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Parameter Tuning Method for Genetic Algorithm using Taguchi Orthogonal Array for Non-linear Multimodal Optimization Problem

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Abstract* - Genetic algorithm (GA) is the most widely used meta-heuristic optimization algorithm that can solve complex large scale optimization problems successfully. The only problem lies with the setting of GA control parameters and their levels for the optimal performance of the algorithm. The statistical method can be used for parameter tuning that allows us to collect data properly. Also, it analyzes the collected data accurately and presents the appropriate results. For statistical analysis, Taguchi's robust factorial design which is highly fractional in nature with a special set of L32 orthogonal array (OA) is used. Taguchi's robust design is a proficient method to find an optimum solution with a minimal number of designs of experiment (DOE). Analysis of variance (ANOVA) is conducted to check whether GA control parameters are statistically significant or not for non-linear multimodal optimization problems. Taguchi OA design and ANOVA analysis experimental study is conducted using Stat-Ease software and for the Genetic Algorithm control parameter setting GA solver of MATLAB is used.

Index Terms* – Genetic Algorithm, Parameter optimization, Taguchi Orthogonal Array, ANOVA, Half-normal probability plot, Griewank Function.

I. INTRODUCTION

Genetic Algorithm is a multidimensional optimization global search algorithm that is inspired by Darwin's natural selection theory. Although it is the most widely used subset of evolutionary computation which can solve the complex non-linear multidimensional optimization problems, there is no conventional methodology to identify GA control parameters that can provide an optimum solution. The selection of the optimal parameters to acquire good results is a long-standing problem.

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At times results may be inadequate not because the algorithm is feeble but due to the inaccurate selection of algorithm parameters. The Taguchi method can be used to tackle the aforementioned problem. Unlike other statistical methods, it uses only a minimal number of parameter's combinations that includes required details which may affect performance. Every control parameter has different levels, and they have dissimilar impacts on the various problems. This is to say that a particular engineering design problem requires a specific set of parameters to get an adequate solution. Overview of Genetic Algorithm, Taguchi method and ANOVA are as follows:

A. Genetic Algorithm

Genetic Algorithm was invented by Prof. John Holland at the University of Michigan in 1975; based on the phenomena of "survival of the fittest". In GA, the first phase is to initialize the population of possible solutions referred to as chromosomes. After that GA iteratively applies a set of stochastic operators to obtain the optimal solution to the given problem. To acquire the clear flow of GA procedure, flow graph is presented in Fig. 1. Stochastic operators are as follows:s

1) Fitness Function

Some researchers call fitness function as an objective function. It evaluates the fitness value of each individual to check the closeness of a given solution to the optimal one. Fittest solutions are chosen for reproduction.

2) Selection or reproduction

According to the fitness value calculated in the previous step, two parents are selected for crossing.

3) Crossover or recombination

Crossover produces two new individuals from the parents selected in the selection phase by genetically recombining the information of parents by randomly chosen crossover point. The exploitation of the search space is the basic purpose of using the crossover.

4) Mutation

Mutation is used to make small changes in individuals to maintain diversity in the given search space, a concept known as exploration.s

5) Stopping Criteria

It determines when to terminate generations. It can be set according to research needs such as the maximum number of iterations, value to reach, time limit, etc.

B. Taguchi Method

Taguchi Method is used for statistical analysis of the problem. Taguchi OA is the best tool to work with when there is a large number of parameters [1] .Taguchi OA is a factorial design matrix that is highly fractional in nature proposed by Dr. Genichi Taguchi. It is a balanced design to ensure that all levels of every factor are equally considered. Taguchi robust design conducts the minimal number of experiments that could give full information of every factor and their levels which affect the performance [2, 3].

In Taguchi method, signal to noise ratio (S/N) is used to maximize the objective function's robust design and to minimize quality loss. Taguchi offers many S/N ratios but three of them are used most often that are shown in Table 1, where:

X = Performance characteristic, n = Trial number, m = Mean, s = Variation.

The diagrammatic representation of Taguchi OA is presented in Fig. 2.

