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Application of Neural Networks in Injection Moulding Process Control

S.-J. Huang and T.-H. Lee

Department of Mechanical Engineering, National Taiwan University of Science and Technology, No. 43, Keelung Road, Sec. 4, Taipei, Taiwan, 106

In order to produce precise injection moulding products, a closed-loop controller is employed instead of the open-loop control of a traditional injection moulding machine for monitoring the filling and post-filling phases of the injection processes. Since the injection moulding system has complicated and variable dynamics, the classical control theory is difficult to implement for the precise injection moulding processes. Here, two intelligent neural network control strategies are employed to adjust the injection speed of the filling phase and control the nozzle pressure of the post-filling phase. Since the neural controller has learning ability to track the variation of the injection processes, this control strategy has the advantages of adaptivity and robustness for general purpose application to an injection moulding machine. The experimental results show that this controller has good performance in the actual injection moulding processes.

Keywords: Injection moulding and adaptive neuron; Neural network

1. Introduction

Since plastic material has the advantage of good mechanical properties, low cost, and light weight, it has been adopted as a substitute for some metal material recently. Because of the development of mass production technology in the plastics industry, brought about by economic conditions and the large range of consumer goods, plastic has become an important material both for consumer and industrial products. According to the quality, geometric shape, and purpose of a finished product, various manufacturing methods for plastic products have been developed and are being improved continuously. Injection moulding, extrusion, thermoforming, blowing moulding, compression moulding and transfer moulding are the major plastic forming methods employed currently. Over 60% of thermo-setting plastics are manufactured by the injection moulding method. It has the characteristics of high productivity and precise accuracy and can mass produce complicated finished products at a very low cost. Much work is focused on the study of the injection moulding process control and the optimal design of moulds, in order to improve the product quality.

A complete injection moulding production cycle includes the four steps of plastics melting, injection, cooling and product ejection. Since the plastics properties depend on the temperature, pressure, and the shear stress acting on the raw plastic material, the monitoring conditions during these manufacturing processes are complicated and variable. For example, the material creep and stress relaxation may be 1000 times different owing to injection condition variations [1]. The injection step can be divided further into a filling phase, a compression phase, and a holding phase. The flowrate of the melted plastic in the filling phase will influence the molecular orientation and skin formation [2]. In addition, the flowrate is the most important parameter which influences the material residual stresses of acrylonitrile-butadiene-styrene (ABS) [3]. Since the flowrate is difficult to measure, the speed of the extrusion screw is measured and controlled. The pressure in the compression and holding phases are other important factors in determining the product quality. If the pressure is too large, the mould cavity will expand. The plastic material overflow will then spread out into the clearance between the up and down cavities. The finished product will then have a burr between the cavities, making the product difficult to eject. Conversely, if the pressure is too small, the finished product will have geometric defects and poor mechanical properties [3–5]. The pressure in the compression and holding phases are therefore considered as control variables. Since the pressure inside a mould cavity is difficult to measure and its measurement has certain limitations, the pressure at the injection nozzle is used instead. In this work, a traditional open-loop controlled commercial machine is retrofitted as a closed-loop control

Correspondence and offprint requests to: Professor S.-J. Huang, Department of Mechanical Engineering, National Taiwan University of Science and Technology, 43 Keelung Road, Sec. 4, Taipei, Taiwan. E-mail: sjhuang@mail.ntust.edu.tw
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injection moulding machine to monitor the injection speed and holding pressure.

When designing a controller for an injection moulding machine, a dynamic model of the injection moulding should be developed first. Kamal et al. [6,7] derived the transfer functions for the injection pressure, nozzle pressure, and cavity pressure during the filling phase. Controllers [8,9] were then designed based upon a linearised dynamic model. Paul and Shankar [10,11] proposed a dynamic model for the filling phase by using the state space approach. Wei [12] developed a relationship between the cavity pressure and the flowrate to complete the mathematical model of the filling phase. Pandelidis and Agrawal [13,14] employed self-tuning and optimal control methods to control the filling speed. The compression and holding phases are called the post-filling stage. Kamal and Kenig [15] proposed a model to calculate the plastic flowrate into the cavity, based on the internal pressure difference between cavity and nozzle. The holding pressure influences the molecular orientation and residual stresses in the product [16–18].

Since the hydraulic actuated injection processes have a complicated and nonlinear behaviour, they are difficult to describe with an accurate mathematical model and to control using a traditional controller. In the literature, most studies focus on one part of the injection processes, e.g. the filling phase or post-filling phase. There has been little work on the full injection moulding process. In this paper, model free intelligent controllers are employed to overcome the implementation problems of a complicated mathematical model and the computation burden involved. Two neural network controllers are employed to control the speed of the extrusion screw in the filling stage, and the pressure of the injection nozzle in the post-filling stage. The system structure and dynamic model are briefly described in Section 2. The neural network control strategies are given in Section 3. The experimental results and the signal processing are given and analysed in Section 4.

