

Article

Multi-Objective Optimization of Casting Parameters for Mn70Ni25Cr5 Alloy Using ProCAST Simulation and Response Surface Methodology

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Abstract

To simultaneously suppress shrinkage-related defects and refine the solidification microstructure of Mn70Ni25Cr5 alloy ingots, ProCAST simulation was combined with Box–Behnken response surface methodology to optimize pouring temperature, filling time, and mold temperature. Porosity in the ingot body and secondary dendrite arm spacing (SDAS) were selected as the response variables, and quadratic regression models were established for both responses. The optimized casting parameters were determined using analysis of variance, response surface analysis, and the desirability function approach. The porosity and SDAS models were both statistically significant, with non-significant lack-of-fit terms and R^2 values of 0.9906 and 0.9901, respectively. The optimal parameters were a pouring temperature of 1220.74 °C, a filling time of 6.34 s, and a mold temperature of 294.47 °C, corresponding to a predicted porosity of 0.426% and a predicted SDAS of 47.51 μm . A supplementary simulation and a validation casting experiment were then performed using practical process settings derived from the optimized solution. The supplementary simulation indicated that shrinkage-related defects were concentrated mainly in the riser, while metallographic examination revealed no large continuous shrinkage-porosity region in the examined ingot-body sections. The overall measured SDAS across the center, half-radius, and edge positions was 48.54 μm , differing from the response-surface prediction by approximately 2.2%. These results support the applicability of the combined ProCAST–RSM approach for simulation-assisted optimization of Mn70Ni25Cr5 alloy casting parameters within the investigated process range.

Keywords: Mn70Ni25Cr5 alloy; ProCAST simulation; response surface methodology; multi-objective optimization; porosity; secondary dendrite arm spacing



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1. Introduction

Mn–Ni–Cr brazing filler metals possess an appropriate melting-temperature range and favorable compatibility with heat-resistant structural materials, making them promising candidates for high-temperature joining applications. Way et al. [1] systematically reviewed the composition design, melting characteristics, and application requirements of brazing filler metals, emphasizing the importance of matching filler-metal properties with the base material and service environment. Chen et al. [2] investigated stainless-steel joints produced

using a Mn-based brazing filler and demonstrated that the filler composition strongly affected interfacial reactions and joint performance. Penyaz et al. [3] further summarized the characteristics and application limitations of Ni-based filler metals for joining austenitic stainless steels. More specifically, Yuan et al. [4,5] applied Mn–Ni–Cr fillers to the transient-liquid-phase bonding of heat-resistant alloys and Ni₃Al-based superalloys, confirming the potential of this filler system for high-temperature joining. These studies have mainly focused on brazing behavior, interfacial microstructure, and joint properties, whereas the preparation and quality control of the initial Mn–Ni–Cr alloy ingot have received substantially less attention.

For the production of Mn70Ni25Cr5 alloy foils, the alloy must first be prepared as an ingot and then subjected to subsequent thermomechanical processing. Dong et al. [6] reviewed short-process forming technologies for brazing materials and highlighted the close relationship between initial alloy preparation and downstream forming. Existing investigations of Mn–Ni–Cr alloys have mainly addressed phase equilibria [7], hot-deformation behavior, and microstructural restoration mechanisms [8,9]. These studies provide an important basis for alloy design and subsequent rolling, but they do not address shrinkage-related defects or solidification-structure control during ingot casting. Research on other cast alloys has shown that microstructural inhomogeneity and chemical segregation originating from solidification can influence fatigue behavior and tensile-property uniformity [10,11]. Therefore, controlling the as-cast compactness and solidification microstructure of Mn70Ni25Cr5 alloy ingots is important for providing a stable and homogeneous starting billet for subsequent processing.

Shrinkage cavities and shrinkage porosity form through the combined effects of volumetric contraction, interrupted feeding, local hot-spot development, and the progressive isolation of interdendritic liquid. Campbell [12] summarized the fundamental relationships among melt filling, heat transfer, feeding, and casting-defect formation. Stefanescu [13] reviewed numerical methods for predicting shrinkage-related defects and emphasized the roles of solidification sequence and feeding conditions. Li et al. [14] further discussed the numerical prediction of multiple defects in steel ingots, while Lesoult [15] analyzed the formation principles of microporosity in cast alloys. Reis et al. [16] and Khalajzadeh and Beckermann [17] numerically described shrinkage-defect evolution during alloy solidification, demonstrating that defect formation depends strongly on local thermal and feeding histories. These findings indicate that pouring temperature, mold-filling time, and mold temperature should be considered jointly. Pouring temperature governs melt superheat and fluidity, mold-filling time influences heat loss and the temperature distribution established before solidification, and mold temperature controls interfacial heat extraction and the subsequent solidification sequence.

Simulation-assisted design of experiments has become an effective approach for reducing the cost and time required for casting-process development. Gunasegaram et al. [18] combined permanent-mold casting simulations with design of experiments to identify the principal factors affecting shrinkage porosity, demonstrating the value of numerical factor screening. Raghupathy and Amirthagadeswaran [19] applied Box–Behnken design and response surface methodology to casting-process optimization and showed that nonlinear factor effects and parameter interactions could be evaluated using a limited number of process combinations. Li et al. [20] subsequently coupled finite-element simulation with a Box–Behnken design to optimize the squeeze-casting process of a gearbox cover. These studies established the applicability of simulation-assisted response surface methods to casting optimization. However, their process windows and conclusions were developed for other alloy systems and casting configurations and cannot be directly transferred to the permanent-mold gravity casting of Mn70Ni25Cr5 alloy.

Shrinkage-related porosity and secondary dendrite arm spacing represent two complementary aspects of ingot quality. Porosity provides a quantitative measure of volumetric shrinkage-related defects and is mainly governed by solidification sequence, feeding-channel continuity, and hot-spot evolution [13,17]. SDAS is widely used to characterize the scale of dendritic solidification structures, although its measured value depends on the adopted metallographic procedure, as discussed by Vandersluis and Ravindran [21]. Sari et al. [22] related secondary dendrite arm spacing to dendrite-tip kinetics and cooling rate, while studies of high-carbon steels and Ni–Cr–Co–Mo alloys showed that variations in cooling rate can modify dendritic morphology, microsegregation, and the characteristic scale of the solidification structure [23,24]. Thus, porosity and SDAS are governed by related but distinct physical mechanisms. Minimizing porosity alone does not necessarily produce the finest dendritic structure, and reducing SDAS alone does not ensure favorable feeding. Simultaneous consideration of both responses is therefore required to balance defect suppression and solidification-microstructure refinement.

To the best of our knowledge, no systematic study has established the quantitative relationships among pouring temperature, mold-filling time, mold temperature, shrinkage-related porosity, and SDAS for the permanent-mold gravity casting of Mn70Ni25Cr5 alloy. In particular, the combined thermal effects of the H13 steel mold wall, bottom copper cooling structure, and upper insulated riser have not been incorporated into a unified multi-response optimization framework for this alloy. The contribution of the present work therefore does not lie in proposing a new numerical or statistical algorithm, but in applying an established ProCAST–Box–Behnken–desirability framework to a material-specific alloy and mold system, while simultaneously considering shrinkage-defect suppression and dendritic-structure refinement.

Accordingly, pouring temperature, mold-filling time, and mold temperature were selected as the process variables in this study. ProCAST-predicted porosity in the ingot body and the arithmetic mean of SDAS values extracted from 12 equally spaced radial sampling points on the mid-height transverse section were used as the response variables. Quadratic response surface models were established using a 17-run Box–Behnken design, and the main, interaction, and quadratic effects of the process parameters were analyzed. Multi-objective optimization was then performed using the desirability-function approach to simultaneously minimize porosity and SDAS. Finally, a supplementary ProCAST simulation and a validation casting experiment were conducted to assess the selected optimized condition. This study aims to provide a material-specific process basis for improving the casting soundness and controlling the solidification microstructure of Mn70Ni25Cr5 alloy ingots.

2. Materials and Methods

2.1. Material Preparation, Casting Conditions, and Thermophysical Parameters

The nominal composition of the experimental alloy was Mn70Ni25Cr5. High-purity Mn, Ni, and Cr were used as raw materials, and the alloy ingots were prepared by vacuum melting. Several independent vacuum-melted batches were prepared during the experimental work, and chemical composition analysis confirmed that the obtained alloys were within the specified composition range. The measured composition of the alloy batch used for the casting simulation and validation experiments is listed in Table 1. The measured Ni and Cr contents were 25.46 wt.% and 5.45 wt.%, respectively, both within the specified ranges. The measured C, P, and S contents were also below the individual limits specified in GB/T 13679–2016 [25]. The total content of the measured impurity elements was approximately 0.129 wt.%, which was lower than the maximum allowable value of 0.30 wt.%.

These results confirmed that the prepared alloy met the compositional requirements for BMn70NiCr filler metal.

Table 1. Nominal composition range and measured chemical composition of the Mn70Ni25Cr5 alloy (wt.%).

