Enhancement of Operational Performance of a Foundry

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Abstract: As a result of rapid environmental degradation, there are several adverse impacts like increase in global temperature, Change in monsoon pattern, low air quality etc., which affect the living beings on earth. Hence, more stringent environmental laws are in place to control the release of harmful substances into the environment. Foundries are under tremendous pressure to comply with these environmental standards. The Operational performance of the various foundry departments plays an important role in minimizing the wastage of materials. The molding and melting are the important operations in a foundry. These two departments are more dependent on the skills of the workers for effective functioning. However, foundries yet do not have proper system for measurement of the performance levels of these departments. The present work focuses on the development of a feasible system for monitoring and improving the operational performance of the melting and molding departments in a foundry. The PDCA cycle was adapted to study and suggest a suitable system to the two departments. For the melting department, a Linear Programming model is formulated to calculate the amount of raw materials needed to obtain the required melt composition. For the molding department, The process parameters influencing mold hardness is optimized using Design of Experiments and a regression model is fitted to predict the mold hardness in real time. The study was done and validated in a foundry located in south India.

Index Terms: Foundry, Linear Programming, Melting Molding, Operational performance, Regression, Taguchi design

I. INTRODUCTION

In recent times, there is increased pressure and need among manufacturers to focus on environmental effects created by the processes and products more than the economic benefits. Environmental problems like ozone depletion, Global warming, loss of bio diversity, Green-house effect, Acid rain etc. are in one way or the other associated with products, processes and production systems. People are worried about the environmental pollution and sustained functioning of Earth's natural ecosystems. Moreover, there would be environmental burden left behind for the future generations also.Sustainable development is societal development, economic development and environmental balance combined together. One-sided development of any of the three factors will lead to catastrophic effects. Societal development caters to the availability of basic human needs; Economic development refers to the availability of purchasing power with people. Among the manufacturing industries, foundries release a lot of toxic pollutants into the environment during the operation. Though foundries recycle the metal, they have not yet reached a sustainable state. They release a lot of pollutants which are potentially harmful to humans. Moreover, the spent foundry sand from cores and molding cannot be recycled. The main emissions from foundry comes from mineral dusts released during organic compounds melting, sand molding, core making and cleaning of castings.

There is a close relationship between the operational performance of a foundry and the environmental performance of a company. ISO 14031 enables the measurement of environmental performance by three indicators namely

1. Environmental condition indicators
2. Operational performance indicators
3. Management performance indicators [1]

There is extensive involvement of humans in the operation of machines or equipment in the melting and molding departments of a foundry. Workers are directly involved in the control of process parameters in these two departments. Hence, there is a need for a system that helps the workers in controlling the process parameters. The present work focuses on the improvement of the operational performances of melting and the molding departments in the foundry by suggesting feasible systems to monitor and control the process parameters.

II. LITERATURE SURVEY

Pollution in foundries is of major concern to the environment as it causes health problems to the workers associated with it. There is a high probability that the workers in the foundry could be affected. The organs that are exposed to risk include lungs, stomach, kidney, liver and the brain. Foundry dust is the main source of pollution and mainly affects the personnel employed in molding, core and pouring line. Diseases like silicosis, Lung cancer, pneumoconiosis, etc.[2] Green supply chain performance management system were discussed in detail concerning the data collection , internal and external pressures involved in implementation, PDCA cycle type of decision support system was suggested for the design of a performance management system and also for its continuous improvement [1] Certain authors conducted a review of the entire foundry in order to carry out Green manufacturing practices. The review focussed on the system boundaries, data collection methods, pollution prevention methodologies, etc were discussed [3]. Recent works were done on the barriers for the implementation of Green Supply Chain