2. System Structure and Dynamics

The injection moulding machine used in this work was produced by the Fu-Chun- Shin company. In order to improve the response speed during the injection process, the actuating proportional pressure valve and the proportional flow valve were alternated and installed at the hydraulic injection unit. A coupling temperature and pressure sensor set was installed at the end of the plastic pipe near the injection nozzle. This injection moulding machine is controlled by a PC 486 with Turbo C control software. The system structure is shown in Fig. 1.

Injection process monitoring is the most important step for the production of precise injection moulded products. The material, machine operation, and post fabrication variations influence the product quality. Among them, the machine variation is the most important factor [11]. The dynamic model is therefore important for precise injection moulding control, and for the machine designers. The dynamic model can be used to design an appropriate controller. The main dynamic equations employed here were developed by Paul and Shankar [11] and Wei [12] and are described in [19]. Some of the important equation are given in the following sections.

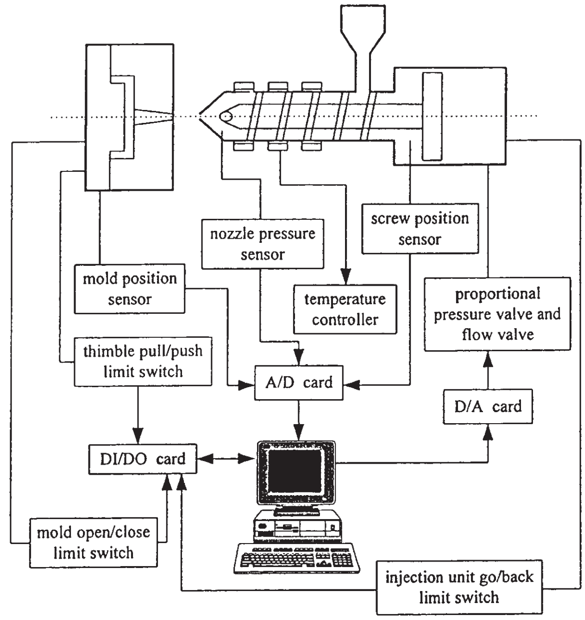

Fig. 1. System control structure of the closed-loop injection-moulding machine.

1. The dynamic equation of the proportional valve :

$$\dot{x} = (-x + K_v E_i)/\tau \quad (1)$$

$$Q_h = K_g x \sqrt{(P_s - P_1)} \quad (2)$$

where x is the spool displacement, E_i is the input voltage and K_v and K_g are the constants. P_s is the oil supply pressure and P_1 is the pressure of the injection cylinder. Q_h is the oil flowrate into the injection cylinder. τ is the hydraulic valve time constant.

2. The dynamics of the filling phase can be described by using mass and momentum conservation equation based upon some assumptions and approximations.

$$\dot{P}_m = K_p(A_2\dot{x} - Q - Q_{1p})/V_2 \quad (3)$$

where Q is the plastic flowrate and Q_{1p} is the leakage rate at the injection screw. V_2 is the total volume of the plastic and P_m is the mean pressure of the plastic. K_p is the bulk modulus of the plastic.

$$\dot{Q} = \frac{P_2 - P_p - \sum(F_{si}/A_i)}{\rho\sum(H_{si}/A_i)} \quad (4)$$

$$P_p = P_2 \exp(-t/\tau_2)$$

$$\dot{P}_{cs} = K_m Q^2 \quad (5)$$

where A_i is the cross-section at the ith flow channel and H_{si} is the equivalent length of the ith plastic section. P_p is the dissipation pressure of the plastic and τ_2 is the constant of pressure dissipation. F_{si} is the shearing force between the ith plastic and the tube wall. P_2 is the plastic pressure near the end of injection screw. P_{cs} is the steady state plastic pressure in the cavity and K_m is a dimension factor.

3. During the compression phase, the plastic flowrate is reduced, the flow resistance is increased and the pressure is increased steeply. The dynamic equation of the cavity pressure is

$$\dot{P}_c = \frac{K_p(P_2 - P_b)}{RV_c} \tag{6}$$

where V_c is the volume of the cavity, R is the flow resistance between the nozzle and the cavity, and P_b is the back pressure of the cylinder after filling. During the holding stage, a relationship exists between the pressure, the specific volume of plastic and the mould temperature which is a function of the cooling effect of product. Generally, the *P-V-T* equation is employed to describe its dynamic behaviour.

$$(P_c + \pi)(\nu_p - \omega) = \bar{R}T_m \tag{7}$$

where T_m is the mean temperature of the plastic inside the mould cavity and ν_p is the plastic density. π, ω, and $\bar{R}$ are the constants.

