

## Implementation of Statistical Process Control (SPC) Techniques as Quality Control in Cast Iron Part Production

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### ABSTRACT

Quality improvement studies are a key factor for the survival of an organization in a production plant. There are plenty of different verified quality tools. Statistical process control (SPC) is one of the important approaches used in quality management. SPC can be applied in plants to obtain good quality and high standard products which have become very popular in many industries. This study contains construction of a system design to observe whether the conditions of an alloy production line are within the specification and control limits. For this purpose, GGG40 spherical ductile iron was selected. The X-bar and R charts were applied to GGG40 samples for 25 days' production to determine the average percentage of C and Si, and hardness value. The lower and upper control limits, and process capability indices were determined for the production. The experimental analyses were also done for a randomly selected sample. Comparison of statistical and experimental results shows that the SPC methods can be simply applied on a foundry floor in order to control the process parameters and improve quality of the cast products.

**Keywords:** Cast Iron, GGG40, Statistical Process Control, X-R Charts

### I. INTRODUCTION

Cast iron is a complex alloy containing mainly a total of up to 10% carbon, silicon, manganese, sulphur and phosphorous as well as varying amount of nickel, chromium, molybdenum, vanadium and copper [1]. The metallic matrix of cast iron mainly consists of pearlite and ferrite. An increase in pearlite percentage in the microstructure results in improved mechanical properties whereas increase in ferrite enhances ductility but lowered

tensile properties [2]. Cast irons generally contain more than 2% C and a variety of alloying elements.

The selection of alloying element addition is based on the influence that they may have on the microstructure. Carbon can either precipitate as carbides or as graphite. For example, carbide stabilizers such as Ni, Cr, Mo, V would promote pearlitic structure (Fig. 1a, b). On the other hand, Si addition would result in graphite precipitation (Fig. 1 b-d). However, Mg and Ce would facilitate spheroidal precipitation of graphite (Fig. 1 d, e) [3].

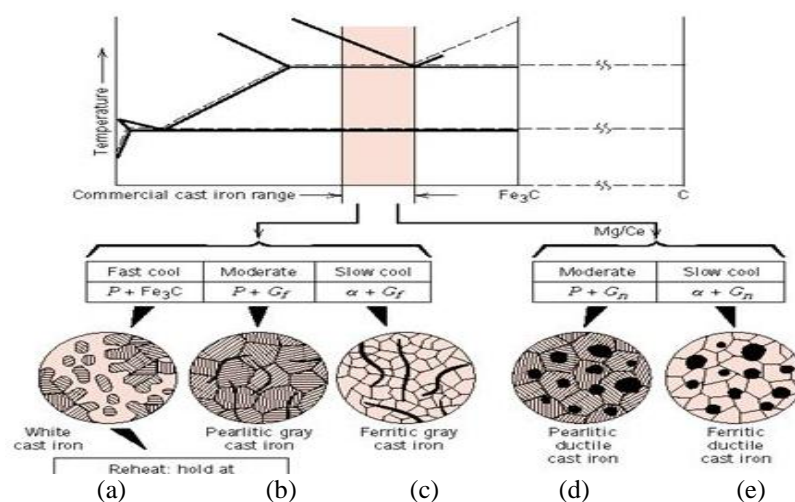


Figure 1. Typical microstructures of cast iron [3].

Over the years, some irons have been evolved which have their name derived from their mechanical property, such as malleable iron and ductile iron. More recently compacted graphite iron and austempered ductile iron have been introduced [3]. There are four factors which lead to the different types of cast irons namely, the carbon content, the alloy and impurity content, the cooling rate during and after freezing, the heat treatment after casting. These parameters control the composition as well as the form of parent matrix phase presents [3,4,5]. The carbon may exist as free carbon in graphite, or may be combined as iron carbide in cementite. The distribution and shape of free carbon particles influence the physical properties of the cast iron [6]. Therefore, it is important to know and characterise the type of microstructure, and as a result, this would determine the properties of the cast part.

Statistical process control (SPC), a sub-area of statistical quality control (SQC), consists of methods for understanding, monitoring, and improving process performance over time [7]. SPC concepts have become very popular in chemical and manufacturing industries. Their objective is to monitor the performance of a process over time in order to detect any special phenomena that may occur. By finding assignable causes for them, improvements in the process and in the product quality can be achieved by eliminating the causes, improving the process and/or its operating procedures. Traditional SPC procedures, based on relying only a small number of final product quality variables, are totally inadequate for most modern process industries. The fact that computers can record nearly every industrial process in such detail has been disregarded. Massive amount of data can be collected continually on perhaps hundreds of process variables in continuous or batch processes. All such data should be used to extract information in any effective scheme for monitoring and diagnosing operating performance. However, all the process variables are not independent of one another. Only a few underlying events are driving a process at any time, and all these measurements are simply different reflections of these same underlying events. Multivariate statistical projection methods like Principal Components Analysis (PCA) [8] and Partial Least Squares (PLS) Höskuldsson, (1988) [9]. are capable of utilizing massive amounts of data and compress the information in this data down into low dimensional latent variable spaces in which monitoring of the process and interpreting the results are much easier [10].

