JMEPEG (2012) 21:492–499
DOI: 10.1007/s11665-011-9933-0

Optimization of LPDC Process Parameters Using the Combination of Artificial Neural Network and Genetic Algorithm Method

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(Submitted December 8, 2009; in revised form March 8, 2011)

In this article, the low-pressure die-cast (LPDC) process parameters of aluminum alloy thin-walled component with permanent mold are optimized using a combining artificial neural network and genetic algorithm (ANN/GA) method. In this method, an ANN model combining learning vector quantization (LVQ) and back-propagation (BP) algorithm is proposed to map the complex relationship between process conditions and quality indexes of LPDC. The genetic algorithm is employed to optimize the process parameters with the fitness function based on the trained ANN model. Then, by applying the optimized parameters, a thin-walled component with 300 mm in length, 100 mm in width, and 1.5 mm in thickness is successfully prepared and no obvious defects such as shrinkage, gas porosity, distortion, and crack were found in the component. The results indicate that the combining ANN/GA method is an effective tool for the process optimization of LPDC, and they also provide valuable reference on choosing the right process parameters for LPDC thin-walled aluminum alloy casting.

Keywords artificial neural network, genetic algorithm, LPDC, numerical simulation, process parameters

1. Introduction

Owing to the advantages of producing low-porosity and semi-automatic production, high-quality casting and high productivity, low-pressure die-cast (LPDC) process is considered as the dominant preparation process for casting aluminum alloy. During the last decades, the evolution of the LPDC process and its development as a major manufacturing technology has been studied by a number of researchers (Ref 1-3). With the increasing requirements of light-weight aluminum alloy castings in the automotive, developing a lighter and thinner aluminum alloy casting is becoming a common study subject for researchers of the whole world (Ref 4-6). Unfortunately, it is difficult to design the best appropriate process of LPDC with permanent mold for a thin-walled casting with the thickness less than 2 mm because of its poor filling-ability. In recent years, the numerical simulation technology has been rapidly developed and applied successfully in many casting industries to improve the product quality and reduce the manufacturing cost (Ref 7-9). The analyses and interpretations of the simulation results, however, are still empirical, and the substantial computation time cannot also meet the requirement of online control. Advanced methods are highly demanded to model and optimize the LPDC process with the purpose of manufacturing high-quality casting.

ANN and GA are two of the most promising natural computation techniques. In recent years, ANN has become a very powerful and practical method to model very complex non-linear systems (Ref 10-12). And some novel evolutionary neural networks proposed in the literature have greatly improved the flexibility of the network (Ref 13, 14). For example, Pettersson et al. (Ref 14) employed a corrected Akaike's criteria to construct the network model with the best compromise between the goodness of fit and the number of parameters. The optimized model can effectively avoid over-fitting and under-fitting of data during the training of the network. GA can be found in various research fields for parameter optimization (Ref 9, 15, 16). And in recent times, GA has also been successfully used to solve numerous problems in the materials areas, such as materials design, alloy design, polymer processing, continuous casting, metal rolling, metal cutting, welding, production at industrial scale, and so on (Ref 17-20). Therefore, ANN and GA are both considered to be appropriate in the process optimization of LPDC, and the researchers began to use these two techniques in process optimization of die-casting process and injection molding recently (Ref 21, 22). During these applications of soft computing, back-propagation (BP) ANN is often applied to map the relationship between process conditions and quality indexes. However, the poor filling-ability of thin-walled casting in LPDC process makes the optimization of process parameters more complex. And BP ANN alone is insufficient to yield any reasonable results for this process.

For this reason, an ANN model combining learning vector quantization (LVQ) and back-propagation (BP) algorithm is proposed in this article to model the process. And the orthogonal array design and numerical simulation is applied

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to obtain the training samples instead of carrying out a real experiment for the sake of cost saving. A GA is implemented to optimize the process afterward. Finally, by applying the optimized technology parameters, a sound casting with 300 mm in length, 100 mm in width, and 1.5 mm in thickness is successfully prepared and the casting quality is improved obviously.

