Optimization of investment casting process parameters to reduce warpage of turbine blade platform in DD6 alloy

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Abstract: The large warping deformation at platform of turbine blade directly affects the forming precision. In the present research, equivalent warping deformation was firstly presented to describe the extent of deformation at platform. To optimize the process parameters during investment casting to minimize the warping deformation of the platform, based on simulation with ProCAST, the single factor method, orthogonal test, neural network and genetic algorithm were subsequently used to analyze the influence of pouring temperature, shell mold preheating temperature, furnace temperature and withdrawal velocity on dimensional accuracy of the platform of superalloy-DD6 turbine blade. The accuracy of investment casting simulation was verified by measurement of platform at blade casting. The simulation results with the optimal process parameters illustrate that the equivalent warping deformation was dramatically reduced by 21.8% from 0.232295 mm to 0.181698 mm.

Key words: ProCAST; optimization of process parameters; warping deformation of platform; orthogonal test; genetic algorithm; BP-neural network

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Complex hollow turbine blades are the core components of aircraft engines demanding for high precision in size and dimension, and its quality and technology advancement are critical to the development and manufacture of aircraft engines. The operating conditions experienced by hollow turbine blades are mainly thermal shocks and complex cyclic thermal stresses^[1,2]. In recent years, single-crystal turbine blades manufactured domestically showed a series of problems including low forming precision, unstable quality and high rejection rate. The statistical analysis results on domestic hollow turbine blades illustrated that 50% of the rejected blades were resulted from over tolerance of blade profile and wall thickness^[3]. For many years, the researchers in investment casting team of aero-engine turbine blades at Northwestern Polytechnical University have conducted intensive studies on dimensional control of turbine blades, and already obtained pioneering

achievements. However, the main objective of the research focused on the blade body, the quality control of platform was ignored or simplified.

Platform, which has a thin thickness but a large area and sectional mutations, connects the blade body and fir tree root. Due to its aptness to produce stress concentration, larger warping deformation usually emerges in platform, which severely reduces the assembling accuracy and aerodynamic characteristics of blades, consequently leading to a considerable negative impact on aero-engine performance. Warpage is one of the common quality defects during forming process, referring to the phenomenon that the shape of products deviates from that of the mold cavity^[4].

A great deal of research illustrates that in addition to reasonable mold design, a low dimensional accuracy of castings is often caused by improper control of process parameters during casting process^[5]. Therefore, in this study, in order to decrease the warpage and reach the target of dimensional precision control, the single factor analysis based on ProCAST software was used to identify the influence of process parameters on warpage of platform. Then, orthogonal test was adopted to obtain local optimal combination of process parameters and training samples of neural network. Finally, the global optimization of investment casting process parameters

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concerning platform were obtained by using neural network and genetic algorithm, and the result of simulation with optimal process parameters indicated that the warping deformation was reduced dramatically.

1 Modeling of gating system and platform warpage

1.1 CAD & CAE modeling of turbine blade gating system

Figure 1 shows the model of the turbine blade and its gating system. The second generation superalloy-DD6 was selected as the material for turbine blades, and its chemical composition is given in Table 1^[6]. Figure 2 illustrates the conductivity, density and specific heat of DD6 at different temperatures. The liquidus and solidus temperatures of DD6 are 1,380 °C and 1,310 °C, respectively. Interfacial heat-transfer coefficient (IHTC) of turbine blade during casting process was determined based on

Fig. 1: Turbine blade model and its directional solidification gating system design

Table 1: Chemical composition of alloy DD6 (wt.%)^[6]

Cr	Co	Mo	W	Ta	Re	Nb	Al	Hf	Ni
4.3	9	2	8	7.5	2	0.5	5.6	0.1	Bal

the inverse solution of measured temperature field. The material for shell mold is silica sand.

Fig. 2: Physical properties of DD6

There are mainly three types of stresses generated during the casting process of a hollow turbine blade, including thermal stress, mechanical stress (obstruction), and phase transformation stress. Supposed that the castings have a good feeding ability, then, the phase transformation stress can be ignored. The mechanical properties of DD6 including Young's modulus and yield stress^[8] are illustrated in Fig. 3. The thermal elastoplastic model written as Eq. (1), was used to describe the casting stress-strain relationship^[7]:

$$\{\varepsilon\} = \{\varepsilon\}_e + \{\varepsilon\}_p + \{\varepsilon\}_{th} \quad (1)$$

where $\{\varepsilon\}$ is total strain; $\{\varepsilon\}_e$ is elastic strain; $\{\varepsilon\}_p$ is plastic strain and $\{\varepsilon\}_{th}$ is thermal strain.

