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# Adjustment of Genetic Algorithm Parameters Using Response Surface Methodology

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***Abstract***-The present study is aimed to adjust the parameters of the genetic algorithm using Response Surface Methodology. The main parameters of the genetic algorithm, i.e., “maximum number of iterations”, “population size”, “parents (offsprings) population size ratio”, “mutants population size ratio”, “tournament selection size”, and “selection pressure” is considered. The lower and upper levels of each are selected by reviewing previous studies and assigned to the Design-Expert software. Then the proposed table of Central Composite Design is completed using MATLAB codes related to the genetic algorithm. Mathematical modelling of genetic algorithm parameters and their optimization with all statistical details related to prediction and optimization is investigated. The best cost obtained of two soft wars is compared. The optimal response obtained with the adjusted parameters is approximately the same, and it confirms the consistency of the results obtained from these two software.

***Keywords-*** *Genetic Algorithm, Response Surface Methodology, Modelling, Optimization*

## I. INTRODUCTION

Genetic algorithms are one of the evolutionary algorithms a kind of computer search based on optimization algorithms inspired by the structure of genes and chromosomes. This algorithm is nowadays used in many different sciences such as biology [1-2], engineering and technical sciences (neural networks, image processing, pattern recognition, etc.) [3-12], fundamental sciences [13-15], social sciences and more [16-17].

Because of the importance and widespread use of this algorithm, optimization of its parameters can be an important topic. For this reason, in this paper, the modelling and optimization of six main parameters of genetic algorithm and their effects on the cost function are discussed.

The experimental part of the work is done using MATLAB codes related to the genetic algorithm and the prediction, estimation, modelling and optimization is done using Central Composite Design of Response Surface Methodology by Design Expert Software. This software has high capabilities for modelling and optimizing various science and engineering problems, [18-22].

The combination of these two powerful optimization software, one for precision computing and the other for approximate computing, has produced some interesting results for adjusting the parameters of the genetic algorithm. Also, a regression plot of a fitted mathematical model is drawn which shows the accuracy of the predicted model. These results are presented in sections 2 and 3 and sub-sections of them with all relevant details and programs. Numerous tables and figures have been inserted for better understanding. The results of the comparison are also clearly stated.

## II. MAIN STRUCTURE

Genetic algorithms are the effective way of searching in very large spaces that eventually leads to the orientation of finding an optimal answer that one may not be able to find in a lifetime. Genetic algorithms are very different from traditional optimization techniques. In these algorithms, the design space must be transformed into the genetic space. So genetic algorithms work with a set of coded variables. The advantage of working with encoded variables is that codes are capable of converting continuous space into discrete space.

The other difference is that in the genetic algorithm (GA) a population or set of points at a particular moment can be examined while in the old optimization methods can only work for a specific point. This means that GA processes a large number of designs at a time. Another interesting point is that the principles of GA are based on a random process, or more correctly, guided random process. Therefore, random operators adaptively examine the search space. If the three main parts of GA, namely the objective function or cost function, defining and implementing the genetic representation, and defining and implementing GA operators are correctly defined, this algorithm works well. Finally, it can be improved the system performance by making changes.

## III. METHODOLOGY

### *A. Modelling*

Suppose the genetic algorithm is used to solve an optimization problem and six parameters according to Table I are used.