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Management practices in industries. Moreover a connected platform for the design and carrying out of Green practices has been proposed.[4] Certain authors have done work on initiative for implementation of green manufacturing practices inside the foundry including green production, green, logistics, green warehousing and green distribution, green procurement etc. The benefits of undertaking these approached were outlined and the suitability of application of lean principles, ISO 14001, Six sigma tools to enable green practices were also briefed. [5] Case studies of large manufacturers in Japan were extensively studied for green supply chain management implementation practices. The various drivers were examined and the results indicate that these companies were able to produce a increase in their environmental performance but no changes was observed in their productivity[6]. Authors have also discussed various barriers involved in the implementation of green practices in Indian foundries in a detailed manner. The barriers were found to be influencing each other and were complex in nature. Hence an ISM Interpretive Structural Modeling Technique was used to break down the complex barriers into smaller sub-problems and a Driver and Dependence Power Analysis was also carried out to prioritize the barriers[7]. Various works were carried out in order to reduce energy usage in a foundry. This includes usage of metal shots in the sand molds to absorb the heat during cooling of sand molds. Later these shots were used to heat the metal scraps which are a part of the melt. Results indicate that a 6.4% of energy could be recovered on following this process[8]. Further separate work was carried out to evaluate the efficiencies of various materials that could be used as metal shots among aluminium, copper, and steel shots to carry out the heat absorption. Copper shots was found to be the most effective material [9]. Another work was reported in the area of eco-friendly foundry. The authors have used the scraps which are the raw materials for the melt directly in to the mold. They have found out that the energy consumption was reduced by 12% instead of melting the scrap again in the furnace.[10]. Some authors discussed various Efforts for prevention of the pollution. Cleaner production methods was used to minimize the pollution effects to the environment [11]. Wet scrubbers are pollution control devices installed in a foundry. The performance efficiencies of the device was carried out some authors[12]. Certain authors have tried to use latest technology like the Internet of Things (IoT) to capture data directly from the machine using various sensors, which could be used to take meaningful decisions. IoT based pollution control device was designed and installed in real time traffic signals to monitor the air quality of cities. Further the power consumption of these devices was discussed to achieve cost benefit out of the installation. The device data was also stored in the cloud servers.[13]. Further some authors discussed the benefits of these new age devices to the foundry. A platform for the design of IoT devices and barriers surrounding it were also discussed [14], [15].

III. ORGANIZATION PROFILE

The study was done in a foundry in south India. The foundry manufactures castings for the automotive, hydraulic, tractor and valve segments. The foundry utilizes induction furnace for melting and simultaneous jolt and squeeze machine for molding.

IV. METHODOLOGY

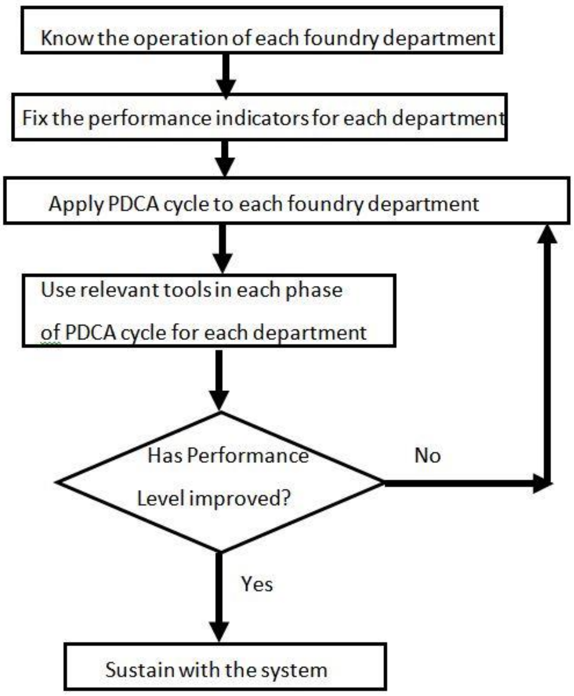

Fig 1 Methodology followed for study

In order to develop a suitable system to monitor and sustain the environmental performance of various foundry departments, the continuous improvement tool Plan-Do-Check-Act is implemented for each department.

