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Designing the Least Expensive Charge Mix using Data Analytics and Optimization for Gray Cast Iron (Grade FG 220)

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ABSTRACT

In a foundry, optimizing the charge mix is critical to achieving consistent quality, cost-efficiency, and desired qualities in the final metal or alloy product. This paper describes a data analytics-driven strategy for optimizing the charge-mix by lowering the cost of the scrap used to prepare the molten metal while maintaining the required chemical composition, tensile strength, and hardness required by the foundry for manufacturing gray cast iron products (Grade FG 220). The linear programming approach is used for this purpose where all the constraints are strictly met. Three categories of constraints are used for this purpose: i.e., composition constraint, foundry constraint, and material grade constraint. In the linear programming approach, the feasible region is considered as an ellipsoidal region and the developed convex optimization problem is iteratively solved. The result suggested that a considerable amount of cost savings of approximately 0.7 million Indian rupees per month can be achieved, accompanied by the needed alloy chemical composition and quality.

Keywords: data analytics, charge mix, linear programming, tensile strength, hardness.

INTRODUCTION

The charge mix is the combination of several metals and alloying ingredients that are mixed together and melted to generate the cast product in a metalcasting facility. It is crucial in determining the quality of the final generated component. The raw material composition of the charge mix affects mechanical qualities such as: tensile and compressive strength, hardness, toughness, corrosion resistance, etc., as well as thermal properties such as thermal conductivity, thermal expansion, melting point, etc. Because it is so important in determining the ultimate quality of the product, it must be carefully created to satisfy the intended product specifications.

In general, a low carbon and silicon percentage should be combined with a high manganese, chromium, and tin percentage to maximize the tensile strength of the cast iron component. Some of the scrap is intended to be used in each range for casting a specific grade. It should also be noted that if the tensile strength of the generated component gets too high, subsequent processing of the material, such as machining and polishing, becomes difficult. As a result, the element composition of the melt must remain tightly within the specified range. Traditionally, foundries determine the needed composition of the charge mix melt through prior testing (experimental) and experiential knowledge. However, with the help of these methods, it becomes extremely difficult to adequately quantify the exact amount that will simultaneously reduce the cost and achieve the material properties requirement.

In this regard, data analytics-driven solutions can be a useful way to handle this problem. The use of appropriate numerical models and the judicious application of optimization tools can assist in getting the optimum combination of melt materials that can provide the required material qualities at a lower material cost. Some researchers have worked diligently over the years to determine the right chemical composition and qualities of the melt material that influence the final cast product.

Shinde et al.[1] showed that the casting orientation, section orientation, and composition significantly influence the cooling rate, microstructure, and mechanical properties of the ductile iron castings. It was observed that apart from the casting orientation, the simultaneous increase of the copper and manganese as the alloying element can improve the tensile strength and hardness.

In the other work of Shinde et al.[2] the investigation regarding the influence of casting thickness and the melt chemical composition on the microstructure of the produced ductile iron castings was reported. A considerable increase in the tensile strength and hardness was observed when the copper content in the melt mixture was increased.

Labrecque et al.[3] investigated the effect of various charge materials including high-purity iron grades, ferritic ductile iron returns, and steel scrap on the slag formation on ductile iron melts. The study also revealed that meticulous control of the melt composition can significantly reduce the melt cost of cast products without affecting the final component properties.

It has also been observed in some of the studies that implementing data analytics and optimization techniques for charge mix melt analysis can effectively reduce costs and minimize wastage in the foundry industry.[4,9] By carefully controlling the selection of raw materials used in the charge mix melt, it becomes easier to attain the desired mechanical properties in the final casting product. Additionally, by considering the cost-benefit trade-offs while ensuring the quality of the material, overall cost savings can be achieved.