TABLE I. RESULTS OF GA ACCORDING TO SUGGESTED RUNS OF RSM

| Run | Factor 1 A: MaxIt | Factor 2 B: Npop | Factor 3 C: Pc | Factor 4 D: Pm | Factor 5 E: TourSize | Factor 6 F: SP | Response Best Cost | Run | Factor 1 A: MaxIt | Factor 2 B: Npop | Factor 3 C: Pc | Factor 4 D: Pm | Factor 5 E: TourSize | Factor 6 F: SP | Response Best Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3000 | 200 | 0.7 | 0.1 | 2 | 15 | 7.9555E-009 | 44 | 3000 | 50 | 0.7 | 0.1 | 2 | 5 | 1.3388E-011 |
| 2 | 2000 | 125 | 0.8 | 0.15 | 4 | 10 | 3.0641E-010 | 45 | 1000 | 50 | 0.7 | 0.2 | 4 | 15 | 2.5276E-007 |
| 3 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 1.5392E-013 | 46 | 1000 | 50 | 0.9 | 0.1 | 2 | 5 | 7.7518E-007 |
| 4 | 3000 | 200 | 0.9 | 0.1 | 4 | 15 | 3.5386E-011 | 47 | 2000 | 50 | 0.8 | 0.15 | 3 | 10 | 2.1069E-008 |
| 5 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 5.51E-010 | 48 | 3000 | 50 | 0.7 | 0.1 | 2 | 15 | 5.42E-008 |
| 6 | 3000 | 50 | 0.9 | 0.1 | 2 | 15 | 5.5098E-012 | 49 | 1000 | 50 | 0.9 | 0.1 | 4 | 5 | 3.5962E-007 |
| 7 | 1000 | 50 | 0.9 | 0.2 | 2 | 15 | 2.2416E-008 | 50 | 3000 | 200 | 0.7 | 0.2 | 2 | 5 | 3.8465E-019 |
| 8 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 3.1E-007 | 51 | 1000 | 200 | 0.9 | 0.2 | 4 | 5 | 8.1124E-010 |
| 9 | 2000 | 125 | 0.8 | 0.2 | 3 | 10 | 1.1454E-008 | 52 | 1000 | 200 | 0.7 | 0.2 | 4 | 5 | 3.5722E-013 |
| 10 | 1000 | 50 | 0.7 | 0.2 | 4 | 5 | 1.0548E-008 | 53 | 3000 | 50 | 0.7 | 0.2 | 4 | 5 | 1.6204E-008 |
| 11 | 1000 | 200 | 0.9 | 0.2 | 2 | 15 | 2.661E-016 | 54 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 7.2035E-010 |
| 12 | 3000 | 50 | 0.7 | 0.1 | 4 | 15 | 1.3366E-008 | 55 | 1000 | 200 | 0.7 | 0.2 | 2 | 5 | 3.8567E-010 |
| 13 | 1000 | 50 | 0.9 | 0.2 | 4 | 5 | 1.448E-008 | 56 | 2000 | 125 | 0.8 | 0.15 | 3 | 15 | 1.8037E-010 |
| 14 | 3000 | 50 | 0.9 | 0.2 | 4 | 5 | 1.3846E-008 | 57 | 3000 | 50 | 0.9 | 0.1 | 4 | 5 | 3.6854E-008 |
| 15 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 4.5135E-011 | 58 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 7.3273E-012 |
| 16 | 3000 | 200 | 0.9 | 0.1 | 2 | 15 | 2.3154E-017 | 59 | 3000 | 200 | 0.9 | 0.2 | 2 | 15 | 7.5568E-010 |
| 17 | 1000 | 200 | 0.9 | 0.2 | 4 | 15 | 2.5242E-008 | 60 | 1000 | 50 | 0.7 | 0.1 | 2 | 15 | 5.0425E-007 |
| 18 | 2000 | 125 | 0.9 | 0.15 | 3 | 10 | 1.6101E-014 | 61 | 3000 | 50 | 0.9 | 0.1 | 4 | 15 | 9.0708E-008 |
| 19 | 3000 | 200 | 0.7 | 0.2 | 4 | 15 | 7.8023E-010 | 62 | 3000 | 200 | 0.9 | 0.1 | 2 | 5 | 2.8525E-013 |
| 20 | 1000 | 200 | 0.9 | 0.1 | 2 | 15 | 4.0948E-009 | 63 | 3000 | 50 | 0.7 | 0.2 | 2 | 15 | 3.6508E-010 |
| 21 | 3000 | 50 | 0.9 | 0.2 | 2 | 15 | 5.3394E-008 | 64 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 4.7383E-009 |
| 22 | 3000 | 125 | 0.8 | 0.15 | 3 | 10 | 2.488E-009 | 65 | 3000 | 200 | 0.9 | 0.2 | 2 | 5 | 1.7537E-011 |
| 23 | 3000 | 50 | 0.9 | 0.2 | 4 | 15 | 2.1674E-009 | 66 | 2000 | 125 | 0.7 | 0.15 | 3 | 10 | 2.0318E-009 |
| 24 | 1000 | 50 | 0.7 | 0.1 | 4 | 5 | 4.7199E-007 | 67 | 1000 | 50 | 0.7 | 0.2 | 2 | 15 | 8.8529E-008 |
| 25 | 1000 | 50 | 0.9 | 0.2 | 4 | 15 | 7.0605E-008 | 68 | 1000 | 200 | 0.7 | 0.1 | 4 | 15 | 3.2262E-008 |
| 26 | 2000 | 125 | 0.8 | 0.15 | 2 | 10 | 7.7055E-009 | 69 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 7.366E-009 |
| 27 | 1000 | 50 | 0.7 | 0.2 | 2 | 5 | 2.7088E-008 | 70 | 3000 | 50 | 0.7 | 0.2 | 2 | 5 | 3.0425E-008 |
| 28 | 1000 | 50 | 0.9 | 0.1 | 4 | 15 | 1.1917E-007 | 71 | 1000 | 200 | 0.9 | 0.1 | 4 | 15 | 3.1238E-008 |
| 29 | 3000 | 50 | 0.9 | 0.1 | 2 | 5 | 1.418E-010 | 72 | 1000 | 50 | 0.7 | 0.1 | 2 | 5 | 5.2763E-007 |
| 30 | 1000 | 200 | 0.7 | 0.2 | 4 | 15 | 7.763E-009 | 73 | 1000 | 200 | 0.9 | 0.1 | 4 | 5 | 2.081E-011 |
| 31 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 3.438E-009 | 74 | 3000 | 200 | 0.9 | 0.1 | 4 | 5 | 3.2015E-013 |
| 32 | 1000 | 200 | 0.9 | 0.2 | 2 | 5 | 1.2077E-008 | 75 | 1000 | 200 | 0.7 | 0.1 | 4 | 5 | 4.5774E-010 |
| 33 | 1000 | 125 | 0.8 | 0.15 | 3 | 10 | 4.1413E-009 | 76 | 3000 | 200 | 0.7 | 0.1 | 2 | 5 | 3.4915E-009 |
| 34 | 2000 | 200 | 0.8 | 0.15 | 3 | 10 | 2.6267E-009 | 77 | 1000 | 50 | 0.7 | 0.1 | 4 | 15 | 6.9169E-007 |
| 35 | 1000 | 50 | 0.9 | 0.1 | 2 | 15 | 1.1135E-006 | 78 | 3000 | 50 | 0.7 | 0.2 | 4 | 15 | 5.1264E-010 |
| 36 | 3000 | 50 | 0.9 | 0.2 | 2 | 5 | 1.8229E-009 | 79 | 3000 | 200 | 0.9 | 0.2 | 4 | 15 | 3.0936E-010 |
| 37 | 2000 | 125 | 0.8 | 0.15 | 3 | 10 | 7.9778E-009 | 80 | 1000 | 200 | 0.7 | 0.1 | 2 | 15 | 7.8412E-009 |
| 38 | 3000 | 50 | 0.7 | 0.1 | 4 | 5 | 1.2909E-017 | 81 | 2000 | 125 | 0.8 | 0.1 | 3 | 10 | 7.4359E-008 |
| 39 | 1000 | 200 | 0.9 | 0.1 | 2 | 5 | 1.4856E-015 | 82 | 3000 | 200 | 0.7 | 0.2 | 4 | 5 | 1.9573E-013 |
| 40 | 2000 | 125 | 0.8 | 0.15 | 3 | 5 | 1.8036E-009 | 83 | 1000 | 200 | 0.7 | 0.2 | 2 | 15 | 1.3567E-008 |
| 41 | 3000 | 200 | 0.7 | 0.2 | 2 | 15 | 1.2844E-009 | 84 | 3000 | 200 | 0.7 | 0.1 | 4 | 15 | 1.1923E-010 |
| 42 | 3000 | 200 | 0.7 | 0.1 | 4 | 5 | 1.917E-009 | 85 | 1000 | 50 | 0.9 | 0.2 | 2 | 5 | 2.0665E-010 |
| 43 | 3000 | 200 | 0.9 | 0.2 | 4 | 5 | 1.7374E-009 | 86 | 1000 | 200 | 0.7 | 0.1 | 2 | 5 | 3.8969E-013 |

