Maximising Performance of Genetic Algorithm Solver in Matlab

Son Duy Dao, Kazem Abhary, and Romeo Marian

Abstract—**Genetic Algorithm solver in Matlab is one of the popular commercial optimisation solvers commonly used in scientific research. Performance of the solver heavily depends on its parameters. To maximise the solver performance, this paper proposes a systematic and comprehensive approach based on Taguchi experimental design for the parameter tuning. Effectiveness of the proposed approach is demonstrated through a number of case studies.**

Index Terms—**Genetic algorithm solver, global optimisation, parameter tuning, Taguchi experimental design**

I. Introduction

GENETIC Algorithm (GA) is a popular optimisation algorithm, often used to solve complex large-scale optimisation problems in many fields [1-3]. GA solver in Matlab is a commercial optimisation solver based on Genetic Algorithms, which is commonly used in many scientific research communities [4-8]. Using the solver requires an objective function and corresponding constraints. To maximise the solver performance, appropriate solver parameters such as population size, fitness scaling function, selection function, elite count, crossover fraction, mutation function, crossover function, etc. need to be chosen. There are many options of the solver parameters to choose from. When using the GA solver, selecting the right parameter set is very beneficial but it is really challenging and requires a systematic approach.

Literature review conducted in this study revealed that the common methods of choosing the GA solver parameters are trial-and-error and user-experience based methods. As a result, there have been a number of papers [6, 7, 9-13] where the GA solver parameters were just chosen, without explaining how. Obviously, these approaches could not choose the optimal parameter set and consequently performance of the solver could not be maximised.

Another way of selecting the GA solver parameters is to use the default values such as the one by Rezk and Al-Dadah [14]. Clearly, this approach cannot maximise the solver performance because different problems have different characteristics and therefore different solver parameter sets for different problems are often required.

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Mr Son Duy Dao, a PhD student, is with School of Engineering, University of South Australia, Australia (corresponding author to provide e-mail: son.dao@mymail.unisa.edu.au).

Prof. Kazem Abhary is with School of Engineering, University of South Australia, Australia

Dr. Romeo Marian is with School of Engineering, University of South Australia, Australia

More advanced methods of tuning the GA solver parameters are so called the combined methods in which some parameters are selected by trial-and-error/user-experience based methods, some are default parameters, some are taken from available publications and others are chosen by Design of Experiment (DoE) method. Housh, Ostfeld and Shamir [15], Sindhuja et al. [16], Lai et al. [17] and Bornschlegell et al. [4] used trial-and-error/user-experience based methods and default parameters while Kadiyala, Kaur and Kumar [18] took some default parameters of the solver and chose the rest by DoE method. In addition, trial-and-error/user-experience based methods, default parameters as well as DoE method were applied by Zomorrodi et al. [19]. Finally, Debnath, Deb and Dutta [5] chose some solver parameters based on their experiences, some by DoE method and the rest by adopting from other publications. It can be seen that above combined methods are not capable of comprehensively investigating the effects of parameters on the GA solver performance because trial-and-error/user-experience based methods, default parameters and parameters adopted from other sources are still involved.

To overcome these limitations, this paper proposes a comprehensive systematic approach based on Taguchi Experimental Design for tuning the parameters of the GA solver in Matlab to maximise the solver performance.

The rest of this paper is organised as follows. The proposed approach for the solver parameter selection is presented in Section 2. A case study used to demonstrate the robustness of the proposed approach is then provided in Section 3. Finally, conclusions are presented in Section 4.

II. Proposed Approach

There are nine parameters that can significantly affect the performance of the GA solver in Matlab: *population size*, *fitness scaling function*, *selection function*, *elite count*, *crossover fraction*, *mutation function*, *crossover function*, *migration direction* and *hybrid function*. Some of them are integer parameters such as *population size*, *elite count*, continuous parameter such as *crossover fraction*, and the rest are discrete ones. For the sake of simplicity, both integer and continuous parameters are referred to as continuous parameters hereafter. To maximise the solver performance, an optimal parameter set is required. To find the optimal set of the parameters, the following four-step approach is proposed.

