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OPTIMIZATION OF PROCESS PARAMETERS USING DIFFERENT STATISTICAL DESIGNS

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Abstract

Industries expect optimal solutions for the problems with a few experiments to reduce the cost and time of the experimentation. Many statistical methods are introduced to fulfil the demands of the industries. In the present study, three statistical methods namely Taguchi's design of experiments, central composite designs (CCD) and balanced incomplete block design (BIBD) are considered. The adequacy of these methods is examined considering the test data of tensile shear strength of resistance spot welding for galvanized steel. Since the data is insufficient for the test runs demanded by the statistical methods, an empirical relation is developed from the test data using the response surface methodology (RSM). From the developed empirical relation, the necessary data is generated for CCD and BIBD. Empirical relations are also developed from the data of the test runs in CCD and BIBD. The optimal process parameters are identified from these methods and verified with the test data. The best method is identified based on the number of experiments and the adequacy in estimating the performance indicator for the identified optimal input variables. The maximum tensile shear strength estimated for the optimal input variables using Taguchi approach is close to the test results. Estimates from CCD and BIBD are slightly low to that of test results.

Keywords: Balanced incomplete block designs, Central composite designs, Response surface method, Taguchi method.

1. Introduction

Majority of engineering problems are complex in *nature* and exact solution for the problems is very difficult. Development of a mathematical model for a new problem (whose behavior is unknown) is practically impossible. One has to depend on experimentation. More number of input variables demands a greater number of experiments. For example, four input variables with '3' levels demand 81 experiments. For the case of 'n' input variables with '3' levels it is necessary to perform 3^n experiments. Repetition of experiments indicates scatter in test results.

Statistical methods can only handle the acceptance of the scatter in test data. These methods also help the designer to develop empirical relations for the performance indicator (output responses) in terms of input variables. Many statistical methods are being used to minimize the number of experiments and obtain the solution for the full factorial design of experiments. Each method has its own limitations.

It is essential to understand such limitations prior to the selection of suitable statistical model for the intended application. More popular among many statistical methods are Taguchi method, central composite design (CCD) and balanced incomplete block design (BIBD) for response surface methodology (RSM), which are briefly highlighted below.

1.1. Taguchi's Design of Experiments

Genichi Taguchi has developed a statistical method to improve the quality of manufactured goods. According to Taguchi method, the control factors should be selected in such a way that the effect of noise factors is nullified. To attain optimum results of a process, Taguchi method identify the appropriate control factors. Robust systems that are reliable under uncontrollable conditions can be designed using Taguchi method.

Thakur et al. [1] have applied Taguchi method for resistance spot welding of a galvanized steel to specify optimal process parameters. Buddi et al. [2] have identified optimal process parameters for plywood manufacturing using soya meal adhesive. Dutta and Nageswara [3] have investigated the performance of chevron type plate heat exchangers.

Satyanarayana et al. [4] have adopted Taguchi based CFD simulations and identified optimal laser beam welding (LBW) process parameters for E110 Zirconium alloy butt joint. Ganguly and Patel [5] have studied the statistical design of X-bar control chart while optimizing the multi-objective function.

Rajyalakshmi and Nageswara [6] have suggested a modified Taguchi approach to trace the optimum GMAW process parameters on weld dilution for ST-37 steel plates. Rajyalakshmi and Nageswara [7] have presented the expected range of the performance indicator (output response) for the optimal input process variables.

Dharmendra et al. [8] have presented optimal abrasive water jet machining process parameters of Inconel 800. Kumar and Rajyalakshmi [9] have made a comparative study on CCD and the modified Taguchi approach. Dharmendra et al. [10] have identified optimal process parameters for nano-powder-mixed EDM (electrical discharge machining) of INCONEL800 (with copper electrode).

1.2. CCD for RSM

Response surface methodology (RSM) is a powerful statistical tool to explore the relationship between several explanatory variables and a dependent variable. It is also named as Box and Wilson CCD. CCD plays a key role in investigating the effects of process parameters on the output response. These methods will be helpful in fitting the output response as a second-order polynomial model in terms of input process variables for optimizing the several research problems.

Box and Behnken [11] have introduced a few three-level designs for the quantitative variables and presented different combinations of the factors with coded levels. Prasad et al. [12] have constructed various designs for conducting agricultural experiments.

