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MULTI-RESPONSE OPTIMIZATION OF GREEN SAND MOULDING USING PCA & UTILITY CONCEPT BY EMPLOYING TAGUCHI METHOD

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Abstract:

Optimization is the process of finding the best solution out of all possible obtained solutions. But any processes rely on more than one process parameters and thus, we need to optimize all the parametric combination to obtain the best result. This technique of multi-parametric optimization is also known as multi-response optimization. This project deals with the multi-response optimization of the green sand moulding process. In this study, grain fineness number, the percentage of clay, the percentage of water and number of strokes are considered as input parameters and the mould properties such as green compression strength, permeability, hardness and bulk density are treated as a response (output parameters). So by using this multi-response optimization concept, we optimize the responses obtained for the various combinations of input parameters by using the traditional type of optimization techniques.

1. Principal component analysis
2. Utility concept

Various optimized results, obtained by using the above processes are tabulated and represented graphically in a comparison sequence.

Keywords: Green sand moulding, principal component analysis, utility concept, optimization

1. Introduction:

Greensand mould casting is one of the most popular casting methods. In order to maintain consistent quality of the castings, it is necessary to control the process efficiently. The eminence of green sand create transmitting is basically manipulated by the properties of mould, such as green firmness vigour, permeability, mould long-lastingness and others, which depend on many input restrictions, such as sand grain size and outline, the sum of file and water etc., is complex in nature. The major source of defects in sands castings is the moulding sand mixture itself. The defects can be minimised by proper control of the moulding sand properties such as green compression strength, permeability, hardness and bulk density. Hence, it is important to establish their relationships with the input variables (moulding sand ingredients), namely sand grain fine-ness number (GFN), amount of binder and moisture for a given ramming condition. Hence, it is important to identify the levels of the input variables that provide the required mould properties, which improves the quality of the parts produced by this mould.

Most of the research work on moulding sand during the 1960s and 1970s was based on experimental and theoretical approaches. The relationship between permeability and transformation zones, mould pressure, void space control, etc., was developed by Marek [1] through substantial mathematical equations. Additionally to this, Frost and Hiller [2] established the heaviness and inflexibility divisions in polish moulds. This approach was completely theoretical and not supported by a large number of experiments. Moreover, statistical design of experiments (DOE) had been used by various investigators to study the effects of different variables on the green sand mould properties. In [4], DOE technique was applied to study the effect of process variables on bulk density and green compression strength. Besides to this draw nearer, Casalino et al. [5] operated Taguchi performance to institute third instructs model for permeability and firmness potency in laser sintered sand moulds. Moreover, Parappagoudar et al. [6, 7] developed linear and non-linear statistical models utilizing full factorial DOE, central composite design (CCD) and Box-Behnken design. Among the non-linear regression equations developed by the abovementioned three approaches, CCD-based model was found to be the more accurate model for prediction of the responses. Later on, the optimization of process parameters of green sand casting was established in [8] utilizing Taguchi parameter design. The process parameters such as green firmness strength, wetness satisfied, driving temperature and mould inflexibility upright and the level was considered to identify the effect of these parameters on casting defects. B. Surekha [9] obtained a compromise solution, which satisfies all the four objectives (input parameters). Casalino et al.[10] used the Taguchi technique to establish a third order model for compression strength and permeability in laser sintered sand mould. Their model showed an average of 8% deviation in the prediction for the test cases.

In the present work, the following things have been attempted:

1. Experiments were conducted as per the requirement Of analysis. The performances were tested for in^k test cases, where k is the number of input parameters, n is the number of levels.
2. The Taguchi is created and the experimentation is conducted by the different process explained below for the obtained matrix.
3. The obtained values are then optimized by using different techniques.

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2. Experimentation Data Collection

Formulation Of The Problem:

The quality of the parts produced in green sand mould system mainly depends on the properties (responses) of the mould, such as green compression strength (GCS), permeability (P), hardness (H) and bulk density (BD),which in turn depends on the process variables (that is, grain fineness number, percentage of clay, percentage of water and number of strokes). Figure 4.1 shows the schematic diagram of green sand mould system as an input-output model. The ranges of the process variables used in this study are given in Table 1.

