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IDENTIFICATION OF PROMINENT CASTING DEFECTS AND ITS IMPACT ON QUALITY OF CASTINGS

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Abstract

Defective casting is a critical problem and it has significant impact on the casting manufacturing industries. Selecting the best casting sample among many samples is a Multi-Criteria Decision Making (MCDM) problem. This research aims to identify the prominent casting defects and selection of best casting sample, with a minimum number of defects. This study has developed an evaluation model, based on the Analytic Hierarchy Process (AHP). In this study, AHP was used, to analyze the most prominent casting defects, selection of best casting sample, with minimum defects and to determine the weights of the criteria. A total of nine casting defects was considered, with fifty-seven subfactors. An experimental study was conducted, to illustrate the utilization of the model, for the best casting sample selection problem, for three different nonferrous materials. According to this study, a sample, with LM6 as a material (with final weight 0.1560), stood out undisputedly as the best casting sample. The proposed study and its application, will be useful for the casting industries, to better understand the prominent casting defects and the selection of the best casting, with the least casting defects. The statistical software SPSS was used for reliability of data and one sample t-test was conducted for finding the significant factors.

Keywords: *Casting Defects, Multi-Criteria Decision Making (MCDM), Analytic Hierarchy Process (AHP), SMEs*

JEL Code: *L61, C12, C83*

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1. Introduction

Casting is a highly complex process which leads to various casting defects. Casting rejection is one of the major issues in the foundry industry. Defective casting may lead to reduced yield and productivity of the casting industry. Therefore, identification and minimization of casting defects, play an important role in getting a sound casting. Casting parameters, related to parts, tooling and method design affect the cast quality. The effect of material and design, parameters plays an important role in identifying the casting defects. The defects are considered to be geometry integrity and property related defects **(Mane, 2010).**

There are solidification parameters such as optimizing the design parameters, temperature history, to identify the hot spot region, with time temperature contours. The simulation software can be used to determine solidification time and behavior of different material accurately **(Vijayram, 2006).** The casting simulation software, Autocast and solid modeling for optimization of risers and gating, can be used. It helps in verifying the manufacturability of a casting and improving it by minor modifications of part geometry, before freezing the design **(Ravi, 2007).** The identification of prominent casting defects and selection of best casting samples is a Multi-Criteria Decision Making (MCDM) problem. Multi-criteria decision-making, also known as MCDM, is essential in decision-making processes. Analytic Hierarchy Process (AHP) is one of the most commonly used MCDM methods as a management tool, in several industrial sectors such as supply chain, logistics, and training, among others, with the aim of assessing strategy and performance **(Tramarico, et.al, 2015).** The AHP is a decision-making method that was developed by **Saaty (1978).** This technique calculates the qualified priorities of a given set of alternatives, on a scale, based on the judgment of the decision-maker.

The strength of AHP approach is that it organizes tangible and intangible factors in a systematic way and offers a structured, simple solution to decision-making problems **(Skibniewski, 1992).** Analytical Hierarchy Process (AHP) is one of the best ways for deciding, among the complex criteria structure, at different levels. AHP is a method of measurement, for formulating and analyzing decisions, applied to the various spectrum of the day to day's life, including engineering and management applications. A theoretical foundation for the AHP is a decision support tool, which can be used to solve complex decision problems, taking into account tangible and intangible aspects **(Saaty, 1980).**

This study explains the identification of prominent casting defects and their impact on quality of casting, from the various samples, selected from different companies. A total of nine defects (gas porosity, shrinkage porosity, metal penetration, slag inclusion, sand inclusion, air inclusion, hot tears, crush, and drop) was considered, with fifty-seven subfactors. Various casting parameters were identified in this study, which help to minimize the casting defects. The reliability test was conducted on data. The Cronbach's alpha coefficient was calculated, for each factor. The significance of each factor was calculated, using one sample t-test. The effect of casting defects and its impact on the quality of castings, was identified.

