Robust parametric optimization for investment casting process of a turbine vane

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Abstract. Investment casting technology is an important manufacturing technology for the turbine guide vanes of the aero-engine, which directly affects the performance of the engine. However, most of the researches on the investment casting process of the vane is mainly based on the development of the materials, while the process parameters are less researched. The purpose of this paper is to perform a robust optimization for the process parameters of the investment casting of a typical vane. Firstly, a three-dimensional casting simulation model is established based on the ProCAST® software. Five key process parameters are chosen and their uncertainties are specified. A set of desired parameters are firstly obtained by conducting a deterministic optimization using a design of experiment (DOE) method. Next, a second-order response surface model (RSM) is built with Box-Behnken design based on the initial optimization results. Finally, an RSM-based robust parametric optimization with AMGA algorithm is proposed, deriving several Pareto solutions. By comparing and analyzing every solution, an optimal parameter scheme is developed by considering high quality of the casting and robustness of the casting process.

1. Introduction
Turbine vanes are one of the key components of aero-engines and the quality of the process is closely related to the performance of the engine. In the 1950s, the United States pioneered the use of investment casting technology to develop turbine blades successfully, replacing the forging process that gradually failed to meet the demand [1][2]. So far, the investment casting technology has been used in the aviation industry for more than 70 years and has become the main manufacturing technology for aero-engine component [3]. Its application shortened the manufacturing cycle, reduced the cost of the product and greatly improved the quality. However, there are still casting defects such as shrinkage and pouring metal defects in the production of high-precision products. Closed shrinkage defects, also known as shrinkage porosity, are the main problem that form in the casting. Shrinkage defects can occur when alloy liquid is not available to compensate for shrinkage as the thick metal solidifies. Inside of solidified metal form isolated liquid points, which are called hot spots. The shrinkage defect usually occurs at the top of the hot spots. They require a nucleation point, so impurities and dissolved gas can induce closed shrinkage defects. The defects are broken up into macro-porosity and micro-porosity, where macro-porosity can be seen by the naked eye and micro-porosity cannot.
In recent years, for the rapid development of computer-aided design (CAD) and computer-aided engineering (CAE), casting numerical simulation technology has been widely used in turbine blade casting process optimization and defect prediction. The numerical simulation technology of casting can not only effectively predict the defects that may occur in the casting process, but also analyze the causes of defects based on numerical simulation results, thereby improving the process plan, repeatedly simulating experiments, and finding the optimal process [4][5]. For example, Pan D [6] used numerical simulation for directional solidification of single crystal turbine blade casting to increase the productivity and avoid the grain defects. Wheeler [7] established a benchmark data set of a generic high-pressure (HP) turbine vane generated by direct numerical simulation (DNS) to resolve fully the flow. Furthermore, optimization of process parameters is used widely based on numerical simulation. The Design of Experiment (DOE) proposed by British statistician R.A. Fisher in the 1930s is a common method for process optimization [8][9]. It is easy to analysis the effective and trend of factors. Dabade U A [10] did some research about casting defect analysis using design of experiments (DOE) and computer aided casting simulation technique. What’s more, the response surface method (RSM) was first proposed by G E.P Box [11] to establish continuous variable surface models. Vining and Myers suggested that the idea of robustness should be considered in conjunction with the response surface method and practical examples were given. Pagratis N [12], used metallographic validation of simulation findings in terms of correlating microstructure and defects of the casting and introduced the neural network modeling and genetic algorithms as an optimization tool.

In this paper, the shrinkage defects, the main problem of turbine vane casting defects, were optimized by RSM and AMGA with algorithm DOE. Firstly, the five parameters (model shell temperature, casting temperature, casting time, thickness of inner and outer mold shell) were selected as the key factors to optimize the casting process. Based on ProCAST® simulation, full coverage experiment scheme with a small number of times was implemented by DOE, which was scientific and efficient. Secondly, considering the process uncertainty in actual production, robust parametric optimization was designed based on the optimized scheme. RSM (response surface methodology) to establish effective approximation model and AMGA algorithm to obtain the robust parameter combination were used to obtain the comprehensive consideration of the optimal solution with maximum porosity of 2.01%. Considering high quality of the casting and robustness of the casting process, the results of this study suggested the process production.

