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Optimisation of Plastic Injection Moulding Process with Soft Computing

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The paper presents a hybrid strategy in a soft computing paradigm for the optimisation of the plastic injection moulding process. Various plastic injection molding process parameters, such as mold temperature, melt temperature, injection time and injection pressure are considered. The hybrid strategy combines numerical simulation software, a genetic algorithm and a multilayer neural network to optimise the process parameters. An approximate analysis model is developed using a Back-propagation neural network in order to avoid the expensive computation resulting from the numerical simulation software. According to the characteristic of the optimisation problem, a nonbinary genetic algorithm is applied to solve the optimisation model. The effectiveness of the improved strategy is shown by an example.

Keywords: Mutilayer neural network; Non-binary genetic algorithm; Numerical simulation; Plastic injection molding; Soft computing

1. Introduction

The manufacturing industry for plastic products has been growing rapidly in recent years, and more and more plastics are used widely to substitute for metals. Injection moulding has many advantages, such as short product cycles, excellent surfaces of the product and easily moulded complicated shapes, so it is the most popular moulding process for making thermoplastic parts. Generally, it comprises three phases, filling, packing and cooling. The filling stage is the critical stage in the production of a good quality moulding. In the filling stage, the injection moulding process parameters include melt flow rate, injection pressure, mould temperature and melt temperature, some of which have a direct influence on the quality of the injection products.

In the past, the design of the injection moulding process has been considered to be a “black art”, which relies heavily on the experience and knowledge of experts and involves a trial-and-error process. Recently, with the development of the numerical simulation and intelligent technology, some progress towards the design of injection moulding process has been made. Lee and Kim used a modified complex method to reduce warpage by adjusting the thickness of different surfaces [1]. Seow proposed an approach to balancing the mould cavity based on numerical simulation. By balancing the flow, overpacking and residual stress are decreased [2]. Sadeghi combined a neural network and numerical simulation to provide a back-propagation neural network (BPNN) predictor model for the plastic injection moulding process [3]. Shellesh and Siores developed an intelligent system for the prediction of the plastic injection moulding process parameters by combining both a rule-based and a case-based approach [4]. Zhou et al. established a rule set for determining the location of the gate based on an analysis of the plastic parts. The location of the gate was determined through reasoning with the rules [5]. Pandelidis et al. developed a system which can optimise gate location based on the initial gating plans. The system uses Moldflow software for flow analysis, and controls the temperature differential and the number of elements overpacked [6].

As stated above, numerical simulation and artificial intelligent technologies can improve the design of the plastic injection moulding process. However, the process design schemes provided by these methods though generally feasible are not optimal. Soft computing is a consortium of methodologies that works synergetically and provides a flexible information processing capability for handling real-life ambiguous situations [8,9]. The intention of soft computing is to exploit the tolerance to achieve tractability, robustness and low-cost solutions. There are ongoing efforts to integrate artificial neural networks, genetic algorithms and other methodologies in a soft computing paradigm [10]. This paper presents a hybrid optimal model in combination with a neural network and a genetic algorithm for the plastic injection moulding process. Computer-aided engineering (CAE) software, Moldflow, is used to simulate the

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flow of the plastic. Genetic algorithms (GAs), which have high capability to obtain a global optimal solution, are applied to solve the optimal model. In order to reduce the expensive computation arising from the numerical simulation, a BPNN is used to establish the approximate analysis model.

In this paper, a soft computing approach to the optimisation of the plastic injection moulding process, which combines GAs and NN, is proposed. Section 2 presents the optimal mathematic model, including the selection of the objective function and the design variables. In Section 3, an optimal method integrating GAs and NN in a soft computing paradigm is discussed in detail. Section 4 provides a case study that illustrates the application of the proposed approach. Section 5 concludes the paper and outlines some work for future research.

