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Influence of Component Proportions in Casting Process on Hardness and the Quality of Cast Iron

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Abstract

The purposes of this study were to investigate the impact of proportions of cast iron scrap, steel scrap, carbon and ferro silicon on hardness and the quality of cast iron and to obtain an appropriate proportion of the four components in iron casting process using a mixture experimental design, analysis of variance and response surface methodology coupled with desirability function. Monte Carlo simulation was used to demonstrate the impacts of different proportions of the four components by varying the proportions of components within ±5% of the four components. Microstructures of the cast iron sample obtained from a company and the cast iron samples casted with the appropriate proportions of the four components were examined to see the differences of size and spacing of pearlite particle. The results showed that linear mixture components were statistically significant implying a high proportion of total variability for hardness of the cast iron samples explained by the casting mixtures of raw materials. The graphite of the sample casted from the appropriate proportion has shorter length and more uniform distribution than that from the company. When varying percentages of the four components within ±5% of the appropriate proportion, simulated hardness values were in the range of 237 to 256 HB.

Keywords: Sand casting, Scrap, Cast hardness, Mixture design, Monte Carlo simulation

1. Introduction

Generally, there are many factors influencing the quality of castings during sand molding process and casting process. The factors include pattern design, molding material preparation, characteristics of sand mold and quality of raw materials. Quality of raw materials is one of the most important aspects in casting process before delivering high quality castings to the customers. Raw materials are deemed necessary to investigate the impact of proportions of components on mechanical properties and quality of the castings. A variety of scraps has been added as casting mixtures of materials in casting processes. Some previous researchers stated that addition of some materials with various fractions in the compositions of raw materials has impact on the properties and quality of castings.

Iron scrap is one of mainly recycled raw materials for iron casting processes. Li et al. [1] recycled iron scraps from machining process by compressing into iron scrap cake, which was used appropriately for replacing pig iron for producing ductile iron and grey cast iron. They stated that use of iron scrap cake in place of pig iron can improve mechanical properties of the iron castings with lower material cost and environmental pollution, less energy consumption and gas emission. Weiss et al. [2] expressed that adding higher recycled steel scrap can increase hardness of grey cast iron. Janerka et al. [3] also confirmed that grey cast iron melting on steel scrap base can be produced with less sulphur and phosphorus than that melting on the pig iron base.

Adding of alloying constituents during smelting process can improve the performances of cast irons such as improving morphology and distribution, increasing pearlite content, decreasing interlamellar spacing of pearlite [4, 5]. Ferro silicon (FeSi) is one of the conventional inoculants used to add in some amount to adjust melting and cooling process for quality improvement of castings. Xue & Li [6] investigated the effect of adding FeSi75 of 0.4-1.2 wt% and another inoculant during the smelting process on morphology and distribution of graphite. They found that morphology and distribution of type A graphite in the matrix of grey cast iron samples can be improved with increasing the content of FeSi75. Hossain & Rashid [7] reported that zirconium bearing FeSi has better mechanical properties and machinability than SiC for producing high quality of low sulphur grey cast iron. The nucleation of liquid metal and the amount of graphite present in ductile cast iron depended on the amount of FeSi [8]. Petrus et al. [8] also confirmed that the quality of cast iron depends on proper amounts of iron scrap, pig iron, charge materials and other raw materials.

Consequently, recycled raw materials, carbon and ferro silicon contents were deemed necessary to evaluate the impact of their different compositions on mechanical properties and the quality of cast iron. However, one of its major drawbacks is that mechanical properties of the recycled castings are not good enough for some applications. Hence the objective of this study was to assess the influence of casting raw materials on a mechanical property and to determine the component proportions of the casting raw materials so as to maximize hardness of the cast iron in sand casting process.