2. Review of Literature

For the purpose of evaluating and selecting best casting sample, qualitative factors must be considered. Thus, the importance of casting defects and selection of best sample, with different alloy compositions, is a kind of multiple criteria decision making (MCDM) problem and it needs to employ MCDM methods to handle it appropriately. The AHP method had been used by various researchers for multi-criteria decision making. But very less work had been done, by the researchers, in identifying the importance of casting defects, by using AHP. AHP is a multi-attribute, decision-making method that is especially useful while dealing with the complex problems by using a nine-point scale **(Karthik et al., 2002).** Various criteria like critical, objective and subjective type were identified, to evaluate the suitability of a casting process for a given design. The criteria were assessed, using linear weighing and fuzzy logic models, and their relative importance was determined, using analytical hierarchy process, to finally arrive at the product-process compatibility index **(Akarte, 1999).** AHP was used to obtain the relative importance of the evaluation criteria. In the light of the heterogeneous capabilities of suppliers, the decision makers can objectively assess each supplier interface and detect when corrective action may be necessary **(Raut et al., 2010).** AHP is considered an ideal method for ranking alternatives when multiple criteria and sub-criteria are present in the decision-making process **(Buyukozkan and Cifci, 2012). Dickson (1966),** on supplier selection and evaluation, identified twenty-three different criteria. The overall assessment of suppliers should not only consider quantitative performance data but also some other criteria that are critical for successful partnerships and are not directly quantifiable, e.g., trust and commitment **(Mohr and Speckman, 1996).** AHP method is used to select the best supplier for computer and printer purchasing. The hierarchy process consists of four main criteria and sixteen sub-criteria, of which the relative importance ratings are computed to select the potential supplier **(Ozkan, et.al, 2011).** A green supplier selection was done, by using AHP technique and a model was presented for high-tech industry **(Lee, et.al, 2009).** The algorithm is driven by product attributes, related to geometry, quality, and production. Shape complexity, which plays an important role in process planning, has been quantified on the basis of geometric parameters of the casting model. Weights to attributes have been determined, using analytic hierarchy process. The complete methodology is implemented, in a web-based framework, to enable early manufacturability assessment of castings, through cost estimation and process simulation, both of which require process planning information **(Chougule and Ravi, 2007).** The weight coefficients are then obtained by synthesis analysis **(Yang et al., 2013).** The AHP-based approach has become quite popular primarily due to its simple and systematic implementation steps **(Fong, 2000).** The methodology is capable of taking into account important requirements of metal stampings and it strengthens the existing procedure, by proposing a logical and rational method of strip-layout evaluation and selection. The proposed strip-layout index, helps to evaluate and rank any given set of strip-layout alternatives **(Rao, 2004).** The seven performance measures, the key elements of supplier selection, consist of cost, resource utilization, quality, flexibility, visibility, trust, and innovativeness. For each measure, the factors are identified, which are commonly used for vendor selection **(Chan, 2003).** Small and Medium Scale Enterprises (SMEs) are used, to evaluate the percent weightings of the criteria, that are synonymous with Total Quality Management (TQM) implementation **(Kalpande, 2010).** The AHP method is applied in the field of project management, to select the best contractor, to perform the project, based on six criteria, which are experience, financial stability, quality performance, manpower resources, equipment resources, and current workload **(Al-Harbi, 2001).** A methodology, for the load shedding scheme for electrical power system, was studied by using the AHP method. The study demonstrated that an effective method can solve multiple criteria and multiple objective decision-making problems, introduced in the load shedding scheme in electrical power system problem **(Goh, and Kok, 2010).** In metal casting industries, the defective casting is a critical problem and has significant impact on the overall productivity. This research aims to identify the prominent casting defects and selection of best casting sample, with a minimum number of defects. Major casting defects, affecting the foundry sector, were considered in this study.

3. Statement of the Problem

There are numerous casting defects, which occur during the manufacturing of castings and they affect the quality of castings. Researchers studied the individual casting defects and their impact on quality of castings. The Small and Medium scale Enterprises (SME) recorded lots of defective castings during production. The current study proposes to study the impact of various casting variables, on all major casting defects and ultimately, the quality of castings.

4. Need of the Study

Various factors, which are responsible for casting defects, were identified and based on prominent casting defects, the quality of castings was improved. Minimization of casting defects is necessary to improve the quality of castings and to avoid economic loss. The present study will help the small and medium scale foundries, to control such factors which cause defects and enhance the performance and quality of the final casting product in the process.