2. Optimal Model for Injection Moulding Process

During the injection moulding, there are many process conditions which affect the quality of the plastic parts, such as melt flow rate, injection pressure, injection time, mould temperature and melt temperature. The different process conditions can produce different defect phenomena. In developing the optimal model, only the major process parameters are considered from the viewpoint of feasibility and tractability. In order to describe the optimisation method, a butter container lid with a minimal thickness of 1.5 mm, is discussed. The butter container lid is made of SAN. The thickness of the rim is 2.5 mm. The material grade code of the part is TSAN01, and the material supplier is Moldflow. The part shape and injection location are shown in Fig. 1.

2.1 Design Variables and Objective Function

It is known that there are many factors that have an influence on the quality of parts, such as mould temperature, melt temperature, injection time, injection pressure, gating scheme design (style, size, location of the gate) and the geometry of the parts. For considering feasibility and tractability, the study is focused on the key process operating parameters, including mould temperature (T_{mould}), melt temperature (T_{melt}), injection time (T_{inj}) and injection pressure (P_{inj}), given the gating scheme design and geometry of the parts. Mould temperature (T_{mould}) ranges from 50 to 75º C, melt temperature (T_{melt}) ranges from 230 to 280º C, injection time (T_{inj}) ranges from 1.5 to 3.5 seconds and injection pressure (P_{inj}) is from 25 to 60 MPa. The above injection process conditions are based on numerical simulation software and the manufacturer's specifications.

The quality of the plastic parts is tested in terms of lack or existence of short shot, air traps, weld lines and warpage. It is known that short shot, air traps and weld lines are dependent largely on the gating scheme design and geometry of the parts. As stated above, the study is focused on process operating parameters on the assumption that the gating scheme design and geometry of the parts are given. Shear stress in the product should be within the recommended limit for the material, and parts that will be subjected to intense and local mechanical forces, such as regions of snap fits and screw holes, are particularly sensitive to high stress levels. It is shown that there is a correlation between shear stress during filling and residual stress in the part, i.e. the quality of the part. Moreover, residual stress may cause warpage of the part [11]. The maximum stress permitted in such parts should be significantly less than the maximum recommended. To eliminate the inner stress of the plastic parts, the objective function chosen for this study is the maximum shear stress (S_{shear}).

2.2 Optimal Design Model

The mathematical model of the optimisation problem can generally be described as follows:

Find $\boldsymbol{X} = [x_1 \;\; x_2 \;\; x_3 \;\; ...., \;\; x_n]^{\mathrm{T}}$

$$\text{Min}\, f\,(\boldsymbol{X})\text{s. t} \begin{array}{ll} x_j^{(l)} \le x_j \le x_j^{(u)} & (j = 1, 2, ..., n) \\ G_i(X) \le 0 & (i = 1, 2, ..., m) \end{array} \tag{1}$$

where f ($\boldsymbol{X}$) is the objective function. G_i ($\boldsymbol{X}$) represents the constraint. The variables of $x_j^{(l)}$ and $x_j^{(u)}$ are the lower and upper limits of the design variable x_j, respectively.

For optimizing the plastic injection moulding process, the optimal design model can be represented as follows:

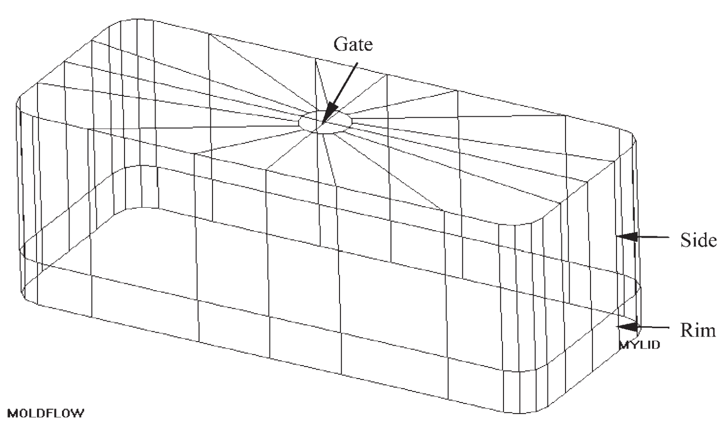

Fig. 1. A butter container lid.

$$\begin{aligned} &\text{Find } \boldsymbol{X} = \lfloor T_{mould} \;\; T_{melt} \;\; T_{inj} \;\; P_{inj} \rfloor^{\mathrm{T}} \\ &\text{Min } S_{shear} \qquad (2) \\ &\text{s. t. } x_j^{(l)} \le x_j \le x_j^{(u)} \quad (j = 1, 2, ..., 4) \end{aligned}$$

To solve the optimisation problem described by Eq. (2), a hybrid strategy, which combines CAE software, GAs and a BPNN, is used. In next section, the strategy is discussed in detail.

