Three-Dimensional Quantitative Characterization and Process Optimization for Simulating Shrinkage Defects of Titanium Alloy Aeroengine Casing in Investment Casting

Tao Sun, Peng Yu, Xiaoyuan Ji *, Wenhao Zhou, Xuzheng Pan, Tianyou Li, Yajun Yin, Jianxin Zhou
State Key Laboratory of Materials Processing and Die & Mould Technology, Huazhong University of Science and Technology, Wuhan 430074, China
*Corresponding address:e-mail: jixiaoyuan@hust.edu.cn

Abstract:A three-dimensional characterization system of shrinkage defects in numerical simulation and a multi-objective optimization method are proposed for titanium alloy aeroengine casing in investment casting using the traditional optimization methods of subjective evaluation and trial-and-error method. The method extracts the three-dimensional quantitative characterization system of shrinkage defects in the criterion of size, location and shape based on the numerical simulation results of titanium alloy aeroengine casing, and establishes a prediction model based on the three-dimensional feature values of shrinkage obtained from multiple sets of numerical simulations through a machine learning algorithm. Using the characteristic prediction model of size and location as the objective function, the second-generation non-dominated sorting genetic algorithm (NSGA-II) is employed to perform multi-objective optimization of the casting process parameters, obtaining a craft window for shrinkage defects in numerical simulation.

Keywords: titanium alloy casing; defect characterization; machine learning; multi-objective optimization

1 Introduction

In the actual production process, the casting and solidification process of titanium alloy castings are in a closed and opaque environment (as shown in Figure 1), making it difficult to observe the solidification process. It relies on the experience of previous production batches and difficult to evaluate shrinkage defects quantitatively. The casting process of titanium alloy castings requires the three-dimensional quantitative characterization system of shrinkage defects of numerical simulation and the optimization of process parameters using intelligent optimization algorithms. In terms of quantitative characterization of shrinkage defects, ASTM (American Society for Testing and Materials) uses the ASTM E155-2005 standard to classify various defects in castings, with the defect level based on the volume, maximum diameter, depth of influence, and cross-sectional thickness of the defect area [1]. Wenbo Yu from Beijing University of Technology used the volume of shrinkage defects, sphericity, defect band width, and average external solidification crystal size to characterize shrinkage defects [2]. Shantanu Shahane from the University of Illinois at Urbana-Champaign used the NSGA-II algorithm to solve multi-objective optimization problems in low-pressure die casting [3].

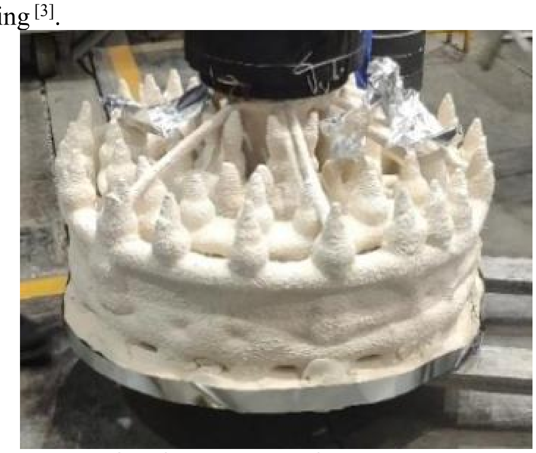

Figure 1 Solidification process of titanium alloy castings

2 Characterization System

The initial results of numerical simulation of the solidification process of aeroengine casing using InteCast CAE post treatment software show a large number of tiny and clustered shrinkage defects. These defects are analyzed using by DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm.

Firstly, a quantitative characterization system is established for individual shrinkage defects after clustering, based on the criteria of "size, location, and shape". At the size level, the characteristic values are volume and minimum enclosing sphere diameter. For the location level, two characteristic values are used to represent the defect's belonging region and depth, with the casting region divided into internal and external areas. At the shape level, the sphericity of the shrinkage defect is defined, which is the ratio of the diameter of a sphere with the same volume as the defect to the diameter of the minimum enclosing sphere, serving as the characteristic value.

