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Automated process parameters tuning for an injection moulding machine with soft computing[*§]

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Abstract: In injection moulding production, the tuning of the process parameters is a challenging job, which relies heavily on the experience of skilled operators. In this paper, taking into consideration operator assessment during moulding trials, a novel intelligent model for automated tuning of process parameters is proposed. This consists of case based reasoning (CBR), empirical model (EM), and fuzzy logic (FL) methods. CBR and EM are used to imitate recall and intuitive thoughts of skilled operators, respectively, while FL is adopted to simulate the skilled operator optimization thoughts. First, CBR is used to set up the initial process parameters. If CBR fails, EM is employed to calculate the initial parameters. Next, a moulding trial is performed using the initial parameters. Then FL is adopted to optimize these parameters and correct defects repeatedly until the moulded part is found to be satisfactory. Based on the above methodologies, intelligent software was developed and embedded in the controller of an injection moulding machine. Experimental results show that the intelligent software can be effectively used in practical production, and it greatly reduces the dependence on the experience of the operators.

Key words: Injection moulding machine (IMM), Process parameters, Case based reasoning (CBR), Empirical model (EM), Fuzzy logic (FL)
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1 Introduction

There are three major factors affecting the quality of an injection moulded part: process parameters, polymer material, and mould design. In production, the type of polymer and the shape of the mould are usually predetermined; hence, optimizing the process parameters is the most convenient approach to improve the moulded part's quality. However, the tuning of process parameters for an injection moulding machine (IMM) is very complex and difficult, because there are two dozen parameters included in the process, and the relationships between the part quality and the process parameters is not easily represented mathematically (Chen and Turng, 2005). Traditionally, the tuning of parameters for IMM was a procedure of trial and error, which relied heavily on the experience of skilled operators. Unfortunately, an unskilled operator generally needs over ten years to become a skilled one, and skilled operators are in short supply (Mok *et al.*, 1999).

To reduce the dependence on the experience of skilled operators, some soft computing methods, such as neural network, expert system, case based reasoning (CBR), and fuzzy logic (FL), have been employed. Chen W. *et al.* (2008) addressed a dynamic

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quality predictor through a self organizing map and a back propagation neural network. Bozdana and Eyercolu (2002) proposed an expert system called EX-PIMM to determine the injection moulding process parameters. Kwong (2001) developed an intelligent system for designing the injection moulding process based on CBR technology. Chen M. *et al*. (2008) established a fuzzy optimization approach for optimizing the process parameters to control weld line positions. Among these studies, the availability of an artificial neural network depends on sufficient training samples, which decreases its practicability. For the expert system method, the main bottleneck is the acquisition of knowledge. The CBR technique hardly deals with moulding defects, and it is difficult to obtain the initial process parameters using FL.

In this paper, based on the operators' reported considerations during moulding trials and the advantages of soft computing methods, CBR, empirical model (EM), and FL methodologies are integrated into an intelligent model for automated tuning of process parameters. CBR and EM were employed for setting the initial process parameters, while FL was used to optimize the process parameters on-line. The proposed model was verified by performing trials on a real part.

2 Theory and implementation

In most practical production, the tuning of process parameters for IMM is a procedure of trial and error. When a new mould is installed, the operators first recall some previous similar cases to setup the process parameters for the mould. If there is no similar case, the operators determine the process parameters based on their intuitive thoughts acquired through long-term experience. Then a moulding trial is performed, and usually some defects are encountered. Next the operators optimize the parameters repeatedly until the moulded part is found satisfactory. According to the operators' considerations during moulding trials, a hybrid intelligent model was constructed, as illustrated in Fig. 1. CBR and EM were employed to determine initial process parameters, imitating the skilled operators' recall and intuitive thoughts, respectively. FL was employed for optimizing parameters and correcting defects, simulating the operators' optimization thoughts.

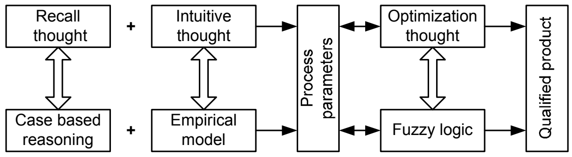


Fig. 1 Architecture of hybrid intelligent model

2.1 Case based reasoning

CBR is a kind of similarity reasoning method, which solves a new problem (target case) by reusing solutions of past similar problems (source cases) in a case base (CB). That is, CBR=CB+similarity reasoning (Sun and Finnie, 2005).