5. Objective of the Study

The objective of the study was to find the impact of prominent casting defects on the quality of castings.

6. Hypothesis of the Study

The alternate hypothesis of the study was framed as follows

H-1: Prominent casting defects have significant impact on the quality of castings.

7. Research Methodology

Primary data were collected through a survey. The questionnaire was developed, to understand the impact of prominent casting defects on the quality of castings. It contained nine main factors, with fifty-seven subfactors **(Annexure- I).**

Step-1: Establishment of structural hierarchy

To establish structural hierarchy, a complex decision had to be structured into a hierarchy, descending from an overall objective to various criteria', sub-criteria', and so on, until the lowest level. The objective or the overall goal of the decision is represented at the top level of the hierarchy. Criteria and sub-criteria, contributing to the decision, are represented at the intermediate levels. Finally, the decision alternatives or selection choices are laid down at the last level of the hierarchy. **Figure-1** shows the hierarchy, for the selection of the best casting sample. The decision alternatives like sample 1, sample 2, and sample 3, are placed at the last level of the hierarchy.

Step-2: Establishment of comparative judgments

Once a hierarchy is structured, the next step is to determine, the priorities of elements, at each level. A set of comparison matrices of all elements, in the respective level of the hierarchy, with respect to an element of the immediately higher level, is constructed so as to prioritize and convert individual comparative judgments into ratio scale measurements. As the AHP approach is a subjective methodology, information and priority weights of the elements were obtained from a decision maker of the company, using direct questioning **(Table-4).**

Step 3: Synthesis of priorities and measurement of consistency

The maximum Eigenvalue (λ_{max} value) is an important validating parameter in AHP **(Saaty, 2008).** It is used as a reference index, to screen information, by calculating the consistency ratio (CR) of the estimated vector in order to validate whether the pairwise comparison matrix provides a completely consistent evaluation **(Table-3).** A measure of how far a matrix is from consistency, is performed by Consistency Ratio. After all matrices are developed, and all pairwise comparisons are obtained, Eigen vectors or the relative weights (the degree of relative importance amongst the elements), global weights, and the maximum Eigen value (λ_{max}) for each matrix, are then calculated. **Table-1** shows the fundamental scale adopted by Saaty. The preferences are quantified by using a nine-point scale. The pairwise comparisons generate a matrix of relative rankings, for each level of the hierarchy. The number of matrices depends on the number of elements at each level. The order of the matrix, at each level, depends on the number of elements of the lower level that it links to.

The consistency ratio is calculated by the following steps:

1. Calculate the Eigenvector or the relative weights and λ_{max} for each matrix of order n.
2. Compute the consistency index (CI) for each matrix of order n by the formulae:

   $CI = \frac{\lambda \max - n}{n-1}$ .... (1), Where n is the number of criteria
3. The consistency ratio (CR) is then calculated using the formulae:

   $CR = \frac{CI}{RI}$ .... (2), Where RI is known as random consistency index.

The acceptable CR range varies according to the size of the matrix, i.e., 0.52 for a 3 by 3 matrix, 0.89 for a 4 by 4 matrix and 1.0 for all larger matrices, ne”5. The number 0.1 is the accepted upper limit for CR. If the value of CR is equal to, or less than that value, it implies that the evaluation of the matrix is acceptable or indicates a good level of consistency in the comparative judgments represented in that matrix **(Table-2).** In contrast, if CR is more than the accepted value, then the inconsistency of judgments, within that matrix, had occurred and the evaluation process should, therefore, be reviewed, reconsidered, and improved. If the consistency test is not passed, the expert will be asked to re-do the part of the questionnaire **(Ozdagoglu and Ozdagoglu, 2007).** The comparative judgments are reconsidered with respect to the issues raised in the section of the establishment of comparative judgments. Acceptable consistency properties help to ensure decision-maker reliability in determining the priorities of a set of criteria.

7.1 Sample Selection

A convenient survey method was employed, to collect the data, regarding casting defects and quality of castings from foundry industries. The target sample size of one hundred and seventy-four was considered for the empirical investigation. Out of one hundred and seventy-four questionnaires, distributed by email and social forum, one hundred and two questionnaires were returned. Responses were obtained from small and medium scale industries, located in Mumbai, Thane and Vasai region of Maharashtra. The survey response rate was calculated to be 58.62%, which conforms to the standard of social science research.

