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Araştırma / Research

APPLICATION OF FUZZY STATISTICAL PROCESS CONTROL FOR A MANUFACTURING OF GG25 GRAY CAST IRON MATERIAL

Murat ÇOLAK (ORCID: 0000-0001-8226-8067)[1*]
Metin UÇURUM (ORCID: 0000-0002-0725-9344)[2]
Mehmet ÇINAR (ORCID: 0000-0002-0184-0082)[2]
Ümit ATICI (ORCID: 0000-0003-2213-6155)[3]

[1]Malzeme ve Nanoteknoloji Mühendisliği Bölümü, Mühendislik Fakültesi, Bayburt Üniversitesi, Bayburt, Türkiye
[2]Endüstri Mühendisliği Bölümü, Mühendislik Fakültesi, Bayburt Üniversitesi, Bayburt, Türkiye
[3]Maden Mühendisliği Bölümü, Mühendislik Fakültesi, Niğde Ömer Halisdemir Üniversitesi, Niğde, Türkiye

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ABSTRACT

The group of ferrous materials with more than 2% carbon in their chemical composition is commonly referred to as cast iron materials. Carbon Equivalent (CE) is an empirical value in weight percent, relating the combined effects of different alloying elements used in the making of cast iron to an equivalent amount of carbon. Statistical process control (SPC) can be applied in plants to obtain good quality and high standard products which have become very popular in many industries. Fuzzy process capability analysis by using X-R control charts gives more realistic results, developed with fuzzy theory. Fuzzy control charts are more sensitive than SPC. 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. To determine the average percentage of CE values, the fuzzy X-bar and R charts were applied to GG25 gray cast iron samples for 20 days' production. In order to control the process parameters and improve quality of the cast products, the comparison of the statistical and experimental results show that the fuzzy SPC methods can be simply applied on a foundry.

Keywords: GG25 gray cast iron, carbon equivalent, fuzzy statistical process control

GG25 GRİ DÖKME DEMİR MALZEMESİNİN ÜRETİMİNDE BULANIK İSTATİSTİKSEL PROSES KONTROLÜNÜN UYGULANMASI

ÖZ

Kimyasal bileşimlerinde %2'den fazla karbon içeren demirli malzemeler grubuna yaygın olarak dökme demir malzemeleri denir. Karbon Eşdeğeri (CE), dökme demir üretiminde kullanılan farklı alaşım elementlerinin kombine etkilerini eşdeğer miktarda karbon ile ilişkilendiren, ağırlık yüzdesi olarak ampirik bir değerdir. İstatistiksel proses kontrol (SPC), çok popüler hale gelen kaliteli ve yüksek standartlı ürünler elde etmek için fabrikalarda yaygın olarak uygulanmaktadır. Bulanık proses kontrol analizi, X-R kontrol çizelgelerini kullanarak, bulanık teori ile geliştirilmiş daha gerçekçi sonuçlar veren bir tekniktir. Bu çalışma, bir gri dökme demir üretim hattı koşullarının, şartname ve kontrol sınırları dâhilinde olup olmadığını bulanık istatistiksel proses kontrol tekniği ile gözlemlemek için gerçekleştirilmiştir. Bulanık X-R grafikleri, 20 günlük üretim için GG25 gri dökme demir numunelerine uygulanmıştır. Sonuçlar, bulanık istatistiksel proses kontrol (SPC) yöntemlerinin bir dökümhaneye basitçe uygulanabileceğini göstermektedir

Anahtar Kelimeler: GG25 gri dökme demir, karbon eşitliği, bulanık istatistik kontrol

[*]Corresponding author / Sorumlu yazar. Tel.: +90 388 211 11 53/1645; e-mail / e-posta: mcolak@bayburt.edu.tr

1. INTRODUCTION

The term Cast iron refers to an alloy of iron containing more than 2.0 percentage of carbon. The brittle behavior associated with the cast iron is an outdated and widely held misconception which implies all cast irons are brittle and none of them are ductile in nature.

Ductile iron is one form of cast iron which is ductile and it offers the designer a unique combination of high strength, wear resistance, fatigue resistance, toughness and ductility in addition to good castability, machinability and damping properties. Unfortunately, these properties of GG25 gray cast iron are not widely well known because of the misconception about its brittle behavior. [1, 2]. Investigations of the continuously cast iron microstructure are important, because, by change of casting parameters it is possible to obtain necessary ingots properties in these parts of cross-section, where damaging effect of operational factors is most strong. It is well known that the quality and properties of cast products are strongly related to the chemical composition of cast iron too. However, only limited information is available in the literature about the effect of chemical composition on continuously cast iron ingots properties. Consequently, the aim of the present paper was to investigate the effects of the solidification rate and various chemical elements on the microstructure and mechanical properties of continuously cast products [3].

