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Research Article

IDENTIFICATION OF CRITICAL PARAMETERS IN SINTERING PROCESS THROUGH INTEGRATED GREY RELATION ANALYSIS PRINCIPAL COMPONENT ANALYSIS AND RESPONSE SURFACE METHOD

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ABSTRACT

Sintering process is an important step in iron and steel manufacturing. Sinter is the main raw material for iron making in the blast furnace. Productivity of Sinter plant, comprehensive coke ratio, Quality of Sinter, specific power consumption and stack emissions are output parameters in a sintering process. In this paper, Input material composition and sinter machine operating parameters are analyzed clearly to get sintering mechanism. The present work examined is identification of various critical parameters of sinter plant in an integrated steel plant by utilizing response surface method based onGRA integrated with PCA approach. GRA works like a discovery idea where known and obscure components are aggregated to get optimum level of the multiple responses. GRA utilizes normalization of values to compute grey relational coefficient. Initially data on input and output parameters considered based on the literature survey and the data on these parameters are collected from sinter plant operations. Grey relation coefficients of the output parameters are obtained from grey relation analysis. Then, the grey relation coefficients are subjected to principal component analysis to derive the principle component scores which represent the aggregated response of multiple output variables. Finally, response surface methodology is implemented by considering the input parameters of sinter plant as factors and PCA score as response to analyze the impact of input parameters on the sinter plant aggregated output parameters of sinter plant.

INTRODUCTION

The aim of the agglomeration process is preparing the high-quality raw materials for blast furnace production using ore concentrates, sludge, and other iron-containing materials by means of sintering them with an appropriate bulk of fuel (coke) into hard and porous chunks. The process is performed on a moving sinter machine strand consisting of special pallets. The mixture of iron ore, coke fines, off-grade sinter return, and other additives containing dosed water is continuously fed to the strand forming a bed. Immediately after the feeding, the charge is ignited by ignition hood and hot gases resulted from coke combustion are sucked then through the charge by means of vacuum chambers located under the strand. The sinter machine strand area, suction power, and permeability of bed to gases determine the maximum speed of the sinter machine, and consequently, the process efficiency

Literature Review

Egorova, Rudakova, Rusinov and Vorobjev (2016) diagnosedsintering process faults for improving sinter quality based on principal component analysis and Neural network model. Raju.B. S, Chandra Sekhar.U and Drakshayani.D.N (2017) investigated optimization of stereo lithography process for SL5530 epoxy resin material to enhance part quality. The results of confirmation experiments reveal that grey relational analysis coupled with principal component analysis can effectively acquire the optimal combination of process parameters

Nik MizamzulMehat, ShahrulKamaruddinandAbdul Rahim Othman (2014), made a systematic studytodevelop a hybrid optimization method for multiple quality characteristics by integrating the Taguchi parameter design, grey relational analysis and principal component analysis. A plastic gear is used to demonstrate the efficiency and validity of the proposed hybrid optimization method in controlling all influential injection moulding process parameters during plastic gear manufacturing.

Narinder Kaushik & Sandeep Singhal (2018), examined the creation of aluminum alloy AA6063/SiCp metal matrix composites by liquid metallurgy stir casting route and

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optimization of wear properties by utilizing Taguchi-based GRA integrated with PCA approach.

Suman Chatterjee, Arpan Kumar Mondal, SibaSankar Mahapatra (2014), presenteda mathematical model for prediction of burr height and circularity of AISI-304 stainless steel hole using response surface methodology (RSM) and principal component analysis (PCA) to investigate the influence of control parameters, such as spindle speed, feed rate, and drill bit diameter on burr height and surface roughness while drilling AISI-304 stainless steel.

G. K. SinghȦ, N. K. Chauhan, Rajeev Kumarand V. Yadava (2014), investigated thedesign of an Electro-Discharge Diamond Grinding (EDDFG) process performed on high speed steel (HSS).The major performance characteristics are selected to evaluate the processes are material removal rate (MRR) and wheel wear rate (WWR), and the corresponding EDDFG parameters are wheel RPM, current, pulse ontime and duty factor. The principal component analysis is applied to evaluate the weighting values corresponding to various performance characteristics so that their relative importance can be properly and objectively described.

Mohanty, S.D., Mahapatra, S.S.and R.C. Mohanty (2019), studied multi-response optimization problem by applying Principal Component Analysis (PCA) combined with Taguchi method. The investigation has been carried out through a case study in Electric Discharge Machining (EDM) of D2 steel by using copper, brass and Direct Metal Laser Sintered (DMLS) electrode produced by direct metal laser sintering using Directmetal20.

Xiang Zhang, CaimeiGu, Bashir Ahmad, and Linfang Huang (2017), evaluated the quality of Cynomorium songaricum Rupr from different producing areas, which is an edible, holophrastic and desert plant that has been used in traditional medicine for improving immunity and kidney function and eating constipation.The authors optimized the extract conditions by response surface methodology (RSM).

Atul, S.C. (2016) investigated the vitality of response surface methodology (RSM) in predicting the optimal combination of pack chromizing parameters to achieve the desired depth of diffusion and surface hardness. Experiments are conducted using Taguchi's L18 orthogonal array design and the optimal chromizing parameters are endorsed.

Rohit Upadhyay and Hari Niwas Mishra (2016) studied the simultaneous optimization of a synergistic blend of oleoresin sage (SAG) and ascorbyl palmitate (AP) in sunflower oil (SO) using central composite and rotatable design coupled with principal component analysis (PCA) and response surface methodology (RSM).

Sankar. B.R and P. UmamaheswarRao (2015) optimized the operating parameters namely: Rotational speed, welding speed and tool diameter for maximum Hardness and Tensile strength of the friction stir welded joint on AA6061 alloy. Response Surface Methodology (RSM) was adopted to develop mathematical model between the response and process parameters. Grey relational Analysis (GRA) was deployed to convert multi objective case into single objective one by calculating Grey Relational Grade (GRG).

D. Fernández-González, I. Ruiz-Bustinza, J. Mochón, C. González-Gasca andL. F. Verdeja (2017) made an analysison sinter plant process for obtaining a product with the suitable characteristics (thermal, mechanical, physical, and chemical) for being fed to the blast furnace.

HU Jie, WU Min, CHEN Xin andCAO Wei Hua (2016), analyzedchemical reactions and physical changes to get sintering mechanism and the comprehensive coke ratio (CCR). By using principal component analysis (PCA) method, the principal components affecting CCR are generated, which serve as the input of back propagation (BP) neural network model.Adding MgO to sinter is considered to be a popular counter measure to cope with the use of high Al_2O_3 ores.

He Guo, Fengman Shen, Huaiyu Zhang, QiangjianGao and Xin Jiang (2019)investigated the effect of the MgO content on the reduction melting behavior in order to clarify the main mechanism of melting and dripping under simulated blast furnace (BF) conditions. Principal component analysis (PCA) was used to analyze the sinter.