The structure of the developed CB is illustrated in Fig. 2. CB contains a number of cases, which are pre-defined in an organization. Each case includes a problem description and a problem solution. As the name implies, the problem description part represents the case's characteristics, and the problem solution part states the case's solutions. The problem description includes polymer data (thermal properties, pressure-volume-temperature parameters, and rheological parameters, etc) and cavity data (cavity volume, average thickness, and flow length, etc), whilst the problem solution is the process parameters of the IMM, including injection, packing, cooling, and melting parameters. Currently, there are 56 cases involved in the constructed case base. The ranges of the average thickness, flow length, and cavity volume for these cavities are 0.76–4.09 mm, 27.52–490.52 mm, and 702.89–1 469 300.21 mm^3, respectively, and the number of polymers is 23.

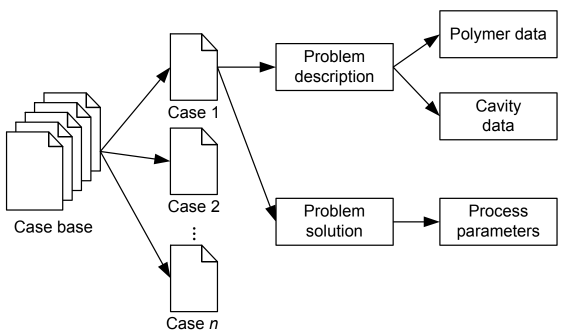


Fig. 2 Structure of the case base

Based on the constructed CB, similar cases are selected by applying the similarity analysis sequentially to each case. The global similarity S between the target case and the source case is shown as

$$S = \sum_{i=1}^{m}\left(W_i \times s_{\mathrm{c}}(i)\right) \times \sum_{j=1}^{n}\left(v_j \times s_{\mathrm{p}}(j)\right), \tag{1a}$$

$$s_{\mathrm{c}}(\mathrm{or}\ s_{\mathrm{p}}) = \frac{1}{1+\lambda \times |x_{\mathrm{obj}} - x_{\mathrm{src}}|}, \tag{1b}$$

where W_i and v_j are weight coefficients, and λ is the sensitivity factor. $s_{\mathrm{c}}(i)$ and $s_{\mathrm{p}}(j)$ are local similarities for cavity data and polymer data, respectively. x_{obj} denotes one parameter of the cavity data or polymer data for the target case, whilst x_{src} represents the corresponding parameter for a source case.

Once some similar cases are chosen, their solutions are adapted to the target case by case adaptation strategies. If the number of chosen similar cases is one, and the similarity of the similar case is greater than 0.95, then the solution for the case can be used for the target case directly. If several similar cases are selected and they fulfil a case matrix (x-coordinate is the flow length, y-coordinate is the average thickness), the solution of the target case can be calculated by interpolation method.

Note that if the number of selected similar cases is zero, or there is no strategy for case adaptation, CBR fails for setting the initial process parameters.

2.2 Empirical model

The procedure of determining the initial process parameters based on EM is summarized in the following steps.

Step 1: Determine the process parameters based on a polymer database, including the recommended parameters. Some process parameters (the mould temperature T_{w}, and the injection temperature T_0) are primarily dependent on the type of moulding polymer, so the polymer database is adopted to set these parameters.

Step 2: Optimize the process parameters according to some optimization objectives. The relationship between the injection pressure P_{inj} and the injection time t_{inj} is a complex U-shaped curve, as shown in Fig. 3 (Shoemaker, 2006). With short injection time, the injection pressure is very high because of high flow rate. As the filling slows down, the injection pressure drops. However, if the injection time is too long, the flow front temperature during filling will decrease and the viscosity will increase, which causes the pressure to rise again. The optimum injection time is the point on the curve where the injection pressure is the lowest. In this study, a fast strip analysis model is first employed to predict the U-shaped curve between the injection pressure and the injection time. Then a search method is adopted to optimize the injection time and the corresponding injection pressure based on the predicted U-shaped curve. The fast strip analysis model is described in detail in (Zhao *et al*., 2010).