2. Process Parameters Optimization of LPDC Using the Combining ANN/GA Method

In this article, an L-shape thin-walled casting with 300 mm in length, 100 mm in width, and 1.5 mm in thickness was studied, shown in Fig. 1. A356 (Al-7Sil-0.4Mg) was selected as the materials of casting. The sketch map of the model section is shown in Fig. 2. It can be seen that the cooling channels and gating system located in bottom of the die. And considering the poor filling-ability of thin-walled casting and entrap gas during casting filling die cavity, some essential vents are designed at the interface of top die and bottom die. The combining ANN/GA method was used to optimize the process parameters of LPDC for the thin-walled casting. The procedure of combining ANN/GA optimization is shown in Fig. 3. It involves selection of LPDC process parameters and quality indexes, preparation of train/test samples, creating of predictive ANN models, and optimization of process parameters via a genetic algorithm. The detail of each part of this procedure will be given in the following sections.

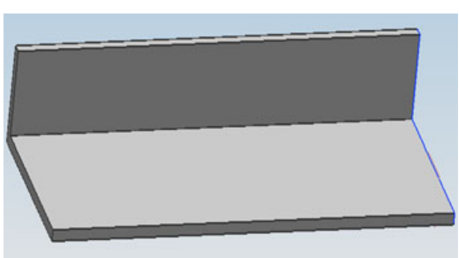

Fig. 1 3-D appearance of casting

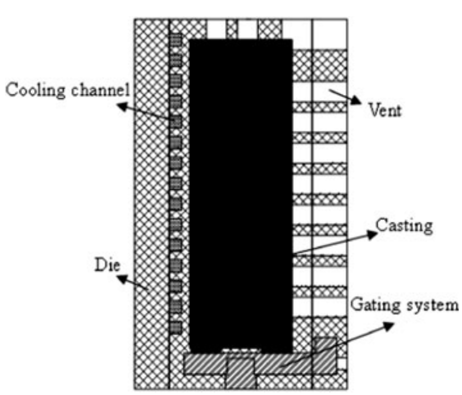

Fig. 2 The model section sketch map

2.1 Selection of LPDC Process Parameters and Quality Indexes

Many process parameters may affect the casting quality in LPDC, such as exerting pressure velocity, holding pressure, pressure holding time, melt temperature, mold temperature, etc. (Ref 3, 23). It is well known that the most significant parameters are melt temperature, mold temperature, and exerting pressure velocity in thin-walled part casting. Because of poor filling-ability of the thin-walled part, improper selection of any of these parameters may cause defects (such as cold shuts, distortions and cracks) in the casting and longer process cycle time. For instance, too lower melt and mold temperature may cause cold shut or short fill because of the decrease of casting filling-ability. Too high temperature would shorten the mold life and increase cooling time consequently the production time. In addition, exerting pressure velocity is having its own significance as too high filling velocity may lead to incomplete filling of the casting cavity, however, too low exerting pressure velocity results in longer process cycle time and the higher temperature difference in the cavity. The difference of temperature gradient in the part may cause residual stresses at the end mold filling stage. Therefore, in this study inlet melt temperature, initial mold temperature, and exerting pressure velocity were considered as ANN inputs and defect prediction, filling time, and maximum temperature difference in the casting as ANN outputs.

2.2 Train/Test Samples

The training samples for the initial training of the ANN model consist of a number of sets of inputs and outputs. In order to identify the relation between the given input-output parameters, these training samples should be carefully selected and cover the wide variety of possible ranges. Therefore, orthogonal array was introduced in the training samples design in this study. The orthogonal array is a procedure to systematically organize experiment runs to improve processes in the most effective way, which results in conducting a minimum

