Digital Twin Model of Casting Temperature and Shrinkage Porosity Prediction

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Abstract: Shrinkage porosity is one of the main defects of investment castings. In this work, a simulation-based digital twin (DT) methodology of porosity distribution prediction is proposed. The methodology is based on a regression supervised learning approach to predict porosity from thermal history time series. The temperature reduced order model (ROM) based on Proper Orthogonal Decomposition (POD) and Radial Basis Function (RBF) network interpolation is developed. Learning data are generated by casting simulation with different process parameters. Furthermore, the optimal distribution of temperature measurement points is determined and the POD coefficient is updated based on the thermocouple data in casting process, so that the time series of temperature field are update, and then the porosity distribution is predicted.

Keywords: digital twin; reduced order model; casting; shrinkage porosity

1 Introduction

Porosity is one of the major defects that can affect a casting part. Optimizing the porosity formation in casting parts can greatly reduce the time cost of the optimization process through machine learning techniques such as artificial neural networks [1]. This effectiveness has been exemplified in the work of Tsoukalas [2], where the total porosity volume is reduced with a rate of 66% in aluminum alloy pressure die casting. To predict shrinkage porosity in real time, the ROM was used to calculate real-time temperature field [3], and the machine learning models can quickly respond and integrate with actual measurement data to construct real-time digital twin models for shrinkage porosity prediction [4].

2 Experimental procedure

Basic architecture

An overview of proposed digital twin methodology is presented and detailed. As shown in Figure 1, a dataset is created from the results of the simulations, primarily consisting of nodal thermal histories and corresponding porosity distribution values, and then, utilizing a POD approach to create ROM. For a case with fixed process parameters, the modal coefficient is computed through radial basis function (RBF) interpolation, enabling the reconstruction of the temperature field. During the supervised learning process, essential features, such as solidification time and temperature gradients, are extracted from the temperature field. A regression model is then trained using the porosity distribution as the outcome.

In the online stage, by correcting the pod coefficient, the predicted temperature is consistent with the collection of time-series data, thereby establishing the complete temperature field. Then the features are extracted and imported into the regression model. Thus, completing the online prediction of porosity. Take group of parts as casting, presented in Figure 2, consists of parts, runner and sprue cups.

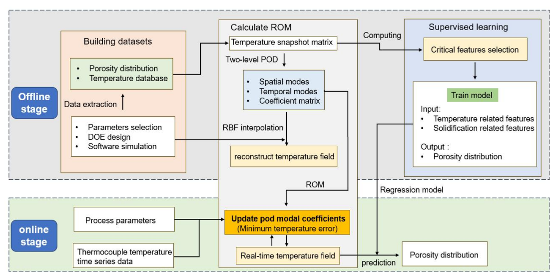


Figure 1 Digital twin implementation architecture of shrinkage porosity prediction

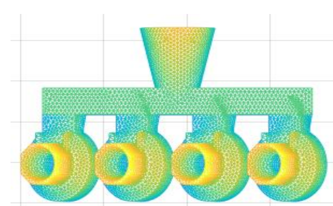
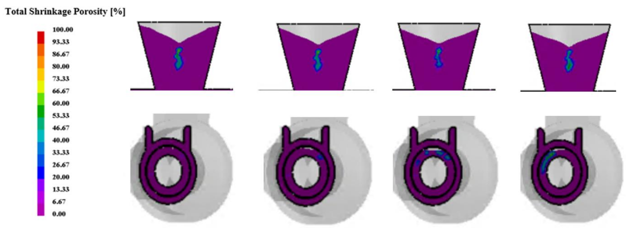


Figure 2 Geometric model of casting

3 Result and discussion

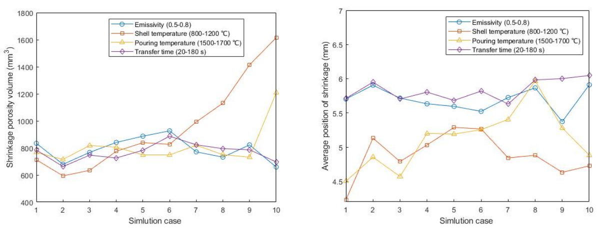
Study of processing parameter

Based on the simulation result, extract the shrinkage and porosity distribution results. Statistically analyze the distribution of shrinkage porosity at the riser. Calculate the volume occupied by shrinkage cavities and their average location. As shown in Figure 3, it can be found that the temperature change of the mold shell has a greater impact on shrinkage porosity when the shell temperature changes from 900 ℃ to 1,200 ℃. The simulation result of other cases are shown in Figure 4.



