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Utilization of scrap in casting process to increase inventory turnover: A case study in a Thai foundry

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Abstract

This research aims to enhance inventory turnover by optimizing the utilization of in-house riser scrap in a Thai foundry manufacturing EN 1.4469 stainless steel casting. The foundry currently faces a challenge with excess riser scrap containing high carbon content, which restricts its reuse in the melting process. To address this issue, a mixture design approach using quadratic regression analysis was applied to develop a predictive model for carbon content based on four charge material components: iron, gate-and-runner scrap, high-carbon riser scrap, and additives. Historical production data from 2022 were analyzed, and the optimal charge composition was identified through response optimization. The resulting model exhibited high predictive accuracy, with an adjusted R^2 of 94.20% and a mean absolute percentage error (MAPE) of less than 10%. Implementation of the optimized charge mix increased the average proportion of riser scrap from 3% to 13%, leading to a significant improvement in inventory turnover from 47 to 128 within a two-month period. These findings demonstrate the practical value of integrating statistical modeling into foundry operations to improve material efficiency and reduce production waste.

1. Introduction

Metal casting remains a cornerstone of modern manufacturing, providing essential components across various sectors such as automotive, infrastructure, electronics, and heavy machinery [1]. On account of dramatical industrial growth and excessive demands, current various range of casting materials, from casting iron and casting steels to nonferrous, particularly aluminum alloys and copper-base alloys, are provided for foundry companies and their customer to satisfy the demands of the markets [2]. In an era of rising material costs and environmental concerns, the efficient utilization of raw and secondary materials has become increasingly critical. Among these, in-house scrap—particularly riser scrap from the gating system—represents both a challenge and an opportunity for foundries seeking to improve sustainability and reduce costs.

Global fluctuations in the metals and mining industry, such as the downturn observed during the COVID-19 pandemic, have further emphasized the need for resilient, resource-efficient operations. The market is projected to recover, with a growth of 20.4% expected from 2020 to 2025 [3]. It seems fair to point out that metal casting manufacturing is regarded to be one of the major sectors impacting the global economy's developments since supplying casting products to various sectors and industries [4]. Foundries must therefore adapt by optimizing resource usage to remain competitive in this dynamic landscape.

Riser scrap, characterized by a high carbon content, is typically underutilized due to the risk it poses to chemical composition control in low-carbon steel casting. However, strategic reuse of this material could significantly enhance inventory turnover and reduce the cost of purchased metals. Several researchers have addressed material optimization and process improvement through methods such as regression modeling [5], Six Sigma [6], and lean manufacturing [7]. Kumaravadivel and Natarajan [8] proposed the prediction model in a foundry industry to reduce the flywheel casting's defect related to the sand preparation process by finding the optimized combination for improving the defect's reduction and the process capability. These methodologies offer structured frameworks for problem-solving and performance enhancement.

Regarding the localized non-homogeneity observed within the riser, it is important to highlight that the riser acts as a thermal and fluid feeder designed to capture impurities and assist shrinkage away from the castings. Several studies have demonstrated that non-homogeneity, particularly carbon segregation, occurs within this region. Beckermann and Schneider [9] deployed casting simulations to model carbon, silicon, and sulfur distributions in risers, while Carlson and Beckermann [10] combined numerical modeling with experimental casting validation to observe this behavior. Both studies established that carbon exhibits a vertical concentration gradient, with carbon content increasing toward the upper portion of the riser. Fluid flow acts as the primary mechanism behind this carbon segregation pattern in the riser. These contributes to the non-homogeneous composition of riser.

Specifically, within the foundry industry, studies have examined the effects of incorporating various scrap materials into the casting process. Gao *et al.* [11] highlighted the use of varying ratios of returned

and pure materials in superalloy casting to evaluate the nitrogen behavior of melting the superalloy material. Futáš *et al.* [12] explored the influence of steel scrap on the quality of gray cast iron, while Li *et al.* [13] analyzed machining scrap reuse in iron casting. Dutta *et al.* [14] demonstrated that direct reduced iron could serve as an effective substitute for virgin metal in steel production, improving both yield and mechanical properties.

In the context of process optimization, mixture design regression models have proven effective in determining ideal material ratios for desired properties. Researchers such as Poornesh *et al.* [15] and Singh *et al.* [16] have successfully applied quadratic models to optimize mechanical properties like hardness and tensile strength in metal matrix composites.

This research focuses on a Thai foundry, referred to as Company A, which manufactures stainless-steel castings and non-ferrous castings. The company has identified an excess accumulation of high-carbon riser scrap in its inventory, primarily from EN 1.4469 stainless-steel casting. By applying a regression-based mixture design model, this study aims to optimize the use of riser scrap in the melting process, thereby increasing inventory turnover, reducing waste, and maintaining the required chemical composition of the final product.