According to the choice of the quadratic model that has all the appropriate statistical conditions, the results of the analysis of variance are shown in Table 2.

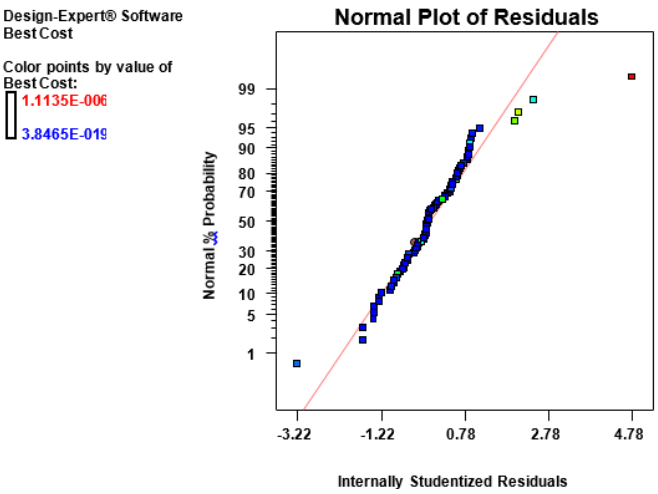
According to the fitted model, the final equation in terms of actual coded factors is obtained in equation (1).

This large equation well predicts the magnitude of the effect of each factor and the extent of the interaction of the factors predicting the response. The statistical graphs corresponding to the modelling are also shown in Fig. 1 (a-p).

$$Best\ Cost\ = +1.60515E-006-4.45994E-010 MaxIt-6.54531E-009\times Npop+6.12141E-007\times Pc-1.12658E-005\times Pm+1.73675E-008\times TourSize+1.72389E-008\times SP+9.62142E-013\times MaxIt\times Npop+2.48847E-011\times MaxIt\times Pc+1.25227E-009\times MaxIt\times Pm+1.61374E-011\times MaxIt\times TourSize-2.07795E-012\times MaxIt\times SP+2.91005E-011\times Npop\times Pc+1.72010E-008\times Npop\times Pm+2.26223E-010\times Npop\times TourSize-83024E-11\times Npop\times SP-1.38659E-006\times Pc\times Pm-2.26580E-007\times Pc\times TourSize-8.44590E-009\times Pc\times SP+4.10715E-007\times Pm\times TourSize-5.14485E-009\times Pm\times SP-2.60740E-010\times TourSize\times SP+4.19727E-015\times MaxIt^2+2.26320E-012\times Npop^2+1.89853E-007\times Pc^2+1.75156E-005\times Pm^2+4.88858E-009\times TourSize^2+7.49843E-011\times SP^2 \quad (1)$$

