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Reinventing quality in foundry castings through gearbox housing optimization: A case study approach

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Abstract

The Indian Foundry cluster is a key player in the production of metal castings used across various industries, including automobiles, railways, machinery, sanitary appliances, pipes, gears, earth-moving equipment, cement, electric circuits, pumps, valves, and wind turbines. Grey iron is the predominant material, constituting around 68% of all cast parts. In this context, Kolhapur plays a pivotal role in the production of diverse castings in India, primarily focusing on grey iron and SG iron castings, both of which are ferrous materials. The Kolhapur Cluster of Foundries is expected to produce approximately 650,000 tonnes annually, contributing about 7% of India's total cast iron production. However, this cluster encountered challenges related to higher rejection rates for castings due to a variety of defects. One established foundry in Kolhapur faced stricter rejection standards for specific castings. To address these issues, a comprehensive case study was conducted to reduce rejection rates in this foundry. The primary focus of the study was on a specific casting, the Gearbox Housing, which had an initial average rejection rate of 13%. In some instances, this rejection rate spiked to as high as 18% in a single month, resulting in significant revenue losses for the company. The defects observed in Gearbox Housing castings were categorized into two main types: Methoding, Filling, and Solidification-related defects, which included issues like shrinkage porosity and hot tears. Sand and mold-related defects, such as sand inclusion, sand drop, and mold quality issues. The initial step in addressing these defects involved utilizing casting simulation techniques to analyze and tackle shrinkage and porosity issues. A new gating system was designed to enhance the casting process. In the subsequent stage of defect reduction, the Design of Experiment (DoE) tool was employed. This data-driven approach helped refine and optimize the manufacturing process to minimize defects and enhance the overall quality of Gearbox Housing castings. By implementing these strategies, the foundry in Kolhapur successfully reduced rejection rates, thereby safeguarding company revenue and ensuring the production of high-quality castings for various industrial applications.

Keywords: Casting Defects; Optimization and Analysis; Design of Experiment; Gray Relation Analysis; Sand Inclusion; Parameter optimization

1. Introduction

Foundry operations involve the intricate process of creating castings within molds crafted from materials like sand or other substances. This time-honored production method entails crafting hollow spaces in a porous and heat-resistant material using a pattern, followed by the introduction of molten metal into the mold to shape the desired product. Among the casting methods, green sand casting stands out as the most widely employed due to its ability to produce a diverse range of castings in terms of size, its cost-effective use of raw materials, and the potential for recycling the molding sand. The versatility of green sand casting extends to accommodating metals with high melting points, such as

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copper and cast iron. However, the casting process is not without its challenges, as it can give rise to various defects that significantly diminish the overall casting output. Flawed castings result in substantial productivity losses.

Casting defects represent deviations from meeting customer requirements in terms of (i) geometry, including issues like mismatch and swelling, (ii) integrity, encompassing problems such as porosity and inclusions, and (iii) material properties, such as segregation and the presence of hard spots. The resulting consequences, including a loss in foundry productivity and a decline in customer confidence, are quite significant. Foundries, in their efforts to reduce rejection rates, initially experiment with process parameters, such as adjusting alloy composition, mold coatings, and pouring temperatures. If these measures prove ineffective, modifications are made to method design, involving changes in gating and feeding systems. When even this doesn't yield the desired results, adjustments are made to tooling design, including part orientation, parting line, and the layout of cores and cavities. The impact of any alterations to tooling, methods, or process parameters is assessed through the pouring and inspection of test castings.

Design of Experiments (DoE) is a systematic and precise approach for addressing engineering challenges. It employs specific methods and techniques during the data collection phase to ensure that the resulting engineering insights are reliable, defensible, and well-supported. Importantly, all of this is achieved with minimal investments in engineering trials, time, and resources. DoE is a methodical approach aimed at establishing the connection between the inputs and outputs of a process, effectively identifying cause-and-effect relationships. This knowledge is crucial for managing process inputs and optimizing outcomes. To fully grasp DoE, it's necessary to comprehend certain statistical methods and experimental concepts. While DoE can be analyzed using various software tools, it's essential for practitioners to have a solid grasp of fundamental DoE principles for effective implementation.

2. Literature Review

To address the issue, a comprehensive literature review was conducted, encompassing published works in journals and conferences. This review meticulously examined previous studies related to the problem at hand. Given that a significant portion of casting defects are linked to processing parameters, it's imperative to have effective monitoring in place to ensure that parts are defect-free. Understanding which process parameters influence casting and how they affect defect occurrence is crucial. Numerous researchers are actively engaged in enhancing processes and reducing defects using a variety of tools. These studies build upon one another, forming a collective effort to tackle this issue.

In their study, Patil and Naik explored the use of quality control tools to mitigate rejection rates in gear box housing production. The initial analysis revealed a high rejection rate in the casting process, primarily due to defects like sand inclusions and shrinkage. The average rejection rate over the past 6 months stood at 13.02%. This not only resulted in substantial revenue losses, given a unit cost of 5000/- per housing but also highlighted the potential for process improvement. The study proposes that a combination of simulation techniques and design of experiments can be employed to effectively minimize defects in the product under investigation [1].

