Grey Relational Analysis of Thin Wall Ductile Iron Casting

Bharat Ashok Tare
P.G.Student, Textile and Engineering Institute, Ichalkaranji 416115, Maharashtra (India),

Vasudev D.Shinde
Professor, Textile and Engineering Institute, Ichalkaranji 416115, Maharashtra (India)

Abstract- Development of thin wall ductile iron is essential to permit designers for energy consuming equipment to choose the most appropriate material based on material properties, and not solely on weight or density. This paper analyzes various significant process parameters of the casting process. An attempt has been made to develop thin wall casting in order to obtain good mechanical properties. In the present work, ductile iron castings with varying thickness from 2 to 6mm were cast with suitable casting design to assure accurate mold filling. The process parameters considered are: Chemical composition (% Cu variations), Pouring Temperature, Type of inoculants and section thickness. The effect of selected process parameters and its levels on the Tensile Strength, Vickers hardness and percentage Elongation and the subsequent optimal settings of the parameters have been accomplished using Taguchi's parameter design approach. The result indicates that the selected process parameters significantly affect the thin wall ductile iron castings. GRA is employed to search for grey relational grade (GRG), which can be used to describe the relationships among the factors and to determine the important factors that significantly influence some defined objectives. The estimation of the optimum performance characteristics of thin wall casting at the optimum levels of parameters is achieved by using grey relational analysis and the results are verified by confirming with practical experiments.

Keywords: Ductile iron, thin wall casting, Taguchi, grey relational analysis, optimization.

I. INTRODUCTION

To achieve fuel economy in automotive industry, reducing the vehicle weight has been a major thrust research area over the last few decades. Although the general trend has been to use low density materials (aluminum, magnesium and composites) instead of cast iron and steel in the automotive industry, numerous examples have been recently noted in the literature where iron castings started again to replace aluminum in this industry. Applications for ductile iron have increased steadily due to its relatively low production cost and ability to achieve a range of microstructures with different mechanical properties. In particular, there has been an increase in demand for thin-wall ductile iron castings to provide components with high strength-to-weight ratios [1]. The need to save weight in the automotive industry calls for development of lighter constructions. This can be achieved either by using lighter materials or by optimizing existing constructions so that they become lighter e.g. by reducing the wall thickness or removing superfluous material [2]. Thin-walled ductile cast iron has good mechanical properties and is more economical in production compared with many other materials. By geometrical optimization of the casting it can be favourable to replace traditionally light materials with thin-walled ductile cast iron [3].

When mechanical properties, density and cost are included in material evaluation, ductile iron may offer more advantages than aluminum, particularly if thin wall ductile iron parts could be produced without further heat treatment processes[4]. The potentials for ductile iron applications for lightweight automotive components have been limited by the capability to produce as-cast carbide free thin wall parts (2-3 mm) [5]. Production of thin-wall ductile iron castings still represents a daily challenge in modern foundries due to casting defect produced during casting process [6]. Review of the recent literature shows that thin-wall ductile iron has been successfully produced for many years, thanks to the optimization of some critical production parameters: pouring temperature, chemical composition and thermal conductivity of the molding materials, type and amount of inoculating material in combination [7].

Dr.Taguchi has introduced several new statistical concepts which have proven to be valuable tools in the field of quality improvement. Many Japanese manufacturers have used his approach for improving product and process quality with unprecedented success. Taguchi has built upon W.E. Deming's observation that 85% of the poor quality is attribute to the manufacturing process and only 15% to the worker. Hence an attempt has been made

to develop manufacturing systems that are robust or in sensitive to daily and seasonal variations of environment machine wear and other external factors [9]. His methods focus on the effective application of engineering strategies rather than advanced statistical techniques. It includes both upstream and shop-floor quality engineering. Upstream methods efficiently use small-scale experiments to reduce variability and cost-effective, robust designs for large scale production and market place. Shop-floor techniques provide cost-based, real time methods for monitoring and maintaining quality in production. The further upstream a quality method is applied, the greater leverages it produces on the improvement, and the more it reduces the cost and time. Taguchi proposes an “off-line” strategy for quality improvement in place of an attempt to inspect quality into a production the production line. He observes that poor quality cannot be improved by the process of inspection; screening and salvaging. No amount of inspection can put quality back into the product. Taguchi recommends a three-stage process: system design, parameter design and tolerance design [10]. Taguchi's method is focused on the effective application of engineering strategies rather than advanced statistical techniques. The primary goals of Taguchi method are [11]:

- A reduction in the variation of a product design to improve quality and lower the loss imparted to society.
- The proper product or process implementation strategy reduces the level of variation.

