Optimization of high-pressure die-casting process parameters using artificial neural network

Article *in* The International Journal of Advanced Manufacturing Technology · October 2009

DOI: 10.1007/s00170-008-1886-6

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Int J Adv Manuf Technol (2009) 44:667–674
DOI 10.1007/s00170-008-1886-6

ORIGINAL ARTICLE

Optimization of high-pressure die-casting process parameters using artificial neural network

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Received: 3 August 2008 / Accepted: 28 November 2008 / Published online: 9 January 2009

Abstract High-pressure die casting is a versatile process for producing engineered metal parts. There are many attributes involved which contribute to the complexity of the process. It is essential for the engineers to optimize the process parameters and improve the surface quality. However, the process parameters are interdependent and in conflict in a complicated way, and optimization of the combination of processes is time-consuming. In this work, an evaluation system for the surface defect of casting has been established to quantify surface defects, and artificial neural network was introduced to generalize the correlation between surface defects and die-casting parameters, such as mold temperature, pouring temperature, and injection velocity. It was found that the trained network has great forecast ability. Furthermore, the trained neural network was employed as an objective function to optimize the processes. The optimal parameters were employed, and the castings with acceptable surface quality were achieved.

Keyword Die casting · Process parameter · Neural network · Levenberg–Marquardt algorithm · Optimization

1 Introduction

High-pressure die casting is an economical and efficient method for producing magnesium alloy components requiring low surface roughness and high dimensional accuracy in automotive industry [1]. Although die-casting parameters have been studied by various researchers, a unified method that can optimize all process parameters simultaneously regarding one criterion or a combination of criteria is still at its infancy [2]. For instance, the surface quality of a die casting is related principally to the mold temperature, the injection velocity, and pouring temperature, and the combination of these process parameters affects the surface quality of the cast components; thus, various surface defects are expected to be generated if these parameters are not optimized adequately. Therefore, the accurate simulation of the correlation between important die-casting parameters and the surface quality is of considerable practical interest [3]. Neural network, which is developed through the understanding of the biological nervous system with learning and generalization abilities, is an effective method to map the outcome to the input examples and have been widely applied by Negnevitsky [4], Rao and Prasad [5], and Shelesh-Nezhah and Siores [6] in manufacturing industry.

Lam. et al. [7] used a modular system for the slip-casting process that integrates neural networks, a dual-objective optimization algorithm, and fuzzy logic techniques to improve both the quality and efficiency of the slip-casting step. The predictive module estimates cast rate and moisture gradient. The process improvement module optimizes the controllable settings for the given ambient

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conditions and slip characteristics using the neural network prediction module in the objective function. The fuzzy logic expert system recommends the processing time customized to a production line given the localized ambient state and the condition of the plaster molds.

To map the relationship between the die-casting process parameters of Zn-Da3 alloy and injection time, Yarlagadda and Chiang [8] have developed a multi-layer feed-forward network using three different algorithms, namely the error back-propagation algorithm, the momentum and adaptive learning algorithm, and Levenberg–Marquardt approximation algorithm. The characteristics of the three algorithms were analyzed.

Park and Rhee [9] welded AA5182 aluminum alloy with AA5356 filler wire, and a neural network model was used to predict the tensile strength of the weld. To optimize the process parameters, such as laser power, welding speed, and wire feed rate, a fitness function was formulated in order to take into account weldability and productivity. A genetic algorithm was used to optimize the parameters.

Karunakar and Datta [10] developed a neural network to simulate the relationship between sand casting parameters like green compression strength, permeability, moisture percent, composition of the charge, and melting conditions as inputs and the presence/absence of defects as outputs. The set of inputs of the casting that is going to be made was fed to the network, and the network could predict whether the casting would be sound or defective. If defective, the neural network could predict cracks, misruns and air-locks accurately in most of the cases. The causes for the defects were investigated, and the defects were prevented by altering the molding parameters and through appropriate treatment of molten metal.