The work of Mitra et al.[5] used the neural network-based meta-models to optimize the burden distribution programs for a blast furnace. It helped them to get a rise in the desired gas flow distribution, characterized by the temperature distribution at an in-burden probe located in the shaft. The genetic algorithm was used to solve this multi-objective optimization problem that was used to achieve the targeted temperature profile using the proper charging program.

It can be observed from the work of Zablotskii et al.[6] that with the help of the regression model and correlation analysis, proper quantification of the charge material for the blast furnace can be achieved. This in turn will help in choosing the optimal charging parameters that enable the formulation of recommendations for the intensification of reduction operations and the overall improvement of the smelting process.

Chaudhari and Aloni[7] showed the importance of the design of experiment techniques accompanied with the machine learning algorithms, principal component analysis, and the Grey Relational Analysis (GRA) can be a useful tool in reducing the defects in the green sand casting process by optimizing the input parameters. Identifying the proper parameters, followed using proper optimization tools can provide very effective strategies in reducing the casting rejections that will in turn help in increasing the profit margins for the industry.

Similar strategies can be also used for the estimation of the required quantity of the charge-mix composition. The researchers have used the mass balance method to develop the model for the charge mix composition. It was observed that the several non-linearities associated 'charge-mix' melting mixture like contamination, material-loss, and melt corrections can be integrated into the linear programming formulation as an optimization problem. Furthermore, the use of the iterative solving method can further aid in solving the model using the linear programming-based optimization problem.[8]
The mass balance technique was also used by Boin and Bertram[10] to understand the effectiveness of the recyclability of the aluminum scrap in the European metalcasting industry. Their analysis suggested that the recovery of ~94% of the aluminum was achieved by the European industry for the 2002 analysis period.

These studies provided evidence that a foundry process can be made more efficient by using data analytics tools effectively. These tools can be an efficient means of managing the melt composition, particularly in the case of a charge mix. Even though some researchers have used cost as a constraint in their work, a much more thorough investigation is needed, one that should also take material properties into account. Additionally, it is important to properly analyze the specific investigation of the gray cast iron components by taking into account foundry scenarios. As a result, it will be easier to comprehend the effectiveness of these analytical techniques. Furthermore, it is important to look into how constraints (i.e., low- carbon scrap and high-carbon scrap) are used that are uniquely needed for manufacturing cast iron components.

To address the aforementioned challenges, this study focused on optimizing the charge mix to achieve the desired chemical composition, and tensile strength, and meet the requirements of the foundry conditions, all while reducing costs.

The optimization process considers three categories of constraints: foundry, grade, and composition. By incorporating these constraints into the objective function, the study aimed to find the ideal charge mix (a raw material combination for the melt). The subsequent sections present the formulation and discuss the results obtained from this optimization process. The methodology followed for this optimization process is displayed in Figure 1, starting with data processing to completing the formulation and the problem solver.

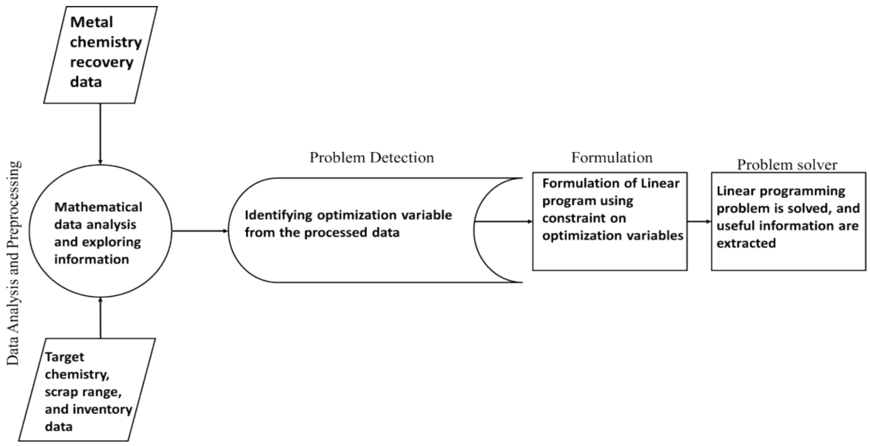

Figure 1. Methodology followed for the present work.