Table1 shows the ranges of the input process parameters used for conducting the experiments. Once the levels of the input process parameters are determined, the experiments are conducted with the help of central composite design (CCD) of experiments. The experimental design consists of 27sets of experiments that allow for the estimation of linear, square and two-way interaction effects of the input parameters.

s.no	**Parameters**	**Symbol**	**Range**		
			High	**Medium**	**Low**
1	Grain fineness number	A	94	73	52
2	% clay content	B	12	10	8
3	% water content	C	3	2.25	1.5
4	Number of strokes	D	5	4	3

Table 1 Process parameters and their ranges.

Experimentation Setup:

High silica sand and sodium based bentonite clay were used in the experiments. The sand used was collected from the coastal Karnataka, India. The following tests experiments were conducted as discussed below touchstone method has been worn to prepare the analysis cases. An individual measure of hardener is added to the chromate sand and incorporation is done homogeneously. Then the required quantity of resin is added to the sand-hardener mixture and mixed it properly so that the reaction product of resin and hardener is coated to sand particles uniformly. The prepared and is then poured in the core box and rammed with the help of ramming machine (refer to Fig.2.1(a)) to acquire the desired compaction

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FIG 2.1.(a)Sand ramming machine

Grain Fineness Test:

Sieve analysis test Sieve analysis test was carried out and a standard procedure was used to determine the grain fineness number of the sand. The distribution of different grain sizes present in the sand is a more significant index. For good compaction of sand, the amounts retained on three or four consecutive sieves should be in the range of 75– 80%. In addition, the sieve distribution (percentage of sand retained on various sieves) should not show a double peak in the relationship between sieve size and percentage of sand retained. The sieve analysis test was performed for both fine.

1 The sand held on each sieve (grains that are too hefty to traverse) is then weighed and recorded.

4. The weight retained on each sieve is carried out through calculations to get the AFS-GFN

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Fig 2.1(b).Grain Analyser

Gelling index test and 0.1 gm of clay were placed in the first test tube. The weight of clay was incremented by 0.1 gm for the successive test tubes. The water–clay mixture was kept for 24 h and observed for the formation of the gel. The gel was found to form in the sixth test tube. Thus, the gelling index was calculated as follows: gelling index=volume of water/weight of clay

=10/0.6=16.67

Thus, in the present work, sodium-based clay having the gelling index of 16.67 is used. This clay will provide good bonding between the sand particles.

Strength Test:

This is the might of temper and expressed by its capability to clasp a mould in outline. Sand moulds are subjected to compressive, tensile, shearing, and transverse stresses. The green compression strength, measured in psi was converted to kilo Pascal (SI unit).

Mould Hardness Test:

- This test is performed by a mould hardness tester.
- In an A.F.S. s steel hemispherical ball is loaded with a spring load of 980 gm.

This ball is made to penetrate into the moulding sand or core sand surface

Gelling index test was conducted to know the suitability of the binder used in the experiments. The gelling index is expressed as the ratio of the volume of water to the minimum weight of clay used. Ten test tubes with 10 mL of water in each, were labelled from 1 to 10

- The penetration of the ballpoint into the mould surface is indicated on dial-in thousands of an inch.

Fig 2.1(f) Sand Hardness Tester

Bulk Density:

Bulk density was determined by utilizing the following relationship:

bulk density=weight of the specimen/volume of the specimen.

For each combination of input parameters, five observations were made to minimize the error of variation and the average value was considered. Thus, a set of 27 test cases was generated as per DOE.

3.Methodology :

In the present work, the following steps are adopted.

Step 1: *selecting parameters and their levels* The principal properties of green sand mould are governed by the type of sand used and the amount of clay and water present in it. It is to be noted that the properties also depend on mulling time and in the present study, it has been kept constant at 30 min. The degree of ramming has its effect on mould strength, permeability, hardness and bulk density. In this work, the following parameters are considered for

experimentation:

(i) AFS grain fineness number of silica sand

(ii) percentage of (bentonite) clay content

(iii) clay/water ratio

(iv) a number of strokes.

With a high amount of clay and a low amount of water, the water present may not be sufficient to activate (plasticise) the whole amount of clay added to the sand. Similarly, a high level of water with a low level of clay will result in excess of water. In both the cases, green compression strength will be very less. Since water is added to activate clay, instead of water, clay/water ratio was selected as one of the variables. The levels of the variables were set in consultation with the foundry industries and a detailed literature survey on the sand casting of aluminium alloys.11–15

The parameters and their levels are listed in Table 1.

Step 2: *conducting experiments*

The following tests/experiments were carried out one after another:

(i) sieve analysis test to determine the grain fineness number and size distributions of the silica sands

(ii) gelling index test to know the strength of clay

(iii) conducting experiments with different combinations of parameters as per the DOE.