Asghar et al. [13] have made a comparative study utilizing Taguchi and CCDs while optimizing the Fenton process. Barbuta et al. [14] have performed statistical analysis on the tensile strength of coal using CCD.

Managamuri et al. [15] have optimized the culture conditions by RSM and unstructured kinetic modelling. Hassan et al. [16] have utilized CCD while optimizing the high-strength blended concrete. Sankha Bhattacharya [17] has made a review on the CCD for RSM and its applications in pharmacy.

1.3. BIBD for RSM

BIBD plays an important role in the design of experiments especially in field experiments (Das and Narasimham [18]). In BIBD, an arrangement of ‘v’ treatments in ‘b’ blocks such that every block contains k (k<v) treatments and satisfies the following conditions:

(i) Each treatment does not appear in a block or appears exactly once in a block;
(ii) Each treatment appears exactly in ‘r’ blocks; and
(iii) Each pair of treatments occurs together in exactly ‘λ’ blocks.

Das and Narasimham [18] have constructed rotatable designs using BIBD. Rajyalakshmi and Victorbabu [19, 20] have examined second-order rotatable designs under tri-diagonal correlated structure of errors using BIBD and symmetrical unequal block arrangements with two unequal block sizes. Rajyalakshmi and Victorbabu [21] have constructed second-order slope rotatable designs under tri-Diagonal correlated structure of errors using BIBD.

1.4. Objectives of the present study

In the present study the adequacy of Taguchi, CCD and BIBD methods are examined considering the existing test data [1]. Since the test data is available only for Taguchi’s L_{27} orthogonal array for four input process variables with three levels, which may be insufficient for all the test runs demanded by CCD and BIBD. An empirical relation is developed from the test data using RSM. From the empirical relation the output response for the specified process parameters in each test run for the methods are generated. The optimal process parameters are identified and confirmed with test results. The best among the three methods is selected based on the number of experiments and the adequacy in estimating the output response for the specified input process variables.

2. Analysis

Thakur et al. [1] have examined the effect of welding parameters on the tensile shear strength of spot-welded galvanized steel useful in the automobile and aerospace industry. The chemical composition of (wt %) galvanized steel consists of 0.065C+0.095Si+0.107Cr+0.032Ni+0.053Cu+0.404Mn+0.017S+0.018P +balance Fe. The size of the sheet samples is 100X30X1 mm. Varying diameters of Cu Cr alloy are used as electrode. They have conducted '27' runs of the experiments based on Taguchi's L_{27} orthogonal array. Varying current, weld time, electrode diameter and force are the core process parameters designated by X_1, X_2, X_3 and X_4. Each parameter is assigned '3' levels. Table 1 gives the levels of the input parameters and the output response (tensile shear strength) of the '27' experiments. Using RSM and the test data in Table 1 an empirical relation is developed for the tensile shear strength $\hat{y}$ (kN) in terms of process variables in coded form.

Table 1. Levels of RSW process parameters with levels and the performance indicator (tensile shear strength) of galvanized steel.

RSW process parameters	Designation	Level-1	Level-2	Level-3
Welding current (kA)	X_1	8	10	12
Weld time (Cycle)	X_2	8	12	16
Elelctrode diameter (mm)	X_3	4	6	8
Welding force (kN)	X_4	2	3.5	5
Coded values of X_1, X_2, X_3, X_4		-1	0	1