Vante and Naik conducted research to address the growing issue of rejection in a foundry, focusing on the component, a three-cylinder metric block. They identified variations in casting wall thickness as a significant factor contributing to rejection. Quality control tools such as Pareto analysis, cause-and-effect diagrams, and why-why analyses were employed to examine casting defects. To mitigate rejection, various chaplets were tested, with the rectangular v-make chaplet replacing the previous 3-disc round chaplet. Fine-tuning of pouring temperatures and chaplet dimensions was also recommended. As a result, the rejection rate for dimensional variation in the water jacket decreased from 7% to 2.13%, signifying improved control and enhanced quality of the three-cylinder metric block [2].

Kinagi and Mench employed a combination of Design of Experiments (DoE) and Failure Mode and Effects Analysis (FMEA) to evaluate casting defects such as cold shuts and blow holes. They applied the FMEA technique and Pareto analysis to assess defects, identify potential causes of failure, evaluate their impact, and determine suitable actions to enhance both productivity and quality. Their primary objective was to optimize sand casting process parameters using the DoE and Taguchi methods. For their experiments, they utilized a Taguchi-based L9 orthogonal array and employed Minitab software for analysis, including the use of an Average Normalized Optimization Method (ANOM) plot. This approach led to the identification of the optimal levels for key process parameters, which included pouring temperature (ranging from 1380°C to 1440°C), inoculants, moisture content, and the sand-binder ratio (60:1) [3].

Sushil Kumar and his team conducted an analysis of casting defects and determined that the Six Sigma methodology, specifically the DMAIC (Define, Measure, Analyze, Improve, Control) approach, can effectively improve quality while keeping costs in check. The researchers found it feasible to identify optimal signal strength levels that minimize the impact of noise factors on response characteristics. Their case study resulted in the optimization of operating parameters for the green sand casting process, leading to a reduction in casting defects. Specifically, they fine-tuned the following parameters: moisture content (4.0%), green strength (1990 g/cm2), pouring temperature (1410°C), and mold hardness numbers (vertical: 72, horizontal: 85) for the sand casting process [4].

Patil and Naik's study underscored that the quality of the sand, the production process, and the molten metal's quality all play pivotal roles in influencing the quality of castings. To ensure the production of defect-free castings, meticulous control of process parameters is of paramount importance. Most researchers in their field have employed the Pareto principle and seven quality control techniques to identify and assess various issues and the underlying causes of defects leading to component rejection. Some individuals also utilize methods such as Failure Mode and Effects Analysis (FMEA), Six Sigma, and Value Stream Mapping to manage processes effectively. Many researchers have harnessed design-of-experiments techniques like the Taguchi method to conduct experiments on sand process parameters, demonstrating the potential to reduce casting defects by as much as 6%. Furthermore, the use of simulation to replicate the component has been effective in reducing porosity defects caused by shrinkage [5].

Chatrad B and their team conducted an investigation into several factors that influence casting defects. These factors encompassed the melting points of the metals, alloying agents, pouring temperature, pouring procedure, pouring time, and the presence of contaminants in the ladle, among others. Their study resulted in the establishment of objectives and optimal parameters, as well as an assessment of the economic impact of crucial industrial operations through specific case studies. It was observed that rejection rates were lower within the temperature range of 1420°C to 1480°C. However, rejection percentages increased when the temperature fell below 1400°C or exceeded 1480°C. Longer pouring times were also found to be associated with higher rejection rates, likely due to extended handling times leading to more defective components. Additionally, impurities in the ladle and mold, resulting from inadequate cleaning, led to increased occurrences of porosity and inclusions in the castings [6].

Singh and Kumar conducted an analysis of casting defects, specifically cold shut, scab, and shrinkage in check valve components. The researchers employed Taguchi's approach to address the root causes of these issues, focusing on factors such as pouring temperature, permeability, mold hardness, and sand particle size. In their study, a trial involving an L9 orthogonal array was conducted. They evaluated and examined the effectiveness of various process parameters by analyzing the S/N Ratio responsiveness and their correlation with the levels of these parameters. Through a series of tests and methodologies, they determined the optimal process parameters for mitigating defects. These included a pouring temperature of 1340°C, a permeability level of 150 (No), a sand particle size of 42 AFS, and a mold hardness of 91.132 [7].

Patil S.S. et.al. categorized defects in the casting of gear box housing into two groups: methoding, filling, and solidification-related flaws, such as shrinkage porosity and hot tears, and sand and mold-related issues like sand drop and mold quality. They first used a casting simulation technique to analyze and address shrinkage and porosity defects, leading to the design of a more effective gating system. This process involved several iterations using simulation software to achieve the optimal design, with a focus on minimizing metal usage and increasing casting yield to enhance cost-efficiency. Proper gating system design is crucial for efficient and effective operation. Visualization of the mold filling process aids in user understanding. The simulation results indicated that altering the number of ingates and their area reduces shrinkage tendencies, while controlling the molten metal flow velocity through the ingates significantly improves sand inclusion defects. Comparing the previous gating method, which had a yield of 83%, with the newly designed system, they found a 2.5% increase in production yield with the new gating system [8].