From the above equation, it can be seen that the dynamics of an injection moulding cycle are very complicated. Even with appropriate assumptions, the dynamic model still has high-order nonlinear behaviour. This makes it difficult to implement a model-based controller design for injection moulding machine process control. In addition, the plastic flowrate and the cavity pressure are difficult to measure and control. However, the speed of the injection screw has some relationship to the flowrate and the pressure at the injection nozzle can be taken as a function of the cavity pressure. For practical considerations, the injection screw speed and the injection nozzle pressure are chosen as the control variables of the filling and post-filling stages, respectively. Since the dynamic model of the injection cycle is too complicated for control design implementation, model-free neural network control methods are employed to design the controller. They can overcome the computation problem of high-order nonlinear equation and eliminate the problem of accurate system modelling. In addition, the learning ability of the neural controllers can overcome the system parameter variations owing to the change of mould shape and material. Neural network control is also tolerance variations in switching point, i.e. the time at which the filling phase ends and the post-filling phase begins.

3. Neural Network Control

The control performance of a traditional controller depends entirely on the accuracy of the system dynamic model. The dynamics of injection moulding are nonlinear and have uncertainty, so it is impossible to obtain an accurate mathematical model of a complicated injection moulding system for designing a model base controller to achieve the desired control performance and accuracy. A model-free intelligent controller is therefore introduced to solve this kind of problem by using a neural network. A neural network has the abilities of learning, high-speed parallel processing, and good fault tolerance and environmental adaptivity. It can be used to solve complex nonlinear problems. Neural networks have been successfully employed in image processing, robotic control, and other industrial applications.

The mathematical model of an MP neuron was proposed by McCulloch and Pitts in 1943. However, the field of neural networks had not attracted the attention of researchers until the presentation of the HNN model proposed by Hopfield [20] in 1982. He introduced the energy function concept into neural networks. This approach provided a criterion for the stability analysis of neural networks. Rumelhart and McClelland [21] proposed a multilayer feedforward neural network with a back-propagation learning scheme. The learning results are fed back to the neurons of the hidden and output layers to adjust the weighting matrix for the objective of predictive learning. Here, a feedforward neural network combined with a back-propagation algorithm is employed to control the pressure of the injection nozzle in the post-filling stage. A single adaptive neuron neural network strategy is adapted to control the speed of the injection screw and the pressure of the injection nozzle in the filling and post-filling stages, respectively.

3.1 The Feedforward Neural Network with Back-Propagation-Scheme

The multilayer feedforward neural network combined with a back-propagation learning algorithm to modify the weighting of the neural network is the most popular neural network for the current application. It has the learning abilities which reflect the basic characteristic of a human brain neural network. A multilayer feedforward neural network consists of many processing elements which are interconnected with data weighting. If the weighting between processing elements is large, the influence of that connection is strong. The summation of the input signal multiplied by their corresponding weighting is used to determine the activation value.

$$net_j^k = \sum W_{ji}^k O_i^{k-1} - \theta_j^k \tag{8}$$

$$O_j^k = f(net_j^k) \tag{9}$$

where net_j^k is the net input function of the jth processing element on the kth layer. W_{ji}^k is the weighting between the interconnection of the ith and jth processing elements. O_i^{k-1} is the output of the ith processing element on the $(k-1)$th layer. θ_j^k is a biased term employed as an internal threshold value for any activation to occur. $f(\cdot)$ is the activation function which must be differentiable and not reducing. Each processing element can be interconnected arbitrarily. In general, it is interconnected by a sequential method as shown in Fig. 2. The neurons of each layer are connected with the neurons of the other layer. Each layer has one or more neurons without interconnection. The complete connection consists of an input layer, a hidden layer and an output layer.

The back-propagation learning method uses the error between the real output of a neural network and the desired value to adjust the weighting values in network. the object function is defined as

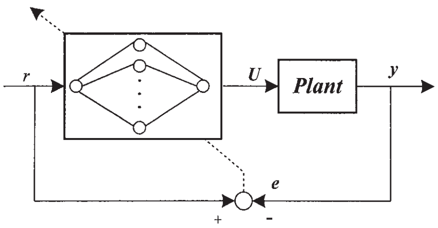

Fig. 2. Block diagram of the feedforward back-propagation neural network.

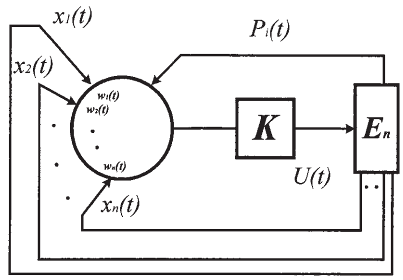

Fig. 3. Activation flow diagram of adaptive neuron.

$$E = \frac{1}{2}\sum_j (Y_{dj} - O_j)^2 \tag{10}$$

By using the steepest-descent method to modify the weighting values in order to minimise the objective function, the correction value of the weighting can be obtained:

$$W_{ji}^k = \eta\delta_j^k O_i^{k-1} \tag{11}$$

$$\theta_j^k = -\eta\delta_j^k \tag{12}$$

where η is the learning rate parameter and δ_j^k is defined as

$$\delta_j^k = -\frac{\partial E}{\partial net_j^k} \tag{13}$$

If the processing element j is on the output layer, then

$$\delta_j^k = (y_{dj} - O_j)f'(net_j^k) \tag{14}$$

Otherwise,

$$\delta_j^k = f'\ (net_j^k)\sum_l \delta_l^{k+1}\ W_{lj}^{k+1} \tag{15}$$

The activation function used in this work is a linear function, $f(net_j^k) = m \times net_j^k$, for the output layer and a sigmoid function for the hidden layer.

