COMPUTER SIMULATION USE IN SAND CASTING PROCESS OPTIMISATION

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Abstract:

The main aim of this paper was to determine the optimal design of a sand mould using computer simulation and statistical optimisation techniques. Simulations of the sand-casting process were performed using NovaFlow&Solid software. The geometry of the mould and the type of sand used were varied according to the Taguchi L18 design of experiments. Output variables used to assess process quality and efficiency were total casting time, volume shrinkage, and melt efficiency. Taguchi-based grey relational analysis was used to identify the optimal process parameters. The combination of input parameters represents the optimal solution for process simulation resulting in minimal total casting time, minimal volume shrinkage and maximum melt efficiency. The proposed methodology provides an effective framework for simplifying the casting process and enhancing the reliability of gravity-cast components.

1 Introduction

The casting process involves introducing molten material into a mould cavity, where, after solidification, the material takes the shape of the cavity. Although this sounds straightforward, casting is not as simple as it appears. During solidification, many properties of the casting are established. Depending on the casting procedure, numerous process parameters affect the quality of the casting. Pouring temperature, mould temperature, melt velocity, and mould geometry are just a few examples. Small variations in these parameters can have unexpected consequences for the final casting outcome, so it is necessary to carry out multi-criteria optimisation of the process parameters. The aim is to produce a quality casting with the best possible process productivity.

The requirement is to produce a high-quality casting while also achieving the lowest possible cost. If the pouring temperature is reduced, there is a risk that the casting will solidify improperly or that the mould will not be completely filled. Increasing the melt velocity in the ingate system and the mould introduces the risk of melt turbulence and air entrapment, which can result in porosity. As casting processes consume significant amounts of energy and materials and are also environmentally demanding, various casting simulation software is increasingly being used. Software such as NovaFlow&Solid enables simulation of mould cavity filling, casting cooling and solidification, air entrapment within the casting, volume shrinkage, and related phenomena.

A systematic overview of the various methods for optimisation and casting simulation currently used in industry was provided by Bhatt et al. [1]. He et al. [2] optimised the process parameters in low-pressure die casting of aluminium wheels using numerical simulation, response surface methodology (RSM), and a genetic algorithm (NSGA-II). The casting parameters (casting temperature, mould temperature, holding pressure, holding time) and their influence on the occurrence of defects in the casting microstructure were studied. The optimal parameters were a casting temperature of 703 °C, a mould temperature of 409 °C, a holding pressure of 1086 kPa, and a holding time of 249 s. Altinbalik and Yuksel [3] simulated high-pressure die casting in NovaFlow&Solid and examined the influence of mould design and speed in the second phase of the HPDC

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process on the occurrence of porosity. They confirmed the simulation results experimentally using the optimal input parameters obtained. Dojka et al. [4] used NovaFlow&Solid and MagmaSoft to simulate bottom-up filling of the mould to avoid turbulence and used filters to minimise casting defects. Zheng et al. [5] optimised a mould for casting a complex, thin-walled water meter. They used SOLIDWORKS for 3D modelling and PROCAST for casting simulation. They tested three different mould designs: without a riser, with a preliminary riser, and with an optimised riser. The optimised mould significantly improved casting performance at critical locations. Finally, the simulation results were experimentally confirmed. Šabik et al. [6] analysed and optimised a gating system to reduce defects and the total mass of metal. Casting and solidification simulations were performed in NovaFlow&Solid. Shahana et al. [7] presented a generic method for casting process simulation and optimisation. By combining machine learning and three-dimensional simulation of low-pressure die casting, they observed the heat transfer and solidification processes.

In the foundry industry, casting very thin components is a major challenge, and Zhang et al. [8] contributed to this by applying artificial neural networks (ANN) and genetic algorithm (GA) in multi-objective optimisation. They determined the optimal process parameters such as pouring temperature, mould temperature, and exerting pressure velocity, while simultaneously minimising shrinkage, porosity, distortion, and thermal cracks.

Vergnano et al. [9] investigated the influence of casting parameters on the occurrence of porosity in castings made from recycled aluminium alloy. They used a design of simulated experiments (DOSE) and genetic algorithms for optimisation. The noise factor was the chemical composition, which is critical in aluminium recycling. Simulations were conducted using the Magmasoft programme. The results showed that chromium has the greatest impact on reducing porosity, followed by iron. Khan and Sheik [10] presented, in their review paper, a simulation-based methodology for mould design through several studies. They summarised their results in the following main aspects: filling, solidification, and quality and stress analysis of the castings. Bhatt et al. [11] used online web resource simulations. They optimised the number and shape of the riser to produce castings with as low thermal shrinkage as possible and to improve melt efficiency. Sun et al. [12] simulated the mould filling and solidification of a truck rear axle housing casting made of ductile iron in ZCast. They observed the influence of temperature and melt flow on casting defects. Through improvements, they achieved directional solidification of the casting, from the centre to the edges. The results of casting simulations can provide a useful basis for studying the mechanical properties of castings. Hardin and Beckermann [13] used the results of a casting simulation in Magmasoft to investigate the mechanical properties of a casting. The porosity distribution was an important aspect of their research. They continued their research [14], predicting the fatigue life of castings with porosity. They demonstrated that the presence and size of porosity have a significant influence on service life.

As the fabrication of sand moulds is an essential part of the casting process, the review paper by Kumar Sahoo et al. [15] is particularly noteworthy. This article reviews research on the usability of locally available silica sands and clays for mould making for ferrous and non-ferrous alloys. The paper discusses the role of various additives in the sand mould composition and the effects of various trace elements on the mechanical properties and microstructure of sand castings. In the study by Papanikolaou et al. [16], CFD (Computational Fluid Dynamics) simulations were used to confirm Campbell's [17] conclusions regarding the running and gating system for improving casting quality. The simulations also included a filter location to reduce air entrainment, which was significantly decreased but not eliminated. In the research by Chen et al. [18], the optimisation of riser diameter, pouring temperature, melt velocity, and ingate system geometry was presented. Multi-criteria optimisation using the culture-based quantum-behaved particle swarm optimisation (CBQPSO) algorithm aimed to minimise filling time, solidification time, and oxide ratio. Compared to the initial model, reductions of 68.14% in filling time, 50.56% in solidification time, and 20.20% in oxide ratio were achieved.