TABLE II. ANALYSIS OF VARIANCE FOR RESPONSE SURFACE QUADRATIC MODEL

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 2.1E-12 | 27 | 7.79E-14 | 5.024642 | < 0.0001 | significant |
| A-MaxIt | 3.57E-13 | 1 | 3.57E-13 | 23.02772 | < 0.0001 | |
| B-Npop | 4.14E-13 | 1 | 4.14E-13 | 26.70551 | < 0.0001 | |
| C-Pc | 5.45E-18 | 1 | 5.45E-18 | 0.000352 | 0.9851 | |
| D-Pm | 2.72E-13 | 1 | 2.72E-13 | 17.57039 | < 0.0001 | |
| E-TourSize | 1.49E-14 | 1 | 1.49E-14 | 0.959239 | 0.3314 | |
| F-SP | 1.23E-14 | 1 | 1.23E-14 | 0.795488 | 0.3761 | |
| AB | 3.33E-13 | 1 | 3.33E-13 | 21.49116 | < 0.0001 | |
| AC | 3.96E-16 | 1 | 3.96E-16 | 0.025558 | 0.8735 | |
| AD | 2.51E-13 | 1 | 2.51E-13 | 16.18076 | 0.0002 | |
| AE | 1.67E-14 | 1 | 1.67E-14 | 1.074794 | 0.3042 | |
| AF | 6.91E-15 | 1 | 6.91E-15 | 0.445524 | 0.5071 | |
| BC | 3.05E-18 | 1 | 3.05E-18 | 0.000197 | 0.9889 | |
| BD | 2.66E-13 | 1 | 2.66E-13 | 17.17238 | 0.0001 | |
| BE | 1.84E-14 | 1 | 1.84E-14 | 1.188105 | 0.2802 | |
| BF | 7.21E-15 | 1 | 7.21E-15 | 0.464911 | 0.4981 | |
| CD | 3.08E-15 | 1 | 3.08E-15 | 0.198379 | 0.6577 | |
| CE | 3.29E-14 | 1 | 3.29E-14 | 2.11886 | 0.1509 | |
| CF | 1.14E-15 | 1 | 1.14E-15 | 0.073602 | 0.7871 | |
| DE | 2.7E-14 | 1 | 2.7E-14 | 1.740528 | 0.1923 | |
| DF | 1.06E-16 | 1 | 1.06E-16 | 0.006828 | 0.9344 | |
| EF | 1.09E-16 | 1 | 1.09E-16 | 0.007015 | 0.9335 | |
| A^2 | 4.21E-17 | 1 | 4.21E-17 | 0.002713 | 0.9586 | |
| B^2 | 3.87E-16 | 1 | 3.87E-16 | 0.024961 | 0.8750 | |
| C^2 | 8.61E-18 | 1 | 8.61E-18 | 0.000555 | 0.9813 | |
| D^2 | 4.58E-15 | 1 | 4.58E-15 | 0.295333 | 0.5889 | |
| E^2 | 5.71E-17 | 1 | 5.71E-17 | 0.003681 | 0.9518 | |
| F^2 | 8.39E-18 | 1 | 8.39E-18 | 0.000541 | 0.9815 | |
| Residual | 8.99E-13 | 58 | 1.55E-14 | | | |
| Lack of Fit | 8.14E-13 | 49 | 1.66E-14 | 1.758853 | 0.1840 | not significant |
| Pure Error | 8.5E-14 | 9 | 9.45E-15 | | | |
| Cor Total | 3E-12 | 85 | | | | |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Normal Plot of Residuals
Normal % Probability
99
95
90
80
70
50
30
20
10
5
1
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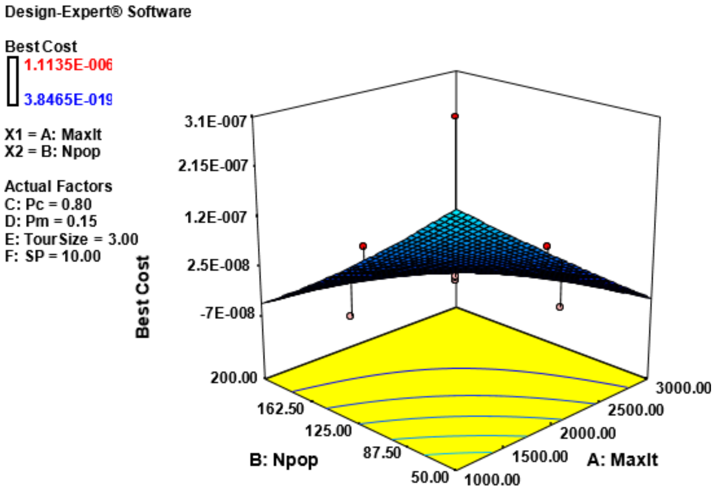
-1.22
0.78
2.78
4.78
Internally Studentized Residuals

(a)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X2 = B: Npop
Actual Factors
C: Pc = 0.80
D: Pm = 0.15
E: TourSize = 3.00
F: SP = 10.00
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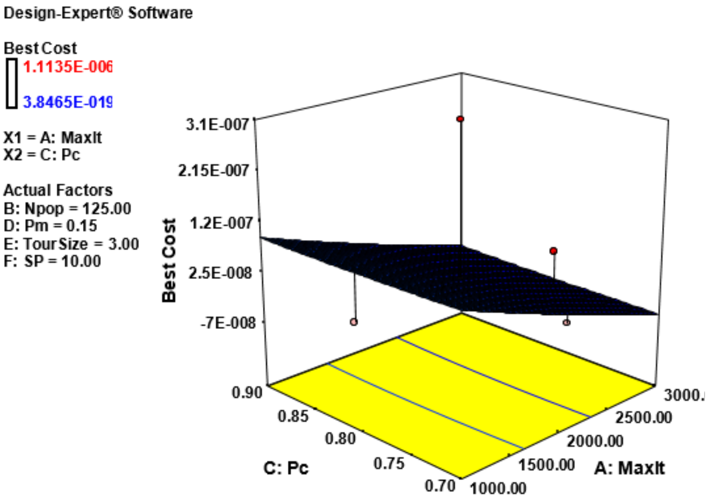
3.1E-007
2.15E-007
1.2E-007
2.5E-008
-7E-008
200.00
162.50
125.00
87.50
50.00
B: Npop
1000.00
1500.00
2000.00
2500.00
3000.00
A: MaxIt