2. Equipment and measurement system

To analyze the chemical composition of casting materials, a standardized procedure was employed using Company A's in-house equipment. Prior to testing, each metal sample was surface-prepared through grinding and machining to ensure accurate readings. Chemical composition was then measured using an optical emission spectrometer (OES) (see Figure 1), which operates by generating an electric arc on the surface of the sample. The emitted light is analyzed by the OES to quantify elemental concentrations, with results displayed in percentage units through the integrated OXSAS software.

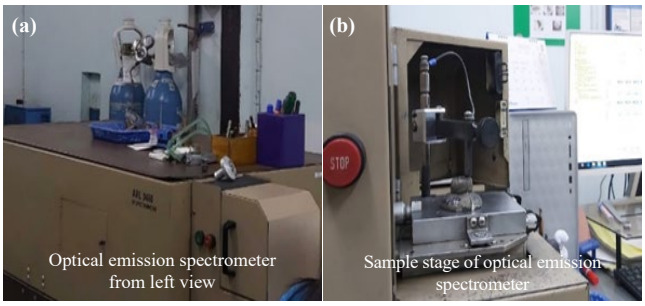


Figure 1. Overview of the optical emission spectrometer for chemical composition analysis.

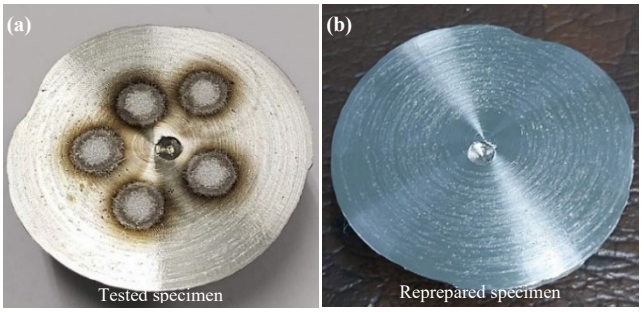


Figure 2. Example of specimen for chemical composition analysis.

Company A's OES is equipped with 42 optical detectors capable of identifying 28 different elements, with a resolution of 0.00001%. Each sample was typically arced 5 time to 7 time to ensure consistency, and the final chemical composition was calculated as the average of the valid readings. In cases where spark emission produced unclear or unreliable data, the corresponding measurements were discarded. Final results were selected based on the judgment of trained laboratory personnel to ensure the reliability of the analysis.

For this research, ten randomly selected EN 1.4469 stainless steel specimens were prepared using the company's standard operating procedure. Due to staffing constraints and the technical expertise required, only two experienced quality control technicians were assigned to conduct the chemical composition analysis. Each technician independently operated the spectrometer and performed two measurement rounds per specimen. Between rounds, the specimen surfaces were reprocessed to remove burn marks left by the initial spark test, ensuring consistent and uncontaminated conditions for subsequent readings as shown in Figure 2. The figure illustrates the sample condition before and after surface repreparation by grinding and machining.

3. Carbon content in riser scrap

Concerning the chemical composition of the riser, it is essential to note that parameter estimation is employed to define the mean carbon content of Company A's riser by sampling from the inventory and testing on the prepared surface as illustrated in Figure 3. During the composition analysis and data collection, an abnormality in the carbon percentage of the tested riser was presented. The riser's chemical composition, especially the carbon, seemed to be not homogeneous as the casting's characteristic. The examples of carbon content in riser scraps are tested as shown in Figure 4. A considerable percentage of carbon tended to present the edge of the riser workpiece compared to its center, which leads to the difficulty in determining the carbon content in the riser. The new method to find the carbon content instead of testing by piece was conducted by melting those sampling risers in a furnace in order to provide a homogeneous mixture. It was performed by using the exact same sets of equipment and methodology under conditions as the usual melting and casting processes to avoid discrepancies between experimental and usual workflows and prevent over-controlling the shop-floor environment. However, the riser samples were remelted in a furnace with a renewed lining for each observation to ensure carbon cross-contamination and composition diluting during remelting. Before sampling for chemical composition analysis, the liquid melt was thoroughly stirred to ensure that the sample accurately represented the melted risers. Then, the analysis of the chemical composition of molten metal was performed to collect the data.

As to the issue of the riser's chemical composition, the riser data were also plotted on an individual chart to monitor the data distribution from a centerline. Figure 5 shows the distribution of points around the centerline without exceeding the upper and lower control limits. In addition, trends or patterns were not demonstrated in the chart. Following that, the additional individual chart also was created as a means of observing the differences in carbon content between a riser and a casting product.