7.2 Source of Data

Primary data were collected, from the experts of foundry and casting manufacturing sector **(Annexure-I).** The survey was conducted through online, as well as in hard forms. Respondents were mainly managers, casting experts and supervisors, from various casting industries, with an average experience of more than five years.

7.3 Period of the Study

Eight months were required to collect data and the period of the study was from September 2015 to April 2016.

7.4 Tools used for the Study

The AHP method was used to identify the most prominent casting defects. The data collected were analyzed by statistical software SPSS-16 for finding the reliability of data. The weights of each casting defects were calculated and most important casting defects were identified, which affected the quality of the castings.

8. Data Analysis

Reliability test and one sample-t test were conducted to find the reliability of all variables and its significance level.

8.1 Reliability Analysis

Pallant (2001) states that the reliability of a scale indicates how free it is from random error. It indicates the extent to which an experiment, test or any other measuring procedure, yields the same results. The Cronbach's alpha coefficient was more than 0.6, which was sufficient and within the acceptable range **(Table-9).**The t values and significance p-value of all factors are shown in **Table-10.** After collecting all the responses, data were first subjected to descriptive statistics. Pie charts were used in the study so that the results were well represented and easy to understand. To achieve the objective, data contained in the questionnaire, were first fed into the SPSS 16 spreadsheets. The analysis was carried out on the Tables, filled out by the respondents. Reliability analysis was first carried out, measuring the Cronbach's alpha value. The significance value of all factors, except Crush and Drop, were found to be less than 0.05.

8.2 Hypothesis Testing

The analysis of t-test showed that factors such as Gas Porosity (GP), Shrinkage Porosity (SP), Hot Tears (HT), Metal Penetration (MP), Sand Inclusion (SI), Air Inclusion (AI), and Slag Inclusion (SLI), were found statistically significant. P-values of these factors were found to be less than 0.05, at 95% confidence level. The alternate hypothesis **H1 was accepted,** for these seven factors, as the p-value was less than 0.05, as shown in **Table-10.**

8.3 Final overall weight and ranking calculations

The final overall weights and ranking of the samples, were calculated, from the samples ratings given for each sub-criterion. Weights were calculated by first multiplying each sub-criterion, with its respective major criteria and the sample rating associated with it. The values obtained from each of the sub-criteria, were added up, to give the final weight of a sample. These calculations of AHP gave criteria and sub-criteria weights and sample ratings in a crisp form. The obtained values of weights were processed in Microsoft Excel 2007, to obtain results. The performance of samples, with respect to each main criterion, is shown in **Table-6.** Also, the corresponding values are shown in **Figure-2.** The main attributes of the main goal are shown in **Table-7.** There was a total of nine main attributes. The alternative priority weights, for three different material compositions, are shown in **Table-7.** This Table helps in finding rank for three different samples viz. LM2, LM6, and LM12. **Table-8** shows the final weight calculations and corresponding ranking of the samples of casting. Also, from **Figure-3,** it can be seen that LM12 recorded maximum weights, for all nine casting defects identification measures. The best casting sample, with minimum defects, is shown diagrammatically in **Figure-3.**

9. Conclusion

The result of this research paper revealed that the effect of prominent casting defects was statistically significant, for the quality of the castings. Factors like Gas Porosity (GP), Shrinkage Porosity (SP), Hot Tears (HT), Metal Penetration (MP), Sand Inclusion (SI), Air Inclusion (AI), and Slag Inclusion (SLI), were found statistically significant. All these factors' p-values were found to be less than 0.05, at 95% confidence level. The Crush (CR) and Drop (DR) factors' p-values were not found significant as their p-values were more than