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 [4]. 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 [5]. Cast irons generally contain more than 2% C and a variety of alloying elements.

Cast iron materials are called cast iron because their final shape and dimensions can only be given by casting. Cast irons have variable properties in a wide range such as resistance, strength, hardness, corrosion resistance, easy machinability, abrasion resistance and absorbing vibrations. These properties open up a wide range of applications to the cast irons. Another important reason for their widespread use is low costs Despite the strong competition of new materials, cast irons are still popular as suitable and economical materials in thousands of engineering applications [6, 7].

Most of the amount of carbon in cast irons is decomposed during solidification, and seen as a separate construction element in the microstructure of cast iron. The shape of the carbon determines the type of cast iron and therefore affects its properties. Formation of different groups in cast irons depends on different variables such as chemical composition of the material, cooling rate, production method, heat treatment methods after production. The phases occur in microstructures of cast irons have great effect on their properties [8, 9].

During slow cooling of cast iron containing high carbon and silicon, the carbon in liquid iron separates and solidify to form graphite lamellae. This type of cast iron is called lamellar graphite cast iron. Scanning electron microscope (SEM) images of gray cast iron structures are shown in Figure 1. This figure GG25 gray cast iron shows the overall structure as a whole.

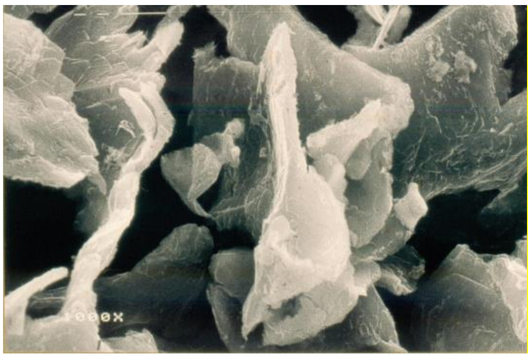


Figure 1. Scanning electron microscope images of lamellar graphite cast iron [9].

Statistical process control (SPC) concept has become very important in chemical and manufacturing industries. Its objective is to monitor the performance of a process over time in order to detect any special events 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 or improving the process or its operating procedures [10]. The use of statistical process control techniques in mineral processing plants is as important as in many other industries, as management aims for a certain quality, which will enhance reputation and future progress. Control charts are among the most effective means for controlling process control systems via statistical methods in an economical and secure way. Control charts are used for determining quantitative and qualitative variations that occur in a process over a certain time frame [11]. To use a control chart such as the X-chart to monitor the process mean or the R-chart to monitor variability, samples are taken over time and values of a statistic are plotted [12]. Control chart type X-R is a very important quality tool. Its determined statistical measures are recorded properties of products obtained as a result of inspections taken randomly from the samples of products in the determined place of the process. The aim of control chart type X-R is to observe and register the changing ability of the characteristics of the researched element of the production process. The example of implementing control chart type X-R shows the possibility of monitoring parameters of the production process according to an idea of defect prevention. Using this method allows monitoring the production process, provides opportunities for cost reduction, and maintains the production process stability [13].

Statistical process control (SPC), an internationally recognized technique for improving product quality and productivity, has been widely employed in various industries. SPC relies on the use of control charts to monitor a manufacturing process for identifying causes of process variation and signaling the necessity of corrective action for the process [14]. Conventionally, for monitoring a manufacturing process, the Shewhart control charts are applicable on the condition that collected sample data are real-valued numbers only. However, in many cases the key quality characteristic of manufactured products, such as the color-intensity quality of produced pictures or screens and the reading-precise quality shown on analogue measurement equipments, apparently inheres with imprecise character, whose samples data are collected by taking certain imprecise information into consideration, known as interval-v alued or fuzzy numbers/data [15, 16]. Besides the fuzzy data may also come from output measurements judging with humans' partial knowledge or subjectivity or gathered from the manufacturing process with scarce or coarse samples [17,18,19]. Therefore, based on the fuzzy sample data to identify whether a manufacturing process exists special causes variation, or is needed to makes certain correction. traditional Shewhart control charts must be expanded so as to possibly carry out the process monitoring in this fuzzy environment [20].