Variable control charts are used to study a process when quantity can be measured, for example, cycle time, processing time, waiting time,

height, area, temperature, cost or revenue. Measurement data provides more information than attribute data: consequently, variable charts are more sensitive in detecting special cause variation than are attribute charts. Variable charts are typically used in pairs. One chart studies the variation in a process, and the other studies the process average. The chart that studies variability must be examined before the chart that studies the process average. This is so because the chart that studies the process average assumes that the process variability is stable over time. One of the most commonly employed and popular pair of charts is the X-bar-chart and the R-chart [11]. Through the use of control charts, similar gains can be realized in the manufacturing sector. Users of control charts report savings in scrap, including material and labour, lower rework costs, reduced inspections, higher product quality, more consistent part characteristics, greater operator confidence, lower trouble shooting, reduced completion time, faster deliveries and others [12, 13]. SPC is an effective and powerful methodology for analysing, monitoring, managing, and improving process performance. Among seven SPC tools, control diagram is the most important one. The process variations can be controlled using control diagrams, and defective products can be avoided by some preventive actions.

The term  $C_p$  denotes the process potential capability index, and similarly, the term  $C_{pk}$  denotes the process performance capability index.  $C_p$  gives an indication of the dispersion of the product dimensional values within the specified tolerance zone during the manufacturing process. Similarly, the index  $C_{pk}$  denotes for the centering of the manufacturing process with respect to the mean of the specified dimensional tolerance zone of the product.  $C_{pk}$  gives us an idea on whether the manufacturing process is performing at the middle of the tolerance zone or nearer the upper or lower tolerance limits. If the manufacturing process is nearer the lower limit, then the process performance capability index is given by  $C_{pk1}$ , and if the manufacturing process is nearer the upper limit, then the process performance capability index is given by  $C_{pk2}$ . As a measure of precautionary safety, the minimum value between the two values is taken as the value of  $C_{pk}$  [14].

In this paper, variations such as C and Si contents (wt%) and hardness value in the characteristics of GGG40 cast iron samples that collected from a foundry in Turkey were investigated using control charts, process capability index. Additionally, for a randomly selected sample, the elemental analysis of C and Si, and the hardness value was determined by experimental techniques. The microstructural images of sample were taken

before and after polishing by the optical microscope and image analysis program.

## II. EXPERIMENTAL PROCEDURE

In  $\bar{X}$  chart, means of small samples are taken at regular intervals, plotted on a chart, and compared against two limits. The limits are known as upper control limit (UCL) and lower control limit (LCL). These limits are defined as below:

$$LCL = \bar{X} - A_2 * R, \text{ and}$$

$$UCL = \bar{X} + A_2 * R$$

where,  $\bar{X}$  is the target mean and factor  $A_2$  depends on sample size (Table 1). The process is assumed to be out of control when the sample average falls beyond these limits.

**Table 1.** Constants for Control Charts [15]

Subgroup size (n)	$A_2$	$D_3$	$D_4$
2	1.880	0	3.267
3	1.023	0	2.574
4	0.729	0	2.282
5	0.577	0	2.114

In these charts, the sample ranges are plotted in order to control the variability of a variable. The centre line of the R chart is known as average range. The range of a sample is simply the difference between the largest and smallest observation. If  $R_1, R_2, \dots, R_k$ , be the range of k samples, then the average range ( $\bar{R}$ ) is given by:

$$\bar{R} = (R_1 + R_2 + R_3 + \dots + R_n) / k$$

The upper and lower control limits of R chart are:

$$\text{Upper control limit: } UCL_R = D_4 * \bar{R}$$

$$\text{Lower control limit: } LCL_R = D_3 * \bar{R}$$

where, factors,  $D_3$  and  $D_4$  depend only on sample size (n) (Table 1) [16].

Process Capability ( $C_p$ ) is the ratio of the distribution curve of a quality characteristic which is required to be under control, to a normal distribution curve. The numerical definition of  $C_p$  is called Process Capability Ratio ( $C_{pr}$ ). Since the process is under control, the process capability indices can be calculated with Eq. (1) and Eq. (2).  $C_p$  controls only the distribution of the process; on the other hand,  $C_{pr}$  controls both the distribution and the average. If  $C_p$  and  $C_{pr}$  values are below 1, it is obvious that the process is inadequate [17].

The highest and the lowest tolerance ranges were treated as the controlled upper and lower specification limits (USL and LSL, respectively) in the calculation of  $C_p$  and  $C_{pk}$  values. The indexes are

given Eqs. 1 and 2.

$$C_p = \frac{USL - LSL}{6\sigma} \quad (1)$$

$$C_{pr} = \min\left[\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right] \quad (2)$$

where  $\mu$  denotes the process mean.  $C_{pr}$  indicates, in addition, how well the distribution is centred about the nominal (target) value, a property that can better reveal the relationship between the mean and objective values.  $C_p$  index values fall into three cases:

- (i) When  $C_p > 1$ , the quality control data tends to be unstable or abnormal. This situation corresponds to a lack of process capability,  $6\sigma > (USL - LSL)$ , meaning that products fail to meet the standard specification. In this case, prompt corrective actions and precautions are highly recommended.
- (ii) When  $C_p = 1$ , the process capability equals the specification tolerance, or  $6\sigma = (USL - LSL)$ , most quality characteristics meeting the specification requirements. If this situation occurs in manufacturing, an uncontrolled process would lead to unqualified products and relevant staff should identify the causes of defects and make improvements.
- (iii) When  $C_p < 1$ , the process capability is lower than the specification tolerance;  $6\sigma < (USL - LSL)$ , and the process capability is excellent. However, there is a target value within the tolerance, and it is advised that the machines must be adjusted and the process must be revamped so that the product specification is closer to the target value. This goal of perfection provides a good example for clinical laboratories to follow [18]. Since the one of the aim of this study is comparison of the product quality obtained by experimental studies and statistical analysis, the experimental procedure given below was implemented for a randomly selected sample.