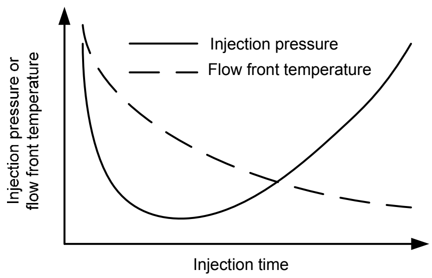


Fig. 3 Schematic diagram of injection pressure and flow front temperature at different injection time

Step 3: Calculate the process parameters through some empirical formulae. The injection stroke L_{inj} can be calculated by the cavity volume V and the sectional area of screw A_{screw}:

$$L_{\mathrm{inj}} = \frac{V}{A_{\mathrm{screw}}}. \tag{2}$$

The cooling time t_{cool} is calculated from an empirical equation:

$$t_{\mathrm{cool}} = -\frac{h^2}{2\pi\alpha}\ln\left(\frac{T_{\mathrm{eject}} - T_{\mathrm{w}}}{T_0 - T_{\mathrm{w}}}\right), \tag{3}$$

where h is the average part thickness, α denotes the thermal diffusivity, and T_{eject} represents the ejection temperature. The packing time t_{pack} is estimated to be 10 times the injection time:

$$t_{\mathrm{pack}}=10\times t_{\mathrm{inj}}. \tag{4}$$

Step 4: Transform the above parameters to machine related parameters. The nozzle temperature T_{nozzle} and the hydraulic pressure P_{hyd} are given by

$$T_{\mathrm{nozzle}}=T_0, \tag{5}$$

$$P_{\mathrm{hyd}} = f \times \frac{A_{\mathrm{screw}}}{A_{\mathrm{piston}} - A_{\mathrm{rod}}} \times P_{\mathrm{melt}}, \tag{6}$$

where P_{melt} is the pressure of polymer melt, f denotes a frictional factor for pressure loss, and A_{piston} and A_{rod} represent the sectional areas of the piston and the cylinder rod, respectively.

2.3 Fuzzy logic

FL is an approximate inference methodology that imitates human uncertain reasoning capabilities (He *et al.*, 2001). Fig. 4 shows the structure of the presented fuzzy inference system. The inputs of the fuzzy system include the encountered defect D and the current process parameters P_i (i=1, 2, …, n), and the outputs of the fuzzy system are the adjustments for the process parameters ΔP_i (i=1, 2, …, n), which contain the adjustment ratio and direction. The adjustment ratio of P_i is calculated by a fuzzy inference engine based on the current value of P_i and the seriousness of D, and the adjustment direction of P_i is generated by a rule based reasoning engine accroding to the types of P_i and D.

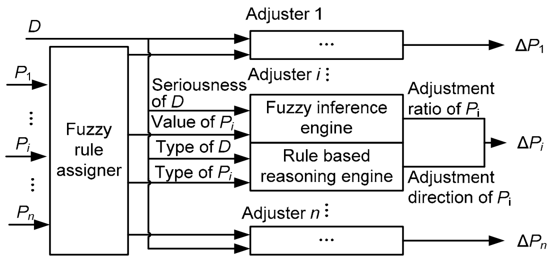


Fig. 4 Structure of the fuzzy inference system

Obviously, the key point for the fuzzy inference system is the fuzzy inference engine. Fig. 5 illustrates the schematic diagram for the fuzzy inference engine with two inputs and one output. Fuzzification transforms the seriousness of D and value of P_i to a fuzzy value for fuzzy inference, and defuzzification converts the inference result from a fuzzy value to a crisp value, i.e., the adjustment ratio of P_i.

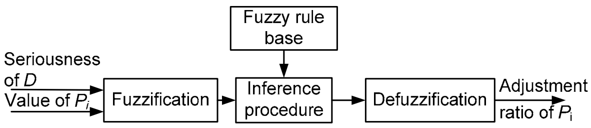


Fig. 5 Schematic diagram for the fuzzy inference engine

In the fuzzy rule base, there are plenty of fuzzy rules. These fuzzy rules are collected from the domain experts and/or from the observation data of moulding trials. A fuzzy rule with two antecedents is described as

if x is A and y is B, then z is C,

where x, y, and z represent linguistic variables for defect seriousness, parameter current value, and parameter adjustment ratio, respectively. For ease of use, high accuracy, and avoiding dimension disasters, linguistic values A and B are both naturally described by the fuzzy set {small, medium, big}, while the fuzzy set for linguistic value C is {lowest, lower, low, medium, high, higher, highest}. The definition of these fuzzy sets is shown in Fig. 6, where μ denotes the fuzzy membership function of linguistic value. As such, the fuzzy rule can be used linguistically. For example, "if short shot is big and the injection pressure is small, the adjustment ratio of the injection pressure is the highest" is a fuzzy rule that might be used in correcting the defect of short shot.