(b)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D: Pm = 0.15
E: TourSize = 3.00
F: SP = 10.00
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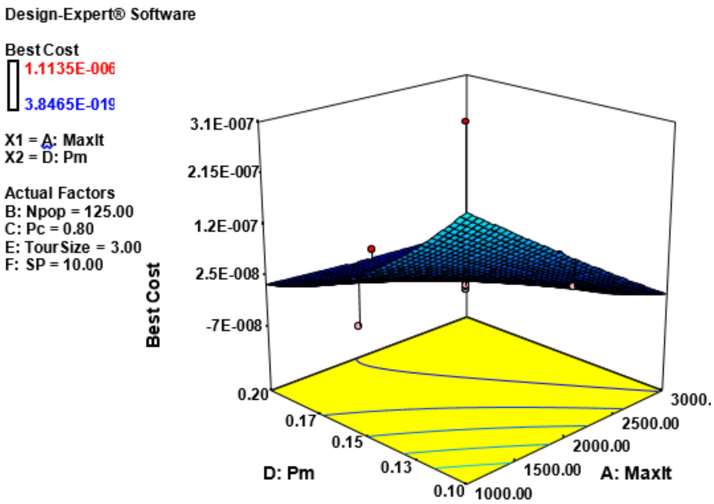
2.15E-007
1.2E-007
2.5E-008
-7E-008
0.90
0.85
0.80
0.75
0.70
C: Pc
1000.00
1500.00
2000.00
2500.00
A: MaxIt

(c)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Best Cost
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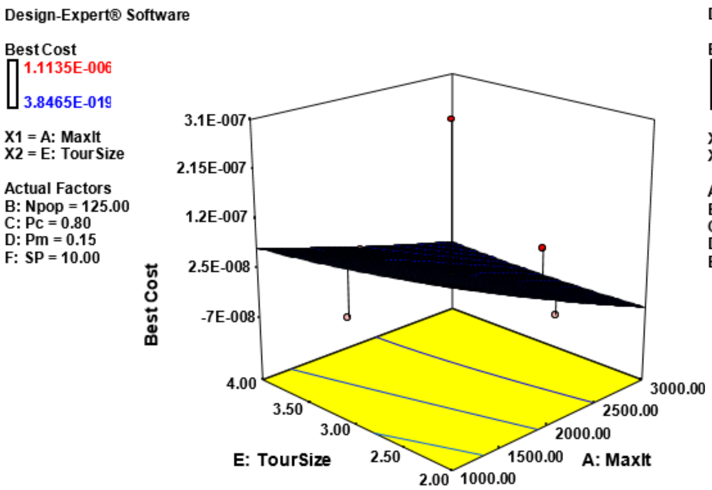
2.15E-007
1.2E-007
2.5E-008
-7E-008
0.20
0.17
0.15
0.13
0.10
D: Pm
1000.00
1500.00
2000.00
2500.00
A: MaxIt

(d)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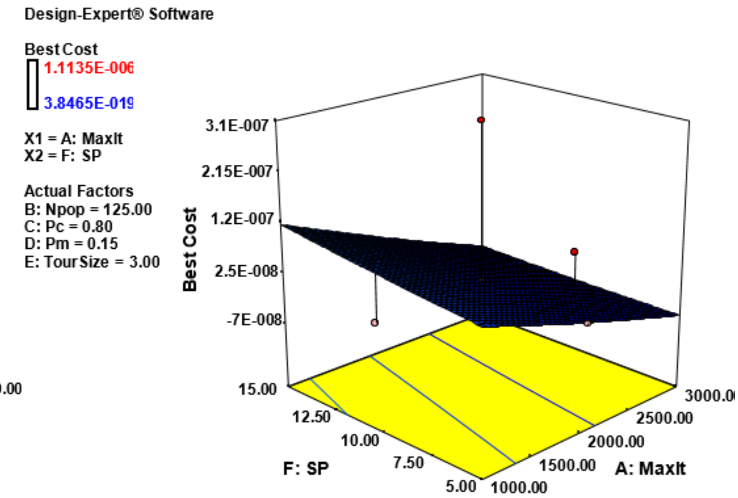
C: Pc = 0.80
D: Pm = 0.15
F: SP = 10.00
Best Cost
3.1E-007
2.15E-007
1.2E-007
2.5E-008
-7E-008
4.00
3.50
3.00
2.50
2.00
E: TourSize
1000.00
1500.00
2000.00
2500.00
3000.00
A: MaxIt

(e)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D: Pm = 0.15
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Best Cost
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2.15E-007
1.2E-007
2.5E-008
-7E-008
15.00
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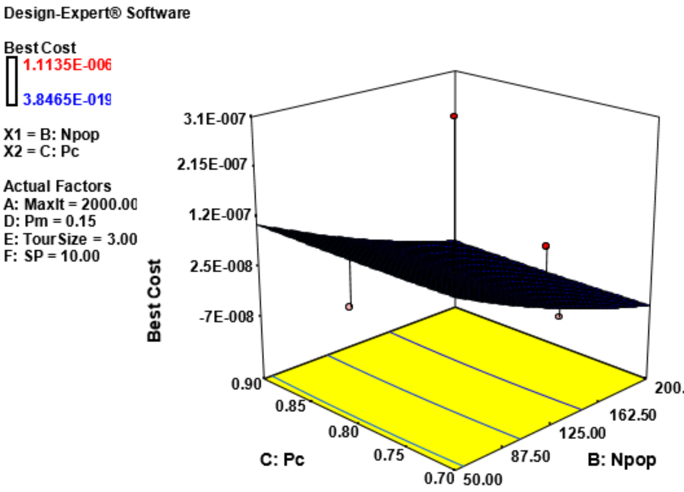
10.00
7.50
5.00
F: SP
1000.00
1500.00
2000.00
2500.00
A: MaxIt