METHODOLOGY

The methodology consists of application of Grey relation analysis, Principal component analysis, Response surface methodology. These three methodologies are explained below.

Grey Relation Analysis

Grey relational analysis is a kind of method which enables determination of the relational degree of every factor in the system. The method can be used for systems that are incompletely described with relatively few data available, and for which standard statistical assumptions are not satisfied. Grey relation analysis quantifies all influences of various factors and their relations. It uses information from the Grey system to dynamically compare each factor quantitatively, based on the level of similarity and variability among factors to establish their relation. GRA analyzes the relational grade for discrete sequences.

In this paper, GRA method is proposed to find the grey relation coefficients which are used to determine principle components of the sintering process performance variables. GRA methodology is explained in the following steps

Step-1: Obtain the data on performance variables of sintering process.

The data on the performance variables of the sintering processis collected.

Step-2: Standardize the Data

It is difficult to compare between the different kinds of factors because they exert a different influence. Therefore, the standardized transformation of these factors must be done. The following formulae is used to standardize the data based on the following types of factors

Benefit type:

$$xs_i(j) = \frac{|x_i(j) - \min x_i(j)|}{\max x_i(j) - \min x(j)} \quad (1)$$

Cost type:

$$xs_i(j) = \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)} \quad (2)$$

Nominal type:

$$xs_i(i) = 1 - \frac{|x_i(j) - x(j)|}{\max(\max x_i(j) - x(j), x(j) - \min x_i(j))} \quad (3)$$

where $x_i(j)$ is the reference value of j^{th} enabler of i^{th}alternative where$x(j)$is thetarget value/objectivevalue of j^{th} enabler.

Step-3: Determine absolute differences

The absolute difference in the compared series and the referential series should be obtained by using the following equation.

$$\Delta x_i(j) = |x_0(j) - xs_i(j)| \quad (4)$$

$x_0(j)$= reference value of j th enabler of ith bank

Step-4 Find out the maximum and minimum absolute differences

The maximum ($\Delta \max$) and the minimum ($\Delta \min$) difference should be found from the absolute difference of the compared series and the referential series.

Step-5: Determine grey relation coefficient

In Grey relational analysis, Grey relational coefficient ξcan be expressed as shown in equation (5)

$$\xi_i(j) = \frac{\Delta \min + p\Delta \max}{\Delta x_i(j) + p\Delta \max} \quad (5)$$

The distinguishing coefficient p is between 0 and 1. Generally, the distinguishing coefficient p is set to 0.5.

In this paper, using the grey relational method, different output parameters of sintering process were optimized to achieve the best multiple quality characteristics.

Principal Component Analysis

Principal Component Analysis (PCA) is a commonly used multivariate statistical method, it is widely used in the evaluation of related problems in sociology, economy and management, and it gradually becomes a multi-index evaluation technique of actual value (Zhang, 2010).

PCA studies the way to illustrate the structure of multivariate variance-covariance through some minority principal components. In detail: export the minority principal components and try to keep their source information, and make them irrelevant to each other.

Principal Component Analysis explains the correlation structure explained by the correlated number of p variables with the uncorrelated number of k variables which the linear combinations of the original variables provide (p > k). Eigen values and Eigen vectors of the covariance or correlation matrices are used to find the linear combinations of the p variables in the X data matrix. Let Let $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \lambda_p$the Eigen values and, $l_1 l_2$, , . . . , l_p bethe orthogonal Eigen vectors of the correlation matrix. Linear combinations of the variables can be calculated as $PC_i = l_i^1 * X$, (i =1,2,...,p). The explanation ratio of total variance of k principal component is described as

$\frac{\lambda_k}{\lambda_1 + \lambda_2 + \ldots \lambda_p}$. The main steps are discussed below.

Step-1 Collect the data

Original matrix is formed by collecting the data on the variables for the given number of samples. In this paper, the grey correlation coefficient matrix is considered as standardized decision matrix.

Step-2 Determine the Eigen value and Eigen vector

Eigen values and Eigen vectors are determined for the matrix using PCA of SPSS-statistical software.

Step-3 Identify the principal components based on Eigen values.

Only factors with an Eigenvalue of more than 1 will be considered as significant and will be extracted. The value of 1 is the SPSS default setting Kaiser stopping criterion for deciding how many factors to extract

Step-4 Determine the weighted principal component values(t-values)

WeightedPCA values are determined from the following relation.

$$t = \sum_{k=1}^{m} w_k PC_k$$

where w_k is weight of the 'k^{th}' principal component.

Determination of weights: if $\lambda_1 + \lambda_2 + \ldots \lambda_p$ are Eigen values of the principle components, 1,2,…n are the principal components having Eigen value more than one, then explanation ratio is given by the following relation.

$\lambda_1 / (\lambda_1 + \lambda_2 + \ldots \lambda_n)$

$\lambda_2 / (\lambda_1 + \lambda_2 + \ldots \lambda_n)$

.

.

$\lambda_n / (\lambda_1 + \lambda_2 + \ldots \lambda_n)$

For determining the sign of w_k s, signs of the components of the PC_k are considered. If all the components of the PCs are negative, then the weightis negative, and if all the components of thePC are positive, then the weightis positive. If more than half of the components of the k PC is negative then weight is negative, otherwise it becomes positive.

Step-5 Determine principal component scores

The PCA scores are determined from the following equation

$PC_{score} = D_z t$ (whereD_z= standardized decision matrix)

Response Surface Methodology

Response surface methods are used to examine the relationship between one or more response variables and a set of quantitative experimental variables or factors. These methods are often employed after you have identified a "vital few" controllable factors and one want to find the factor settings that optimize the response.

It is important to note that the PCA can only be applied when significant correlation between the principal components and original responses are observed. In this case, the original response variables can be replaced by the score values of a principal component which could explain the maximum variance in the data set. The score of first few principal components could act as new response variable for the optimization using RSM (Beebe *et al*. 1998). The methodology is explained in the following steps.

Step-1 Obtain the data on factors

In this paper, input parameters like coke consumption, composition of input material, operating conditions of sinter machine are considered as factors.

Step-2 Determine Critical parameters

Critical parameters that effect the output parameters are determined by knowing the significance of model terms (input parameters) on principal component scores based on output parameters of the samples is evaluated by the F–test using Analysis of variance (ANOVA).

Proposed Methodology

The application of proposed methodology is useful to continuous monitoring and diagnostics of sintering process faults for improving iron-ore sinter quality.Sinter quality control and productivity are important because allow blast furnace operate at low fuel rate, stable and efficient operation, and economically profitable. It is possible to see the quality requirements for sinters to be used as burden materials in the blast furnace (Mochón *et al*. 2014; Cores *et al*. 2010a). In this paper, the main quality indices and input operating parametersare reviewed according to the most recent research papers. These quality indices allow knowing how the sinter product will behave in the blast furnace.