2. Methodology

2.1. Experimental design

Mixture experimental design has been used when responses depend only on proportions and not the amount of ingredients [9]. It is noted that the proportions of the compositions are defined in percent form [10]. The feasible design space is an irregular hyperpolytope whereas the feasible region for this experiment is not a simplex. Generally, the extreme vertices of the constrained area are formed by the combinations of the upper- and lower-bound constraints [11]. Thus, there are eight extreme vertices for four components in the mixture experimental design. Practically, there are constraints on the component proportions in many mixture experiments. The *D*-optimal criterion is used to randomly select design points from a listed of candidate points in a constrained region using the routine in Design Expert® software package [12] so that the variances of the model regression coefficients are minimized. Response surface methodology (RSM) coupled with desirability function is used to determine the appropriate proportion of the components. The Design Expert® software package uses direct search and downhill simplex methods to maximize desirability function based on the experimenter's objectives [12].

In green sand molding process, Kul et al. [13] used *D*-optimal mixture design to investigate the effect of humidity, coal dust and bentonite on green compressive strength, shear strength and gas permeability and to optimize the proportion of the components for reducing the number of defects on the surface of the casting parts. Saikaew and Wiengwiset [14] also employed a systematic experimental design based on *D*-optimal criterion and RSM to determine the optimal proportion of recycled molding sand, bentonite and water influencing the green compressive strength and gas permeability in iron casting process. The appropriate proportion of recycled molding sand, bentonite and water was obtained at 93.3%, 5% and 1.7%, respectively. They also stated that surface roughness and hardness of the cast iron samples with the optimized mixture proportion of sand mold were better than those with the conventional mixture proportion of sand mold.

2.2. Materials and procedure

Four components of raw materials in melting process consisted of cast iron scrap, steel scrap, carbon and ferro silicon. The upper- and lower-bound constraints of the four components in iron casting process were specified based on literature review and experience of foundry manufacturers. Proportions of the four components were randomly selected within the constraints using the *D*-optimal criterion in mixture experimental design. The upper- and lower-bound constraints of the four components of casting mixture materials were mathematically expressed as follows:

$$A + B + C + D = 100 \tag{1}$$

$$73 \le A \le 80 \tag{2}$$

$$13 \le B \le 20 \tag{3}$$

$$2.5 \le C \le 4 \tag{4}$$

$$1 \le D \le 3 \tag{5}$$

where *A*, *B*, *C* and *D* were the contents of cast iron scrap, steel scrap, carbon and ferro silicon, respectively. It was noted that the constraints used in the formulas (1)-(5) were based on the experience of foundry manufacturers and literature review. However, the upper- and lower-constraints were automatically adjusted by Design Expert® software based on the *D*-optimal criterion.

Induction furnace with maximum capacity of 100 kg was used to melt the four raw materials according to the mixture experimental design. Green sand for sand casting experiments was based on the appropriate proportion, consisting of 93.3% of recycled molding sand, 5% of bentonite and 1.7% of water [14]. Sand molding was performed in the same manner as described in the previous study [14].

After solidification, each cast iron sample was machined on CNC milling machine (Micron VCE 750) to a test bar with 10 mm in width, 15 mm in length and 10 mm in thickness. Hardness measurement was performed on the machined surface of a cast iron sample with a 10-mm-diameter hardened steel ball using a Brinell hardness testing machine (Hollywood International Ltd., FM-800). The hardness values were recorded at three different points to avoid statistical bias of measurements. Averages from three observations were used for analysis of variance (ANOVA). Furthermore, microstructures of the cast iron samples were examined by optical microscope (Olympus BX60M).

Monte Carlo simulation (MCS) is one of the useful methods for evaluating sensitivity and uncertainty of a variety of processes. Intanon et al. [15] applied MCS to validate the appropriate operating condition of the TiN coating process coated on a machine component of a fishing net weaving machine. They stated that this method could be used to verify whether the hardness of the TiN-coated machine component and wear performance were sensitive to the variations of the coating process factors. In drilling of forging brass using uncoated- and AlCrN coated-WC tools, Timata & Saikaew [16] employed this method to assess the uncertainty of cutting speed and feed rate on tool life prediction for sensitivity analysis. For lost foam casting and gravity die casting of aluminum alloys, MCS was used to predict the fatigue behavior and the sensitivity of two cast aluminum alloys to the size effect and to investigate the effect of porosity and other defects on mechanical properties [17]. For sand casting process, Khalifa & Mzali [18] used simulation techniques to identify the interfacial heat transfer coefficient by varying the initial value of the coefficient during the solidification process. They found that the technique of MCS outperformed the competitive technique and was then used to obtain the optimal thickness of the rectangular cast iron part and the optimal position for the temperature measurement.