Subsequently, the study of the current carbon content in a product and riser scrap was completed to determine their mean, resulting in

0.01770 wt% and 0.08969 wt%, respectively. There was a significant difference between those two materials. Consequently, the project baseline measurement was created, and its indicator was the average proportion of riser scrap in charge materials.

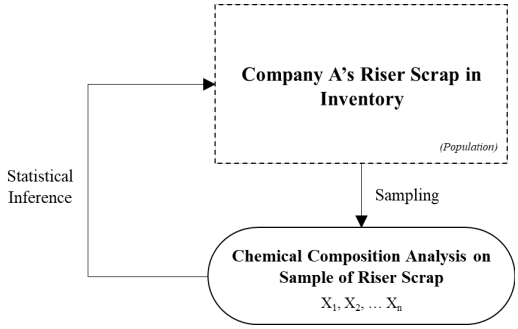


Figure 3. The framework of determination on carbon content in company A's riser scrap.

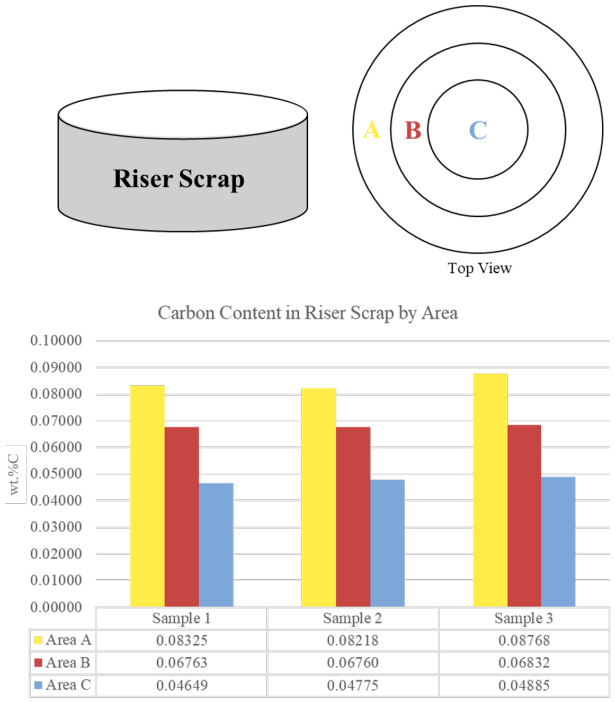


Figure 4. Examples of carbon content in riser scraps tested by piece.

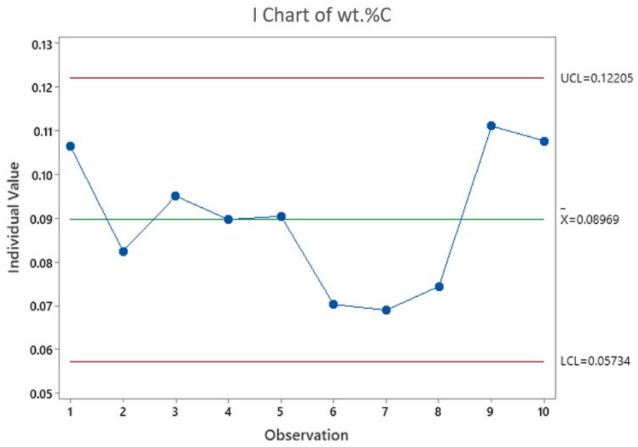


Figure 5. The individual chart of percentage of carbon.

4. Design of regression model

To develop a predictive model for carbon content in casting mixtures, this study employed a regression-based mixture design approach using the extreme vertices method. The model was constructed from historical production data, focusing on four primary charge material components: iron, gate-and-runner scrap, high-carbon riser scrap, and additives. These components were treated as proportions of the total charge to comply with the requirements of the mixture design methodology.

In typical foundry practice, the chemical composition of a melt is initially estimated using a mass balance calculation, as shown in Equation (1), which considers the elemental content of each charge material and its corresponding mass. This approach, however, assumes no chemical interactions during melting and is therefore insufficient in capturing the dynamic and reactive nature of furnace operations, particularly in the presence of oxidation, reduction, or volatilization reactions. Consequently, the well-defined chemical composition of each charge material along with the consistency of chemical composition are significant factors in calculating to achieve accurate results for this approach.

$$\%i_{mtrl} = \frac{\sum_{j=1}^{N} \%i_j^{Estimated} \times m_j^{kg}}{m_{mtrl}^{kg}} \quad (1)$$

$\%\ i_{mtrl}$ = The calculated content of element i in the charge material, wt%

m_{mtrl}^{kg} = The weight of the calculated charge material, kg

N = Number of charge material

$\%\ i_j^{Estimated}$ = The estimated content of element i in the charge component j, wt%

m_j^{kg} = The weight of the charge component j, kg

The principle of mass balance is to calculate from the components without considering chemical reactions in the mixing, which can refer to a multiple regression model. However, it is fair to suggest that the multiple regression model seems unfit to construct a model for Company A's research because there are various reactions and interactions in a furnace during the melting process, particularly chemical reactions, and the non-uniformity of riser's chemical composition. Meanwhile, a quadratic regression model is a common mixture design method mostly suggested and developed to fit a model in several casting mixture research. Therefore, the quadratic regression model for a mixture design will be used in this study to develop a model to assess the mixes of four charge materials and their carbon content.