Taguchi method is used as tool for optimization of sand casting, process parameters of the castings manufactured in iron foundry by maximizing the signal to noise ratios and minimizing the noise factors. The process parameters considered are moisture, sand particle size, green compression strength, mould hardness, permeability, pouring temperature, pouring time and pressure test. The results indicated that the selected process parameters significantly affect the casting defects in the foundry [12].

Grey relational analysis (GRA) has been widely applied in analyzing multivariate series data as a solution to the traditional statistical limitations. GRA, which has been proven to be simple and accurate method for analysing relationship in multivariate series data and broadly used in various disciplines such as economics, sociology and engineering. GRA is employed to search for grey relational grade (GRG), which can be used to describe the relationships among the factors and to determine the important factors that significantly influence some defined objectives [13].

In the grey relational analysis, experimental results were first normalized and then the grey relational coefficient was calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. Then, the grey relational grade was computed by averaging the grey relational coefficient corresponding to each process response. The overall evaluation of the multiple process responses is based on the grey relational grade. As a result, optimization of the complicated multiple process responses can be converted into optimization of a single grey relational grade. In other words, the grey relational grade can be treated as the overall evaluation of experimental data for the multi response process. Optimization of a factor is the level with the highest grey relational grade [14, 15]. In the present work Taguchi-Grey rational analysis (TGRA) is used for parameter design approach to study and optimize the effect of process parameters on the mechanical properties of thin wall ductile iron casting.

II. PROCESS PARAMETERS

An Ishikawa diagram (cause and effect diagram) was constructed as shown in Figure 1 to identify the casting process parameters which influence quality of casting. The process parameters can be listed in five categories as follows:

- Mould machine related parameters
- Cast metal related parameters
- Casting design parameter
- Inoculation related parameters
- Temperature related parameters

From Figure1, the most significant parameters are Chemical composition, Pouring temperature, Type of inoculants and section thickness. The selected casting process parameters, along with their ranges, are given in Table 1.

Table-1 Process parameters with their ranges

Parameter designation	Process parameters	Range
A	Chemical composition (% Cu)	0.1-0.9
B	Pouring Temperature (^{0}C)	1380-1420
C	Type of Inoculant	FeSi Based, Ba Based, Ca Based
D	Section Thickness (mm)	2,4,6

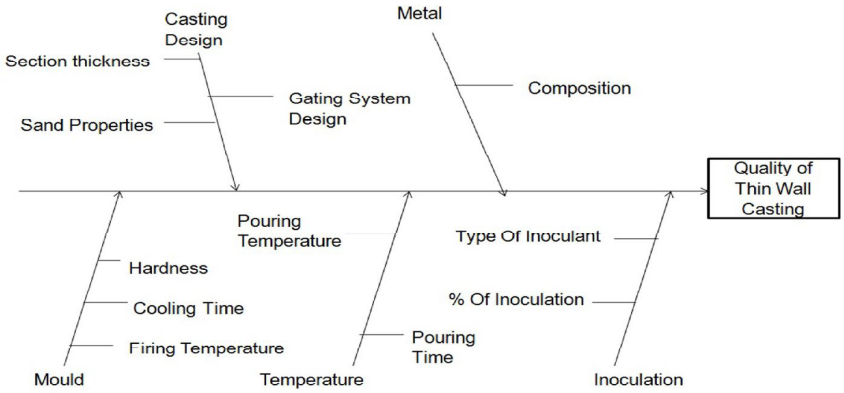

Figure 1.Cause and effect diagram

III. SELECTION OF ORTHOGONAL ARRAY (OA)

For analysis of thin wall ductile iron casting, the four casting process parameters each at three levels have been selected (Table 2).The selection of a particular orthogonal array is based on the number of levels of various parameters. Now, the Degree of Freedom (DOF) can be calculated by using the equation as:

$$(DOF)R = P \times (L - 1)$$

Where,
(DOF)R = degree's of freedom
P = number of parameters
L = number of levels of each parameter

$$(DOF)R = 4 \times (3 - 1) = 8$$

However, total DOF of the orthogonal array (OA) should be greater than or equal to the total DOF required for the experiment. The DOF calculated as 8 so L9 (3^4) orthogonal array is selected to assign various columns, the experiments were performed according to the trial condition as per L9 Orthogonal Array shown in Table 2.The control parameters at three different levels and three different response parameters considered for multiple performance characteristics in this work are shown in Table 3.