In this study, MCS was used to demonstrate the impacts of different proportions of the four components in the casting process. When varying the proportions of components within ±5% of the four components, the data set of 3000 for different proportions of the components was generated based on the *D*-optimal criterion in mixture experimental design using Design Expert® software package [12]. Based on the hardness model, hardness values of 3000 data points were predicted and plotted against simulation run order.

3. Results and discussion

3.1. Effect of component compositions on hardness of cast iron

Table 1 shows the experimental matrix of the component proportions of raw materials based on the mixture experimental design and *D*-optimal criterion in the Design Expert® software package. There are many treatment combinations of the mixture components for the casting process that could produce and improve quality and hardness of the cast iron. In this display, the actual mixture components and the results of average hardness values of the cast iron samples in different proportions are shown. The variations of hardness values of the samples produced in various compositions are illustrated in Fig. 1. It should be noted that error bars represent the variation of hardness values from three cast iron samples. It is seen that hardness values of the cast iron samples varied depending on different proportions of components. Consequently, analysis of variance (ANOVA) was used to evaluate the significance of the effect of components on average hardness of the cast iron samples.

Table 1.
An experimental matrix of the mixtures of materials and test results for hardness

Run #	Components				Average hardness (HB)
	A	*B*	*C*	*D*	
1	74.1020	19.9991	2.8989	3.0000	169.78
2	73.0031	19.9970	3.9998	3.0000	212.82
3	79.9988	15.9431	3.0581	1.0000	224.62
4	78.0187	17.5487	2.5000	1.9326	169.82
5	80.0000	14.3563	2.6457	2.9980	173.30
6	76.4364	20.0000	2.5566	1.0070	242.64
7	75.6875	19.2617	4.0000	1.0508	183.01
8	77.1982	15.8023	4.0000	2.9995	159.04
9	74.5649	20.0000	3.3883	2.0468	221.21
10	80.0000	14.5275	3.9967	1.4758	138.72
11	75.3704	17.6317	3.9986	2.9993	165.47
12	76.4081	18.5117	2.8375	2.2426	180.87
13	78.3470	16.2437	3.9247	1.4845	175.83
14	77.1660	17.8346	3.9994	1.0000	154.71
15	78.6233	15.5807	2.8248	2.9712	182.15

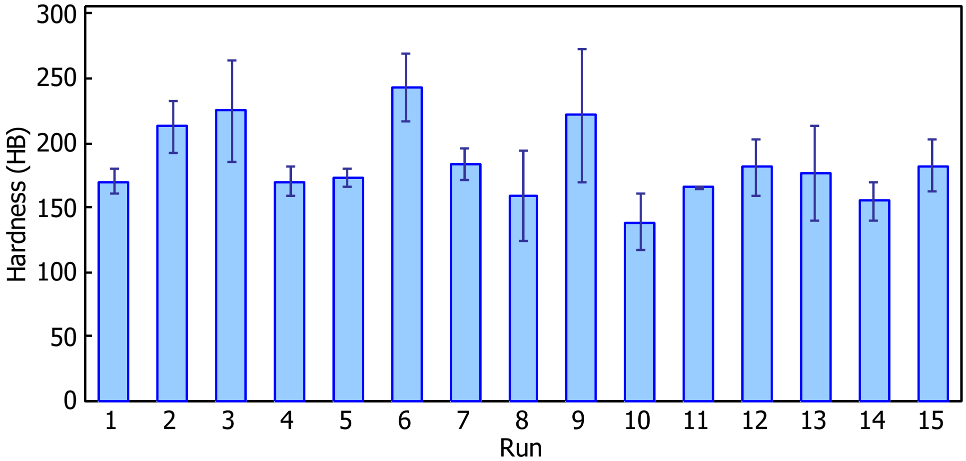

Fig. 1. Variations of hardness values of the cast iron samples produced in various compositions