Raghupathy and Amirthagadeswaran employed a Box-Behnken Design of Experiments (DoE) to conduct parametric optimization in order to mitigate casting defects in FG 200 Pump adapters. Their experiments were conducted in a foundry specializing in pump component manufacturing. The key parameters they focused on included the clay ratio, humidity level, and mold hardness, all of which played crucial roles in preventing casting defects in pump components. The researchers conducted three different levels of analysis for each parameter and utilized the ANOVA technique to assess the effects of these parameters, both individually and in their interactions. The ANOVA F-tests indicated that both the clay ratio and mold hardness were equally significant factors in casting quality. Through the optimization process using Design Expert software, the ideal parametric settings were determined as follows: 2% for clay ratio, 3.87% to 4% for humidity level, and 5.21 to 5.45 kg/cm2 for mold hardness [9].

Dabade and Bhedasgaonkar applied a combination of the Design of Experiment (DoE) method and computer-aided casting simulation to analyze casting defects in the context of wheel hub production. Their aim was to identify the optimal configuration for mold characteristics and green sand casting techniques. They utilized the Taguchi method to determine the ideal values for several key process parameters, including moisture content (4.7%), green compressive strength (1400 gm/cm2), permeability number (140), and mold hardness number (85). This approach significantly reduced rejection rates from 10% to 3.59%. In addition, they employed computer-aided casting simulation to address issues like shrinkage porosity. Their recommendation included the implementation of a novel gating system, specifically a feeder with two components of the right size. This change led to a 15% reduction in shrinkage porosity and a 5% increase in yield, further enhancing the casting process [10].

Bhujugade and Sabnis employed a two-part approach to address casting defects. In the first part, computer simulation techniques and the design of experiments were used. The second part involved a casting simulation technique specifically aimed at analyzing shrinkage porosity defects. They designed a gating system to reduce shrinkage by around 2.85% and increase yield by approximately 9.85%. For the second part, they used Design of Experiments (DoE), taking into consideration parameters related to sand quality and pouring practices, such as moisture content, particle size, mold hardness, and pouring temperature. An experimental setup was conducted using a Taguchi-based L9 Orthogonal Array, and the analysis was carried out with Minitab's ANOVA software. After implementing the casting simulation technique, they achieved a reduction in methoding-related defects by up to 0.89% and an improvement in yield by 9.85%, resulting in optimized levels for selected process parameters. The Taguchi optimization approach led to the following ideal process parameter values: moisture content (2.0-2.5%), particle size (35-40), mold hardness (75-80), and pouring temperature (1570-1585°C). This approach successfully reduced casting rejection due to sand-related flaws and pouring practices-related issues from 8% to a maximum of 3.5%, contributing to improved casting quality [11].

Yadav and their team addressed casting defects by adopting a systematic approach. Casting units traditionally rely on trial and error to eliminate flaws, but this study aimed to pinpoint the root causes of the problem through a more methodical methodology. They focused on analyzing sand and mold-related defects using Taguchi's approach and experimental techniques. By applying Taguchi's reliable experimental design method, they sought to standardize and optimize the process parameters for the best results. Key variables considered in this study included sand grain size, clay content, moisture percentage, pouring temperature, pouring time, green strength, permeability, mold hardness, number of vent holes, and the number of ramming cycles. They utilized an orthogonal array L27 based on Taguchi's principles. The study specifically centered on a tractor retainer made of cast iron alloy FG260. The study's findings categorized the process variables into two groups: those that contribute to defects and those that do not. It was determined that factors such as moisture content, clay content, pouring time, green strength, mold hardness, and the number of vent holes were contributing factors, whereas sand grain size, pouring temperature, permeability, and ramming cycles had less influence on casting defects. Through the Taguchi optimization method, the study identified the optimal values for process parameters as follows: moisture content: 4%, sand particle size: 70, clay content: 18%, pouring temperature: 1430°C, pouring time: 20 seconds, green strength: 1350 g/cm2, number of vent holes: 10, and the number of ramming cycles: 6. This approach reduced casting rejection rates from 8% to 5.095%, demonstrating its effectiveness in enhancing casting quality [12].

2.1. Research Gaps

On exhaustive literature survey, the research gaps were identified on the underexplored aspects of gating system optimization, the size of orthogonal arrays used in DoE, and the need for more theoretical explanations alongside simulation-based approaches to defect minimization. Addressing these gaps could significantly enhance the knowledge and practices in the field of solidification-related defect reduction in casting processes.

The research gaps related to the use of simulation techniques for minimizing solidification-related defects are enlisted below:

- Limited Attention to Gating System Optimization was found. While there is a substantial body of research focused on optimizing process parameters through the use of design of experiments (DoE) for process improvement, there is a noticeable lack of work that addresses the optimization of gating systems to reduce solidification defects and enhance overall processes.
- It was found that there is a limited use of adequate orthogonal arrays. Many research studies employing DoE tend to use smaller orthogonal arrays, which can make it challenging to achieve an optimal casting solution. The systematic selection of process parameters that have minimal or negligible impact on defect occurrence in the casting under investigation has received less attention within the framework of DoE.
- Insufficient focus on gate system optimization was observed. In comparison to the substantial research conducted on process parameter optimization using experimental designs, there is a relative scarcity of documented studies that have explored the optimization of gate systems for mitigating solidification defects and thereby improving casting processes.