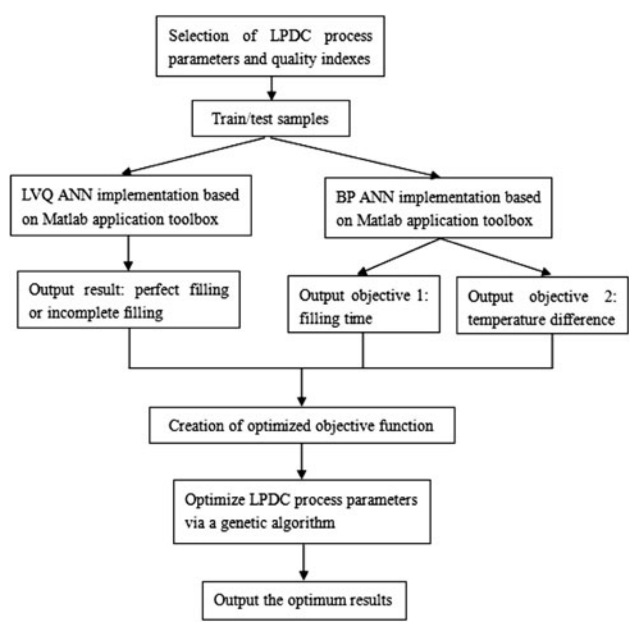

Fig. 3 Flow chart of combining ANN/GA optimization

number of experiments without losing significant information. The parameters and their chosen levels are shown in Table 1. Table 2 depicts the combinations of parameter levels for each experiment. Based on orthogonal array design of three parameters with five levels, total 25 set of experimental samples were generated. A commercial finite-element package, ProCAST was used to calculate and obtain the training samples instead of carrying out a real experiment for the sake of cost saving. The other advantage of finite-element method is that the time required to train a network is much less than that with real experiments because there is no noise existing in the computation data compared to the experimental data (Ref 21, 22). The main objectives of the simulation experiments are to determine whether or not there is a defect either on the surface or inside the casting and what filling time and the maximum temperature difference in the casting are. The numerical simulation results are presented in Table 2.

Table 1 The process parameters and their levels

Melt temperature, °C	Mold temperature, °C	Exerting pressure velocity, MPa/s
670	350	0.05
685	400	0.04
700	450	0.03
715	500	0.02
730	550	0.01

2.3 Predictive ANN Models

An ANN model is referred to as a type of computational models that consists of hidden-layer neurons connected between the input and the output neurons. The connections between the neurons are described by weights which are to be determined through training. The nonlinear hyperbolic functions are usually used as the activation functions to increase the modeling flexibility. In this study, a learning vector quantization (LVQ) ANN model was applied to predict defect existence in the casting. Defect existence in LPDC products constitutes an importance criterion in characterizing the manufacturing process as successful or not. The ANN models with back-propagation (BP) algorithm were used to map the relationship between filling time, maximum temperature difference, and process parameters. BP network is a typical ANN that has been widely used in many research fields (Ref 10-12). The data sets in Table 2 were used to train and test the ANN model. This data set of 25 data series was divided into two representative subsets of 20 and 5 data series, respectively (see Table 2). The first subset was used for ANN training and the second for checking the trained ANN's prediction accuracy using unknown inputs. Implementation was carried out in the application toolbox of Matlab.

2.3.1 Defect Prediction Through LVQ ANN Implementation. The LVQ ANN model was used to predict defect existence in the casting, owing to its predominance in classifying problems (Ref 22). This is a two-class problem, where the first, denoted with "1" in Table 2, implies perfect filling and the second, denoted with "2", implies a defect in the casting.

Table 2 25 set of training samples and corresponding numerical simulation results (perfect filling is denoted by 1 and defect existence by 2)

Trail number	Melt temperature, °C	Mold temperature, °C	Exerting pressure velocity, MPa/s	Perfect filling	Filling time, s	Temperature difference, °C
Training subset						
1	670	350	0.05	1	3.643	22.6
2	685	350	0.04	2	5.503	7.8
4	715	350	0.02	2	7.26	13.5
5	730	350	0.01	2	2.089	2.3
6	670	400	0.04	2	7.12	8.1
7	685	400	0.03	2	7.07	6
8	700	400	0.02	1	7.09	26.8
10	730	400	0.05	1	3.265	12.7
11	670	450	0.03	2	2.706	4.8
12	685	450	0.02	2	9.11	7.5
14	715	450	0.05	1	2.566	6.9
15	730	450	0.04	1	3.727	11.5
17	685	500	0.01	2	12.88	1.6
18	700	500	0.05	1	2.996	9.9
19	715	500	0.04	1	4.508	9.6
20	730	500	0.03	1	3.265	5.6
21	670	550	0.01	2	10.5	38.4
22	685	550	0.05	2	11.21	25.5
23	700	550	0.04	2	4.016	22.1
24	715	550	0.03	1	7.075	29
Testing subset						
3	700	350	0.03	1	4.89	24.3
9	715	400	0.01	2	7.9	13.7
13	700	450	0.01	2	9.36	3
16	670	500	0.02	2	2.59	12.8
25	730	550	0.02	1	7.248	29.8

Using a LVQ ANN, modeling needs to determine:

- the minimum and maximum input values
- the number of neurons in the competitive layer
- the percentage of class participation in the training subset
- the training rate.