In this study, the CE values in the characteristics of GG25 cast iron were investigated. The GG25 samples were collected from a foundry in Turkey, and fuzzy control charts and process capability index were used for investigation. Furthermore, the elemental analysis Carbon Equivalent values of randomly selected GG25 samples were obtained using experimental techniques. Before and after polishing samples, the microstructural images were recorded by the optical microscope, and also obtained by image analysis program

2. MATERIAL AND METHODS

2.1. Experimental Work

The composition of cast iron (CI) varies significantly depending upon the grade of pig iron used in its manufacture. CI contains carbon in the range of ~2 to 4 wt%. The mode and concentration of carbon in the CI is controlled to produce various grades of CI, which differ significantly in their mechanical properties and weldability. The carbon equivalent (CE) of a CI helps to distinguish the gray irons, which cool into a microstructure containing graphite, and the white irons, where the carbon is present mainly as cementite. The CE is defined in Equation (1).

$$\text{CE (wt\%)}=\text{C}+(\text{Si}+\text{P})/3 \quad (1)$$

A high cooling rate and a low CE favor the formation of white CI whereas a low cooling rate or a high CE promotes gray CI [21].

In 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:

$$\text{LCL} = \bar{X} - A_2{*}R, \text{ and} \quad (2)$$

$$\text{UCL} = \bar{X} + A_2{*}R \quad (3)$$

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.

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, ..., R_k, be the range of k samples, then the average range (R bar) is given by:

$$\bar{R} = (R_1+R_2+R_3 \ldots\ldots\ldots\ldots\ldots Rn)/k_i \quad (4)$$

The upper and lower control limits of R chart are:
Upper control limit:

$$UCL_R=D_4 * \bar{R} \quad (5)$$

Lower control limit:

$$LCL_R=D_3 * \bar{R} \quad (6)$$

where, factors, D_3 and D_4 depend only on sample size (n) (Table 1) [22]

Table 1. Constants for control charts [23]

Subgroup size (n)	A_2	D_2	D_3	D_4
2	1.880	1.128	0	3.267
3	1.023	1.693	0	2.574
4	0.729	2.059	0	2.282
5	0.577	2.326	0	2.114

The purpose of this study is to apply fuzzy statistical process control techniques for a GG25 Gray Cast Iron Plant in Turkey. In the experiment, fuzzy control chart was established in order to determine whether the results from CE analysis GG25 in a metal mill were under control or not. One-day total of one samples were collected during consecutive 20 days and the CE analysis were conducted fuzzy X and R control charts.

Assume that a quality characteristic is defined as "approximately X". Considering the fuzzy sets concept, this value can be converted to the triangular fuzzy number (TFN) $\check{X}$= (X_1; X_2; X_3). After measuring a sample of size n from triangular fuzzy numbers (X_{1j},X_{2j}. ;X3j) j = 1;……….. ; n, the average of this sample can be calculated by extension principle as follows:

$$\tilde{\bar{X}} = (\overline{X1},\ \overline{X2},\ \overline{X3}) = (\frac{\sum_{j=1}^{n} X1j}{n}, \frac{\sum_{j=1}^{n} X2j}{n}, \frac{\sum_{j=1}^{n} X3j}{n}) \quad (7)$$

Also considering extension principle. the range of the sample can be calculated by

$$\bar{R} = (R1, R2, R3) \quad (8)$$

$$\bar{R}= (\max X1j, \max X2j, \max X3j)-(\min X1j, \min X2, \min X3j) \quad (9)$$

$$\bar{R} = (\max X1j- \min X1j, \max X2j- \min X2j, \max X3j- \min X3j) \quad (10)$$

where ($\max X_{1j}$; $\max X_{2j}$; $\max X_{3j}$) and ($\min X_{1j}$; $\min X_{2j}$; $\min X_{3j}$) represent the maximum and minimum values of fuzzy measurements, respectively. One method to determine the maximum and minimum values of fuzzy measurements is assign from ranking method [24].

For m subgroups with size n, the fuzzy grand average and the average range of samples are [25]:

$$\tilde{\bar{\bar{X}}} = \left(\overline{\overline{X1}}, \overline{\overline{X2}}, \overline{\overline{X3}}\right) = \frac{\sum_{i=1}^{m} \overline{X1\iota}}{m}, \frac{\sum_{i=1}^{m} \overline{X2\iota}}{m}, \frac{\sum_{i=1}^{m} \overline{X3\iota}}{m} \quad (11)$$