- The absence of comprehensive theoretical explanations was found. Although numerous studies involve the use of virtual trials and simulation software to minimize defects, a limited number of these studies provide comprehensive theoretical explanations for the design of gating systems, making it crucial to bridge this gap in understanding the underlying principles.

2.2. Problem Definition

A local foundry producing Gear Box Housing has been grappling with a substantial issue of high rejection rates, primarily attributed to various process-related defects. Over a six-month observation period, it was noted that the rejection rate averaged around 15%. These defects included sand inclusions (8%), shrinkage (4%), and other issues like cracks and mismatches (3%). The monthly production volume for gear box housing is approximately 1000 units, each valued at Rs. 5000. Consequently, the organization is incurring a substantial monthly revenue loss of approximately 7.5 lakhs due to subpar casting quality. The organization is keen on minimizing these defects to enhance its production process and mitigate financial losses.

3. Material and methods

3.1. Research Objectives

This paper aims to optimize the sand casting process in a Kolhapur, Maharashtra job foundry, with the following objectives:

- Identify the most influential process parameters affecting the quality characteristics.
- Focus on casting defects as the key quality indicator in green sand casting, as it reflects various internal flaws. The goal is to minimize casting defects while mitigating the impact of uncontrollable factors.
- Implement the green sand casting process under specified experimental conditions based on chosen parameter levels, and collect relevant data.
- Generate an Analysis of Variance (ANOVA) table to assess the statistical significance of the parameters. Create response graphs to determine the optimal level for each parameter.
- Determine the ideal settings for control parameters and predict outcomes at these new optimal levels.
- Validate that the optimal settings indeed lead to the predicted reduction in casting defects, thus enhancing the casting process.

3.2. Sand parameters and their levels

Rejection in castings often arises from factors like improper patterns, gating systems, control of sand parameters, and molten metal composition. Key process parameters in sand casting include sand particle size, moisture percentage, green compression strength, mold hardness, permeability, pouring temperature, and pouring time. For these parameters, we've chosen three levels based on industry standards and the organization's expertise, also accounting for significant interactions within control parameters. The specific parameters and their ranges are detailed in Table 1.

Table 1 Ranges and Levels of Input Parameters

Input parameters ranges	**Level**		
	Level 1	**Level 2**	**Level 3**
Moisture (%)	3.0-3.5	3.5-4.0	4.0-4.6
Green Compressive Strength(gm/cm^2)	1500-1800	1800-2100	2100-2400
Permeability(Number)	65-80	81-95	95-115
Mould Hardness(Number)	80-84	84-88	88-92

3.3. Analysis Technique

Renowned Japanese engineer Genichi Taguchi introduced a set of experimental design strategies known as 'Taguchi Methods' employing various factorial designs, including mixed-level and two- to three-level fractional factorial designs. Taguchi emphasizes the application of experimental design as a means of ensuring effective performance during the product or process design phase. While some experimental designs, like those in evolutionary operations, can be used in real-time during ongoing processes, Taguchi's approach focuses on off-line quality control. Taguchi's innovative approach to Design of Experiments (DoE) relies on a well-defined set of rules and utilizes orthogonal arrays. These arrays provide a structured framework for conducting the fewest trials needed to comprehensively understand all variables affecting performance metrics. Notably, Taguchi orthogonal arrays like L9, L18, L27, and L36 simplify the complexity associated with traditional experimental design techniques. These traditional methods often become intricate and demanding when dealing with numerous process parameters, requiring a high number of experiments. In contrast, Taguchi's experimental design approach streamlines the process, enabling a thorough exploration of the parameter space with just a few experiments. In this study, the L9 orthogonal array was chosen due to its capacity to explore four parameters, each with three distinct levels. The response variable considered was the rejection percentage of castings due to defects, calculated as the ratio of rejections attributable to specific process parameters to the total volume poured. Nine random trials were conducted according to the orthogonal array, and the rejection percentage in each trial was used to determine the response. Table 2 depicts the Design Matrix Table.

Table 2 Design Matrix Table

Exp. No	**Moisture**	**Green Comp. Strength**	**Permeability**	**Mould Hardness**
01	1	1	1	1
02	1	2	2	2
03	1	3	3	3
04	2	1	2	3
05	2	2	3	1
06	2	3	1	2
07	3	1	3	2
08	3	2	1	3
09	3	3	2	1

3.3.1. Calculation of S/N ratio

The output variables are normalized using a formula:

$$Nij = Xi(Max) - Xij/Xij(Max) - Xij(Min)$$

Here,

Nij= Normalized value after grey relational generation
(Xij) max= Maximum value of response parameter
(Xij) min= Minimum value of response parameter and
Xij= Value of response in it column and j^{th} raw of design matrix.