Minimum and maximum input values and percentage of class participation in the training subset can be calculated from the data of Table 2. The results are shown in Table 3 and 4. Neurons in the competitive layer and training rate practically represent the ANN architecture and training algorithm, respectively. Four competitive layer neurons and a training rate of 0.001 are used in the LVQ ANN model, where they are determined by train trails. In addition, in order to speed up the training phase and enhance training algorithm behavior, the values of exerting pressure velocity in Table 3 are multiplied by 10000. Table 5 depicts the comparison of simulation results to the ANN prediction. Figure 4 shows the training error versus epochs. Given the sizes of training and testing subsets, performance achieved is considered to be adequate.

2.3.2 Prediction of Filling Time and Maximum Temperature Difference Through BP ANN Implementation. The ANN model was trained using the BP algorithm to map the relationship between filling time, maximum temperature difference, and process parameters. The ANN architecture adopted in the model is shown in Fig. 5. It consists of three layers: an input layer, a hidden layer, and an output layer. Hidden layer has seven neurons, whereas input and output layers have three and two neurons, respectively. Neurons in input layer correspond to melt temperature, mold temperature, and exerting pressure velocity. Output layer corresponds to filling time and maximum temperature difference.

In the network, the inputs are operated and transformed into the output by the state transition rule

$$v_j = \sum w_{ij} y_i \qquad \text{(Eq 1)}$$

$$y_j = f(v_j) \qquad \text{(Eq 2)}$$

where y_i in Eq 1 and y_j in Eq 2 is the output from a neuron i acting as an input of neuron j and the output of neuron j, respectively. w_{ij}^k is the connection weight. v_j is the state variable of the weights, which imply the connection strength between the neurons. The weighted signals are summed up in v_j

Table 3 Minimum and maximum input values

	T_{inlet}, °C	T_{mold}, °C	$V_{exerting}$, MPa/s
Min	350	670	0.01
Max	550	730	0.05

Table 4 Percentage of class participation in the training subset

Class	Class 1 (perfect filling)	Class 2 (incomplete filling)
Percentage	(9/20) × 100 = 45%	(11/20) × 100 = 55%

Table 5 Comparison of simulation results to the LVQ ANN defect-existence prediction model

Trail number	Simulation results	LVQ ANN prediction
Training subset (90% predictive precision)		
1	1	1
2	2	2
4	2	2
5	2	2
6	2	2
7	2	2
8	1	2
10	1	1
11	2	2
12	2	2
14	1	1
15	1	1
17	2	2
18	1	1
19	1	1
20	1	1
21	2	2
22	2	2
23	2	2
24	1	2
Testing subset (80% predictive precision)		
3	1	1
9	2	2
13	2	2
16	2	2
25	1	2

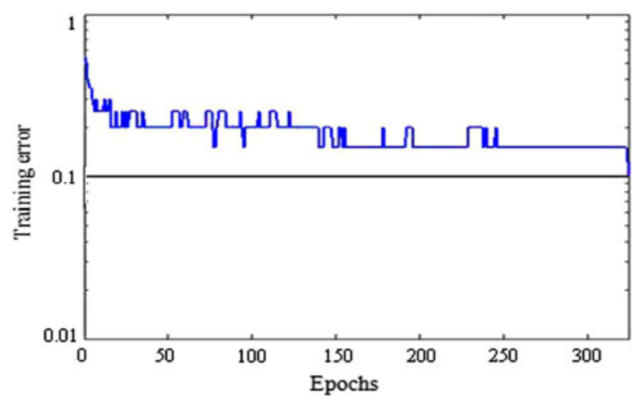

Fig. 4 Training error versus epochs for the LVQ ANN

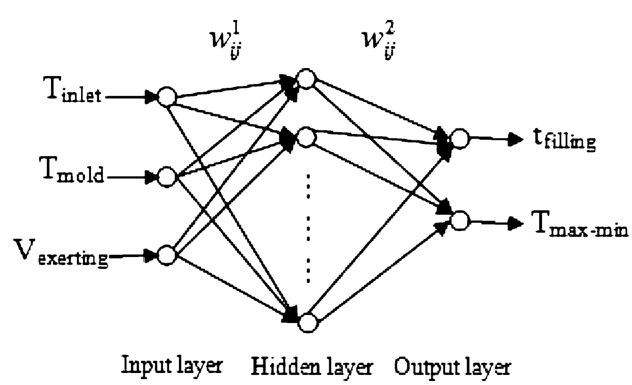

Fig. 5 Neural network architecture used in this study

and transformed into the output signal through an activation function. In this study, the activation function is given by the smooth sigmoid function