0.05.The reliability analysis indicated that the data were highly reliable as all factors' Cronbach's coefficient values were above 0.6. The analysis showed that the alternate hypothesis was accepted for seven factors, except for Crush and Drop, as the p values were less than 0.05. The identification of most prominent defects and selection of best casting sample, was a complicated task. The production of best quality casting (with minimum defects) is necessary to satisfy customer needs and to remain competitive in the market. Casting, with minimum defects was selected by the AHP method. The selection of sample with minimum defects, is a crucial aspect for the long-term survival of any casting firm. In the study, the robust analytical hierarchy process (AHP) model, for casting sample (with minimum defects) selection, was used. Evaluation of three samples was conducted in this study. In evaluating these samples, all the fifty-seven criteria were considered so that each criterion adds its weight to the sample selection process. From the experimental study, a sample, with alloy composition LM6 (with final weight 0.1560), stood out as the undisputedly the best casting sample. The proposed methodology will be highly useful as a decision-making tool. The strategy followed here can be applied, to a variety of problems, associated with getting the best casting. It can also be applied to a wide range of problems, having a similar requirement.

10. Suggestions

This study showed that there was significant impact of various casting defects, on the quality of castings, which need to be taken care of during manufacturing of a product. Factors like GP, SP, HT, MP, SI, AI, and SLI were found statistically significant. All these factors' p-values were found to be less than 0.05 at 95% confidence level. The Crush and Drop factors' p-values were not found significant as their p-values recorded more than 0.05. Main defects, as per their weights, were Gas Porosity (0.22), Shrinkage Porosity (0.25), Hot Tears (0.17), Metal Penetration (0.09), Sand Inclusion (0.11), Air Inclusion (0.03), Slag Inclusion (0.06), Crush (0.02) and Drop (0.01) **(Table-5).** Casting defects, with higher weights, occurred mainly during the casting product manufacturing. Factors, which were responsible for reducing these casting defects, had been identified in this study. These factors help in minimizing the casting defects and enhancing the quality of casting in the process.

11. Limitations of the Study

The study focused only on casting defects and selecting the best casting sample, among three different materials. The quality of casting was studied by considering only nine major casting defects. The sand casting process alone was considered in this study, using the non-ferrous material.

12. Scope for Future Research

The future work could be taken on the selection of best casting process, among various casting processes. The critical casting parameters, related to process, can be selected for the study, which reduce the casting defects. The researchers can also study the remaining casting defects and their effects on quality of castings. The same study can be applied to ferrous materials also.