Table 1. S/N ratios

Larger – the better	$-10.\log(\sum_{i=1}^{r}(1/X_i^2)/n)$ (1)
Nominal – the best	$-10.\log(m^2/s^2)$ (2)
Smaller – the better	$-10.\log(\sum_{i=1}^{r}(X_i^2)/n)$ (3)

In this study parameter tuning method is used to minimize the non-linear multimodal problems; therefore, smaller – the better S/N ratio is considered.

C. Analysis of Variance

Analysis of variance was invented by R. A. Fisher, hence, some time referred by the name Fisher's ANOVA. It is a Statistical analysis tool that finds out the difference between means of two or more population and relative variance between them.

ANOVA has three types- one way ANOVA, Two-way ANOVA and K-way ANOVA. For the problem statement, K-way ANOVA is used [29].

ANOVA is tested on two hypotheses. Null hypothesis states that all the means are equal

$$H_0 = m_{ij} = m_{ij} = ... = m_{nj} . \qquad (4)$$

Alternative hypothesis which is considered to be true by researchers stated that at least two of the means are not equal

$$H_a = m_{ij} \neq m_{ij} \neq .... \neq m_{nj} . \qquad (5)$$

ANOVA calculation five steps approach are as follows:

1) Evaluate the mean, m and arithmetic mean, $\overline{m}$ of the observed characteristics.

2) Calculate the sums of square effects, SS_{effect} and sums of square errors (residuals), SS_{error} by using (6) and (7):

$$SS_{effect} = \sum_{i=1}^{a} n_i (m - \overline{m})^2 , \qquad (6)$$

$$SS_{error} = \sum_{i=1}^{a}\sum_{j=1}^{n_i} (x_{ij} - m)^2 . \qquad (7)$$

Where:

n_i = number of random variables

x_{ij} = the value of single property measurement.

Sums of SS_{effect} is represented by the SS_{total} used to measure the difference between the groups and SS_{error} represents the variation within the groups.

3) Now calculate the number of independent variables for each factor denoted by the degree of freedom (df).It is represented in (8) and (9).

$$df_{effect} = a - 1 , \qquad (8)$$

$$df_{error} = \sum_{i=1}^{a} n_i - a . \qquad (9)$$

4) Equation (10) and (11) determine mean of the sums of square, which are the variance estimator for all the parameters.

$$MS_{effect} = \frac{SS_{effect}}{df_{effect}} , \qquad (10)$$

$$MS_{error} = \frac{SS_{error}}{df_{error}} . \qquad (11)$$

5) Equation (12) represents F test value to verify null hypothesis.

$$F = \frac{MS_{effect}}{MS_{error}} . \qquad (12)$$

Value calculated by (12) is compared by the critical value F_α that is read from tables. If the calculated F value is larger than F_α , null hypothesis will be rejected and alternative hypothesis will be approved.

The paper is organized in six sections including introduction followed by related work, in section 2. Section 3 depicts the problem definition and proposal. Section 4 describes experimental settings and section 5 analyses the simulated results followed by section 6, which concludes the paper

II. RELATED WORK

Extensive studies on GA parameters, their interactions, and values have been presented in the literature survey.

Many researchers zeroed in on mutation and crossover control parameters as they believe these are the most effective parameters among all. In order to get optimum result, mutation rate should not exceed 0. 05 and the population size should be kept between 30 to100. Also, elitism plays an imperative role [4, 5].

A study has shown that a small population is more sensitive to mutation rate and for large population size crossover proved to be more effective [6]. Mutation rate offers good solutions to simple problems, and it can be kept variable [7]. Crossover is a key operator for complex problems, and it provides globally optimized solution [8], but [9] disagree this analysis, pointing out that most influenced GA parameters are mutation rate, Selection and population size. Reference [10] proposes that combination of mutation and crossover give best solution, but too less mutation rate leads to premature convergence and too high prevents global optimum value. Reference [11] suggests that crossover does not have significant influence on solution, while high mutation rate is highly significant parameter. Some studies use trial and error and user experienced based method to choose GA parameters [12, 13].

Studies continued and the researches on GA parameters and their interactions are well documented in the related literature [14, 15, 16, 17, 18, 19, 20, 21, 22].