The elemental analysis of C and Si was determined using optical emission spectrometer. The upper and lower surfaces of cast parts were sanded with 60 grid sandpaper for the hardness investigation. The hardness tests were done by 187.5 kg load and 2.5 mm diameter balls (Brinell hardness test). For the microstructure investigations, the cast samples were grinded with 80, 180, 320, 600, 800, 1000 and 1200 grid sandpaper, respectively and polished on the mat with  $3\mu\text{m}$  diamond paste suspension. After polishing, the microstructure photographs of samples were taken using Nikon

Eclipse L150 model microscope. The images were then processed by Clemex Vision Lite Image Analysis program. The percentage, sphericity, the percent area occupied by the spherical graphite structure, average number of spheroids and average sphere diameter of the sample were determined.

### III. RESULTS

#### 3.1. Application of Statistical Process Control (SPC)

In this study, X-R control charts created with C wt%, Si wt% and hardness of GGG40 cast iron samples produced at the foundry were examined. In order to analyse the mentioned variations, data for 25 days have been gathered. The data arranged as  $m=25$  (number of sample) and  $n=3$  (subgroup, 3 different sample per day) are given in Tables 2-4. Control limits for  $\bar{X}$  and R charts for the parameters were calculated using given information in the Experimental Procedure. The results are presented in Table 5. As seen in Fig. 2, on the  $\bar{X}$  chart for C% value, most of the values are above or below the centre line, exhibiting a random and balanced distribution. In addition, on the R chart for C% value in Fig. 3, no point is seen on the outside of upper control limit and the other points are seen to display normal and regular distribution, near the centre line.  $\bar{X}$  and R Chart for Si% value is given in Figs. 4 and 5. In this charts, all points exist among the upper and lower control limits.  $\bar{X}$  Chart for hardness value, all of the points are found above or near the centre line and they show distribution randomly but wide range above and below the centre line (Fig. 6). On the R Chart for hardness value given in Fig. 7, no point is seen outside the upper control limit.

Process capability indexes represent an overview for process performance which gives useful knowledge to analyse process capability or incapability. USL and LSL values were obtained from the management of the foundry. The calculated capability indexes for C%, Si% and hardness were given in Table 6. The  $C_p/C_{pr}$  values after performing few iterations of data collection were obtained greater than 1.0, and hence the process is declared as a capable process for important parameters such as C%, Si% and hardness. In general, it was determined that the foundry procedures are adequate.

#### 3.2. Properties of GGG40 Cast Iron

For the microstructural characterisation of the cast GGG40 parts, a randomly selected sample was subjected to metallographic and image analyses. The chemical composition of a randomly selected sample is given in Table 7. The microstructural images of cast samples at 50X and 100X magnification are presented in Fig. 8. The pictures taken with an optical microscope after polishing were processed by Clemex Vision Lite Image Analysis program (Fig. 9). The results obtained from samples are summarised in Table 8.

When the image analysis results were evaluated, sphericity (%) and diameter of spheroidal graphite of cast irons were observed to be in accordance with the expected specs. After polishing, the samples were etched with 2% congenital, thus the ferrite pearlite percentage were determined. These images are given in Fig. 10. In order to measure the ferrite and pearlite ratios, the images had to be coloured as seen in Fig. 11 as an example. The percentage of phases is given in Table 9. However, as can be seen from the results of image analysis, the pearlite and spheroidal graphite are assessed as the same phase by the program. To determine the real perlite percentage, the percentage of spherical graphite obtained before polishing is excluded from percentage of perlite that calculated by program.

**Table 2.** Case study data for C% values

Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R	Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R
1	3.68	3.69	3.76	3.71	0.08	14	3.72	3.66	3.73	3.70	0.07
2	3.79	3.62	3.74	3.72	0.17	15	3.75	3.61	3.72	3.69	0.14
3	3.86	3.78	3.72	3.79	0.14	16	3.89	3.68	3.74	3.77	0.15
4	3.92	3.63	3.70	3.75	0.29	17	3.86	3.71	3.70	3.76	0.16
5	3.76	3.62	3.61	3.66	0.15	18	3.78	3.73	3.64	3.72	0.14
6	3.72	3.66	3.70	3.69	0.06	19	3.79	3.83	3.72	3.78	0.11
7	3.87	3.64	3.76	3.76	0.23	20	3.86	3.71	3.67	3.75	0.19
8	3.84	3.65	3.72	3.74	0.19	21	3.88	3.78	3.76	3.80	0.12
9	3.78	3.65	3.67	3.70	0.13	22	3.66	3.75	3.73	3.71	0.09
10	3.79	3.59	3.69	3.69	0.20	23	3.63	3.68	3.63	3.65	0.05
11	3.70	3.75	3.72	3.72	0.05	24	3.67	3.75	3.68	3.70	0.08
12	3.85	3.62	3.73	3.73	0.23	25	3.72	3.70	3.69	3.70	0.03
13	3.81	3.59	3.71	3.70	0.22						