Table-2 Taguchi L9 standard orthogonal array matrix

Expt. No	Parameter 1	Parameter 2	Parameter 3	Parameter 4
E 1	1	1	1	1
E 2	1	2	2	2
E 3	1	3	3	3
E 4	2	1	2	3
E 5	2	2	3	1
E 6	2	3	1	2
E 7	3	1	3	2
E 8	3	2	1	3
E 9	3	3	2	1

Table-3 Response parameters and control parameters with levels

Response Parameter		Tensile Strength (N/mm^2) Vickers Hardness (VN) % Elongation		
Sr. No.	**Control Parameters**	**Levels**		
		1	**2**	**3**
1	Chemical Composition (%Cu)	0.1	0.4	0.9
2	Pouring Temperature (^{0}C)	1420	1400	1380
3	Type of base Inoculant	FeSi based	Ba based	Ca Baesd
4	Section Thickness (mm)	2	4	6

IV. EXPERIMENTAL WORK AND ANALYSIS

A step casting was designed with four sections of thickness, 2, 4, 6 and 8mm respectively. Each step is 50 mm long, making the total length of casting 200 mm. The width of the casting is 100 mm so as to avoid end freezing effect in the middle of all sections as shown in Figure 2. Multiple gates were provided (one at the end of each section of the casting) for rapid and uniform filling .Metallic pattern of the above design was fabricated and used to prepare the Shell moulds. Each shell mould containing two cavities of same design as sown in Figure 3 so as to prepare tensile samples. A total of 27 moulds were prepared and poured.

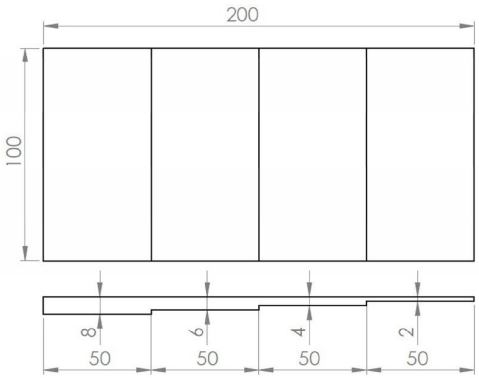

Figure 2.Design of step casting

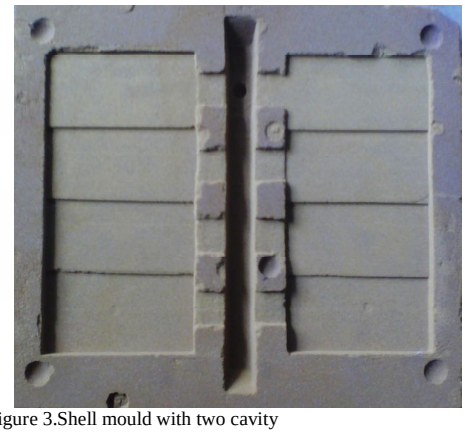

Figure 3.Shell mould with two cavity

Nine experiment each having three repetitions with varying chemical composition(% Cu) as shown in Table 4, with three different type of inoculant is used for this study. Charge consisting 50kg pig iron, 100kg S.G return and 100kg steel scrap were melted in 250kg capacity coreless medium frequency induction furnace. The molten metal was tapped in a preheated ladle containing Ferro silicon magnesium alloy of size 15-25mm at the

bottom covered with steel scrap. The tapping temperature of molten metal was 1465^{0}C. At this time the sample was taken from the melt for final chemical analysis. The treated iron was poured into furan resin shell molds bonded with epoxy resin and catalyst as shown in Figure 4. Similarly all melts were prepared with varying chemical composition, Pouring temperature, type of inoculants. The in-mould inoculation processing method is used for all the experimentation carried out in this work wherein the weighted amount of inoculant is placed at the bottom of the sprue well.