The PDCA cycle is applied to study the data collection procedures, for the decision of a suitable tool for improvement in the indicator and the sustaining of the system proposed as shown in the fig 1. The Plan phase describes about the methods used to study and observe the present working conditions and deciding a suitable performance indicator for the department. The Do phase encompasses works like deciding the method to measure the performance indicator in the current state, performing relevant analysis to find ways to improve the current level of performance indicator, development of systems to conduct relevant experiments in each department analyse the experiment results and draw conclusions from the experiments. The Check phase includes the incorporation of the new system, assessing the performance after the implementation. Finally, the Act phase focuses on the satisfaction levels of the performance of new system and calls for initiation of the plan phase based on the recommendations received from the managers and supervisors in order to rectify the errors or further improvise the system.

V. MELTING DEPARTMENT

The PDCA cycle comprising the various activities in each phase for the melting department is shown in fig 2

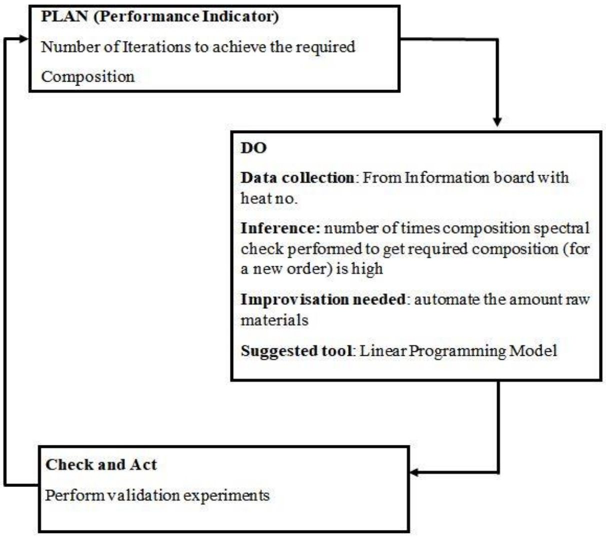

Fig 2 PDCA cycle for melting department

A. *Plan Phase*

When a new composition of cast iron had to be achieved or if the grades of the raw material used had changed, new trial experiment is conducted in order to know the individual percentage of elements in the final melt. This involves expenditure of time and energy. Thus the performance indicator selected for this department is the number of iterations required to achieve the required composition.

B. *Do Phase*

A Linear Programming model was proposed to predict the amount of raw materials that has to be used in order to achieve a particular composition of the melt. In order to predict the amount of raw materials needed, the elemental composition of each raw material had to be found. This data was obtained from the Mass Spectrometer in the company and is tabulated in table 3.The percentage of Iron in the final melt is calculated by subtracting the individual percentages of other elements from 100 which is given in the last column of table 3.

Table 3 Percentage Elemental composition of Raw materials

	Carbon (%)	Silicon (%)	Manganese (%)	Sulphur (%)	Phosphorus (%)	Chromium (%)	Iron (%)
petroleum coke	92	0	0	3.4	0	0	4.6
Mild steel scrap	0.42	0.2	0.66	0.002	0.011	0	98.707
Runners	3.5	2.1	0.5	0.004	0.01	0	93.886
Cast iron scrap	3.3	2.5	0.55	0.005	0.008	0	93.637
Ferro Silicon	0	60	0	0	0	0	40
Fe Manganese	0.5	1	80	0.04	0.05	0	18.41
Ferro Sulphur	0	3	0	30	0	0	67
Ferro Chrome	8.5	3.5	0	0.05	0.03	60	27.92
Base metal	3.5	2	0.45	0.008	0.02	0	94.022

C. *Problem formulation*

The variables used in the LP model are the percentages of raw materials in the final melt and the final melt quantity in tons as shown in table 4.