To optimize pressure die-casting process parameters, Krimpenis et al. [2] designed a die-casting evaluation system according to experimental methods corresponding to a total of 16 sets of tests. It was considered as a two-class problem, where the perfect castings were denoted with “1,” and the castings with defects were denoted with “2.” A neural network system was used to simulate the relationship between the process parameters and the defect, solidification time. Optimal die-casting parameters could be searched for based on the trained network by a genetic algorithm that can yield the set of input parameters which achieves the best output parameter values.

Though the review of the literature clearly reveals that neural network has been widely used to optimize the process parameters, few investigators aimed at finding out the way to harmonize the relationship between various defects and improve product’s quality when these defects could not be prevented entirely. The aim of the present work is to research a methodology to optimize process parameters in case that the surface defects of die casting is hard to prevent completely. In this work, an evaluation

Table 1 Chemical composition of AXJ530 alloy

Alloy	Chemical composition								
	Mg	Al	Ca	Zn	Sr	Mn	Fe	Ni	Cu
AXJ530	Bal.	5.4	3.2	0.16340	0.13	0.39812	0.00307	0.00121	0.00367

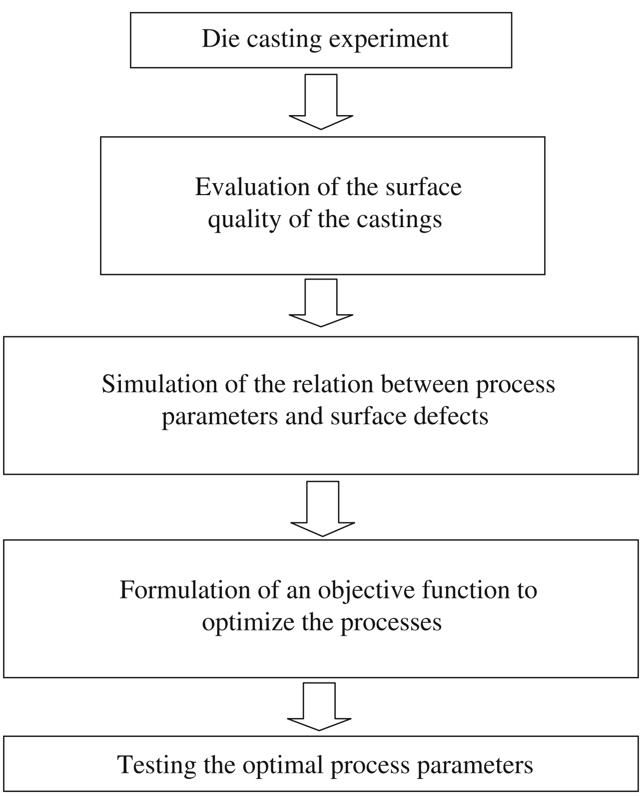

Fig. 1 Workflow of this work

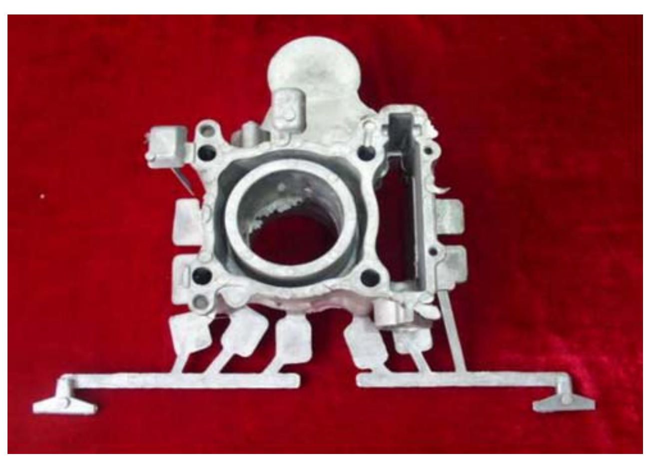

Fig. 2 Die casting employed in this study

Table 2 Practical die-casting process parameters

Number	Mold temperature (°C)	Pouring temperature (°C)	Injection velocity (m/s)
P1	155	658	1.5
P2	172	661	1.5
P3	194	662	1.5
P4	228	667	1.5
P5	228	670	1.5
P6	226	670	1.0
P7	236	675	0.5
P8	239	683	1.5
P9	245	710	1.5
P10	285	740	1.5