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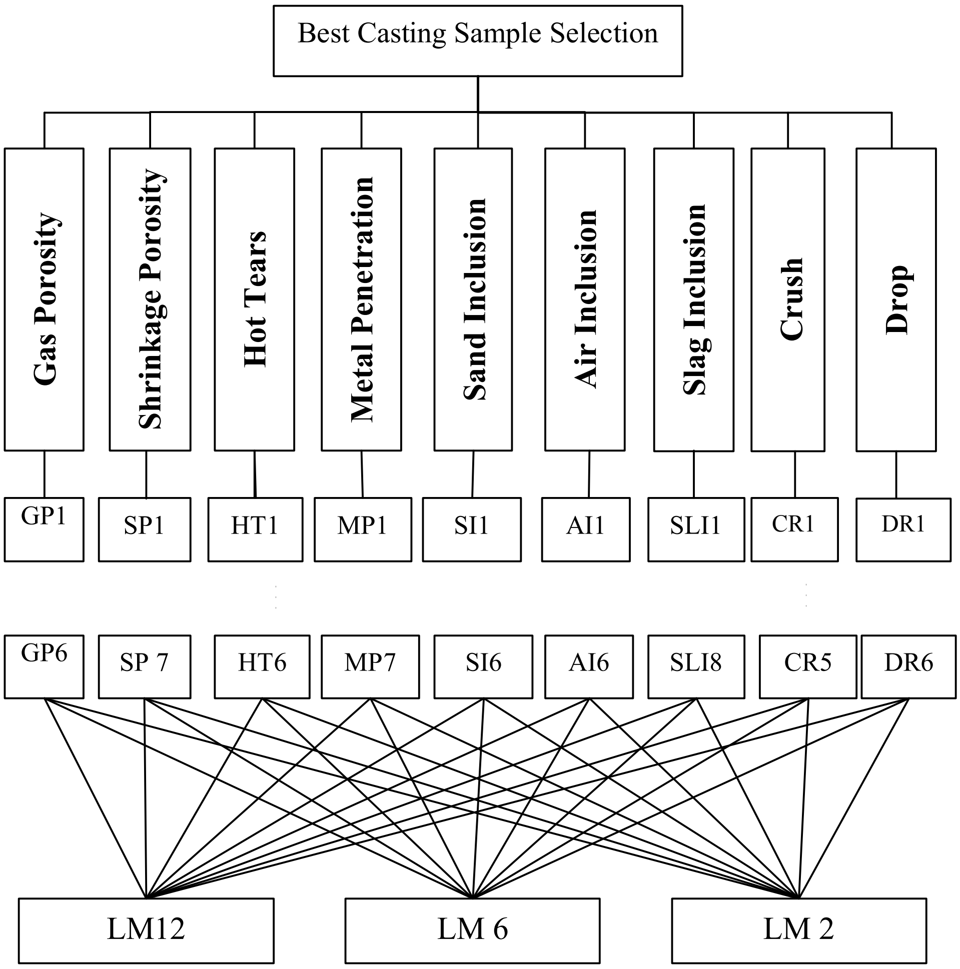
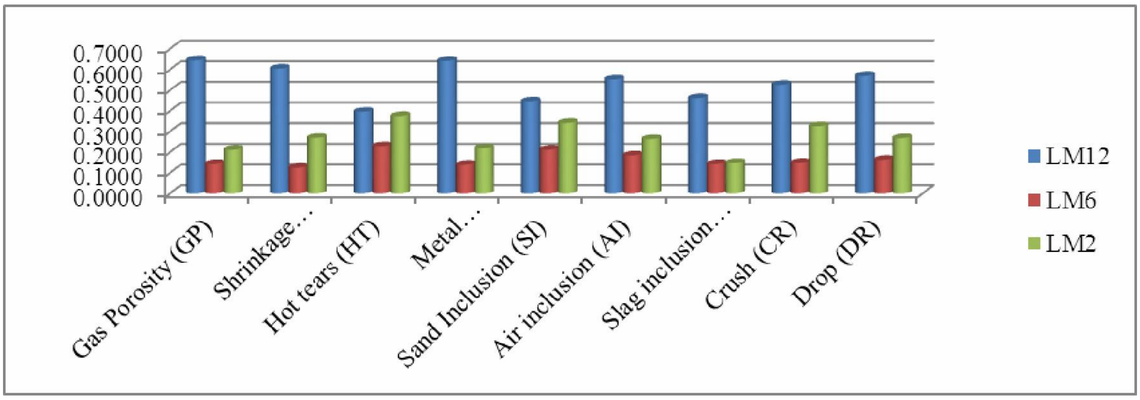
Figure-1: The Hierarchy for the Selection of the Best Casting Sample



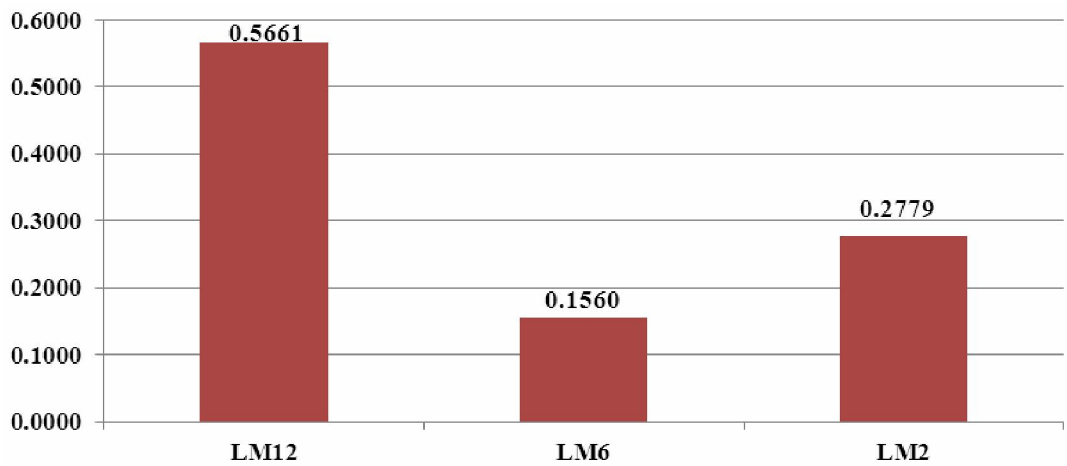
Source: Developed by the authors for the present study, 2016