Item	Mn	Ni	Cr	C	P	S	O	N	H
Nominal composition	Bal.	24–26	4.5–5.5	≤0.10	≤0.020	≤0.020	N.S.	N.S.	N.S.
Measured composition	Bal.	25.46	5.45	0.09	0.0027	0.017	0.0098	0.0095	0.00016

Note: N.S. indicates that no individual limit is specified in GB/T 13679–2016. The maximum allowable total impurity content is 0.30 wt.%, whereas the measured total impurity content of the present alloy was approximately 0.129 wt.%.

The casting process was conducted by permanent-mold gravity casting. The mold consisted of an insulated riser, an H13 steel mold wall, and a bottom copper cooling structure. The mold structure and sampling locations are shown in Figure 1. An insulated riser was placed at the upper part of the mold to improve feeding conditions [26]. The side wall was made of H13 steel, and the bottom copper cooling structure was used to promote directional solidification from bottom to top [27]. In subsequent simulations, the statistical region for response extraction was limited to the ingot body and excluded the riser region, thereby avoiding interference from riser-localized shrinkage-related defects when evaluating the quality of the ingot body.

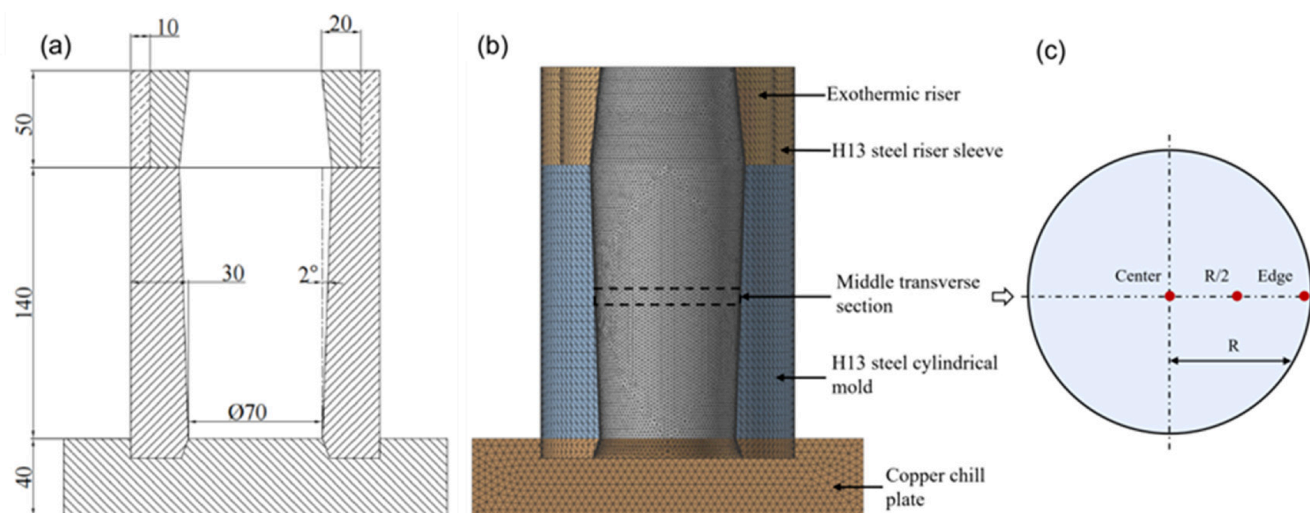


Figure 1. Schematic illustration of the mold structure and sampling scheme: (a) cross-sectional geometry and key dimensions, with all dimensions given in mm except for the 2° taper angle; (b) three-dimensional meshed model, in which the colors distinguish the exothermic riser, H13 steel mold components, and copper chill plate, and the black dashed line marks the mid-height transverse section; (c) sampling locations on the mid-height transverse section, where the red dots indicate the center, half-radius ($R/2$), and edge positions, and the dashed lines indicate the diametral reference directions.

Differential scanning calorimetry (DSC) was performed using an STA 449 F3 Jupiter simultaneous thermal analyzer (NETZSCH-Gerätebau GmbH, Selb, Germany) at a heating rate of $10\text{ }^{\circ}\text{C}\cdot\text{min}^{-1}$ under an argon atmosphere. As shown in Figure 2, the DSC heating curve exhibited a distinct endothermic event, with a melting onset at approximately $1040\text{ }^{\circ}\text{C}$ and an endothermic peak at approximately $1080\text{ }^{\circ}\text{C}$. These characteristic temperatures were close to the reference solidus and liquidus temperatures of 1035 and $1080\text{ }^{\circ}\text{C}$, respectively, reported for BMn70NiCr filler metal in previous studies and GB/T 13679–2016 [2]. Therefore, considering both the DSC results and the reference data, 1035 and $1080\text{ }^{\circ}\text{C}$ were

adopted as the solidus and liquidus temperatures, respectively, in the ProCAST simulations. The same temperature interval was used to calculate the local solidification time in the SDAS model.

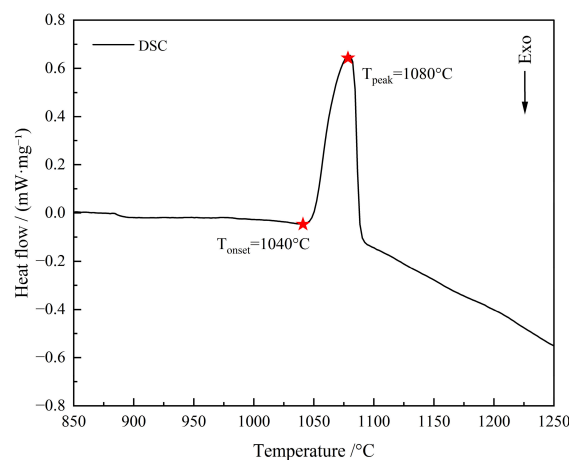


Figure 2. DSC heating curve and characteristic temperatures of the Mn70Ni25Cr5 alloy. The red stars indicate the melting onset at approximately 1040 °C and the endothermic peak at approximately 1080 °C.

Temperature-dependent thermophysical parameters of the Mn70Ni25Cr5 alloy, including thermal conductivity, density, enthalpy, and solid fraction, were calculated using JMatPro 7.0.0 (Sente Software Ltd., Guildford, UK) and imported into ProCAST 18.0 (ESI Group, Rungis, France) as temperature-dependent data. JMatPro has been widely used to calculate thermophysical and physical properties of multicomponent alloys and to provide material-property inputs for solidification and casting process simulations [28–30]. In this study, the measured chemical composition of the alloy was used as the input composition for the JMatPro calculation. Because directly measured high-temperature thermophysical-property data for the Mn70Ni25Cr5 alloy are limited, the calculated thermophysical parameters were used as approximate material inputs for the ProCAST simulations. The main thermophysical parameters are shown in Figure 3. Thermal conductivity governs heat transport within the alloy, while the temperature-dependent density contributes to the melt flow, buoyancy, and solidification–shrinkage calculations. Enthalpy and solid-fraction data were used to describe latent-heat evolution and the liquid-to-solid phase transformation. In addition, the liquidus and solidus temperatures adopted on the basis of the DSC results and the reference data were used to verify the solidification-temperature interval and to define the temperature range for determining the local solidification time in the SDAS model. Accordingly, the DSC characterization, the adopted phase-transition temperatures, and the JMatPro-calculated thermophysical properties collectively provided the material input data for the subsequent filling and solidification simulations. Although uncertainties may exist in the JMatPro-calculated thermophysical properties owing to the use of thermodynamic databases and model assumptions, the same material-property dataset was used for all simulation cases. Therefore, these parameters were mainly used to compare the relative effects of process parameters within the investigated range.

According to the mold materials and interfacial contact states, the interfacial heat-transfer coefficients between the alloy melt and the H13 steel mold wall, the copper base, and the insulated riser were specified, as listed in Table 2. To ensure comparability among different process-parameter combinations, all simulation groups used the same geometric model, mesh model, thermophysical parameters, interfacial heat-transfer coefficients, and response-extraction region. Only the pouring temperature, mold-filling time, and mold temperature were varied.