system for the surface defects of die castings was established, and surface defect index was introduced to quantify the level of severity based on castings. A back-propagation neural network was constructed to learn the relationship between process parameters and surface defects. The trained network with great mapping ability was used in optimizing the process parameters and improving the surface quality of die casting. The methodology presented in this work is demonstrated in Fig. 1.

2 Experiment

The commercial AXJ530 magnesium alloy was used for conducting these experiments, and its composition is listed in Table 1. The alloy was melted with the protection of a mixed gas atmosphere of SF_6 (0.5 vol.%) and CO_2 (99.5 vol.%). Mold was preheated in the temperature range of 155°C to 285°C, and the pouring temperatures were maintained in the range of 658°C to 740°C. A 650 t cold-chamber die-cast machine was used to produce cylinders, as shown in Fig. 2, with injection velocity in the range of 0.5 to 1.5 m/s. Ten sets of cylinders were cast with different process parameters given in Table 2, and three to five parts were cast under each set of process parameters. Surface quality of the parts collected under each set of process parameters was evaluated quantitatively.

3 Quantitative evaluation of surface defects in cylinder

3.1 Establishment of evaluation system for the surface defects in cylinder

The evaluation system was established based on the performance requirements of casting, and the ratings P were used to assign the level of severity for various surface defects, ranging from 1 (slight) to 5 (most severe). In addition, effects of various defects were determined by introducing impact factor η. Impact factor is high when the influence of defect is severe, and vice versa.

In the present work, the major surface defects include hot cracking, cold shut, misrun, and die sticking, as shown in Fig. 3. An overview of the said defects is given below, and the evaluation standards of defect rating and impact factor η are shown in Table 3.

Hot cracks are formed when the casting is hot and may occur during cooling in the cavity [10]. Hot cracking can

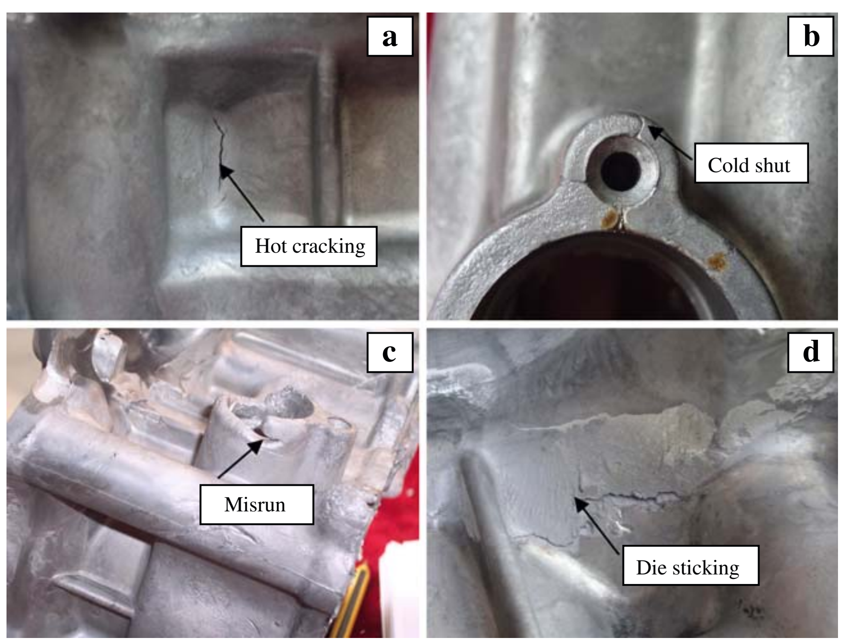

Fig. 3 Surface defects of the castings. **a** Hot cracking. **b** Cold shut. **c** Misrun. **d** Die sticking