Table-4 Elemental analysis of three set of experiments

Melt / Elements	**Chemical Composition (%)**							
	C	**Si**	**Mn**	**S**	**P**	**Cr**	**Cu**	**Mg**
A1	3.61	2.55	0.410	0.005	0.051	0.056	0.10	0.035
A2	3.60	2.47	0.407	0.009	0.045	0.024	0.40	0.048
A3	3.64	2.50	0.411	0.003	0.071	0.027	0.90	0.031

The tensile specimen is prepared according to the ASTM E8-04 standard; the final geometry is as below shown in Figure 5. Tensile test specimens were repapered from each step casting poured and tensile strength and elongation were measured using Universal Testing Machine as shown in Figure 6 (model- UNITEK 9450, max.capacity-50 KN, Make-Fuel Instruments & engineer's pvt.ltd, Maharashtra, India) as per ASTM standard. The hardness test is taken on middle cut section of all the casting for respective thickness as shown in Figure. 7. Experiments were conducted as per L9 orthogonal array, assigning various values of the levels to the process parameters. The experimental results are shown in Table 5.

Figure 4.Mould pouring process

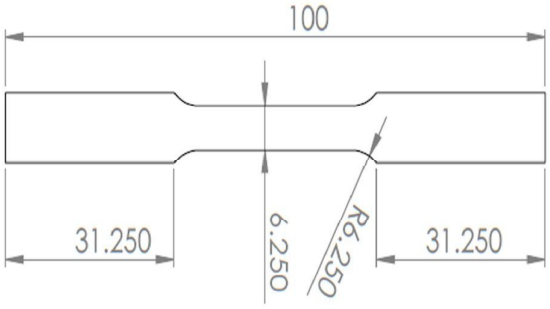

Figure 5.Tensile specimen (ASTM E8-04)

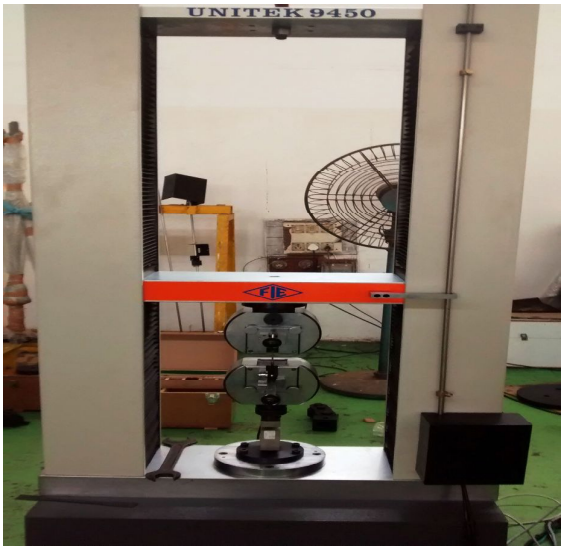

Figure 6.Tensile testing of casting

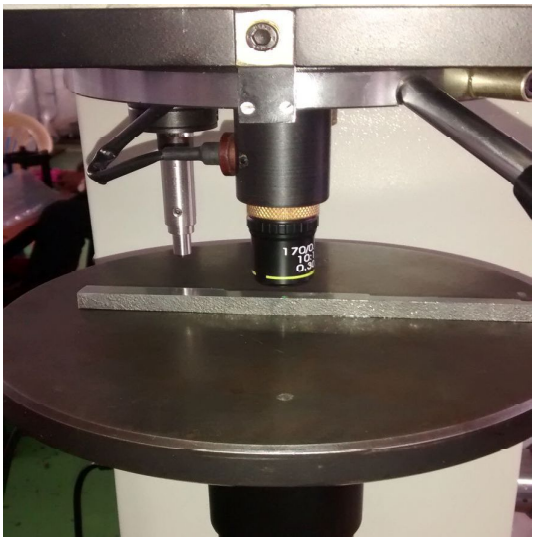

Figure 7. Vickers Hardness testing

Table-5 Experimental Results

Expt. No.	Chemical Composition %Cu	Pouring Temperature (^oC)	Type of Inoculant	Section Thickness (mm)	Tensile Strength (N/mm^2)	Hardness (VN)	% elongation
1	0.1%Cu	1420	FeSi-Based	2	535	223	8.05
2	0.1%Cu	1400	Ba-Based	4	520	193	8.63
3	0.1%Cu	1380	Ca-Based	6	513	181	9.20
4	0.4%Cu	1420	Ba-Based	6	611	232	7.50
5	0.4%Cu	1400	Ca-Based	2	660	265	5.98
6	0.4%Cu	1380	FeSi-Based	4	653	253	6.90
7	0.9%Cu	1420	Ca-Based	4	705	285	2.63
8	0.9%Cu	1400	FeSi-Based	6	677	250	3.20
9	0.9%Cu	1380	Ba-Based	2	740	315	2.01

V. OPTIMIZATION USING GREY RELATIONAL ANALYSIS

The steps involved in Taguchi`s Grey Relational Analysis are:

Step 1: Normalization of S/N ratio: The transformation of S-N Ratio values from the original response values was the initial step. For that the equations of “larger the better”, “smaller the better” and “nominal the best” were used. Subsequent analysis was carried out on the basis of these S/N ratio values as shown in Table 6.