1.2 Analysis on warping deformation distribution of platform

Since the optimization in this study is based on simulation, whether the simulated results are accurate or not directly affect the reliability of subsequent research results. Thus, a laser scanner, scanCONTROL 2700-25 produced by German Micro-Epsilon, was used to measure the platforms of two

Fig. 3: Mechanical properties of DD6^[8]

turbine blades which were produced according to process parameters in actual production in Table 2. Meanwhile, investment casting simulation of turbine blade based on

ProCAST was conducted according to the same process parameters shown in Table 2.

Table 2: Process parameters in actual production

Pouring temperature (°C)	Shell mold preheating temperature (°C)	Furnace temperature (°C)	Withdrawal velocity (mm·min ⁻¹)	Copper-cooled plate temperature (°C)
1,550	1,550	1,550	5	20

As illustrated in Fig. 4, the lower surface of platform has a simple structure and smooth modes of transition, so that it is convenient to conduct measurement. Therefore, the calculation result of deflection at the lower surface was used as the warping deformation of platform. As illustrated in Fig. 5, along the width direction, 6 equidistant intercepted cross-sections (I-IV) were measured and calculated. Since blade body was set as a barrier, cross-sections II, III, IV, and V were divided into several segments and 100 sample points were selected from each line segment evenly. The distribution of sample point is also shown in Fig. 5. Measured and simulated results are illustrated in Fig. 6.

Figure 6 demonstrates that both the simulated and the measured deformation results have a very similar trend that

Fig. 4: Schematic diagram of platform

Fig. 5: Schematic diagram of extracted cross-section lines

edges of platform have bigger deformation, while deformation in central part is relative small. In particular, the maximum deformation emerges at left edge of VI cross-section. This verifies the accuracy of simulation. However, there are some disparities such as that the measured data are comparatively larger than the simulated values, and the measured deformation distribution curve is not as smooth as that of simulated one. Error analysis is explained as follow:

(1) The simulated data are based on the casting model before removal of shell mold and ceramic core, while the measured casting is without them. Due to the fact that measured platforms deformation is free from shell mold and ceramic core's hindering, the measured data are comparatively larger than

Fig. 6: Comparison between measured and simulated deflection of platform

simulated data.

(2) Some fluctuations of the measured deformation distribution curve are the result of the surface roughness on turbine blade after removal of shell mold.

The deviation between the simulated and measured results can be reduced by no longer considering the shell mold and ceramic core as rigid body during the process of parameter setting in simulation.

1.3 Definition of equivalent warping deformation

Warping is generally represented by nodal displacements in the finite element mesh^[9]. In order to accurately describe the warping deformation of platform, it is necessary to consider comprehensive data of displacement field by using the method of weighting function. Thus, the equivalent warping deformation is proposed, which is defined as F . F can be written as

$$F = aX + bY + cZ \quad (2)$$

where a , b , c are weighting factors for X , Y , Z , respectively; and X is the maximum warpage; Y is the average of top 10% of warpage; and Z is the overall average warpage.

Then, the weighting factors a , b , c need to be established. According to simulation result in Fig. 6, and by using of Analytic Hierarchy Process (AHP) to put great emphasis on maximum warpage and simultaneously to give attention to average of top 10% of warpage and overall average warpage, weighting factors, a , b , c , were established^[10]. Thus, equivalent warping deformation F is formally written as

$$F = 0.75X + 0.18Y + 0.07Z \quad (3)$$

According to Eq. (3), the equivalent warping deformation of platform simulated according to process parameters in actual production (shown in Table 2) is $F = 0.232295$ mm, which is defined as original equivalent warping deformation.

2 Effect of investment casting process parameters on platform's warping deformation

To verify the effect of process parameters on equivalent warping deformation, single factor method is used. The test results are shown in Table 3 and Fig. 7.

Figure 7 demonstrates that the equivalent warping deformation

Table 3: Simulation results of single factor test

Serial No.	Pouring temperature (°C)	Shell mold preheating temperature (°C)	Furnace temperature (°C)	Withdrawal velocity (mm·min ⁻¹)	Copper-cooled plate temperature (°C)	F (mm)
1	1,450					0.24302
2	1,500					0.23371
3	1,550	1,550	1,550	5	20	0.23230
4	1,600					0.24838
5		1,450				0.24525
6		1,500				0.23641
7	1,550	1,550	1,550	5	20	0.23230
8		1,600				0.23120
10			1,450			0.24682
11			1,500			0.23753
12	1,550	1,550	1,550	5	20	0.23230
13			1,600			0.23051
15				2		0.26049
16				3		0.24403
17				4		0.23668
18	1,550	1,550	1,550	5	20	0.23230
19				6		0.23414
20				7		0.23423
21				8		0.23596
22					10	0.23312
23					15	0.23132
24	1,550	1,550	1,550	5	20	0.23230
25					25	0.23058
26					30	0.22974

Fig. 7: Simulation results of single factor test

F obviously changes with the change of each investment casting process parameter. Meanwhile, range analysis was used to figure out clearly the influence of process parameters on warping deformation, and the results are listed in Table 4.