$$\widetilde{\bar{R}} = (\bar{R}1. \bar{R}2. \bar{R}3) = \frac{\sum_{i=1}^{m} \overline{R1\iota}}{m}, \frac{\sum_{i=1}^{m} \overline{R2\iota}}{m}, \frac{\sum_{i=1}^{m} \overline{R3\iota}}{m} \quad (12)$$

respectively, therefore. the control limits for $\tilde{X}$ control charts are calculated as follows:

$$\widetilde{UCL\bar{X}} = \bar{\bar{X}} + A2\bar{\bar{R}} = (\bar{\bar{X}}1 + A2\bar{R}1, \bar{\bar{X}}2 + A2\bar{R}2, \bar{\bar{X}}3 + A2\bar{R}3) \quad (13)$$

$$\widetilde{CL\bar{X}} = \bar{\bar{X}} = (\bar{\bar{X}}1, \bar{\bar{X}}2, \bar{\bar{X}}3) = (\mathrm{CL}(\bar{X})1, \mathrm{CL}(\bar{X})2, \mathrm{CL}(\bar{X})3) \quad (14)$$

$$\widetilde{LCL\bar{X}} = \bar{\bar{X}} - A2\bar{\bar{R}} = (\bar{\bar{X}}1 - A2\bar{R}1, \bar{\bar{X}}2 - A2\bar{R}2, \bar{\bar{X}}3 - A2\bar{R}3) \quad (15)$$

and similarly, for $\tilde{R}$ control chart.

$$\widetilde{UCLR} = \bar{R}D4 = (\mathrm{D}4\bar{R}1, \mathrm{D}4\bar{R}2, D4\bar{R}3) \quad (16)$$

$$\widetilde{CL\bar{X}} = \bar{R} = (\bar{R}1, \bar{R}2, \bar{R}3) = (\mathrm{CL}(\bar{R})1, \mathrm{CL}(\bar{R})2, \mathrm{CL}(\bar{R})3) \quad (17)$$

$$\widetilde{LCLR} = \bar{R}D3 = (\mathrm{D}3\bar{R}1, \mathrm{D}3\bar{R}2, D3\bar{R}3) \quad (18)$$

There have been a number of process capability indices proposed over the years for the purpose of assessing the capability of a process to meet certain specifications. The two most widely used standard PCIs are Cp and Cpk. The index Cp which is the first process capability index (PCI) to appear in the literature and called precision index [26] is defined as the ratio of specification width (USL-LSL) over the process spread (6r). The specification width represents customer and/or product requirements. The process variations are represented by the specification width. If the process variation is very large. the Cp value is small and it represents a low process capability. Cp indicates how well the process fits within the two specification limits. It is calculated by using Eq. (22). Cp simply measures the spread of the specifications relative to the six-sigma spread in the process [24, 27]. The process capability ratio Cp does not take into account where the process mean is located relative to specifications [24]. Cp focuses on the dispersion of the studied process and does not take into account centering the process and thus gives no indication of the actual process performance. Kane (1986) [26] introduced index Cpk to overcome this problem. The index Cpk is used to provide an indication of the variability associated with a process. It shows how a process confirms to its specifications. The index is usually used to relate the ‘‘natural tolerances (3r)” to the specification limits. Cpk describes how well the process fits within the specification limits. taking into account the location of the process mean. Cpk should be calculated based on Eqs. (19)-(20) [26, 27].

$$\mathrm{Cp} = \frac{\mathrm{USL}-\mathrm{LSL}}{6\sigma} \quad (19)$$

$$\mathrm{Cpk} = \min\left[\frac{\mathrm{USL}-\mu}{3\sigma} . \frac{\mu-\mathrm{USL}}{3\sigma}\right] \quad (20)$$

where μ denotes the process mean. Cpk, l 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.

Assume that specification limits (SLs) and measurements of the considered quality characteristic are defined by linguistic variables such as ‘‘approximately” or ‘‘around”. Triangular fuzzy numbers (TFNs) are more suitable for this case. SLs can be defined as follows:

$$\widetilde{USL} = TFN\ (u1, u2, u3) \quad (21)$$

$$\widetilde{LSL} = TFN\ (l1, l2, l3) \quad (22)$$

Also fuzzy process mean $\tilde{\mu}$ and standard deviation $\tilde{\sigma}$ can be calculated as follows [28]:

$$\tilde{\mu} = \bar{\bar{X}} = \mathrm{TFN}\ (\mu 1, \mu 2, \mu 3) \quad (23)$$

$$\tilde{\sigma} = \frac{\bar{R}}{d2} = \left(\frac{\bar{R}1}{d2}, \frac{\bar{R}2}{d2}, \frac{\bar{R}1}{d2}, \frac{\bar{R}3}{d2}\right) = \mathrm{TFN}\ (\mathrm{s}1, \mathrm{s}2, \mathrm{s}3) \quad (24)$$