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Table 1: Solver parameters and their experimental levels

No.	Parameter	Code	Level			
			1	2	3	4
1	Migration direction	A	Forward	Both	-	-
2	Population size	B	50	100	150	200
3	Fitness scaling function	C	Proportional	Rank	Top	Shift linear
4	Selection function	D	Uniform	Tournament	Roulette	Stochastic uniform
5	Elite count	E	1	5	10	15
6	Crossover fraction	F	0.3	0.5	0.7	0.9
7	Mutation function	G	Uniform	Constraint dependent	Adaptive feasible	Gaussian
8	Crossover function	H	Single point	Two point	Arithmetic	Scattered
9	Hybrid function	I	None	Fminsearch	Patternsearch	Fminunc

Step 1: Generating Taguchi experimental design

As large number of parameters are involved, Taguchi experimental design [20] is the best tool to employ herein. Based on the number of parameters considered and number of parameter levels available in the solver, Taguchi Orthogonal Array Design L32 (2^1 4^8) was chosen and details of the experimental design are shown in Tables 1-2. It should be noted that one parameter (*migration direction*) has two levels and the rest, each has four levels as shown in Table 1.

Table 2: Experimental design L32 (2^1 4^8) generated by Minitab

Experiment	Parameter of GA solver								
	A	B	C	D	E	F	G	H	I
1	1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3	3
4	1	1	4	4	4	4	4	4	4
5	1	2	1	1	2	2	3	3	4
6	1	2	2	2	1	1	4	4	3
7	1	2	3	3	4	4	1	1	2
8	1	2	4	4	3	3	2	2	1
9	1	3	1	2	3	4	1	2	3
10	1	3	2	1	4	3	2	1	4
11	1	3	3	4	1	2	3	4	1
12	1	3	4	3	2	1	4	3	2
13	1	4	1	2	4	3	3	4	2
14	1	4	2	1	3	4	4	3	1
15	1	4	3	4	2	1	1	2	4
16	1	4	4	3	1	2	2	1	3
17	2	1	1	4	1	4	2	3	2
18	2	1	2	3	2	3	1	4	1
19	2	1	3	2	3	2	4	1	4
20	2	1	4	1	4	1	3	2	3
21	2	2	1	4	2	3	4	1	3
22	2	2	2	3	1	4	3	2	4
23	2	2	3	2	4	1	2	3	1
24	2	2	4	1	3	2	1	4	2
25	2	3	1	3	3	1	2	4	4
26	2	3	2	4	4	2	1	3	3
27	2	3	3	1	1	3	4	2	2
28	2	3	4	2	2	4	3	1	1
29	2	4	1	3	4	2	4	2	1
30	2	4	2	4	3	1	3	1	2
31	2	4	3	1	2	4	2	4	3
32	2	4	4	2	1	3	1	3	4

Step 2: Conducting the experiments

After defining objective function and constraints, the solver parameters are set according to the experiment layout shown in Table 2. Each experiment should be repeated for a number of times, say five, to increase the consistency of the experiment response. To make a fair comparison, computing time is set exactly the same for every experiment.

Step 3: Analysing the experimental data

To determine the effects of the parameters on the solver performance, Minitab ANOVA analysis is used. In ANOVA analysis, according to Yang and El-Haik [20], the relative importance of an effect to the experiment response is presented by the corresponding *F value*; the larger, the more important. In addition, *p value* is used to determine whether an effect is statistically significant to the experiment response. An effect is commonly considered significant if its *p value* is less than 0.05.

Step 4: Selecting the parameter values

Based on ANOVA analysis in Step 3, the solver parameters are classified into two groups: significant and insignificant. For insignificant parameters, their levels will be selected based on the main-effect chart generated by Minitab, in which the levels associated with the highest fitness values should be chosen. For significant parameters, the rule for selecting the parameter level is still the same as the one for insignificant parameters, except for the continuous parameters. Further tuning process, using Hill Climbing technique, can be done for the continuous significant parameters to find the optimal values if users desire; otherwise, the experimental parameter levels that give the highest fitness values are chosen.

The effectiveness of the proposed approach is demonstrated by a case study.

III. CASE STUDIES

3.1. Two-Dimensional Problem

A two-dimensional function with multiple optima and known global optimal solution was chosen to preliminarily verify the robustness of the proposed approach. There are two reasons for choosing such kind of test function. The first one is that it is only possible to visualise the shape of fitness landscape of a test function which has less than or equal to two dimensions and this fitness landscape visualisation can allow the user to intuitively determine the difficulty of the function. The second reason is that a test function with multiple optima and known global optimal solution can help easily evaluate the true capability of the solver. To satisfy above conditions, a function expressed by Eqs. 1-3 and shown in Fig.1 was adopted from the research of Hall [21] herein. As can be seen from Fig. 1, this function is quite "hard" for any meta-heuristic algorithm since it is more likely to get trapped in the "big" local optimum.