**Table 3.** Case study data for Si% values

Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R	Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R
1	2.16	2.12	2.17	2.15	0.05	13	2.20	2.05	2.22	2.16	0.17
2	2.11	2.08	2.08	2.09	0.03	14	2.12	2.23	2.17	2.17	0.11
3	2.02	2.10	2.17	2.09	0.15	15	2.08	2.18	2.20	2.15	0.12
4	2.36	2.07	2.20	2.21	0.29	16	1.81	2.23	2.11	2.05	0.42
5	2.33	2.17	2.16	2.22	0.17	17	1.98	2.15	2.18	2.10	0.20
6	2.30	2.15	2.11	2.19	0.19	18	2.15	2.09	2.22	2.15	0.13
7	2.14	2.03	2.24	2.14	0.21	19	2.18	2.10	2.26	2.18	0.16
8	2.31	2.06	2.00	2.12	0.31	20	2.06	2.14	2.25	2.15	0.19
9	2.41	2.11	2.12	2.21	0.30	21	2.11	2.08	2.18	2.12	0.10
10	2.14	2.23	2.09	2.15	0.14	22	2.31	2.16	2.23	2.23	0.15
11	2.02	2.20	2.45	2.22	0.43	23	2.01	2.18	2.36	2.18	0.35
12	2.04	2.16	2.04	2.08	0.12	24	2.35	2.16	2.28	2.26	0.19
						25	2.11	2.09	2.28	2.16	0.19

**Table 4.** Case study data for hardness values

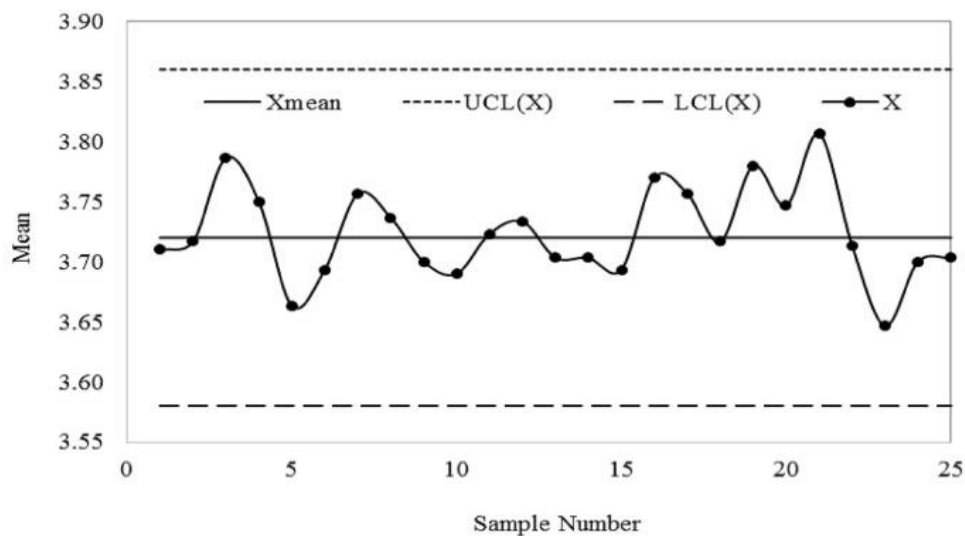
Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R	Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	X	R
1	148	151	153	150	5	13	150	150	153	151	3
2	147	149	155	150	8	14	152	149	151	150	3
3	149	157	154	153	8	15	155	152	155	154	3
4	153	154	149	152	5	16	155	159	155	156	4
5	147	152	151	150	5	17	157	155	150	154	7
6	155	153	148	152	7	18	156	157	152	155	5
7	151	155	152	152	4	19	154	154	153	153	1
8	150	155	154	153	5	20	152	153	149	151	4
9	150	154	153	152	4	21	152	153	152	152	1
10	152	151	155	152	4	22	154	152	155	153	3
11	154	150	158	154	8	23	158	150	157	155	8
12	149	153	152	151	4	24	150	150	153	151	3
						25	149	153	150	150	4

**Table 5.** Control chart values of C, Si and hardness for  $\bar{X}$  and R

	C%	Si%	Hardness
$\bar{X}$ Chart	Lower Control Limit $3.72-(1.023*0.14)$ = 3.58	Lower Control Limit $2.16-1.023*0.20)$ =1.96	Lower Control Limit $152.52-1.023*4.64)$ =147.76
	Center Line 3.72	Center Line =2.16	Center Line =152.52
	Upper Control Limit $3.72+(1.023*0.14)$ = 3.86	Upper Control Limit $2.16+(1.023*0.20)$ =2.36	Upper Control Limit $152.52+(1.023*4.64)$ =157.27
	Lower Control Limit $0.14*0=0$	Lower Control Limit $0.20*0=0$	Lower Control Limit $4.64*0=0$
R Chart	Center Line =0.14	Center Line =0.20	Center Line =4.64
	Upper Control Limit $2.57*0.14=0.36$	Upper Control Limit $2.57*0.20=0.51$	Upper Control Limit $2.57*4.64=11.94$