$$f(v_j) = \frac{1}{1 + e^{-v_j}} \quad \text{(Eq 3)}$$

The goal of the ANN training process is to modify the weights which characterize the BP neural network such that the actual output vector Y^p approximates the target output vector Y^t as closely as possible. The error norm E between the determined output Y^p vector and the targeted output vector Y^t is defined as

$$E = \|Y^p - Y^t\|_2 \quad \text{(Eq 4)}$$

As the sigmoid transfer function is used in the BP algorithm, the system cannot actually reach its extreme values of 0 and 1 without infinitely large weights. Therefore, the ANN model requires the normalization of the input and the output data. However, it is found better, in practice, to normalize the input patterns as well as output patterns to between 0.1 and 0.9 (Ref 24, 25). The inputs of the training samples are normalized linearly based on the following formulas.

$$\bar{\chi}_i = \frac{\chi_i - \chi_{i\,\min} + \varepsilon_1}{\chi_{i\,\max} - \chi_{i\,\min} + \varepsilon_2} \quad \text{(Eq 5)}$$

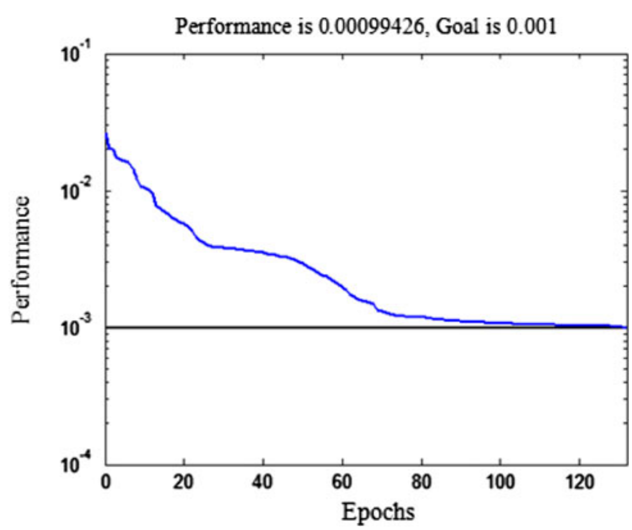

Fig. 6 Training error versus epochs for the BP network

where $x_{i\,\min}$ and $x_{i\,\max}$ are the minimal and maximal values of the ith input value x_i, respectively, in the sample data set; $\bar{x}_i$ is the normalized value of parameter x ranging between 0.1 and 0.9. The ε_1, ε_2 $(0 \le \varepsilon_1 < \varepsilon_2 \le 1)$ are the scaling factors for ensuring that the normalized values would not be close to 0 or 1. The outputs can be normalized in the exactly same way.

Figure 6 shows the training error during training. The mean square error of all 20 training samples is 0.00099426. The remaining five samples are then used to test the performance of the ANN. As shown in Table 6, the results predicted from the ANN model are compared with those obtained by numerical simulation. It is seen from Table 6 that ANN prediction is in good agreement with the simulation results. This indicates that the ANN has a good performance, and it can accurately map the relationship between process conditions and quality indexes of the casting.

2.4 Optimization of Process Parameters Via a Genetic Algorithm

A genetic algorithm is a stochastic optimization procedure, which can solve complex problems by imitation Darwin's theory of evolution on a computer (Ref 21, 22, 25). The concept behind the creation of genetic algorithms is the global optimization of an objective function in a complex multi-modal search space. Solution of the optimization problem with genetic algorithm begins with a set of chromosomes that are randomly selected. The entire set of these chromosomes constitutes a population. The chromosomes evolve during several iterations or generations. New generations (offspring) are generated using the crossover and mutation technique. Crossover involves splitting two chromosomes and then combining one-half of each chromosome with the other pair. Mutation involves flipping a single bit of a chromosome. The chromosomes are then evaluated using a certain fitness criteria and the best ones are kept while the others are discarded. This process is repeated until one chromosome has the best fitness. That chromosome is taken as the best solution of the problem.