Based on these definitions. fuzzy process capability indices can be calculated as follows:

$$\tilde{C}p = \frac{\widetilde{USL}-\widetilde{LSL}}{6\sigma} = \mathrm{TFN}\left(\frac{u1-l1}{6S1}, \frac{u2-l2}{6S2}, \frac{u3-l3}{6S3}\right) \quad (25)$$

$$\tilde{C}pu = \frac{\widetilde{USL}-\mu}{3\sigma} = \text{TFN}(\frac{u1-\mu1}{3S1}, \frac{u2-\mu2}{3S2}, \frac{u3-\mu3}{3S3}) \quad (26)$$

$$\tilde{C}pl = \frac{\mu-\widetilde{LSL}}{3\sigma} = \text{TFN}(\frac{\mu1-l1}{3S1}, \frac{\mu2-l2}{3S2}, \frac{\mu3-l3}{3S3}) \quad (27)$$

Cp index values fall into three cases:

1- Cp>1 has process capability for producing a component in the range being considered by the customer

2- Cp =1 has process capability for producing a component in the range being considered by the customer with the probability of producing a defective component

3- Cp<1 has not process capability for producing a component in the range being considered by the customer and a defective component is certainly produced by this process [29].

3. RESULTS AND DISCUSSION

In this study, the fuzzy statistical process control by X-R control cards of GG25 cast iron production line was done using Carbon Equivalent values. The reason for using the fuzzy method is; in consequence of the changes in the hearth entries (amount of scrap material, pig and alloy elements) and production process the deviations may be occurred in Carbon Equivalent values of the final product. Process control study was performed using obtained data from twenty samples with four groups. The obtained results are given in Table 2.

Table 2. Case study data for E% values

Number of sample	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4
1	4.154	4.117	4.347	4.118
2	4.224	4.117	4.071	4.460
3	4.248	3.876	4.263	4.236
4	4.364	4.146	4.096	4.349
5	3.962	4.135	4.203	4.024
6	4.004	4.178	4.108	4.210
7	3.953	4.274	4.337	4.332
8	3.995	4.188	4.060	4.152
9	3.891	4.236	4.227	4.305
10	4.006	4.182	4.156	4.049
11	3.718	4.151	4.288	4.297
12	3.764	4.220	4.357	4.188
13	3.822	4.199	4.047	4.341
14	4.086	4.242	4.076	4.084
15	4.353	4.349	4.174	4.330
16	4.23	4.179	4.015	4.282
17	4.294	4.344	4.088	4.373
18	4.282	4.204	4.007	4.392
19	4.009	4.346	4.078	4.113
20	4.096	4.204	4.037	3.992

Firstly, a normal distribution test was made with SPSS program. The results showed that the process is said to be normally distributed because the value obtained, 0.052, is larger than $\alpha = 0.05$ (%95 reliability level). Therefore, it can be said that the process is normal distribution.

In this study, $\bar{X}$-R control charts were redesigned when the quality characteristics are defined as fuzzy measurements. While the $\tilde{\bar{X}} - \tilde{R}$ charts are designed, one case in which measurements represent triangular fuzzy numbers (TFNs) was taken into account. The calculations in Table 3 have been determined as approximate values. Then, the process is checked to determine whether or not it is in statistical control. The results are shown in Table 4. Using Eqs. 21-26, UCL_X, CL_X, LCL_X and UCL_R, CL_R, LCL_X are calculated as Table 5.

Table 3. Total color difference as triangular fuzzy numbers (TFNs)