Table 2 presents the results of ANOVA for average hardness values. The results show that *p*-value for the linear mixture model for hardness was found to be less than 0.05. Linear mixture components were statistically significant model terms including *AB*, *AC*, *BC* and *CD*. In addition, R^2 of 0.9335 and adjusted R^2 of 0.8449 were high indicating a reasonably high proportion of total variability for hardness explained by the casting mixtures of raw materials. This indicated that the casting mixtures of materials significantly affected the property of the cast iron and the casting process at the significance level of 0.05.

Table 2.
ANOVA for hardness of the cast iron

Source of variation	Sum of squares	Degree of freedom	Mean square	*F*-value	*p*-value
Model	10997.12	8	1374.64	10.53	0.0051
Linear mixture	4947.49	3	1649.16	12.63	0.0053
AB	789.69	1	789.69	6.05	0.0492
AC	1437.84	1	1437.84	11.01	0.0161
BC	1786.45	1	1786.45	13.68	0.0101
BD	611.45	1	611.45	4.68	0.0737
CD	3005.05	1	3005.05	23.02	0.0031
Error	783.31	6	130.55		
Total	11780.42	14			

The final equation in terms of actual components for hardness was given in Eq. (6):

$$\text{Hardness} = 10.2031A + 146.9837B - 5960.9738C - 92.7389D - 2.4572AB + 61.1651AC + 68.3895BC - 4.9327BD + 99.6733CD \quad (6)$$

In addition, Fig. 2 shows the plots of relationship between the actual and predicted values for hardness. It was clearly that most data points between the actual and predicted values lied closely along the experimental runs as illustrated in Fig. 2(a) and lied along a straight line with high R^2 as shown in Fig. 2(b). This signified that the mixture model was valid and could fit about 93% of the variability in the hardness test results. Thus, the model could be used for prediction of hardness of the cast iron.

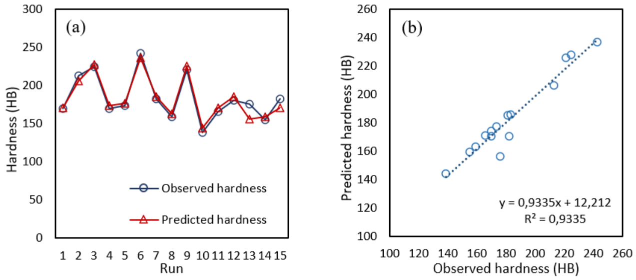

Fig. 2. Actual observations and predicted values of hardness

Contour plots for hardness in terms of the four components illustrated in various compositions within the ranges of the upper- and lower-constraints were constructed from Eq. (6) as illustrated in Fig. 3. In Fig. 3(a) at a constant wt% of ferro silicon, highest hardness was observed at mid-values of carbon component. Fig. 3(a) also shows that hardness increased as either cast iron scrap or steel scrap increased. This result agreed with previous findings that hardness and tensile strength of the grey cast irons increase with increasing the content of steel scrap [19]. This attributed to the statements that graphite of cast iron sample becomes smaller and more uniformly [1]. In addition, Li et al. [1] stated that pearlite content in matrix increases whereas interlamellar spacing of pearlite decreases after adding iron scrap cakes instead of pig iron. By contrast, in Fig. 3(b), the highest hardness shows significant dependence to ferro silicon by moving toward higher proportion of ferro silicon. In addition, Fig. 3(c) shows that the hardness increased as ferro silicon content increased by holding cast iron scrap constant. Similarly, at a constant wt% of iron steel scrap, the hardness also increased with increasing the ferro silicon content as presented in Fig. 3(d).