Here i={1,2,3,4} and j={1,2,…..,9}

Calculation of S/N ratio,

$$\frac{\boldsymbol{S}}{\boldsymbol{N}}\boldsymbol{Ratio} = -\boldsymbol{10log}\{\boldsymbol{1/n}\sum_{\boldsymbol{k=1}}^{\boldsymbol{n}} \boldsymbol{x^2ijk} \ldots..$$

Minitab software was employed to create response graphs and identify the optimal values for each process parameter. Subsequently, a validation experiment based on the Signal/Noise (S/N) ratio was conducted to confirm the results. The focus of design quality revolves around achieving nominal values for each selected parameter, establishing acceptance criteria. Any deviations from these target values can result in product losses. The S/N ratio, representing three common characteristics—nominal value (higher is better), smaller is better, and higher is better—is calculated to determine the desired target value and assess the deviation from experimental values in relation to the S/N ratio. The primary objective of this study is to minimize casting defects, and in this context, smaller values signify improved casting quality.

Consequently, a 'smaller-the-better' quality attribute was adopted for this study to drive enhancements in casting quality.

3.3.2. Analysis of Variance (ANOVA)

The objective of the analysis of variance ANOVA was in the direction of to identify the factors that substantially influenced the quality attribute.

The overall addition of square deviation, *SSt* can be

Designed using,

$$SS_t = \pi \sum_{i=1}^{y} yi^2 - C.F$$

Here,
n represent the no. of experiments or trails in orthogonal array and *yi* is the entire % rejection of i^{th} experiment furthermore *C.F.* is the correction factor. *C.F* may be computed as

$$C.F = T^2/N$$

where, *T* is the addition of all rejected castings.

The total sum of square deviations (SSt) was divided into two components: the sum of square errors (SSe) and the sum of square deviations (SSd) attributed to each process parameter. The percentage contribution (denoted as P) of each process parameter's sum of square deviations (SSd) to the total sum of square deviations (SSt) was calculated. To determine which factors held significant influence, a statistical analysis employed the F-ratio (variance ratio) test. Before conducting the F-test, it's crucial to accurately compute the mean of square deviations (SSm) associated with each process parameter. SSd, divided by the degrees of freedom linked to process parameters, yields SSm. The F value for each process parameter is then determined as the ratio of mean square deviation (SSm) to mean square error (SSe). In the experiment, 95% confidence level F-ratios were obtained, and the percentage contribution for each parameter was assessed. Notably, green compressive strength emerged as the most influential factor, making the most substantial contribution to the occurrence of sand inclusions.

3.3.3. Analysis for Sand Inclusion

The primary objective of this study was to minimize casting defects, with an optimal value of 0 as the goal. The analysis was conducted using MINITAB-17 statistical software. The Signal-to-Noise (S/N) ratio was computed based on the 'less is better' quality characteristic formula ($S/N = -10*\log 10 * Y^2/n$). In the Taguchi method, S/N serves as a data transformation approach, assessing both the average and the variation in data across different noise levels within the control array row.

Table 3 Sand Inclusion DoE Results

Moisture	Green Comp.	Permeability	Mould Hardness	Rejection %	SNRA1
1	1	1	1	7.0	-16.90
1	2	2	2	6.0	-15.56
1	3	3	3	5.5	-14.80
2	1	2	3	6.2	-15.84
2	2	3	1	6.5	-16.25
2	3	1	2	5.8	-15.26
3	1	3	2	6.7	-16.52
3	2	1	3	6.5	-16.25
3	3	2	1	6.3	-15.98

The formulae for calculating the Signal-to-Noise ratio are guided by the nature of the response variables being evaluated, emphasizing that nominal is best, less is better, and greater is preferable. In this study, the primary focus was on minimizing rejections in the casting of gear box housing, particularly assessing the fraction of rejections attributed to inclusions in all trials. These details were obtained through MINITAB-17 software. The results for Sand Inclusion are presented in Table 3.

The critical findings from the experimental analysis are presented in Table 4 and Figure 1, illustrating the major effect graphs and the ANOVA results. Table 4's ANOVA indicates that both mold hardness and green compression strength are notably influential factors impacting the percentage of rejection.

Table 4 ANOVA for S/N Ratio

Source	Degree of freedom	Adj SS	Adj MS	F-Value	P-Value	% Contribution
Regression	4	1.53500	0.38375	8.50	0.031	
Moisture	1	0.16667	0.16667	3.69	0.127	9.71
Gcs	1	0.88167	0.88167	19.53	0.012	51.39
Permiability	1	0.06000	0.06000	1.33	0.313	3.49
Mold hard	1	0.42667	0.42667	9.45	0.037	24.87
Error	4	0.18056	0.04514			
Total	8	1.71556				

Table 5 Table of Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	7.444	0.354	21.02		
Moisture	0.1667	0.0867	1.92	0.127	1.00
Gcs	-0.3833	0.0867	-4.42	0.012	1.00
Permeability	-0.1000	0.0867	-1.15	0.313	1.00
Mould hardness	-0.2667	0.0867	-3.07	0.037	1.00