**Table 6.** Capability indexes for C, Si and Hardness

C	Si	Hardness
4.00	2.50	185
3.20	1.80	130
1.65	1.03	3.37
2.16	1.05	2.51
1.14	1.00	4.04



**Figure 2.**  $\bar{X}$  chart for C

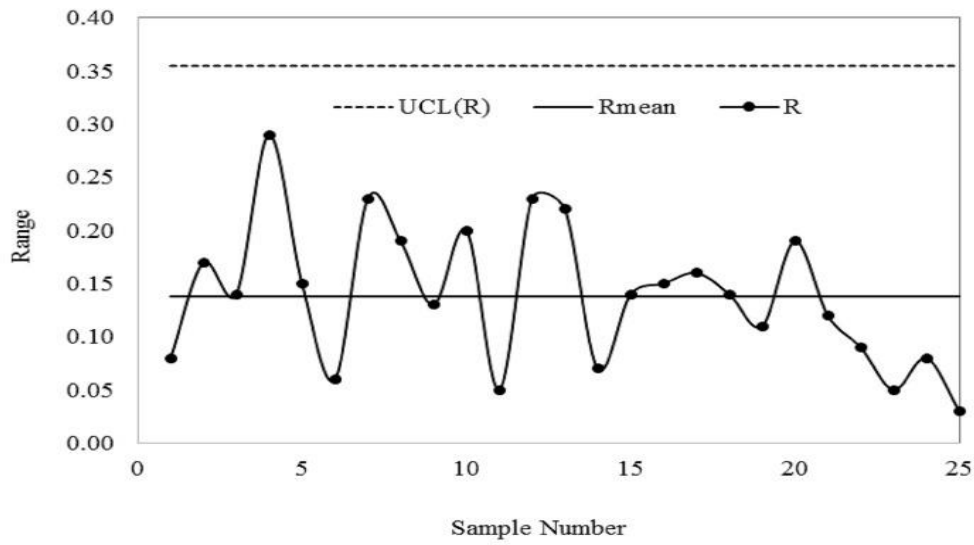


Figure 3. R chart for C

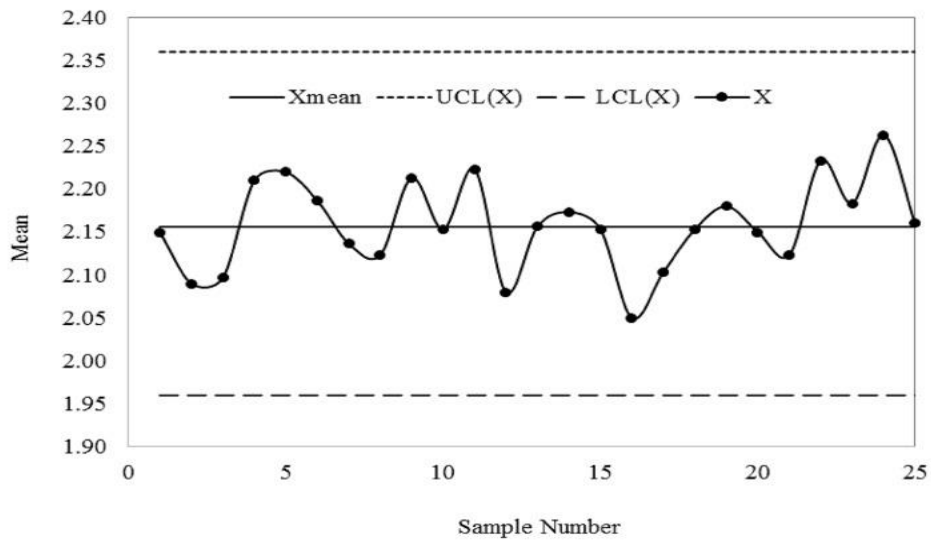


Figure 4.  $\bar{X}$  chart for Si