Question now is how to solve the described case study problem efficiently and effectively.

$$Maximise\ z = \frac{0.4}{1+0.02[(x+20)^2+(y+20)^2]} + \frac{0.2}{1+0.5[(x+5)^2+(y+25)^2]} + \frac{0.7}{1+0.01[x^2+(y-30)^2]} + \frac{1}{1+2[(x-30)^2+y^2]} + \frac{0.05}{1+0.1[(x-30)^2+(y+30)^2]} \quad (1)$$

$$Subject\ to: \quad -40 \le x \le 40 \quad (2)$$

$$-40 \le y \le 40 \quad (3)$$

- *Results and Discussions*

The proposed four-step approach was applied to solve the described case study problem. The experiments were conducted and data is shown in Table 3. In addition, ANOVA table and main-effect chart generated by Minitab are presented in Table 4 and Fig. 2. The *p values* in Table 4 indicate that parameters B, C, D, F, G and I are statistically significant to the solver performance; among them, parameters B and F are continuous. However, the authors decided not to conduct the further tuning process for these two parameters simply because their slopes in the main-effect chart, Fig. 2, are not significant. As a result, the solver parameter set for solving the case study problem was chosen as shown Table 5.

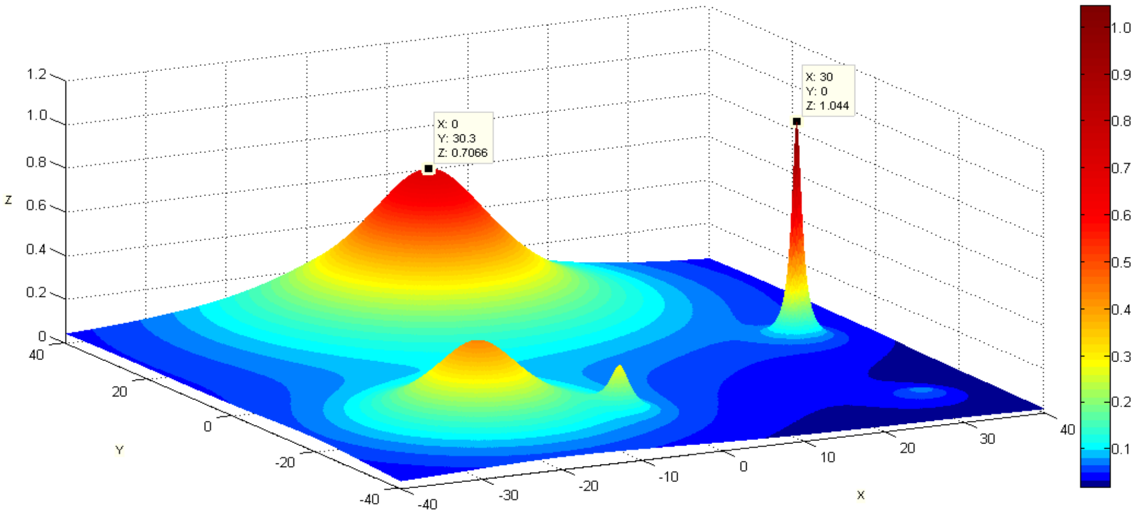

Fig. 1: Test function (adapted from [21])