A review of the literature demonstrates the significant benefits of computer simulations in the casting process, aimed at determining the appropriate parameters for mould construction, melt chemical composition, and process parameters. The purpose of this work is to optimise gravity casting in a sand mould through virtual experiments, specifically computer simulations. Casting simulations will be conducted using the NovaFlow&Solid programme, and multi-objective optimisation will be applied to optimise the mould design and sand type to achieve the highest quality casting.

2 Experimental investigation

Sand casting is the most commonly used process and accounts for a significant majority of the total volume of cast products [19]. This process is one of the few that allows casting of almost all alloys, especially those with a very high melting point. It is flexible, as it enables casting of both small and very large components in terms of mass and dimensions.

To obtain experimental data for further statistical analysis, the aforementioned virtual experiments will be conducted in the NovaFlow&Solid programme, simulating the sand-casting process. The casting of the bearing bracket, the sketch of which is given in Figure 1, was simulated.

The flow chart of experimentation and optimisation is given in Figure 2.

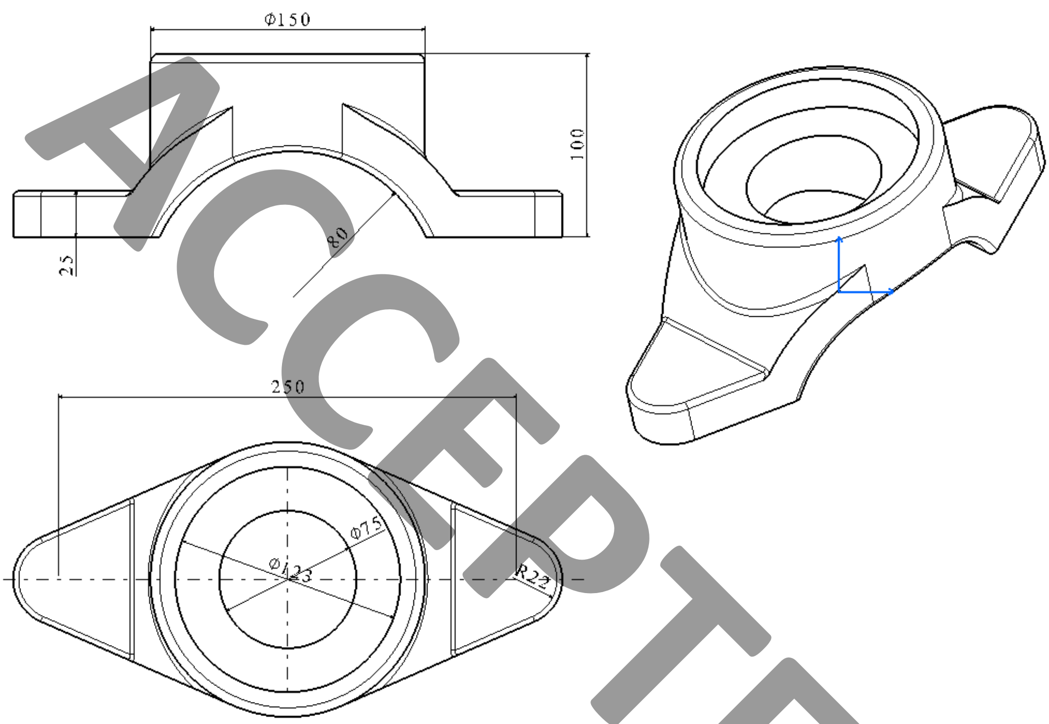

Figure 1. Casting sketch and 3D model

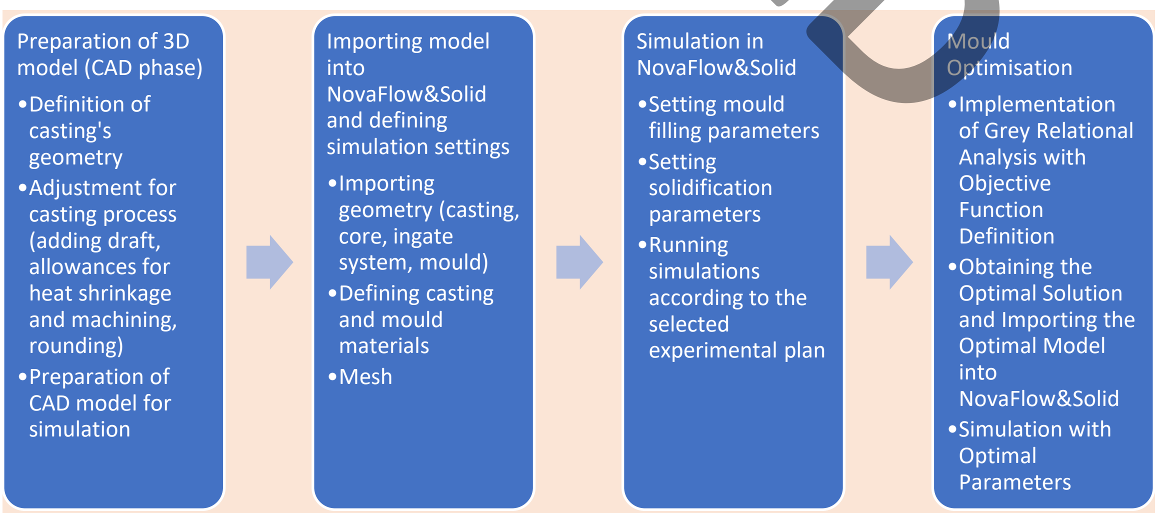

Figure 2. Casting process optimisation workflow

First, a CAD model of the castings, shown in Figure 3, was created according to the technical requirements, and the ingate system was designed based on empirical data and previous simulations. CAD models were designed and assembled in CATIA V5, and prepared for import into the NovaFlow&Solid programme. Two castings will be produced simultaneously. The castings will be made of aluminium alloy EN AC 42100. The alloy has good castability due to its silicon content (about 7%), while the addition of magnesium provides good mechanical properties. This alloy is prone to porosity due to shrinkage during solidification, which poses a challenge for the correct selection of casting parameters [20].