Number of sample	X1	X2	X3	X4
1	4.149, 4.154, 4.159	4.112, 4.117, 4.122	4,342, 4,347, 4,352	4.113, 4.118, 4.123
2	4.219, 4.224, 4.229	4.112, 4.117, 4.122	4.066, 4.071, 4.076	4.455, 4.46, 4.465
3	4.243, 4.248, 4.253	3.871, 3.876, 3.881	4.258, 4.263, 4.268	4.231, 4.236, 4.241
4	4.359, 4.364, 4.369	4.141, 4.146, 4.151	4.091, 4.096, 4.101	4.344, 4.349, 4.354
5	3.957, 3.962, 3.967	4.130, 4.135, 4.140	4.198, 4.203, 4.208	4.019, 4.024, 4.029
6	3.999, 4.004, 4.009	4.173, 4.178, 4.183	4.103, 4.108, 4.113	4.205, 4.210, 4.215
7	3.948, 3.953, 3.958	4.269, 4.274, 4.279	4.332, 4.337, 4.342	4.327, 4.332, 4.337
8	3.990, 3.995, 4.000	4.183, 4.188, 4.193	4.055, 4.060, 4.065	4.147, 4.152, 4.157
9	3.886, 3.891, 3.896	4.231, 4.236, 4.241	4.222, 4.227, 4.232	4.300, 4.305, 4.310
10	4.001, 4.006, 4.011	4.177, 4.182, 4.187	4.151, 4.156, 4.161	4.044, 4.049, 4.054
11	3.713, 3.718, 3.723	4.146, 4.151, 4.156	4.283, 4.288, 4.293	4.292, 4.297, 4.302
12	3.759, 3.764, 3.769	4.215, 4.220, 4.225	4.352, 4.357, 4.362	4.183, 4.188, 4.193
13	3.817, 3.822, 3.827	4.194, 4.199, 4.204	4.042, 4.047, 4.052	4.336, 4.341, 4.346
14	4.081, 4.086, 4.091	4.237, 4.242, 4.247	4.071, 4.076, 4.081	4.079, 4.084, 4.089
15	4.348, 4.353, 4.358	4.344, 4.349, 4.354	4.169, 4.174, 4.179	4.325, 4.330, 4.335
16	4.225, 4.230, 4.235	4.174, 4.179, 4.184	4.010, 4.015, 4.020	4.277, 4.282, 4.287
17	4.289, 4.294, 4.299	4.339, 4.344, 4.349	4.083, 4.088, 4.093	4.368, 4.373, 4.378
18	4.004, 4.009, 4.014	4.199, 4.204, 4.209	4.002, 4.007, 4.012	4.387, 4.392, 4.397
19	4.091, 4.096, 4.101	4.341, 4.346, 4.351	4.073, 4.078, 4.083	4.108, 4.113, 4.118
20	4.091, 4.096, 4.101	4.199, 4.204, 4.209	4.032, 4.037, 4.042	3.917, 3.922, 3.927

Table 4. Average and range values with control results

Number of sample	X	Decision	R	Decision
1	4.179, 4.184, 4.189	In control	0.230, 0.230, 0.230	In control
2	4.213, 4.218, 4.223	In control	0.389, 0.389, 0.389	In control
3	4.150, 4.155, 4.160	In control	0.387, 0.372, 0.372	In control
4	4.233, 4.238, 4.243	In control	0.268, 0.253, 0.253	In control
5	4.076, 4.081, 4.086	In control	0.241, 0.241, 0.241	In control
6	4.120, 4.125, 4.130	In control	0.206, 0.206, 0.206	In control
7	4.190, 4.224, 4.229	In control	0.384, 0.384, 0.384	In control
8	4.093, 4.098, 4.103	In control	0.157, 0.157, 0.193	In control
9	4.159, 4.164, 4.169	In control	0.414, 0.345, 0.414	In control
10	4.093, 4.098, 4.103	In control	0.176, 0.176, 0.176	In control
11	4.108, 4.113, 4.118	In control	0.579, 0.579, 0.579	In control
12	4.127, 4.132, 4.137	In control	0.593, 0.593, 0.593	In control
13	4.097, 4.102, 4.107	In control	0.519, 0.519, 0.519	In control
14	4.117, 4.122, 4.127	In control	0.158, 0.158, 0.166	In control
15	4.296, 4.301, 4.306	In control	0.179, 0.179, 0.179	In control
16	4.172, 4.176, 4.182	In control	0.267, 0.267, 0.179	In control
17	4.269, 4.274, 4.279	In control	0.285, 0.285, 0.285	In control
18	4.216, 4.221, 4.226	In control	0.385, 0.385, 0.385	In control
19	4.131, 4.136, 4.141	In control	0.337, 0.337, 0.337	In control
20	4.059, 4.064, 4.069	In control	0.282, 0.282, 0.282	In control
Average	4.157, 4.162, 4.167		0.322, 0.317, 0.318	

Process capability indices, histogram, normal probability marking and control graph approaches can be used in process capability analysis. Process competence is a statistical measure and summarizes how variable a process is according to customer expectations (Specification limits). The parameters considered at this stage are the indices Cp and Cpk. The Cp index indicates the relationship between specification limits and process control limits. The Cpk index indicates the position of the process average relative to the target value, and the between the specification limits [29]. The difference of Cpk is that it takes into account the shift in the process data as well as having a similar computational logic to the Cp and Cpk values [30]. The following formulations are used to calculate Cp and Cpk values. The values given in Table 2 are used to decide on the adequacy of the process according to the values of Cp and Cpk [31].