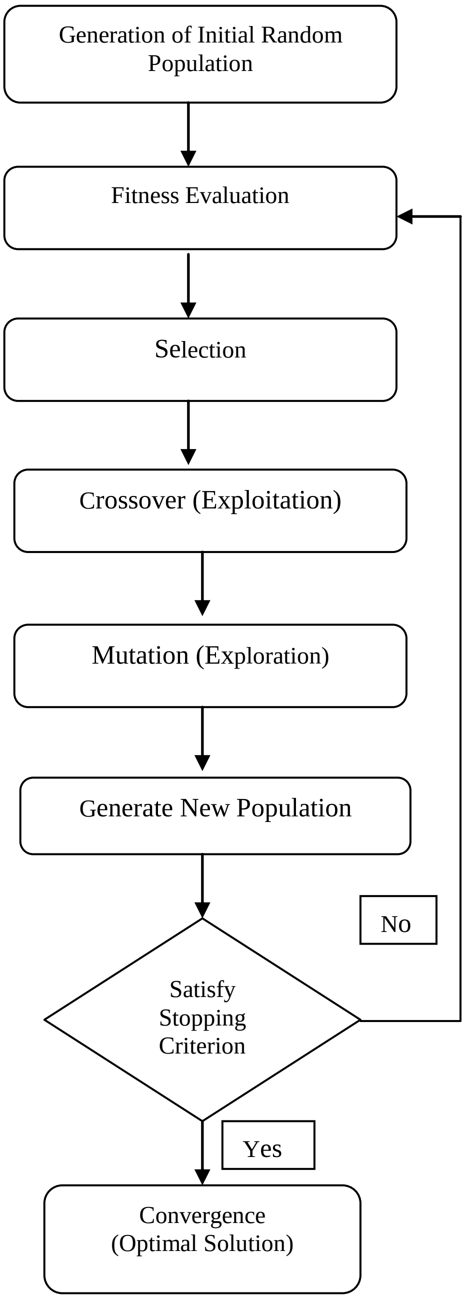

Fig. 1. GA flow graph

After analyzing the aforementioned researches, it is concluded that the selection of combinations of GA parameters and their levels is not an easy task as there is a myriad number of combinations available. Also, considering all of them is not worthwhile. That is why Taguchi method is preferred which involves the use of least number of experiments.

III. PROPOSED APPROACH

In proposed approach, Griewank function is used as a problem statement to identify GA parameters using Taguchi's OA method.

A. Problem formulation

Some widely used benchmark functions, which are Non-linear and multimodal in nature, are Rastrigin, Griewank, and Schwefel. Griewank function is used for statistical analysis as a case study to identify the parameter tuning method for the Genetic Algorithm. Griewank function is defined as follows:

$$f(x) = \sum_{i=1}^{d} x_i^2 \Big/ 4000 - \prod_{i=1}^{d} \cos\left(x_i \Big/ \sqrt{i}\right) + 1 . \qquad (4)$$

The function is usually evaluated on the bounds $x_i \in [-600, 600]$, for all i = 1, …, d. Parabola is produced by the summation term and a local minimum for the function exists above the parabola level. Search space dimensions are set according to the product term. Function tends to get flattered with the increase of search range. The complexity of the Griewank function is O(nln(n)), where n represents the function parameter numbers. It is considered as a good function for GA control parameter performance testing because subpopulation created by product function mutually depends on parallel GA models [23, 24, 25].

B. Proposed Method

To minimize the computational time and produce an optimized solution using optimal parameter tuning of GA parameters, Taguchi Orthogonal Array Design is used. Explanation steps of the proposed approach are given below:

1) Identification of GA parameters and levels

GA solver of MATLAB is considered for experiment execution. Table 2 depicts all the GA factors and their levels. Population size and elite count are integer value parameters, crossover fraction is continuous value parameter and rests are discrete ones. The direction has two levels whereas other parameters are of four levels.