(iv) conducting experiments with randomly generated 27 combinations of the process parameters for testing the performances of the developed models.

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Step 3: Developing Models In the present paper, Taguchi design was used to develop models for responses such as permeability, green compression strength, mould hardness and bulk density.

Step 4: *Performing Analysis Of Data And Comparison Of one another*

PCA and utility concept was performed for each of the responses separately. The models were compared response-wise for 27 test cases and the best model was identified.

4. Tools And Techniques Used

Taguchi Design:

These days Taguchi process is generally worn as a controlling tool for manipulative first-rate classification during delve into and development so that high-quality products can be produced in a minimum time and minimum cost. This kind of scheme applies an unusual device of orthogonal displays to revision the entire parameter space with a minimum number of experiments The OA consists of 3 columns and 27. The OA follows a random run order.

S.No	A	B	C	D
1	94	12	3	5
2	94	12	2.25	4
3	94	12	1.5	3
4	94	10	3	5
5	94	10	2.25	4
6	94	10	1.5	3
7	94	8	3	5
8	94	8	2.25	4
9	94	8	1.5	3
10	73	12	3	4
11	73	12	2.25	3
12	73	12	1.5	5
13	73	10	3	4
14	73	10	2.25	3
15	73	10	1.5	5
16	73	8	3	4
17	73	8	2.25	3
18	73	8	1.5	5
19	52	12	3	3
20	52	12	2.25	5
21	52	12	1.5	4
22	52	10	3	3
23	52	10	2.25	5
24	52	10	1.5	4
25	52	8	3	3
26	52	8	2.25	5
27	52	8	1.5	4

Table 2: Creation Of Taguchi Design

PRINCIPAL COMPONENT ANALYSIS

The number of chief modules is less than or one and the same to the number of creative variables. This kind of conversion is definite in such a way that the original major element has the largest probable inconsistency (that is, portrayals for as much of the variation in the data as possible), and each succeeding component, in turn, has the maximum difference promising under the limitation that it be orthogonal to (i.e., uncorrelated with) the former modules. Principal machinery is guaranteed to be self-determining only if the data set is in assistance on the whole circulated.

The first step in the Principal Component analysis is to pre-process data in order to normalize the raw data for the analysis. To normalize various parameters depending on their nature, eqs. (1) ,(2) (3) are used

$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)}$.......(1) higher is better

$X_i^*(k) = \frac{\min X_i(k)}{X_i(k)}$........(2) lower is better

$X_i^*(k) = \frac{\min\{X_i(k), X_{ob}(k)\}}{\max\{X_i(k), X_{ob}(k)\}}$......(3) nominal is better

Where x_i^* is the normalized value $X_i(k)$ is the current value, min $X_I(k)$ is the minimum value, max $X_i(k)$ is the max value. $X_{ob}(k)$ is the desired value of the k^{th} quality characteristic. After data normalization, the value of $X_i^*(k)$ will be in between 0 and 1.

$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)}\right)$ ....(4)

Where J=1,2,…,n; L=1,2,…,n. Cov ($x_i(j)$, $x_i(l)$) is the covariance of sequences $x_i(j)$ and $x_i(l)$ $\sigma_{x_i}(j)$, $\sigma_{x_i}(l)$ is the standard deviation of sequence $x_i(j)$and $x_i(l)$ respectively.The Eigen values and eigenvectors are determined from the correlation coefficient array,

$(R - \lambda_\kappa I_m)V_{i\kappa} = 0$ ----- (5)

Where λ_κ Eigen values, $\sum_{\kappa=1}^{n} \lambda_\kappa = n$, κ =1,2,…,n; $V_{i\kappa} = [a_{\kappa 1} a_{\kappa 2} \dots . a_{kn}]^T$ is the eigenvector corresponding to the Eigen valueλ_κ.

$Z_{m\kappa} = \sum_{i=1}^{n} x_m(i) \,.\, V_{i\kappa}$...............(6)

V relates to the respective eigen vector &x determines the normalized value.

$MPI_j = \sum_{i=1}^{n} W_i \times Z_{ij}$ ---------- (7)

Where, j=1,2,…,m.

W_i is the proportion of overall variance of the responses explained by i^{th} principal component.