S. No.	Coded values				Tensile shear strength (kN)		
	X_1	X_2	X_3	X_4	Test	RSM	Additive Law
1	-1	-1	-1	-1	3.83	3.8236	3.9766
2	-1	-1	0	0	4.6	4.5888	4.7589
3	-1	-1	1	1	3.6	3.6408	3.7800
4	-1	0	-1	0	5.43	5.3697	5.3544
5	-1	0	0	1	4.86	4.7847	4.7644
6	-1	0	1	-1	4.47	4.4680	4.5033
7	-1	1	-1	1	5.23	5.2694	5.1111
8	-1	1	0	-1	5.43	5.3889	5.2389
9	-1	1	1	0	5.67	5.7849	5.6323
10	0	-1	-1	-1	5.63	5.7128	5.7266
11	0	-1	0	0	6.57	6.4930	6.5089
12	0	-1	1	1	5.64	5.5600	5.5300
13	0	0	-1	0	6.94	7.1130	7.1044
14	0	0	0	1	6.43	6.5430	6.5144
15	0	0	1	-1	6.17	6.2164	6.2533
16	0	1	-1	1	6.93	6.8668	6.8611
17	0	1	0	-1	7.03	6.9764	6.9889
18	0	1	1	0	7.53	7.3894	7.3823
19	1	-1	-1	-1	6.27	6.1932	6.0676
20	1	-1	0	0	6.9	6.9884	6.8499
21	1	-1	1	1	6.03	6.0704	5.8710
22	1	0	-1	0	7.56	7.4475	7.4454
23	1	0	0	1	6.93	6.8925	6.8554
24	1	0	1	-1	6.6	6.5560	6.5943
25	1	1	-1	1	7.03	7.0554	7.2021
26	1	1	0	-1	7.06	7.1551	7.3299
27	1	1	1	0	**7.56**	7.5831	7.7233

$$\hat{y} = 7.1952 + 1.0456X_1 + 0.5778X_2 - 0.1000X_3 + 0.0222X_4 - 0.7044X_1^2 - 0.1244X_2^2 - 0.1822X_3^2 - 0.6744X_4^2 - 0.1542X_1X_2 + 0.0067X_1X_3 + 0.0083X_1X_4 + 0.023X_2X_3 - 0.0244X_2X_4 \quad (1)$$

Table 2 gives analysis of variance (ANOVA) for the data in Table 1 based on the Taguchi approach. The % contribution of each parameter is worked out and presented in Table 2. Table 2 shows that X_1 contribution is high with 69.9%, X_2 is 18.7%, X_3 is with 1.1% and X_4 is with 8.7%. X_3 parameter has insignificant contribution when compared to other parameters (X_1, X_2 and X_4).

Table 2. Analysis of Variance (ANOVA).

Parameters	Mean1	Mean2	Mean3	Grand Mean	Sum of squares	% Contribution
X_1	4.7911	6.5411	**6.8822**	6.0715	22.6546	69.9
X_2	5.4552	6.1544	**6.6078**	6.0725	6.0689	18.7
X_3	6.0944	**6.2011**	5.9189	6.0715	0.3655	1.1
X_4	5.8322	**6.5289**	5.8533	6.0715	2.8268	8.7

Using the additive law (Ross 2005) and the data in ANOVA Table 2 one can find the output response for the specified all the combinations of input variables $X_{1_i}, X_{2_j}, X_{3_k}, X_{4_l}$.

$$\eta = \eta(X_{1_i}) + \eta\left(X_{2_j}\right) + \eta(X_{3_k}) + \eta(X_{4_l}) - 3\hat{\eta}_m \quad (2)$$

where $\hat{\eta}_m$ is the grand mean of the output response.

Table 1 gives the estimates of tensile shear strength using the empirical relation (1) of RSM and the additive law of Eq. (2). The estimates are reasonably in good agreement with test result. Using the mean values of Table 2 generated and additive law (2) one can develop the empirical relation in the form

$$\hat{y} = 7.211 + 1.0455X_1 - 0.7045X_1^2 + 0.5778X_2 - 0.1244X_2^2 - 0.08775X_3 - 0.19445X_3^2 - 0.01055X_4 - 0.68615X_4^2 \quad (3)$$

From the ANOVA Table 2 the process parameters identified for achieving the maximum tensile shear strength are X_{13}, X_{23}, X_{32}, X_{42}. Subscripts denote the levels of the parameters. For these levels the maximum tensile shear strength obtained from Eq. (2) is 8.0055 kN. Table 3 gives the levels of the process parameters as per CCD. The tensile shear strength values corresponding to the levels in Table 3 are obtained from Eqs. (1) and (2).

Table 3. Levels of RSW process parameters and the performance indicator (tensile shear strength) of galvanized steel as per CCD.