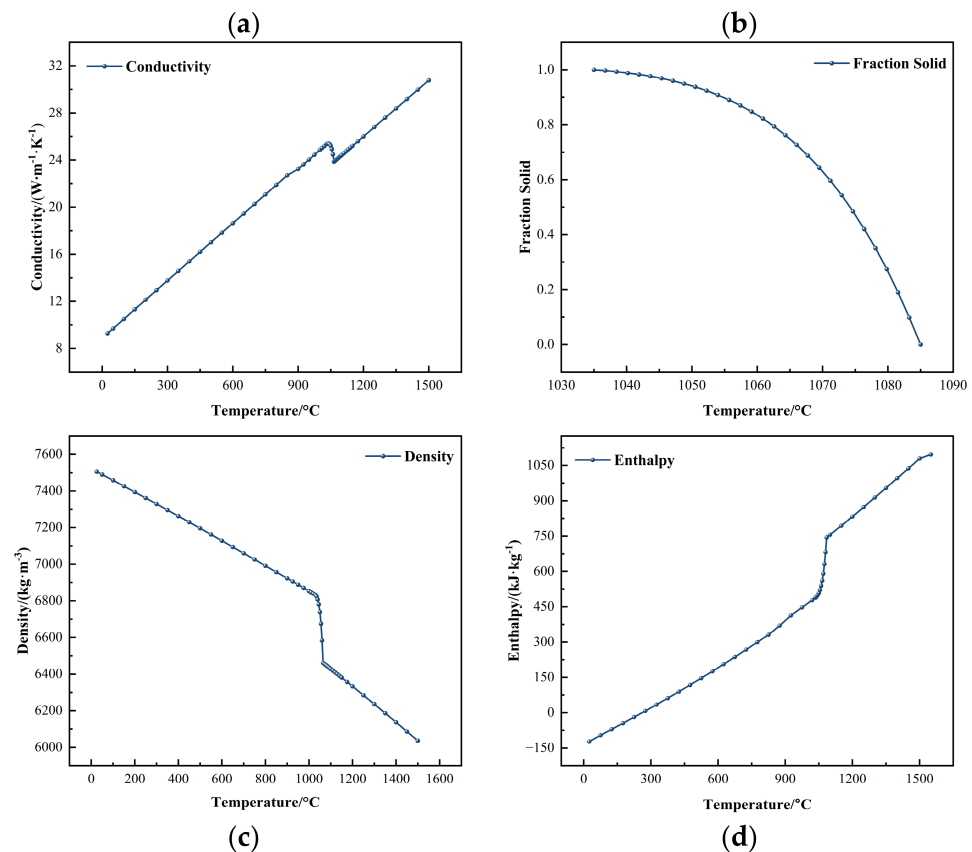


Figure 3. Main thermophysical properties of the Mn70Ni25Cr5 alloy: (a) thermal conductivity; (b) solid fraction; (c) density; (d) enthalpy.

Table 2. Interfacial heat-transfer coefficients used in the casting simulation.

Heat-Transfer Interface	Heat-Transfer Coefficient/W·m ⁻² ·K ⁻¹
Alloy melt-H13 mold wall	1000
Alloy melt-copper base	2000
Alloy melt-insulated riser	200
H13 mold wall-copper base	1000
Insulating sleeve-H13 mold wall	500

As shown in Table 3, the 1.5 mm mesh was used as the reference mesh because it had the largest number of elements among the tested meshes. Compared with the 1.5 mm mesh, the 2.0 mm mesh showed only a small difference in simulated porosity, with an absolute difference of 0.02 percentage points, while the simulated SDAS remained unchanged at 48.0 μm . Meanwhile, refining the mesh from 2.0 mm to 1.5 mm increased the number of 3D elements from 1,087,910 to 5,127,676, which substantially increased the computational cost. Therefore, considering both numerical accuracy and computational efficiency, the 2.0 mm mesh was adopted for the subsequent ProCAST simulations.

Table 3. Mesh-sensitivity analysis under the center-point casting condition.

Mesh Size/mm	Nodes	3D Elements	Simulated Porosity/%	Relative Deviation in Porosity/%	Simulated SDAS/ μm	Relative Deviation in SDAS/%
3	144,643	734,596	0.47	17.5	48.1	0.21
2	190,456	1,087,910	0.42	5	48	0
1.5	941,575	5,127,676	0.4	-	48	-

Note: The 1.5 mm mesh was used as the reference mesh for calculating the relative deviations.

2.2. Numerical Simulation Model and Extraction of Response Variables

ProCAST 18.0 was used to simulate melt filling, heat transfer, solidification, and shrinkage-related defect formation during permanent-mold gravity casting of the Mn70Ni25Cr5 alloy. Unless otherwise specified, the default transient-solver, automatic time-stepping, and convergence settings of ProCAST were adopted consistently for all simulation cases. The melt was treated as an incompressible Newtonian fluid. The filling and solidification processes were described by the mass, momentum, and energy conservation equations [31–34]:

The continuity equation is expressed as:

$$\nabla \cdot U = 0 \quad (1)$$

$$\rho \left[\frac{\partial U}{\partial t} + (U \cdot \nabla)U \right] = -\nabla p + \mu \nabla^2 U + \rho F \quad (2)$$

$$\rho c_p \left(\frac{\partial T}{\partial t} + U \cdot \nabla T \right) = \nabla \cdot (k \nabla T) + Q \quad (3)$$

where U is the melt-velocity vector, ρ is the density, p is the pressure, μ is the dynamic viscosity, F is the body force per unit mass, c_p is the specific heat capacity, T is the temperature, k is the thermal conductivity, and Q is the heat-source term associated with latent-heat release during solidification.

The ingot body, excluding the riser, was defined as the response-extraction domain [35]. Within this domain, elements with a Total Shrinkage Porosity value greater than 1% were identified as shrinkage-related defective regions according to the criterion adopted in a previous numerical study [36]. The porosity percentage statistically obtained from ProCAST using this criterion was used as the Y_1 response. The same extraction domain and threshold criterion were applied to all simulation cases to ensure consistent comparison among the investigated process conditions.

SDAS was calculated using the dendrite-coarsening model implemented in the Metallurgical Tools module of ProCAST:

$$\lambda_2 = \left(M t_f \right)^{(1/3)} \quad (4)$$

where λ_2 is the secondary dendrite arm spacing, t_f is the local solidification time, and M is the alloy-dependent dendrite-coarsening constant. Because the thermodynamic and kinetic data required for an independent determination of M are not sufficiently available for the multicomponent Mn70Ni25Cr5 alloy, M was set to $3000 \mu\text{m}^3 \cdot \text{s}^{-1}$, referring to the typical alloy-dependent values provided in the ProCAST User's Guide 18.0, and was kept constant in all simulation cases. The local solidification time was defined as the time required for the local temperature to decrease from the adopted liquidus temperature of 1080°C to the adopted solidus temperature of 1035°C . The exponent $1/3$ is prescribed by the dendrite-coarsening model and was not treated as an adjustable parameter.

For each simulation case, 12 equally spaced sampling points were selected along a radial line extending from the center to the edge on the transverse section at the mid-height of the ingot body. The SDAS values extracted at these points were arithmetically averaged and used as the Y_2 response. The same sampling locations and extraction procedure were applied to all 17 simulation cases. Therefore, Y_2 represents the mean SDAS along the selected radial path rather than a single-point value or a volume-averaged value for the entire ingot body.

2.3. Box–Behnken Response Surface Design

Based on the melting temperature range of the alloy, casting-process feasibility, and preliminary simulation results [37], pouring temperature (A), mold-filling time (B), and mold temperature (C) were selected as the response surface design factors, each at three

levels. The pouring temperatures were set at 1180, 1215, and 1250 °C, corresponding to melt superheats of 100, 135, and 170 °C, respectively, relative to the adopted liquidus temperature of 1080 °C. The mold-filling times were 4, 6, and 8 s, and the mold temperatures were 250, 300, and 350 °C. A three-factor, three-level Box–Behnken design was employed, resulting in 17 runs, including five center-point runs. The factor levels are listed in Table 4, and the design matrix and simulated responses are presented in Table 5.

Table 4. Factors and levels of the Box–Behnken design.

Level	Factor		
	Pouring Temperature (A)/°C	Mold-Filling Time (B)/s	Mold Temperature (C)/°C
−1	1180	4	250
0	1215	6	300
1	1250	8	350

Table 5. Box–Behnken design matrix and simulated response results.

Run	A/°C	B/s	C/°C	Y ₁ (Porosity)/%	Y ₂ (SDAS)/μm
1	1180	6	250	0.82	52.2
2	1250	8	300	0.68	49.3
3	1180	8	300	0.86	48.8
4	1215	8	250	0.68	48.5
5	1180	6	350	0.81	50.2
6	1250	4	300	0.68	50.2
7	1215	4	350	0.53	52.1
8	1215	6	300	0.42	48.0
9	1215	6	300	0.40	47.5
10	1250	6	250	0.72	47.8
11	1215	6	300	0.42	48.1
12	1215	4	250	0.55	51.2
13	1250	6	350	0.64	52.4
14	1215	6	300	0.41	47.5
15	1215	6	300	0.44	47.8
16	1180	4	300	0.78	52.1
17	1215	8	350	0.63	49.5

Note: Y₁ and Y₂ represent the ProCAST-predicted porosity and SDAS, respectively. The variation among the repeated center-point responses was used to estimate the pure error. Because the response values were generated by numerical simulations, the resulting pure error reflects numerical and post-processing variability rather than physical experimental variation.