(f)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E: TourSize = 3.00
F: SP = 10.00
Best Cost
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2.15E-007
1.2E-007
2.5E-008
-7E-008
C: Pc
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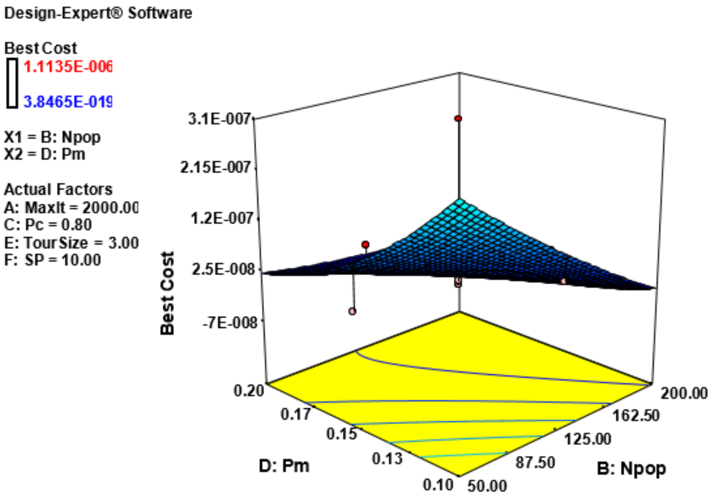
0.85
0.80
0.75
0.70
B: Npop
50.00
87.50
125.00
162.50
200.00

(g)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F: SP = 10.00
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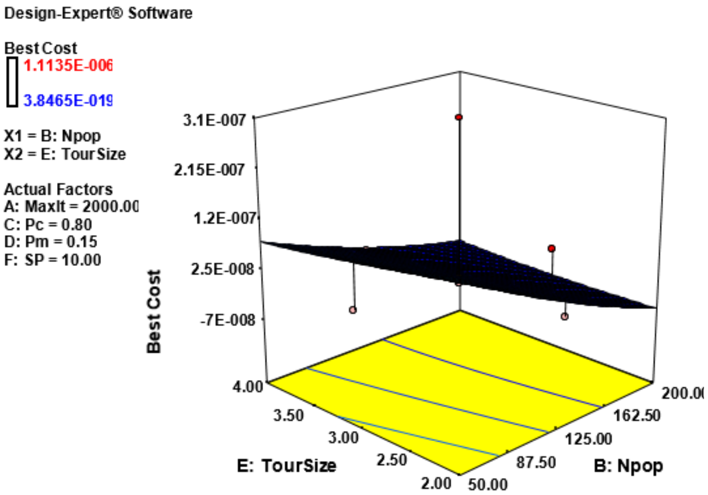
2.15E-007
1.2E-007
2.5E-008
-7E-008
D: Pm
0.20
0.17
0.15
0.13
0.10
B: Npop
50.00
87.50
125.00
162.50
200.00

(h)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2.15E-007
1.2E-007
2.5E-008
-7E-008
E: TourSize
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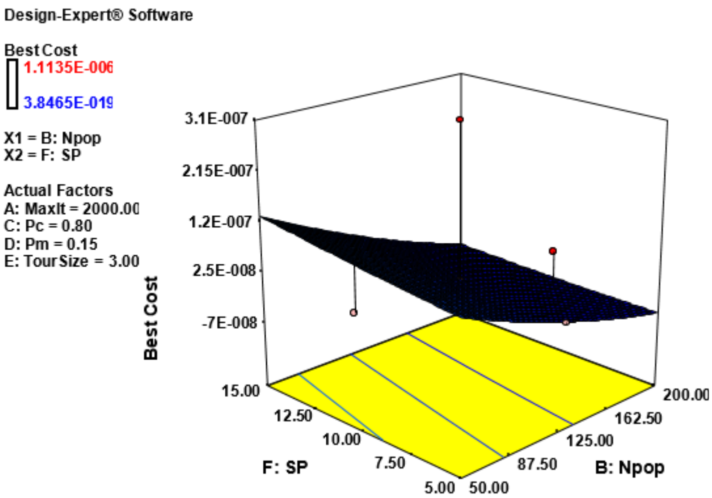
162.50
200.00