2. Materials and methods

2.1. Casting simulation

The main function of turbine vane is to rectify the high-temperature and high-pressure airflow erupted in the combustion chamber. Due to the consideration of commercial confidentiality, the structure of the vane employed in this study is not presented. Besides, the values regarding to the process parameters of the investment casting process are all normalized. The principle of casting is to first make a fusible model, and then apply several layers of special refractory coatings on the mold. Secondly, the model is dried and hardened to form an integral module, and then melted the module to obtain a hollow shell. Finally, the shell mold is poured into molten metal at high temperature to obtain castings [13][14]. Among various processes, the filling-solidification process is the most crucial process in the investment casting. In this study, the casting process of the turbine vane was investigated by performing casting simulation. The widely used commercial software, i.e., the ProCAST®, is used to achieve the casting simulation. Figure 1 showed the meshing results of the casting system which was generated through the MeshCAST module in the ProCAST® software. The casting was composed of a kind of high-temperature nickel alloy. The properties of the alloy were obtained by using the model provided by the ProCAST®. Other boundary conditions are reasonably set according to the engineering experience and expert knowledge.
The optimization goal of this paper is to reduce the shrinkage on the vane. The position and size of the shrinkage are the key. Based on simulation, defects are fully visualized, and the maximum porosity was used to characterize the degree of casting defects. Porosity is the percentage of the volume of the pores in the material to the volume of the material in its natural state, which shows the density of the reactive material. According to the technician experience and calibration, the benchmark porosity was determined to be 2.1%. To better determine the degree of defects, this paper used the maximum porosity to characterize the merits of each scheme, that is the maximum value when the porosity is adjusted to no shrinkage defects appeared on the vane.

2.2. Design of Experiment

Design of experiment (DOE) is the most commonly used experimental design method in engineering. The experiment points are tested for uniformity and cover the entire parameter space, with fewer trials, that is more efficient and economical. There are many parameters in the pouring process. Usually, model shell temperature ($T_1$), casting temperature ($T_2$), casting time ($t$) are three key parameters. In addition, the thickness of the membrane shell was considered a potential key factor in this paper. Therefore, the orthogonal table was implemented based on DOE method to find a better combination in the entire space. A hybrid orthogonal design was applied in the initial simulation. According to the number and level of parameters reported in table 1, $L_{18}(2^{3}×3^{5})$ was selected. The hybrid orthogonal design scheme and results were shown in table 2.

Table 1. Parameters and their levels.

| Factor                        | Model shell temperature ($T_1$, °C) | Casting temperature ($T_2$, °C) | Casting time ($t$, s) | Thickness of inner mold shell ($d_1$, mm) | Thickness of inner mold shell ($d_2$, mm) |
|-------------------------------|------------------------------------|---------------------------------|-----------------------|-------------------------------------------|-------------------------------------------|
| level                         | 3                                  | 3                               | 3                     | 3                                         | 2                                         |

Table 2. Hybrid orthogonal design scheme and results.

| NO. | $d_2$(mm) | $d_1$(mm) | $T_1$(°C) | $T_2$(°C) | $T$(s) | Maximum porosity |
|-----|-----------|-----------|-----------|-----------|--------|------------------|
| 1   | -1        | -1        | -1        | -1        | -1     | 2.58             |
| 2   | 0         | 0         | 0         | 0         | -1     | 2.30             |
| 3   | 1         | 1         | 1         | 1         | -1     | 2.32             |
| 4   | -1        | -1        | 0         | 0         | -1     | 2.15             |
| 5   | 0         | 0         | 1         | 0         | -1     | 2.50             |
| 6   | 1         | 1         | -1        | 0         | -1     | 2.45             |
| 7   | -1        | 0         | -1        | 1         | -1     | 2.02             |
It can be obtained from the result that No. 7 solution was the best, which was blow benchmark porosity (2.1%).

3. Results and analysis

3.1. Establishment and analysis of RSM

To improve the robustness of the scheme, this thesis used the response surface model (RSM) to carry out the experimental design, for obtaining accuracy model and credibility optimization analysis. A second-order response model to the maximum porosity and the five parameters was redesigned based on the preliminary optimization results (No.7 scheme in table 2). Three levels are set for these five parameters. So, this was a five-factor, three-level test using the Box-Behnken design, which was an incomplete three-level partial factor test design method commonly used to estimate the coefficients of a second-order polynomial approximation model. The results obtained by redesigning the experiment and carrying out simulation were shown in figure 2. The expression of the second-order response model is as in equation (1).