The results in Table 4 show that the range of equivalent warping deformation obtained from each process parameter reaches 0.01 to 0.02 mm, except the range of chill plate temperature. Because the dimensional accuracy of aeroengine

components usually should reach 0.01 mm, even 0.005 mm, the result of single factor method illustrates that process parameters including pouring temperature, shell mold preheating temperature, furnace temperature and withdrawal velocity, play a vital role in the result of equivalent warping deformation, while chill plate temperature makes little influence on that. Thus, the temperature of copper-cooled plate is set as an instant value, no longer to be optimized in the following work.

Table 4: Range analysis of process parameters' influence on warping deformation

Process parameters	Pouring temperature	Shell mold preheating temperature	Furnace temperature	Withdrawal velocity	Copper-cooled plate temperature
Range (mm)	0.016088	0.014047	0.016316	0.028196	0.003379

3 Orthogonal test designs

3.1 Establishment of orthogonal process parameters

According to the results of single factor method, the reasonable value selection of process parameters and factors and the levels of orthogonal test can be established. Referring to optimal process parameters of blade body illustrated in Table 5^[11], which has been verified by actual pouring experiment, the range of process parameters for platform should be established under the premise of ensuring the dimensional accuracy of blade body.

Besides, considering castings' aptness to produce shrinkage and thermal cracks if pouring temperature is excessively high^[12], the range of pouring temperature was established from 1,520 °C to 1,580 °C. The range of shell mold preheating temperature and furnace temperature were from 1,450 °C to 1,500 °C and from 1,520 °C to 1,580 °C, respectively. In addition, stray grain is apt to generate at the sectional mutation site of turbine blade such as platform^[13-15]. In order to avoid generation of stray grain, a withdrawal velocity of 2 mm·min⁻¹ for platform should be selected^[16]. According to this, variable withdrawal velocity method was proposed, which means that the range of withdrawal velocity at platform and above platform was set as

Table 5: Optimal process parameters for blade body

Pouring temperature (°C)	Shell mold preheating temperature (°C)	Furnace temperature (°C)	Withdrawal velocity (mm·min ⁻¹)	Copper-cooled plate temperature (°C)
1,570	1,480	1,550	4.8	24

2–3 mm·min⁻¹ and withdrawal velocity at blade body was set as optimal value, namely 4.8 mm·min⁻¹. The temperature of copper-cooled plate was set as 24 °C. Therefore, orthogonal factors table is established, which is illustrated in Table 6.

3.2 Orthogonal test and results

Orthogonal test, the main method of fractional factorial design [17], is an efficient, rapid and economical way to verify a design. According to the result of single factor method in Section 2, the process parameters that need to be optimized include platform's withdrawal velocity, pouring temperature, shell mold preheating temperature and furnace temperature. Three levels are selected for

each factor. Considering the interaction of platform's withdrawal velocity, pouring temperature and shell mold preheating temperature, a L27(313) interacted table was established. Casting simulation was performed according to the parameters in the orthogonal test table. Equivalent warping deformation *F* with respect to lower surface of blade platform was calculated according to Eq. (2), and the range analysis was given in Table 7.

According to the result of orthogonal test in Table 7, the optimal process parameters are obtained. The optimal furnace temperature, pouring temperature and shell mold preheating temperature are 1,580 °C, 1,550 °C and 1,450 °C, respectively. The optimal withdrawal velocity of the platform is 2 mm·min⁻¹.