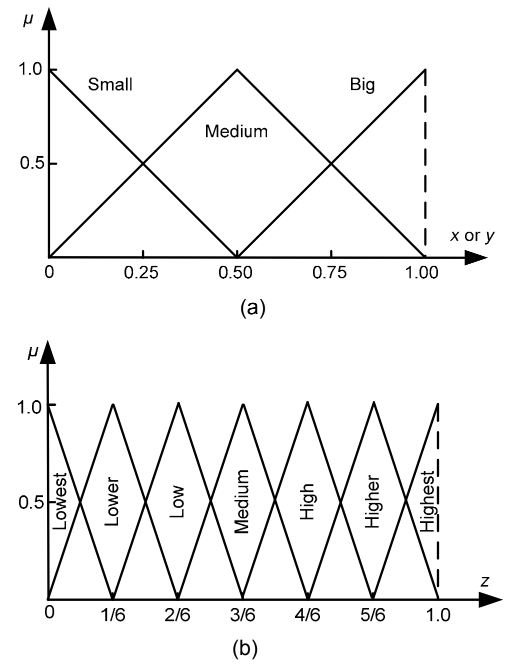


Fig. 6 Fuzzy sets
(a) Linguistic values A and B; (b) Linguistic value C

The Mamdani inference model is adopted for inference, and maximum/minimum operators are used as T-norm/T-conorm operators (Zhang and Sun, 1997). For each fuzzy rule "$A_k \times B_k \to C_k$", the result C_k

can be defined by the inputs A_k, B_k, and the fuzzy relation R_k as

$$\begin{aligned} C_k &= (A_k \times B_k) \circ R_k \\ &= (A_k \times B_k) \circ \int_{X \times Y \times Z} \mu_{A_k}(x) \wedge \mu_{B_k}(x) \wedge \mu_{C_k}(x) \big/ (x, y, z). \end{aligned} \tag{7}$$

During the inference process, several fuzzy rules may be considered simultaneously, and then Eq. (7) becomes

$$C = (A \times B) \circ \bigcup_{k=1}^{r} R_k = \bigcup_{k=1}^{r} [(A \times B) \circ R_k] = \bigcup_{k=1}^{r} C_k, \tag{8}$$

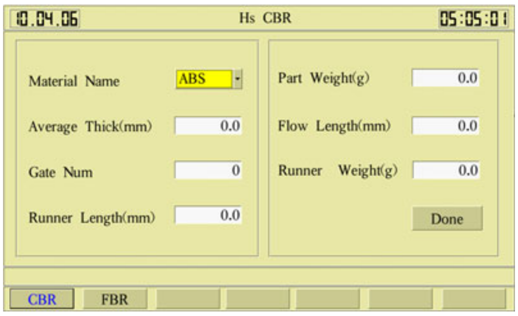
where r is the fuzzy rules' number. Hence, the fuzzy result C is generated by aggregating inference results C_k for all considered fuzzy rules. Finally, the centroid of area strategy is adopted to defuzzify the fuzzy result C to a crisp value (Zhang and Sun, 1997).

3 Verification

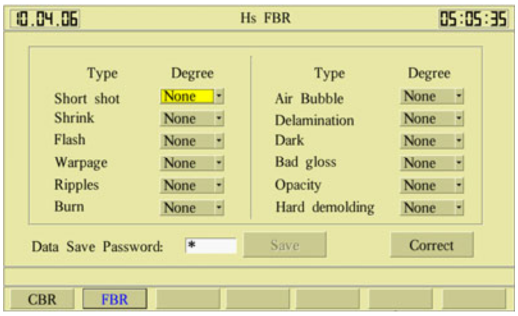
Based on the above methodologies, intelligent software for automated tuning IMM process parameters was developed. The developed software was run in the IMM controller (P10CY, EST control technology Co., Ltd., China), and its interfaces are given in Fig. 7.