3.3.4. Gray Relation Analysis (GRA)

Deng's Grey System theory addresses decision-making in situations involving partial information that falls between known and unknown knowledge. It is particularly valuable for tackling complex problems and data. Grey Relation Analysis (GRA) is a quantitative method derived from Grey System theory, frequently applied in solving intricate systems. It finds applications in financial, logistical, and process optimization, especially in scenarios with multiple criteria and intricate interrelationships. GRA helps identify the key process parameters affecting multiple response variables, making it useful for managing multi-criteria situations. In GRA, the Grey Relational Grade (GRG) is calculated to evaluate the interaction between elements and determine the influential factors impacting several objectives. To establish the connection between desired and actual experimental data, grey relational coefficients are computed from normalized experimental data. These coefficients are then averaged to yield the Grey Relational Grade, which provides an overall assessment of the experimental data for multiple responses. The level with the highest Grey Relational Grade represents the optimal factor.

In this study, the impact of process parameters on the rejection percentage in casting is analyzed and optimized using the Taguchi-Grey Relational Analysis (TGRA), an approach for parameter design.

For larger the better quality characteristic, normalized value (Xi) is given by,

$$X_i = (x_i - x_{min})/(x_{max} - x_{min})$$

For smaller the better quality characteristic, normalized value (Xi) is given by,

$$Xi = (x_{max} - x_i)/(x_{max} - x_{min})$$

Where $(xi)_{max}$ and $(xi)_{min}$ are the maximum and minimum values of the original sequence x_i.

GRC for all the experiments expresses the connection between the ideal (best) and actual normalized S/N ratio. When two sequences be in agreement to each other at every juncture, their grey relational coefficient is 1.The Grey relational co-efficient can be articulated by equation as shown below.

Grey Coefficient, γ_i is given by,

$$\gamma i = (\delta i\ \mathrm{max} + (\delta i)in)\ /(\delta i\ max + \delta i)$$

Where, Delta value, δi is known by

$$\delta i = Xi\ max - Xi$$

Experimental outcomes are standardized in a range from 0 to 1. Typically, the figures in the original series are divided by their average to normalize each series as depicted in Table 6.

Table 6 Rejection Percentage and Normalized Rejection Percentage for Experimental Trials

Expt. No.	Rejection %	Normalized Rejection percentage
1	7.0	0
2	6.0	0.666
3	5.5	1
4	6.2	0.533
5	6.5	0.333
6	5.8	0.8
7	6.7	0.2
8	6.5	0.333
9	6.3	0.466

For all experiments deviation sequences, GRC and gray relational grades are indicated in Table 7.

Table 7 Grey Relational Coefficients and Corresponding Grey Relational Grades

Expt. No.	Deviation Sequences	Grey Relational Coefficient	Grey Relational Grade	Rank
1	1	0.333	0.333	9
2	0.333	0.6	0.6	3
3	0	1	1	1
4	0.467	0.517	0.517	4
5	0.666	0.428	0.429	6
6	0.2	0.714	0.714	2
7	0.8	0.385	0.385	8
8	0.667	0.429	0.429	6
9	0.533	0.484	0.484	5

In Table 7 experiment no. 3, with a grade value of 1, is identified as the optimum choice out of the total 9 experiments. The optimization process involves the utilization of the Taguchi method for selecting the most effective process parameters in casting. An orthogonal array, specifically L9, was employed for this purpose. The statistical analysis was carried out using Minitab software, facilitating the calculation of Signal-to-Noise (S/N) ratios and ANOVA tables, along with their respective graphical representations. Through this optimization approach, the optimal process parameters were determined.

4. Results and discussion

Minitab is a software tool designed for statistical and graphical data analysis, particularly in the context of Six Sigma projects and Design of Experiments. It assists in gathering and analyzing data to enhance an organization's processes and products. Minitab equips users with the skills to collect, analyze, and interpret sample data, while also promoting the use of graphical analysis techniques.