Table 6: Factors and levels of orthogonal test

Factors	Levels			
	Pouring temperature (°C)	Shell mold preheating temperature (°C)	Furnace temperature (°C)	Platform's withdrawal velocity (mm·min ⁻¹)
1	1,520	1,450	1,520	2
2	1,550	1,470	1,550	2.5
3	1,580	1,500	1,580	3

Table 7: Results of orthogonal test

Serial No.	A	B	(A*B) ₁	(A*B) ₂	C	(A*C) ₁	(A*C) ₂	(B*C) ₁	D	(B*C) ₂	Equivalent warping deformation (mm)			
1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.209124
2	1	1	1	1	2	2	2	2	2	2	2	2	2	0.217031
3	1	1	1	1	3	3	3	3	3	3	3	3	3	0.219212
4	1	2	2	2	1	1	1	2	2	2	3	3	3	0.213534
5	1	2	2	2	2	2	2	3	3	3	1	1	1	0.223243
6	1	2	2	2	3	3	3	1	1	1	2	2	2	0.203932
7	1	3	3	3	1	1	1	3	3	3	2	2	2	0.235306
8	1	3	3	3	2	2	2	1	1	1	3	3	3	0.205912
9	1	3	3	3	3	3	3	2	2	2	1	1	1	0.220421
10	2	1	2	3	1	2	3	1	2	3	1	2	3	0.216484
11	2	1	2	3	2	3	1	2	3	1	2	3	1	0.227756
12	2	1	2	3	3	1	2	3	1	2	3	1	2	0.204688
13	2	2	3	1	1	2	3	2	3	1	3	1	2	0.220214
14	2	2	3	1	2	3	1	3	1	2	1	2	3	0.200396
15	2	2	3	1	3	1	2	1	2	3	2	3	1	0.205251
16	2	3	1	2	1	2	3	3	1	2	2	3	1	0.204344
17	2	3	1	2	2	3	1	1	2	3	3	1	2	0.214697
18	2	3	1	2	3	1	2	2	3	1	1	2	3	0.226148
19	3	1	3	2	1	3	2	1	3	2	1	3	2	0.223104
20	3	1	3	2	2	1	3	2	1	3	2	1	3	0.190684
21	3	1	3	2	3	2	1	3	2	1	3	2	1	0.210336
22	3	2	1	3	1	3	2	2	1	3	3	2	1	0.189113
23	3	2	1	3	2	1	3	3	2	1	1	3	2	0.202796
24	3	2	1	3	3	2	1	1	3	2	2	1	3	0.213116
25	3	3	2	1	1	3	2	3	2	1	2	1	3	0.215032
26	3	3	2	1	2	1	3	1	3	2	3	2	1	0.226013
27	3	3	2	1	3	2	1	2	1	3	1	3	2	0.203642
K1	0.216	0.213	0.210	0.213	0.214	0.213	0.214	0.213	0.201	0.213	0.214	0.212	0.213	
K2	0.213	0.208	0.215	0.212	0.212	0.213	0.212	0.212	0.213	0.213	0.212	0.214	0.214	
K3	0.208	0.217	0.212	0.213	0.211	0.212	0.211	0.213	0.224	0.211	0.212	0.212	0.211	
Range	0.008	0.009	0.005	0.001	0.003	0.001	0.003	0.001	0.023	0.002	0.002	0.002	0.003	

A-Furnace temperature (°C); B-Pouring temperature (°C); C-Shell mold preheating temperature (°C); D-Platform's withdrawal velocity (mm·min⁻¹)

4 Genetic neural network optimization

The optimum combination of process parameters can be obtained through the orthogonal test above. However, these process parameters just have a relatively high priority in the scope of selected factor levels, which cannot realize the prediction of warping deformation or obtain optimal process parameters globally. In order to obtain optimal process parameters, it is required to process mass of data; however, these data are difficult to describe with unified rules, formulas and mathematical models as the mechanism of investment casting is complex^[11]. Thus,

artificial neural network has become a powerful tool to solve this problem for its great flexibility and adaptability^[18, 19]. Genetic algorithm, which has strong macro-search capability and is able to perform global optimization, can stimulate evolutionary optimization of biological populations^[20]. In addition, genetic algorithm can not only optimize the structural parameters of BP-neural network to improve speed and precision of convergence, but also can combine with BP-neural network prediction model to establish optimization model of investment casting process parameters. Figure 8 illustrates the procedures of optimization of investment casting process parameters and BP-neural network with the use of genetic algorithm.

Fig. 8: Flow chart of optimization of investment casting process parameter and BP-neural network with genetic algorithm

4.1 Establishment of process optimization model

Process optimization model is illustrated as follows:

Design variables: $find. M = [T_1 T_2 T_3 V]$;

Objective function: $\min.F(M)$;

Constraint condition: s.t. $1,520\text{ }^{\circ}\text{C} \leq T_1 \leq 1,580\text{ }^{\circ}\text{C}$
 $1,520\text{ }^{\circ}\text{C} \leq T_2 \leq 1,580\text{ }^{\circ}\text{C}$
 $1,450\text{ }^{\circ}\text{C} \leq T_3 \leq 1,500\text{ }^{\circ}\text{C}$
 $2\text{ mm}\cdot\text{min}^{-1} \leq V \leq 3\text{ mm}\cdot\text{min}^{-1}$;

where M is design variable; T_1 , T_2 , T_3 represent furnace temperature, pouring temperature and shell mold preheating temperature, respectively; V is platform's withdrawal velocity; and F refers to equivalent warping deformation.