D. *Conversion of percentages into weights*

This calculation is narrated with the help of a numerical for a single raw material (Petroleum Coke). The final melt quantity is assumed as 2 tons. The value for variable X1 is assumed as 4%, the weight of Carbon, Sulphur and Iron in Petroleum coke is found from the equations 1 to 3, and the sum of the weights of all elements gives the weight of the raw material in the final melt.

In the similar way, the weights of other raw materials are calculated by the summation of the weights of individual elements that are calculated from the percentage composition of the corresponding raw materials as shown in the numerical illustration. For the assumed values for the variables (in %), the fully completed matrix containing the weights of each raw material is shown in tables 5 and 6 respectively.

Weight of Carbon (kg) in Petroleum Coke for 4% of final melt = (((0.3474/100)*2*1000)/100)*92 (1)
= 6.393 kg
Weight of Sulphur (kg) in Petroleum Coke for 4% of final melt = (((0.3474/100)*2*1000)/100)*3.4 (2)
= 0.2362 kg
Weight of Iron (kg) in Petroleum Coke for 4% of final melt = (((0.3474/100)*2*1000)/100)*4.6 (3)
= 0.3196 kg
Total weight of Petroleum Coke in final melt = 6.393+0.2362+0.3196
= 6.9486 kg

Table 4 Variables of LP model

Description of the variable	Variable name
Percentage of final melt of Petroleum coke (%)	X1
Percentage of final melt of Mild steel scrap (%)	X2
Percentage of final melt of Runners (%)	X3
Percentage of final melt of Cast iron scrap (%)	X4
Percentage of final melt of Ferro Silicon (%)	X5
Percentage of final melt of Fe Manganese (%)	X6
Percentage of final melt of Ferro Sulphur (%)	X7
Percentage of final melt of Ferro Chrome (%)	X8
Percentage of final melt of Base metal (%)	X9
Final melt quantity (tons)	X10

Table 5 Assumed values for variables

	C (%)	Si (%)	Mn (%)	S (%)	P (%)	Cr (%)	Fe (%)	Variables (%)
Petroleum coke	92	0	0	3.4	0	0	4.6	0.3474
MildSteel scrap	0.42	0.2	0.66	0.002	0.011	0	98.707	5
runners	3.5	2.1	0.5	0.004	0.01	0	93.886	10
Casti scrap	3.3	2.5	0.55	0.005	0.008	0	93.637	24.5036
Fe Si	0	60	0	0	0	0	40	0
Fe Mn	0.5	1	80	0.04	0.05	0	18.41	0.1489
Fe S	0	3	0	30	0	0	67	0
Fe Cr	8.5	3.5	0	0.05	0.03	60	27.92	0
Base metal	3.5	2	0.45	0.008	0.02	0	94.022	60

Table 6 Total weights for the assumed values for variables

	C (kg)	Si (kg)	Mn (kg)	S (kg)	P (kg)	Cr (kg)	Fe (kg)	Amount (kg)
petroleum coke	6.39272	0	0	0.236253	0	0	0.319636	6.94861
ms scrap	0.42	0.2	0.66	0.002	0.011	0	98.707	100
runners	7	4.2	1	0.008	0.02	0	187.772	200
ci scrap	16.1723	12.2518	2.695397	0.024504	0.039206	0	458.8889	490.072
Fe Si	0	0	0	0	0	0	0	0
Fe Mn	0.01489	0.02979	2.3833629	0.001192	0.00149	0	0.548471	2.9792
Fe S	0	0	0	0	0	0	0	0
Fe Cr	0	0	0	0	0	0	0	0
Base metal	42	24	5.4	0.096	0.24	0	1128.264	1200
Total weight in final melt	72	40.6816	12.13876	0.367948	0.311695	0	1874.5	2000
Percentage in final melt	3.6	2.0341	0.60694	0.0184	0.0156	0	93.725	-

After obtaining the weights of all raw materials and the individual weights of each element, the total weights of individual elements present in the melt are obtained by summing the values in each column in table 6. These individual element weights are converted into percentages of elements. From the percentages of individual elements, the percentage of iron in the final melt can be found out, which gives the objective function which is 93.725 in the present case.