MATHEMATICAL FORMULATION

The main objective of this work was to reduce the cost of the charge mix in cast iron foundries by attaining the desired tensile strength and grade. It should be noted that for an optimization problem, an important step is to deduce the problem statement and analyze the variables to be optimized. These variables are called optimization variables. Considering the given problem statement and description, the optimization variables are the mass of each scrap and alloy used for making the cast iron.

Once the optimization variables are finalized, and the objective function is formulated, the constraints followed for solving the optimizing problem need to be decided. These constraints are used for defining a feasible region, a region in the n-dimensional space where the objective function is optimized. In case there is no such space then the problem is said to be infeasible i.e., all the constraints can be met. The objective function for this work is mentioned in Equation 1

Objective function:

$$y = \min_{x} C^T x \qquad \textbf{Eqn. 1}$$

Subject to the constraints mentioned below.

COMPOSITION CONSTRAINT:
It is the constraint on the target composition that is to be followed to prepare the cast iron. It gives the constraints on the quantity of the elements that should be present in the finally produced cast iron.

$$comp_{lower} \leq \frac{J^T x}{furnace\_capacity} \leq comp_{upper} \qquad \textbf{Eqn. 2}$$

$$1^T x = melt\_amount \qquad \textbf{Eqn. 3}$$

Equation 2 is the constraint on the target chemical composition that is to be followed to prepare the cast iron. Equation 3 is the constraint on the melt amount that can be made on the furnace.

FOUNDRY CONSTRAINT:
It can be divided into two types.

1. Maximum furnace capacity, i.e., the maximum amount of cast iron that can be produced.
2. Availability of scrap: weight of each type of scrap.

$$x_{i,min} \leq x_i \leq x_{i.max} \qquad \textbf{Eqn. 4}$$

$$x_i \leq availability_i \qquad \textbf{Eqn. 5}$$

Equation 4 is the constraint on the maximum amount of scrap that can be used.
Equation 5 is the maximum amount of each scrap that can be used depending on the availability of the scrap.

GRADE CONSTRAINT:
It can be divided into two types.

1. Empirical tensile strength and the hardness constraint that the given cast iron product under investigation should follow. It is generally decided by the requirement of the final product mentioned by the customer.

2. Constraint on the total weight percentage of the low-carbon scrap should be used for the given material. Its values depend on the grade of the cast iron that needs to be produced.

$$\left(1049.40611 - 209.1522411 \times \frac{(J^T x_C + 0.25 \times J^T x_{Si} + 0.5 \times J^T x_P)}{furnace\_capacity}\right) = UTS \quad if\ UTS < 250 \qquad \textbf{Eqn. 6}$$

$$\left(559.98433 - 91.67733 \times \frac{(J^T x_C + 0.25 \times J^T x_{Si} + 0.5 \times J^T x_P)}{furnace\_capacity}\right) \geq HB_{min} \quad if\ UTS < 250 \qquad \textbf{Eqn. 7}$$

$$(980 - UTS) \times 4.3 - 0.3(J^T x_{Si} + J^T x_P) = 785 \times J^T x_C if\ UTS \geq 260 \qquad \textbf{Eqn. 8}$$

$$(559.98433 - 91.67733 \times \frac{(J^T x_C + 0.25 \times J^T x_{Si} + 0.5 \times J^T x_P)}{furnace\_capacity}) \geq HB_{min} \quad if\ UTS < 250$$ **Eqn. 9**

$$(559.98433 - 91.67733 \times \frac{(J^T x_C + 0.25 \times J^T x_{Si} + 0.5 \times J^T x_P)}{furnace\_capacity}) \leq HB_{max} \quad if\ UTS < 250$$ **Eqn. 10**

$$(538.6 - HB_{min}) \times 4.3 - \frac{1}{3}(J^T x_S + J^T x_P) \geq 354.75 \times J^T x_C \quad if\ UTS \geq 250$$ **Eqn. 11**

$$(538.6 - HB_{max}) \times 4.3 - \frac{1}{3}(J^T x_{Si} + J^T x_P) \leq 354.75 \times J^T x_C \quad if\ UTS \geq 250$$ **Eqn. 12**

$$low\_C\_scrap_{min} \leq x_{i,low\ carbon} \leq low\_C\_scrap_{max}$$ **Eqn. 13**