4.2 Design of neural network structure

Artificial neural network with 3 layers was adopted, namely input layer, hidden layer and output layer. In the choice of transfer function, considering that Sigmoid function has some advantages including better smoothness, robustness and continuous derivative^[21], it was used as the activation function

of BP neural network. The extracted four process parameters including furnace temperature, pouring temperature, shell mold preheating temperature and withdrawal velocity are chosen as parameters for 4 nodes of input layer. Output layer has one node, and the result of simulation is as its parameter, namely equivalent warping deformation of platform. Figure 9 illustrates the structure of BP-neural network.

4.3 Optimization of genetic algorithm based on BP neural network

The elements optimization of genetic algorithm based on BP neural network includes population initialization, fitness function, selecting operator, crossover operator and mutation operator^[22]. The parameters of genetic algorithm are shown in Table 8. The probability that each population can be selected is identified according to Eq. (4):

$$P_i = \frac{f_i}{\sum_{j=1}^N f_j} \quad (4)$$

$$f_i = \frac{1}{F_i} \quad (5)$$

The objective of optimization is to achieve minimal equivalent warping deformation F , so the output value of neural network, namely equivalent warping deformation F , is selected as adaptability value:

$$F = \text{abs}(o) \quad (6)$$

where o is the output value of neural network.

According to the theory of genetic algorithm and neural network, simulation of genetic neural network is achieved through programming in MATLAB. Figure 10 illustrates the iterative process of genetic neural network optimization, showing that under the condition of 150 total iterations, optimal fitness value becomes unvarying and is substantially coincident with the average fitness value after 120 generations, reaching minimum, namely 0.174024 mm, which illustrates that minimum equivalent warping deformation after optimization is 0.174024 mm. Under the premise of ensuring the dimensional accuracy of blade body, the optimized investment casting process parameters of platform is shown in Table 9.

5 Verification of optimization results

The accuracy of simulation in Section 1.3 has been verified by experimental results, so the simulation was used to verify the validity of optimization results. Optimal process parameters in Table 9 and variable withdrawal velocities were used to simulate

Fig. 9: Structure of BP neural network

Fig. 10: Training results of genetic neural network

Table 8: Parameters of genetic algorithm

Population size	Maximal hereditary generation	Crossover probability	Mutation probability	Selection probability
40	150	0.1	0.1	p_i

Table 9: Optimal process parameters for platform

Pouring temperature ($^{\circ}\text{C}$)	Shell mold preheating temperature ($^{\circ}\text{C}$)	Furnace temperature ($^{\circ}\text{C}$)	Platform's withdrawal velocity ($\text{mm}\cdot\text{min}^{-1}$)	Equivalent warping deformation (mm)
1,535	1,490	1,578	2.05	0.174024

the process of solidification. According to Table 5 and 9, the optimal withdrawal velocities, $4.8 \text{ mm}\cdot\text{min}^{-1}$ for blade body and $2.05 \text{ mm}\cdot\text{min}^{-1}$ for platform were selected, which can not only ensure the dimensional accuracy of blade body but also avoid generation of stray grain at platform. According to the result of simulation, equivalent warping deformation is $F = 0.181698 \text{ mm}$, and the warping deformation of each cross-section at platform is illustrated in Fig. 11.

6 Conclusions

(1) According to the experiment results, the measured warping deformation distribution has a similar trend as the simulated one, both showing that the edges of platform have aptness to emerge

bigger warping deformation than the central part.

(2) The results of single factor method show that equivalent warping deformation changes dramatically with the change of process parameters. In particular, the influence of withdrawal velocity, furnace temperature, pouring temperature and shell mold preheating temperature on warping deformation is great, while the copper-cooled plate exerts little impact on that.

(3) Three optimal solutions: orthogonal test, neural network and genetic algorithm were applied to the optimization of process parameters to improve the forming precision at platform. The simulation with optimized process parameters obtained the good results, and equivalent warping deformation was reduced by 21.8%, from 0.232295 mm to 0.181698 mm .

Fig. 11: Comparison between results before and after genetic neural network optimization

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