$$f(net_j^k) = \frac{1 - \exp(-\lambda net_j^k}{1 + \exp(-\lambda net_j^k)} \tag{16}$$

During the learning procedure, an inertial term is introduced into the learning equation of the weighting correction [22] in order to improve the oscillation phenomenon of the learning interval. This term is a certain portion of the correction value of the last step.

$$W_{ji}^k(t) = \alpha W_{ji}^k(t-1) + \eta\delta_j^k O_i^{k-1} \tag{17}$$

$$\theta_j^k(t) = \alpha\theta_j^k\ (t-1) - \eta\delta_j^k \tag{18}$$

3.2 Intelligent Control of Adaptive Neuron

An adaptive neuron was proposed by Ning et al. [23,24]. Its learning structure and environmental adaptivity can be explained as in Fig. 3. The neuron has n inputs $X_i(t)$ with a corresponding weighting value $W_i(t)$. $P_i(t)$ is a progressive signal or a performance index and E represents the environment. k is a positive constant called a neuron proportional coefficient. Generally, it is assumed that the weighting value $W_i(t)$ of the neuron is proportional to $P_i(t)$ and gradually decays during the learning interval. Then, the learning rule of the neuron can be represented as

$$W_i(t+1) = (1-c)W_i(t) + d_iP_i(t) \tag{19}$$

where d_i is a learning speed parameter and c is a constant. For the requirement of adaptive control, the learning strategy should combine the concepts of Hebbian self-learning and supervised learning. This learning structure is self-organisation learning and the control is based on environmental signals under the supervision of a teaching signal. It also evaluates implicitly the activation signal of neurons. If the constant c is small enough, it can be proved that the weighting value $W_i(t)$ can converge to a stable value W^*_i. If the performance index is defined as the error squared,

$$J = \tfrac{1}{2}[r(t) - y(t)]^2 \tag{20}$$

where r is the reference input and the system output y can be described as a function of

$$y(t) = f(X(t), W(t), U(t)) \tag{21}$$

where X, W and U are the input, weighting value and control output vectors. In order to make sure of the convergence of this progressive learning scheme, the constant c is chosen as zero and the control output are normalised as

$$U(t) = k[\sum_{i=1}^{n} W_i(t)X_i(t)]/\sum_{i=1}^{n} W_i(t) \tag{22}$$

Let

$$P_i(t) = -d\frac{\partial J}{\partial W_i(t)}X_i(t) \tag{23}$$

then the weighting value of the next step can be obtained as

$$W_i(t+1) = W_i(t) + d[r(t) - y(t)]\frac{\partial f(\cdot)}{\partial W_i(t)}X_i(t) \tag{24}$$

Since the function f is unknown for general implementation, the term $\partial f(\cdot)/\partial W_i(t)$ can be substituted by the increment of $\Delta f(\cdot)/\Delta W_i(t)$. The correction of the weighting value of this learning scheme, eq. (24), is along the negative direction of the gradient. When the weighting value reaches the converged value, W^*_i, the performance index J is also a minimum. For this injection moulding control, the input variables are $X_1(t) = r(t), X_2(t) = r(t) - y(t)$ and $X_3(t) = X_2(t)/(1 - Z^{-1})$. The normalised weighting factor is

$$\overline{W}_i(t) = W_i(t)/\sum_{i=1}^{3} W_i(t)$$

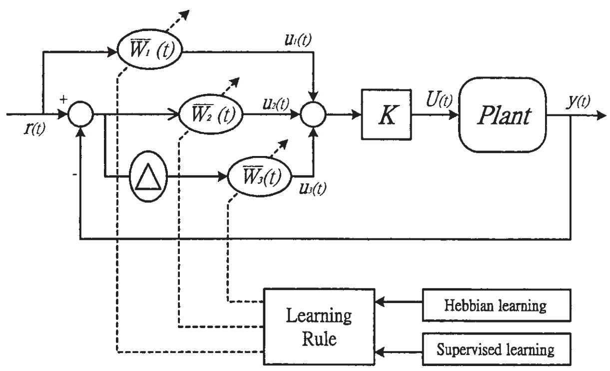

Fig. 4. Adaptive neuron control structure.

The adaptive neuron control block diagram is shown in Fig. 4. The control signal includes feedforward proportional control $u_1(t)$, feedback proportional control $u_2(t)$ and feedback differential control $u_3(t)$ The feedforward loop can improve the system response due to a known variation. The feedback proportional control can reduce the system tracking error quickly. The differential control loop can improve the dynamic characteristics of the system response.