Where:

- $x_{n \times 1}$ = vector of mass of the scrap and n = number of scrap with k = low carbon scrap
- $C_{n \times 1}$ = a vector of cost per kg of scrap (Indian rupees).
- $x_{i,min}$ and $x_{i,max}$ = min and max amount of scrap.
- $melt\_amount$ = amount of melt produced.
- $comp_{lower}$ and $comp_{upper}$ gives target composition bounds.
- UTS_{req} = tensile strength to be attained (Mpa).
- $J \in R^{n \times r}$ = composition of scrap and alloys.
- low_C_scrap$_{min}$ and low_C_scrap$_{max}$ for low carbon
- $availability$ inventory data
- HB_{min} = minimum hardness requirement.
- HB_{max} = maximum hardness requirement.

From Equation 6 to 12 represents the constraint on the tensile strength and the hardness for a given grade of the sample that needs to be followed.[11]

Equation 13 is the constraint on the range of how much minimum or maximum amount of low-carbon scrap needs to be added to the mixture.

Solving strategies:

To minimize the objective function first the feasibility region needs to be analyzed. The feasibility region can be classified based on the boundary conditions and boundness as:

- Linear or quadratic or…
- Bounded or unbonded feasible region.

Linear constraints add planer boundaries to the feasible region and if the objective function has the order of the optimization variable 1, then this kind of problem can be solved using linear programming. In linear programming, the analytical approach is used to optimize the objective function. The analytical approach starts by considering all the corner points of the feasible region and calculating their respective values of the objective function. Based on the problem, whether to minimize or maximize, the corner points are chosen, and the values are assigned to the optimization variables.

Materials and Methods

In the present work, a test case is considered where a component block with Grade FG 220 is to be manufactured. The minimum tensile strength that needs to be achieved is 220 MPa. The chemical composition of the target product is mentioned in Table 1.

Table 1. Chemical Composition of the Required Product

Operating range for chemical composition		Percent (%)
TC (C (%))	Low	3.25
	High	3.4
	Target	3.3
Si (%)	Low	2
	High	2.2
	Target	2.1
Mn (%)	Low	0.65
	High	0.75
	Target	0.7
Cr (%)	Low	0.1
	High	0.2
	Target	0.15
P (%)	Low	0.040
	High	0.070
	Target	0.055
S (%)	Low	0.060
	High	0.080
	Target	0.07
Sn (%)	Low	0.000
	High	0.040
	Target	0.02
Grade		FG220

The chemical composition of the charge mix melt material (raw material) that is available for making the produced component mentioned in Table 1 is displayed in Table 2.

Table 2. Chemical Composition of Raw Material used in Charge Mix Melt Preparation