S. No.	X_1	X_2	X_3	X_4	RSM	Additive Law
1	0	0	0	0	7.1952	7.2111
2	0	0	0	0	7.1952	7.2111
3	1	1	1	1	6.9148	7.0266
4	**0**	**1**	**0**	**0**	7.6486	7.6645
5	1	-1	1	1	6.0704	5.871
6	0	0	0	0	7.1952	7.2111
7	-1	-1	-1	1	3.9002	3.9555
8	-1	1	1	-1	5.123	4.9567
9	0	0	0	1	6.543	6.5144

10	1	0	0	0	7.5364	7.5521
11	-1	0	0	0	5.4452	5.4611
12	-1	-1	-1	-1	3.8236	3.9766
13	-1	-1	1	1	3.6408	3.78
14	0	0	0	0	7.1952	7.2111
15	1	-1	-1	1	6.303	6.0465
16	0	-1	0	0	6.493	6.5089
17	-1	1	-1	1	5.2694	5.1111
18	0	0	0	0	7.1952	7.2111
19	1	1	-1	-1	7.0432	7.2232
20	1	-1	-1	-1	6.1932	6.0676
21	-1	1	-1	-1	5.2904	5.1322
22	0	0	-1	0	7.113	7.1044
23	1	1	-1	1	7.0554	7.2021
24	1	1	1	-1	6.9026	7.0477
25	0	0	0	-1	6.4986	6.5355
26	-1	1	1	1	5.102	4.9356
27	0	0	1	0	6.913	6.9289
28	0	0	0	0	7.1952	7.2111
29	-1	-1	1	-1	3.5642	3.8011
30	1	-1	1	-1	5.9606	5.8921

The output responses from Eqs. (1) and (2) are matching well for all the levels of the parameters in Table 3. Figure 1 represents the estimates of tensile shear strength from the developed empirical relation (1) utilizing RSM and comparison with test data [1].

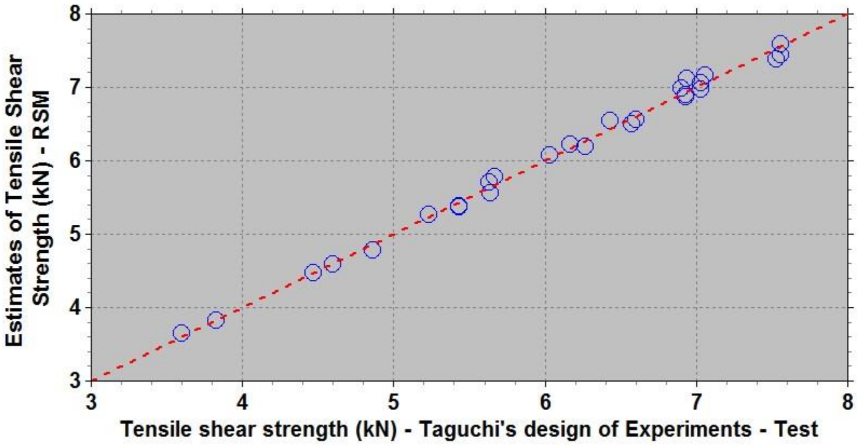

Fig. 1. Estimates of tensile shear strength from the developed empirical relation (1) utilizing RSM and comparison with test data [1]).

Figure 2 provides the estimates of tensile shear strength from the developed empirical relation (3) utilizing the additive law and comparison with test data [1].

Using the generated data for the output responses in Table 3 the empirical relation obtained from the data of RSM is exactly matching with Eq. (1) whereas the data from the additive law of Table 4 gives the empirical relation almost same as that of Eq. (3).

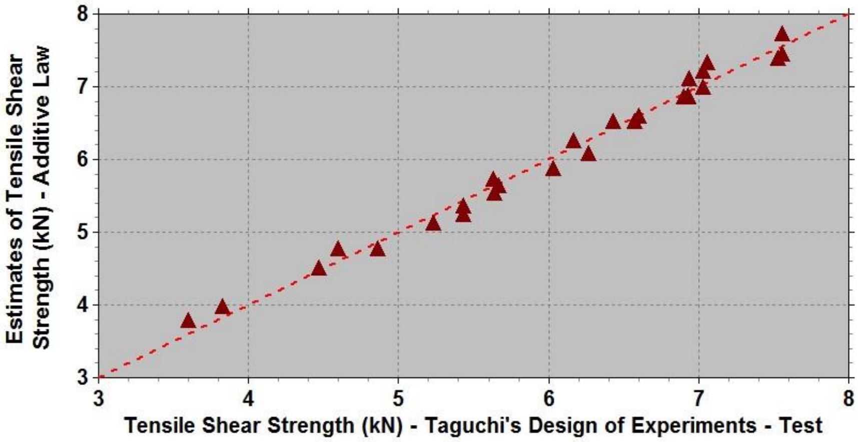

Fig. 2. Estimates of tensile shear strength from the developed empirical relation (2) utilizing the additive law and comparison with test data [1].