Table 5. UCL_X, CL_X, LCL_X and UCL_R, CL_R, LCL_X values

X	UCL_X	4.389, 4.394, 4.399
	CL_X	4.157, 4.162, 4.167
	LCL_X	3.924, 3.929, 3.934
R	UCL_R	0.734, 0.723, 0.725
	CL_R	0.322, 0.317, 0.318
	LCL_R	0.000, 0.000, 0.000

The TFNs of USL and LSL as expected values for calculations indexes were obtained from the management of the plant. Fuzzy process capability indices (PCIs) are determined for the Carbon Equivalent values. The measurements in Table 6 are shown as approximate values. Then, the process is checked to determine whether or not it is in statistical control. According to Table 7 and μ, σ, Cp, Cpu and Cpl were obtained by using Equation 25-27. The index Cp, Cpu and Cpl were determined as 3.889-3.866-3.1795, 6.084, 6.039, 5.499 and 1.695, 1.694, 1.653, respectively. The parameters values after performing the few iterations of data collection were greater than 1.0 and it was determined that the plant was adequate for produce GG25.

Table 6. Fuzzy capability indexes total color difference of plant

	E
USL	4.70, 4.75, 4.80
LSL	3.40, 3.45, 3.50

Table 7. Values of μ, σ, Cp, Cpu and Cpl parameters

Parameters	Values
μ	4.157, 4.162, 4.167
σ	0.156, 0.154, 0.154
Cp	1.388, 1.406, 1.406
Cpu	1.160, 1.272, 1.370
Cpl	1.618, 1.606, 1.443

When the image analysis results were evaluated, length, width of graphite and % graphite level of cast irons were observed to be in accordance with the expected specs. However, as can be seen from the results of image analysis, the pearlite and lamellar graphite are assessed as the same phase by the program. For the microstructural characterisation of the cast GG25 parts, a randomly selected sample was subjected to metallographic and image analyses. The chemical composition of a randomly selected sample is given in Table 8.

Random samples were selected for microstructure examination from casting production. Selected samples were metallographically sanded with 180, 400, 800 and 1200 grit abrasives, respectively, and then polished with 6 and 3 μm diamond suspension. Microstructure studies of the samples after polishing were carried out with Nikon brand Eclipse L150 optical microscope. The recorded 50X and 100X enlarged images of samples are given in Figure 2. When the microstructure pictures given in Figure 2 are examined, it is understood that lamellar graphites which are seen in black color on the main structure of ferrite are exist. This is thought to be due to slow cooling and chemical composition during solidification. From the obtained structure, it has been observed that the material has microstructure of GG25 standard as expected and targeted for the production of the related alloy.

In order to determine the length and thickness of the graphite formed in the structure, measurements were done on the microstructure pictures of the polished samples by image analysis method. For image analysis examinations, images obtained with a camera operating under microscope were evaluated with Clemex Vision

Lite image analysis software. In Figure 3, a sample microstructure image examined with image analysis program and image obtained after processing in the image analysis program are shown.

The operating logic of the program is based on the principle of separating the different colors which are formed by the phases formed on the microstructure. As a result of this reason, 2 main phases and lamellar graphite were selected as 2 different phases in the program, 2 colors were selected for these two phases and the program automatically determined the percentage of the relevant graphites, the average thickness and length of the lamellar graphites. Table 9 gives the average result values from the image analysis program.

Table 8. Chemical composition of a GG25 casting sample

Element	%
C	3.61
Si	1.78
Mn	0.49
P	0.041
S	0.035
Mg	0.001
Cr	0.054
Ni	0.036
Mo	0.016
Cu	0.151
Ti	0.016
V	0.009
Hardness	196