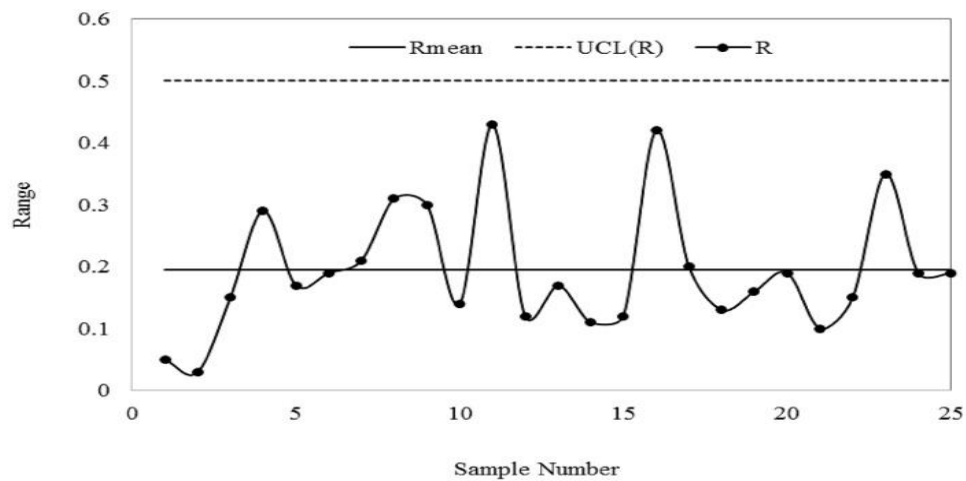


Figure 5. R chart for Si

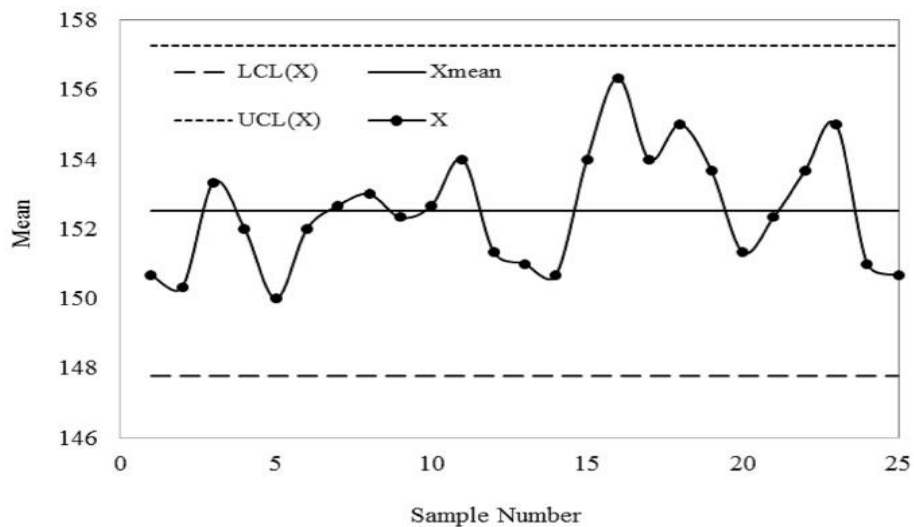


Figure 6.  $\bar{X}$  chart for hardness

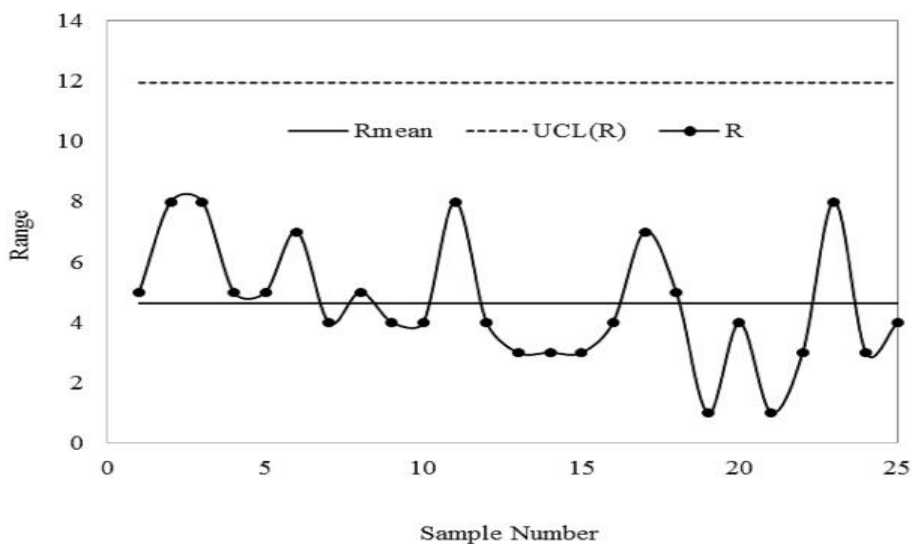


Figure 7. R chart for hardness

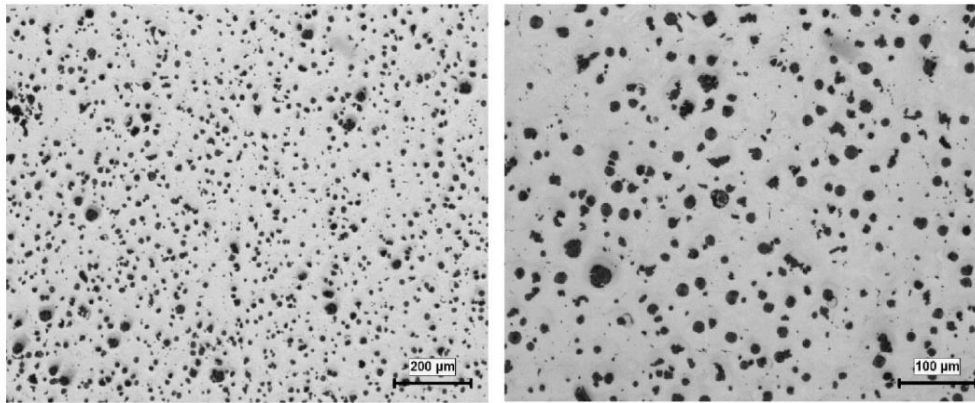
Table 7. Chemical composition of a GGG40 casting sample