Table 4. Levels of RSW process parameters and the performance indicator (tensile shear strength) of galvanized steel as per BIBD.

S. No.	X_1	X_2	X_3	X_4	RSM	Additive Law
1	-1	-1	0	0	4.5888	4.7589
2	-1	1	0	0	6.0528	5.9145
3	1	-1	0	0	6.9884	6.8499
4	**1**	**1**	**0**	**0**	7.8356	8.0055
5	0	0	-1	-1	6.4164	6.4288
6	0	0	-1	1	6.4608	6.4077
7	0	0	1	-1	6.2164	6.2533
8	0	0	1	1	6.2608	6.2322
9	0	0	0	0	7.1952	7.2111
10	-1	0	-1	0	5.3697	5.3544
11	-1	0	1	0	5.1563	5.1789
12	1	0	-1	0	7.4475	7.4454
13	1	0	1	0	7.2609	7.2699
14	0	-1	0	-1	5.772	5.8333
15	0	-1	0	1	5.8652	5.8122
16	0	1	0	-1	6.9764	6.9889
17	0	1	0	1	6.972	6.9678
18	0	0	0	0	7.1952	7.2111
19	0	-1	-1	0	6.4338	6.4022
20	0	-1	1	0	6.1878	6.2267
21	0	1	-1	0	7.5434	7.5578
22	0	1	1	0	7.3894	7.3823
23	1	0	0	-1	6.8315	6.8765
24	1	0	0	1	6.8925	6.8554
25	-1	0	0	-1	4.7569	4.7855
26	-1	0	0	1	4.7847	4.7644
27	0	0	0	0	7.1952	7.2111

The maximum output response (tensile shear strength from Table 3) corresponding to the sl.no (4) is 7.6486 kN. The input process parameters in sl. no (4) are X_{12}, X_{23}, X_{32} and X_{42}. The set of parameters identified for the maximum output response from Table 3 are found be different to that of obtained from the ANOVA Table 2. Figure 3 represents the estimates of tensile shear strength from the developed empirical relation (1) for the test runs in CCD.

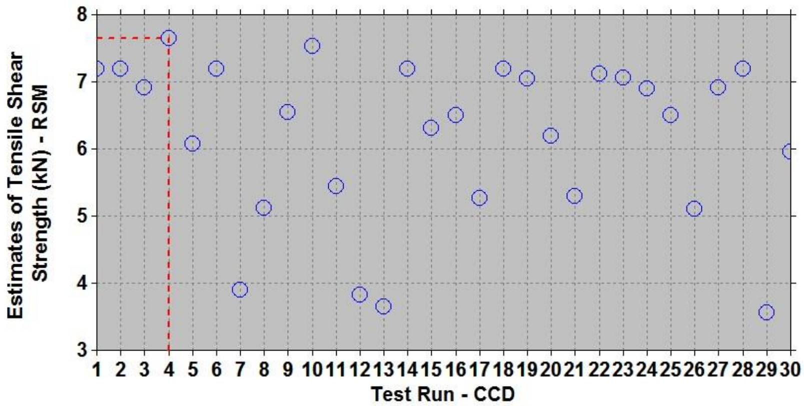

Fig. 3. Estimates of tensile shear strength from the developed empirical relation (1) for the test runs in CCD.

Table 4 gives the levels of the process parameters as per BIBD. The tensile shear strength values corresponding to the levels in Table 4 are obtained from Eq. (1) and Eq. (3). The output responses from Eq. (1) and Eq. (3) are matching well for all the levels of the parameters in Table 3. Using the generated data for the output response in Table 4 the empirical relation obtained from the data of RSM is exactly matching with Eq. (1) whereas the data from the additive law of Table 4 gives the empirical relation almost same as that of Eq. (2). The maximum output response (Tensile shear strength from Table 4) corresponding to sl. no (4) is 7.8356 kN. The input process parameters in sl.no (4) are X_{13}, X_{23}, X_{32}, X_{42}. The set of parameters identified for the maximum output response from CCD Table 3 are different to that of obtained from the ANOVA Table 2. Figure 4 represents the estimates of tensile shear strength from the developed empirical relation (1) for the test runs in BIBD.