2.4. Regression Model Establishment and Multi-Objective Optimization Method

Design-Expert 13 was used for Box–Behnken response surface design, quadratic regression model fitting, analysis of variance, response surface plotting, and multi-objective numerical optimization [38,39]. A quadratic polynomial model was used to describe the relationship between process parameters and response values:

$$Y = \beta_0 + \sum_{i=1}^3 \beta_i X_i + \sum_{i=1}^3 \beta_{ii} X_i^2 + \sum_{i < j}^3 \beta_{ij} X_i X_j \quad (5)$$

where Y is the response value; X_i and X_j are the coded process parameters; β₀ is the constant term; and β_i, β_{ii}, and β_{ij} are the coefficients of the linear, quadratic, and interaction terms, respectively. Analysis of variance was used to evaluate model significance, lack-of-fit values, coefficient of determination, adjusted coefficient of determination, and predicted coefficient of determination. Response surface and contour plots were then used to analyze the effects of individual factors and their interactions on porosity and SDAS.

In the multi-objective optimization, porosity and SDAS were simultaneously minimized using the desirability function approach. Pouring temperature, mold-filling time,

and mold temperature were constrained within 1180–1250 °C, 4–8 s, and 250–350 °C, respectively. For a single-response objective, a response value closer to the specified minimization target corresponds to a higher desirability. A larger overall desirability indicates that the parameter combination is more favorable for simultaneously reducing porosity and decreasing SDAS. The overall desirability can be expressed as:

$$D = (d_1 d_2)^{1/2} \quad (6)$$

where D is the overall desirability, and d_1 and d_2 are the individual desirability values corresponding to porosity and SDAS, respectively. During optimization, pouring temperature, mold-filling time, and mold temperature were set within the design ranges, while porosity and SDAS were both set as minimization objectives. The weights of the two responses were both set to 1, and their importance levels were both set to +++, ensuring equal optimization priority for shrinkage-related defect suppression and microstructural refinement.

2.5. Procedures for Numerical Confirmation and Experimental Assessment of the Optimized Condition

A supplementary ProCAST simulation and a validation casting experiment were conducted using the practically implemented condition of 1220 °C, 6.3 s, and 295 °C, which was derived from the exact optimized solution. The supplementary simulation was used to examine the consistency between the response-surface predictions and the ProCAST results, whereas the casting experiment was used to assess the defect distribution, bulk compactness, and solidification microstructure under the optimized condition. To quantify the numerical improvement, an additional baseline simulation was performed at a pouring temperature of 1180 °C, a mold-filling time of 4 s, and a mold temperature of 250 °C. The baseline and optimized simulations employed identical geometrical models, material properties, boundary conditions, mesh settings, response-extraction domains, and defect cutoff criteria, with only the prescribed process parameters being different.

The casting was sectioned at the mid-height of the ingot body, and specimens were taken from the center, half-radius, and edge positions, as shown in Figure 1c. Metallographic specimens were mounted, ground, polished, and etched for microstructural observation. SEM–EDS characterization was performed using a SEM5000 field-emission scanning electron microscope (CIQTEK Co., Ltd., Hefei, China) equipped with an energy-dispersive X-ray spectroscopy detector for auxiliary analysis of isolated local defects and their elemental distributions.

Bulk density was measured at room temperature using a JA5003J electronic density balance (Shanghai Shunyu Hengping, Shanghai, China), with deionized water as the immersion medium. Nine independent specimens were tested, with three specimens taken from each radial position. The measured Mn, Ni, and Cr contents were normalized to 100 wt.% before calculation, and the theoretical density was estimated using the inverse rule of mixtures:

$$\rho_{th} = \left(\sum_{i=1}^3 \frac{w_i}{\rho_i} \right)^{-1} \quad (7)$$

The calculated theoretical density was 7.575 g·cm^{−3}, and the density-based porosity was determined as:

$$P_p = \left(1 - \frac{\rho_b}{\rho_{th}} \right) \times 100\% \quad (8)$$

where ρ_b is the Archimedes' bulk density, and ρ_{th} is the estimated theoretical density. Mean values and standard deviations were calculated from the three specimens at each position.

SDAS was measured from metallographic images using ImageJ 1.54 and the line-intercept method. Three independent fields of view were analyzed at each radial position.

The mean and standard deviation of the three fields were used to represent the SDAS at each position, and the overall mean was calculated from all nine fields. The radial variation in the measured SDAS was compared with the spatial distribution obtained from the supplementary ProCAST simulation. The overall measured mean was compared with the response-surface-predicted Y_2 value for the optimized condition, where Y_2 was defined as the arithmetic mean of the SDAS values extracted from 12 equally spaced radial sampling points on the mid-height transverse section.

3. Results and Discussion

3.1. Box–Behnken Simulation Results

Table 5 shows the Box–Behnken design matrix and the corresponding ProCAST-simulated responses. Within the investigated parameter ranges, the predicted porosity in the ingot body ranged from 0.40% to 0.86%, while the predicted SDAS ranged from 47.5 to 52.4 μm . At the repeated center points, porosity ranged from 0.40% to 0.44%, and SDAS ranged from 47.5 to 48.1 μm . The limited dispersion among the repeated center-point responses was used to estimate the pure error. Because all responses were generated by ProCAST simulations, this term reflects numerical and post-processing variability rather than physical experimental variation, and the ANOVA and lack-of-fit analyses assess the adequacy of the quadratic models relative to the simulated dataset.

Overall, both porosity and SDAS changed markedly with variations in pouring temperature, mold-filling time, and mold temperature, but their minimum values did not occur under exactly the same parameter combination. Lower porosity values were mainly concentrated near the central parameter region, whereas higher porosity values mostly appeared under low pouring temperature or poorly matched parameter conditions. This indicates that moderate process–parameter combinations are more favorable for maintaining the balance among filling, solidification, and feeding. Low SDAS values were also located near the central parameter region, but their variation trend differed from that of porosity, indicating that defect suppression and microstructural refinement were governed by different dominant mechanisms. Therefore, it is necessary to establish separate response surface models for porosity and SDAS and further conduct multi-objective optimization [40,41].

3.2. Response Surface Model and Analysis of Variance for Porosity

Based on the Box–Behnken simulation results, a quadratic polynomial regression model was fitted for porosity. The regression equation relating porosity to pouring temperature, mold-filling time, and mold temperature is as follows:

$$Y_1 = 0.4180 - 0.0688A + 0.0387B - 0.0200C - 0.0200AB - 0.0175AC - 0.0075BC + 0.2410A^2 + 0.0910B^2 + 0.0885C^2 \quad (9)$$

where Y_1 is porosity, and A, B, and C are the coded values of pouring temperature, mold-filling time, and mold temperature, respectively. The ANOVA results of the porosity model are shown in Table 6.

As shown in Table 6, the porosity response surface model was statistically significant, with an F-value of 81.70 and $p < 0.0001$. The lack-of-fit term was not significant ($p = 0.0945$), indicating that the residual deviation of the quadratic model was not statistically significant relative to the numerical variability among the repeated center-point responses. The model R^2 , adjusted R^2 , and predicted R^2 were 0.9906, 0.9784, and 0.8810, respectively. The adequate precision value was 25.8675, which was greater than the recommended threshold of 4. These statistical results indicate satisfactory agreement between the quadratic model and the ProCAST-generated porosity responses within the investigated design space.

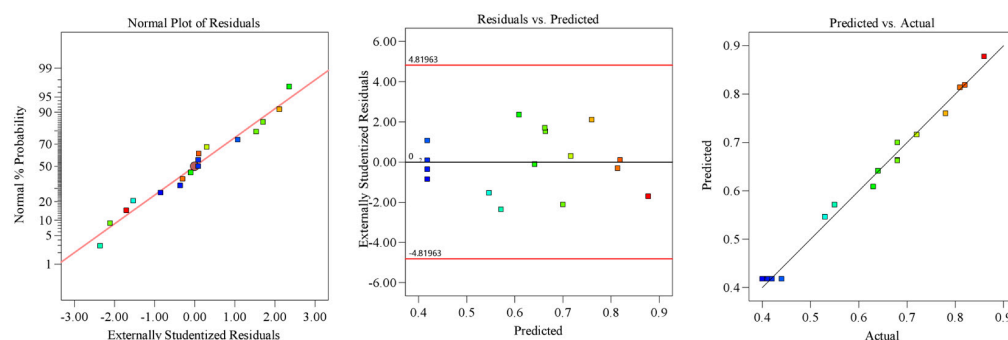
Table 6. ANOVA results of the response surface regression model for porosity.

Source	Sum of Squares	Df	Mean Square	F-Value	p-Value	Significance
Model	0.3945	9	0.0438	81.70	<0.0001	Significant
A	0.0378	1	0.0378	70.49	<0.0001	
B	0.0120	1	0.0120	22.39	0.0021	
C	0.0032	1	0.0032	5.97	0.0446	
AB	0.0016	1	0.0016	2.98	0.1278	
AC	0.0012	1	0.0012	2.28	0.1745	
BC	0.0002	1	0.0002	0.4194	0.5379	
A ²	0.2446	1	0.2446	455.89	<0.0001	
B ²	0.0349	1	0.0349	65.00	<0.0001	
C ²	0.0330	1	0.0330	61.48	0.0001	
Residual	0.0038	7	0.0005			Not Significant
Lack of fit	0.0029	3	0.0010	4.36	0.0945	
Pure error	0.0009	4	0.0002			
Corrected total	0.3982	16				

Note: ($R^2 = 0.9906$), adjusted ($R^2 = 0.9784$), predicted ($R^2 = 0.8810$), and adequate precision = 25.8675.

