Inclusion Defect Prediction and Multi-process Process Control of Outlet Pipe Casting

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Abstract: Inclusion defects have a great influence on the performance of investment casting. When optimizing the process for inclusion defects, due to the production fluctuation in the casting site, the actual value of the process parameters will deviate from the set value. Therefore, this paper proposes a defect prediction and multi-process process control strategy combining BP neural network and improved particle swarm optimization algorithm. Firstly, data mining is carried out based on Huazhu ERP, and data cleaning is carried out on the collected process parameters. Secondly, an inclusion defect prediction model based on particle swarm optimization and BP neural network (PSO-BP) is established. Compared with the ordinary BP neural network, the accuracy is improved from 92.1% to 94.7%. Thirdly, a multi-process process control strategy combining K-nearest neighbor interpolation method and improved particle swarm optimization algorithm (KNN-IPSO) is proposed to control the process parameters of the subsequent process according to the deviation of the process parameters of the previous process, so as to ensure the stability of the casting quality. Finally, the simulation experiment was carried out. Compared with the ordinary pre-production process optimization method, the defect rate was reduced by 23%.

Key words : investment casting ; BP neural network ; improved particle swarm optimization algorithm ; k nearest neighbor interpolation method.

1 Introduction

Inclusion defects seriously affect the performance of castings, and the formation process is complex and difficult to eliminate. Therefore, it is very important to take preventive measures against inclusion defects. In recent years, researchers have made some progress in defect prediction using deep learning network models[1], and used meta-heuristic algorithms[2][3][4] to optimize process parameters to ensure casting quality. However, in the production process of investment casting, the actual value of the process parameters often deviates from the set value, and the deviation is accumulated, which is likely to cause huge product quality fluctuations. Therefore, it is urgent to control the process of the subsequent process in time for the production fluctuation. In this paper, a defect prediction and multi-process process control strategy combining BP neural network and improved particle swarm optimization algorithm is proposed. The technical route is as follows.

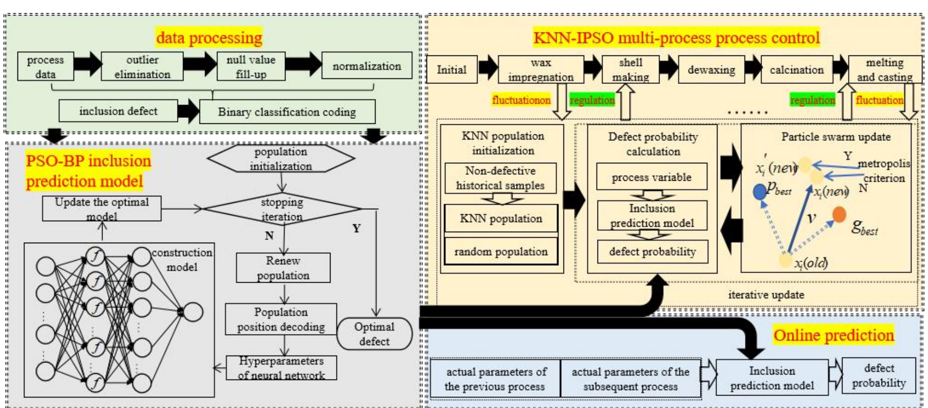

Figure 11 Inclusion defect prediction and multi-process process control

2 Experimental procedure

(1) Based on the Huazhu ERP system of a factory, through the process parameters of the original mold cleaning, wax leaching, shell making, dewaxing,

roasting, vacuum melting and pouring process of the single-piece number-related outlet pipe casting, the abnormal value is detected and eliminated based on the quartile distance criterion. The null value is filled with the mode, and the shell-making parameters with similar data distribution are reduced in dimension. After removing the unchanged parameters in the data, a total of 24 process parameters in the data set are obtained, and 251 single-piece records of the complete casting are obtained.

(2) The training set and test set are divided according to the ratio of about 7 : 3. The inclusion defect results are binary coded, and the process parameters are normalized by Z-score. At the same time, the sigmod ( ) function is used to process the output layer data and obtain the probability of defect occurrence, and then the threshold judgment is converted into a binary classification result. The particle swarm optimization algorithm is used to optimize the neural network hyperparameters, and the number of hidden layer nodes, the type of activation function and other hyperparameters are determined. Combining the F_1 score and the number of nodes, the objective function of neural network hyperparameter optimization is established as follows :

$$fitness\_net = F_{\beta} + 0.01 \prod_{i=1}^{n} hidden\_size_i / (50^n) \qquad (1)$$

Here n is the number of layers of the neural network, and $hidden\_size_i$ is the number of nodes in the i-th layer.

(3) After each step of single-piece production, the improved particle swarm optimization algorithm combined with KNN nearest neighbor interpolation method can be used to search the hyper-parameter combination of subsequent processes, and the KNN-IPSO multi-process process control model can be established. When the population is initialized, the KNN nearest neighbor interpolation method is used to search for records similar to the process parameters of the previous process in the historical defect-free samples, and the parameters of the subsequent process in the first ten records are selected, and then 10 corresponding records are randomly generated to form the KNN initial population. In the update stage of the particle swarm, because the population initialization refers to the historical solution set, the particles are more likely to converge quickly and fall into the local optimal solution. In order to reduce the impact of this problem, the Metropolis criterion is used to consider whether to accept a worse solution set.

3 Result and discussion

In order to test the effect of KNN-IPSO solution strategy, the following simulation experiment is designed : after the planned parameters of the previous process are determined, Gaussian white noise is added to simulate the production fluctuation, and then the KNN-IPSO control process is carried out to change the planned value of the process parameters of the subsequent process. At the same time, 100 single-piece pre-production optimization experiments were carried out as a control group. The results are shown in Table 1. The results show that the KNN-IPSO multi-process process control scheme can effectively improve the inclusion defects of castings, and the inclusion rate is reduced by 23 % compared with the pre-optimized inclusion rate.

Table 2 Comparison of the number of inclusions in simulated experimental castings

Control group	Total number	Number of inclusions	Inclusion rate
Historical data	251	18	86.1%
Pre-production optimization	100	44	44%
Multi-process control	100	21	21%

4 Conclusion

In this paper, the particle swarm optimization algorithm is used to optimize the hyperparameters of BP neural network. Compared with the ordinary BP neural network, the accuracy of PSO-BP inclusion defect prediction model is improved from 92.1% to 94.7%. The KNN-IPSO multi-process process control strategy is proposed. Compared with the pre-production optimization strategy, the inclusion rate is reduced from 44% to 21%. Although the simulation experiment can not fully represent the effect of engineering application, it shows the advancement and effectiveness of the method to a certain extent.

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References

[1] Sata, B. Ravi. Bayesian inference-based investment-casting defect analysis system for industrial application. The International Journal of Advanced Manufacturing Technology, 2017, 90(9): 3301-3315.

[2] J. Kim, J. Y. Lee. Development of a cost analysis-based defect-prediction system with a type error-weighted deep neural network algorithm. Journal of Computational Design and Engineering, 2022, 9(2): 380-392.

[3] Beheshti Z, Shamsuddin S M H. A review of population-based meta-heuristic algorithms[J]. Int. j. adv. soft comput. appl, 2013, 5(1): 1-35.

[4] Kennedy J, Eberhart R. Particle swarm optimization[C]//Proceedings of ICNN'95-international conference on neural networks. ieee, 1995, 4: 1942-1948.