5. Predictive model and analysis

The primary objective of this phase was to develop a predictive regression model to estimate the carbon content in EN 1.4469 stainless steel castings, based on the proportions of four charge materials: pure virgin iron (I), gate-and-runner scrap (S), high-carbon riser scrap (HC), and additives (A). These variables were identified as the most influential components in the melting process at Company A. The component definitions are presented in Table 1.

Table 1. Components for regression model.

Component	Identification	Acronym
Pure virgin Iron	Iron	I
Gate and Runner Scrap	Scrap	S
High Carbon Riser Scrap	HC Scrap	HC
Additives	Additives	A

Table 2. MAPE criteria for model evaluation.

MAPE	Interpretation
< 10	Highly Accurate Prediction
10-20	Good Prediction
20-50	Reasonable Prediction
> 50	Inaccurate Prediction

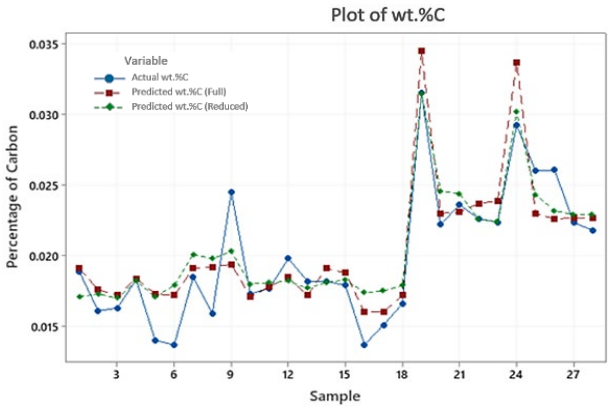


Figure 6. Comparison of actual and predicted percentage of carbon.

To construct the model, historical production data from 2022 were collected from Company A's production and quality control departments. This dataset included 138 records, each containing the mass of charge materials and the corresponding chemical composition of the molten metal. The material usage was first converted to proportional values, as mixture regression models require the sum of all components to equal one.

From the total dataset, 110 records were used to build the regression model, while the remaining 28 were reserved for validation. The regression analysis was performed, applying a quadratic mixture design approach to capture both linear and interaction effects between components.

The analysis of variance (ANOVA), and model summary statistics indicated that only one interaction term—I × HC—was statistically significant ($p < 0.05$), with a p–value of 0.008. Other interaction terms had p-values greater than 0.05 and were thus excluded from the final model. The overall regression model itself was statistically significant ($p < 0.001$), and the lack-of-fit test yielded a p-value of 1.000, indicating a good model fit with no significant unexplained variability.

The adjusted R^2 value for the full model was 94.20%, suggesting that the model explained a substantial portion of the variation in carbon content. However, the predictive R^2 value was relatively low at 51.93%, indicating a potential overfitting issue.

To address this, a reduced model was developed by retaining only the four main components and the significant I × HC interaction. This revised model improved the predictive performance, yielding an adjusted R^2 of 94.13% and a predictive R^2 of 90.4%. The p–values for regression (< 0.001), interaction (0.009), and lack-of-fit (1.000) all satisfied the criteria for a robust and reliable model.

The models were validated using the remaining 28 data points. Figure 6 compares the actual and predicted carbon content values from both the full and reduced models. While both models followed the same trend, the reduced model exhibited slightly better predictive accuracy.

At first glance, it is clear that the predicted carbon content showed higher-and-lower percentages compared to their actual value without presenting any patterns among different carbon content. The prediction of those two models presented the same trend with a slightly different result due to factors in the model. However, having only a general examination of the results does not provide information on forecasting accuracy related to the error. So as to measure the error of a percentage of carbon resulting from a regression model, the Mean Absolute to Percentage Error (MAPE) was applied to this research by using the abovementioned 28 sets of data. 8.32 and 8.51, which were a MAPE of a full regression model and a reduced regression model, were determined from a calculation on an error between actual and predicted carbon percentages. Both models show a value less than 10, interpreted as having a highly accurate prediction as shown in Table 2.