2) Taguchi OA design designation

According to the number of parameters and their levels, DOE is decided. Taguchi robust DOE with L32 (2^1*4^9) OA is chosen for the set of experiments. L32 means only 32 sets of experiments for the given problem. Stat-Ease software is used for statistical analysis of experiments.

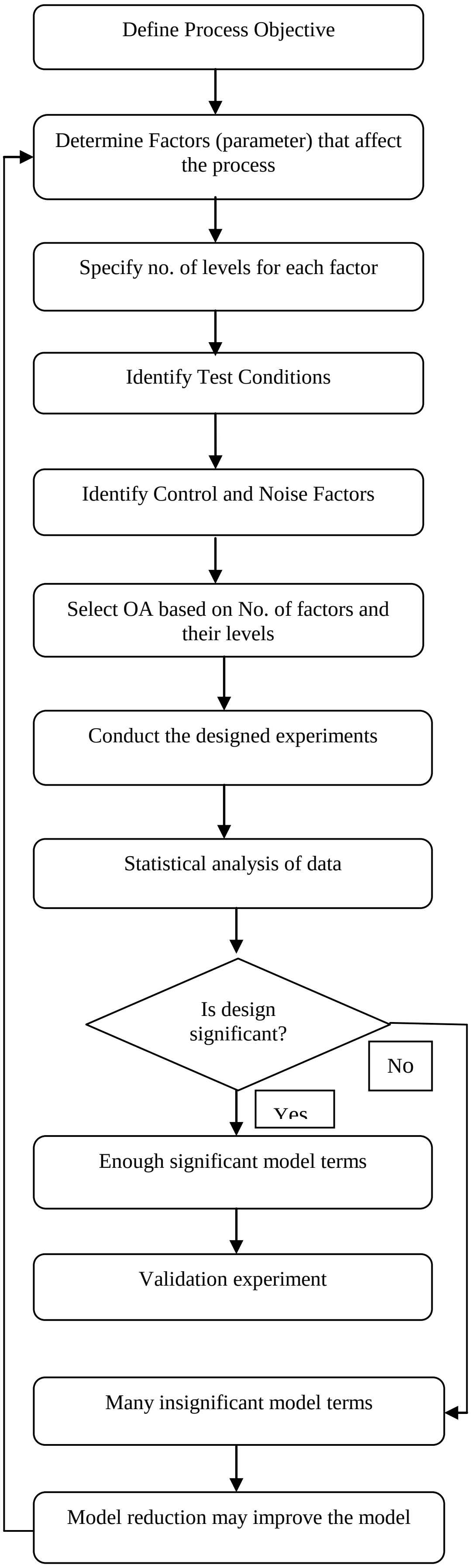

Fig. 2. Taguchi OA flow chart

Table 2. GA factors and levels

Name	Levels	L[1]	L[2]	L[3]	L[4]
Direction	2	Forward	Both		
Population Size	4	50	100	150	200
Fitness Scaling Function	4	Rank	Top	Proportional	Shift linear
Selection	4	Stochastic Uniform	Uniform	Tournament	Roulette
Elite Count	4	2	6	8	10
Crossover Fraction	4	0.4	0.6	0.8	1.0
Mutation	4	Constrain Dependent	Uniform	Gaussian	Adaptive Feasible
Crossover Function	4	Single Point	Two Point	Arithmetic	Heuristic
Hybrid Function	4	None	Fminsearch	Pattern Search	Fminunc

IV. EXPERIMENTAL SETUP

After characterizing the problem statement and its constraints, control parameters of the genetic algorithm are set according to the options produced by the Taguchi OA experiment and are specified in Table 3. The response of every parameter setting is also shown in Table 3 that is referred to global optimize value. To maintain the consistency of the response, every experiment should be repeated 10 times and the best value should opt as a response.

PC configuration for the experiment execution is as follows – Windows 7 (2009); processor- Intel(R) Core(TM) i3 CPU M50@2.27GHz; RAM 2.99GB; 32-bit operating system, simulated in Stat-Ease and MATLAB.

V. ANALYSES OF THE RESULTS

For the analyses of the results, statistical Analysis is carried out to check the significance of every parameter involved in the given problem [26].