The optimized objective function based on the genetic algorithm is formulated according to the simulation function obtained by ANN in the previous section

$$f(X) = 10000 \times (netlvq(X) - 1) + netbp(X) \quad \text{(Eq 6)}$$

where X is the process parameter values, $netlvq(X)$ is the output value of the LVQ ANN model for defect existence, $netbp(X)$ is the output value of the BP ANN model for filling time and maximum temperature difference. The various calculation parameters for GA are shown in Table 7.

Table 6 Comparison of ANN predictions with simulation results for the test samples

	Process parameters			Simulation results		ANN predictions	
Trail number	Melt temperature, °C	Mold temperature, °C	Exerting pressure velocity, MPa/s	Filling time, s	Temperature difference, °C	Filling time, s	Temperature difference, °C
3	700	350	0.03	4.89	24.3	6.97	20.63
9	715	400	0.01	7.9	13.7	9.14	16.47
13	700	450	0.01	9.36	3	7.52	5.39
16	670	500	0.02	2.59	12.8	1.51	10.14
25	730	550	0.02	7.248	29.8	7.41	27.27

Table 7 The calculation parameters for GA

Parameters	Population size	Maximum number of generations	Decoding	Selection	Crossover	Mutation
Values/method	30	80	Floating-point	Rank-based model	One-point crossover	Simple mutation

Table 8 Chemical compositions of A356 alloy used in present study

Element	Si	Mg	Cu	Mn	Sr	Ti	Others	Al
Content (%)	7	0.4	0.2	0.1	0.03	<0.1	<0.15	Bal.

3. LPDC Experiment

The experimental materials, A356 alloy, are melted in an electrically heated furnace using a graphite crucible. Its chemical composition is shown in Table 8. For experimental need, a small type of LPDC machine is selected as the experimental equipment. The sketch map is shown in Fig. 7. The LPDC process parameters are obtained by the combining ANN/GA method as mentioned above.

4. Results and Discussion

4.1 Optimized Process Parameters of LPDC

The common LPDC process parameters include pouring temperature, die temperature, filling pressure, etc. In this study, by applying the combining ANN/GA method based on ProCAST, the optimized parameters are obtained through analyzing the filling state of casting and the major influence factors of the casting quality. Figure 8 shows the evolution of the generations based on a genetic algorithm. It is obvious that convergence is achieved approximately in the 30th generation. The optimized process conditions are as the following: the melt temperature is 726 °C, the mold temperature is 493 °C, and exerting pressure velocity is 0.04 MPa/s; accordingly as ANN outputs, the filling is perfect, and the filling time and maximum temperature difference in the casting is 2.987 s and 3.5 °C, respectively.

4.2 Simulation Results

Figure 9 presents the evolution of filling state at different filling times during LPDC processing simulation using the above process parameters. The whole filling time is about 3.39 s and the filling is perfect without cold shut and short fill at the end of filling, which is in agreement with the results of ANN. In Fig. 9, it can also be clearly seen that the molten metal flows steadily in the die cavity. No obvious turbulence or entrapment of gas is observed when the molten metal fills the cavity. This is very advantageous for the preparation of casting with better mechanical properties. If the filling is not appropriate, the casting would suffer from filling-related defects such as gas porosity (Ref 26). In addition, through the observation of temperature distribution during casting filling from Fig. 9(c) to (e), it can be obviously found that the maximum temperature difference in the casting is very small with less than 5 °C. The value is also in agreement with the ANN predictions. According to Ref 27, 28, the grain size, distribution of intermetallic phases, and residual stresses in the casting are strongly influenced by temperature distribution in the process of casting solidification, and ultimately affect the casting quality. Therefore, the simulation results indicate that a desired casting could be obtained by the optimized process parameters.