Although the predicted R^2 was lower than the ordinary R^2 , indicating somewhat weaker internal predictive performance than goodness of fit, its difference from the adjusted R^2 was less than 0.2, and the adequate precision value was 25.8675. Therefore, the model was considered suitable for interpolation and optimization within the investigated design space, although these statistics do not constitute independent experimental validation.

Figure 4 presents the diagnostic plots of the porosity response surface model. The residuals were generally distributed along the normal probability line, indicating an approximately normal residual distribution. The predicted and simulated values were close to the 45° reference line, confirming good agreement within the fitted design space. No obvious pattern was observed in the residual distribution, suggesting that the model did not show systematic bias. Combined with the ANOVA results, these diagnostics support the use of the porosity response surface model to analyze parameter effects and guide process optimization within the studied parameter range.

**Figure 4.** Diagnostic plots of the response surface regression model for porosity.

3.3. Effects of Process–Parameter Interactions on Porosity

To analyze the effects of pouring temperature, mold-filling time, and mold temperature on porosity, response surface and contour plots were constructed, as shown in Figure 5. These plots were used to evaluate the interaction effects between two process parameters, while the third parameter was fixed at the center level.

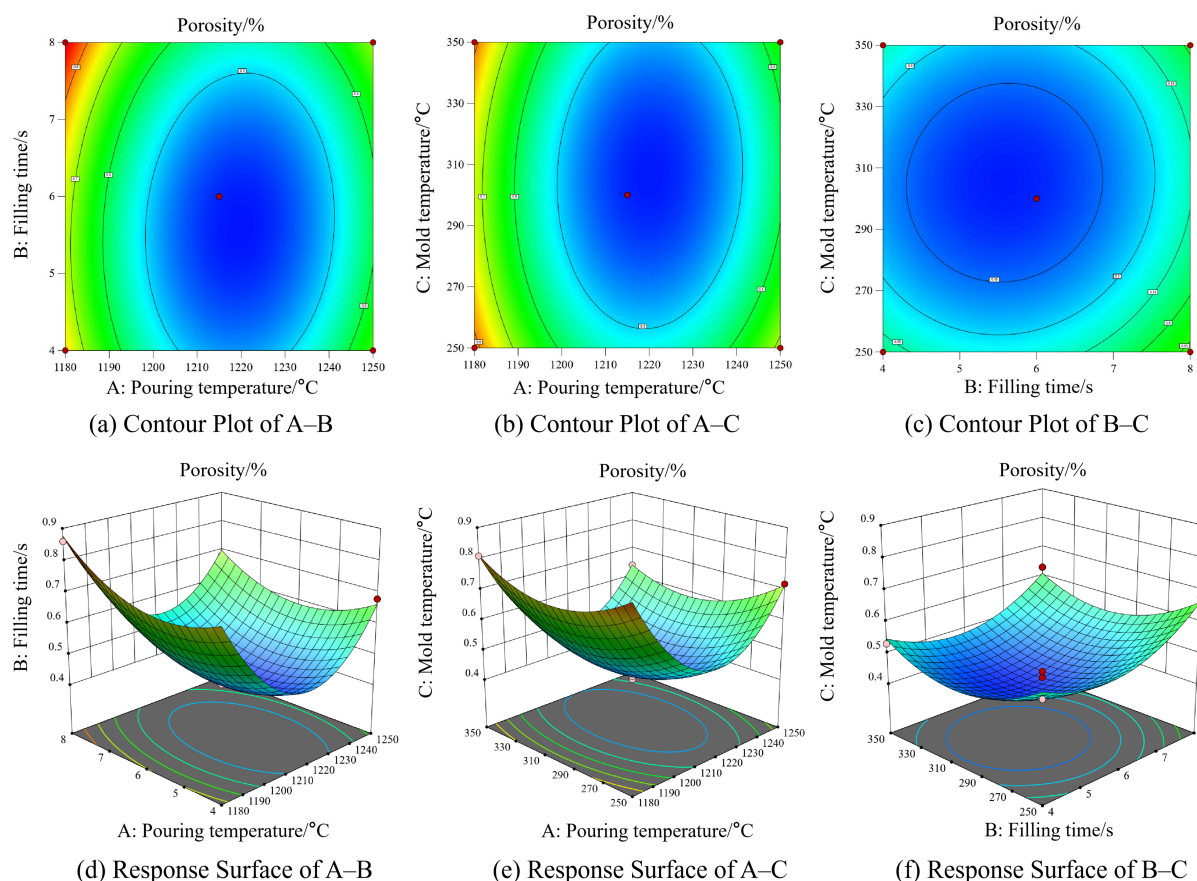


Figure 5. Response surface and contour plots showing the effects of process–parameter interactions on porosity.

To supplement the qualitative interpretation of the response surfaces, a one-factor sensitivity analysis was further performed using the established porosity regression model. The center point of the Box–Behnken design, namely 1215 °C pouring temperature, 6 s mold-filling time, and 300 °C mold temperature, was selected as the reference condition. Each factor was varied by one coded level while the other two factors were fixed at the center level. The calculated porosity changes are listed in Table 7.

Table 7. One-factor sensitivity analysis of predicted porosity based on the response surface regression model.

Factor	Y_1 at $-1/\%$	Y_1 at $0/\%$	Y_1 at $+1/\%$	Mean Absolute Change in Porosity/Percentage Points
A	0.7237	0.41	0.5863	0.245
B	0.4663	0.41	0.5437	0.095
C	0.5225	0.41	0.4825	0.0925

Note: A, B, and C represent pouring temperature, mold-filling time, and mold temperature, respectively. The coded levels -1 , 0 , and $+1$ correspond to the factor levels listed in Table 4. When one factor was varied, the other two factors were fixed at their center levels.

As shown in Table 7, when the other two factors were fixed at their center levels, pouring temperature caused the largest variation in predicted porosity. The mean absolute porosity change caused by pouring temperature was 0.2450 percentage points, which was larger than those caused by mold-filling time and mold temperature, namely 0.0950 and 0.0925 percentage points, respectively. This quantitative sensitivity analysis confirms that pouring temperature had the strongest influence on porosity within the studied parameter

range, followed by mold-filling time and mold temperature. This result is consistent with the ANOVA results.

As shown in Figure 5, porosity exhibited a nonlinear response to pouring temperature, mold-filling time, and mold temperature. For the A–B interaction, relatively low porosity was obtained near the intermediate levels of both factors. A low pouring temperature reduces melt superheat and fluidity, while a prolonged mold-filling time increases heat loss during filling. Both conditions may promote premature local solidification and interrupt feeding channels, thereby increasing the tendency for shrinkage porosity formation [42]. The relatively regular contour lines indicate that the interaction between pouring temperature and mold-filling time was weak, consistent with the ANOVA results.

For the A–C interaction, the response surface varied more markedly along the pouring-temperature direction, confirming that pouring temperature had a stronger influence on porosity than mold temperature. A low mold temperature increases heat extraction at the casting–mold interface and may promote early formation of a solidified shell, which can restrict subsequent feeding. In contrast, an excessively high mold temperature reduces the heat-extraction rate, prolongs local solidification in hot-spot regions, and may increase shrinkage porosity [43]. The B–C response surface was comparatively gentle, indicating a weak interaction between mold-filling time and mold temperature. Overall, porosity was governed mainly by the main effects and quadratic terms of the process parameters rather than by strong two-factor interactions. Appropriate coordination of the three parameters is therefore necessary to maintain a favorable solidification sequence and feeding condition in the ingot body [44].

3.4. Response Surface Model and Significance Analysis for SDAS

Using the same method, a quadratic polynomial regression model was fitted for SDAS. The regression equation relating SDAS to pouring temperature, mold-filling time, and mold temperature is as follows:

$$Y_2 = 47.78 - 0.4500A - 1.19B + 0.5625C + 0.6000AB + 1.65AC + 0.0250BC + 1.32A^2 + 0.9975B^2 + 1.55C^2 \quad (10)$$

where Y_2 is SDAS, and A, B, and C are the coded values of pouring temperature, mold-filling time, and mold temperature, respectively. The ANOVA results of the SDAS model are shown in Table 8.

Table 8. ANOVA results of the response surface regression model for SDAS.

Source	Sum of Squares	Df	Mean Square	F-Value	p-Value	Significance
Model	51.84	9	5.76	67.14	<0.0001	Significant
A	1.62	1	1.62	18.88	0.0034	
B	11.28	1	11.28	131.50	<0.0001	
C	2.53	1	2.53	29.51	0.0010	
AB	1.44	1	1.44	16.79	0.0046	
AC	10.89	1	10.89	126.94	<0.0001	
BC	0.0025	1	0.0025	0.0291	0.8693	
A ²	7.36	1	7.36	85.84	<0.0001	
B ²	4.19	1	4.19	48.84	0.0002	
C ²	10.08	1	10.08	117.54	<0.0001	
Residual	0.6005	7	0.0858			
Lack of fit	0.2925	3	0.0975	1.27	0.3985	Not Significant
Pure error	0.3080	4	0.0770			
Corrected total	52.44	16				

Note: $R^2 = 0.9901$, adjusted $R^2 = 0.9773$, and predicted $R^2 = 0.9044$.

