_D \\ 0 & otherwise \end{cases} \tag{6}$$

$$\frac{\partial \mu_C}{\partial \mu_B} = \begin{cases} 1 & when \quad \mu_B = \mu_C \\ 0 & otherwise \end{cases} \tag{7}$$

And in the layer B, we can derive $\frac{\partial \mu_B}{w_L}$ and $\frac{\partial \mu_B}{w_R}$ from Equation (1).

$$\frac{\partial \mu_B}{\partial w_L} = \frac{-(x-c)}{w_L^2} \tag{8}$$

$$\frac{\partial \mu_B}{\partial w_R} = \frac{(x-c)}{w_R^2} \tag{9}$$

After all, the increments of w_R ($\triangle w_R$) and w_L($\triangle w_L$) are obtained by the following equations.

$$\Delta w_R = -\eta \frac{\partial E}{\partial y^*} \sum \frac{\partial y^*}{\partial \mu_D} \frac{\partial \mu_D}{\partial \mu_C} \frac{\partial \mu_C}{\partial \mu_B} \frac{\partial \mu_B}{\partial w_R} \tag{10}$$

$$\Delta w_L = -\eta \frac{\partial E}{\partial y^*} \sum \frac{\partial y^*}{\partial \mu_D} \frac{\partial \mu_D}{\partial \mu_C} \frac{\partial \mu_C}{\partial \mu_B} \frac{\partial \mu_B}{\partial w_L} \tag{11}$$

With obtained $\triangle w_R$ and $\triangle w_L$, we can update w_R and w_L as shown in Equation (12) and (13), which is the process to minimize the error of y^*.

$$w_L^{(k)} = w_L^{(k-1)} + \Delta w_L^{(k)} \tag{12}$$

$$w_R^{(k)} = w_R^{(k-1)} + \Delta w_R^{(k)} \tag{13}$$

Overall, the learning algorithm can be summarized by the following steps:

Begin
· Initialize the parameters with the initial membership functions and rules
· Set iteration = 0
Repeat
· Update the parameters w_L , w_R by computing the adjustment $\triangle w_L$ and $\triangle w_R$
· iteration = iteration + 1
Until
$E \le E_{\max}$ or $iteration \ge iteration_{\max}$
END

III. Evaluation of the FNN

3.1 Filling simulation with a CAE tool

To evaluate the FNN, filling simulations of a cell phone flip were conducted instead of experiments in injection molding. The simulations were conducted in two ways; one was based on Golden Section Search method which simulates the expert's behavior in troubleshooting of short shot, and the others on the FNN.

Figure 5 shows the finite element model of a cell phone flip.

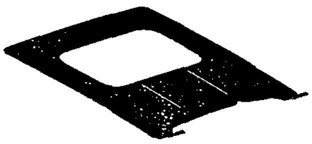

Figure 5 Finite element model for the simulations

Process conditions used in the simulations are in Table 1. As shown in Table 1, melt temperature and fill time have the ranges, but not specified because they were used as variables in the simulations. In the case of the cell phone flip, the fill time range was estimated from 0.16(s) to 0.28(s). The simulations were conducted with 10 cases as shown Table 2.

Table 1 Process conditions

Injection pressure	120 MPa
Packing pressure	100 MPa
Gate type / number	Side gate / 2
Melt temperature	Variable(200~280℃)
Fill time	Variable(0.16~0.28sec)
Mold temperature	Output variable

Table 2 The simulation data

No.	Fill time (sec)	Melt temperature (℃)
01	0.16	220
02	0.17	260
03	0.18	230
04	0.19	280
05	0.20	240
06	0.21	220
07	0.22	280
08	0.23	230
09	0.24	260
10	0.25	270

3.2 Simulation results

For the simulation data, Figure 6 graphically shows the iteration number of the two ways for the simulation data.

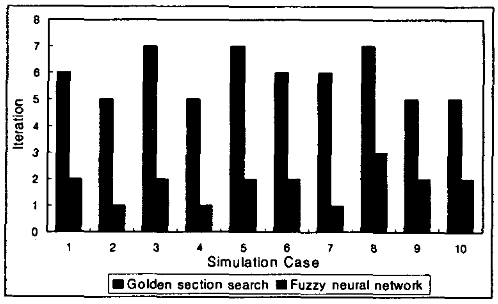

Figure 6 Iteration number of the simulations

As shown in Figure 6, average iteration number of filling simulation conducted by Golden Search Method is 5.9 and by the proposed FNN is 1.8.

IV. Conclusions

A FNN has been applied to injection molding system to reduce troubleshooting time of short shot. As a result, the trained FNN helped to reduce the troubleshooting time by about 69% within reliable mold temperature range. And the FNN is expected to give not only non-experts but also experts of injection molding an easy and reliable way to determine mold temperature so that short shot can be solve quickly.

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