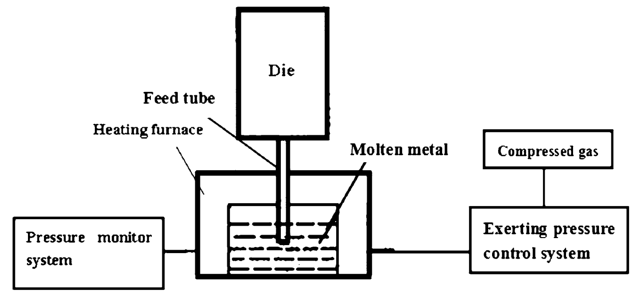

Fig. 7 Schematic diagram of LPDC machine

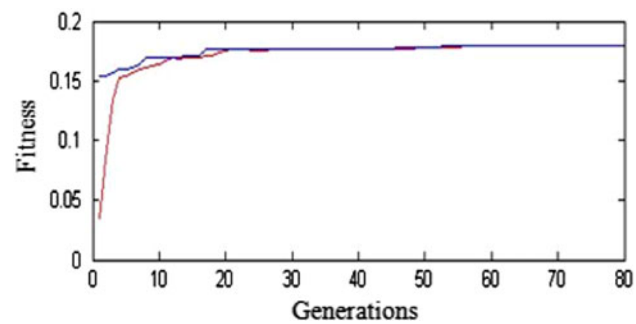

Fig. 8 Objective function values for the best chromosome in each generation

Figure 10 shows the evolution of filling state at different filling times during LPDC processing before the process parameters optimization. The real process parameters are as follows: pouring temperature 760 °C, die temperature 530 °C, and exerting pressure velocity 0.03 MPa/s. Compared with the optimized process parameters, the pouring and die temperature are much higher. The whole filling time is about 4 s. It is longer than the one obtained with the optimized process parameters. This means higher productivity efficiency can be obtained by applying the optimized process parameters. Moreover, in Fig. 10, it can be clearly seen that the maximum temperature difference in the casting is very big with over 25 °C when the casting filling ends. The too big maximum temperature difference in the casting may cause residual stresses at the end mold filling stage.

4.3 LPDC Experiment Result

Figure 11 shows the result of LPDC experiment. Fig. 11(a) shows the casting prepared before the process parameters optimization. The surface of casting is rough. The rough

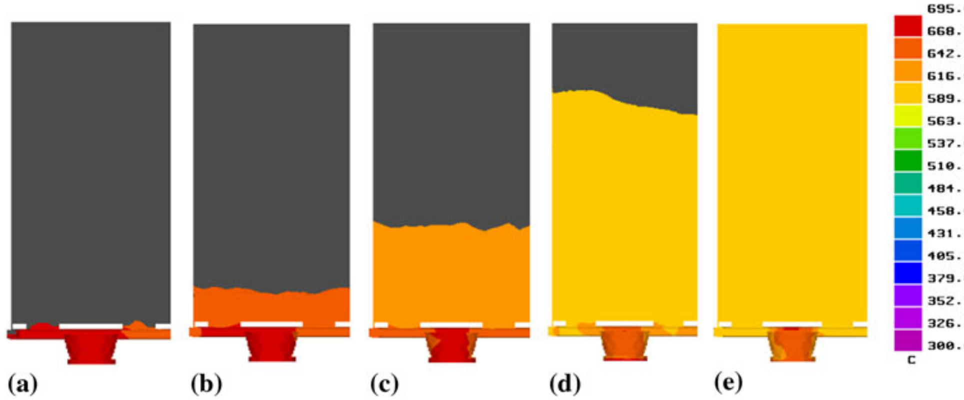

Fig. 9 The filling state at different times of LPDC simulation with optimized process parameters. (a) 0.85, (b) 1.04, (c) 1.58, (d) 2.54, and (e) 3.39