E. Objective function

The objective of the Linear Programming model is to arrive at the optimum values for the individual elements present in the final melt. Since there are six principal elements in the melt whose percentages have to be simultaneously optimized, the simplex method used to solve the problem could not arrive at an optimal solution. Hence, the iron percentage in the melt was considered as the objective function to the problem.

The iron percentage would be a minimum when the percentages of all other elements are a maximum. Thus the required composition of the melt could be achieved.

F. Constraints

The constraints for the LP problem are

1. The total percentage of all raw materials equals 100
2. Minimum base metal is 50%
3. Minimum MS scrap is 100 kg
4. Maximum runners, gates amount = 200 kg
5. Minimum iron content = 100-(Maximum allowable percentage of all other elements
6. Maximum carbon percentage is 3.61(the required carbon percentage)

G. Problem representation in terms of variables

Minimise the total iron Percentage in final melt

$$\frac{\left[(X1\times 4.6)+(X2\times 98.707)+(X3\times 93.886)+(X4\times 93.637)+(X5\times 40)+(X6\times 18.41)+(X7\times 67)+(X8\times 27.92)+(X9\times 94.022)\right]}{X10\times 10}$$

Subject to Constraints

1. The total percentage equals 100
   (X1 +X2 +X3 +X4 +X5 +X6 +X7+X8+X9) =100
2. Minimum base metal is 50%
   $X9 \geq 50$
3. Minimum MS scrap is 100 kg (for melt quantity of 2 tons)
   $X2 \geq 5$

4. Maximum runners, gates is 200 kg (for melt quantity of 2 tons)
   $X3 \leq 10$

5. Minimum iron content = 100-(Maximum allowable percentage of all other elements

$$\frac{[(X1\times4.6)+(X2\times98.707)+(X3\times93.886)+(X4\times93.637)+(X5\times40)+(X6\times18.41)+(X7\times67)+(X8\times27.92)+(X9\times94.022)]}{X10\times10} \geq 93.725$$

6. Maximum carbon percentage = 3.61

$$\frac{[(X1\times92)+(X2\times0.42)+(X3\times3.5)+(X4\times3.3)+(X6\times0.5)+(X9\times3.5)]}{X10\times10} \leq 3.61$$

H. *Solution of the LP model*

The data to be given to the model are the final melt quantity X10, Iron percentage required in the constraint, the carbon percentage required, percentage values of X2 and X3 according to the final melt quantity. The LP problem is solved using Solver add-in of MS-Excel.

I. *Check and Act phase*

In order to validate the proposed model, real time data of a furnace was captured and the final output of both the methods were compared, which is shown in table 7

Table 7 Comparison between LP model and Actual data

	amount of raw material (kg)		MAPE
	LP model	Actual melt	
Pet coke	6.95	7	0.7143
MS scrap	100	100	0
Runners	200	200	0
CI scrap	490	500	2
FeSi	0	5	100
FeMn	2.979	2	48.95
Fe S	0	2	100
Fe Cr	0	0	
Base metal	1200	1200	0

The Mean Absolute Percentage Error is computed by taking the absolute value for the difference between the amount of raw material given by the LP model and the actual raw material amount. The absolute value is used to determine the percentage error. The results of the LP model are analyzed by computing the Mean Absolute Percentage Error and are discussed in detail in the results and discussions.