Element	C	Si	Mn	P	S	Cr	Cu	Mg	Hardness
%	3.71	2.09	0.098	0.053	0.018	0.035	0.012	0.049	157

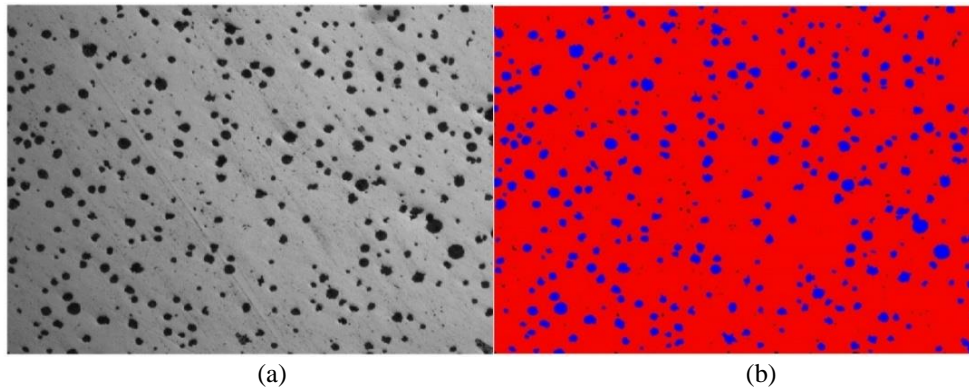
Table 8. Results of microstructure image analysis measurement

Image analysis	Sphericity (%)	Sphere diameter ( $\mu\text{m}$ , average)	Amount of spherical graphite (percentage)	Number of spheres (at 100X magnification)
1	86.40	14.10	10.20	281
2	83.80	14.80	10.90	256
3	84.50	14.30	10.40	264
Average	84.90	14.40	10.50	267





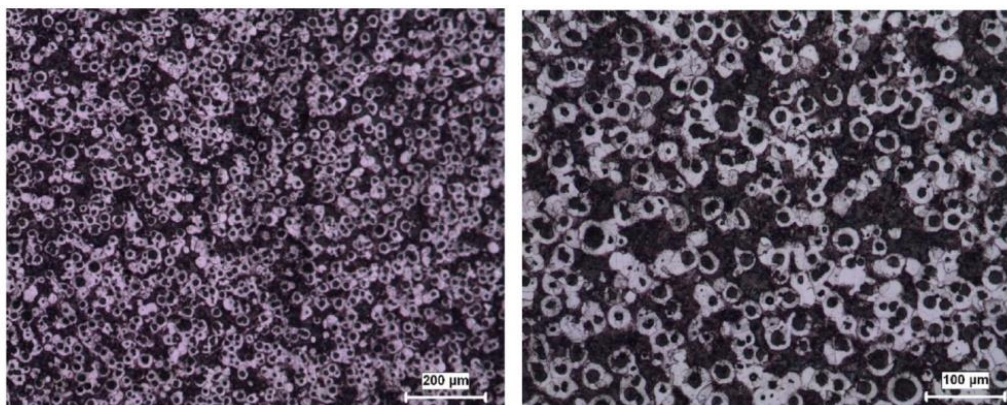
**Figure 8.** Microstructures after polishing



**Figure 9.** (a) microstructure after polishing, (b) threshold application in image analysis

**Table 9.** Results of branded sample phase analysis

Image analysis	Calculated by program		Spherical Graphite %	Perlite amount %	Ferrite amount %
	Blue range %	Red range %			
1	60.70	39.30	10.40	50.30	39.30
2	58.90	41.10	10.20	48.70	41.10
3	60.30	39.70	10.50	49.80	39.70
Average	59.96	40.03	10.36	49.60	40.03



**Figure 10.** Microstructures after etching

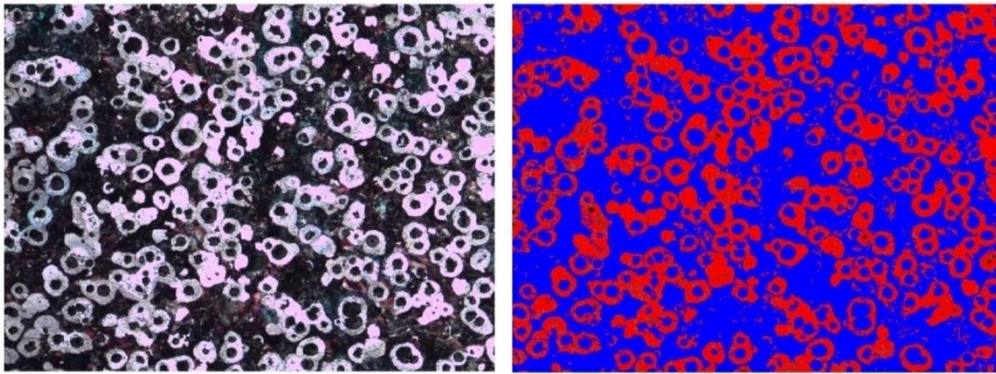


Figure 11. Threshold application with different colours in image analysis software