The appropriate proportion of the four components consisted of approximately cast iron scrap of 76%, steel scrap of 20%, carbon of 3% and ferro silicon of 1% based on the results from RSM coupled with desirability function. According to Eq. (6), the predicted value of maximum hardness of the cast iron was 254 HB. It is also noted that the average hardness of cast irons obtained from the company was approximately 195 HB.

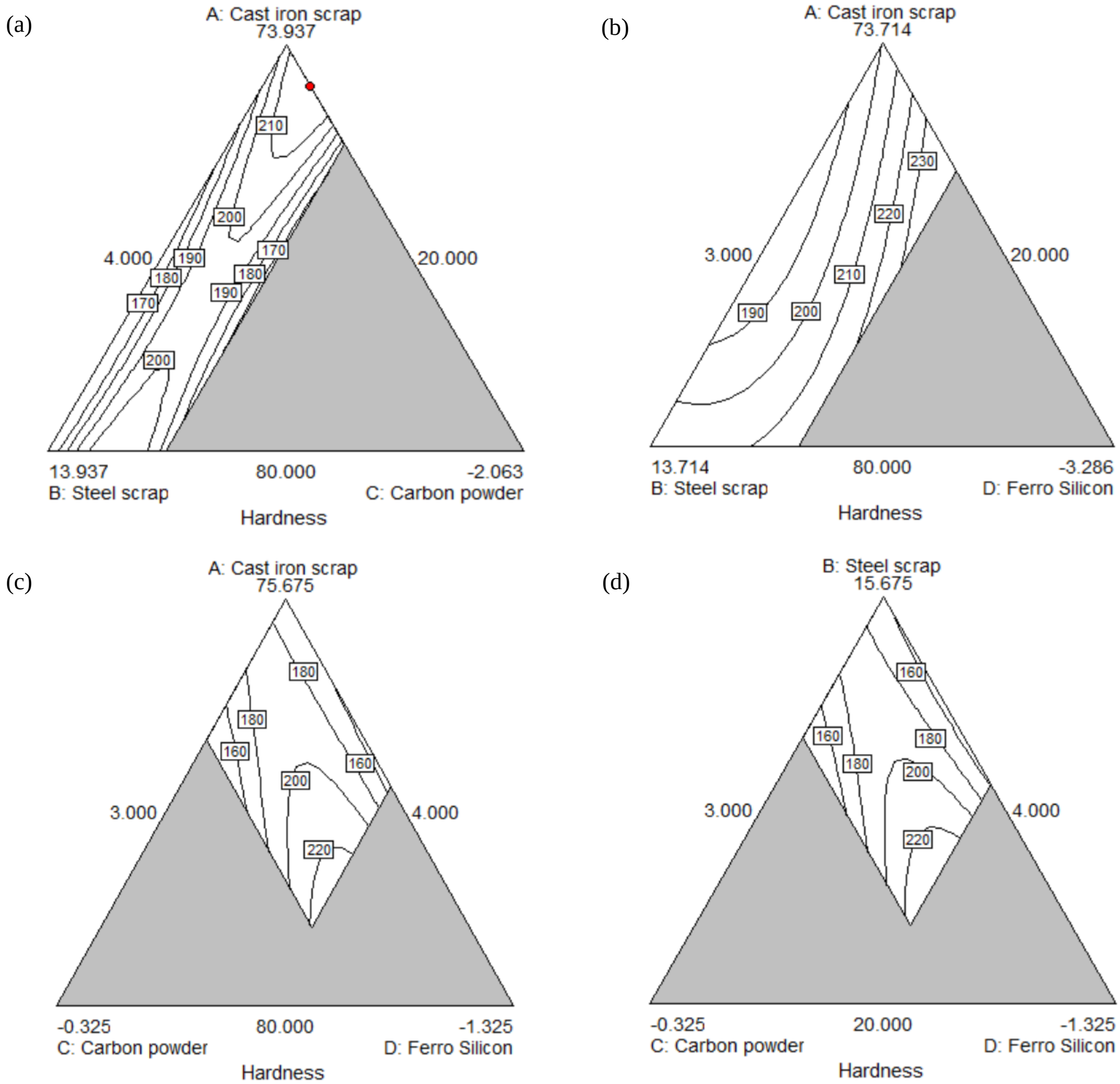

Fig. 3. Contour plots for hardness illustrated in various compositions

3.2. Monte Carlo simulation results

Based on the appropriate proportion of the four components, the new constraints of proportions of the four components have been proposed for MCS as listed in Eqs. (7)-(11)

$$A + B + C + D = 100 \tag{7}$$

$$75.85 \leq A \leq 77.2 \tag{8}$$

$$19 \leq B \leq 20 \tag{9}$$

$$2.85 \le C \le 3.15 \tag{10}$$

$$0.95 \le D \le 1.05 \tag{11}$$

The proposed constraints have been defined according to the variations plus-minus around 5% of the appropriate proportion of each of the four components. Fig. 4 illustrates the variations of simulated