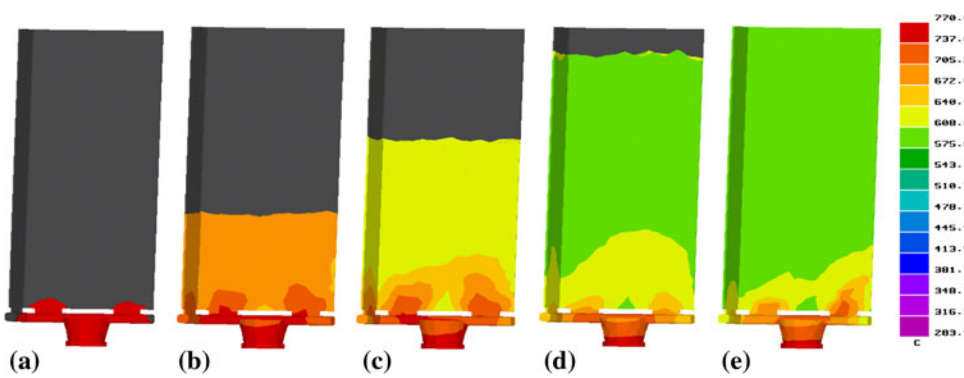

Fig. 10 The filling state at different times of LPDC simulation without optimized process parameters. (a) 0.95 s, (b) 1.64 s, (c) 2.34 s, (d) 3.68 s, and (e) 4.38 s

surface is due to the excessively high pouring and mold temperature mentioned above in the simulation results. In Fig. 11(b), the casting is prepared using the optimized process parameters. Figure 11(b) illustrates that a sound casting with 300 mm in length, 100 mm in width, and 1.5 mm in thickness can be successfully prepared using the optimized LPDC process parameters. It can be clearly seen that the surface of the casting is smooth, and no obvious defects such as shrinkage, gas porosity, distortion, and crack are found, which is in well agreement with simulation result in Fig. 9. In addition, compared with the casting in Fig. 11(a), the quality of casting surface is obviously improved, which verifies the feasibility of using the ANN modeling and GA searching techniques to model and optimize LPDC process.

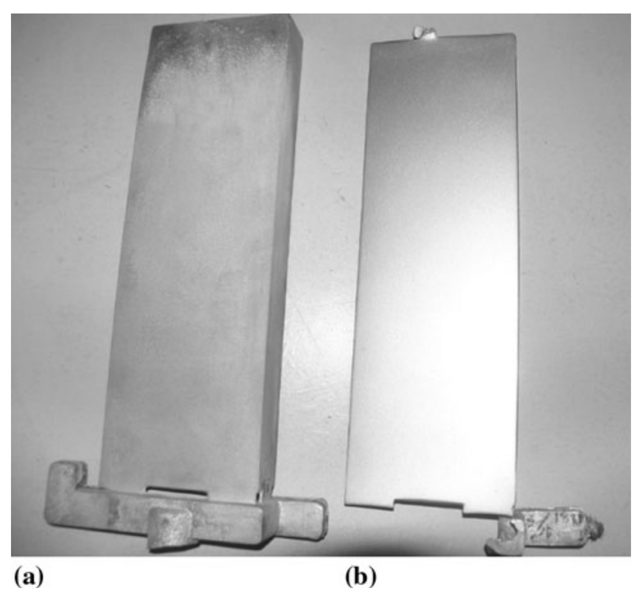

Fig. 11 Cast A356 alloy parts: (a) before the process parameters optimized and (b) after the process parameters optimized

5. Conclusions

1. The proposed ANN model combining learning vector quantization (LVQ) and back-propagation (BP) algorithm has been shown as an effective method to map the complex relationship between process conditions and quality indexes of LPDC parts.
2. The LPDC process parameters of A356 aluminum alloy thin-walled component with permanent mold have been optimized using the combining ANN/GA method. The orthogonal array and finite-element method are successfully applied to obtain the training samples for the sake of experimental accuracy and cost saving. The optimized

process parameters are as follows: melt temperature 726 °C, die temperature 493 °C, and exerting pressure velocity 0.04 MPa/s.

3. By applying the optimized parameters, a thin-walled component with 300 mm in length, 100 mm in width, and 1.5 mm in thickness has been successfully prepared and no obvious casting defects such as shrinkage, gas porosity, distortion, and crack can be found in the component. In addition, compared with the casting prepared before process parameters optimized, the quality of casting surface is obviously improved. The results demonstrate adequately that the combining ANN/GA method proposed in this article is a feasible and an effective tool for mapping the complex relationship between process parameters and part quality indexes and optimizing the LPDC process parameters.
4. The modeling and optimization methods proposed in this article show the great potential in complicated industrial applications.

Acknowledgments

The authors gratefully acknowledge research support from Hunan Science Fund for Distinguished Young Scholars No. 09JJ1007, International Cooperation and Exchanges MOST No.2008DFA50990 and the Science Fund of State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body No. 60870005.

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