VI. MOLDING DEPARTMENT

The PDCA cycle comprising the various activities in each phase for the melting department is shown in fig 3

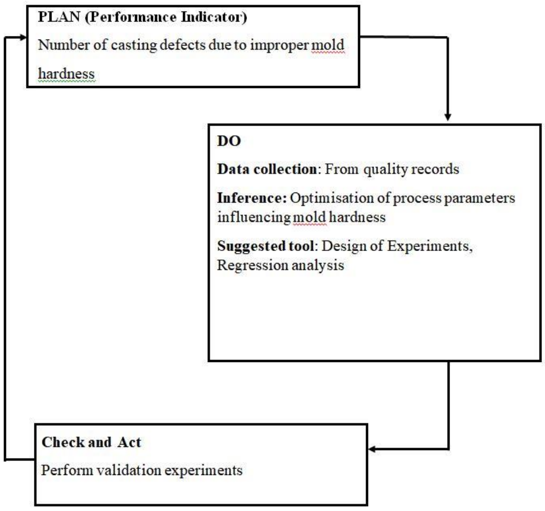

Fig 3 PDCA cycle for molding department

A. *Plan phase*

Mold hardness is one of the most important quality parameter to ensure a defect free casting. Mold hardness is influenced by factors like permeability, compactability and the moisture content in the sand. In order to know the effects of these parameters on the mold hardness, few mold hardness data were captured by varying these factors within the permissible levels. The data is shown in figures 3 to 5.

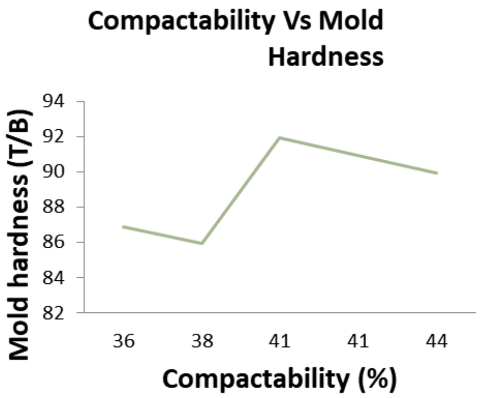

Fig 3 Effect of compactability on mold hardness

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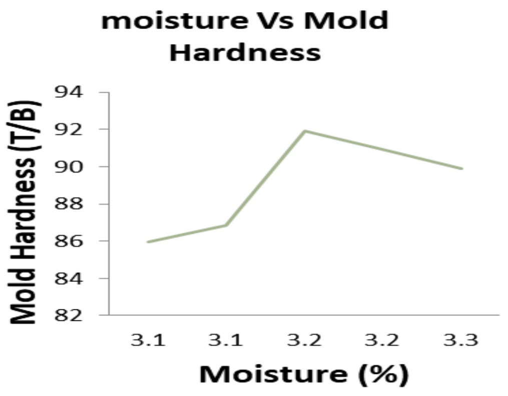

Fig 4 Effect of Moisture on mold hardness

From the figures 3 and 4, it can be inferred that on increasing compactability and moisture, the mold hardness also increases. This increase is observed only up to a threshold value. There is a decreasing trend observed when compactability and moisture is increased beyond this threshold value. The maximum increase of slope for mold hardness is observed when compactability varies from 38 % to 41% and moisture varies from 3.1% to 3.2%. Figure 5 shows the effect of varying the permeability on mold hardness. It can be seen that mold hardness decreases as permeability is increased. The maximum decrease of slope for mold hardness is observed when permeability varies from 142 to 146. However the values of permeability, compactability and moisture can be modified only varying the sand ingredients. It can be seen that the maximum achieved hardness was 91.92 T/B.

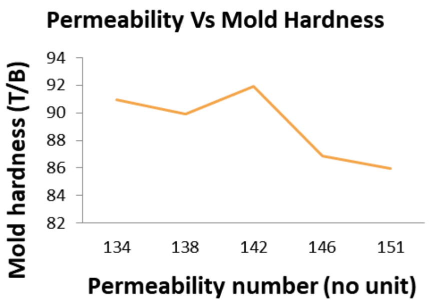

Fig 5 Effect of Permeability on mold hardness

B. *Do phase*

Mold hardness has direct impact on the molding machine parameters such as the vibration frequency and the amount of sand used for molding. In order to find the extent of influence of these parameters on the mold hardness ANOVA test was conducted. Sand amount (factor A) denotes the mass of sand used before ramming in order to produce the mold. Vibration frequency (factor B) denotes the frequency of ramming process. The experiment is conducted in a sand rammer with a weight base as shown in fig 6 [16].