Based on the comparison of adjusted R^2, predictive R^2, and MAPE values, the full regression model was selected for process optimization. While the reduced regression model exhibited a higher predictive R^2 than the full model (90.4% vs. 51.93%), it is important to highlight that the reduced regression model was simplified by removing non-significant terms, which restricted its scope to the four primary raw materials and a single interaction term. It resulted in the fact that the equation of this regression model aligned closely with a standard mass balance formulation. This directly contrasted with the core objective of applying a Mixture Design, which aimed to investigate the interaction effects among individual materials and capture the physical and chemical phenomena. Its strong explanatory power and acceptable predictive accuracy made it suitable for determining optimal charge compositions for carbon control in stainless steel casting. Consequently, the equation which will be applied to find the optimal setting condition is as follows:

$$\begin{aligned}\text{wt\% Carbon} = {} & 0.00404\text{Iron} + 0.01959\text{Scrap} + 0.12738\text{HC Scrap} + \\ & 0.112\text{Additives} + 0.0179\text{Iron*Scrap} - \\ & 0.0583\text{Iron*HC Scrap} - 0.202\text{Iron*Additives} + \\ & 0.0266\text{Scrap*HC Scrap} - 0.1337\text{Scrap*Additives} - \\ & 0.145\text{HC Scrap*Additives}\end{aligned}$$

6. Surface responses analysis

The mixture surface plot was used to study the relationship between two continuous components fitted in a 3D surface, as revealed in Figure 7. To begin with, observing the independent component, it can be seen that iron (I) and scrap (S) caused a decrease in the wt% C in the mixture with a downward curve depending on the amount of iron and scrap due to the relatively low wt% C in a component. They began at approximately 0.00404 and 0.01959, respectively, which matches Company A's data. Iron was 0.002 wt% C and scrap was 0.017 wt% C. At the same time, overall high carbon scrap (HC) and additives (A) contributed to the increase in wt% C in the mixture due to the relatively

high wt% C of those two components starting from 0.12738 wt% and 0.112 wt%, respectively. It seems slightly higher than the estimated wt% C of the riser scrap (0.08969 wt%).

When I and S interacted with all other values constant at 0, the C (wt%) in the mixture increased slightly, somewhere between C (wt%), I, and S as shown in Figure 8. At the same time, when I interacted with HC scrap, C (wt%) was significantly reduced compared to C (wt%) of HC due to the dilution of C (wt%) in HC scrap from iron. The pattern also presented with the I interaction with A. However, the decreasing trend is somewhat greater than the interaction between I and HC, as demonstrated in the curve and their coefficient. The slight or significant decrease of C (wt%) in the mixture depended on the proportion of each component.

Regarding the interaction between S and the other components, a downward trend still occurs when there is an interaction between S and A, illustrating the slope of the curve as shown in Figure 9. However, the C (wt%) increased slightly when S was mixed with HC, as seen from the surface convexity. It was due to the significant component of HC with high carbon content.

Lastly, the surface of interaction between HC scrap and additives shows concave curves. This indicates that the C (wt%) of the mixture tends to decrease from the interaction between HC scrap and additives.

7. Optimization of charge materials

After obtaining a regression equation and testing the accuracy of prediction, the optimal condition of proportion for each component was achieved using the response optimization. In order to find the appropriate proportion and produce a mixture containing a carbon content according to Company A's acceptance criteria, a goal of response optimization was set to hit a target value with lower and upper limits. Although the maximum carbon content of this stainless-steel material is 0.03 wt%, the determination of the target percentage to be a similar value as a material's standard seems to be improper due to several variations, such as a process, a raw material, or tools and equipment. It contributed to a discussion session with a factory manager and a quality control manager to specify the values. The target value was set equal to 0.0230 based on the carbon content information in 2022, especially the mean, standard deviation, and Company A tolerance. Whereas the lower limit was determined as 0.0180 rounded up from the mean, 0.0240 was the upper limit defined from a target value with a slight increase. Furthermore, starting values of iron, scrap, high carbon scrap, and additives in a design based on historical usage were pointed at 0.2, 0.4, 0.2, and 0.2, respectively.

As to the result of the response optimization analysis, Figure 10 shows the outputs of an analysis with an optimization plot. It was found that the optimum proportions of those four charge materials for achieving 0.0230 wt% of carbon in a mixture were 0.2938 of iron, 0.3810 of scrap, 0.1302 of high carbon scrap, and 0.1950 of additives. Furthermore, it can be seen that the composite and individual desirability, which have a range of zero to one, were 1, resulting in a high satisfaction on the given setting from the optimization analysis. It is because the closer desirability to 1 is presented, the more achievable goal's response is provided. Consequently, this setting will be implemented into the melting process and specified in a charge material production document for casting EN 1.4469.