Sintering Process Quality Indices: In this paper, cold strength (CS), Reduction Degradation Index (RDI), High Reducible Index (HRI), Yield of Sinter (YS), Specific Power Consumption (SPC) and Stack emission-PM (SE) are considered as quality indices or output parameters of Sintering process.

Process Parameters of Sintering Process: Sintering process is the process of producing sinter by thephysical and chemical reactions of the sinter material at hightemperature. The reactions can affect the quality of the sinter. Coke Consumption, input material composition (T.Fe, SiO_2, Al_2O_3, LOI, CaO, MgO, Fe_2O_3) Moisture, Speed, GCP Temperature and Vaccum are considered as process parameters of sintering process. The frame work for the proposed integrated methodology is presented below.

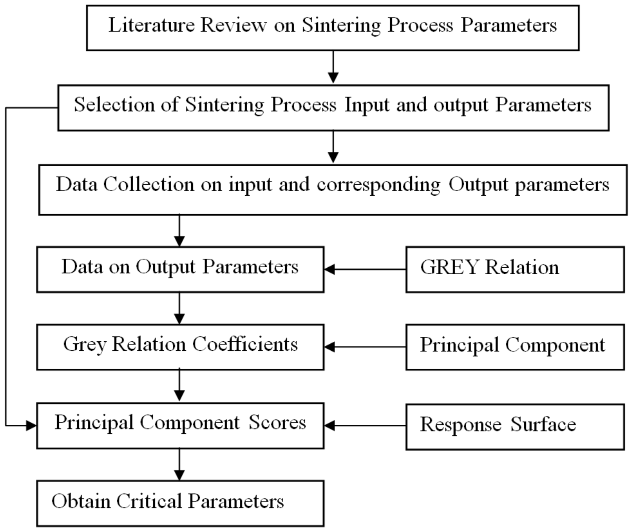

Figure 1 Frame work for the proposed integrated methodology

Case Study

Input and Output Parameters of Sinter Plant

Input parameters

Table 1 Input parameters

S.No.	Parameter	Units	Norm-Min. value	Norm-Max. value
1.	Coke Consumption	Kg/Ton of Sinter	39	54
2.		Input material composition		
i)	Total Fe	%	51	61
ii)	SiO_2	%	5.3	5.4
iii)	Al_2O_3	%	0.6	1.8
iv)	LOI	%		
v)	CaO	%	4	2
vi)	MgO	%	0.7	2.2
vii)	Fe_2O_3	%	55	

Table 2 Output parameters

S.No.	Parameter	Units	Norm- Min. Value	Norm-Max. Value
1	Cold strength (CS) –Tumbler Index	% > 6.3mm	63	79
2	Reduction Degradation Index (RDI)	% <3mm	27	33
3	High Reducible Index (HRI)	R60, %	49	78
4	Yield of Sinter (YS)	% Sinter produced/Input material consumed		
5	Specific Power Consumption (SPC)	KWh per Ton of Sinter		
6	Stack emission (SE)	PM		50

Data Collection

Data on input and output parameters of sintering process is collected for a data elements of 200 and is presented at Appendix, Table-A.1.

RESULTS AND DISCUSSION

Grey Relation Analysis

In grey relation analysis the output variables are considered only. Normalized matrix is obtained as discussed in step 2 of section 3.1. During normalization yield of sinter (Y) is considered as benefit type and the variable is normalized accordingly. Specific power consumption (SPC) and Stack Emission-PM(SE) are considered as cost type for normalization. Cold strength(CS), Reduction degradation index(RDI) and High reducibility index(HRI) are considered as nominal type with target values of 77, 33 and 78 respectively. After normalizing the data as discussed in section-3.1, step-3 for absolute differences and step-4 for grey relation coefficients are done and are presented in Tables-A.2, A.3, A.4 in Appendix.

Principle Component Analysis

Principal Component Analysis (PCA) methodology discussed in section-3.2 is employed using SPSS 14 software to determine the principal component scores from grey relation coefficients of the output sintering process parameters. Results of the principle component analysis are presented and discussed below.

Input data for the principle component analysis: Grey relation coefficients presented in Table-A-4 is considered as input data to the principle component analysis.

Eigen value and Eigen vector: Eigen values and Eigen vectors are determined for the matrix using SPSS-statistical software and are presented in the Table-3.

Table 3 Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.236	70.596	70.596	4.236	70.596	70.596
2	1.542	25.696	96.292	1.542	25.696	96.292
3	0.206	3.430	99.722	0.206	3.430	99.722
4	0.009	0.148	99.870	0.009	0.148	99.870
5	0.005	0.089	99.959	0.005	0.089	99.959
6	0.002	0.041	100.000	0.002	0.041	100.000

Extraction Method: Principal Component Analysis.

From Table-3 it is clear that only 1, 2 components are having Eigen value more than 1.0. Hence for our analysis only two components are selected. Now from Eigen values Table-3, it is clear that incase of step-4, the value of K = 2. Hence $\lambda_1 = 4.236$ and $\lambda_2 = 1.542$.

Principal Components Based on Eigen Values

Only factors with an Eigenvalue of more than 1 will be considered as significant and will be extracted. The value of 1 is the SPSS default setting Kaiser stopping criterion for deciding how many factors to extract. The principal components are shown in the Table-4.

Table 4 Component matrix

Output variables	Components	
	PC1	PC2
CS	0.564	0.757
RDI	–0.005	0.958
HRI	0.996	–0.063
Y	0.981	–0.156
SPC	0.994	–0.078
SE-PM	0.987	–0.130

From the component matrix Table-4, it is clear that PC1 is having more positive values (correlation coefficient) and hence the sign of w_1 will be with positive sign and from the same table it clear the PC2 is having four values (correlation coefficient) with negative sign out of six values. Hence the sign of w_2 will be with negative sign.

Weighted principal component values (*t-values*): Weighted PCA values are determined as discussed in step-4 of section 3.2.

Now $$w_1 = \frac{\lambda_1}{\lambda_1 + \lambda_2} = \frac{4.236}{4.236 + 1.542} = 0.7331$$

Similarly $$w_2 = \frac{\lambda_2}{\lambda_1 + \lambda_2} = \frac{1.542}{4.236 + 1.542} = 0.2669$$

As stated above, the value of $w_1 = +0.7331$ and the value of $w_2 = -0.2669$.

The weights of the two principal components are 0.7331 and -0.2669. Then t-values are are deermined as discussed in section-3.2 and presented in Table-5.

Table 5 Weighted principal component values

	Components		Linear Combination
	PC1	PC2	(t-values)
CS	0.564	0.757	0.211
RDI	–0.005	0.958	–0.259
HRI	0.996	–0.063	0.7471
Y	0.981	–0.156	0.7609
SPC	0.994	–0.078	0.7499
SE-PM	0.987	–0.130	0.7581

t-value calculation incase of CS = w_1 * PC1 + w_2 * PC2
= 0.564 * 0.7331 + 0.757 * (–0.2669)
= 0.211
Similarly the t-value calculation incase of RDI = w_1 * PC1 + w_2 * PC2
= (–0.005) * 0.7331 + 0.958 * (–0.2669)
= 0.259

Similarly the other t-values for HRI, Y, SPC and SE-PM are calculated.

