Integrated Computational Framework for Controlling Dimensional Accuracy of Thin-Walled Turbine Blades During Investment Casting

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Abstract: To control the dimensional accuracy of the turbine blades, this study proposed a novel integrated computational framework named AICAST, implanted with the response surface methodology optimization model and multi-layer perceptron neural network is proposed. The deformation of the blade casing reaches the minimum via AICAST of 0.1504 mm. The maximum prediction difference of the MLP neural network model is 0.0123 mm, and the mean absolute percentage error is 2.71%, indicating that the deformation of blade casting can be modeled and predicted.

Keywords: turbine blade; dimensional accuracy; ICME; investment casting

1 Introduction

The increasing sophistication of computer hardware and software led to the computer simulation area towards the new stage of ICME (Integrated Computational Materials Engineering), which was first launched by the U. S. National Materials Advisory Board Committee in 2008 [1-3]. ICME is a simulation-driven design approach that employs batch-processing script files to realize multiscale-multiphysics modelling [4]. It is based on the understanding of structure-process-dimension relationships . In this study, the core concept of the ICME approach from gas turbine perspectives is that it employs bottom-up modeling and simulation, calibrated and validated by experiments and measurement, combined with the top-down requirements-driven exploration of deviation transmission during different stages in IC. Many stages are involved in the ICME approach from a gas turbine perspective, such as ceramic core preparation, wax injection, shell roasting, and metal casting. To achieve better dimensional accuracy of turbine blades, the causes and effects of each stage during IC should be analyzed.

2 Experimental procedure

The traditional manual settings of these numerical simulations are a long cycle and cost-inefficient. To solve this problem, an ICME framework named AICAST is proposed to provide a simulation service framework for simulation tools integration and process optimization for IC. The main pages and functional architecture of the AICAST platform are shown in Figure 1. The overall architecture is divided into three layers: the resource, functional, and application layers. Since the ICME framework is designed as a platform for general use, the users can build their workflows and automatically operate the script files on this platform conveniently following the steps (a - c): (a) Firstly, users should build the module and workflow, including name, input, the output of DOE (Design Of Experiments). (b) Secondly, users should upload all the simulation files to the workflow. The platform will automatically replace the process parameters according to DOE. (c) Finally, users can choose appropriate optimization algorithms or neural networks to achieve satisfactory results. In this study, all the numerical simulations for turbine blades can be integrated and optimized via the AICAST platform, including wax pattern deformation simulation and solidification process simulation. The RSM (Response Surface Methodology) model and MLP (Multi-Layer Perceptron) neural network are chosen to realize the optimization of wax injection and alloy solidification processes via the AICAST platform. In this study, all the numerical simulations for turbine blades can be integrated and optimized via the AICAST platform, including wax pattern deformation simulation and solidification process simulation. The RSM (Response Surface Methodology) model and MLP (Multi-Layer Perceptron) neural network are chosen to realize the optimization of wax injection and alloy solidification processes via the AICAST platform. In addition, the RSM and MLP models are encapsulated in the AICAST platform so that users can use these algorithms directly.

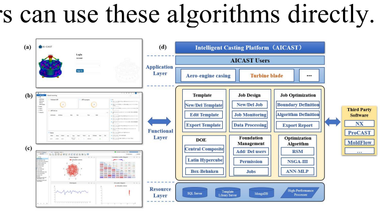

Figure 1 The details of AICAST: (a) login page; (b) home page; (c) data post-processing; (d) functional architecture diagram of AICAST

3 Result and discussion

RSM is a statistical approach that integrates the DOE technique and regression analysis for modeling the relationship between multiple inputs and responses. The response surfaces of the injection velocity, packing pressure, melt temperature, and warpage deformation are modeled. The optimal combination of process parameters for key nodes and X direction is X = [2.0, 64.8, 140], and the warpage deformation of key nodes is 1.79 mm, which is 60.39% lower than that of the original (4.519 mm). The optimal combination of process parameters for Y and Z directions is X = [2.0, 64.8, 108] and X = [2.0, 64.0, 100], respectively. MLP is one of the most widely used neural network architectures in literature for classification or regression problems. The output of the MLP structure is produced by linear combinations of the outputs of hidden layer nodes in which every neuron maps a weighted average of the inputs through a sigmoid function. The MLP neural network performs well in blade casting deformation prediction under the influence of process parameters. The MAPE (Mean Absolute Percentage Error) of the MLP neural network is 2.71%. The max difference between true values and predicted values is 0.0123 mm, indicating that the prediction accuracy is satisfactory in the MLP model when X = [1490, 1220, 8], the deformation of the blade casing reaches the minimum amount, which is 0.1504 mm. The real wax pattern, the shell, and the final blade casting are shown in Figure 2.

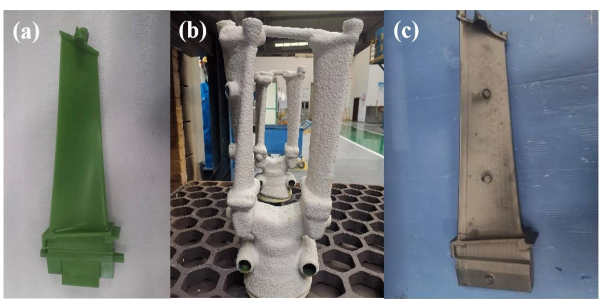

Figure 2 Experimental verification:
(a) wax pattern; (b) the shell; (c) blade casting

4 Conclusion

A novel ICME framework (AICAST) coupled with the RSM and MLP model is proposed to investigate the mechanisms of blade deformation and achieve the appropriate process parameters. The optimal combination of process parameters for key nodes is $X1$ = [2.0, 64.8, 140], and the warpage deformation of key nodes is 1.79 mm, which is 60.39% lower than that of the original (4.519 mm). When $X2$ = [1490, 1220, 8], the deformation of the blade casting reaches the minimum amount of 0.1504 mm. The max difference of MLP neural network model is 0.0123 mm and MAPE is 2.71%, indicating that deformation of the blade casting can be modeled and predicted.

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