900°C 1000°C 1100°C 1200°C

Figure 3 Shrinkage position porosity changed with shell temperature

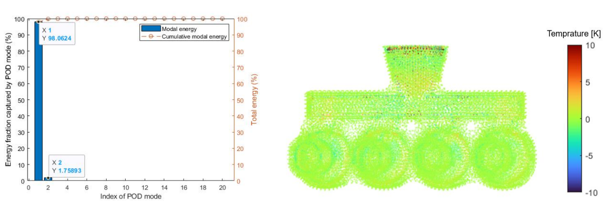


(a) (b)

Figure 4 Statistical distribution of shrinkage porosity position changed with process parameters, porosity in riser (a) and part (b)

Temperature field reconstruction of reduced order model

The transient temperature field is established with numerical simulation to calculate the node temperature value at each discrete time. POD was used to analyze the snapshots and perform an eigenvalue analysis according t in Figure 5, the first two eigen values accounts for 99.82% of the sum of the eigenvalues and the first four eigenvalues account for more than 99.99% of the total. when the solidification fraction reaches 98%, the reconstructed temperature field error is shown in the Figure 5(b).



(a) (b)

Figure 5 Shrinkage position porosity changed with shell temperature (a), and reconstructed temperature field error (b)

In the arrangement of temperature measurement points, the correlation of the node temperatures is analyzed, and the greedy algorithm is used to select the eight least relevant node as shown in Figure 6(a). Nodes location is shown in Figure 6(b). The error of temperature field reconstructed by measuring point temperature based on simulation is shown in Figure 6(c).

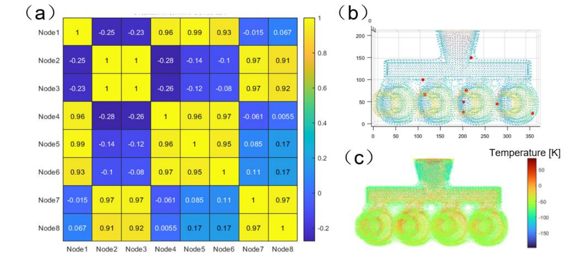
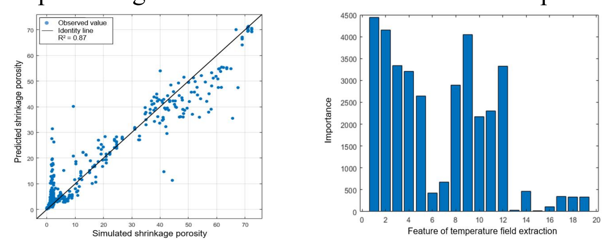


Figure 6 Correlation matrix of vectors at the locations of the eight nodes (a), nodes location (b), and reconstructed temperature field error (c)

Shrinkage porosity prediction model

The characteristics of the temperature field were extracted, including 20 related feature, such as critical solidification moment (initial solidification, solid fraction equal to 0.7, solidification end), temperature gradient, Laplace operator, etc. As shown in Figure 7(a), when the shrinkage porosity value is greater than 1, the prediction model has a better prediction effect. We analyze the importance of the characteristics of temperature field. In this model, temperature gradient and solidification time are important.



(a) (b)

Figure 7 Porosity prediction of our solution against Procast simulation (a), and importance of temperature feature (b)

4 Conclusion

The digital twin model is constructed by POD and machine learning model, which can real-time predict the temperature field according to the actual measured point temperature. Shrinkage porosity distribution prediction model is based on temperature field feature.

References

[1] Cheng Y W. Optimization of die casting processing parameters based on BP neural network and GA algorithm [J]. Journal of Plasticity Engineering, 2011, 18(3): 105-110.
[2] Tsoukalas V D. Optimization of porosity formation in AlSi9Cu3 pressure die castings using genetic algorithm analysis [J]. Materials & Design, 2008, 29(10): 2027-2033.
[3] Wu T, Yang F, Farooq U, et al. An online learning method for constructing self-update digital twin model of power transformer temperature prediction [J]. Applied Thermal Engineering, 2024, 237: 121-728.
[4] Nouri M, Artozoul J, Caillaud A, et al. Shrinkage porosity prediction empowered by physics-based and data-driven hybrid models [J]. International Journal of Material Forming, 2022, 15(3): 25.