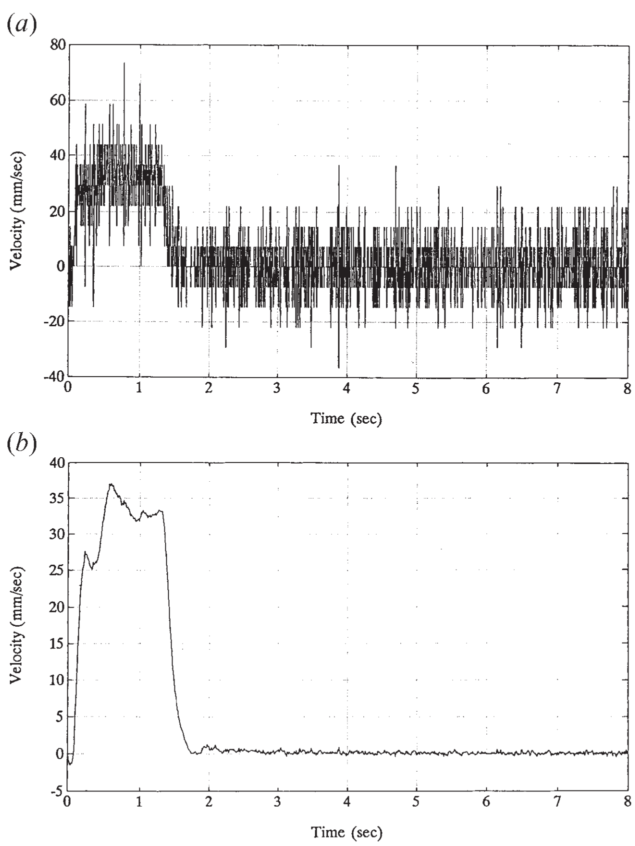

Fig. 5. Velocity curve of the infection screw (*a*) before filtering and (*b*) after filtering.

4. Experimental Results

Since an injection moulding machine has obvious nonlinear behaviour and the switching point between the filling phase and the post-filling phase has varying characteristics for general application, the application of a traditional PID controller requires intricate gains adjustment for each product mould. Hence, the neural network control is employed to improve the system robustness and reduce the implementation effort. The speed control of the injection screw in the filling phase and the pressure control in the post-filling phase are selected as the control targets for the closed-loop injection moulding machine. In order to handle the numerous machine parameters and the complicated moulding processes, a simple man–machine interface Turbo C program was designed. This includes the injection processes control, data transformation, plotting, and advice functions. The sampling frequency for controlling this injection process is chosen as 200 Hz.

The voltage signal of the potentiometer in the speed control loop is liable to be influenced by environmental noise. The speed information is extracted from the position data by using a central difference scheme, so disturbance involved in the measurement data will be magnified. Hence, a digital filter [25] is employed to filter out the noise.

$$\hat{y}(k) = \beta\hat{y}(k-1) + (1-\beta)y(k) \tag{25}$$

where $y(k)$ and $\hat{y}(k)$ are the velocity signal of the injection screw derived from the potentiometer data, and the estimated velocity signal after filtering, respectively. β is a design parameter between 0 and 1. A smaller β has a smaller filtering effect, whereas a larger β has a better filtering effect but involves a slower following tendency. Since the speed signal is derived from a central difference scheme which induces high-frequency noise, a second-order digital filter is employed instead of a first-order filter to obtain a suitable control signal. During the experiments, the design parameter β is chosen as 0.8. The speed signals of the injection screw before and after the filter are shown in Fig. 5(*a*) and 5(*b*), respectively, for comparison.

The switching point in the injection cycle is the point at which the process switches from the filling phase to the post-filling phase and the control is changed from a speed control to a pressure control. The switching point can be defined as a time, or a position of the injection screw, or a pressure of the hydraulic cylinder or a cavity pressure. Since the filling amount of plastic material and the volume of the cavity for each mould is fixed, the position of the injection screw is used as the switching signal. This choice eliminates the problem of re-calculation when the injection speed is changed. For a new mould, the switching point can be estimated from the displacement curve of the injection screw in an open-loop injection test. During the filling phase, the voltage of the proportional pressure valve is fixed (5.0 V) and a proportional flow valve is used to control the injection speed. Conversely, the voltage of the proportional flow valve can be fixed (3.0 V) and the proportional pressure valve can be used to control the clamping pressure during the post-filling phase. This approach can simplify the two-input and two-output control problem by replacing it with two single-input and single-output problems.

4.1 Feedforward Neural Network with Back-Propagation Scheme

The neural network is first trained off-line with the input and output data of a PID control loop. During the learning interval, the inertial proportional constant is chosen as $\alpha = 0.025$. The initial values of the network weighting and the biased term are selected as random values between -1 and 1. The parameters of the activation function are $m = 0.9$ and $\lambda = 0.025$. The neural network has one input neuron, 40 hidden neurons and one output neuron. The first and 30th learning pressure responses and the error function of a four-step holding pressure in the post-filling stage are shown in Fig. 6. The first and second learning pressure responses of a two-step post-filling stage control are shown in Fig. 7. The overshoot occurs because of the back-propagation learning scheme which forces the error function to approach the minimum value.