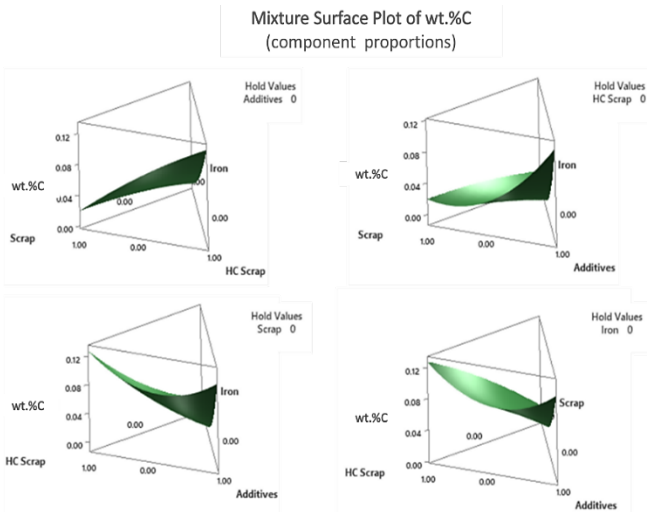


Figure 7. The 4 mixture surface plots of percentage of carbon.

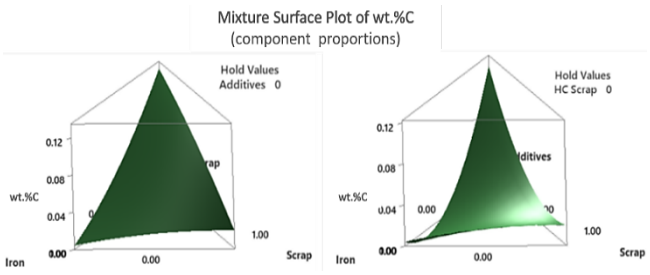


Figure 8. The 2 mixture surface plots of percentage of carbon.

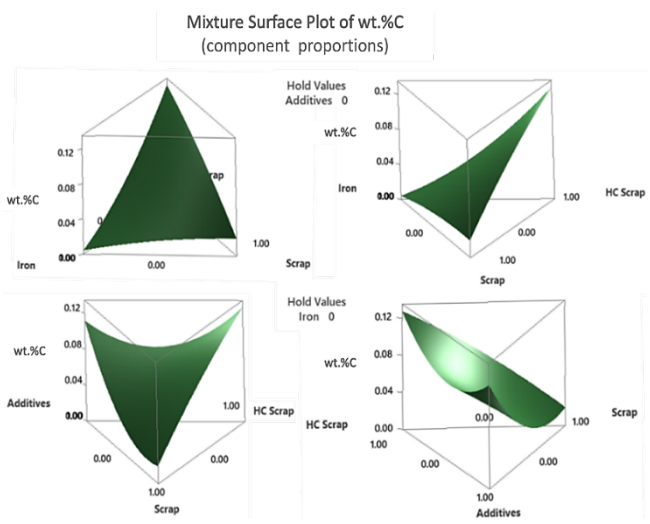


Figure 9. The 2 mixture surface plots of percentage of carbon with different perspectives.

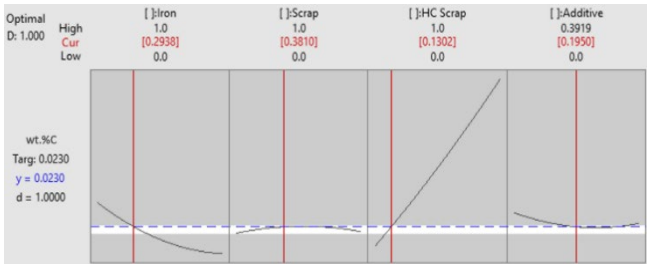


Figure 10. The response optimization plot.

Table 3. Three setting conditions for test and implementation.

Condition	Predicted wt%C	Iron (I)	Scrap (S)	High carbon scrap (HC)	Additives (A)
Optimal setting	0.0230	0.2938	0.3810	0.1302	0.1950
Minimized HC	0.0189	0.2938	0.4262	0.0850	0.1950
Maximized HC	0.0238	0.2938	0.3716	0.1396	0.1950

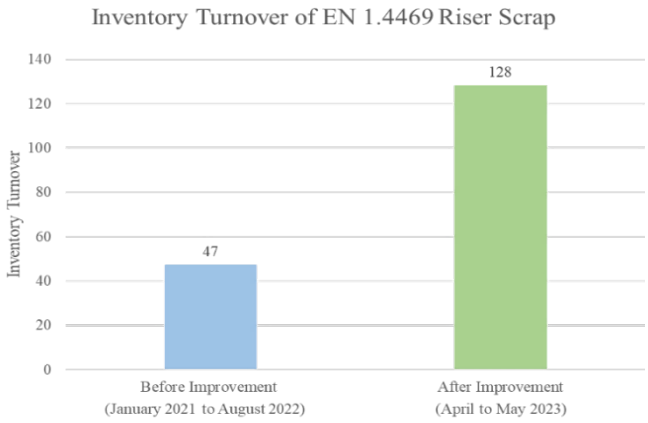


Figure 11. The inventory turnover of riser scrap before and after improvement.