#### IV. CONCLUSION

The results obtained from this study which aims the controlling of the relevance of the production of GGG40 standard Cast Iron of a commercial foundry are summarized below;

- i) The process variations have to be controlled using control diagrams and process capability index which is one of the important aspects in any production line. Controls diagrams R, and X are the most popular control charts. X-R control charts created with C%, Si% and hardness of GGG40 were observed to be within the limits. In addition, the calculated Cp values such as 1.65, 1.03 and 3.37 for C, Si and hardness, respectively, are upper than 1.0. Meanwhile, the Cpr<sub>1</sub> and Cpr<sub>2</sub> values are greater than 1.0 (Cpr<sub>2</sub> of Si is equal to 1.0). Therefore, it can be said that the process is adequate. (ii) The hardness values were obtained in the range of 150-156 which show quite good agreement with experimentally obtained value of 157, and these results are appropriate and within the expected range for the GGG40 standard material. (iii) The investigations of microstructures after polishing show that the shape of the graphite spheres formed in the structure are appropriate, the average diameter of spheres is about 15 µm, and the number of spheres per mm<sup>2</sup> is in the range of standards. (iv) The percentage of phases in casting structure was determined by processing pictures of microstructures taken after etching on image analysis program. Accordingly, approximately 50% perlite, 40% ferrite and 10% spherical graphite in the structure was determined, and these results are in accordance with properties of the targeting material. (vi) Taking into account the agreement of statistical and experimental analysis results, Statistical Process Control (SPC) methods can be simply applied on a foundry floor in order to control the process parameters and improve quality of the cast products.

#### REFERENCES

- [1]. C. G. Chao, S. Luit, M.H. Hon, A study of tensile properties of ferritic compacted graphite cast irons at intermediate temperatures, *Journal of Materials Science*, 24 (7), 1998, pp.2610-2614.
- [2]. M.A. Kenawy, A.M. Abdel-Fatah, N. Okasha, M. El-Gazary, Ultrasonic measurements and metallurgical properties of ductile cast iron, *Egyptian Journal of Solids*, 24 (2), 2001, pp.133-140.
- [3]. B. L. Bramfitt, B.L., A.O. Benscoter, *Metallographer's Guide: Practice and Rocoedures for Irons and Steels*, ASM International, Metals Park, 2002, Ohio, USA.
- [4]. S. H. Avner, *Introduction to Physical Metallurgy*, 1974, McGrawhill International Editions.
- [5]. M. Hafiz, Mechanical Properties of SG-Iron Subjected to Variable and Isothermal Austempering Temperatures Heat Treatment, *Material Science and Engineering: A*, 2003, Vol. 340, Elsevier.
- [6]. A. K. Chakrabarti, *Casting Technology and Cast Alloys*, 2005, PHI Learning, New Delhi. [15] A Brief Introduction to Neural Networks. Available at <http://www.world-class-quality.com>(accessed on March 09 st., 2015).
- [7]. W.H. Woodall, Controversies and Contradictions in Statistical Process Control, *Journal of Quality Technology*, 2000, 32(4).
- [8]. I.T. Jolliffe, *Principal Component Analysis*, Springer-Verlag, 2002.
- [9]. A. Höskuldsson PLS Regression Methods, *Journal of Chemometrics*, 1998, 2(3) 211-228.
- [10]. T. Kourti, J. Lee, J.F. Macgregor, Experiences with Industrial Applications Of Projection Methods For Multivariate Statistical Process Control, *Computers &*

- Chemical Engineering*, 1996, 20 (supplement), 2745-s750.
- [11]. D.C. Montgomery, *Introduction to Statistical Quality Control*, 2005, John Wiley & Sons, Inc.
- [12]. D.C.S. Summers, *Quality*, Pearson Prentice Hall. Manchester, 2006, United Kingdom
- [13]. A. Mostafaeipour, A. Sedaghat, A. Hazrati, M. Vahdatzad, The Use of Statistical Process Control Technique in The Ceramic Tile Manufacturing: A Case Study, *International Journal of Applied Information Systems*, Foundation of Computer Science, 2012, 2 (5).
- [14]. G.V.S.S Sharma, P.S. Rao, V. Jagadeesh, A. Vishwakarma, Process capability improvement – a case study of an engine connectingrod manufacturing process. *Int J Mech Eng Technol (IJMET)* 2013,4(5):116–129.
- [15]. A Brief Introduction to Neural Networks. Available at <http://www.world-class-quality.com>(accessed on March 09 st., 2015).
- [16]. D.R. Prajapati, Implementation of SPC Techniques in Automotive Industry: A Case Study, *International Journal of Emerging Technology and Advanced Engineering*, 2012, 2 (3) 227-241.
- [17]. H. Ipek, H. Ankara & H. Ozdag, The Application of Statistical Process Control, *Mineral Engineering*, 1999, 12(7) 827-835.
- [18]. M.S. Chen, M.H. Wu., C.M. Lin, Application of Indices Cp and Cpk to Imprve Quality Control Capability in Clinical Biochemistry Laboratories, *Chinese Journal of Physiology*, 2014, 57 (3): 63-68.