Virtual experiments were conducted according to the Taguchi experimental design, with an orthogonal array labelled L18 selected. This design allows testing of one variable at two levels and seven variables at three levels. As input parameters, that is, independent variables, the geometric characteristics of the mould and the type of sand used to make the mould were selected.

Preliminary simulations indicated the necessity of using a riser due to the occurrence of hot spots. The geometric characteristics affecting casting quality were the dimensions of the sprue, runner, and riser.

Two types of sand will be used in the simulations: silica and zircon. Silica sand is the most commonly used sand for making moulds. A disadvantage of silica sand is its allotropic modification (from 560 °C to 580 °C), which causes an increase in volume. Zircon is not widely used in mould making due to its price and availability, but it is characterised by very high refractoriness, a low coefficient of thermal expansion, and a low ability to absorb the melt ("wetting").

Table 1 presents the input variables with their values and possible levels according to the L18 experimental design. According to the experimental plan, 18 models were created in CATIA for simulation in the NovaFlow&Solid software package. Simulation time savings result from the programme's ability to automatically adjust the model mesh depending on the model geometry. Where the profiles are thick-walled, a higher mesh resolution is used, and for sensitive areas, a finer mesh is applied. In version 6.5 of the NovaFlow&Solid programme (released in April 2021), an irregular mesh in the mould has been implemented, which further reduces the calculation time for solidification [21].

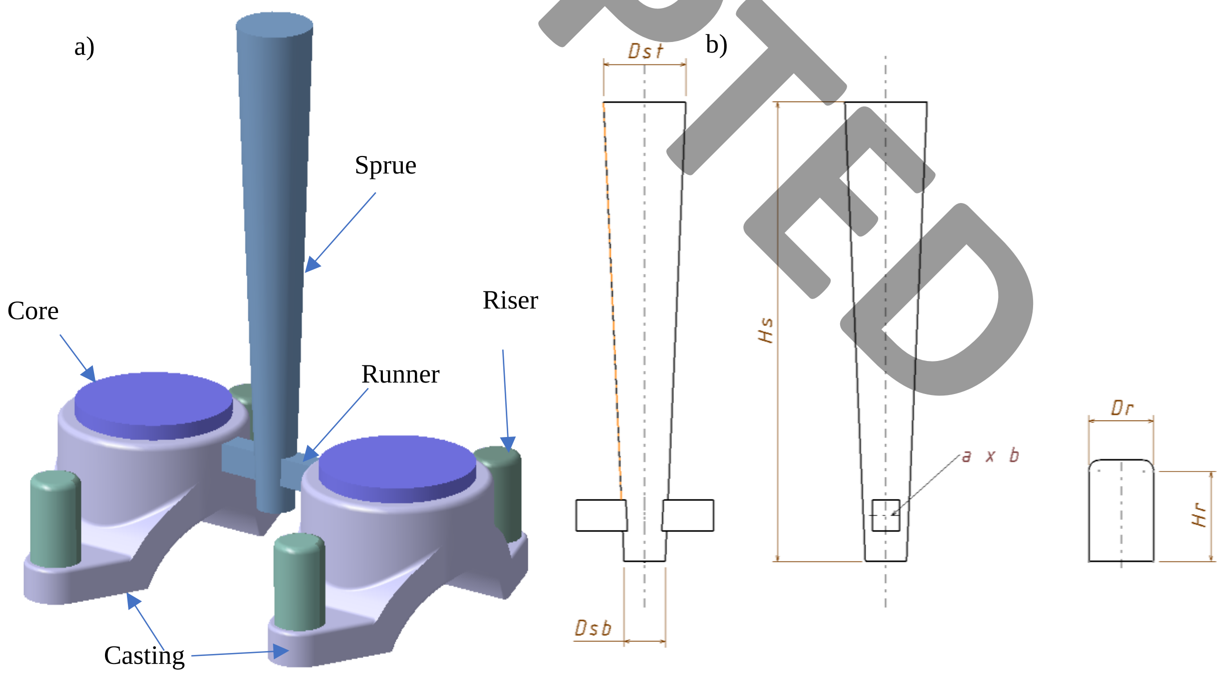

Figure 3. a) CAD model of the two casting and ingate system b) Sketch of the sprue, runner, and riser

Table 1. Experimental factors and their levels.

Level of exp. run	Type of sand	Sprue diameter (top) D_{st} [mm]	Sprue diameter (bottom) D_{sb} [mm]	Sprue height H_s [mm]	Runner dimension a x b [mm²]	Riser diameter D_r [mm]	Riser height H_r [mm]
	A	B	C	D	E	F	G
1	Silica sand	60	30	200	20 × 20	30	50
2	Zircon sand	75	40	250	25 × 20	40	60
3	–	90	50	300	30 × 20	50	70

Casting quality and productivity were assessed using parameters such as total casting time, volume shrinkage (both obtained from the simulation report), and calculated melt efficiency.

Total casting time comprises mould filling and solidification times, and depends on factors such as casting wall thickness, casting weight, alloy type, mould geometry, and mould preheating temperature.

During solidification, the alloy transforms from a liquid to a solid state, resulting in a reduction in volume, or volumetric shrinkage, due to the difference in density between the liquid and solid phases. The riser system must compensate for this volumetric shrinkage during solidification.

Melt efficiency is calculated as the ratio of the mass of the casting to the total mass of the molten metal (see equation 1). The total mass of molten metal includes, in addition to the casting, the metal retained in the gating system, runners, risers, and any mould additions. A more complex gating system is required for castings with intricate geometries, particularly those with varying wall thicknesses. Higher melt efficiency leads to lower production costs.

$$\eta = \frac{m_c}{\Sigma m} \tag{1}$$

Experimental runs and results are presented in Table 2.