In normalization step a series of various units must be transformed to dimensionless quantities. Experimental results are thus normalized in a range of 0-1. Usually, each series is normalized by dividing the data in the original series by their average.

Let the original reference sequence and sequence for comparison be represented as $x_o(k)$ and $x_i(k)$, i=1, 2, . . ., m; k =1, 2, . . ., n, respectively, where m is the total number of experiment to be considered, and n is the total number of observation data.

1. The "Larger-the-better" is a characteristic of the original sequence, and it is used to compare levels in the GRA

$$x_i^*(k) = \frac{x_i^0(k) - min\ x_i^0(k)}{max\ x_i^0(k) - min\ x_i^0(k)}$$

2. The "smaller-the-better" is a characteristic of the original sequence, and it is used to compare levels in the GRA.

$$x_i^*(k) = \frac{max\ x_i^0(k) - x_i^0(k)}{max\ x_i^0(k) - min\ x_i^0(k)}$$

Table-6 S/N ratio with Normalized S/N ratio for conducted experiments

Expt. No.	S/N ratios			Normalized S/N Ratios		
	Tensile Strength	Hardness	Elongation	Tensile Strength	Hardness	Elongation
1	54.567	46.966	18.793	0.115	0.377	0.963
2	54.320	45.711	18.720	0.037	0.116	0.958
3	54.202	45.154	19.276	0.000	0.000	1.000
4	55.721	47.310	16.922	0.477	0.448	0.822
5	56.391	48.465	15.534	0.688	0.688	0.717
6	56.298	48.062	16.777	0.659	0.604	0.811
7	56.964	49.097	8.399	0.868	0.819	0.177
8	56.612	47.959	9.832	0.757	0.583	0.285
9	57.385	49.966	6.064	1.000	1.000	0.000

Step 2: Determination of deviation sequence: The deviation sequence $\Delta_{oi}(k)$ is the absolute difference between the reference sequence $x_i^0(k)$ and the comparability sequence $x_i^*(k)$ after normalization. It is determined using equation as shown below. The values of deviation sequence are shown in Table 7.

$$\Delta_{oi}(k) = |x_0^*(k) - x_i^*(k)|$$

Step 3: Calculation of Grey Relational Coefficient (GRC): GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, and then their Grey relational coefficient is 1. The Grey relational coefficient can be expressed by equation as shown below. The values of GRC are shown in Table 7.

$$\gamma(x_0(k), x_i(k)) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}\ (k) + \zeta\Delta_{max}}$$

Where,

$\Delta_{min} = min.min\ \Delta_{0,i}\ (k)$, $\Delta_{max} = max.max\ \Delta_{0,i}\ (k)$,$\Delta_{0i}\ (k)$ is the deviation sequence and ζ = distinguishing coefficient, $\zeta \in (0,1)$and for present study, ζ is set as 0.5.

Step 4: Determination of Grey Relational Grade (GRG): The overall evaluation of the multiple performance characteristics is based on the Grey relational grade. The Grey relational grade is an average sum of the Grey relational coefficients, which can be calculated using equation as shown below. The values of GRG are shown in Table 7.

$$\gamma(x_0, x_i) = \frac{1}{m}\sum_{i=1}^{m}\gamma(x_0(k), x_i(k))$$

Where, $\gamma(x_0, x_i)$ is the Grey relational grade for the i_{th}experiment and m is the number of performance characteristic.