As shown in Table 8, the SDAS response surface model was statistically significant, with an F-value of 67.14 and $p < 0.0001$. The lack-of-fit term was not significant ($p = 0.3985$). The model R^2 , adjusted R^2 , and predicted R^2 were 0.9901, 0.9773, and 0.9044, respectively, indicating satisfactory fitting and interpolation performance relative to the ProCAST-generated SDAS dataset. The model was therefore considered suitable for analyzing parameter effects and conducting optimization within the investigated design space.

The significance analysis showed that the linear terms A, B, and C all had significant effects on SDAS. Among them, term B had the largest F-value, indicating that mold-filling time had the strongest linear effect on SDAS, followed by mold temperature, whereas the effect of pouring temperature was relatively weaker. Unlike the porosity model, SDAS was more sensitive to interactions among process parameters. The interaction terms AB and AC were both significant, and the F-value of AC was markedly higher than that of AB, indicating that the coupling effect between pouring temperature and mold temperature had the most significant influence on SDAS, whereas BC was not significant. The quadratic terms A^2 , B^2 , and C^2 were all highly significant, indicating that SDAS also exhibited an evident nonlinear response.

Figure 6 shows the diagnostic plots of the SDAS response surface model. The model residuals generally followed a normal distribution, and the predicted and simulated values showed good agreement, indicating high fitting accuracy of the SDAS regression model. Combined with the ANOVA results, this model can be used to analyze and interpolate the ProCAST-predicted SDAS responses within the studied parameter range.

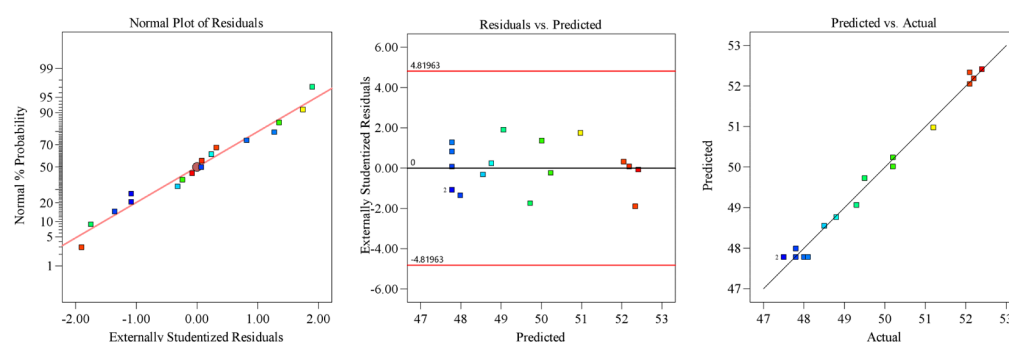


Figure 6. Diagnostic plots of the response surface regression model for SDAS.

3.5. Effects of Process Parameter Interactions on SDAS

To further analyze the effects of process–parameter coupling on SDAS, response surface and contour plots for SDAS were constructed, as shown in Figure 7.

As shown in Figure 7, SDAS exhibited a pronounced nonlinear response to the casting parameters. The inclined contours of the A–B response indicate a significant interaction between pouring temperature and mold-filling time. Pouring temperature determines the initial superheat of the melt, whereas mold-filling time influences heat loss and the temperature distribution established before solidification [45]. Their combined effect changes the local solidification conditions and consequently affects dendrite growth and coarsening.

The A–C response surface showed the greatest curvature and the most pronounced contour elongation, consistent with the highly significant A–C term in the ANOVA results. Pouring temperature controls the initial thermal state of the melt, while mold temperature affects heat extraction at the casting–mold interface. Their combined influence determines the local cooling rate and solidification time, which are the principal thermal factors controlling secondary dendrite arm coarsening. In particular, at otherwise comparable conditions, increasing the mold temperature can reduce the casting–mold heat-extraction rate and prolong the local solidification time, thereby providing more time for secondary

dendrite-arm coarsening and tending to increase SDAS [46]. By contrast, the B–C response surface was relatively gentle, indicating that the interaction between mold-filling time and mold temperature was not significant. These results demonstrate that SDAS was more sensitive to process–parameter coupling than to porosity.

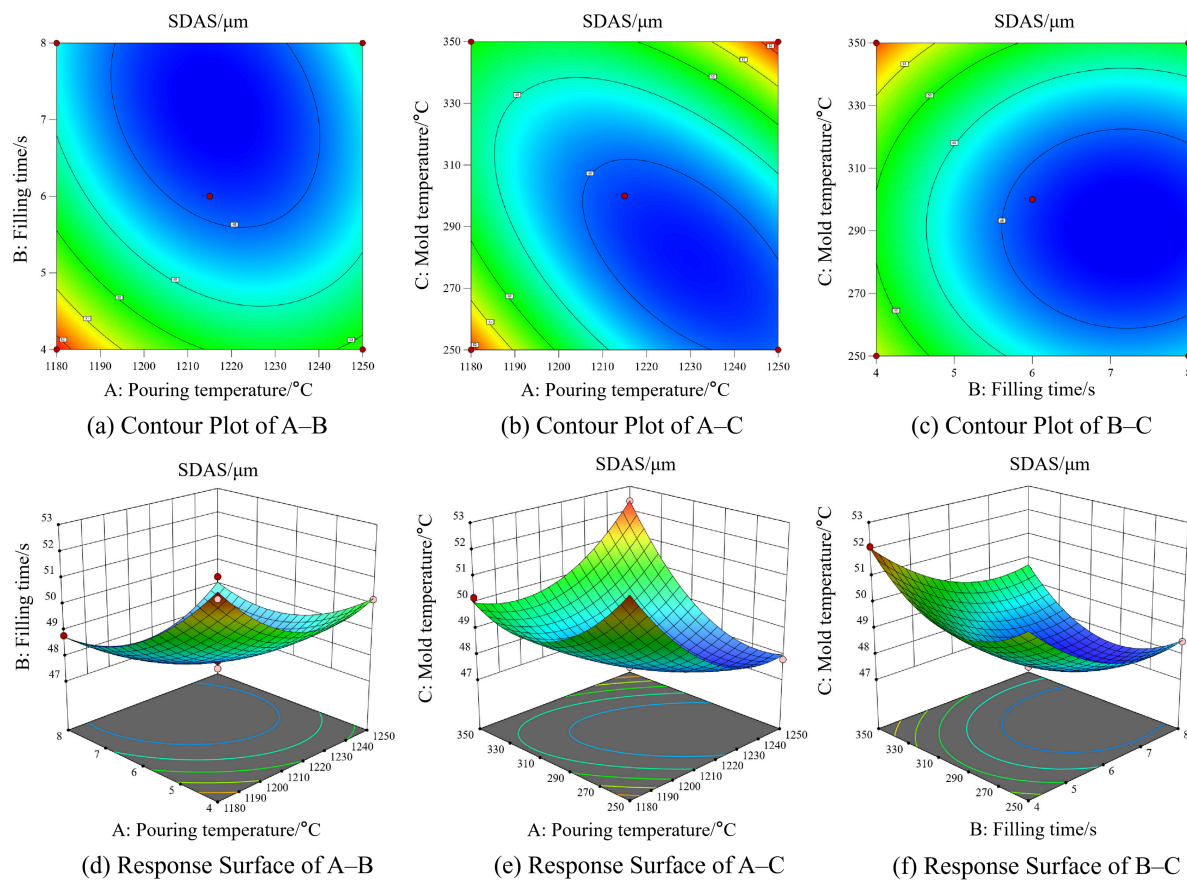


Figure 7. Response surface and contour plots showing the effects of process–parameter interactions on SDAS.

3.6. Comparison of Porosity and SDAS Response Mechanisms and Multi-Objective Optimization

Comparison of the two response surface models indicates that porosity and SDAS were governed by different aspects of the solidification process. Porosity in the ingot body was primarily associated with the solidification sequence, feeding-channel continuity, and hot-spot evolution. Accordingly, the porosity response was dominated by the linear and quadratic terms of the investigated process parameters, whereas the two-factor interaction terms were not statistically significant within the selected parameter ranges. This result suggests that maintaining each parameter within an appropriate range was more important for porosity control than the interaction between any two individual factors.

By contrast, SDAS was more directly governed by the local thermal history, including the cooling rate, temperature gradient, local solidification time, and dendrite-arm coarsening. These quantities were jointly affected by multiple casting parameters, which explains the significant A–B and A–C interaction terms in the SDAS model. In particular, the strong A–C interaction reflects the combined influence of melt superheat and casting–mold heat extraction on the local solidification time. Therefore, the low-porosity and low-SDAS regions overlapped only partially, indicating that minimizing either response alone would not necessarily provide the most favorable combination of defect suppression and microstructural refinement.