Utility Concept:

In the modern competitive nonconventional manufacturing scenario, it is most vital to optimize the parameters of a process to exploit its full utility. In most of the manufacturing processes, more than one quality characteristic has to be considered for optimization of process parameters making it necessary that several response characteristics have to be simultaneously optimized. After normalizing date as same in principal component analysis. Determine the preference scales for each quality characteristics is constructed for determining its utility value. Two arbitrary numerical values(preference number) 0 to 9 are assigned to the just acceptable and the just acceptable and the best value of the quality characteristic, respectively.

$P_i = A * \log(X_i / X_i^*)$

X_i^*:: just suitable value of superiority attribute or attribute i

A constant, The charge of A can be established by the circumstance that if $X_i = X_i^*$

Usually, $A=9/\log(Xi^*/Xi)$

Assign the weights to various quality characteristics based upon the importance and their use keeping in view that the total sum of weights is equal to 1 usually, equal-weighted systems are preferred

i.e; w1=w2=w3=w4=1/4

The overall utility number is to be calculated by using the equation

$$U=\sum_{i=1}^{n} Wi * Pi$$

Consequently, if the efficacy meaning is taken full advantage of, the eminence uniqueness measured for its appraisal will repeatedly be optimized.By means of the above formulae.

5.Experimentation Data:

Data is collected by conducting the experiments and the values are collected on average.

GCS	P	H	BD
83.56	54.97	91.52	1.60
78.32	52.81	90.68	1.58
65.95	49.79	87.58	1.59
66.41	58.77	89.41	1.59
63.27	62.37	88.07	1.57
53.00	65.12	84.48	1.57
50.01	66.17	87.28	1.58
48.98	75.54	85.43	1.56
40.81	84.05	81.34	1.55
63.43	65.28	88.99	1.58
54.94	83.30	87.07	1.56
58.84	43.68	88.28	1.62
49.52	77.68	86.43	1.57
43.13	101.47	84.01	1.55
45.31	55.67	85.88	1.60
36.37	93.68	83.84	1.56
32.08	123.23	80.92	1.54
32.54	71.26	83.45	1.58
51.34	167.61	86.01	1.50
68.02	109.29	89.88	1.51
50.32	128.30	87.11	1.53

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40.67	188.61	83.00	1.49
55.63	124.12	87.54	1.50
40.03	148.89	84.27	1.51
30.76	213.21	79.96	1.48
43.99	142.54	85.16	1.48
30.50	173.08	81.39	1.49

Table 3: output values calculated for the test values

Calculation using PCA:

The principal components and multi-performance index values are calculated using the formulas stated above is tabulated below.

S.No	Z_1	Z_2	Z_3	Z_4	MPI
1	16.00	-73.83	10.98	112.05	-4.45
2	13.25	-70.58	8.45	109.18	-5.76
3	6.99	-64.91	2.42	101.16	-9.21
4	5.95	-73.81	0.57	101.87	-12.20
5	4.22	-76.61	-1.52	98.81	-14.26
6	-1.02	-77.00	-7.10	90.60	-18.46
7	-3.90	-77.45	-10.00	91.57	-20.72
8	-4.61	-86.31	-11.64	88.31	-23.53
9	-8.82	-92.75	-16.78	79.92	-28.48
10	3.78	-79.50	-2.23	99.33	-15.31
11	-2.13	-95.19	-9.89	91.53	-23.82
12	2.89	-57.46	-1.09	99.27	-10.47
13	-4.79	-88.54	-12.01	89.18	-24.21
14	-9.67	-110.28	-19.23	81.18	-33.47
15	-5.47	-66.18	-10.61	89.49	-19.13
16	-13.14	-101.24	-21.95	78.90	-33.87
17	-17.01	-129.04	-28.72	70.72	-43.89
18	-13.63	-78.57	-20.30	79.57	-28.56
19	-10.39	-176.53	-26.28	78.53	-50.62
20	2.89	-123.39	-7.29	96.78	-26.98
21	-8.40	-138.05	-20.47	83.89	-39.40
22	-17.47	-194.63	-35.43	68.40	-60.67
23	-5.01	-135.12	-16.63	87.21	-36.04
24	-15.28	-155.83	-29.37	74.13	-49.21
25	-24.34	-216.39	-44.74	58.14	-71.48
26	-12.70	-150.52	-26.13	77.51	-45.87

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27	-21.95	-177.28	-38.42	64.24	-59.78

Table 4: principal components and multi-performance index values

Factors	High Level 1	Medium Level 2	Low Level 3
Grain fineness number	-48.8946	-25.8586	-15.2295
% of clay	-39.5758	-29.7386	-20.6683
% of water	-29.1891	-28.1807	-32.613
No of strokes	-37.7879	-29.4803	-22.7145

The levels indicating minimum value for each parameter is considered as the optimum level for that particular parameter. C2-D3 i.e parameter ‘a’ at level 3, ‘b’ at level 2,’c ‘at level 2, ‘d’ at level 3,or it can said that grain fineness number is 52,% of clay at range 8, % of water is range 2.25, no of strokes at range 3.