hardness values after performing MCS on different proportions of components for the original constraints and for appropriate proportion of the four components. Fig. 4(a) shows that the range of simulated hardness values spreads from 117 to 254 HB. On the other hand, Fig. 4(b) displays lower spread of simulated hardness values, which is ranging from 237 to 256 HB. Fig. 4(c) also reveals that some simulated hardness values, which were obtained from MCS results around the appropriate proportion of each of the four components, were higher than those obtained from MCS results at the original proportion of each of the four components. The results demonstrated that some proportions (around 5% of the appropriate proportion of each of the four components) could be used to produce cast irons with higher hardness values than those of components at the original constraints.

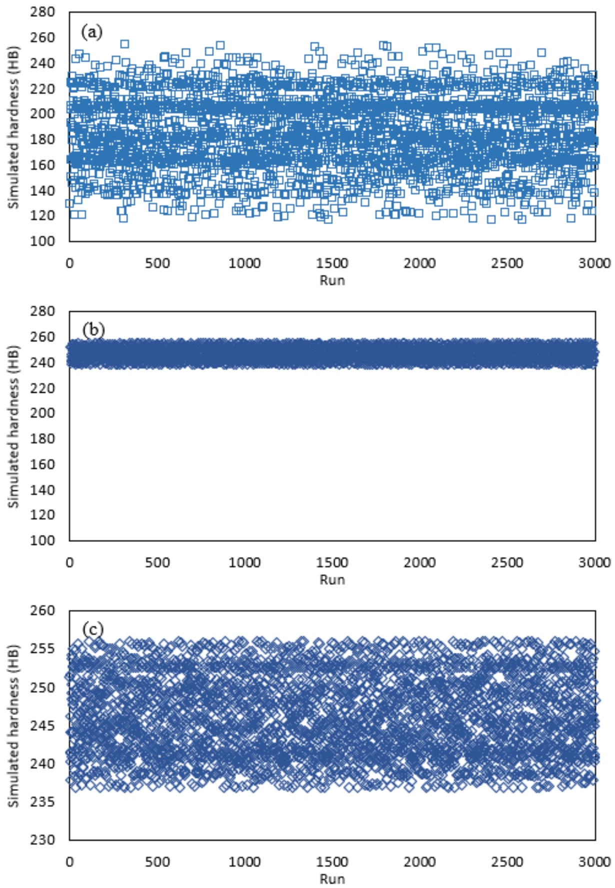

Fig. 4. Variations of simulated hardness values after performing MCS on different proportions of components for (a) previous constraints (b) and (c) for appropriate proportion of the four components