\[ Y = 168.132 - 0.117217T_1 - 0.161275T_1^2 + 1.78667d_2 + 0.665833d_2^2 + 2.60063T_1^2T_2 \\
+ 0.0000253T_1^3 + 0.0000407T_1^2T_2 + 0.005417T_1^2d_2 - 0.0333333d_2^2 + 0.000052T_1^2T_2 \\
+ 0.00575T_1T_2d_1 - 0.0005T_1T_2d_2 + 0.000975T_1^2T_2^2 - 0.0095T_2^2d_4 + 0.001125T_2^2T_4 \\
- 0.01125T_1d_2^2 + 0.00875d_1^2T_2 \\
\]

(1)
The accuracy \( S \) (regression standard deviation) was 0.0181168 and R-Squared was 97.20%, closing to predicted R-Squared (93.51%), which indicates that the model fits the prediction of the response very well. Through the residual graph of \( Y \) in figure 2, it is found that the normal probability map of \( Y \) is close to the immediate vicinity, and the residual is basically between \( \pm 0.05 \), indicating that the error is small. So, the model fitting degree is good, and the residual value can be accepted.

### 3.2. RSM-based robust parametric optimization

To solve the problem of parameter fluctuations in process production caused by machine precision, this section is RSM-based robust parametric optimization. Monte Carlo Simulation (MCS) was used based on Isight® software, which simulates the probability distribution of the response caused by inputting random variable. Archive micro-genetic algorithm (AMGA) embedded in Isight® was introduced to design variable combination with the optimization both mean and variance of response \( Y \). Mean and variance optimization are often contradictory, so the optimization solution will not be a single solution, but a collection of all optimal solutions, also called Pareto solution which first proposed by economist V. Pareto. The purpose of this study was not only to minimize process indicators, but also to be more robust. So, the mean and variance were measured essentially, which are equally important for each target.

Firstly, the study assumed that random variables follow a normal distribution, \( X \sim N(\mu, \sigma^2) \). Therefore, the distribution characteristics of the five variables were determined, and the initial optimization combination (No. 7 in table 2) was the mean value. In order to protect confidential information, the actual value will not be shown, while the ratio of \( \mu \) and \( \sigma \) was given instead, as shown in table 3.

| Variable | \( T_1(\degree C) \) | \( T_2(\degree C) \) | \( t(s) \) | \( d_1(mm) \) | \( d_2(mm) \) |
|----------|-------------------|-------------------|--------|-------------|-------------|
| \( \mu/\sigma \) | 106.25 | 187.5 | 4 | 10 | 4 |

Secondly, basing on the Isight® software, the Optimization, Six Sigma, and Calculator component platforms were built to establish an optimization environment, as shown in figure 3.

**Figure 3.** Isight-based multi-objective optimization environment construction.

Optimization module selected AMGA algorithm, Six Sigma applied Monte Carlo Sampling, and RSM-based model of \( Y \) was in the calculation center. After completing the software parameter configuration, the Pareto solutions were obtained, as shown in table 4. The specific value of each parameter was normalized by maximum value among the same parameters.
Table 4. Pareto solutions based on AMGA algorithm.

| NO. | $d_1$   | $d_2$   | $t$     | $T_1$   | $T_2$   | Six Sigma Results, Mean $Y$ | Six Sigma Results, Std Deviation, $Y$ | Objective Function |
|-----|---------|---------|---------|---------|---------|-----------------------------|------------------------------------------|--------------------|
| 1   | 0.9992  | 0.7308  | 0.6506  | 0.988   | 0.9989  | 1.9829                      | 0.0739                                   | 2.0569             |
| 2   | 0.9992  | 0.7308  | 0.6506  | 0.988   | 0.9989  | 1.9848                      | 0.0714                                   | 2.0562             |
| 3   | 0.9992  | 0.7253  | 0.6506  | 0.988   | 0.9977  | 1.9890                      | 0.0702                                   | 2.0592             |
| 4   | 1       | 0.7253  | 0.6603  | 0.988   | 0.9977  | 1.9906                      | 0.0699                                   | 2.0605             |
| 5   | 1       | 0.8571  | 0.6506  | 0.9662  | 1       | 1.9965                      | 0.0676                                   | 2.0641             |
| 6   | 1       | 0.7253  | 0.6506  | 0.9662  | 0.9977  | 1.9972                      | 0.0673                                   | 2.0645             |
| 7   | 0.9933  | 0.6868  | 0.6506  | 0.9662  | 0.9977  | 1.9979                      | 0.0648                                   | 2.0627             |
| 8   | 1       | 0.8571  | 0.6891  | 0.9662  | 0.9985  | 2.0098                      | 0.0595                                   | 2.0693             |
| 9   | 0.9808  | 0.8681  | 0.8558  | 0.9815  | 0.998   | 2.0311                      | 0.056                                    | 2.0871             |
| 10  | 0.9625  | 0.9396  | 0.6891  | 0.9877  | 0.9821  | 2.0535                      | 0.0538                                   | 2.1073             |
| 11  | 0.9616  | 0.9505  | 0.9423  | 0.988   | 0.9825  | 2.0732                      | 0.053                                    | 2.1262             |
| 12  | 0.9616  | 1       | 0.9423  | 0.9874  | 0.9825  | 2.0738                      | 0.0516                                   | 2.1254             |
| 13  | 0.97    | 0.967   | 0.8077  | 1       | 0.9762  | 2.0743                      | 0.0506                                   | 2.1249             |
| 14  | 0.9216  | 1       | 0.9423  | 0.9874  | 0.9825  | 2.0829                      | 0.0505                                   | 2.1334             |
| 15  | 0.9216  | 1       | 0.9423  | 0.9801  | 0.9825  | 2.0837                      | 0.0502                                   | 2.1339             |
| 16  | 0.96    | 0.9505  | 1       | 0.988   | 0.9823  | 2.0875                      | 0.0403                                   | 2.1278             |