Figure 8 presents the multi-objective optimization results obtained using the desirability-function approach, with porosity and SDAS assigned equal importance and simultaneously minimized. The optimal parameter combination within the investigated design space was a pouring temperature of 1220.74 °C, a mold-filling time of 6.34 s, and a mold temperature of 294.47 °C. The corresponding predicted porosity and SDAS were 0.426% and 47.51 µm, respectively, and the overall desirability was 0.971.

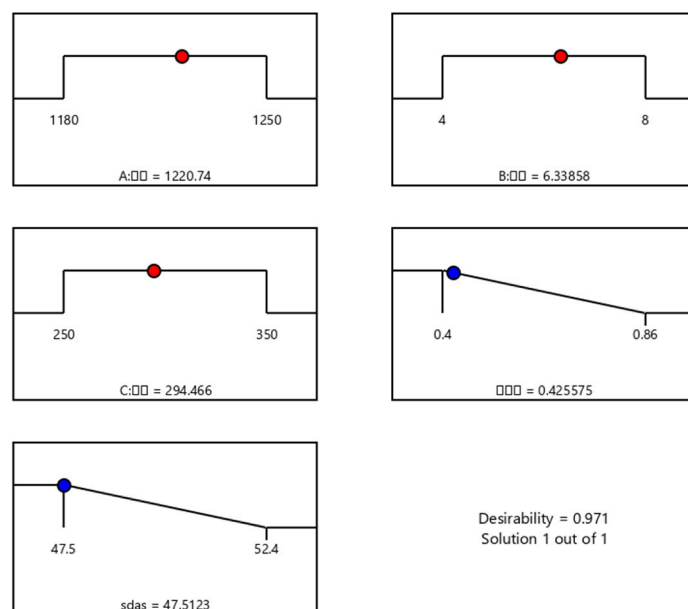


Figure 8. Multi-objective optimization results for porosity and SDAS obtained using the desirability-function approach.

The optimized solution was located close to the center of the Box–Behnken design, and its predicted responses were within the range of the repeated center-point results. The center condition had been selected as a practical reference on the basis of preliminary simulations and casting-process feasibility. Therefore, the proximity of the optimized solution to the center indicates that the favorable process region had been reasonably identified during the preliminary selection. The optimization should thus be interpreted as identifying the best multi-response compromise within the investigated parameter ranges, rather than an isolated condition that was substantially superior to the center point or a global optimum over all possible casting conditions.

For practical process control, nearby implementable set points of 1220 °C, 6.3 s, and 295 °C were selected for the subsequent simulation and casting assessment. Substitution of these practical set points into the regression equations changed the predicted porosity by only 0.0019 percentage points and the predicted SDAS by only 0.0233 µm. These differences were negligible relative to the predicted response values, indicating that implementation at these set points had a negligible influence on the predicted responses.

4. Numerical Confirmation and Experimental Assessment of the Optimized Condition

4.1. Numerical Confirmation Under the Optimized Condition

A supplementary ProCAST simulation was performed using the practical set points derived from the optimized solution to examine the consistency between the response-surface prediction and the original numerical model. The practical process settings were a pouring temperature of 1220 °C, a mold-filling time of 6.3 s, and a mold temperature of

295 °C. Figure 9 presents the simulated distributions of Total Shrinkage Porosity and SDAS under this condition.

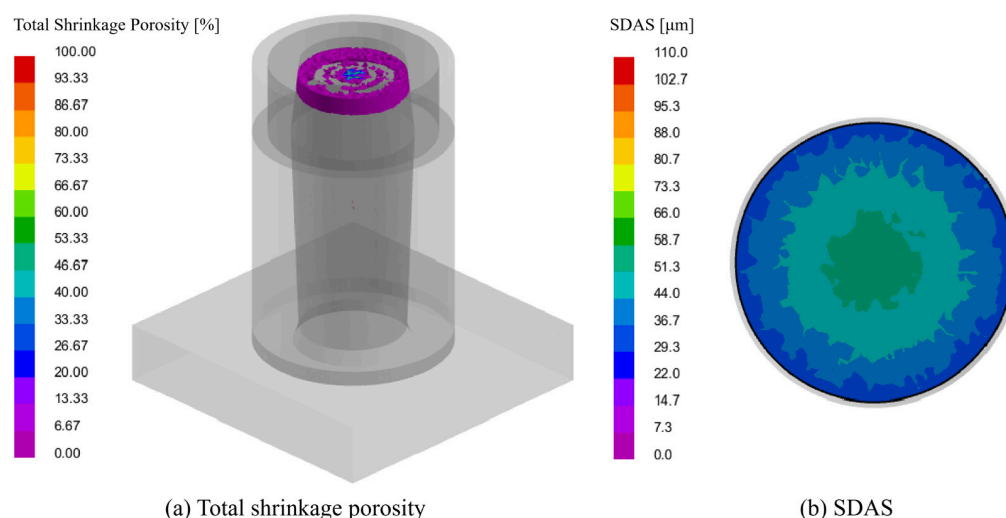


Figure 9. Simulated distributions of total shrinkage porosity and SDAS under the optimized process condition: (a) total shrinkage porosity; (b) SDAS on the mid-height transverse section.

As shown in Figure 9a, the principal shrinkage-related defects were concentrated in the riser, whereas only a limited residual defective zone remained in the ingot body, and no large continuous shrinkage-porosity region was predicted. This distribution indicates that the combined action of the bottom copper cooling structure and the upper insulated riser produced a relatively favorable solidification sequence and feeding condition under the optimized parameters [47].

To quantitatively evaluate the numerical difference, the defective-zone volume and integrated porosity volume in the ingot body were compared between the selected low-level baseline condition and the practically implemented optimized condition using the same extraction domain and cutoff criterion.

As shown in Table 9, the defective-zone volume and integrated porosity volume decreased by 81.79% and 86.78%, respectively, after optimization. The simultaneous reduction in these two metrics indicates that the optimized thermal and feeding conditions reduced both the spatial extent of the region susceptible to shrinkage and the predicted amount of void space within the usable ingot body. From a processing perspective, this improvement is favorable for increasing ingot compactness and providing a sounder starting billet for subsequent deformation processing. However, these reductions are numerical ProCAST metrics used for relative comparison and should not be interpreted as direct experimental measurements of the total casting porosity.

Table 9. Quantitative comparison of shrinkage-related defects in the ingot body under the selected baseline and optimized conditions.

Process Condition	Defective-Zone Volume/cm ³	Integrated Porosity Volume/cm ³
Baseline condition: 1180 °C, 4 s, 250 °C	0.476372	0.006984
Optimized: 1220 °C, 6.3 s, 295 °C	0.086741	0.000923
Reduction/%	81.79	86.78

Figure 9b shows that the predicted SDAS increased gradually from the edge toward the center of the mid-height transverse section. The edge region was adjacent to the permanent mold wall and therefore experienced stronger heat extraction and a shorter local

solidification time, resulting in a smaller SDAS. By contrast, heat dissipation was weaker in the central region, allowing more time for secondary dendrite-arm growth and coarsening and consequently producing a larger SDAS [48].

4.2. Experimental Assessment of Casting Compactness and Local Defects

The bulk compactness of the validation casting was quantitatively assessed using Archimedes' density measurements. Three independent specimens were tested at each of the center, half-radius, and edge positions. The corresponding density-based porosity was calculated using the theoretical density estimated from the normalized Mn, Ni, and Cr contents by the inverse rule of mixtures.

As shown in Table 10, the bulk density increased slightly from $7.411 \pm 0.005 \text{ g}\cdot\text{cm}^{-3}$ at the center to $7.434 \pm 0.003 \text{ g}\cdot\text{cm}^{-3}$ at the edge, while the corresponding density-based porosity decreased from $2.16 \pm 0.07\%$ to $1.86 \pm 0.04\%$. The overall bulk density and density-based porosity obtained from all nine specimens were $7.423 \pm 0.011 \text{ g}\cdot\text{cm}^{-3}$ and $2.00 \pm 0.14\%$, respectively. The slightly higher density toward the edge may be associated with stronger interfacial heat extraction and a reduced tendency for shrinkage-related void formation near the permanent mold wall. The small standard deviations indicate good repeatability of the measurements and relatively limited local variation within each radial position.

Table 10. Bulk density and density-based porosity at different radial positions of the validation casting under the optimized condition.

Radial Position	Bulk Density, $\rho_b/\text{g}\cdot\text{cm}^{-3}$	Density-Based Porosity, $P\varrho/\%$
Center	7.411 ± 0.005	2.16 ± 0.07
Half-radius	7.424 ± 0.004	1.99 ± 0.05
Edge	7.434 ± 0.003	1.86 ± 0.04
Overall	7.423 ± 0.011	2.00 ± 0.14

The density-based porosity should not be considered numerically equivalent to the ProCAST-predicted porosity response. The ProCAST value represents shrinkage porosity predicted by the solidification model within the predefined ingot-body domain, whereas the density-based value is derived from the difference between the measured bulk density and an estimated theoretical density. The latter may also be affected by fine pores, inclusions, surface-connected defects, composition-related density variation, and uncertainty in the theoretical density estimation. Therefore, the Archimedes results were used as an independent assessment of bulk compactness rather than as a strict point-by-point validation of the simulated porosity value. Figure 10 presents the microstructures at the center, half-radius, and edge positions, together with the SEM-EDS analysis of an isolated local defect under the optimized condition.