Figure-2: The Performance of Samples with respect to each Main Defect



Source: Developed by the authors in MS- Excel for the present study, 2016

Figure-3: Selection of Best Casting Sample (with minimum defects) using AHP



Source: Developed by the authors in MS- Excel for the present study, 2016

Table-1: Saaty's Fundamental Scale

Saaty's Scale	Relative importance of the two sub-elements
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	Intermediate values

Source: Rao (2004)

Table-2: Average Random Index (RI) based on Matrix Size

n	3	4	5	6	7	8	9	10
RI	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Source: Rao (2004)

Table-3: Chemical Composition of Alloys (As per BS 1490:1988 Std.)

Alloy Percent	Cu	Mg	Si	Fe	Mn	Ni	Zn	Pb	Sn	Ti	Others
LM12	9.0 -11.0	0.2 – 0.4	2.5	1	0.6	0.5	0.8	0.1	0.1	0.2	0.2
LM6	0.1	0.1	10 - 13.0	0.6	0.5	0.1	0.1	0.1	0.05	0.2	0.2
LM2	0.7 – 2.5	0.3	9.0 - 1.5	1	0.5	0.5	2	0.3	0.2	0.2	0.5

Source: Cast-alloys.com

Table-4: Pairwise Comparison of the Goal

Goal	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1	1/2	5	5	6	7	6	9	9
C2	2	1	6	7	4	7	7	8	8
C3	1/5	1/6	1	2	1/2	6	4	7	8
C4	1/5	1/7	1/2	1	1/2	5	4	8	9
C5	1/6	1/4	2	2	1	7	4	9	9
C6	1/7	1/7	1/6	1/5	1/7	1	1/2	5	5
C7	1/6	1/7	1/4	1/4	1/4	2	1	6	7
C8	1/9	1/8	1/7	1/8	1/9	1/5	1/6	1	2
C9	1/9	1/8	1/8	1/9	1/9	1/5	1/7	1/2	1

Source: Developed by the authors on the basis of data collected for the present study, 2016

Table-5: Main Criteria Weights

Sr. No.	Criteria	Weight
1	Gas Porosity (GP)	0.2292
2	Shrinkage Porosity (SP)	0.2579
3	Hot Tears (HT)	0.1713
4	Metal Penetration (MP)	0.0918
5	Sand Inclusion (SI)	0.1107
6	Air Inclusion (AI)	0.0383
7	Slag Inclusion (SLI)	0.0638
8	Crush (CR)	0.0208
9	Drop (DR)	0.0160

Source: Developed by the authors on the basis of data collected for the present study, 2016

Table-6: Performance of Samples with respect to each Main Criterion

Criteria	LM12	LM6	LM2
Gas Porosity (GP)	0.6452	0.1429	0.2119
Shrinkage Porosity (SP)	0.6049	0.1257	0.2694
Hot Tears (HT)	0.3957	0.2289	0.3753
Metal Penetration(MP)	0.6422	0.1391	0.2187
Sand Inclusion (SI)	0.4461	0.2123	0.3416
Air Inclusion (AI)	0.5519	0.1847	0.2634
Slag Inclusion (SLI)	0.4617	0.1430	0.1475
Crush (CR)	0.5260	0.1484	0.3256
Drop (DR)	0.5693	0.1626	0.2681

Source: Developed by the authors on the basis of data collected for the present study, 2016

Table-7: Main Attributes of Goal

	GP	SP	HT	MP	SI	AI	SLI	CR	DR	Alternative priority weight
Weight	0.2292	0.2579	0.1713	0.0918	0.1107	0.0383	0.0638	0.0208	0.0160	
LM12	0.6232	0.4905	0.6551	0.4429	0.5390	0.6080	0.5949	0.6333	0.6080	0.5660
LM6	0.1373	0.1976	0.1335	0.1698	0.1638	0.1199	0.1285	0.1062	0.1199	0.1560
LM2	0.2395	0.3119	0.2114	0.3873	0.2973	0.2721	0.2766	0.2605	0.2721	0.2780