3. Soft Computing Approach to the Optimal Model

In soft computing methodology, the individual tools, such as GAs, ANN and other tools, act synergetically, rather than competitively, to enhance each other's application domain [8]. MNNs are powerful tools for prediction of nonlinearities and have many advantages, such as massive parallelism, robustness and learning in data-rich environments [11]. GAs, which are based on the mechanics of natural selection and evolution, have been applied to optimisation problems. GAs have many advantages [13,14]. For one thing, GAs can solve diverse optimisation problems because the derivatives of the objective and the constraint function for the design variables are not required. For another thing, GAs have a higher capability to obtain a global optimal solution than conventional optimisation algorithms, due to the population based search mechanics. In the optimal model for the plastic injection process, it is impossible to obtain the derivatives. Therefore, it is appropriate for GAs to be applied to solve the optimal model. The value of the maximum shear stress is obtained by the commercial software, Moldflow. However, the computation of the numerical simulation is very expensive. To avoid the numerous detailed analyses performed by Moldflow, a soft computing strategy, which integrates the generic advantages of GAs and MNN, is proposed as follows.

3.1 Approximate Analysis Model with BPNN

An artificial neural network (ANN) is one of the effective tools for solving nonlinear problems. Typically, a mutilayer neural network (MNN) has a powerful mapping capability for nonlinear problems [16]. In solving the optimal model, a mutilayer neural network is applied to establish the mapping model between the maximum shear stress (S_{shear}) and the injection process parameters or variables, such as mould temperature (T_{mould}), melt temperature (T_{melt}), injection time (T_{inj}) and injection pressure (P_{inj}). A schematic presentation of a mutilayer neural network for predicting the maximum shear stress is shown in Fig. 2. That is, the following nonlinear mapping relation is established:

$$D = f(\boldsymbol{X}) \qquad (3)$$

where D is the maximum shear stress, $\boldsymbol{X}$ denotes the vector of the design variables, viz. $\boldsymbol{X} = [T_{mould} \;\; T_{melt} \;\; T_{inj} \;\; P_{inj}]$ and f denotes the nonlinear functional relationship between D and $\boldsymbol{X}$. During the optimisation procedure, the approximate model above is used to substitute for Moldflow, in order to avoid the expensive computation. The implementation of the approximate analysis model with a BPNN is shown in Fig. 3. The procedures involved are discussed in the following section.

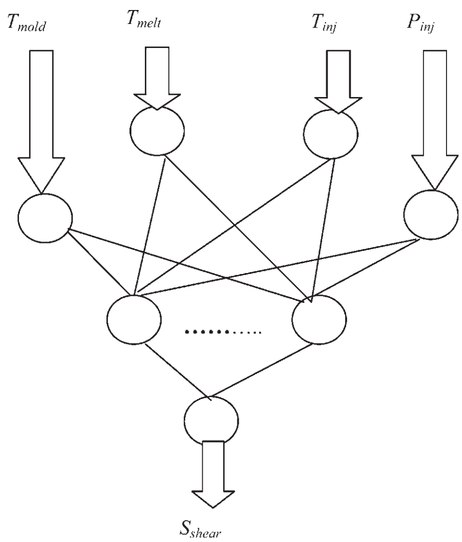

Fig. 2. An MNN for predicting the maximum shear stress.