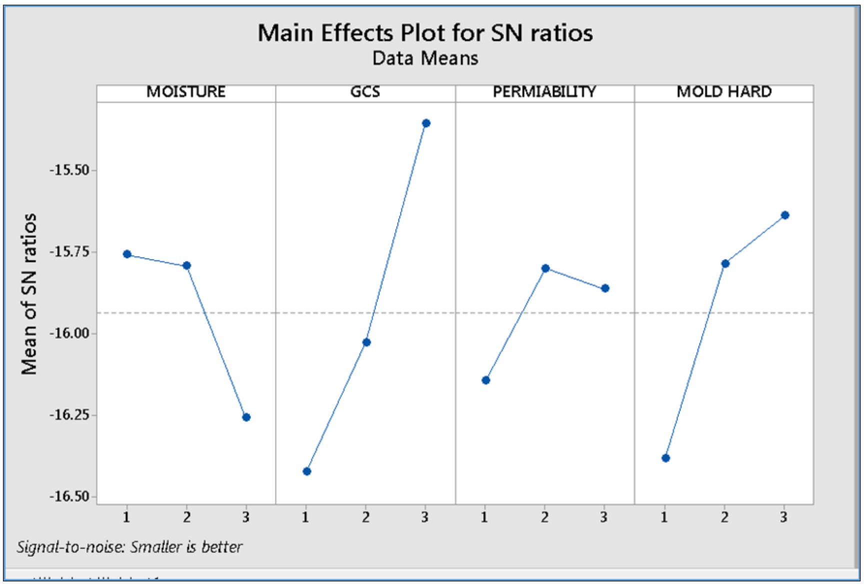


Figure 1 Main Effects Plot for SN Ratio

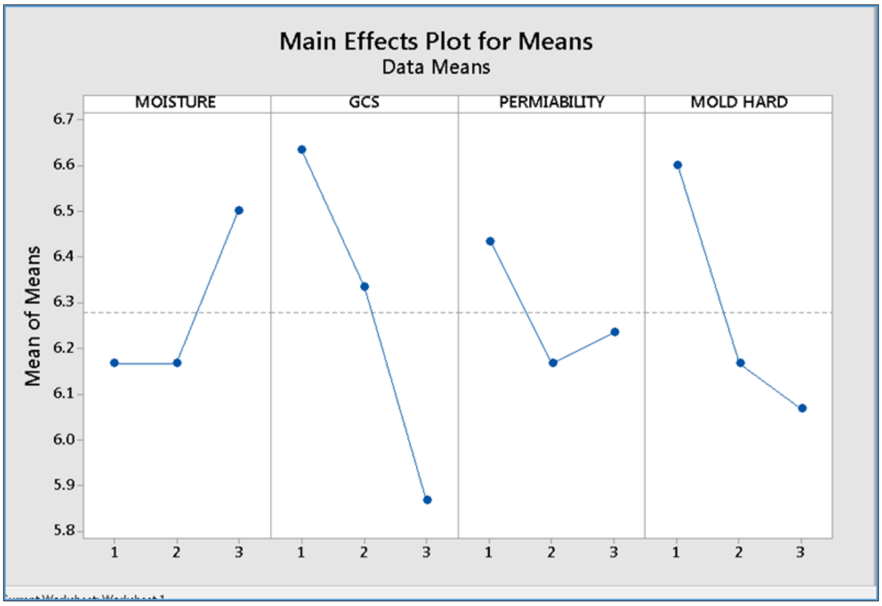


Figure 2 Main Effects Plot for Mean

The Taguchi Method is employed to optimize the outcomes of each experiment, with the L9 orthogonal array utilized for the experimental phase. The study investigates the S/N Ratio's sensitivity to various process parameters and their interactions. Three types of quality characteristics are considered: smaller-the-better, larger-the-better, and nominal-the-best. In this analysis, the smaller-the-better principle is applied to calculate the S/N ratio for all process parameter levels. The Main Effect plot in Figure 1 reveals the ideal ranges for Green Compressive Strength (2100 - 2400 gm/cm2), Mould Hardness (88 - 92 No), Moisture (3 - 3.5%), and Permeability (81 - 95 No) in relation to quality features. The linear regression equation for Sand Inclusion Rejection is as follows:

Rejection = 7.444 + 0.1667 Moisture - 0.3833 Green Compressive Strength - 0.1000

Permeability - 0.2667 Mould Hardness.

The equation reveals that Green Compressive Strength, Permeability, and Mould Hardness have a negative impact. According to the ANOVA table, the p-values for Green Compressive Strength and Mould Hardness are 0.012 and 0.037, respectively. Since the experiments were conducted at a 95% confidence level, it is evident that Green Compressive Strength is more statistically significant compared to Moisture, Green Compressive Strength, Permeability, and Mould Hardness. To ensure optimal results, the optimum parameters are summarized in Table 8.

Table 8 Optimal Process Parameter Values

Parameters	**Optimum Value**
Compressive Strength	2100-2400 gm/cm^2
Mould hardness	88-92 (No)
Moisture	3-3.5 %
Permeability	81-95 (No)

4.1. Confirmation Experiments

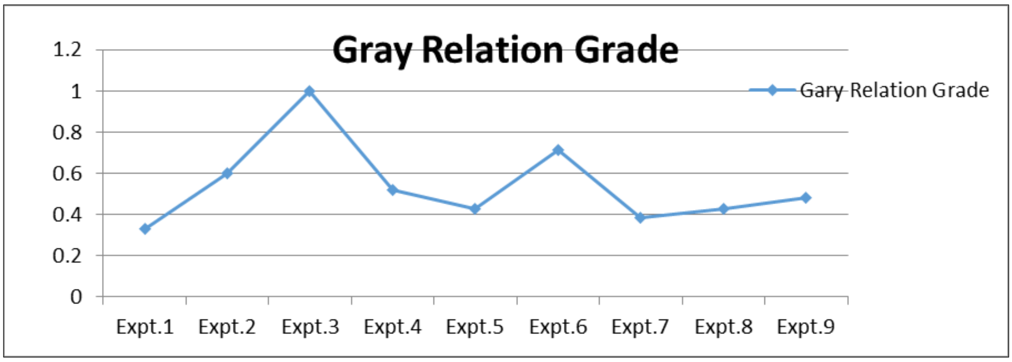
After conducting three confirmation experiments at the optimized values for process parameters, the rejection rate of gear box housing due to sand-related defects, which was initially at 7%, has been successfully reduced to a maximum of 5.6%.