Table-7 Grey Rational Coefficient with Grey Rational Grade

Expt. No.	Deviation Sequences			Grey Relational Coefficient			Grey Relational Grade	Rank
	Tensile Strength	Hardness	% elongation	Tensile Strength	Hardness	% elongation		
1	0.885	0.623	0.037	0.361	0.445	0.932	0.579	5
2	0.963	0.884	0.042	0.342	0.361	0.922	0.542	9
3	1.000	1.000	0.000	0.333	0.333	1.000	0.556	7
4	0.523	0.552	0.178	0.489	0.475	0.737	0.567	6
5	0.312	0.312	0.283	0.616	0.616	0.638	0.623	4
6	0.341	0.396	0.189	0.594	0.558	0.726	0.626	3
7	0.132	0.181	0.823	0.791	0.735	0.378	0.634	2
8	0.243	0.417	0.715	0.673	0.545	0.412	0.543	8
9	0.000	0.000	1.000	1.000	1.000	0.333	0.778	1

VI. RESULT AND DISCUSSION

The higher grey relational grade will have better multi response characteristics. With the help of Table 7, the optimal parameter combination was determined as A3 (Chemical composition % Cu), B3 (1380 ^{0}C) and C2 (Ba Based Inoculant), D1 (2mm Section Thickness)

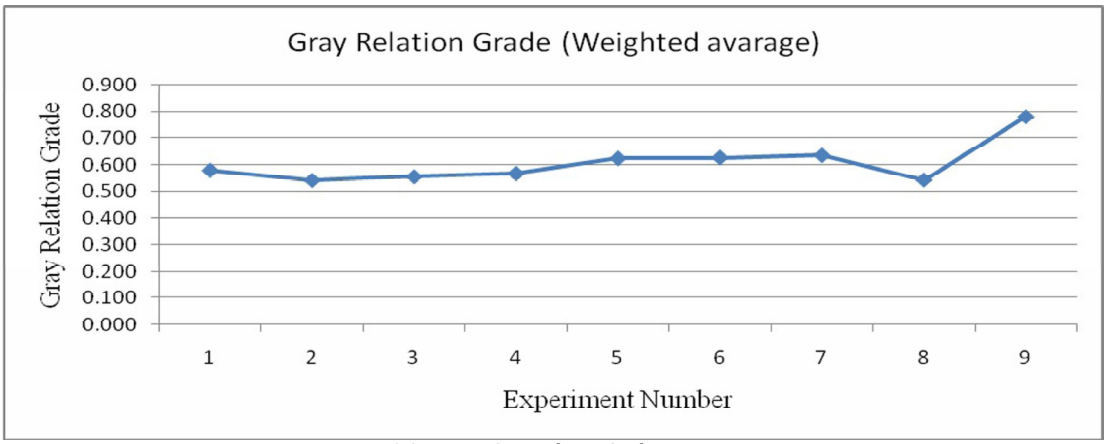

Figure 8.Assigning Grey Relation Grade to experiments

The Figure. 8 shows the graph of Grey relational grades for Tensile strength, Vickers hardness and Percentage Elongation. However, the relative importance among the process parameters for the multiple performance characteristics still needs to be known, so that the optimal combinations of the process parameter levels can be determined more accurately. The experimental design is orthogonal, it is possible to separate out the effect of each parameter on the grey relational grade at different levels .For example, the mean of the grey relational grade for the pouring temperature at levels 1, 2 and 3 can be calculated by averaging the grey relational grade for the experiments 1 to 3, 4 to 6, and 7 to 9 respectively. The mean of the grey relational grade for each level of the parameters is summarized and shown in Table 8.

Table-8 The Main Effects of the Factors on the Grey Relational Grade

Parameter	Level 1	Level 2	Level 3	Max-Min	Rank
Chemical Composition(% Cu)	0.559	0.605	**0.652**	0.093	2
Pouring Temperature	0.594	0.569	**0.653**	0.084	3
Type of inoculant	0.583	**0.629**	0.604	0.046	4
Section Thickness	**0.660**	0.601	0.555	0.105	1

The confirmation tests for the optimal parameters with its level were conducted to evaluate quality characteristics for development of thin wall casting. Table 7 shows highest grey relational grade, indicating the initial process parameter set of (A3B3C2D1) for the best multiple performance characteristics among the nine experiments. Table 9 shows the comparison of the experimental results for the optimal conditions (A3B3C2D1) with predicted results for optimal (A3B3C2D1) casting parameters. The predicted values were obtained by,

Predicted Response = Average of A3 + Average of B3 + Average of C2+ Average of D1
– (3 x overall Mean of response)
= (0.652+0.653+0.629+0.660)-(3 x 0.605)
= 0.778

Finally, three confirmation experiments were conducted using the optimal process parameters (A3, B3, C2 and D1). The measured mean value at optimal parameters for Tensile Strength (N/mm^2), Hardness (VN) and %elongation as shown in Table 9.