When it comes to testing settings in a shop-floor environment rather than a calculation from available records, there is no doubt that examining the model by only the optimal condition seems to be not enough to confirm these findings due to testing on only one point of charge materials' proportion. In order to examine different proportions and ranges of carbon content, the maximum and minimum high carbon riser scraps from the optimization plot result were deployed to perform it. Iron and additives were as same as in the optimal setting. It resulted in changing only a scrap's proportion to provide a total to be 1. As a result, a test and implementation plan with three conditions will be performed as outlined in Table 3.

It resulted in selecting the full regression model for the casting process improvement because of having the highest percentage of R-squared (adj) and the lowest MAPE. In terms of an optimal setting condition from response optimization, it resulted that the proportion of charge materials to obtain 0.023 wt% of carbon in the mixture had to comprise 0.2938 of iron, 0.3810 of scrap, 0.1302 of high carbon scrap, and 0.1950 of additives. Finally, a plan for the test and implementation process was scheduled based on the production planning to be conducted in the future.

After finding root causes and prioritizing the potential cause, an optimal setting condition was obtained from the mixture design regression model with a response optimization. Surprisingly, the fraction of high carbon riser scrap in charge materials increased from 3% to roughly 13% by implementing the optimal setting condition. Consequently, the high carbon content riser scrap used at a 13% charge material ratio is positively affected by a reduction in the number of EN 1.4469 stainless-steel riser scraps in an inventory. It results in increasing the inventory turnover of riser scrap. Only the riser scrap from the current process without overstock scraps in an inventory was calculated to determine the impact of the implemented process. Inventory turnover of riser scrap in a period of two months was found to be 128 as shown in Figure 11, which is a considerable increase compared to the 20 month inventory turnover from January 2021 to August 2022. Due to the timeframe inconsistency between the two inventory datasets, the inventory turnover rate was annualized to enable evaluation on a standardized annual basis. The analysis revealed that the annualized inventory turnover for the pre-improvement baseline was 28.2 turns per year, whereas that of the post-improvement period increased to 768 turns per year. However, it should be acknowledged that the annualized turnover rate for the post-improvement stage may be overestimated due to the limited two-month observation timeframe and potential future fluctuations in customer demand.

After the test and implementation of setting conditions as planned in the improvement phase, 13 production times of implemented optimal charge materials, in which the number of casting operations was based on the customer order, demonstrates that results on the percentage of carbon from those productions were in control limits. They were around the goal of setting conditions, being 0.0230 wt% of carbon. Furthermore, results from testing on minimized and maximized high carbon riser scrap were presented around their centerline as they were predicted to be 0.0180 wt% of carbon and 0.0240 wt% of carbon. As a result, the proportion of high carbon riser scrap in charge materials was considerably increased after achieving an optimal setting and implementing it into production. The high carbon content riser scrap used at a 13% charge material ratio is positively affected by a reduction in the number of EN 1.4469 stainless-steel riser scraps in an inventory.

When it comes to the future uncertainties regarding carbon segregation across different in-house scrap regions and varying wt% C in high-carbon riser scrap, three core control measures are proposed to address these concerns. Firstly, the systematic classification of in-house scrap based on the location of casting gating systems remains an ongoing practice to avoid mixing scrap originating from different sources. Furthermore, semi-annual monitoring of chemical composition has been expanded beyond riser scrap to include runner and gate sections with a view to ensuring in-house scrap quality and compositional reliability. Finally, the collected data on chemical composition is additionally utilized to validate the proposed optimization parameters and ensure that current operational charge ratios do not deviate from optimal settings or exceed acceptable tolerance thresholds.

8. Conclusions

This study successfully addressed the challenge of utilizing high-carbon riser scrap in stainless steel casting at Company A, a Thai foundry producing EN 1.4469 grade materials. The main objective was to increase the inventory turnover of in-house riser scrap by developing a statistically robust and practically implementable optimization strategy for charge material composition.

Using a quadratic regression model for mixture design, a strong predictive relationship was established between the proportions of four key charge materials which are pure virgin iron, gate-and-runner scrap, high carbon riser scrap, and additives resulting carbon content

in the molten metal. The final model exhibited excellent explanatory power (adjusted $R^2 = 94.20\%$) and predictive accuracy (MAPE < 10%). These findings validated the model's ability to estimate and control carbon levels in complex casting mixtures.