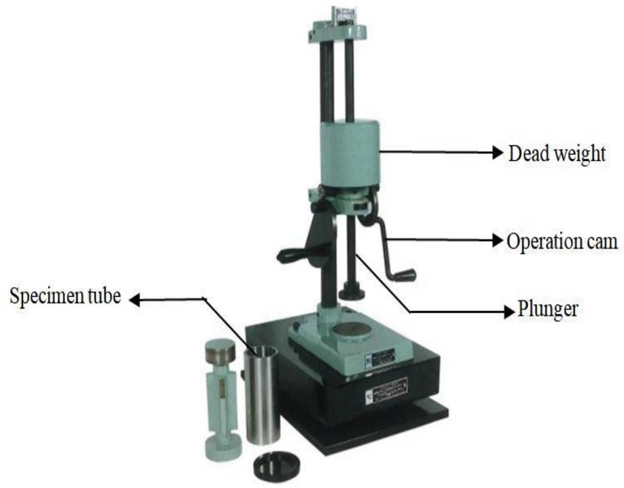

Fig 6 Sand rammer

C. *Selection of Factors and their Levels*

From the dimensions of the specimen tube and the maximum distance the plunger could be inserted inside the specimen cup, the sand amounts that could be accommodated were 280 g and 560 g. Since the operation cam is operated by hand, frequencies of 1 Hz and 2 Hz were selected.

D. *Taguchi Design of Experiments*

The experiments were carried out according to the Taguchi Orthogonal array. The orthogonal array selected for the experiment is L8. For a two factor at two levels, the orthogonal array nearest to the product of the factor and level considered (2*2 = 4) is 8. For each experiment, three replications were performed and are indicated as Y1, Y2 and Y3 in table 7. The factor A is assigned to the column 1 in the orthogonal array and factor B to the second column of the array. The entry 1 denotes the first level of the factor and entry 2 denotes the second level of the factor. The interaction effects between the two factors were not considered.

Table 7 Taguchi experiment design with the observed response values

Expt. No	1 (A)	2 (B)	Y1	Y2	Y3
1	1	1	91.91	91.92	90.90
2	1	1	90.96	91.82	91.91
3	1	2	90.89	90.90	91.24
4	1	2	90.98	90.87	90.99
5	2	1	92.92	93.92	92.93

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6	2	1	92.92	92.92	91.92
7	2	2	92.69	92.85	91.95
8	2	2	92.85	91.93	92.45

The results of the ANOVA is tabulated in table 8 and the results are discussed in detail in results and discussions.

Table 8 ANOVA calculation for mold hardness

Factor	DOF	SS	MS	F-ratio	P value	Contribution (%)
A	1	11.985	11.985	59.19	0.00	66.86
B	1	1.685	1.685	8.32	0.009	9.401
Error	21	4.252	0.2025			23.72
Total	23	17.923				100

E. Regression analysis

A multivariable linear regression model is fitted to the above experiment to predict the mold hardness given the values of sand amounts and vibration frequency. A subset of the dataset obtained is used for arriving at the regression equation. The validation is further performed with the remaining data.

The regression calculation is based on the least squares method. Based on this method, the co-efficient values namely a, B1 and B2 are calculated by solving the three simultaneous equations (1) to (3)

$$\sum Y = n * a + B1 * \sum X1 + B2 * \sum X2 \qquad (1)$$

$$\sum X1Y = a * \sum X1 + B1 * \sum X1^2 + B2 * \sum X1X2 \qquad (2)$$

$$\sum X2Y = a * \sum X2 + B1 * \sum X1X2 + B2 * \sum X2^{\wedge}2 \qquad (3)$$

The regression equation obtained is

Y = 98.821 - 0.005 * X1 – 3.743 * X2.