Table 9 Confirmation Experiment Results

No. of casting poured	**No. of defective castings(sand related)**	**%Rejection**
1195	66	5.5
1075	59	5.5
1061	61	5.7
	Avg. rejection	**5.6**

4.2. Gray relational grade – Graphical Representation.

Figure 3 depicts the graph of Grey Relational Grades for percent rejection. The experimental design is orthogonal, allowing us to discern the impact of each parameter on the Grey Relational Grade at various levels. Higher Grey Relational Grades correspond to better response characteristics. Experiment number 3 is identified as the best optimal experiment out of the total of 9 experiments.



Where on X axis- Experiment Number and on Y axis- Gray Relation Grade.

Figure 3 Graphical Representation of Gray Relation Grades

5. Conclusion

The current case study investigates the high rejection rate in castings due to defects, focusing on reducing sand-related defects, particularly inclusions. To address this issue, the Design of Experiments (DoE) tool, such as Taguchi's method, is employed to identify the optimal sand and mold parameters that minimize casting rejections. Through the Taguchi approach, the following optimum parameter levels are determined: (A) Moisture Content: 3-3.5%, (B) Green Compressive Strength: 2100-2400 gm/cm2, Mould Hardness: 88-92, and Permeability: 81-95. Utilizing the Taguchi optimization approach, casting rejections for sand-related defects have been reduced from 7% to as low as 5.6%. With a monthly casting output of approximately 1000 units, implementing these optimal parameters is expected to increase revenue by 70,000 INR.

Future work in this context involves extending the successful methodologies to other castings, exploring advanced simulation techniques, fine-tuning process parameters, implementing real-time quality control, considering material alternatives and environmental impact, optimizing costs, investing in skill development, collaborative research, and diversifying market reach to ensure sustained growth and quality improvement within the Indian Foundry cluster.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Mr.S.S.Patil, Dr. G.R.Naik, 'Defect Minimisation in Casting through Process Improvement-A Literature Review',IOSR Journal of Mechanical & Civil Engineering,14 (2017) pp 09-13.

[2] Mr. Abhijeet B. Vante, Prof. G. R. Naik, Quality Improvement For Dimensional Variations In Automotive Casting Using Quality Control Tools, IOSR Journal of Mechanical and Civil Engineering e-ISSN: 2278-1684,p-ISSN: 2320-334X, 13(2016), PP 81-88.

[3] Kinagi Prasan, Dr.Mench R.G,A Development of Quality in Casting by Minimizing Defects, International Journal of Recent Research in Civil and Mechanical Engineering,1(2014)31-36.

[4] Kumar Sushil, Satsangi P.S, Prajapati D.R, Six Sigma an Exllent Tool For Process Improvement-A case Study, International Journal of Science and Engineering Research,2(2011)1-10,ISSN 2229-5518.

[5] S.S.Patil, Dr. G.R.Naik, 'Process Improvement in Casting through defect Minimisation', International Journal of Scientific & Engineering Research,4 (2017) pp 271-279

[6] Beeresh Chatrad, Nithin Kammar, Prasanna P Kulkarni, Shrinivas Patil, A study on Minimization of Critical Defects in Casting Process Considering Various Parameters, International Journal of Innovative research in Science, Engineering and Technology,5(2016)8884-8902.

[7] Singh harvir, kumaraman, Minimisation of Casting defects using Taguchi's Method, International Journal of Engineering Science Inovation,5(2016)6-10,ISSN:2319-6734.

[8] S.S.Patil, Dr. G.R.Naik, 'Casting Method Design of gear Box Housing for Yield Improvement through Simulation-A Case Study', International journal of Research in Mechanical Engg. & Technology, 8 (2018),PP 19-26.

[9] Rathish Raghupathy, K.S. Amirthagadeswaran, Optimization Of Casting Process Based On Box Behnken Design And Response Surface Methodology, International Journal for Quality Research , ISSN 1800-6450, PP569–582.

[10] Dabade U.A, Bhedasgaonkar R.C, Casting Defect Analysis Using Design of Experiments(DoE) and Computer Aided casting Simulation Technique, ELSEVIER,(2013)2212-8271.

[11] Atul A.Bhugude, Vijay B. Sabnis, Minimization of Casting Defects Using Casting Simulation Technique and Casting Defects Analysis Using Design of Experiment, International Journal for Research in Applied Science & Engineering Technology (IJRASET), 3(2015)722-727.

[12] Vikas Yadav , Gaurav Kumar , Mukesh Kumar and Peeyush Vats, Optimization of sand- defects process parameters for reducing its defect using taguchi technique, IOP Conf. Series: Materials Science and Engineering, ICFTMM 2020,doi:10.1088/1757-899X/1149/1/012031