Table 3 The standard of defect analysis of the castings

Surface defect	Evaluation standard of defect	Defect rating (P)	Effect of defect (impact factor η)
Hot cracking	Length×width<0.5 mm^2	1	The influence of hot cracking on the tightness and mechanical properties is serious. Impact factor is 1.5
	Length×width 0.5~1.0 mm^2	2	
	Length×width 1.0~4.0 mm^2	3	
	Length×width 4.0~7.0 mm^2	4	
	Length×width>7.0 mm^2	5	
Cold shut	Length×depth<4 mm^2	1	The influence of cold shuts on casts is little slighter than hot cracking. Impact factor is 1.2.
	Length×depth 4~10 mm^2	2	
	Length×depth 10~20 mm^2	3	
	Length×depth 20~40 mm^2	4	
	Length×depth>40 mm^2	5	
Misrun	Square<100 mm^2	1	Misrun is often on the edge of the cases and affects appearance. Impact factor is 1.2
	Square 100~300 mm^2	2	
	Square>300 mm^2	3	
Die sticking	Square<25 mm^2	1	The influence of die sticking on leakage and mechanical properties of casts are slight. Impact factor is 1.0
	Square 25~100 mm^2	2	
	Square 100~200 mm^2	3	
	Square 200~400 mm^2	4	
	Square>400 mm^2	5	

also occur in the event of uneven cooling conditions (differences in wall thicknesses). The typical appearance of hot cracking is shown in Fig. 3a.

Both misrun and cold shut usually take place when fluidity of the melt is not good enough [10]. Thus, they arise when the pouring temperature and the pouring speed drastically decrease, and inclusion in melt also causes these defects. In addition, these defects could originate from low speed of shot. However, the effect of cold shut on the performance is not as serious as misrun. In the present work, the typical appearance of cold shut and misrun are shown in Fig. 3b,c, respectively.

Die sticking occurs when the liquid fraction at the die surface is large enough that, upon solidification, a strong joint between casting and die is formed [11]. Therefore, increases in pouring temperature and mold temperature will lead to die sticking. The general appearance is shown in Fig. 3d.

3.2 Zone division of parts and determination of weight factor

The casting surface was divided into different zones, and every zone with different performance requirement was given a certain weight factor ω, which was grounded on the structure and application environment, as shown in Fig. 4. The basic value of weight factor is 1, and it increases with higher quality requirement. Table 4 reveals application environment, performance requirement of various zones, and estimation standard for weight factor.

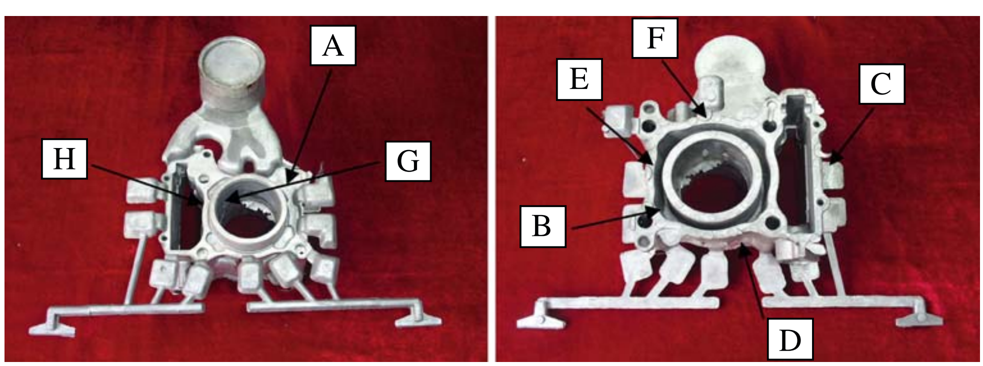

Fig. 4 Division of surface zones

Table 4 Determination of the weight factor of zones

Surface area	Weight factor ω	Application environment
Face G	1.5	Face F is the inner surface of cylinder, and tightness requirement is high
Face A	1.2	Face A supports and fixes it. The bond between face A and blast chamber should be firm
Face B, C, D, E, F, H	1.0	Exterior surface of die casting plays an important role on the appearance of die casting