According to the basic requirements of the process indicators, the study concluded that the response Y and its mean value exceeding 2.1 were not in line with the basic requirements. Therefore, only 9 relatively selectable optimization solutions were combined in the Pareto solutions, which were the 9 schemes from No. 1 to No. 9. They correspond position on the Pareto Frontier was as shown in figure 4.
Figure 4. Pareto frontier based on AMGA algorithm.

Based on the Isight® software, the recommended optimal design point was the No. 2 design point. The corresponding process plan response index average was 1.9848, the variance was 0.0714, and the corresponding response value was 2.0562.

3.3. Analysis and discussion
To give more process alternatives, the study compared the mean and variance of Y in No.1-9 design to the design No.2 respectively. Comparison chart was shown in table 5.

Table 5. Comparison of the solution from No.1 to No.9 based on AMGA algorithm.

| No. | Mean. Y  | Relative deviation from No. 2 | Std Deviation. Y  | Relative deviation from No. 2 | Objective Function | Relative deviation from No. 2 |
|-----|----------|-----------------------------|-------------------|-----------------------------|-------------------|-----------------------------|
| 1   | 1.9829   | -0.10%                      | 0.0739            | 3.50%                       | 2.0569            | 0.03%                       |
| 2   | 1.9848   | --                          | 0.0714            | --                          | 2.0562            | --                          |
| 3   | 1.989    | 0.21%                       | 0.0702            | -1.68%                      | 2.0592            | 0.15%                       |
| 4   | 1.9906   | 0.29%                       | 0.0699            | -2.10%                      | 2.0605            | 0.21%                       |
| 5   | 1.9965   | 0.59%                       | 0.0676            | -5.32%                      | 2.0641            | 0.38%                       |
| 6   | 1.9972   | 0.62%                       | 0.0673            | -5.74%                      | 2.0645            | 0.40%                       |
| 7   | 1.9979   | 0.66%                       | 0.0648            | -9.24%                      | 2.0627            | 0.32%                       |
| 8   | 2.0098   | 1.26%                       | 0.0595            | -16.67%                     | 2.0693            | 0.64%                       |
| 9   | 2.0311   | 2.33%                       | 0.056             | -21.57%                     | 2.0871            | 1.50%                       |

Under the condition that the response Y meet the basic requirements moreover the mean deviation was not large, it is considered that the declining degree of variance is the larger the better. Therefore, AMGA's design plans, No. 4 and No. 8, were included in the alternative robust process plan. Comparing the results of No. 2, No. 4 and No. 8 plans based on the AMGA algorithm with the initial optimization results before the robustness optimization, the result was shown in Table 6. In
order to obtain the most robust and most effective solution, the comparison diagrams were plotted in figure 5.

Table 6. Comparison of Robustness Optimization Results.

| OPT         | Mean Y | Std Deviation Y | Maximum porosity |
|-------------|--------|-----------------|------------------|
| No. 7       | 2.1479 | 0.0471          | 2.02             |
| AMGA-2      | 1.9848 | 0.0714          | 2.04             |
| AMGA-4      | 1.9906 | 0.0699          | 2.05             |
| AMGA-8      | 2.0098 | 0.0595          | 2.01             |

Figure 5. Comparison of robustness optimization result.