(i)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D: Pm = 0.15
E: TourSize = 3.00
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2.15E-007
1.2E-007
2.5E-008
-7E-008
F: SP
15.00
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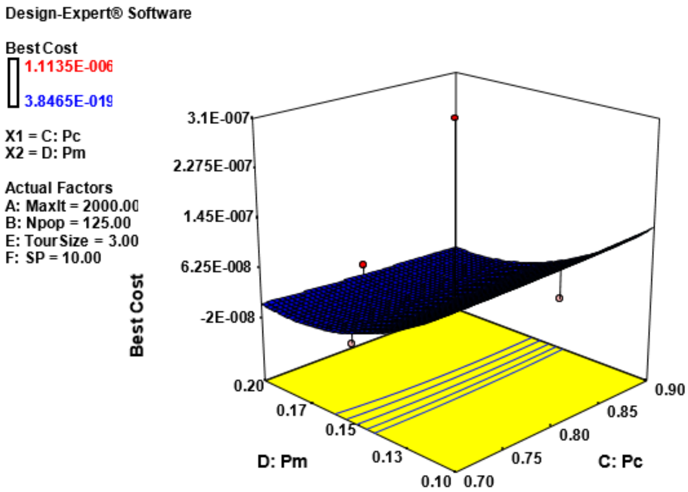
162.50
200.00

(j)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X2 = D: Pm
Actual Factors
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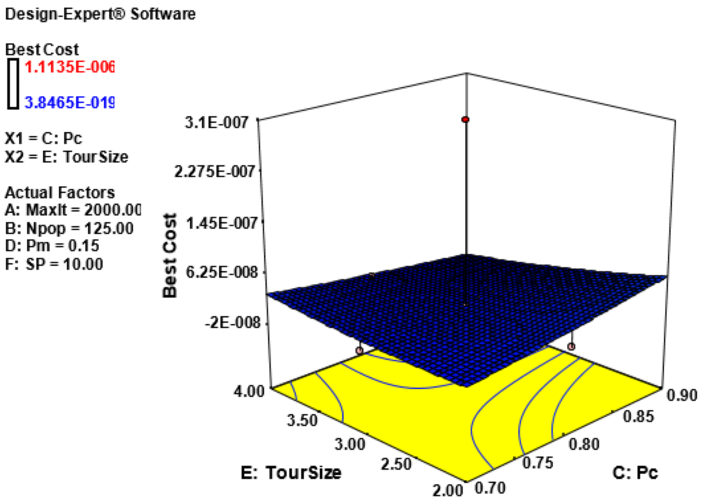
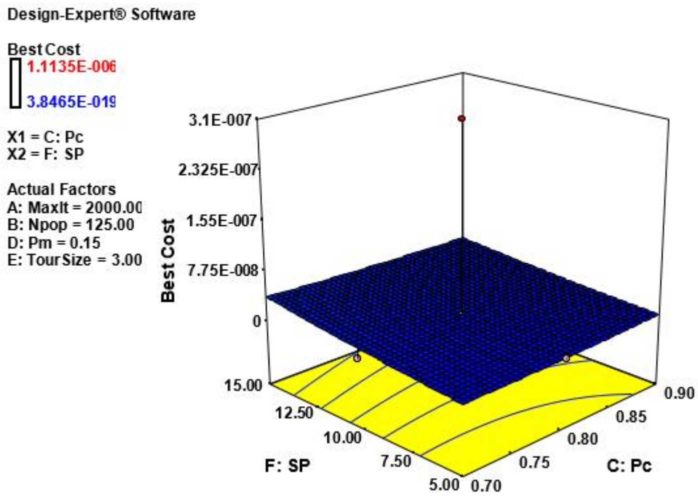
B: Npop = 125.00
E: TourSize = 3.00
F: SP = 10.00
Best Cost
3.1E-007
2.275E-007
1.45E-007
6.25E-008
-2E-008
D: Pm
0.20
0.17
0.15
0.13
0.10
C: Pc
0.70
0.75
0.80
0.85
0.90

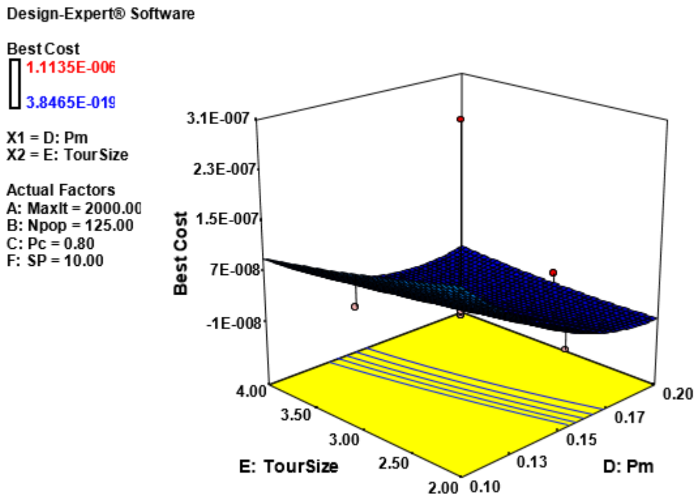
(k)


Design-Expert® Software
Best Cost
1.1135E-006
3.8465E-019
X1 = C: Pc
X2 = E: TourSize
Actual Factors
A: MaxIt = 2000.00
B: Npop = 125.00
D: Pm = 0.15
F: SP = 10.00
Best Cost
3.1E-007
2.275E-007
1.45E-007
6.25E-008
-2E-008
E: TourSize
4.00
3.50
3.00
2.50
2.00
C: Pc
0.70
0.75
0.80
0.85
0.90