Principal component scores: The PCA scores are determined from theequation discussed in step-5 of section-3.2. For this process the input materials data (200 × 6 matrix) and the t-values column in Table-5 are used and we will be getting 200 PCA scores. The PCA scores of 200 samples are considered as single response which aggregated from the multiple responses (six output variables). In this paper, PCA is adopted to obtain a single variable by aggregating the multiple variables. The PCA score values are presented in Appendix Table-A.5

Response Surface Method

In this paper, Response surface Methodology is adopted to know the critical input factors of sintering process that effect the Overall quality of the process aggregated from the six output factors. Hence input parameters of sintering process are considered as factors and PCA score that represent the overall quality is considered as response and Response Surface Methodology using the Design Expert Software (Version10) is implemented. Data on the factors and response is presented in Appendix, Table-A.6.

Data on the input factors and response of the 200 samples are fed to the Response Surface Model to the DOE module of Design Expert 10.0. The results are presented in the following and are discussed.

Analysis of Variance (ANOVA): The significance of model terms is evaluated by the F–test for analysis of variance (ANOVA). The ANOVA analysis for significant factors is only shown in Table-6.

Table 6 ANOVA Results

Table 7 R-Squared and the adequate precision values of the model

Std. Dev.	**0.2407**	**R^2**	**0.7181**
Mean	1.56	Adjusted R^2	0.4445
C.V. %	15.39	Predicted R^2	0.2151
		Adeq Precision	11.1080

From the results it is observed that the model is showing high coefficient of determination (R-squared value of 0.7181) indicates that there exists a moderate degree of correlation between the input parameters and the predicted response of sinter plant quaity. The "Pred R-Squared" of 0.4445 is in reasonable agreement with the "Adj R-Squared" of 0.2151. The adequate model discrimination was also clearly visualized from the value of adequate precision (11.1080), greater than 4. Hence the generated model for the sinter plant quality could be deemed fit and adequate.

APPENDIX

Table A.1 Data on input and output parameters of sintering process

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe (51-61)	SiO 2(5.3-5.4)	Al_2O 3(0.6-1.8)	LOI	CaO	MgO	Fe_2O_3
1	68.75	30.95	60.12	81.59	64.36	9.52	56.07	61.21	2.34	2.72	2.65	32.13	18.73	1.59
2	65.07	29.38	58.03	79.19	66.03	10.26	45.21	62.45	1.96	2.36	2.39	31.32	19.43	1.45
3	80.00	38.98	72.68	94.10	58.23	5.43	52.54	64.91	2.27	2.62	2.58	31.16	18.72	1.52
4	72.26	33.31	64.54	84.50	62.33	8.27	55.41	59.68	1.96	2.60	2.61	30.86	19.04	1.41
5	83.86	42.82	62.84	83.1	62.91	8.52	54.22	64.53	2.18	2.66	2.46	30.94	18.93	1.49
6	69.28	31.12	60.50	82.00	64.00	9.45	56.49	57.83	2.24	2.44	2.34	30.28	18.96	1.57
7	71.08	32.67	63.07	83.75	62.92	8.47	56.88	56.00	2.20	2.46	2.43	29.89	18.31	1.54
S	78.80	38.66	70.38	92.63	58.72	5.94	57.45	53.61	2.26	2.63	2.40	30.55	18.86	1.49
9	78.75	38.45	70.31	92.10	58.74	5.95	55.60	70.06	2.16	2.55	2.48	30.74	18.41	1.44
10	75.83	36.42	68.19	88.88	60.18	6.97	47.84	71.98	2.1 1	2.61	2.52	30.96	18.66	1.43
11	72.40	33.50	64.81	84.75	62.12	8.13	65.08	66.15	2.24	2.65	2.60	31.65	18.69	1.48
12	64.73	28.90	57.04	78.29	66.92	10.53	59.09	64.54	2.10	3.01	2.66	30.94	18.42	1.57
13	79.83	38.90	72.05	93.19	58.31	5.52	60.58	67.25	2.27	2.28	2.52	30.54	17.91	1.51
14	71.65	32.93	63.52	83.84	62.84	8.44	49.42	64.20	2.02	2.65	2.63	30.76	19.37	1.47
15	71.48	32.83	63.47	83.82	62.84	8.45	53.00	70.73	2.09	2.77	2.49	31.90	19.19	1.59
16	70.46	32.12	62.19	82.93	63.25	8.77	46.58	56.05	2.40	2.43	2.40	30.75	18.95	1.53
17	69.42	31.22	60.78	82.10	63.95	9.38	60.02	69.18	2.17	2.63	2.44	30.81	18.54	1.48
IS	67.32	30.54	59.68	81.01	64.95	9.68	50.66	57.90	2.13	2.47	2.43	30.89	19.30	1.52
19	76.95	37.24	69.17	90.23	59.59	6.78	58.13	70.80	2.24	2.82	2.02	30.52	18.99	1.46
20	69.66	31.36	60.96	82.24	63.86	9.29	60.08	64.58	2.20	2.78	2.34	31.18	18.48	1.50
21	71.67	32.95	63.53	83.84	62.82	8.43	64.32	56.72	2.18	2.39	2.44	31.18	18.62	1.43
22	68.23	30.65	59.84	81.16	64.69	9.66	53.75	58.19	2.09	2.80	2.43	30.92	18.59	1.53
23	77.24	37.27	69.37	90.29	59.47	6.75	56.61	75.79	2.22	2.51	2.59	30.95	18.15	1.41
24	71.07	32.54	63.05	83.74	62.94	8.49	52.37	60.11	2.26	2.39	2.40	31.51	19.34	1.44
25	81.28	39.65	75.14	97.36	57.35	4.79	63.85	62.61	2.07	2.72	2.49	30.81	19.05	1.45
26	74.20	34.74	66.31	86.45	61.19	7.58	53.52	63.50	2.05	2.60	2.40	31.32	19.01	1.45
27	74.20	34.83	66.35	86.46	61.13	7.52	57.43	67.52	1.91	2.42	2.26	31.24	18.42	1.40
28	71.05	32.50	63.03	83.58	62.98	8.49	45.59	61.95	2.20	2.63	2.24	30.72	18.22	1.53
29	70.78	32.30	62.51	83.22	63.12	8.65	48.80	62.03	2.27	2.96	2.46	30.53	19.15	1.53
30	69.83	31.62	61.35	82.51	63.59	8.95	51.83	65.21	2.28	2.99	2.49	30.39	18.84	1.48
31	58.42	24.94	46.68	70.06	70.03	12.80	53.66	54.85	2.22	2.67	2.62	31.77	19.32	1.54
32	75.67	36.19	68.03	88.84	60.20	7.01	54.69	64.90	2.09	2.51	2.60	31.08	18.67	1.57

The importance of the model for composite sinter plant quality is confirmed by the model p-value. From the above ANOVA table it is observed that all the input variables under considerationare significant to the sinter plant quality as P-value ≤0.05. R-Squared and the adequate precision values of the model are shown in Table-7.