3.3. Surface quality examination of the cast iron

The chemical composition of the sample casted from the appropriate proportion of the four components was specified as (wt%): 3.05 C, 2.3 Si, 0.32 Mn, 0.14 P, 0.06 S and Fe balance. Similarly, the chemical composition of the sample obtained from the company was 3.13 C, 1.95 Si, 0.4 Mn, 0.07 P, 0.06 S and Fe balance. Fig. 5 shows typical stereomicroscopy images of microstructures of cast irons. Overall, the images showed that microstructure of the cast iron obtained from the company was not significantly different to that of the sample casted from the appropriate proportion of the four components. However, it could be seen that the cast iron sample obtained from the company contains A-type graphite and some B-type graphite whereas the sample casted from the appropriate proportion mainly contains graphite type A and fewer B-type graphite. The graphite of the sample casted from the appropriate proportion has shorter length and more uniform distribution than that from the company due to the effect of adding FeSi. This can be attributed to the increasing the nucleation ability of the molten iron and stimulating the potential inoculation performance [6]. Moreover, interlamellar spacing of pearlite of the sample obtained from the company was not different to that of the sample casted from the appropriate proportion of the four components.

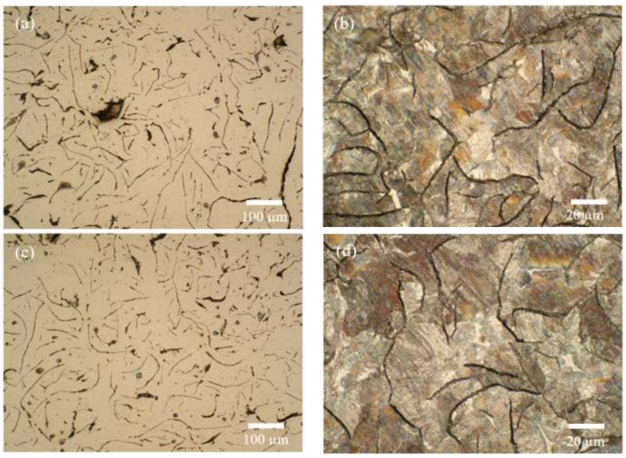

Fig. 5. Stereomicroscopy images of microstructures of cast irons obtained (a) and (b) from the company (c) and (d) from this study

4. Conclusions

This study investigated the impact of proportions of raw materials on hardness and the quality of cast iron and to obtain a proportion of the four components in iron casting process using a mixture experiment (*D*-optimal design), ANOVA and RSM coupled with desirability function. Based on the findings of this study, the following conclusions could be drawn:

- The four components of raw materials significantly affected average hardness values of the cast iron samples at the significance level of 0.05.

- Linear mixture components were statistically significant at the significance level of 0.05 indicating a high proportion of total variability for hardness of the cast iron samples explained by the casting mixtures of raw materials.
- Hardness of the cast iron samples increased as either cast iron scrap or steel scrap increased.
- Hardness increased as ferro silicon content increased by holding cast iron constant.
- The appropriate proportion of the four components was obtained at 76% cast iron scrap, 20% steel scrap, 3% carbon and 1% ferro silicon based on the results from RSM coupled with desirability function.
- Based on the microstructure analysis, cast iron sample obtained from the company contained A-type graphite and some B-type graphite whereas the sample casted from the appropriate proportion mostly contained graphite type A and fewer B-type graphite.
- The graphite of the sample casted from the appropriate proportion has shorter length and more uniform distribution than that from the company.
- According to the results from Monte Carlo simulation, the range of simulated hardness values spread from 117 to 254 HB based on the constraints of proportions of the four components.
- Simulated hardness values were in the range of 237 to 256 HB when varying percentages of the four components within ±5% of the appropriate proportion.

In summary, this study focused on the effect of proportion of raw materials on the mechanical property and the quality of cast iron. However, the research may be extended to enhance the achievement or overcome a limitation of the stage of the metallurgical quality of the melt, which is deemed to be important. The study of holding temperature and time in the furnace and ladle in the furnace influence on the quality of the melt and the cast iron casted with various proportions of raw materials has not been investigated in this work and should be subject of future research.

Conflict of Interest

The authors declare that they have no conflict of interest.

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