Table 2. Experimental layout using L18 orthogonal array and performance results

Input parameters								Responses		
Runs	A	B	C	D	F	G	H	Total casting time (s)	Volumetric shrinkage (%)	Melt efficiency
1	Silica	60	40	250	25 x 20	40	60	606	6.153	0.82
2	Silica	75	50	300	20 x 20	40	60	406	4.751	0.83
3	Silica	90	40	300	20 x 20	50	50	1088	6.16	0.68
4	Zircon	60	40	200	30 x 20	50	60	383	6.145	0.80
5	Zircon	75	40	300	25 x 20	30	70	572	6.147	0.77
6	Silica	60	50	300	30 x 20	50	70	731	6.118	0.71
7	Zircon	60	30	300	25 x 20	40	50	367	6.26	0.84
8	Silica	60	30	200	20 x 20	30	50	500	6.23	0.93
9	Silica	75	30	200	25 x 20	50	70	664	6.317	0.77
10	Silica	90	30	250	30 x 20	40	70	938	6.151	0.74
11	Zircon	60	50	250	20 x 20	30	70	472	6.011	0.83
12	Zircon	75	50	200	30 x 20	40	50	566	6.019	0.80
13	Zircon	90	40	200	20 x 20	40	70	636	6.043	0.76
14	Silica	75	40	250	30 x 20	30	50	799	6.071	0.82
15	Silica	90	50	200	25 x 20	30	60	996	6.023	0.78
16	Zircon	75	30	250	20 x 20	50	60	482	6.25	0.76
17	Zircon	90	50	250	25 x 20	50	50	746	6.031	0.69

18	Zircon	90	30	300	30 x 20	30	60	686	6.204	0.75

3 Results and discussion

3.1 Grey relational analysis

Grey relational analysis (GRA) was applied due to its ability to optimise multiple criteria simultaneously, unlike the Taguchi method. In this case, the criteria are minimum total time, minimum volumetric shrinkage, and maximum melt efficiency. The first step in GRA is to normalise the experimentally obtained output values between zero and one, allowing for their mutual comparison. Normalisation, or pre-processing, is performed according to the output size characteristic. In this study, the normalised value of the original sequence for total casting time and volumetric shrinkage, which are "less is better" performance characteristics, can be expressed as:

$$x_{ij} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \tag{2}$$

where y_{ij} are the original data.

The larger-the-better performance characteristic for melt efficiency can be expressed as:

$$x_{ij} = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \tag{3}$$

The next step is to determine the reference sequence xi_j. Simulation performance i is considered the reference for response j if the value of the grey relation x_{ij} is equal to 1 or closer to 1 than the value for any other simulation. Table 3 shows the normalised simulation results and deviation sequences.

Table 3. Normalised simulation results and deviation sequences

Runs	Normalised results			Deviation sequences		
	Total casting time (s)	Volumetric shrinkage (%)	Melt efficiency	Total casting time (s)	Volumetric shrinkage (%)	Melt efficiency
1	0.6685	0.1346	0.5845	0.331	0.865	0.415
2	0.9459	1	0.5980	0.054	0.000	0.402
3	0	0.1302	0	1.000	0.870	1.000
4	0.9778	0.1395	0.4981	0.022	0.860	0.502
5	0.7157	0.1383	0.3706	0.284	0.862	0.629
6	0.4951	0.1562	0.1338	0.505	0.844	0.866
7	1	0.0685	0.6446	0.000	0.931	0.355
8	0.8155	0	1	0.184	1.000	0.000
9	0.5881	0.0333	0.3589	0.412	0.967	0.641
10	0.2080	0.1358	0.2509	0.792	0.864	0.749
11	0.8544	0.2222	0.5980	0.146	0.778	0.402
12	0.7240	0.2173	0.5032	0.276	0.783	0.497
13	0.6269	0.2025	0.3293	0.373	0.798	0.671
14	0.4008	0.1852	0.5655	0.599	0.815	0.435
15	0.1276	0.2148	0.4183	0.872	0.785	0.582
16	0.8405	0.0747	0.3272	0.160	0.925	0.673
17	0.4743	0.2099	0.0422	0.526	0.790	0.958
18	0.5576	0.1031	0.2755	0.442	0.897	0.724

Next, the grey relational coefficient is used to determine how close x_{ij} is to x_{0j}. The larger the grey relational coefficient, the closer x_{ij} is to x_{0j}. The grey relational coefficient can be determined as follows:

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{ij} + \xi\Delta_{max}} \quad for\ i = 1,2,\ldots,m \ \ and\ j = 1,2,\ldots,n \tag{4}$$

where
$\gamma(x_{0j}, x_{ij})$ is the grey relational coefficient between x_{ij} and x_{0j}.

$$\Delta_{ij} = |x_{0j} - x_{ij}|, \tag{5}$$

$$\Delta_{min} = min\{\Delta_{ij}, i = 1,2,\ldots,m; j = 1,2,\ldots,n\} \tag{6}$$

$$\Delta_{max} = max\{\Delta_{ij}, i = 1,2,\ldots,m; j = 1,2,\ldots,n\} \tag{7}$$

ξ is the distinguishing coefficient, $\xi \in (0,1]$.

In this paper, the value of the coefficient ξ adopted is 0.5.

The grey relational grade (GRG) is calculated as a weighted sum of the grey relational coefficients and is given by:

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(x_{0j}, x_{ij}) \ \text{ for } \ i = 1, 2, \ldots, m \tag{8}$$

where $\sum_{j=1}^{n} w_{jj} = 1$, $\Gamma(X_0, X_i)$ is the grey relational grade between the comparability sequence X_i and the reference sequence X_0. The weight of response *j* is *wj* and usually depends on the judgement of decision makers.

The grey relational grade (GRG) is calculated as the weighted sum of the grey relational coefficients. The experiment with the highest GRG is considered the best, as its sequence is closest to the ideal. Virtual experiment number 8 (marked in grey) has the highest grade and is therefore considered the best among the 18 experiments performed. This parameter combination represents the nearest optimum: type of sand silica (level 1), sprue diameter (top) 60 mm (level 1), sprue diameter (bottom) 30 mm (level 1), sprue height 200 mm (level 1), runner dimension 20 mm × 20 mm (level 1), riser diameter 30 mm (level 1) and riser height 50 mm (level 1). Table 4 presents the grey relational coefficients and grades for all simulations.