Subsequently, a quantitative characterization system targeting three criteria layers is established for the overall casting defects. On the size criteria layer, four feature values are selected: the total volume of casting shrinkage defects, the sum of the minimum bounding sphere diameters, the number of large shrinkage defects, and the number of large-diameter defects. On the location criteria layer, two feature values are chosen: the proportion of internal region shrinkage volume and the weighted average depth based on volume. On the shape criteria layer, the weighted average sphericity is used as the feature value.

3 Multi-objective optimization

138 groups of different process parameters were numerically simulated. The value ranges of the three key process parameters, namely pouring temperature, pouring time, mold temperature, and mold thickness, were 1,680-1,800 ℃, 4-7 s, 230-290 ℃. Three-dimensional feature values were extracted from the simulation results of porosity defects. Finally, a dataset of 138 groups of process parameters and simulated porosity defect three-dimensional feature values was obtained as sample data for machine learning, with a structure of three input variables and six output variables.

Through the dataset, separate second-order and third-order polynomial stepwise regression models were established for each individual feature value. The root mean square error (RMSE) and coefficient of determination (R^2) were compared between the second-order polynomial model and the third-order polynomial model, and the optimal regression analysis model was obtained for each dataset.

For six different input variables, six single-output neural networks were designed to predict six feature values, respectively. Each neural network has a basic structure of [3-X-1]. The training sample dataset consisted of 138 groups, which is a small sample size. Therefore, for each training, the samples were randomly divided into training, validation, and test sets in a ratio of 60%, 20%, and 20%, respectively. A single hidden layer neural network was chosen. For the selection of hidden layer nodes, an empirical formula was used to determine the range of hidden layer nodes as 3-10. The activation function used was the tanh function.

The overall data's mean squared error (MSE), correlation coefficient R, were selected as evaluation metrics. A comparison was made among 11 training algorithms and different hidden layer network structures to obtain the optimal model. The results showed that the models trained using the Bayesian regularization algorithm outperformed other algorithms in all prediction models.For all models, the fitting accuracy of the BP neural network model was higher than that of the regression model. Therefore, the prediction models used in this paper were all based on neural network prediction models.

Table1. Optimal BP neural network model parameters

Feature values	Hidden layer nodes	MSE	R
total volume	7	0.075	0.989
sphere diameters	6	255.6	0.959
number of large	7	0.282	0.881
number of large-diameter	4	0.521	0.795
proportion of internal region	5	0.0015	0.808
average depth	10	21.5	0.890

The feature values on the same criterion layer were normalized and then unified through linear weighting. The constraint ranges of the three process parameters were the same as the data set ranges. Using the NSGA-II algorithm, the pouring temperature, mold temperature, and pouring time obtained from the Pareto front within the constraint ranges were around 1,680 ℃, 290 ℃, and 5 s, respectively.

3 Conclusion

This paper addresses the optimization of casting process parameters for porosity defects in titanium alloy engine casing castings. A three-dimensional quantitative characterization system is established, and multiple groups of process parameter simulation results are collected. A machine learning prediction model is built, and a genetic multi-objective optimization algorithm is used to search for the Pareto front solution set, resulting in a process window with pouring temperatures around 1,680 °C, mold temperatures around 290 °C, and pouring times around 5 s.

Acknowledgments

This work was financially supported by the National Key R&D Program (2020YFB1710100), the Science and Industry Commission Project (2019XXX.XX4007Tm), and the National Natural Science Foundation of China (52275337, 51905188, 52090042).

References

[1] ASTM E155-2005, ASTM E155-2005 Standard Reference Radiographs for Inspection of Aluminum and Magnesium Castings [S].

[2] Diao Y P, Yan L C, Gao K W. A strategy assisted machine learning to process multi-objective optimization for improving mechanical properties of carbon steels [J]. Journal of Materials Science & Technology, 2022, 109: 86–93

[3] Shahane S, Aluru N, Ferreira P, et al. Optimization of solidification in die casting using numerical simulations and machine learning [J]. Journal of Manufacturing Processes, 2020, 51: 130–141.