Multi-objective optimization is a trade-off and comparison process, especially in this optimization. In this article, mean and variance were the two optimization indicators. Firstly, from the optimization results, the average value of response Y was reduced from 2.1479 to 2, which indicates the mean optimization is obvious. Secondly, the variance was relatively stable which illustrates that the optimized process results compared with the original shifted to the left as shown in figure 5. Throughout the three optimization schemes, the mean value was similar, but the standard deviation was relatively large. Therefore, in summary, the AMGA-8 solution was selected the best, which considered the high quality of the casting and robustness of the casting process.

4. Conclusions

This paper proposed that a robust parametric optimization for investment casting process of a turbine vane. Firstly, the method of process optimization was presented based on DOE and finite element simulation. Secondly, a robust design was established based on RSM and AMGA algorithm. In investment casting, we finally get the specify parameters value considering both the quality of the casting and parameter fluctuations. The following conclusions can be drawn:

a) The approach of integrated robust optimization design of process parameters was introduced in investment casting process of a turbine vane, which considering the parameter value, fluctuations and cast of production. A reference method was given in investment casting process.

b) Compared to 5 parameters, the model temperature and the casting temperature have great influence on the entire casting process. To ensure the strength of the model shell, it is a good proposal to low the temperature properly when the pouring temperature is high.

c) For thin-walled casting like turbine vane, with complex cavities, high-temperature and fast-casting are more conducive to casting forming. So, the pouring time is maintained at a low level.

d) The research suggests adjusting the key process parameters according to the AMGA-8 program in actual production, additionally reduce the preheating temperature and appropriately increasing
the pouring temperature.

References
[1] Betteridge, W. and Shaw, S.W.K., 1987. Development of superalloys. Materials science and technology, 3(9) 682-94.
[2] Mondal, B., Kundu, S., Lohar, A.K. and Pai, B.C., 2008. Net-shape manufacturing of intricate components of A356/SiCp composite through rapid-prototyping-integrated investment casting. Materials Science and Engineering: A, 498(1-2), 37-41.
[3] Eylon, D., Froes, F.H. and Gardiner, R.W., 1983. Developments in titanium alloy casting technology. JOM, 35(2) 35-47.
[4] Yang, X.L., Dong, H.B., Wang, W. and Lee, P.D., 2006. Simulation of Stray Grain Formation in Investment Cast Turbine Blades. Solidification and Crystallization.
[5] Dong, Y., Bu, K., Dou, Y. and Zhang, D., 2011. Determination of interfacial heat-transfer coefficient during investment-casting process of single-crystal blades. Journal of materials processing technology, 211(12) 2123-31.
[6] Pan, D., Xu, Q.Y., Yu, J., Liu, B.C., Li, J.R., Yuan, H.L. and Jin, H.P., 2008. Numerical simulation of directional solidification of single crystal turbine blade casting. International Journal of Cast Metals Research, 21(1-4) 308-12.
[7] Wu, C.J. and Hamada, M.S., 2011. Experiments: planning, analysis, and optimization. John Wiley & Sons. Vol. 552.
[8] Wheeler, A.P., Sandberg, R.D., Sandham, N.D., Pichler, R., Michelassi, V. and Laskowski, G., 2016. Direct numerical simulations of a high-pressure turbine vane. Journal of Turbomachinery 138(7).
[9] Pattnaik, S., Karunakar, D.B. and Jha, P.K., 2014. Parametric optimization of the investment casting process using utility concept and Taguchi method. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 228(4) 288-300.
[10] Dabade, U.A. and Bhedasgaonkar, R.C., 2013. Casting defect analysis using design of experiments (DoE) and computer aided casting simulation technique. Procedia CIRP, 7 616-21.
[11] Box, G.E. and Draper, N.R., 1987. Empirical model-building and response surfaces. John Wiley & Sons.
[12] Pagratis, N., Karagiannis, N., Vosniakos, G.C., Pantelis, D. and Benardos, P., 2007. A holistic approach to the exploitation of simulation in solid investment casting. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 221(6), 967-79.
[13] Hashim, J., Looney, L. and Hashmi, M.S.J., 1999. Metal matrix composites: production by the stir casting method. Journal of materials processing technology, 92(1-7).
[14] Wang, D., Sun, J., Dong, A., Shu, D., Zhu, G. and Sun, B., 2018. An optimization method of gating system for impeller by RSM and simulation in investment casting. The International Journal of Advanced Manufacturing Technology, 98(9-12). 3105-14.