A. Half-normal probability plot

To differentiate significant and insignificant effects on the response, the concept of Half-normal probability plot came into existence. The parameter with a higher normal effect value is more significant to the model [27]. Viewed from Fig. 3, factors B, C, D, E, H, and J are significant to the model, and other factors are included in the model for hierarchical reasons in order to conduct further analysis.

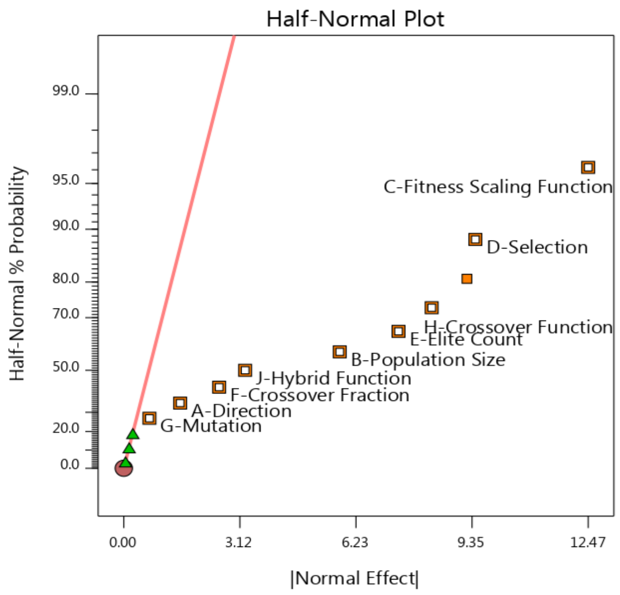

Fig.3. Half-normal Probability plot

B. Analysis of variance (ANOVA)

ANOVA assumptions are checked by the diagnostic plots shown in Fig. 4(a-d). Fig. 4(a) represents a normal probability plot which signifies that residuals are normally distributed or not. In fig. 4(a) all the residuals are scattered around the straight line that indicates that normal distribution assumption is fulfilled. Fig. 4(b) is "residual vs. predicted" value plot. In this plot residual points are scattered only within the upper and lower limit which shows that homogeneity of variance assumption is satisfied. In fig. 4(c), all the residual points are speckled within the upper and lower limit without showing any specific pattern and owing to this the assumption of independence is fulfilled. Viewed from fig. 4(d), all the points are drawn near straight line indicates that the model is significant [28]. ANOVA analysis shown in Table 4 is designed with the use of the half-normal probability plot because all the ANOVA assumptions are satisfied.

In Table 4 F-value is calculated to check that a group of variables is jointly significant or not. P-value range exists between 0 and 1 (no chance to absolute certainty). P-value of 0.05 considered as a borderline for statistical significance testing. Model terms are considered significant if the p-value is less than 0.05 [29].

F-value for the model is 19.06 which implies that there is only a 0.07% chance of occurring a noise due to this large value. P-values for the model terms B, C, D, E, H, and J are less than 0.05 that indicates that these are significant model terms. The overall calculation of F-values and P-values using software Stat-Ease indicates that the overall model is significant, although some terms are not statistically significant. For a model to be statistically significant both F-value and P-value should be in the significant range.

According to Table 4, Fitness Scaling Function is the most important control parameter that affects GA's solution. The second important control parameter is Selection. The next significant parameters are Crossover Function, Elite Count, Population Size and Hybrid Function respectively.

Parameter levels that give optimized result for the non-linear multimodal Griewank function are represented in Table 5.

VI. CONCLUSION

The proposed work presents a systematic and comprehensive methodology for optimum GA's parameter selection based on Taguchi Orthogonal Array. Taguchi OA reduces the computational time and memory usage as it uses only 32 sets of experiments, unlike a traditional method that uses 131072 sets of experiments. Experimental results suggest that Fitness Scaling function and Selection are the highly important and influential parameters for Griewank Function. The proposed approach provides a better solution than the default GA parameter selection. GA's parameter tuning using Taguchi robust design is an effective methodology for all the Genetic Algorithm users; it can be used in any area of the GA to decide the optimal parameter set. Interaction of the Different GA parameters and levels can be statistically analyzed as future work.