3.1.1 Selection and Normalisation of the Patterns

Using the various combinations of the four major process variables, enough simulations are carried out to supply samples

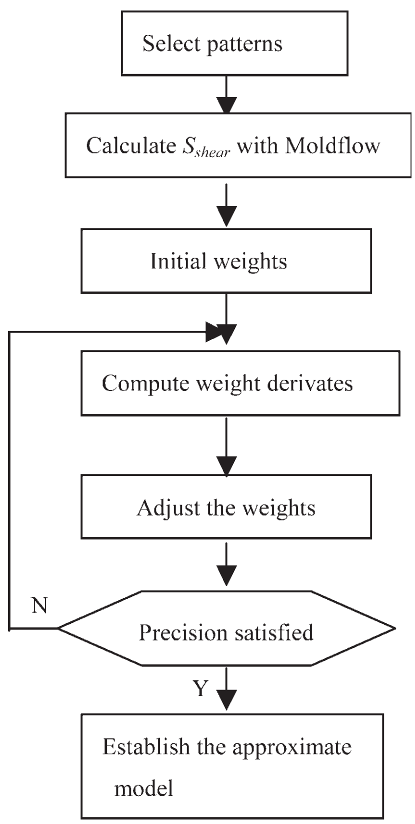

Fig. 3. Approximate model with BPNN.

for a multilayer neural network. The values of the process conditions are altered within the aforementioned ranges.

Generally speaking, the activation function used for the multilayer neural network is the sigmoid function. As the output of the sigmoid function is in the interval [0,1], the learning samples should be normalised as follows:

$$x_j' = \frac{x_j - x_j^{(l)}}{x_j^{(u)} - x_j^{(l)}} \tag{4}$$

3.1.2 Initialising Structure of MNN

The structural design of the MNN includes the determination of the number of the hidden layers and the number of neuron in the different layers. R. Hecht-Nielsen proposed the following mapping theorem [16].

Theorem 1. Given any $\varepsilon > 0$ and any L_2 function f: $[0,1]^n \subset R^n \rightarrow R^m$, there exists a three-layer back-propagation neural network that can approximate f to within ε mean squared error accuracy.

Based on the above theorem, the number of hidden layers can be one. The number of neurons in the input layer must equal four, which is the number of the design variables, and the number in the output layer is one. The size of the hidden layer is one of the most important considerations when solving actual problems using multilayer neural networks. If there are too few hidden units the network will not learn the task. On the other hand, having too many hidden units can degrade the learning rate and decrease the speed with which a learned mapping is performed [17]. The numbers of the hidden neurons can be determined approximately by the following formula [18].

$$H = \sqrt{n+m}+a \tag{5}$$

where H is the size of the hidden layer; n and m are the sizes of the input and output layers, respectively; and $a \in [1,10]$, which is a constant.

3.1.3 Training the MNN

A back-propagation (BP) algorithm is applied to train the MNN. The weights of MNN are firstly initialised randomly. Iterative procedures are adopted to adjust the weights according to the derivatives of the error between the actual and expected outputs. The procedures are continued until the expected precision of the error is obtained. The weights distributed between the neurons in the different layers can represent the mapping relation embodied in the samples.

3.2 Solving Optimal Model with GAs

GAs are applied to solve the optimal model described by Eq. (2) because of their potential as optimisation techniques. Figure 4 is the flowchart of the optimisation strategy with the GAs. The key procedures involved can be stated as follows.