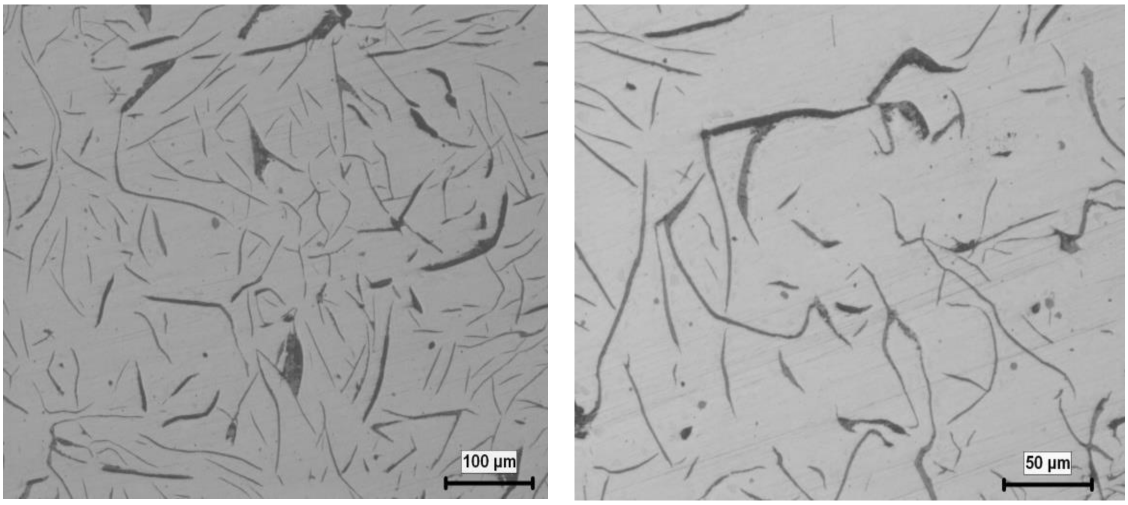
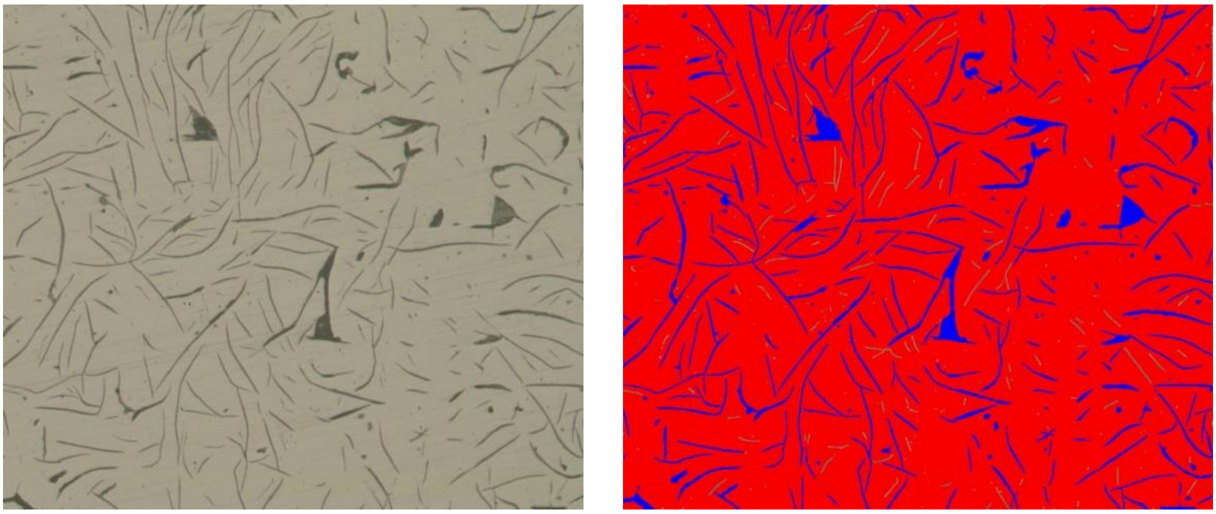


Figure 2. Microstructure image of GG25 samples

Table 9. Result of microstructure image analysis measurement

Measurement Number	Long	Thickness	Graphite Percentage (%)
1.	41.80	9.99	8.60
2.	39.30	10.80	10.40
3.	41.30	10.30	9.70
Average	40.80	10.40	9.57



(a) (b)

Figure 3. a) Microstructure view of after polishing, b) Microstructure view of threshold application in image analysis

4. CONCLUSIONS

In this study, Carbon Equivalent values (CE) was studied using fuzzy observation on a foundry plant product. For this purpose, products of the plant were evaluated using triangular fuzzy number (TFN) and fuzzy process capability indices (PCIs). 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 Carbon Equivalent values of GG25 were observed to be within the limits. In addition, the calculated Cp values such as 1.388, 1.406, 1.406 are greater than 1.0. Meanwhile, the Cpru and Cprl values are greater than 1.0. Therefore, it can be said that the process is adequate. From the obtained structure results, it has been observed that the material has microstructure of GG25 standard as expected and targeted for the production of the related alloy.

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