RESULTS AND DISCUSSION

The integrated GRA-PCA-RSM approach for the determination of critical sintering input parameters has been established methodically to conquer the limitations of single character performance in multiple performance characteristics problems.

Table A.1 continued

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe (51-61)	$SiO_{2(5.3-5.4)}$	$Al_2O_{3(0.6-1.8)}$	LOI	CaO	MgO	Fe_2O_3
33	68.66	30.90	60.04	81.54	64.45	9.56	48.86	64.55	2.23	2.50	2.39	31.90	18.40	1.44
34	74.87	35.13	66.93	86.89	60.90	7.31	49.43	74.50	2.18	2.64	2.35	30.85	19.38	1.53
35	75.00	35.29	67.18	87.12	60.82	7.29	61.39	60.68	2.05	2.75	2.70	31.11	19.47	1.46
36	64.03	28.32	56.03	76.78	67.23	10.75	38.25	68.96	1.99	2.51	2.40	30.29	19.09	1.61
37	71.71	32.96	63.70	83.87	62.82	8.42	52.93	58.20	1.97	2.51	2.44	30.43	18.85	1.44
38	70.42	32.07	62.03	82.92	63.26	8.78	50.70	67.10	2.12	2.63	2.33	31.35	18.90	1.44
39	77.46	37.62	69.53	90.75	59.27	6.41	50.90	60.12	2.21	2.76	2.36	30.77	18.76	1.58
40	74.97	35.25	66.97	86.93	60.89	7.30	60.51	65.11	2.26	2.88	2.51	30.87	18.70	1.60
41	72.79	33.69	65.12	85.17	61.94	8.05	55.31	59.34	2.10	2.65	2.50	29.95	19.02	1.49
42	67.32	30.47	59.60	80.96	65.15	9.69	54.25	66.21	2.3 1	2.38	2.40	30.41	18.70	1.53
43	79.25	38.71	70.81	92.89	58.65	5.82	62.01	59.40	2.35	2.49	2.36	31.20	18.76	1.48
44	74.46	35.00	66.49	86.57	61.12	7.46	58.59	62.34	2.16	2.79	2.50	31.13	19.50	1.47
45	72.44	33.54	64.84	84.86	62.12	8.11	48.75	67.14	2.13	2.63	2.40	31.23	18.72	1.61
46	69.75	31.62	61.30	82.44	63.61	8.95	48.72	65.62	2.05	2.55	2.42	30.87	19.00	1.48
47	60.38	25.47	52.32	73.33	68.42	12.24	47.87	60.38	2.21	2.68	2.72	30.68	19.20	1.48
48	66.12	30.01	58.60	79.74	65.76	9.98	56.59	53.19	2.3 1	2.72	2.36	30.44	19.12	1.50
49	77.47	37.99	69.73	90.75	59.22	6.39	61.00	59.75	2.09	2.73	2.58	31.04	18.98	1.46
50	73.42	34.09	65.61	85.64	61.57	7.88	40.90	68.21	2.20	2.65	2.40	30.14	18.53	1.45
51	65.87	29.87	58.28	79.64	65.85	10.11	54.80	64.57	2.41	2.71	2.33	30.90	19.34	1.45
52	61.39	26.78	53.14	73.54	68.41	12.06	54.24	57.91	2.08	2.81	2.50	30.59	18.64	1.47
53	70.75	32.25	62.39	83.11	63.14	8.72	56.09	71.48	2.16	2.74	2.50	31.46	18.63	1.46
54	64.68	28.89	56.96	78.09	67.02	10.56	53.14	57.89	2.14	2.58	2.38	31.06	18.50	1.56
55	69.84	31.64	61.40	82.55	63.49	8.91	51.49	63.29	2.28	2.72	2.32	30.67	18.49	1.41
56	70.54	32.14	62.33	82.96	63.17	8.75	58.91	68.15	2.00	2.53	2.38	31.95	18.71	1.49
57	66.79	30.27	59.16	80.46	65.34	9.82	61.33	66.59	2.02	2.72	2.61	30.87	18.87	1.58
58	71.79	33.02	63.99	84.10	62.77	8.36	53.87	60.58	2.37	2.87	2.51	30.58	19.30	1.55
59	73.77	34.34	66.02	85.79	61.51	7.82	57.45	58.94	2.17	2.63	2.59	30.48	18.78	1.47
60	71.72	32.98	63.96	83.93	62.79	8.40	57.33	62.26	1.93	2.77	2.54	30.76	19.22	1.47
61	69.65	31.35	60.90	82.16	63.94	9.32	56.01	66.72	2.06	2.64	2.41	31.69	19.02	1.48
62	75.15	35.80	67.51	87.89	60.51	7.15	51.42	68.42	2.28	2.86	2.65	30.51	18.56	1.52
63	73.87	34.37	66.15	86.22	61.37	7.77	59.59	64.45	2.17	2.68	2.46	31.58	19.19	1.40
64	73.27	34.07	65.50	85.58	61.64	7.91	51.88	70.75	2.34	2.91	2.39	30.41	19.18	1.57
65	72.26	33.43	64.58	84.52	62.29	8.26	58.73	63.17	2.14	2.87	2.52	30.91	18.50	1.51
66	68.85	30.95	60.16	81.62	64.34	9.50	50.33	74.79	2.42	2.44	2.46	31.48	18.88	1.59
67	72.02	33.21	64.41	84.45	62.51	8.30	53.81	63.13	2.22	2.45	2.51	30.73	18.93	1.52