Material	C %	Si %	Mn %	P %	S %	Cu %	Cr %	Ti %	Sn %	Ni %	Mo %	
PIG IRON	4.18	2	0.6	0.06	0.007	0.006	0.01	0.09	0.003	0.005	0	High carbon scrap
C.I Boring	3.1	1.8	0.65	0.051	0.07	0.02	0.22	0.028	0.06	0.02	0.004	
CPC	85	0	0	0	0	0	0	0	0	0	0	
Runner Raiser	3.2	1.8	0.65	0.051	0.07	0.02	0.22	0.028	0.06	0.024	0.01	
M.S. Scrap	0.16	0.28	0.8	0.05	0.01	0.005	0.01	0.02	0.001	0.028	0.014	Low carbon scrap
Tin coated scrap	0.1	0.006	0.35	0.032	0.01	0.01	0.02	0.001	0.3	0.0125	0.058	
Silicon Punching scrap	0.003	1.2	0.17	0.023	0.0001	0.01	0.02	0.002	0.003	0.0045	0.01237	
FeSi	0	70	0	0	0	0	0	0	0	0	0	Other Alloying materials
FeMn	0	0	60	0	0	0	0	0	0	0	0	
FeS	0	0	0	0	35	0	0	0	0	0	0	
FeCr	0	0	0	0	0	0	60	0	0	0	0	
Sn	0	0	0	0	0	0	0	0	99.99	0	0	

The cost of the raw material per kg of the melt material is mentioned in Table 3 (in Indian Rupees).

Table 3. Cost per kg of Raw Material used in Melt

Material	Rate per kg (Indian Rupees)
Pig Iron	64.00
M.S.Scrap	53
Tin coated scrap	53.00
Silicon Punching scrap	53
C.I Boring	58.00
Runner Raiser	53
CPC	75
FeSi	153
FeMn	110
FeS	50
FeCr	130
Sn	2500.00
Heel	31.4

In general, in a running foundry, the total furnace capacity is considered as the sum of the furnace capacity, heel, and slag (Figure 2).

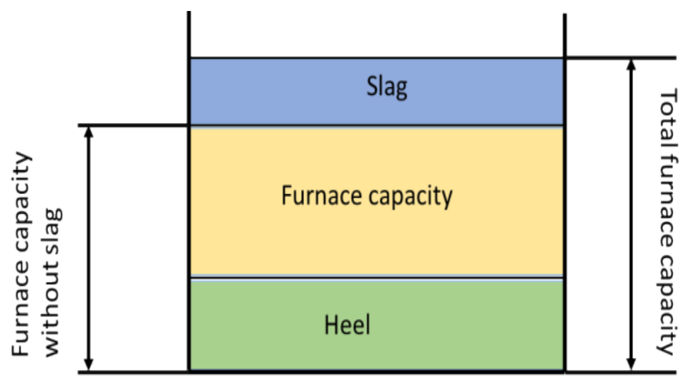

Figure 2. The schematic representation of the furnace capacity.

$$Total\ furnace\ capacity = \ furnace\ capacity + slag + Heel \qquad \textbf{Eqn. 14}$$

The melt material that is prepared using the fresh raw material should adhere to the volume of the furnace capacity indicated in Figure 2. In this study for the simplification of the problem, the slag and the heel amount are considered as zero. The minimum and the maximum amount of low-carbon scrap that needs to be added is 30 to 35 (wt%). The melt capacity is considered 6,000 kg.

To compare the results obtained from the proposed method, a comparison is made with the already available procedure (named "spreadsheet method" in this work) followed by the foundry. The foundry obtained the composition of the melt used in the charge-mix by the previous experimental and experiential inputs along with their customer specification. The cost of the raw materials is also considered while preparing the composition of the melt mixture.

RESULTS AND DISCUSSION

The optimum parameter after the optimization is displayed in Table 4. The tensile strength obtained is 230 Mpa and hardness 201 HB.

The cast component with the obtained chemical composition is mentioned in Table 5. It also contains a comparison with the conventional spreadsheet method followed by the foundry.