A real part in production was used to verify the intelligent software (Fig. 8). Its weight, average thickness, flow length, runner weight, and runner length are 16 g, 2 mm, 60 mm, 3 g, and 80 mm, respectively. The injection was performed with the IMM (HTL110B, Haitai Plastic Machinery Co., Ltd., China), and the selected polymer was polypropylene (PP K8303, Yanshan Petroleum Chemical Co., Ltd., China).

After specifying the type of polymer and mould data on the input page (Fig. 7a), the initial process parameters were calculated, and the first moulding trial was started. Fig. 9a shows the first moulded part with a medium defect of short shot. Next, operators input seriousness of short shot into the software on the feedback page (Fig. 7b). The software automatically optimized the process parameters of IMM, and the second moulding trial was executed, where the short shot disappeared, but a small defect, burn, was encountered, as shown in Fig. 9b. Similarly, seriousness of burn was fed back to the software, and the third moulding trial was performed. This time, the moulded part was found satisfactory, with no defects (Fig. 9c); i.e., optimum process parameters were obtained. Table 1 lists main process parameters of the IMM in the three moulding trails. From the above procedure, it is seen that the developed intelligent software can be used in practical production, and it greatly reduces the dependence on the experience of skilled operators.



(a)



(b)

Fig. 7 Interfaces of developed intelligent software
(a) Input page for polymer and mould information; (b) Feedback page for defects

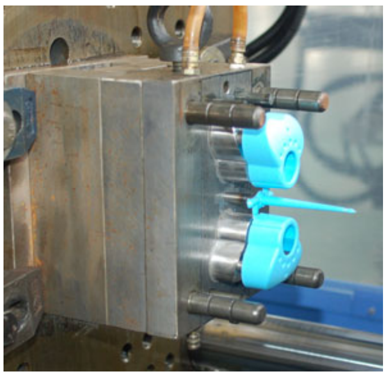


Fig. 8 Example of injection moulded parts

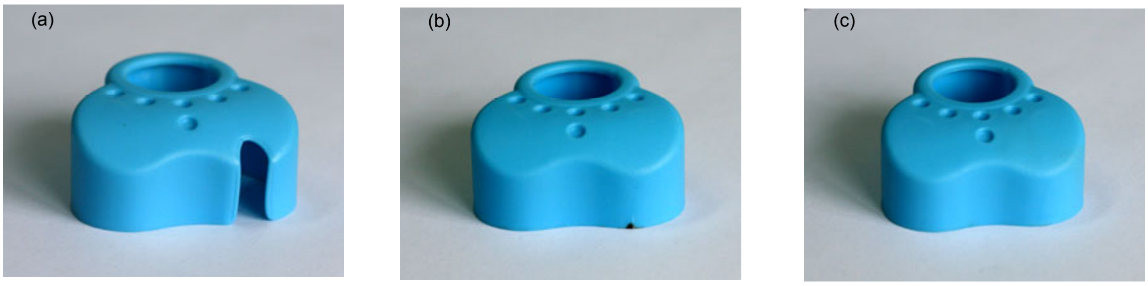


Fig. 9 Moulded parts
(a) First trial run; (b) Second trial run; (c) Third trial run

Table 1 Main process parameters in the moulding trials

Trial	Nozzle temperature (°C)	Cooling time (s)	Injection pressure (MPa)	Injection stroke (mm)	Injection time (s)	Packing pressure (MPa)	Packing time (s)
1	230	8	3.0	30.5	1.1	3	11.0
2	230	8	4.8	54.5	2.0	3	12.5
3	230	8	4.2	54.5	1.7	3	12.5

4 Conclusions

In this study, a hybrid intelligent model combining CBR, EM, and FL was constructed for automated tuning of the process parameters. CBR and EM methodologies were employed for the initial parameters setting, while FL approach was used to optimize parameters on-line. The reliability of the developed model was verified by conducting a real case. Therefore, an unskilled operator can perform tuning of the process parameters reliably and efficiently using the developed model. Although the developed intelligent model provides good results, further research concerning how to use the process parameters adjustment history is required for a more efficient correction of part defects.

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