Table A.1 continued

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe(51-61)	$SiO_{2(5.3-5.4)}$	$Al_2O_{3(0.6-1.8)}$	LOI	CaO	MgO	Fe_2O_3
68	72.52	33.57	64.98	84.89	62.10	8.10	45.08	59.63	1.87	2.49	2.48	31.01	18.74	1.41
69	67.66	30.56	59.81	81.10	64.73	9.66	49.19	69.02	2.35	2.67	2.24	30.70	18.34	1.50
70	79.34	38.86	71.08	93.19	58.61	5.79	42.31	57.41	2.18	2.73	2.39	31.05	19.46	1.46
71	78.85	38.70	70.55	92.79	58.69	5.92	52.92	71.08	2.30	2.60	2.34	31.36	18.75	1.44
72	67.22	30.42	59.52	80.86	65.26	9.74	58.37	66.90	2.14	2.76	2.59	30.95	19.28	1.48
73	76.10	36.45	68.36	88.88	60.09	6.96	51.80	65.60	2.02	2.80	2.50	31.14	18.70	1.52
74	72.20	33.30	64.47	84.50	62.41	8.28	49.34	52.19	2.11	2.60	2.35	31.23	19.38	1.51
75	69.3 1	31.15	60.57	82.00	64.00	9.43	60.33	58.97	2.14	2.84	2.27	30.44	18.34	1.52
76	64.75	29.07	57.15	78.60	66.92	10.52	55.52	62.32	2.20	2.86	2.32	30.70	19.11	1.50
77	75.47	36.02	67.63	88.38	60.36	7.12	50.55	66.44	2.19	3.07	2.52	31.18	19.40	1.50
78	70.80	32.3 1	62.61	83.28	63.11	8.58	54.36	63.45	2.20	2.94	2.49	30.94	18.84	1.45
79	68.39	30.73	59.86	81.30	64.65	9.62	50.53	63.19	2.12	2.82	2.51	30.61	19.49	1.58
SO	72.37	33.45	64.77	84.74	62.24	8.18	49.86	57.20	2.21	2.67	2.42	31.31	18.52	1.49
81	73.80	34.35	66.1 1	85.97	61.45	7.82	62.24	64.25	1.92	2.66	2.42	30.98	20.06	1.51
82	71.93	33.15	64.18	84.16	62.61	8.31	56.83	61.75	2.31	2.56	2.40	31.02	19.18	1.51
83	75.07	35.71	67.49	87.47	60.59	7.23	60.75	74.35	2.21	2.63	2.57	30.60	18.40	1.44
84	72.83	33.71	65.15	85.26	61.94	8.02	47.55	67.00	1.99	3.13	2.43	31.85	19.24	1.45
85	64.26	28.47	56.3 1	76.96	67.17	10.74	52.33	67.49	1.94	2.54	2.45	30.87	18.92	1.40
86	69.41	31.17	60.63	82.08	63.96	9.43	51.18	68.32	2.11	2.65	2.41	31.66	19.18	1.55
87	65.01	29.28	57.92	79.10	66.39	10.34	54.39	62.40	2.15	2.90	2.55	30.91	20.11	1.57
88	75.07	35.57	67.36	87.26	60.68	7.23	59.60	64.30	2.20	2.83	2.43	30.94	19.35	1.44
89	65.55	29.40	58.12	79.51	65.93	10.17	57.24	67.94	2.18	2.85	2.48	30.31	18.71	1.56
90	78.18	38.45	70.25	92.07	58.97	5.95	54.80	51.98	2.32	2.55	2.60	30.60	18.56	1.50
91	72.63	33.61	65.03	84.95	62.06	8.08	48.00	70.30	2.26	2.59	2.19	31.35	18.94	1.47
92	67.01	30.42	59.52	80.82	65.27	9.76	47.32	64.88	2.22	2.62	2.59	31.05	18.20	1.41
93	66.71	30.26	59.13	80.45	65.37	9.83	56.89	62.78	2.08	2.80	2.61	30.47	18.40	1.39
94	70.76	32.27	62.46	83.13	63.13	8.67	57.40	69.68	2.22	2.40	2.46	30.48	19.17	1.42
95	64.53	28.74	56.59	77.59	67.12	10.66	48.29	64.77	2.00	2.55	2.37	31.35	18.93	1.51
96	75.33	35.82	67.57	88.03	60.44	7.14	52.48	66.13	2.31	2.45	2.51	31.04	19.09	1.49
97	69.66	31.41	61.10	82.24	63.85	9.27	60.52	68.20	2.18	2.69	2.45	30.67	18.65	1.46
98	76.38	36.55	68.60	89.70	59.92	6.91	49.85	70.40	2.21	2.59	2.64	29.67	19.06	1.51
99	74.69	35.08	66.71	86.67	61.00	7.32	47.21	51.55	2.43	2.79	2.43	30.71	19.03	1.44
100	62.42	27.10	55.12	74.99	67.97	11.61	42.05	68.25	2.15	2.43	2.40	31.03	18.13	1.46
101	69.32	31.17	60.58	82.08	63.96	9.43	48.54	66.44	2.11	2.54	2.37	30.47	19.06	1.50
102	63.91	27.85	56.01	76.75	67.26	10.87	55.02	63.04	2.45	3.07	2.34	30.98	18.01	1.49

Table A.1 continued

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe(51-61)	$SiO_{2(5.3-5.4)}$	$Al_2O_{3(0.6-1.8)}$	LOI	CaO	MgO	Fe_2O_3
103	62.58	27.24	55.22	75.22	67.91	11.33	57.17	65.78	2.24	3.00	2.51	30.84	18.70	1.51
104	76.5 1	36.80	68.75	89.81	59.82	6.88	45.82	60.48	2.14	2.57	2.37	30.84	19.02	1.44
105	70.84	32.39	62.67	83.31	63.10	8.54	51.59	72.25	2.01	2.39	2.53	30.11	19.14	1.48
106	79.86	38.97	72.3 8	93.89	58.26	5.47	58.38	68.31	2.03	2.39	2.44	30.42	19.35	1.56
107	74.48	35.02	66.57	86.59	61.08	7.39	58.42	72.44	2.07	2.48	2.60	31.71	19.17	1.45
108	74.14	34.67	66.25	86.26	61.27	7.66	50.91	56.59	2.42	2.79	2.39	30.49	18.81	1.46
109	58.56	25.04	50.03	71.61	68.75	12.60	55.36	59.72	2.22	2.82	2.33	30.13	19.10	1.42
110	72.68	33.66	65.08	85.01	62.03	8.07	50.52	65.95	2.25	2.50	2.34	30.42	19.41	1.42
111	75.12	35.79	67.50	87.61	60.57	7.15	54.03	66.71	2.20	2.47	2.35	30.43	19.31	1.52
112	72.08	33.26	64.44	84.48	62.44	8.29	60.73	63.51	2.18	2.83	2.46	31.01	19.37	1.61
113	72.98	33.73	65.25	85.36	61.91	7.97	50.27	63.98	2.16	2.59	2.40	31.74	18.74	1.44
114	71.92	33.03	64.03	84.16	62.71	8.32	54.90	59.35	2.31	2.74	2.39	30.68	18.66	1.60
115	65.62	29.48	58.22	79.57	65.92	10.13	55.46	60.70	2.33	2.51	2.28	30.46	19.30	1.40
116	76.37	36.53	68.57	89.23	59.99	6.92	48.12	64.41	2.41	2.53	2.33	31.03	19.04	1.45
117	70.41	32.01	61.76	82.74	63.34	8.82	55.19	63.63	2.03	2.62	2.40	30.25	19.57	1.52
118	65.00	29.22	57.55	79.04	66.54	10.42	59.93	63.36	2.13	2.68	2.33	31.17	18.59	1.48
119	71.88	33.03	64.02	84.12	62.76	8.36	56.69	68.07	2.14	2.42	2.33	30.79	19.09	1.54
120	70.41	32.02	61.84	82.83	63.32	8.81	66.12	61.51	2.24	2.58	2.62	30.91	19.06	1.44
121	77.71	38.08	69.89	91.00	59.17	6.20	52.84	72.68	2.34	2.45	2.72	30.80	18.59	1.47
122	73.84	34.36	66.15	86.00	61.45	7.79	56.48	64.32	2.12	2.44	2.44	30.24	19.12	1.54
123	74.02	34.56	66.21	86.26	61.32	7.71	50.90	59.12	2.17	2.57	2.45	30.84	18.96	1.49
124	72.01	33.21	64.27	84.21	62.60	8.31	59.49	68.78	2.39	2.71	2.57	30.82	17.93	1.53
125	80.78	39.48	73.05	94.33	58.23	4.90	53.96	72.50	2.11	2.78	2.32	31.08	18.70	1.47
126	71.00	32.50	62.83	83.57	63.00	8.50	50.20	67.61	1.99	2.33	2.58	31.14	18.54	1.49
127	61.76	26.78	53.75	73.88	68.04	11.97	55.77	66.79	1.98	2.61	2.13	31.83	19.43	1.54
128	71.72	33.01	63.97	83.96	62.77	8.39	54.30	66.06	2.05	2.44	2.44	30.52	18.71	1.49
129	69.70	31.56	61.21	82.34	63.78	9.11	52.09	65.21	2.14	2.76	2.46	30.94	19.97	1.49
130	65.85	29.74	58.27	79.59	65.88	10.13	58.05	65.98	2.25	2.80	2.52	31.34	18.98	1.47
131	69.07	30.97	60.36	81.74	64.32	9.47	47.43	57.54	2.19	2.54	2.46	30.77	18.72	1.48
132	69.69	31.47	61.10	82.30	63.83	9.16	52.26	70.74	2.05	2.72	2.43	30.47	18.64	1.47
133	66.24	30.07	58.61	79.84	65.70	9.98	49.20	56.20	2.22	2.66	2.43	31.65	18.82	1.54
134	66.65	30.20	58.89	80.20	65.45	9.93	50.30	54.84	1.91	2.47	2.43	30.86	19.02	1.52
135	75.67	36.15	67.88	88.55	60.31	7.02	51.37	61.26	2.21	2.37	2.44	31.38	20.22	1.54
136	61.79	26.98	53.93	74.60	67.98	11.94	50.28	65.37	2.16	2.56	2.34	30.04	19.16	1.48
137	74.02	34.49	66.20	86.25	61.36	7.75	49.27	61.90	2.11	2.76	2.39	30.89	19.37	1.53