3.3 The determination of total surface defect index

In terms of the evaluation standard shown in Table 3 and the weight factor of each surface zone shown in Table 4, the defect index Q_i of each type of defect was obtained based on formula 1,

$$Q_i = \sum_{j=i}^{m} \omega_j \overline{P_{ij}} \tag{1}$$

Where

- j the number of surface zone
- i the number of surface defect
- m the amount of surface zones
- $\overline{P}_{ij}$ the mean value of surface defect grade obtained under each technical condition
- ω the weight factor

The surface defect index Q was calculated based on formula 2,

$$Q = \sum_{i=1}^{n} \eta_i Q_i \tag{2}$$

Where

- η impact factor shown in Table 4
- n the amount of surface defects

The surface defect indexes of the castings obtained under each technical condition were averaged to reduce experimental error; the results were shown in Table 5.

For example, some defects, including hot cracking, cold shut, misrun, and die sticking occur in area F of the cylinder cast, as shown in Fig. 4, with the process parameter P10, as shown in Table 2. The sizes of the defects on the area are list in Table 6. The product of length and width of the hot cracking is 8 mm^2, and its defect rating is 2 based on Table 3. According to the methods mentioned above, the defect ratings of other defects in this area, such as cold shut, misrun, and die sticking, can also be obtained. Consequently, the defect ratings of various defects on different areas can be collected in terms of the evaluation system, and then the total defect indexes can be achieved.

4 Establishment of neural network model

4.1 Framework of the neural network system

Back-propagation (BP) neural network system with great forecast ability is the most familiar neural network. A three-layer network was constructed with three input neurons in the input layer and one neuron in the output layer, the configuration is shown in Fig. 5. The relationship between surface defect indexes and die-casting process parameters, such as mold temperature, pouring temperature, and injection velocity, etc., was expected to be simulated.

In Fig. 5, there are three input neurons such as mold temperature, pouring temperature, and injection velocity in input layer, and the input set is $A_K=(a^k{}_1,a^k{}_2,a^k{}_3)$, K is the number of samples. Output layer has an output neuron, which is surface defect index of cylinder, and the output set is $C_k=c^k$.

The sigmoid function 3

$$f(x)=1/(1+e^{-x}) \tag{3}$$

was employed as the activation function for the hidden layer to make the outputs reachable, and the identity function $f(x)=x$ was employed for input and output layers in order to reduce computational complexity and take less calculation time.

Table 5 Surface defect indexes of the castings obtained under different technical condition

Number	Surface defect index (Q_i)				Total surface defect index (Q)
	Cracks	Cold shut	Misrun	Die sticking	
P1	11.6	15.4	0	5	55.13
P2	8	8	0	5	43.6
P3	15.5	20	0	5	55.65
P4	21.1	18.5	1	4	68.15
P5	14.5	8	0	0	35.35
P6	21.1	7	1	3	49.45
P7	13.4	8	0	4	47
P8	16	10	0	11	45.4
P9	28.7	11	0	11	77.7
P10	27.7	21	2	6	85.25

Table 6 The size of surface defects in area F

Surface defect	Number	Length (mm)	Width or depth (mm)	Length×width or square (mm^2)	Sum (mm^2)
Hot cracking	1	15	0.6	8	8
Cold shut	1	3.6	1	3.6	3.6
Misrun	1	5.1	1.4	7.1	7.1
Die sticking	1	16	11	176	280
	2	13	8	104	

Table 7 Training subsets used for the network

Number	Mold temperature (°C)	Pouring temperature (°C)	Injection velocity (m/s)	Surface defect index
P1	155	658	1.5	55.13
P2	172	661	1.5	43.6
P3	194	662	1.5	55.65
P4	228	667	1.5	68.15
P6	226	670	1.0	49.45
P7	236	675	0.5	47
P8	239	683	1.5	45.4
P10	285	740	1.5	85.25