Table 4. Grey relational coefficients and grey relational grades

Runs	Total casting time (s)	Volumetric shrinkage (%)	Melt efficiency	Grade	Gray order
1	0.6013	0.3662	0.5462	0.5269	6
2	0.9024	1.0000	0.5543	0.7649	2
3	0.3333	0.3650	0.3333	0.3413	18
4	0.9575	0.3675	0.4991	0.5913	4
5	0.6375	0.3672	0.4427	0.4805	10
6	0.4976	0.3721	0.3660	0.4032	15
7	1.0000	0.3493	0.5845	0.6423	3
8	0.7305	0.3333	1.0000	0.7660	1
9	0.5483	0.3409	0.4382	0.4491	12
10	0.3870	0.3665	0.4003	0.3939	16
11	0.7744	0.3913	0.5543	0.5808	5
12	0.6443	0.3898	0.5016	0.5200	7
13	0.5727	0.3853	0.4271	0.4601	11
14	0.4549	0.3803	0.5350	0.4880	9
15	0.3643	0.3890	0.4622	0.4284	14
16	0.7581	0.3508	0.4263	0.4974	8
17	0.4875	0.3876	0.3430	0.3911	17
18	0.5305	0.3579	0.4083	0.4322	13

The optimal combination of input parameters is determined by calculating the mean values of the grey relation grade for all input parameter levels , as shown in Table 5. A higher grey relation grade indicates better multiple performance characteristics. Therefore, the optimal values of the controlled parameters are as follows: zircon sand type (level 2), sprue diameter (top) 60 mm (level 1), sprue diameter (bottom) 30 mm (level 1), sprue height 200 mm (level 1), runner dimension 20 mm × 20 mm (level 1), riser diameter 40 mm (level 2) and riser height 60 mm (level 2).

Table 5. Response table for grey relational grade

Parameter	Level 1	Level 2	Level 3	Rank (max/min)
Type of sand	0.5069	**0.5106**		7 (0.0038)
D_{st}	**0.5851**	0.4571	0.4078	1 (0.1772)
D_{sb}	**0.5301**	0.4814	0.5147	6 (0.0488)
H_s	**0.5358**	0.4797	0.4995	5 (0.0561)
a x b	**0.5684**	0.4864	0.4714	2 (0.0970)
D_r	0.5293	**0.5514**	0.4714	3 (0.0799)
H_r	0.5248	**0.5402**	0.4613	4 (0.0789)
Total mean value of the GRG = 0.5057				

3.2 Analysis of variance

Analysis of variance (ANOVA) was used to determine how input parameters affect process performance. This was achieved by calculating the percentage contribution of the sum of squares for each process parameter to the total sum of squares of deviation. The sum of squared deviations for the factor under consideration is denoted by SS, the total sum of squared deviations by SS_T, and the percentage contribution P is calculated as the ratio of these two values. Table 6 provides a summary of the ANOVA, showing the percentage contribution of input variables to process performance. The results indicate that the percentage contributions of the diametar of the sprue (top), riser diameter, and riser height are significant at 40%, 15% and 8%, respectively, for the multiple performance characteristic.

Table 6. Response table for grey relational grade

Parameter	SS	Percentage contribution %
Type of sand	0,00006	0
D_{st}	0,09968	40
D_{sb}	0,00746	3
H_s	0,00948	4
a x b	0,00189	1
D_r	0,03737	15
H_r	0,02100	8
Error	0,0709	
Total	0,247	

After each virtual experiment or simulation, it is possible to generate an AutoReport in the NovaFlow&Solid programme, which contains a wealth of useful information as well as graphical representations of the behaviour of the molten metal during and after solidification. Below are images for three simulations: a randomly selected one (experiment number 15; Figure 4 and Figure 5), the best among the avaliable combinations (experiment number 8, Figure 6), and the one obtained with optimal input parameters (Figure 7). Figure 5 shows the solidification of the casting, or the proportion of the liquid phase. It is evident that the gating system is the last to solidify, which indicates correct mould construction.