Table 3. Experimental layout: Taguchi L32 (2^1*4^9) OA generated by Stat-Ease

		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Response 1
Std	**Run**	**A: Direction**	**B: Population Size**	**C: Fitness Scaling Function**	**D: Selection**	**E: Elite Count**	**F: Crossover Fraction**	**G: Mutation**	**H: Crossover Function**	**J: Hybrid Function**	**Global Optimize Value**
1	16	Forward	50	Rank	Stochastic Uniform	2	0.4	Constraint Dependent	Single Point	None	7.9883E-06
2	9	Forward	50	Top	Uniform	6	0.6	Uniform	Two Point	Fminsearch	0.002428
3	18	Forward	50	Proportional	Tournament	8	0.8	Gaussian	Arithmetic	Pattern Search	0.00013501
4	13	Forward	50	Shift linear	Roulette	10	1.0	Adaptive Feasible	Heuristic	Fminunc	0.0003054

5	17	Forward	100	Rank	Stochastic Uniform	6	0.6	Gaussian	Arithmetic	Fminunc	1.134E-10
6	2	Forward	100	Top	Uniform	2	0.4	Adaptive Feasible	Heuristic	Pattern Search	1.3859E-10
7	21	Forward	100	Proportional	Tournament	10	1.0	Constraint Dependent	Single Point	Fminsearch	8.0083E-05
8	7	Forward	100	Shift linear	Roulette	8	0.8	Uniform	Two Point	None	0.0123
9	20	Forward	150	Rank	Uniform	8	1.0	Constraint Dependent	Two Point	Pattern Search	0.00016806
10	26	Forward	150	Top	Stochastic Uniform	10	0.8	Uniform	Single Point	Fminunc	0.02314
11	11	Forward	150	Proportional	Roulette	2	0.6	Gaussian	Heuristic	None	5.3202E-06
12	32	Forward	150	Shift linear	Tournament	6	0.4	Adaptive Feasible	Arithmetic	Fminsearch	0.00054
13	29	Forward	200	Rank	Uniform	10	0.8	Gaussian	Heuristic	Fminsearch	1.6943E-08
14	22	Forward	200	Top	Stochastic Uniform	8	1.0	Adaptive Feasible	Arithmetic	None	0.0542
15	15	Forward	200	Proportional	Roulette	6	0.4	Constraint Dependent	Two Point	Fminunc	4.0421E-06
16	24	Forward	200	Shift linear	Tournament	2	0.6	Uniform	Single Point	Pattern Search	6.9984E-05
17	4	Both	50	Rank	Roulette	2	1.0	Uniform	Arithmetic	Fminsearch	0.027125
18	25	Both	50	Top	Tournament	6	0.8	Constraint Dependent	Heuristic	None	0.00016984
19	1	Both	50	Proportional	Uniform	8	0.6	Adaptive Feasible	Single Point	Fminunc	6.5691E-12
20	27	Both	50	Shift linear	Stochastic Uniform	10	0.4	Gaussian	Two Point	Pattern Search	6.1003E-06
21	14	Both	100	Rank	Roulette	6	0.8	Adaptive Feasible	Single Point	Pattern Search	1.4034E-12
22	6	Both	100	Top	Tournament	2	1.0	Gaussian	Two Point	Fminunc	0.0028182
23	30	Both	100	Proportional	Uniform	10	0.4	Uniform	Arithmetic	None	0.00076001
24	5	Both	100	Shift linear	Stochastic Uniform	8	0.6	Constraint Dependent	Heuristic	Fminsearch	7.9996E-07
25	19	Both	150	Rank	Tournament	8	0.4	Uniform	Heuristic	Fminunc	2.3658E-06
26	3	Both	150	Top	Roulette	10	0.6	Constraint Dependent	Arithmetic	Pattern Search	0.04123
27	23	Both	150	Proportional	Stochastic Uniform	2	0.8	Adaptive Feasible	Two Point	Fminsearch	2.6065E-12
28	12	Both	150	Shift linear	Uniform	6	1.0	Gaussian	Single Point	None	0.00036819
29	10	Both	200	Rank	Tournament	10	0.6	Adaptive Feasible	Two Point	None	2.8966E-11
30	8	Both	200	Top	Roulette	8	0.4	Gaussian	Single Point	Fminsearch	0.05412
31	28	Both	200	Proportional	Stochastic Uniform	6	1.0	Uniform	Heuristic	Pattern Search	0.00065
32	31	Both	200	Shift linear	Uniform	2	0.8	Constraint Dependent	Arithmetic	Fminunc	3.854E-05