4.2 The pretreatment of the pattern

Experimental results (shown in Tables 2 and 3) were used as data sets for training and verification, output variable including total surface defect indexes, and input variables including pouring temperature, mold temperature, injection velocity, etc. Before the neural network was trained, the data have been pretreated to make sure that the input variables vary in a small range to decrease the difficulty of network training. Scaling of the data series was made based on formula 4 in the range of 0.1 and 0.9, and the data series were divided into two representative subsets of eight and two data series, respectively, as shown in Tables 7 and 8.

$$x_N = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times 0.8 + 0.1 \quad (4)$$

The first subset was used for training the network, and the second one was used for testing the trained network's forecast ability.

5 Training and testing of neural network

Levenberg–Marquardt algorithm was adapted to train the network to enhance mapping ability. In the algorithm, weights and biases are adjusted by using transfer function: $\Delta W = \eta(H + \lambda I)^{-1} g$ [12]. The Levenberg–Marquardt algorithm is more efficient than the gradient descent algorithm. The number of neurons is varied from 3 to 5 in the hidden layer, the error goal was set as 0.00001 to capture, and the training rate was 0.01. The lowest mean square error (MSE) obtained by using this algorithm is 4.83e-008 with four neurons in hidden layer in 61 training cycles, while the MSE did not reach the error goal with three and five neurons in hidden layer. By using the Levenberg–Marquardt algorithm, the error goal value could be set much lower, and the network convergence was faster.

As shown in Table 9, for the testing subset, the relative errors were 0.09% and 1.02%, respectively. The error calculation indicates that the forecast ability was relatively reliable, and the network can be dependably used to map the surface defect index to the process parameters.

6 Die-casting parameter optimization

Setting appropriate criteria for the optimization is an important step in optimization methodology. According to the excellent forecast ability of the trained network, the trained BP network can be used as an objective function to achieve the minimum value of the output, namely surface defect index, and find process parameters that offer perfect filling during die casting.

The objective function was formulated in the previous section

$$f(X) = \mathrm{net}(X) \quad (5)$$

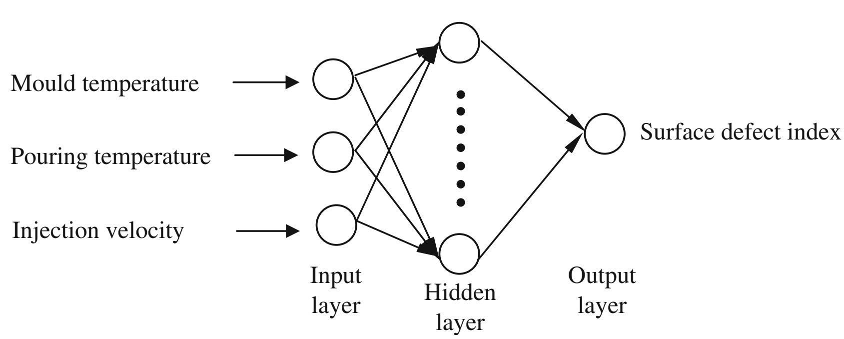

Fig. 5 A neural network for the relationship between technical parameters and surface defect indexes

Table 8 Testing subsets used for the network

Number	Mold temperature (°C)	Pouring temperature (°C)	Injection velocity (m/s)	Surface defect index
P3	228	670	1.5	35.35
P9	245	710	1.5	77.7

where net(X) is the output value of artificial neural network (ANN) model for total surface defect index, $X=(X_1, X_2, X_3)$ is a 3×1 array holding process parameter values.

X_1 the input value for mold temperature, $200°C<X_1<240°C$

X_2 the input value for pouring temperature, $640°C<X_2<700°C$

X_3 the input value for injection velocity, $0.5\ m/s<X_3<1.5\ m/s$

The ANN model was established based on the data sets collected from the experience. Hence, the lower and upper limits for mold temperature, pouring temperature, and injection velocity have to be fixed according to the experimental condition mentioned in Section 2.