Table 4. Optimized Scrap Composition for Spreadsheet (wt%) & Developed Model (wt%)

Materials	Spread sheet method (wt%)	Material type and composition for spread sheet method	Developed model (wt%)	Material type and composition for developed model
PIG IRON	4.86	High carbon scrap (64.6%)	5	High carbon scrap (69.1%)
C.I Boring	0		0	
CPC	1.36		1.39	
Runner Raiser	58.38		62.71	
M.S. Scrap	0	Low carbon scrap (34.05%)	0	Low carbon scrap (30%)
Tin coated scrap	14.59		0	
Silicon Punching scrap	19.46		30	
FeSi	0.94	Other Alloying elements (1.35%)	0.59	Other Alloying elements (0.9%)
FeMn	0.31		0.27	
FeS	0.08		0.04	
FeCr	0.02		0	
Sn	0		0	
Total Cost/Kg (Indian rupees)	54.96		54.59	
Cost Savings/Kg	0.37			

Table 5. Optimized Scrap Composition of the Produced Component

Elements	Spreadsheet method	Developed model
C(%)	3.33	3.397
Si (%)	2.1	2
Mn (%)	0.7	0.65
Cr (%)	0.15	0.144
P (%)	0.055	0.042
S (%)	0.08	0.06
Sn (%)	0.02	0.039

It can be observed from Table 5 that the cost savings per kg (Indian Rupees) obtained with respect to the conventional deployed method is 0.37. As mentioned in the above sections by assuming that the 5 melting of scrap (Heat) is done per shift and a furnace capacity of 6,000kg, the total amount of savings per day that can be achieved is as follows:

$$Cost\ savings\ per\ day = 0.37 \times 5 \times 3 \times 6{,}000 = 33{,}300\ (Indian\ rupees)$$

$$Cost\ savings\ per\ month = 33{,}300 \times 24 = 799{,}200\ (Indian\ rupees)\ \text{(24 working days/month)}$$

$$Cost\ savings\ per\ year = 799{,}200 \times 12 = 9{,}590{,}400\ (Indian\ rupees)(considering\ 12\ months/year)$$

It should be mentioned that the inclusion of both high-carbon scrap and low-carbon scrap is essential for the final gray cast iron produced sample.[7] The high carbon content in the gray cast iron can result in decreased hardness, tensile and wear resistance of the material. Additionally, too low carbon content can hamper the machinability characteristic of the produced component. It should also be noted that the other components and some elements present in the low carbon scrap can aid in the improvement of the material properties of the produced component. Hence to address this issue low carbon scrap is also added in the melt composition. Therefore, to produce the appropriate qualities for the particular application, foundries frequently strive to strike a balance between scrap with high and low carbon content. These two contradictory situations are very well articulated and solved in this paper using the linear programming approach.

The optimized quantities mentioned in Table 4 suggests that the high carbon scrap (69.1%) and the low carbon scrap (30%) are within the desired values mentioned by the foundries to produce gray cast iron. Additionally, the chemical composition of the cast sample mentioned in Table 5 also follows the limits mentioned by the foundry.

CONCLUSIONS

This work describes the development of a linear programming approach for designing the least expensive charge mix combination for the manufacturing of the gray cast iron component. The following conclusions can be drawn from this work:

1. Linear programming can be a useful tool for maintaining a cost-effective way of designing the melt composition (charge-mix) needed to make the cast iron in foundries.
2. For developing the optimization problem, proper inclusion of constraints, i.e., composition constraint, foundry constraint, and grade constraint, should be adequately defined to achieve the desired and meaningful outcome of this technique. The high carbon scrap (69.1%) and the low carbon scrap (30%) were obtained using the proposed technique which are within the limit prescribed by the foundry.
3. Cost savings of approximately 0.7 million Indian Rupees per month can be obtained by the foundry without compromising on the quality of the cast component by following the proposed method.
   In the future work, the feasibility of this developed modelling approach can be validated for the actual experimental/industrial test cases that can improve the efficacy of this technique for the practical scenarios and the actual shop floor condition. Additionally, there is an opportunity to delve into more intricate analyses by taking into account the comprehensive techniques and methodologies employed in foundries. This may involve considering factors such as heel and slag, among others, which can greatly contribute to a more thorough understanding. Furthermore, this approach can be extended beyond its application in current materials to explore the casting of steel components as well, by expanding the scope of analysis and incorporating these considerations.

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