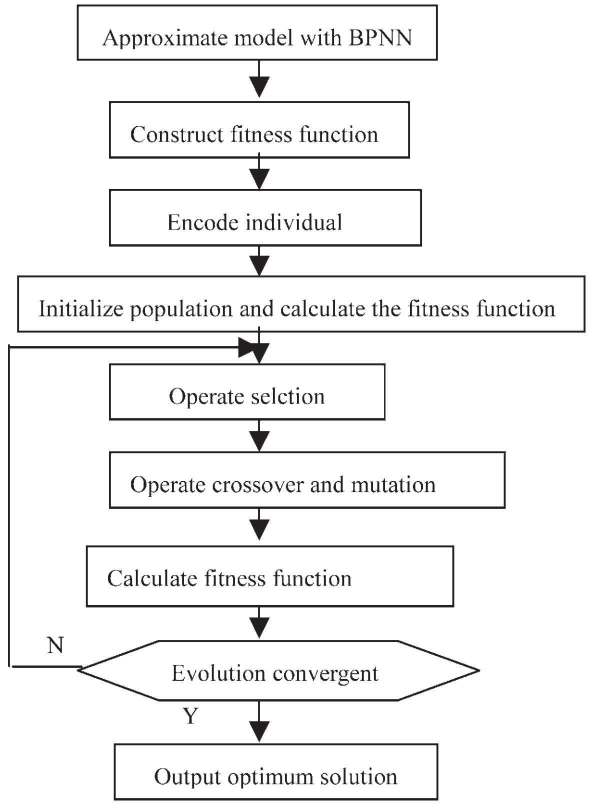

Fig. 4. Optimisation strategy with GAs.

3.2.1 Selecting the Encoding Mode

In GAs, artificial chromosomes are represented by strings of finite lengths. Generally, there are two encoding modes, viz. binary coding and decimal coding. For the binary coding mode, the length of the bit string is determined by the precision [15]. Therefore, the decimal coding mode is applied in terms of the characteristics of the optimisation problem. Let $\boldsymbol{X}$denote one of the results of the optimisation problem, and the corresponding chromosome can be represented as $\boldsymbol{V} = \{x_1, x_2, \ldots.., x_n\}$. The length of the chromosome is equal to the vector of the solution.

3.2.2 Constructing the Fitness Function

To evaluate the performance of the individual string (chromosome), the proper fitness function should be constructed. Normally, the fitness function is transformed from the objective function. In this optimisation problem, the objective function is the maximum shear stress, so the fitness function can be defined as follows:

$$f(\boldsymbol{X}) = S_{max} - D \tag{6}$$

where S_{max} is the maximum shear stress recommended for the material, SAN and S_{max} = 0.5 MPa. D is calculated in terms of Eq. (3).

4. Results and Discussion

In order to prove the effectiveness of the proposed optimal model, the example as shown in Fig. 1 is discussed in this section.

Table 1. Configuration of BPNN.

Number of training data	54
Number of testing data	10
Max. epoch	3000
Number of hidden layers	1
Number of inputs	4
Size of hidden layer	12
Number of outputs	1
Sum-squared error	0.005
Learn rate	0.6

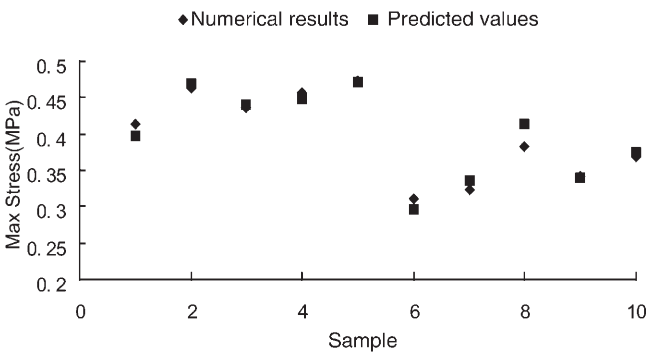

Fig. 5. Comparison between numerical and predicted values.

4.1 Constructing Approximate Analysis Model

As stated above, the approximate analysis model serves as a function approximator that maps the input variables of mould temperature (T_{mould}), melt temperature (T_{melt}), injection time (T_{inj}) and injection pressure (P_{inj}), to produce the output which is the maximum shear stress (S_{shear}). In order to prepare the learning samples for the MNN, simulation studies are carried out using the Moldflow software system. Within the value intervals of the different process conditions, 54 sets of data are formulated as the input training data for the network. The remaining 10 sets are used to test the developed approximate model. A three-layer neural network with a 4–12–1 neuron configuration is used to develop the model based on Theorem 1 and Eq. (5), and a back-propagation algorithm is used to train the network. The parameters of the network configuration are shown in Table 1.

After the training step, the performance of the approximate model is tested on 10 sets of data taken from the simulation works. The verified results, as shown in Fig. 5, reveal that the predicted values and numerical results are in good accordance. The maximum prediction error rate is not more than 4.8% except for one value of 8.5%, which shows the model is a satisfactory one from the engineering viewpoint.