In this work, the objective function can be optimized by MATLAB software. The minimum value of the surface defect index obtained under the restrictive condition was 18.2, and the corresponding solution, namely $X_{optimal}$, is the optimal process parameters, namely mold temperature 210°C, pouring temperature 680°C, injection velocity 1.4 m/s. The optimal process parameters were employed to cast the cylinder, and Fig. 6 shows that the achieved castings have few defects, and the surface quality is acceptable.

7 Discussion

As for the methodology of optimization of process conditions, the popular way is experience accumulation and specific know-how of each company. Optimization of processes has been done by some researchers, but the optimization criteria were only defined as absence or appearance of defects. Though some defects are hard to be prevented completely, they can be accepted to some extent, which was not taken attention to. Therefore, an evaluation system was introduced to quantify surface defects in this research, and the combination of several kinds of surface defects was studied synthetically.

Fig. 6 The cylinder cast with the optimal process parameters

In the back-propagation network, the sigmoid function was only employed for the hidden layer, and the identity function was employed for input and output layers. The calculation indicates that the BP network can accurately map the surface defect indexes to the process parameters and reduce computational complexity. After the training and testing tasks have been completed, the weights of the trained network were stored in the hard disk, and then the objective function could be formulated to optimize the process parameters.

In addition, the process parameters are interdependent and are in conflict in a complex way. It can be seen that the optimal parameters for a kind of defect may not be optimum to another one. In the present analysis, cold shut was observed in castings cast under condition P1, and its defect index is 15.4. This may be due to the fact that cold shut usually takes place when fluidity of the melt is not good enough. Thus, appropriately increasing the pouring temperature and the mold temperature can prevent these defects, which has been proved by the cylinders cast under condition P9. As the pouring temperature and molding temperature are 710°C and 245°C, respectively, the casting has less cold shut, and its defect index is 11. However, die sticking is serious for the cylinders cast under condition P9. Its surface

Table 9 Comparison of experimental results to the prediction values

Number	Process parameter			Surface defect index		Relative error (%)
	Mold temperature (°C)	Pouring temperature (°C)	Injection velocity (m/s)	Experiment value	Prediction value	
P5	228	670	1.5	35.35	35.38	0.09
P9	245	710	1.5	77.7	76.91	1.02

defect index is 11 and higher than the defect index of cylinder obtained under condition P1, namely 5. This can be due to the fact that die sticking occurs when the liquid fraction at the die surface is large enough, and a strong joint between casting and die is formed. The increases in pouring temperature and mold temperature will lead to die sticking.

As already mentioned, various defects are hard to be prevented completely. Therefore, it is necessary to harmonize the relations among these surface defects and keep a balance among them to obtain an effective way to improve surface quality greatly. When the optimal processing technology parameters were applied, the castings with a few of cold shut and little die sticking were obtained.

8 Conclusions

The evaluation system can be established to help the engineer quantify the level of the severity of surface defects such as hot cracks, cold shut, misrun and die sticking, and so on. Defect rating may be introduced to quantify the level of severity, and the surface defect index can also be obtained based on the system, which plays an important role in assisting foundryman to find out how to minimize the various defects.

Based on the evaluation system, the trained BP neural network can be effective on generalizing the correlation between surface defect index and die-casting process parameters, such as mold temperature, pouring temperature, and injection velocity. An objective function can be formulated to optimize the process parameters according to the ANN model. The cylinders cast with the optimal technological parameters have acceptable surface quality.

In the present study, the proposed methodology is introduced to optimize manufacturing technology. The method to establish evaluation system can be applied for various forming technology, including casting, weld, extrusion, and so on. The BP neural network can be used to map process parameters to severity of defects, which make it possible to formulate the objective function in order to achieve the optimal process parameters. Especially when it is hard to prevent defects entirely, the method can successfully help workers to harmonize the relationship of these defects. The product's quality could be improved, and the productivity will increase greatly without excessive numbers of experiment. This is the direction towards which the presented work is being expanded.

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