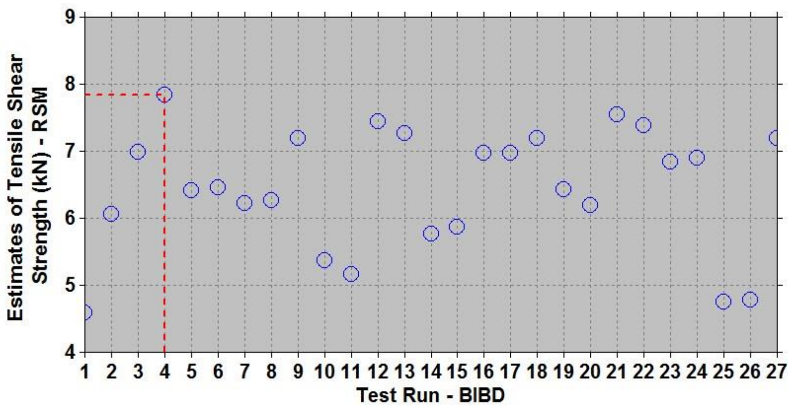

Fig. 4. Estimates of tensile shear strength from the developed empirical relation (1) for the test runs in BIBD.

Careful examination of arriving the same empirical relations using RSM is mainly because of the central point having estimates of output responses same for repeated experiments. In case of scatter in the experimental data, those relations will be slightly different. Figure 5 indicates the variation of tensile shear strength with the coded X1 from the developed empirical relations (1) and (3) for the coded values of X2=1, X3=0, X4=0. Maximum tensile shear strength is at the coded value of X1=1. RSM estimates its value as 7.8356 kN, whereas additive law estimates 8.0055 kN.

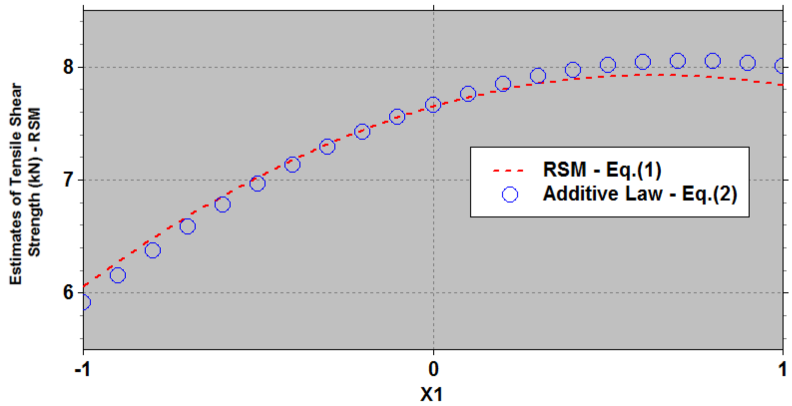

Fig. 5. Variation of tensile shear strength with the coded X1 from the developed empirical relations (1) and (2) for the coded values of X2=1, X3=0, X4=0. Maximum tensile shear strength is at the coded value of X1=1.

Optimal output response and the respective set of process parameters from Taguchi design of experiments and the BIBD are matching well. Optimal set of process parameters are not available in Taguchi's L_{27} orthogonal array (Table 1), whereas they are available in Table 4 of BIBD are adapted from [20-24] RSM Eq. (1) estimates the tensile shear strength for the identified optimal process parameters is 7.8356 kN, which is found to be slightly lower than the confirmation test result of 8.02 kN [1].

3. Conclusions

Three statistical methods namely Taguchi, central composite design (CCD) and balanced incomplete block design (BIBD) are examined considering the data of tensile shear strength $\hat{y}$ of resistance spot welding for galvanized steel (RSW). Empirical relations are developed to generate the data corresponding to the test runs in CCD and BIBD. The optimal process parameters are identified from these methods and verified with the test data. The best method is identified as BIBD. The maximum strength estimated for the optimal input variables using Taguchi approach is close to the test results whereas that of BIBD is slightly low.

Abbreviations

CCD	Central Composite Design
BIBD	Balance Incomplete Block Design
RSM	Response Surface Methodology

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