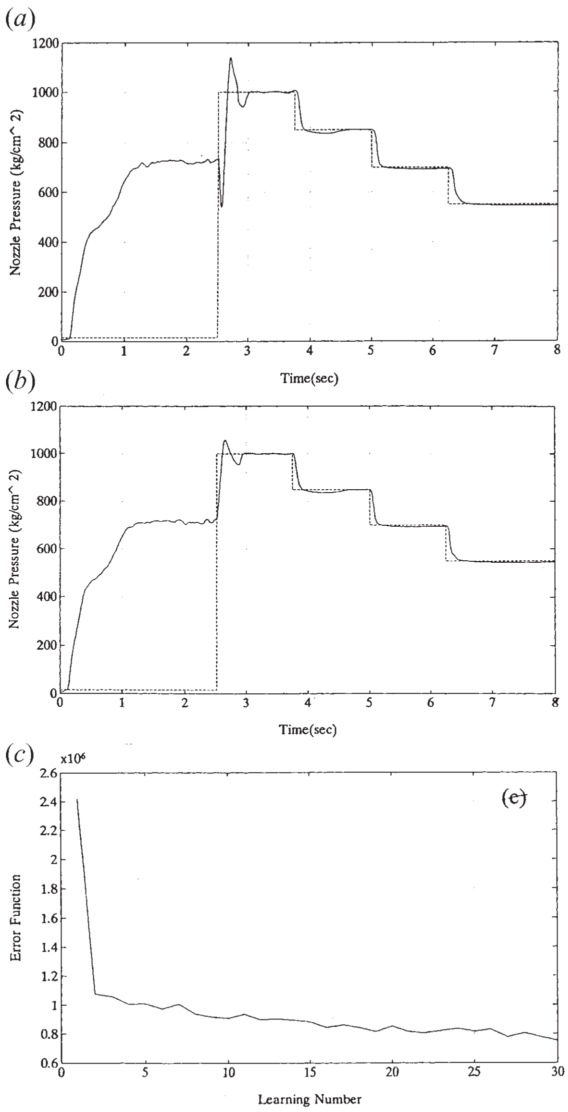

Fig. 6. Pressure responses of (*a*) 1st learning and (*b*) 30th learning, and (*c*) error function.

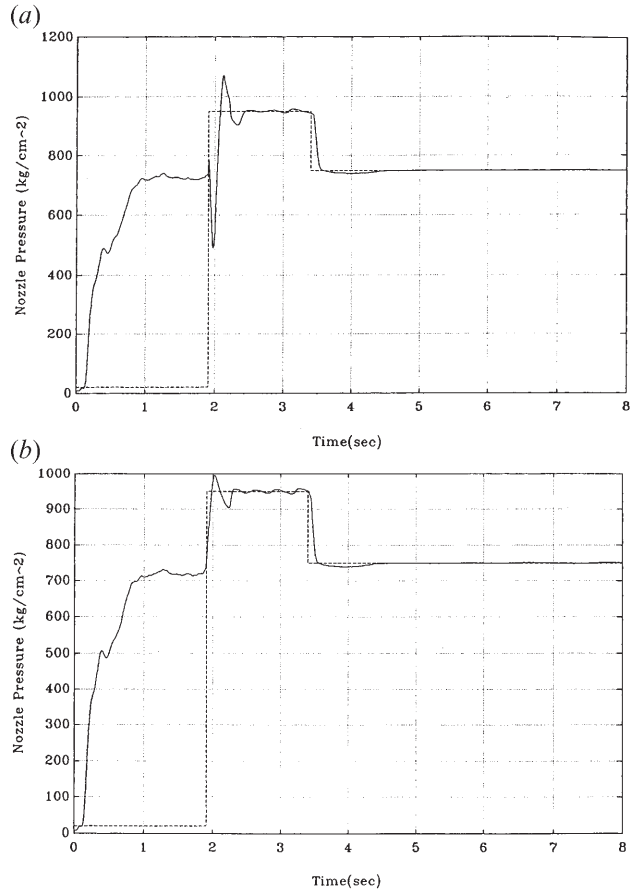

Fig. 7. Pressure responses of (*a*) 1st learning and (*b*) 2nd learning.

4.2 Intelligent Control of Adaptive Neuron

The parameters employed in these experiments are given on Table 1. During the speed control of the injection screw, a 1.5 V control voltage offset is introduced to overcome the system starting friction. This can avoid serious oscillation behaviour due to the system response delay. When the reference speed of the injection screw is 10 mm s^{-1} and the holding pressure has step values of 950 and 750 kg cm^{-2}, the speed and pressure responses and the control voltage are shown in Fig. 8. After the switching point, at 3.75 s, the system is switched into the pressure control stage with a 950 kg cm^{-2} compression pressure and 750 kg cm^{-2} holding pressure. The transient response quickly reaches the specified value within 0.2 s because of the feedforward control loop. The pressure control has effectively suppressed the overshoot during the compression stage, which is important for precise injection

Table 1. Learning parameters of the adaptive neuron.