Table A.1 continued

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe(51-61)	$SiO_{2(5.3-5.4)}$	$Al_2O_{3(0.6-1.8)}$	LOI	CaO	MgO	Fe_2O_3
138	72.74	33.68	65.1 1	85.16	62.01	8.06	49.88	56.26	2.30	2.54	2.57	31.13	19.79	1.47
139	63.04	27.42	55.54	76.01	67.55	11.05	56.97	61.92	1.96	2.85	2.42	31.62	18.96	1.50
140	64.39	28.55	56.41	77.18	67.15	10.67	46.83	54.49	2.24	2.76	2.53	30.68	18.75	1.51
141	77.65	38.05	69.82	90.87	59.17	6.27	51.49	57.77	2.20	2.47	2.28	30.98	18.36	1.56
142	75.66	36.1 1	67.83	88.50	60.33	7.11	52.28	66.99	1.98	2.50	2.72	30.02	18.92	1.44
143	70.59	32.17	62.36	83.11	63.17	8.74	49.67	62.76	2.02	2.49	2.41	30.50	18.93	1.55
144	66.06	29.98	58.29	79.67	65.77	10.06	56.42	61.00	2.31	2.54	2.51	30.65	18.98	1.47
145	76.36	36.5 1	68.46	89.20	60.02	6.93	47.18	57.66	2.25	2.56	2.35	30.92	18.73	1.48
146	69.25	31.01	60.47	81.95	64.03	9.45	53.21	62.99	2.17	2.39	2.40	31.05	18.94	1.51
147	60.23	25.36	50.64	71.87	68.70	12.31	57.90	70.95	2.09	2.76	2.41	31.44	18.94	1.58
148	74.64	35.07	66.63	86.59	61.00	7.38	56.58	65.88	2.10	2.55	2.46	31.17	19.21	1.52
149	77.84	38.13	69.93	91.48	59.17	6.13	55.07	63.55	2.06	2.70	2.26	31.42	18.12	1.49
150	66.66	30.25	59.1 1	80.42	65.44	9.86	58.98	61.91	2.05	2.93	2.51	30.70	19.55	1.41
151	65.01	29.3 1	57.97	79.13	66.12	10.29	55.35	64.11	2.35	2.92	2.41	31.34	19.52	1.44
152	72.36	33.45	64.72	84.66	62.27	8.23	54.41	55.40	2.36	2.78	2.47	31.50	19.28	1.59
153	76.50	36.60	68.67	89.78	59.91	6.89	57.53	58.76	2.26	2.63	2.25	30.47	19.23	1.42
154	73.70	34.18	65.86	85.66	61.54	7.88	61.37	62.10	2.22	2.49	2.32	30.99	18.50	1.51
155	71.34	32.67	63.27	83.75	62.86	8.46	52.82	59.27	2.18	2.22	2.71	31.07	18.62	1.46
156	70.92	32.46	62.80	83.32	63.10	8.51	52.93	60.53	2.14	2.54	2.37	31.40	18.27	1.49
157	70.21	31.92	61.65	82.70	63.38	8.82	61.44	70.79	2.17	2.72	2.70	30.79	18.70	1.47
158	73.76	34.33	65.94	85.77	61.54	7.87	58.14	60.81	2.24	2.78	2.25	30.55	19.02	1.50
159	69.13	30.99	60.47	81.93	64.25	9.45	53.59	74.38	2.16	2.56	2.21	30.38	19.69	1.43
160	65.26	29.40	58.09	79.19	65.95	10.18	51.37	75.14	2.27	2.87	2.37	30.22	18.93	1.44
161	81.20	39.63	74.16	94.78	58.14	4.89	55.12	58.23	2.10	2.51	2.33	31.26	18.51	1.54
162	66.52	30.09	58.70	79.94	65.65	9.95	51.78	64.34	2.05	2.59	2.47	31.75	19.61	1.52
163	68.33	30.65	59.86	81.23	64.68	9.63	52.49	65.13	2.02	2.50	2.29	30.63	18.85	1.47
164	77.93	38.20	70.00	91.72	59.12	6.05	57.64	60.29	2.20	2.82	2.47	31.10	18.96	1.47
165	64.97	29.18	57.24	78.99	66.56	10.47	42.11	60.67	2.07	2.64	2.56	31.47	18.49	1.51
166	76.16	36.49	68.39	88.97	60.06	6.95	56.57	66.21	2.26	2.72	2.50	30.74	19.00	1.55
167	73.25	33.80	65.27	85.46	61.83	7.94	52.06	61.11	2.17	2.24	2.30	31.39	19.45	1.55
168	62.84	27.27	55.40	75.38	67.80	11.15	53.12	54.71	2.25	2.63	2.44	30.54	18.71	1.48
169	74.85	35.09	66.93	86.84	60.90	7.32	49.80	66.22	2.28	2.65	2.42	30.59	18.42	1.61
170	70.21	31.84	61.62	82.66	63.39	8.84	48.94	72.24	2.23	3.02	2.41	30.68	18.96	1.55
171	68.72	30.91	60.07	81.57	64.41	9.54	45.49	62.68	2.13	2.46	2.40	31.62	18.73	1.52
172	63.24	27.62	55.72	76.72	67.40	11.03	48.03	58.12	2.10	2.58	2.49	32.05	19.39	1.54