4.2 Optimisation Results and Analysis

The optimisation problem is solved based on the flowchart shown in Fig. 4. The parameters for the optimisation algorithm are given as follows: population of individuals is 25, probability of crossover equals 0.65, and probability of mutation is 0.12. The optimal solution is obtained after 20 generations, and the optimisation results are shown in Table 2. Figure 6 shows the comparison between the initial scheme and optimal scheme.

It is shown from Table 2 and Fig. 6 that the maximum shear stress calculated by the optimal model is very close to the one obtained by the numerical simulation software. On the other hand, the maximum shear stress has a significant reduction of 24.9% after the optimisation. From the optimal design, we also discover that melt temperature usually has far more effect than mould temperature in reducing the maximum shear stress.

5. Conclusions

The design of the injection moulding process relies heavily on the experience and knowledge of experts and involves a trial-and-error process. An improved strategy for the optimisation of the plastic injection moulding process is presented in this paper. The strategy combines a neural network and a genetic algorithm in a soft computing paradigm. An approximate analysis model is developed with a BPNN so as to reduce the expensive computation required by numerical simulation, so, a nonbinary genetic algorithm is applied to solve the optimisation model. It is shown from an example that the optimisation strategy is effective.

In this paper, the study is focused on process operating parameters, such as mould temperature, melt temperature, injection time and injection pressure. There are other physical factors such as gating scheme design (style, size, location of the gate) and geometry of the parts that are not taken into consideration. In order to improve the capabilities of the system, a rule-based knowledge system can be incorporated into the optimisation system for plastic injection moulding. For future work the main concern is towards integration of more factors.

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Table 2. Design variables and optimal results.

	T_{mould} (ºC)	T_{melt} (ºC)	T_{inj} (sec)	P_{inj} (Mpa)	S_{shear} (Mpa)
Lower limit	50	230	1.5	25	
Upper limit	70	280	3.5	60	
Initial scheme	55	240	1.5	60	0.414
Optimal scheme	60	260	2	55	0.296

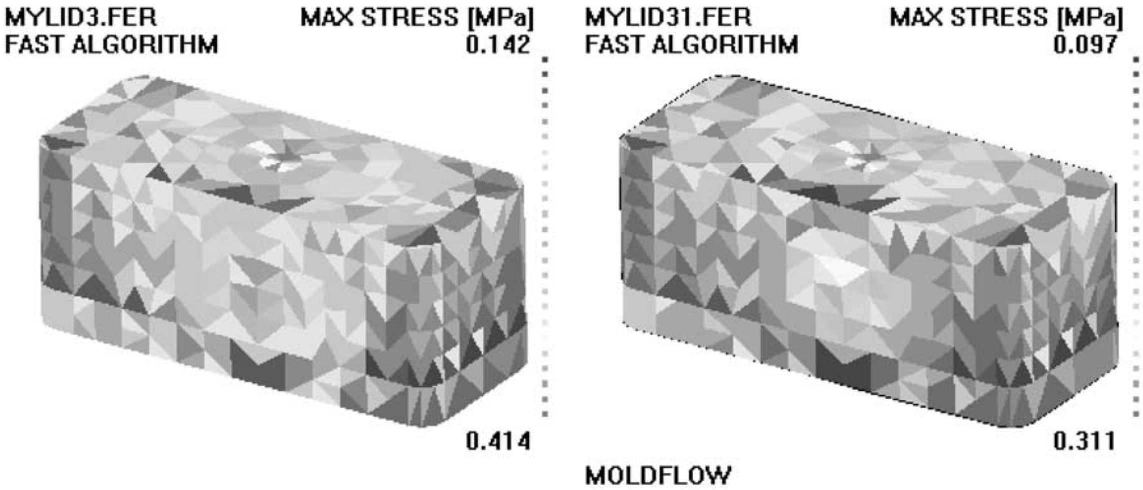

Fig. 6. Comparison between initial scheme and optimal scheme.

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