Source: Developed by the authors on the basis of data collected for the present study, 2016

Table-8: Final Weight Calculations and Ranking

Sample Number	Final Weight	Ranking
LM12	0.5661	3
LM6	0.1560	1
LM2	0.2779	2

Source: Developed by the authors on the basis of data collected for the present study, 2016

Table-9: Reliability Statistics for all Factors (One Sample t Test)

S. No	Casting Defects	Cronbach's Alpha
1	Gas Porosity	0.988
2	Shrinkage Porosity	0.966
3	Hot Tears	0.962
4	Metal Penetration	0.951
5	Sand Inclusion	0.979
6	Air Inclusion	0.969
7	Slag Inclusion	0.969
8	Crush	0.979
9	Drop	0.964

Source: Data analysed using SPSS16

Table-10: One-Sample t-Test Statistics for all Factors

S. No	Casting Defects	Cronbach's Alpha
1	Gas Porosity	0.988
2	Shrinkage Porosity	0.966
3	Hot Tears	0.962
4	Metal Penetration	0.951
5	Sand Inclusion	0.979
6	Air Inclusion	0.969
7	Slag Inclusion	0.969
8	Crush	0.979
9	Drop	0.964

Source: Data analyzed using SPSS16

Annexure-I: Meaning of short forms used for each sub-criteria

Short form	Meaning
GP1	Moulding Sand/ closing: Excessive gassy ingredients and Improper venting
GP2	Patterns: Insufficient prints for venting
GP3	Cores: Excessive binder gas producing additives and Moisture absorption on storage
GP4	Melting: Use of rusty strap and Improper degassing of liquid
GP5	Pouring: Cold metal pouring and Improperly dried ladles
GP6	Gas porosity effect on casting quality
SP1	Improper design and location of riser and gating system
SP2	Improper design of pattern
SP3	Poor Molding practices
SP4	Poor quality of Sand and cores
SP5	Poor Melting practices
SP6	Poor pouring practices
SP7	Shrinkage porosity effect on casting quality
HT1	Hindered contraction
HT2	Hotspot or large thermal gradient.
HT3	Isolated heavy section, or heat concentration at an ingate or riser contact
HT4	Stress caused by mold or core.
HT5	Excess mold/core strength or sand density.
HT6	Hot tears effect on casting quality
MP1	Grain size is too coarse
MP2	Inadequate mold boxes design and packing
MP3	Higher pouring temperature and pressure
MP4	Improper closing and handling
MP5	Improper venting
MP6	Poor quality of mold washes
MP7	Metal penetration effect on casting quality
SI1	Moulding Sand, Poor cutting of gating runners, Improper mixing of sand and poor green strength
SI2	Pouring: Too fast pouring and Excessive metal pressure

Annexure-I Continued...

Annexure - I Continued...

SI3	Closing: Rough handling of closed molds and Careless cleaning of mold after repairs
SI4	Gating system: Turbulence in metal entry and Metal stream hitting cores
SI5	Pattern: Improper draft causing mould-breakage and Rough pattern surface
SI6	Sand inclusion effect on casting quality
AI1	Absorption of gas/ air by the molten metal in the furnace
AI2	Absorption of gas/ air by the molten metal in the mold during pouring
AI3	High temperature
AI4	Poor gating system design
AI5	Slow pouring
AI6	Air inclusion effect on casting quality
SLI1	Insufficient addition of flux during melting
SLI2	Improper tapping process
SLI3	Usage of uncleaned ladle
SLI4	Poor gating system design
SLI5	Oxide content of the charge too high
SLI6	Poor or slow dissolution of inoculants
SLI7	Poor degassing of the molten metal
SLI8	Slag inclusion effect on casting quality
CR1	The insufficient hardness of the mold.
CR2	Improper clamping of the mold boxes.
CR3	Use of inappropriate sand with poor compressive strength
CR4	Improper cleaning the pattern and mold box before molding
CR5	Crush effect on casting quality
DR1	Improper ramming of the cope flask
DR2	Inadequate use of binders.
DR3	Sand grains are too coarse
DR4	Facing sand with inadequate strength
DR5	Improper usage of box size
DR6	Drop effect on casting quality