Table 9 Validation of Multiple regression model

Sand amount (g) X1	Vibration frequency (Hz) X2	Mold Hardness		MAPE
		Actual Value (Y)	Predicted Value Y*	
280	2	90.9	90.038	0.956
560	1	92.92	92.484	0.471
280	1	91.92	93.781	1.984

F. *Check and Act phase*

In real time, when the molds are prepared for the castings, the sand required for the preparation is obtained in the molding station by actuating a lever which makes the sand drop from a belt conveyor. In order to measure the amount of sand consumed for a single mold, the flow rate of the sand can be fixed and the time until the lever is in actuated position could be measured by a stop-watch. From the regression model fitted for prediction of mold hardness, the required mold hardness value and the vibration frequency are entered. The regression model gives the unknown value of sand amount.

G. *Validation experiment*

A trial casting was casted with the values of sand amount predicted from the linear regression equation. Another casting of the same component was casted using the traditional method and the variation in mold hardness was measured. The casting defects were also noted for both the castings.The results of the validation experiment is shown in table 10 and is discussed in detail in the results and discussions

Table 10 Results of Validation Experiment

	Regression model	Traditional method
Mold Hardness (T/B)	91.93	90.91
Sand amount (kg)	336	305
Vibration frequency (Hz)	10	10
Defects observed	Nil	Nil

VII. RESULTS AND DISCUSSIONS

A. *Melting Department*

The results of the linear programming model showed that the LP model can predict the raw material amounts except FeSi and FeS, As FeSi is added only to improve graphite stablility of the final cast iron, the amount of FeSi could be added or subtracted based on customer requirements. The LP model however does not consider other requirements in the melt like hardness, toughness, stability of graphite etc which are additionally provided by the customer. The MAPE values for FeS, FeSi are 100% and that for FeMn was 48.95%. However the MAPE for Petroleum coke and CI scraps was found to be 0.7142% and 2% respectively. These two raw materials are the most important during melting operation.

B. *Molding Department*

The results from the two-way ANOVA are tabulated in table 8. The p-value of both the factors is found to be less than 0.05. Hence, it gives evidence that the two factors influence the mold hardness within a confidence interval of 95%. Moreover the percentage contribution of the error is 23.72% which tells that that the other potential factors influencing the output response mold hardness are the interaction effects between sand amount and vibration frequency. The validation of the regression model is shown in the table 9.

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Y denotes the predicted values for mold hardness according to the regression model*. The Mean Absolute Percentage Error (MAPE) measures the goodness of fit of the model. The maximum MAPE value is only 1.98% that indicates that the fitted model adequately explains the process. Table 10 shows the results of the validation experiment performed based on the sand amount values given by the regression model. The results show that the sand amount required to produce a similar mold hardness values differs by 30 kg. The defects observed were nil in both the cases.

VIII. CONCLUSION

As major outcomes of this study, the areas that require improvement in melting and molding departments were identified and are presented successively. Requirement of excess number of iterations to achieve a particular composition was identified to be one of the areas of major concern in the melting department. In each iteration, the raw materials are added to the melt until the required composition is obtained. The problem required a model to predict the raw materials in a single iteration. Thus a Linear Programming model was formulated to solve the problem. The Chemical composition of the raw materials would be given as input required to the Linear Programming model and the amount of each raw material needed to obtain the required composition of the molten metal would be the output of the model. The lack of optimization of the process parameters influencing the mold hardness resulted in increase of casting defects was a major issue identified in the molding department. Thus, experiments were performed according to the Taguchi Orthogonal array to find the influencing parameters and a regression model was fitted to predict the parameters in real time. Further study should be undertaken to include the effects of hardness, the extent of graphite stability upon the addition of raw materials into the Linear Programming Model. Real time monitoring systems using IoT can be deployed to monitor the sand amount and vibration frequency in molding machines in real time with display.

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