Learning parameters	W_i	d_1	d_2	d_3	k
Speed control	5.0	0.3	0.146	0.405	1.0
Pressure control	5.0	0.025	0.0065	0.065	1.0

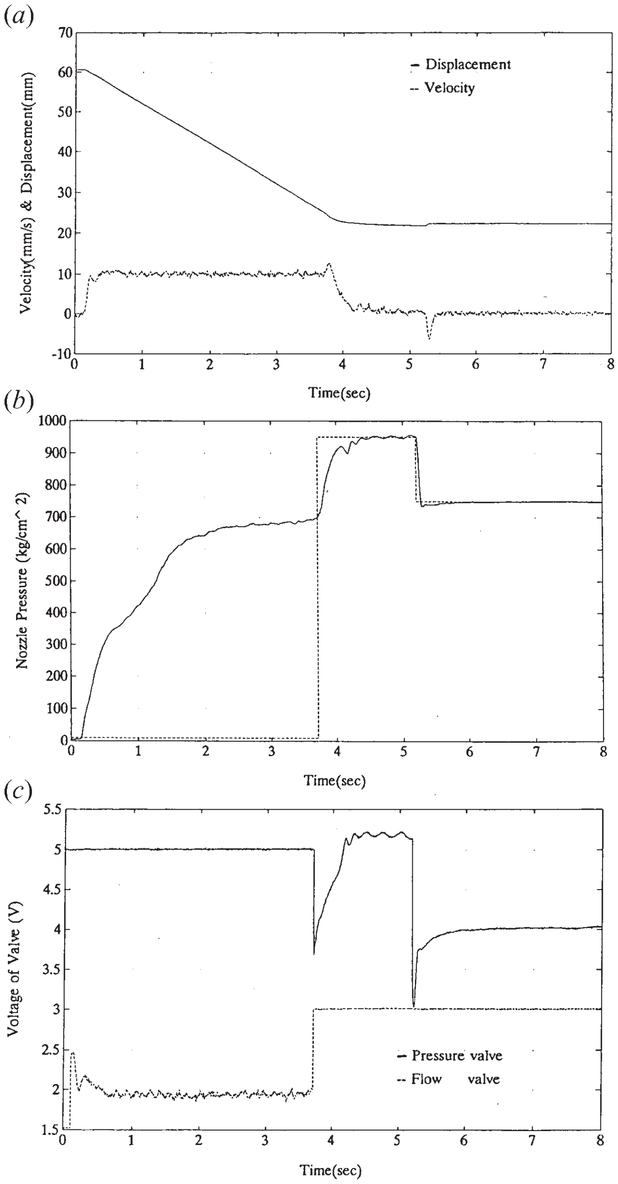

Fig. 8. (*a*) Speed control response, (*b*) pressure control response, and (*c*) control voltage (reference speed of injection screw, 10 mm s^{-1}).

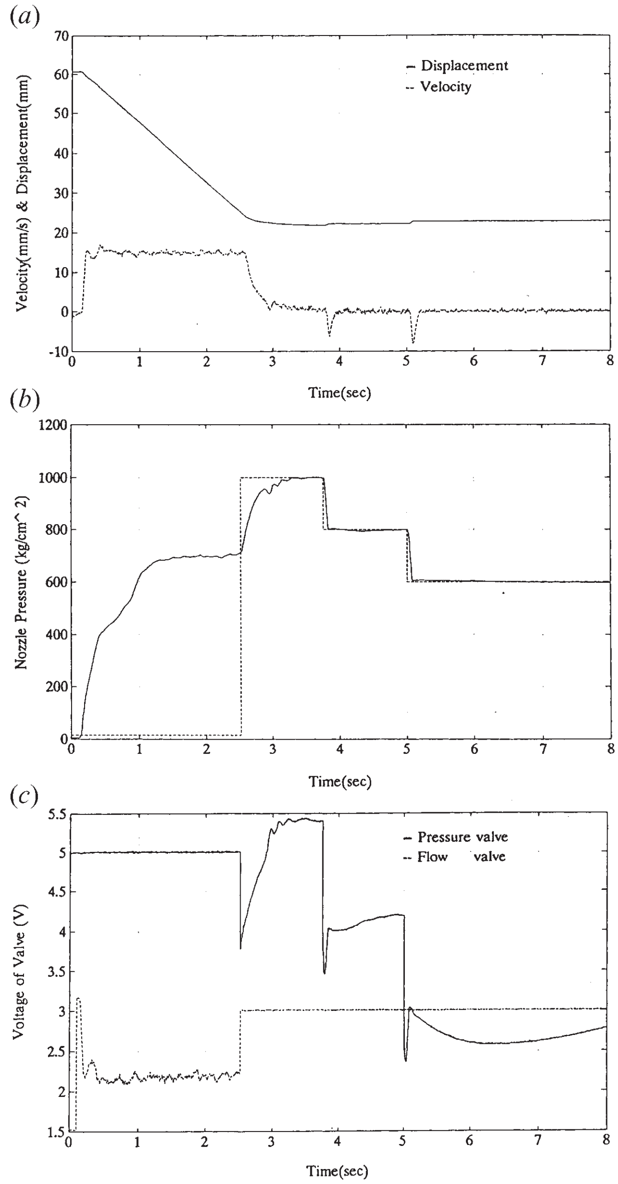

Fig. 9. (*a*) Speed control response, (*b*) pressure control response, and (*c*) control voltage (reference speed of injection screw, 15 mm s^{-1}).