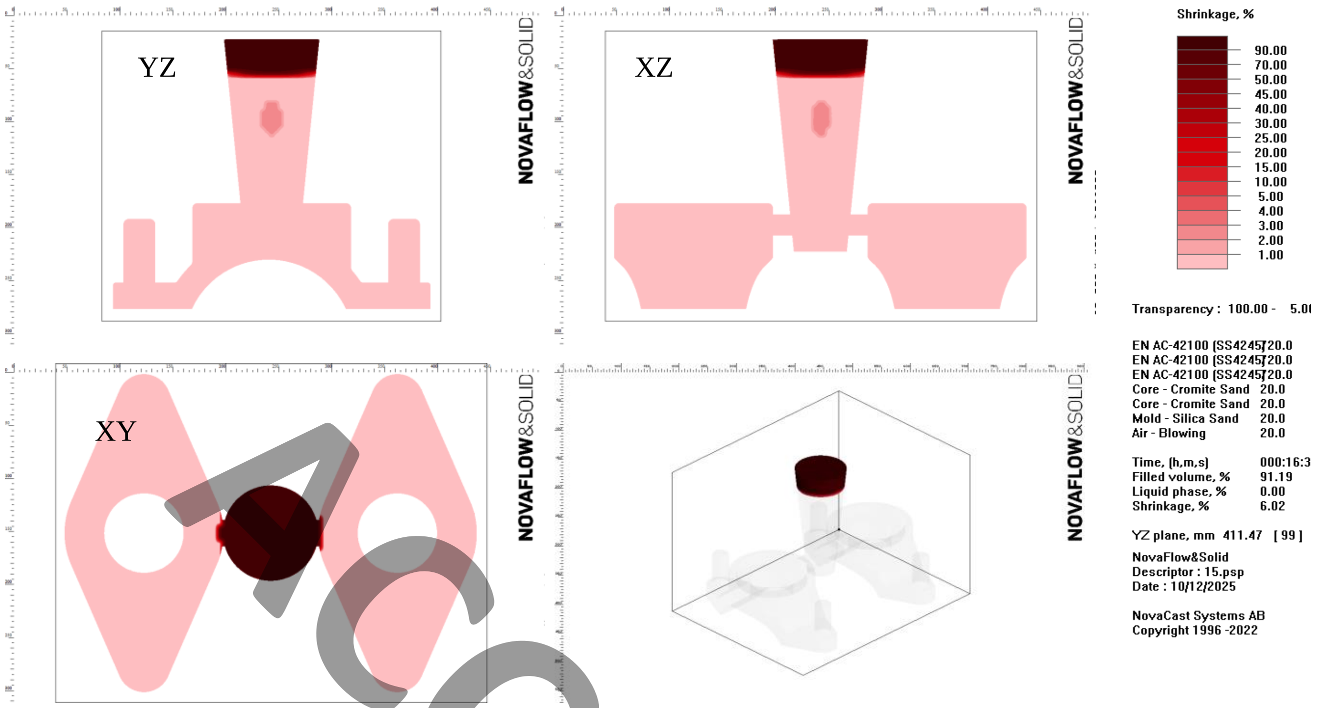

Figure 4. Shrinkage prediction after solidification is completed, run nr.15

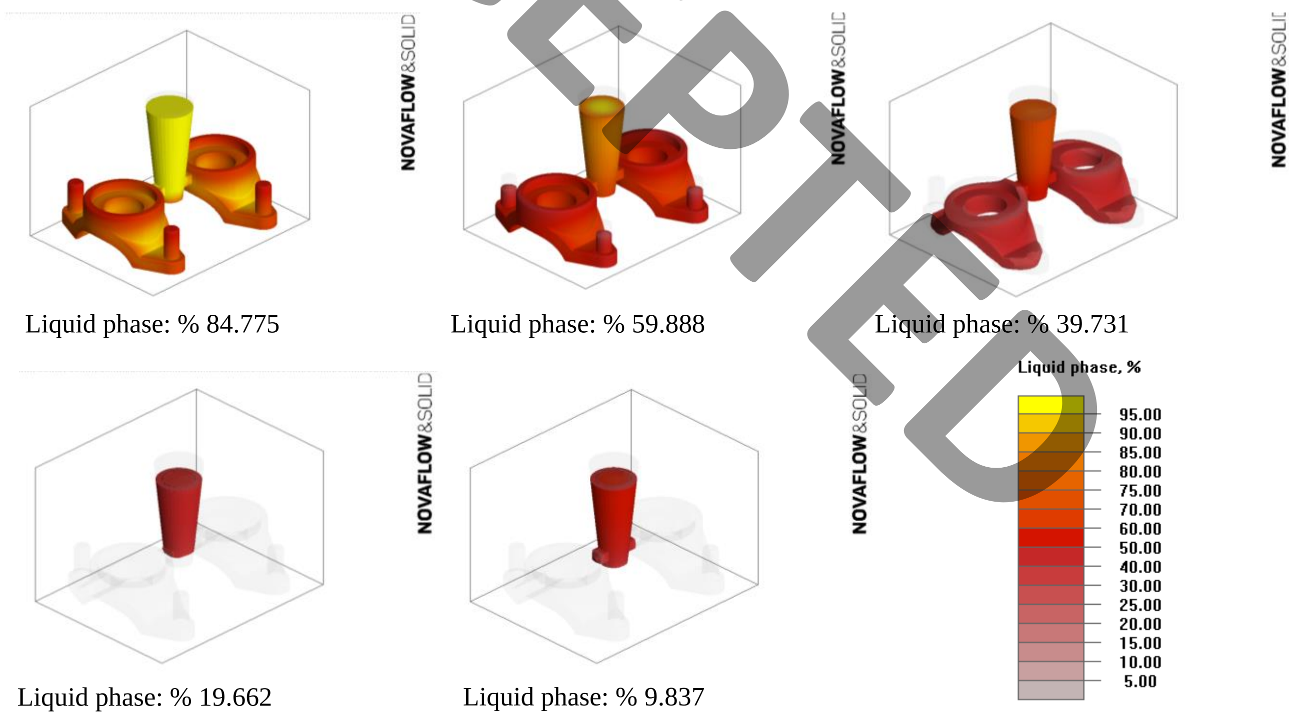

Figure 5. Solidification of castings, run nr. 15

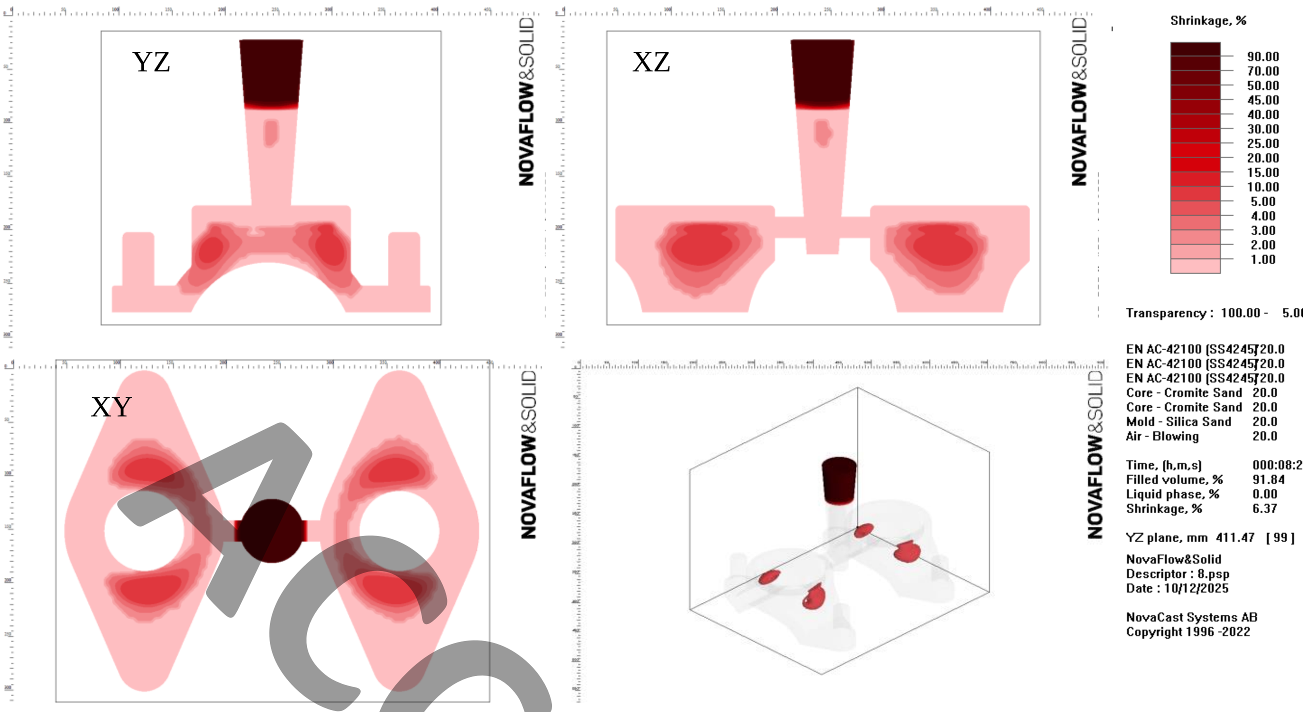

Figure 6. Shrinkage prediction after solidification is completed, run nr.8

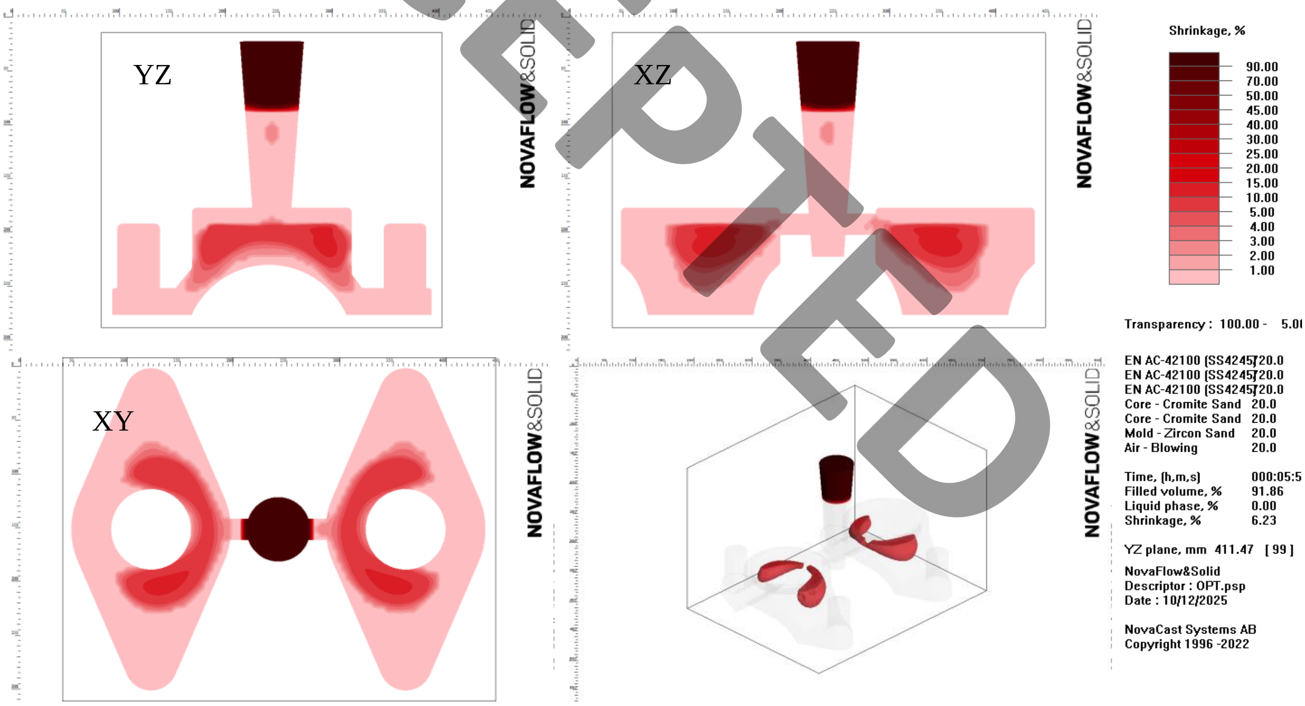

Figure 7. Shrinkage prediction after solidification is completed, optimum parameters

4 Conclusion

This paper describes the effects of individual parameters on the sand-casting process and the final product quality. By carefully selecting these parameters, it is possible to avoid casting defects, such as porosity, bubbles, volume shrinkage and hot cracks which negatively affect the mechanical properties of the casting and, in most cases result in higher costs for the manufacturer. In this paper, the parameters controlling the process are the geometric characteristics of the mould (sprue, runner, and riser dimensions) and the type of sand used to make the mould.

In the NovaFlow&Solid programme, experiments were simulated according to the Taguchi experimental design, and grey relational analysis was used to optimise several criteria simultaneously.

The objective was to identify parameters that would ensure minimal volume shrinkage, minimal total casting time, and maximum melt efficiency.

After optimisation, the following parameters were obtained: zircon sand type, sprue diameter (top) 60 mm, sprue diameter (bottom) 30 mm, sprue height 200 mm, runner dimension 20 mm x 20 mm, riser diameter 40 mm and riser height 60 mm, or a combination of input parameters according to the levels A2B1C1D1E1F2G2. This combination of input parameters resulted in material shrinkage of 6.23%, and a total casting time of 357 minutes. After identifying the optimal combination, it was necessary to determine the extent to which the parameters affect the performance characteristic mentioned above. Using ANOVA, it was concluded that the sprue diameter at the top has the greatest influence, followed by the diameter and height of the runner.

Future work is to verify the results of sand casting in reality.

This study has demonstrated the value of simulations and optimisation of input parameters, when multiple criteria must be met.