Table-9 Predicted and experimental values

Sr. No	Machining characteristics	Predicted Value	Experimental value
1	Optimal parameter	A3B3C2D1	A3B3C2D1
2	Tensile Strength(N/mm^2)	740	742
3	Hardness(VN)	315	316
4	%elongation	2.01	2.09
5	Grey Relational Grade	0.778	0.783

VII. CONCLUSIONS

A TGRA was proposed to study the optimization of thin wall ductile iron casting process parameters. Tensile strength, ductility and Vickers hardness were selected as quality targets. Results indicated that the selected process parameters of casting significantly affect the selected mechanical properties. It also shows that the grey relational analysis tool can be effectively adopted for the analysis of physical processes to explain the relationships between various casting parameters. Also, the experiments give a clear picture of every process parameter contribution to the development of thin wall casting. Twenty-seven experimental runs based on OA were performed. The conclusions based on the single optimization and multi-optimization using TGRA are summarized as follows:

1. Using TGRA, Chemical composition, Pouring Temperature, type of inoculants and section thickness were optimized individually.
2. Using GRA, with optimal set A3B3C2D1 predicts the value 0.778 whereas the experimental value archived is 0.783.
3. The predicted results were checked with experimental results and a good agreement was found.

REFERENCES

[1] Javaid A. and Thomson J. Effect of microstructure on the mechanical properties of thin wall ductile iron castings. *American Foundry Society Transactions* 2001, 82(1), 1-18.

[2] Shinde V.D., Ravi B., Narasimhan K. Solidification behavior and mechanical properties of ductile iron castings with varying thickness. *International Journal of Cast Metals Research* 2012, 25 (6), 364-373.

[3] Shinde V.D., Ravi B. and Narasimhan K. Effect of Orientation, Thickness, and Composition on Properties of Ductile Iron Castings. *Materials and Manufacturing Processes* 2013, 28(5), 1-6.

[4] Stefanescu D.M. and Ruxanda R. Lightweight iron castings-can they replace aluminum castings; In *Proceedings of the 65th World Foundry Congress*, Gyeongju, Korea, Oct 20-24, 2002.

[5] Fras E., Gorny M. and Kapturkiewicz W. Thin Wall Ductile Iron Castings: Technological Aspects. *Archives of Foundry Engineering* 2013, 13(1), 23-28.

[6] Labrecque C., Gange M. and Javaid A. Optimizing the mechanical properties of thin-wall ductile iron castings. *American Foundry Society Transactions* 2005, 116(5), 1-10.

[7] Jamkar S., Deshmukh M. And Vidhate N. Optimization of Green Sand Casting Process Parameter by Taguchi Method: A Review. *International Journal of Mechanical Engineering* 2004, 4(1), 1-7.

[8] Syrcos G. Die casting process optimization using Taguchi methods. *Journal of Materials Processing Technology* 2003,135(1), 68-74.

[9] Barua P., Kumar P. and Gaindhar J. Optimization of mechanical properties of V-process castings by Taguchi method. *Indian Foundry Journal* 1997, 17-25.

[10] Upadhye R. and Keswani I. Optimization of Sand Casting Process Parameter Using Taguchi Method in Foundry. *International Journal of Engineering Research & Technology* 2012, 1(7), 1-7.

[11] Muthuramalingam T. and Mohan B. Taguchi- Grey Relational Based Multi Response Optimization of Electrical Process Parameters In Electrical Discharge Machining. *Indian Journal of Engineering and Material Science* 2013, 20, 471-475.

[12] Chang K. Grey-relational analysis based approach for data clustering", *IEEE Visual Image Signal Process* 2005, Vol.152, 165-172.

[13] Balasubramanian S. and Ganapathy S. Grey Relational Analysis to determine optimum process parameters for Wire Electro Discharge Machining (WEDM). *International Journal of engineering Science and Technology* 2011, 3(1), 95-101.

[14] Raghuraman S., Panneerselvam T., Thiruppathi K. and Santosh S. Optimization of EDM Parameters using Taguchi Method and Grey Relational Analysis for Mild Steel IS 2026. *International Journal of Innovative Research in Science* 2013, Engineering and Technology, 2(7), 3095-3104.

[15] Tosun N. Determination of optimum parameters for multi-performance characteristics in drilling by using grey relational analysis. *International Journal of Advanced Manufacturing Technology* 2006, 28, 450-455.