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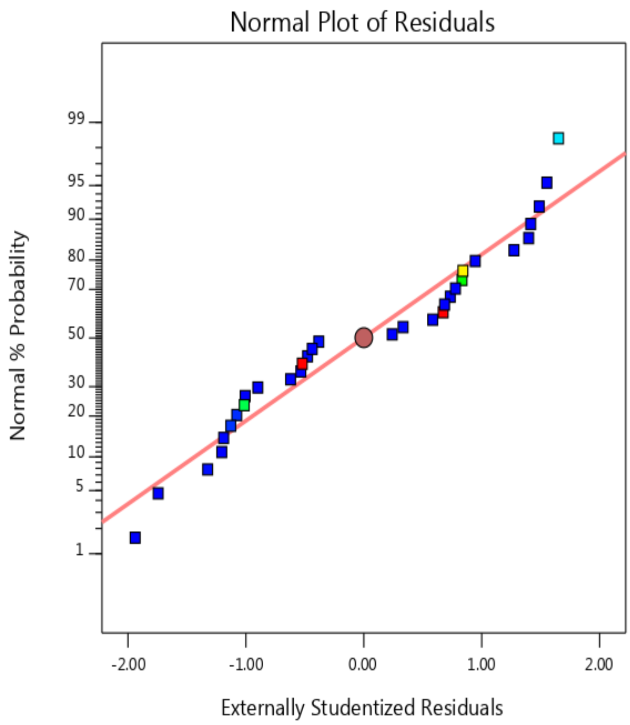