Table A.1 continued

S.No.	Cold Strength (CS)	Reduction Degradation Index (RDI)	High Reducibility Index (HRI)	Yield(Y)	Specific Power consumption (SPC)	Stack Emission-PM (SE)	Coke Consumption (39-54)	T.Fe(51-61)	$SiO_{2(5.3-5.4)}$	$Al_2O_{3(0.6-1.8)}$	LOI	CaO	MgO	Fe_2O_3
173	68.50	30.73	59.89	81.34	64.58	9.61	51.86	64.60	2.05	2.76	2.39	30.81	18.77	1.43
174	66.86	30.28	59.34	80.77	65.34	9.78	57.46	64.17	2.13	2.96	2.79	30.92	19.06	1.47
175	73.26	34.05	65.32	85.57	61.77	7.92	57.65	64.91	2.03	2.75	2.39	30.24	19.77	1.55
176	69.95	31.75	61.51	82.63	63.41	8.87	52.35	64.49	2.23	2.57	2.47	31.25	18.86	1.47
177	64.83	29.09	57.23	78.63	66.86	10.50	52.88	67.38	2.39	2.90	2.54	30.11	18.48	1.43
178	66.54	30.17	58.73	80.06	65.58	9.94	58.30	62.80	2.09	2.35	2.62	30.66	18.16	1.46
179	75.02	35.38	67.20	87.20	60.75	7.27	54.82	74.22	2.15	2.51	2.44	29.97	18.88	1.42
180	63.64	27.79	55.96	76.74	67.33	10.91	44.65	60.81	2.14	2.77	2.49	30.66	18.20	1.52
181	58.15	20.93	45.93	64.74	70.30	13.49	51.29	72.44	2.19	2.53	2.44	30.35	18.56	1.47
182	64.58	28.83	56.77	78.00	67.07	10.64	53.49	64.63	2.13	2.62	2.51	31.58	19.23	1.51
183	72.33	33.44	64.69	84.57	62.29	8.25	55.14	72.53	2.18	2.75	2.41	30.91	18.84	1.55
184	69.72	31.60	61.21	82.39	63.74	8.97	38.77	68.59	2.30	2.60	2.69	29.28	18.95	1.47
185	69.01	30.96	60.22	81.71	64.33	9.49	64.16	64.22	2.35	2.72	2.43	30.92	18.51	1.49
186	81.48	39.93	76.51	99.20	56.05	4.40	59.90	66.04	2.05	2.66	2.66	30.90	19.29	1.50
187	73.25	33.87	65.27	85.46	61.77	7.93	58.28	63.73	2.21	2.60	2.47	31.13	18.25	1.49
188	70.96	32.49	62.82	83.38	63.07	8.51	59.65	72.91	2.14	2.87	2.40	30.40	19.50	1.44
189	73.00	33.79	65.25	85.43	61.84	7.96	55.55	69.68	2.22	2.29	2.62	31.38	19.15	1.54
190	67.44	30.54	59.76	81.04	64.82	9.67	58.72	63.56	2.15	2.65	2.47	30.44	19.18	1.46
191	69.84	31.66	61.48	82.58	63.44	8.87	52.56	68.42	2.23	2.83	2.40	31.23	19.03	1.53
192	66.90	30.28	59.40	80.79	65.28	9.78	48.52	64.24	2.18	3.04	2.40	31.45	19.04	1.45
193	76.91	37.06	68.82	90.07	59.64	6.78	62.28	68.61	2.21	2.65	2.53	30.48	18.04	1.52
194	77.45	37.59	69.40	90.32	59.36	6.69	51.29	58.12	2.27	2.65	2.61	30.62	19.26	1.44
195	74.19	34.73	66.29	86.40	61.23	7.62	48.47	61.72	2.35	2.42	2.30	30.46	19.30	1.57
196	69.44	31.31	60.87	82.13	63.95	9.34	56.61	70.25	2.09	2.65	2.38	30.23	18.89	1.47
197	73.37	34.08	65.53	85.60	61.61	7.89	49.55	69.98	2.26	3.09	2.48	31.47	19.10	1.43
198	70.28	31.94	61.69	82.71	63.38	8.82	60.38	65.17	2.21	2.51	2.52	30.64	18.68	1.51
199	65.90	29.97	58.28	79.66	65.80	10.10	57.29	66.59	2.09	2.49	2.13	31.38	18.78	1.41
200	68.55	30.75	59.92	81.49	64.52	19.58	58.72	67.68	2.21	2.72	2.39	30.50	19.10	1.56

Table A.2 Normalized matrix

Table A.2 continued

Table A.3 Absolute Differences

Table-A.3 continued

Table A.4 Grey Relation Coefficients

Table A.4 continued

Table A.5 PCA scores

Table A.6 Data on the factors and response

Table A.6 continued

Table A.6 continued

Table A.6 continued

The Outcomes of this work can be Summarized as Follows

- ✓ Multiple output parameters of sintering plant are aggregated as single parameters by defining the PCA score.
- ✓ Critical process input parameters that impact the aggregated output parameters is arrived.
- ✓ Individual input parameters such as CC, Al_2O_3,MgO,Fe_2O_3 and Vacuum are arrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of CC with parameters namely: Al_2O_3, Fe_2O_3,Speed anGCP arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of T.Fe with parameters namely: Al_2O_3andGCP arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of SiO_2 with parameters namely: MgOandFe_2O_3 arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of Al_2O_3 with parameters namely: MgOandSpeed arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of LOI with parameters namely: MoistureandGCP arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of CaO with MgO isarrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of Fe_2O_3 with parameters namely: Moisture, Speed, GCPandvaccum arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of Moisture and speed are showing high interaction withvacuum arearrived as critical input parameters since the p-values of these parameters are <0.05.
- ✓ Interaction of three terms and squared terms are also arrived as significant input parameters.

CONCLUSIONS

The integrated GRA-PCA-RSM has successfully identified critical parameters required for efficient running of sintering plant.

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