All three radial positions exhibited continuous dendritic microstructures, and no large-area continuous shrinkage-porosity region was observed in the examined sections. The dendritic morphology became progressively finer toward the edge, consistent with the higher cooling intensity near the mold wall and the radial SDAS distribution predicted in Figure 9b.

SEM observation revealed only isolated small defects in the examined region. The EDS results showed local O enrichment near one defect, suggesting that this feature may be associated with an oxide-containing inclusion or local oxidation around a pore. However, EDS provides only local compositional information and is insufficient by itself to establish the unique formation mechanism of the defect. Accordingly, the EDS result was used only to assist in identifying the nature of the isolated defect and was not regarded as a

quantitative measure of the overall casting porosity or as direct evidence of shrinkage-porosity formation.

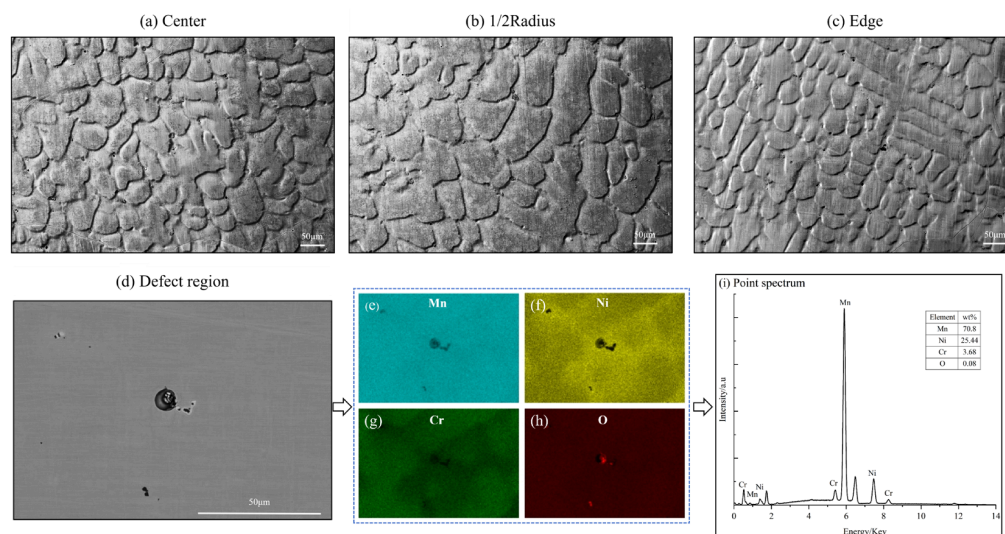


Figure 10. Microstructures at different radial positions and EDS analysis of local defects in the casting under the optimized process conditions: (a) center; (b) half-radius; (c) edge; (d) SEM image of the defect region; (e–h) elemental maps of Mn, Ni, Cr, and O, respectively; (i) EDS point spectrum and corresponding elemental composition.

4.3. Experimental Assessment of SDAS

SDAS was measured from metallographic images at the center, half-radius, and edge positions using the line-intercept method shown in Figure 11b. Three independent fields of view were analyzed at each position, and the mean and standard deviation of the three field-level values were used to represent the local SDAS. The overall measured mean was calculated from all nine field-level values.

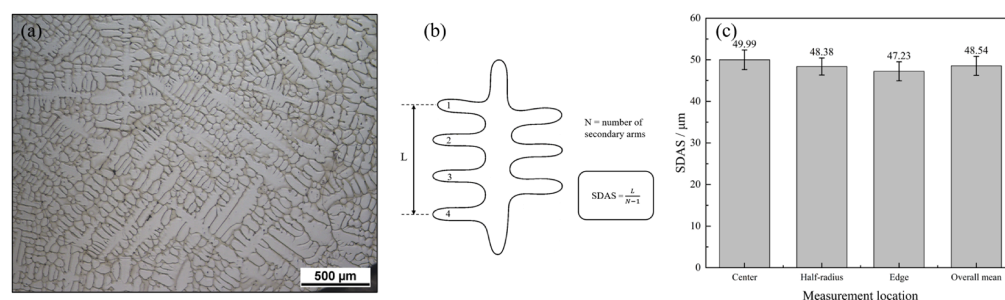


Figure 11. Microstructure and SDAS measurements under the optimized condition: (a) representative dendritic microstructure at the center; (b) schematic illustration of the line-intercept method used for SDAS measurement; (c) mean SDAS values at the center, half-radius, and edge positions, together with the overall mean. Error bars for each radial position represent the standard deviations obtained from three independent fields of view.

The measured mean SDAS values at the center, half-radius, and edge positions were 49.99, 48.38, and 47.23 μm , respectively. The SDAS therefore decreased gradually from the center toward the edge. This radial trend was consistent with the 12-point radial distribution extracted from the ProCAST results and with the spatial distribution shown in Figure 9b. The agreement in the radial trend indicates that the simulation reasonably reproduced the effect of the radial cooling gradient on dendrite-arm coarsening.

The overall measured mean calculated from all nine metallographic fields was 48.54 μm , whereas the response-surface-predicted Y_2 value for the optimized condition

was 47.51 μm . In the response surface model, Y_2 was defined as the arithmetic mean of the SDAS values extracted from 12 equally spaced radial sampling points in ProCAST. The relative deviation between the two values was approximately 2.2%. Because the experimental measurements were obtained from three discrete radial positions, whereas the numerical response was calculated from 12 equally spaced points along a continuous radial path, the two sampling schemes were not spatially identical. Therefore, the comparison was used to assess agreement in the overall SDAS magnitude and radial variation rather than strict point-by-point equivalence.

Taken together, the supplementary simulation predicted that shrinkage-related defects were predominantly transferred to the riser and that the defect volumes in the ingot body were markedly reduced. The Archimedes measurements provided a quantitative assessment of bulk compactness, while the metallographic and SEM observations showed no large continuous shrinkage-porosity region in the examined sections. The measured SDAS exhibited the same radial trend as the ProCAST prediction, and its overall mean differed from the response-surface prediction by approximately 2.2%. These results support the practical applicability of the optimized condition within the investigated process range.

Nevertheless, the response surface models were established using simulation-generated data, and only the optimized condition was experimentally examined. Therefore, the present results should be interpreted as numerical confirmation and experimental assessment of the selected optimized condition, rather than as comprehensive experimental validation of the regression models throughout the entire design space. Accordingly, the regression models are intended primarily for interpolation, factor-effect analysis, and parameter optimization within the investigated ranges of 1180–1250 $^{\circ}\text{C}$ for pouring temperature, 4–8 s for mold-filling time, and 250–350 $^{\circ}\text{C}$ for mold temperature; predictions outside these ranges would constitute extrapolation and require additional independent validation. The resulting models and optimized parameters are specific to the present Mn70Ni25Cr5 alloy composition and mold configuration, and system-specific validation is required before extrapolation to other casting systems.

5. Conclusions

In this study, ProCAST simulation combined with Box–Behnken response surface methodology was used to optimize the casting parameters of the Mn70Ni25Cr5 alloy. The main conclusions are as follows:

- (1) Within the investigated parameter ranges, porosity was governed mainly by the linear and quadratic effects of the casting parameters, whereas SDAS was more sensitive to parameter interactions, particularly the interaction between pouring temperature and mold temperature.
- (2) The optimal parameters were a pouring temperature of 1220.74 $^{\circ}\text{C}$, a mold-filling time of 6.34 s, and a mold temperature of 294.47 $^{\circ}\text{C}$, corresponding to predicted porosity and SDAS values of 0.426% and 47.51 μm , respectively. For practical implementation, nearby set points of 1220 $^{\circ}\text{C}$, 6.3 s, and 295 $^{\circ}\text{C}$ were adopted, and their influence on the predicted responses was negligible.
- (3) Relative to the selected baseline condition, the simulated defective-zone volume and integrated porosity volume in the ingot body decreased by 81.79% and 86.78%, respectively, indicating a marked reduction in both the spatial extent and integrated amount of predicted shrinkage-related defects in the usable ingot body. The principal defects were concentrated in the riser, while the validation casting exhibited an overall bulk density of $7.423 \pm 0.011 \text{ g}\cdot\text{cm}^{-3}$ and no large continuous shrinkage-porosity region in the examined sections.

- (4) The measured SDAS values at the center, half-radius, and edge positions were 49.99, 48.38, and 47.23 μm , respectively. The overall mean was 48.54 μm , differing from the response-surface prediction by approximately 2.2%, and the measured radial variation agreed with the ProCAST-predicted distribution.

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