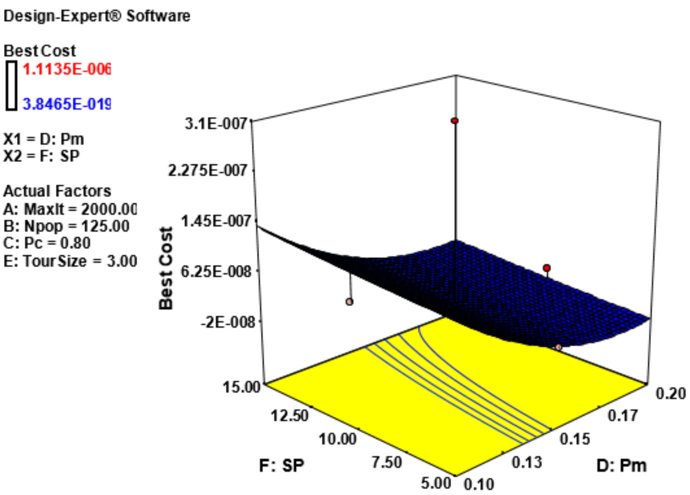
(l)



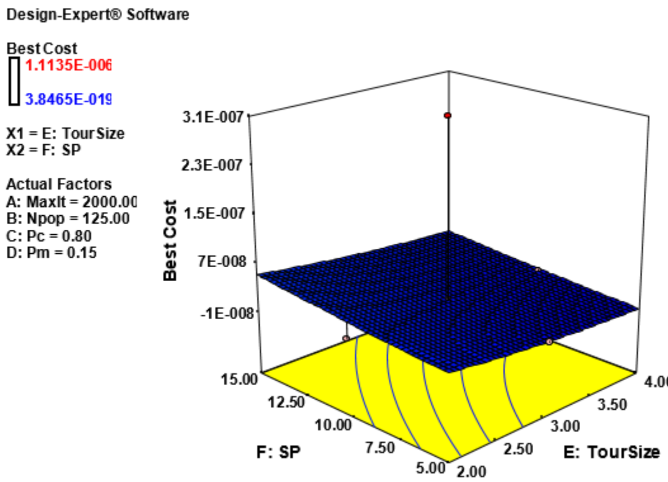

(m)




(n)




(o)




(p)

Figure 1. (a) Normal plot of residuals, (b-p) 3D surface of the impact of the regression model between MaxIt, Npop, Pc, Pm, TourSize and SP as inputs and Best Cost as output

What can be deduced from graphs are as follows:

1) Based on the proposed quadratic model for MaxIt, Npop, Pc, Pm, TourSize and SP as inputs and Best Cost as output, the normal plot of residuals has been shown in Fig. 1 (a).

2) From the 3D diagrams, we can see the positive effects of Pc, TourSize and SP and the negative effects of MaxIt, Npop and Pm on the Best Cost.

3) From 3D plots (b-p) can be found that:

3-1) By increasing the factors MaxIt, Npop and Pm, Best Cost decreases and the increase or decrease of the factors Pc, TourSize and SP are almost ineffective.

3-2) Also, if Npop is at its lowest level, Best Cost decreases with increasing MaxIt, and if it is at its highest level, increasing or decreasing MaxIt will not affect on Best Cost. The same result holds for Pm instead of Npop.

3-3) If Pc is at its lowest or highest level, Best Cost decreases with increasing MaxIt or Npop. The same results hold for TourSize or SP instead of Pc.

3-4) If Pm is at its lowest level, Best Cost decreases with increasing Npop, and if it is at its highest level, increasing or decreasing Npop will not affect on Best Cost.

3-5) When Pm is at its highest or lowest level, increasing or decreasing Pc will not have a significant effect on the response.

3-6) Also, When SP is at its highest or lowest level, increasing or decreasing Pc or TourSize will not have a significant effect on the response.

3-7) If TourSize or SP is at its lowest or highest level, Best Cost decreases with increasing Pm.

3-8) Finally, if TourSize is at its highest level, Best Cost decreases with increasing Pc, and if it is at its lowest level, increasing or decreasing Pc will not affect on Best Cost.

### B. Optimization

The optimization results are summarized in Table 3 for the minimum cost function.

TABLE III. RESULTS OF OPTIMIZATION OF EQUATION (1)

| | |
|---|---|
| MaxIt | 1744.16 |
| Npop | 81.22 |
| Pc | 0.9 |
| Pm | 0.2 |
| TourSize | 4 |
| SP | 13.53 |
| Best Cost | 2.27E-09 |
| Desirability | 0.997959 |

For example, the first optimum solution of Table 4 is 2.27E-09. On the other hand, by selecting MaxIt=1744.16, NPop=81.22, Pc=0.9, Pm=0.2, TourSize=4, and SP=13.53, and applying the genetic algorithm, the response is 2.3234e-09. The closeness of these two answers is remarkable which shows the very high accuracy of the model obtained from Response Surface Methodology.

## IV. CONCLUSION

In this paper the parameters of the genetic algorithm were adjusted using Response Surface Methodology. “maximum number of iterations”, “population size”, “parents (offsprings) population size ratio”, “mutants population size ratio”, “tournament selection size”, and “selection pressure” was considered as the main parameters of the genetic algorithm. The results obtained from the Central Composite Design was presented in the mathematical modelling of genetic algorithm parameters. The optimum solution and the best cost obtained of two soft methodologies was compared. The optimal response obtained with the adjusted parameters is approximately the same which confirms the consistency of the results obtained from these two software. In this way, the response surface methodology can be considered as a very appropriate and accurate method for modifying and adjusting the parameters of other optimization methods, including the powerful method of genetic algorithm.

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