Fig. 4(a). Normal Probability Plot of Residuals

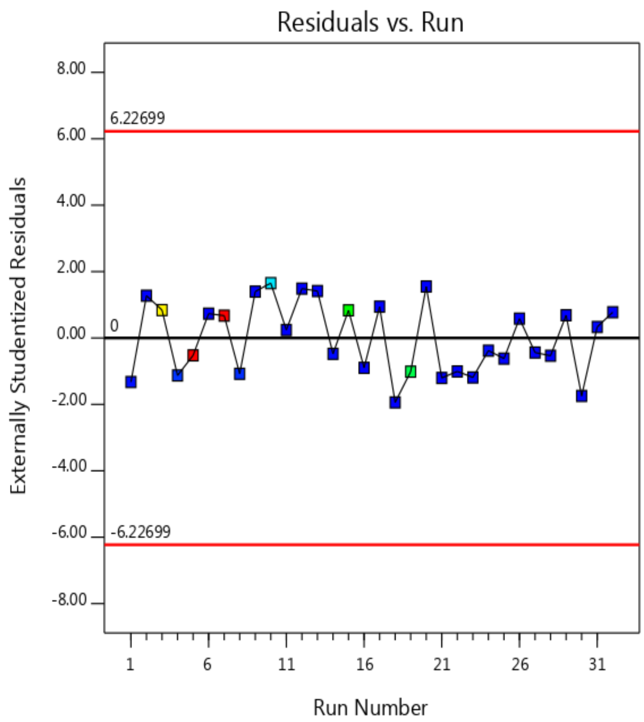

Fig. 4(b). Residuals vs. Run

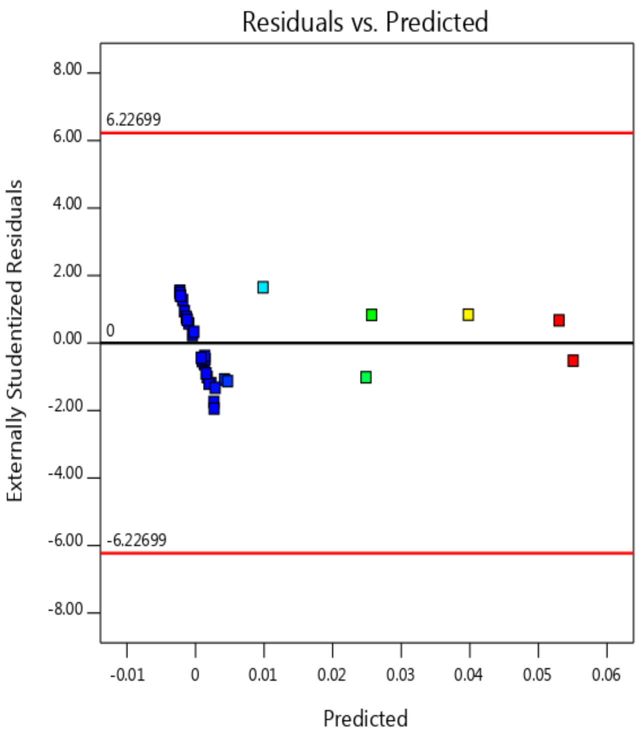

Fig. 4(c). Residual vs. Predicted

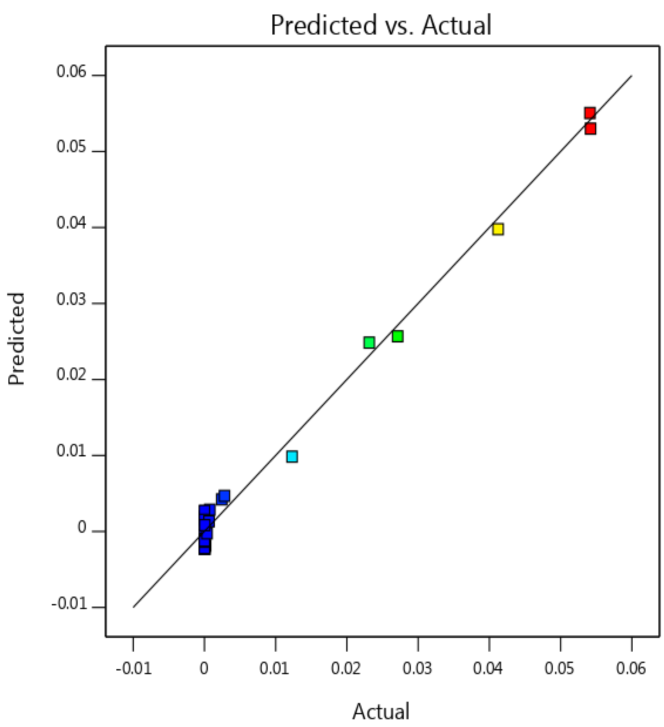

Fig. 4(d). Predicted vs. Actual

Fig. 4(a-d) Diagnostic plots for ANOVA assumptions

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Table 4. ANOVA for factorial model

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.0074	25	0.0003	19.06	0.0007	significant
A-Direction	0.0000	1	0.0000	2.30	0.1805	
B-Population Size	0.0006	3	0.0002	13.66	0.0043	
C-Fitness Scaling Function	0.0026	3	0.0009	55.22	< 0.0001	
D-Selection	0.0015	3	0.0005	32.75	0.0004	
E-Elite Count	0.0010	3	0.0003	20.87	0.0014	
F-Crossover Fraction	0.0002	3	0.0001	3.75	0.0789	
G-Mutation	0.0000	3	0.0000	0.8051	0.5353	
H-Crossover Function	0.0012	3	0.0004	25.66	0.0008	
J-Hybrid Function	0.0002	3	0.0001	5.34	0.0394	
Residual	0.0001	6	0.0000			
Cor Total	0.0075	31				

Table 5. The selected parameter set for the GA solver using MATLAB

Direction	Population Size	Fitness Scaling Function	Selection	Elite Count	Crossover Fraction	Mutation	Crossover Function	Hybrid Function
Forward	200	Shift linear	Roulette	10	0.4	Constraint Dependent	Heuristic	None

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