moulding. When the pressure reaches a steady state, the pressure error is within 2.5 kg cm^{-2}. When the reference speed of the injection screw is 15 mm s^{-1} and the compression and holding pressures have step values of 1000, 800 and 600 kg cm^{-2}, the speed and pressure responses and the control voltage are shown in Fig. 9. From the control voltage on Fig. 8(*c*), it can be observed that the control voltage of the proportional pressure valve drops suddenly then slowly creeps up when the control is switched from speed to pressure. This is because the initial control voltage is different to the value obtained from the control law calculation based on the initial weighting value. When the reference speed of the injection screw is 20 mm s^{-1} and the compression and holding pressures have step values of 1000, 850, 700 and 550 kg cm^{-2}, the speed and pressure responses and the control voltages are shown in Fig. 10. The above experimental results show that this adaptive neural network control has a good control performance for this injection moulding machine. From a comparison of Figs 7(*b*) and 8(*b*), it can be observed that the overshoot of the compression pressure has improved markedly by using this closed-loop adaptive neuron controller. In addition, the adaptive neuron has a weighting learning ability instead of the fixed gains of a traditional PID controller, which takes care of the mould and injection speed changes for different products. The selection range of the adaptive neural parameters is larger than that for the feedforward back-propagation scheme and it is much easier to implement.

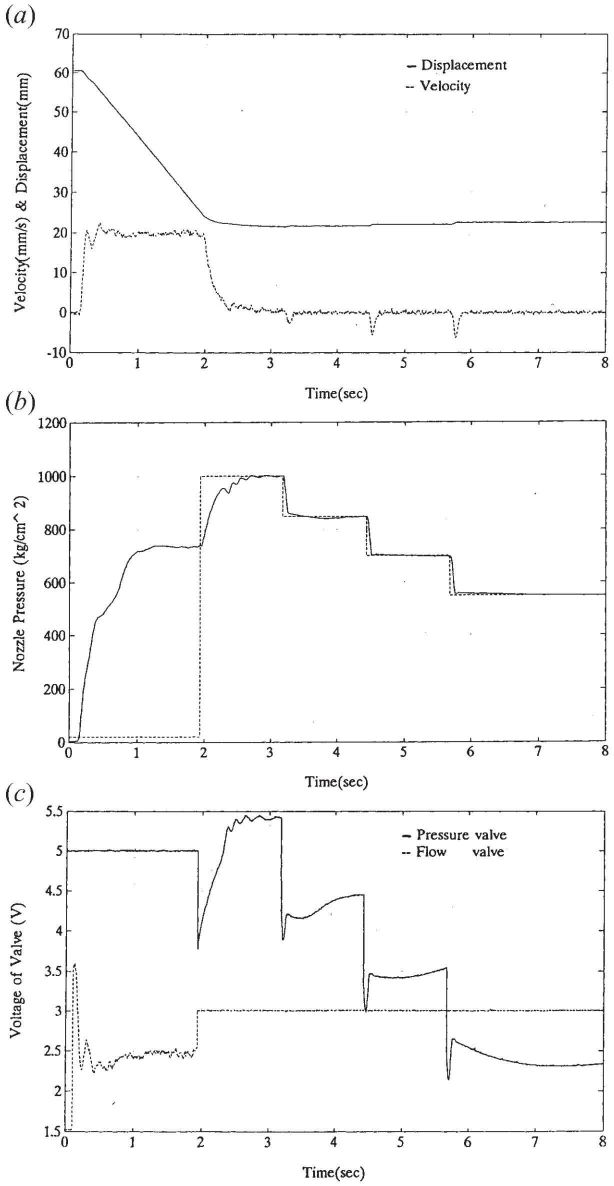

Fig. 10. (*a*) Speed control response, (*b*) pressure control response, and (*c*) control voltage (reference speed of injection screw, 20 mm s^{-1}).

5. Conclusion

The open-loop controller of a commercial injection moulding machine was replaced by a closed-loop neural network controller. The speed of the injection screw and the nozzle pressure were selected as the controlled variables of the filling and post-filling phases, respectively. A feed forward neural network with back propagation learning is used to control the nozzle pressure of the post-filling stage with a certain overshoot. The adaptive neuron control significantly improved the overshoot behaviour of the compression pressure. In addition, this control strategy has a self learning ability which takes care of the variation of injection speed, mould change and system time-varying change. For overshoot prohibition, the adaptive neuron strategy is better than the feedforward back propagation scheme and both neural controllers are better than an open-loop controller. The experimental results have verified this approach and have improved the performance of an industrial injection moulding machine.

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