Calculation using Utility

The utility number is calculated by using the above-discussed formulas and tabulated below

S.No	A	B	C	D	U
1	52	8	1.5	3	7.0220
2	52	8	2.25	4	6.1390
3	52	8	3	5	5.3773
4	52	10	1.5	3	6.3720
5	52	10	2.25	4	5.6294
6	52	10	3	5	4.9527
7	52	12	1.5	3	5.3464
8	52	12	2.25	4	4.6877
9	52	12	3	5	3.9770
10	73	8	1.5	4	5.4101
11	73	8	2.25	5	4.6491
12	73	8	3	3	6.1634
13	73	10	1.5	4	4.9329
14	73	10	2.25	5	2.9287
15	73	10	3	3	5.9206
16	73	12	1.5	4	4.6746
17	73	12	2.25	5	3.9280
18	73	12	3	3	5.3656
19	94	8	1.5	5	0.1784
20	94	8	2.25	3	3.5948
21	94	8	3	4	1.9003
22	94	10	1.5	5	3.2401
23	94	10	2.25	3	6.3621

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24	94	10	3	4	4.8055
25	94	12	1.5	5	1.2340
26	94	12	2.25	3	4.9848
27	94	12	3	4	3.1163

Table 5 Calculation of Utility Number corresponding to each set of trails

Factors	Low Level 1	medium level 2	High Level 3
Grain fineness	5.500	4.886	3.268
% of clay	4.493	5.016	4.146
% of water	4.268	4.767	4.620
No of strokes	5.681	4.588	3.385

The combination obtained is A1-B2-C2-D1. The optimal solution obtained by utility concept is for variable A the range is 52 i.e low range and for parameter B the range is 10 i.e medium range and for parameter C the range is medium and for variable D the optimal range is low.

6.Results And Conclusion

The optimal values obtained by using PCA and utility concept are tabulated & compared below

Factors	**PCA**	**UTILITY**
Grain Fineness number(a)	52	52
% of clay(b)	10	8
% of water (c)	2.25	2.25
Number of strokes (d)	3	3

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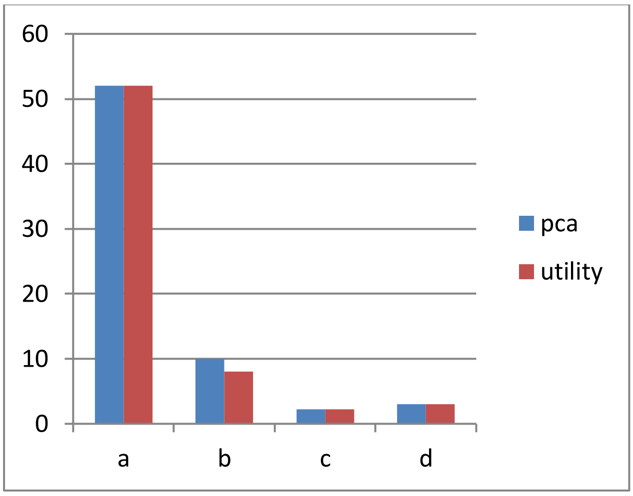

Graph 1: Comparison Of Principal Component Analysis And Utility Concept Processes For The Variables

On the x-axis, it is referred to as factors, y-axis as ranges. The results obtained are same with both principal component analysis & utility concept with the optimum values of grain fineness number, % of clay, % of water, no of strokes to be 52gfn, 10-8, 2.25, 3.

The optimization of green sand moulding multiple performance characteristics for castings was carried out. The optimum conditions for obtaining higher MPI such as (low range of gifts, mean range of 10% of clay, the medium range of % water, low range of strokes were obtained. ANOVA study has to been carried out to obtain the significant factors for GCS, P, H, BD. It is found that GFN, % of clay, % of water and no of strokes are the most influential factor for GCS, P, H, BD. The same parameters are proved to be effective during UTILITY CONCEPT also. With the optimal level of parameters, it has been found that PCA based Taguchi method coupled with UTILITY CONCEPT is best suitable for solving the quality problem.

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