The optimized material mix, determined by response optimization, enabled an increase in the proportion of high-carbon riser scrap from 3% to 13% without violating the acceptable carbon content range. This adjustment led to a significant improvement in inventory turnover from 47 to 128 within a two-month period demonstrating both operational and economic benefits.

Production trials under optimal, minimized, and maximized high-carbon scrap scenarios further confirmed that the carbon content remained within control limits, validating the robustness of the regression model. These results affirm that increased use of in-house riser scrap is not only feasible but also beneficial when supported by a data-driven decision-making framework.

This research demonstrates the practical value of statistical modeling in enhancing resource efficiency, cost control, and sustainability in metal casting operations. Furthermore, it contributes a replicable methodology for other foundries facing similar issues with scrap management and chemical composition variability.

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Declarations

Conflict of interest: The author declares and confirms that they have no conflict of interest.

Consent publications: The author also confirms that the manuscript has not been published elsewhere.

Data availability statement: The data that support the findings of this study are available from the corresponding author, S.T., upon reasonable request.

References

[1] P. Bhandubanyong, and J. T. Pearce, "Appraisal of SME casting industry in Thailand," *International Scientific Journal of Engineering and Technology (ISJET)*, vol. 1, no. 1, pp. 1–8. 2017.

[2] S. Cvetkovski, "World casting industry – Preview," *Machines. Technologies. Materials.*, vol. 9, no. 4, pp. 3–7, 2015.

[3] Marketline. (2022). Global metals & mining. *Marketline*. Retrieved from https://advantage.marketline.com

[4] M. Holtzer, R. Dańko, and S. Żymankowska-Kumon, "Foundry industry – current state and future development," *Metalurgija*, vol. 51, no. 3, pp. 337–340, 2012.

[5] J. De Mast, and J. Lokkerbol, "An analysis of the Six Sigma DMAIC method from the perspective of problem solving. *International Journal of Production Economics*, vol. 139, no. 2, pp. 604–614, 2012.

[6] H. Hsiang-Chin, and S. Ming-Hsien, "Applying Six Sigma to manufacturing processes in the food industry to reduce quality cost," *Scientific Research and Essays*, vol. 6, no. 3, pp. 580–591, 2011.

[7] G., Sharma, and P. S. Rao, "A DMAIC approach for process capability improvement: An engine crankshaft manufacturing process," *Journal of Industrial Engineering International*, vol. 10, no. 2, pp. 1–11, 2014.

[8] A. Kumaravadivel, and U. Natarajan, "Application of Six-Sigma DMAIC methodology to sand-casting process with response surface methodology," *The International Journal of Advanced Manufacturing Technology*, vol. 69, no. 5, pp. 1403–1420. 2013.

[9] C. Beckermann, and M. C. Schneider, "Simulation of convection and macrosegregation in steel casting," in *Proceedings of the 50th SFSA Technical and Operating Conference, Steel Founders' Society of America, Chicago, IL*, p. 1, 1996.

[10] K. D. Carlson, and C. Beckermann, "Prediction of riser carbon macrosegregation due to shrinkage flow in steel casting," in *Proceedings Of The 64th SFSA Technical And Operating Conference,* Paper no. 3.2, 2010.

[11] S. Gao, M. Wang, X. Xie, M. Liu, and Y. Bao, "Behavior of nitrogen in GH4169 superalloy melt during vacuum induction melting using returned materials," *Metals*, vol. 11, no. 7, p. 1119, 2021.

[12] P. Futáš, A. Pribulová, G. Fedorko, and V. Molnár, "Influence of steel scrap in the charge on the properties of gray cast iron," *ISIJ International*, vol. 57, no. 2, pp. 374–379, 2017.

[13] P. Li, X. Li, and F. Li, "A novel recycling and reuse method of iron scraps from machining process," *Journal of Cleaner Production*, vol. 266, p. 121732, 2020.

[14] S. Dutta, A. Lele, and N. Pancholi, "Studies on direct reduced iron melting in induction furnace," *Transactions of the Indian Institute of Metals*, vol. 57, no. 5, pp. 467–473, 2004.

[15] M. Poornesh, S. Bhat, E. Gijo, P. K. Bellairu, and O. McDermott, Multi-response modelling and optimisation of mechanical properties of Al-Si alloy using mixture design of experiment approach," *Processes*, vol. 10, no. 11, p. 2246, 2022.

[16] D. P. Singh, V. K. Dwivedi, and M. Agarwal, "Application of the DoE approach to the fabrication of cast Al_2O_3-LM6 composite material and evaluation of its mechanical and microstructural properties. *Materials Today: Proceedings*, 2023.