References

[1] J. Bhatt, D. Vyas, A. Rajput, M. Somasundaram, and U. Narendra Kumar, ‘A systematic review on methods of optimizing riser and gating system based on energy Nexus approach’, Nov. 01, 2021, Elsevier Ltd. doi: 10.1016/j.nexus.2021.100002.

[2] Y. He, D. Lu, Z. Li, and D. Lu, ‘Multi-Objective Optimization of The Low-Pressure Casting of Large-Size Aluminum Alloy Wheels through a Systematic Optimization Idea’, Materials, vol. 16, no. 18, Sep. 2023, doi: 10.3390/ma16186223.

[3] M. T. Altınbalık and F. A. Yüksel, ‘Theoretical and Experimental Investigation of the Effect of Design Criteria on Porosity in HPDC of AlSi9Cu3(Fe) Alloy’, Trakya University Journal of Engineering Sciences, vol. 23, no. 1, pp. 25–36, 2022, [Online]. Available: http://dergipark.gov.tr/tujes

[4] R. Dojka, J. Jezierski, and J. Campbell, ‘Optimized Gating System for Steel Castings’, J Mater Eng Perform, vol. 27, no. 10, pp. 5152–5163, Oct. 2018, doi: 10.1007/s11665-018-3497-1.

[5] K. Zheng, Y. Lin, W. Chen, and L. Liu, ‘Numerical simulation and optimization of casting process of copper alloy water-meter shell’, Advances in Mechanical Engineering, vol. 12, no. 5, May 2020, doi: 10.1177/1687814020923450.

[6] V. Šabík, P. Futáš, and A. Pribulová, ‘Failure analysis of a clutch wheel for wind turbines with the use of casting process simulation’, Eng Fail Anal, vol. 135, May 2022, doi: 10.1016/j.engfailanal.2022.106159.

[7] S. Shahane, N. Aluru, P. Ferreira, S. G. Kapoor, and S. P. Vanka, ‘Optimization of solidification in die casting using numerical simulations and machine learning’, J Manuf Process, vol. 51, pp. 130–141, Mar. 2020, doi: 10.1016/j.jmapro.2020.01.016.

[8] L. Zhang, L. Li, S. Wang, and B. Zhu, ‘Optimization of LPDC process parameters using the combination of artificial neural network and genetic algorithm method’, J Mater Eng Perform, vol. 21, no. 4, pp. 492–499, Apr. 2012, doi: 10.1007/s11665-011-9933-0.

[9] A. Vergnano, H. Rezvanpour, M. Spessotto, and F. Leali, ‘Robustness Assessment in the Optimization of Low-Pressure Die Casting Subject to Variations in Secondary Alloy Composition’, International Journal of Metalcasting, vol. 19, no. 5, pp. 2864–2880, Sep. 2025, doi: 10.1007/s40962-024-01504-4.

[10] M. A. A. Khan and A. K. Sheikh, ‘Simulation-based mould design, life prediction and reliability assessment of a valve body’, International Journal of Simulation Modelling, vol. 20, no. 2, pp. 219–230, Jun. 2021, doi: 10.2507/IJSIMM20-2-543.

[11] H. Bhatt, R. Barot, K. Bhatt, H. Beravala, and J. Shah, ‘Design Optimization of Feeding System and Solidification Simulation for Cast Iron’, Procedia Technology, vol. 14, pp. 357–364, 2014, doi: 10.1016/j.protcy.2014.08.046.

[12] Y. Sun, J. Luo, G. F. Mi, and X. Lin, ‘Numerical simulation and defect elimination in the casting of truck rear axle using a nodular cast iron’, Mater Des, vol. 32, no. 3, pp. 1623–1629, Mar. 2011, doi: 10.1016/j.matdes.2010.11.009.

[13] R. A. Hardin and C. Beckermann, ‘Integrated design of castings: Effect of porosity on mechanical performance’, in IOP Conference Series: Materials Science and Engineering, 2012. doi: 10.1088/1757-899X/33/1/012069.

[14] R. A. Hardin and C. Beckermann, 'Prediction of the fatigue life of cast steel containing shrinkage porosity', Metall Mater Trans A Phys Metall Mater Sci, vol. 40, no. 3, pp. 581–597, 2009, doi: 10.1007/s11661-008-9755-3.
[15] P. K. Sahoo, S. Pattnaik, and M. K. Sutar, 'A State-of-the-Art Review on Manufacturing and Additive Influences on Sand-Cast Components', Dec. 01, 2019, Springer Verlag. doi: 10.1007/s13369-019-04139-4.
[16] M. Papanikolaou, E. Pagone, M. Jolly, and K. Salonitis, 'Numerical simulation and evaluation of campbell running and gating systems', Metals (Basel), vol. 10, no. 1, Jan. 2020, doi: 10.3390/met10010068.
[17] J. Campbell, "Complete Casting Book – Metal Casting, Processes, Metallurgy, Techniques and Design", Second edition, Butterworth-Heinemann (BH), ISBN: 978-0-444-63509-9, BH is an imprint of Elsevier, UK, USA, 2015.
[18] W. J. Chen, C. X. Lin, Y. T. Chen, and J. R. Lin, 'Optimization design of a gating system for sand casting aluminium A356 using a Taguchi method and multi-objective culture-based QPSO algorithm', Advances in Mechanical Engineering, vol. 8, no. 4, pp. 1–14, Apr. 2016, doi: 10.1177/1687814016641293.
[19] M. P. Groover, "Fundamentals of Modern Manufacturing – Materials, Processes, and Systems" Seventh edition, ISBN: 978-1-119-47529-3 (PBK), ISBN: 978-1-119-47531-6 (EVAL), John Wiley & Sons, 2020
[20] M. Djurdjevic, S. Manasijevic, A. Patarić, S. Stopic, and M. Mihailović, 'Impact of Mg on the Feeding Ability of Cast Al–Si7–Mg(0_0.2_0.4_0.6) Alloys', Crystals (Basel), vol. 14, no. 9, Sep. 2024, doi: 10.3390/cryst14090816See https://pitt.libguides.com/citationhelp/ieee
[21] https://www.novacast.se/our-products/the-story-of-novaflowsolid/ page accessed in Dec 2025.