Table 3: Experiment layout and data

Experiment	Parameter of GA solver									Computing time (s)	Fitness value				
	A	B	C	D	E	F	G	H	I		Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	1	1	1	1	1	1	1	30	0.7073	0.7073	0.7073	0.7073	0.7073
2	1	1	2	2	2	2	2	2	2	30	0.7073	0.7073	0.7073	0.7073	0.7073
3	1	1	3	3	3	3	3	3	3	30	0.7073	0.7073	0.7073	0.7073	0.7073
4	1	1	4	4	4	4	4	4	4	30	0.7073	0.7073	0.7073	0.7073	0.7073
5	1	2	1	1	2	2	3	3	4	30	0.7073	0.7073	0.7073	0.7073	0.7073
6	1	2	2	2	1	1	4	4	3	30	1.0444	1.0444	1.0444	1.0444	1.0444
7	1	2	3	3	4	4	1	1	2	30	0.7073	0.7073	0.7073	0.7073	0.7073
8	1	2	4	4	3	3	2	2	1	30	0.7073	0.7073	0.7073	1.0444	0.7073
9	1	3	1	2	3	4	1	2	3	30	0.7073	0.7073	0.7073	0.7073	0.7073
10	1	3	2	1	4	3	2	1	4	30	1.0444	1.0444	0.7073	0.7073	0.7073
11	1	3	3	4	1	2	3	4	1	30	0.7073	0.7073	0.7073	0.7073	0.7073
12	1	3	4	3	2	1	4	3	2	30	1.0444	1.0444	1.0444	1.0444	1.0444
13	1	4	1	2	4	3	3	4	2	30	1.0444	0.7073	0.7073	0.7073	0.7073
14	1	4	2	1	3	4	4	3	1	30	1.0444	1.0444	1.0444	1.0444	1.0444
15	1	4	3	4	2	1	1	2	4	30	0.7073	0.7073	0.7073	0.7073	0.7073
16	1	4	4	3	1	2	2	1	3	30	0.7073	0.7073	0.7073	0.7073	1.0444
17	2	1	1	4	1	4	2	3	2	30	0.7073	0.7073	0.7073	0.7073	0.7073
18	2	1	2	3	2	3	1	4	1	30	1.0388	0.7071	0.7073	0.7069	0.7073
19	2	1	3	2	3	2	4	1	4	30	1.0444	0.7073	0.7073	0.7073	1.0444
20	2	1	4	1	4	1	3	2	3	30	0.7073	0.7073	0.7073	0.7073	0.7073
21	2	2	1	4	2	3	4	1	3	30	1.0444	0.7073	1.0444	1.0444	0.7073
22	2	2	2	3	1	4	3	2	4	30	0.7073	0.7073	0.7073	0.7073	0.7073
23	2	2	3	2	4	1	2	3	1	30	0.7073	0.7073	0.7073	0.7073	0.7073
24	2	2	4	1	3	2	1	4	2	30	0.7073	0.7073	0.7073	0.7073	0.7073
25	2	3	1	3	3	1	2	4	4	30	0.7073	0.7073	1.0444	0.7073	0.7073
26	2	3	2	4	4	2	1	3	3	30	0.7073	0.7073	0.7073	0.7073	0.7073
27	2	3	3	1	1	3	4	2	2	30	1.0444	1.0444	1.0444	1.0444	1.0444
28	2	3	4	2	2	4	3	1	1	30	0.7073	0.7073	0.7073	0.7073	0.7073
29	2	4	1	3	4	2	4	2	1	30	1.0439	1.0434	1.0428	1.0442	1.0355
30	2	4	2	4	3	1	3	1	2	30	1.0444	0.7073	0.7073	0.7073	0.7073
31	2	4	3	1	2	4	2	4	3	30	0.7073	0.7073	0.7073	0.7073	1.0444
32	2	4	4	2	1	3	1	3	4	30	0.7073	0.7073	0.7073	0.7073	0.7073

Table 4: ANOVA analysis

Source	DF	Seq SS	Adj SS	Adj MS	F	p
A	1	0.000790	0.000790	0.000790	0.090	0.759
B	3	0.212217	0.212217	0.070739	8.460	0.000
C	3	0.081175	0.081175	0.027058	3.240	0.024
D	3	0.131794	0.131794	0.043931	5.260	0.002
E	3	0.013827	0.013827	0.004609	0.550	0.648
F	3	0.093051	0.093051	0.031017	3.710	0.013
G	3	1.589698	1.589698	0.529899	63.400	0.000
H	3	0.007643	0.007643	0.002548	0.300	0.822
I	3	0.092341	0.092341	0.030780	3.680	0.014
Error	134	1.119997	1.119997	0.008358		
Total	159	3.342533				

To validate the effectiveness of the proposed approach, a number of commercial optimisation solvers in Matlab, with different parameter sets were used to solve the case study problem and their performances are reported in Table 6. There are three solvers with default parameters namely: Pattern Search (PS solver), Simulated Annealing (SA solver) and Genetic Algorithm (GA solver 1). In addition, GA solver 2 is Genetic Algorithm solver with population size of 200 and other parameters set default. Genetic Algorithm solver with parameters tuned by the proposed approach is named GA solver 3.

It is noted that each solver had 30 seconds to search for the global optimal solution with fitness value of at least 1.044. In addition, initial solutions required by PS solver as well as SA solver were randomly generated to make a fair comparison. It can be seen from Table 6 that GA solver 3 has success rate of 197 out of 200 while PS solver, SA solver, GA solver 1 and GA solver 2 have success rates of 2, 59, 3 and 10 out of 200, respectively. The success probabilities of the solvers are visualised in Fig. 3. Clearly, success rate of GA solver 3 in solving the “hard” case study problem is very high (98.5%) and it is far better than others as indicated in Fig. 3.

Table 6: Performance comparison

Computing time (s)	Number of trials	Number of successes				
		PS solver	SA solver	GA solver 1	GA solver 2	GA solver 3
30	200	2	59	3	10	197

It should be noted that the authors have attempted to apply the proposed approach to solve two other test functions as shown in Figs. 4-5 and success rate of finding the global optimal solutions is always 100%. Due to space limitation, the details of the two case studies are not presented here, and the test function shown in Fig. 1 is used as an illustrated example for a “hard” problem.

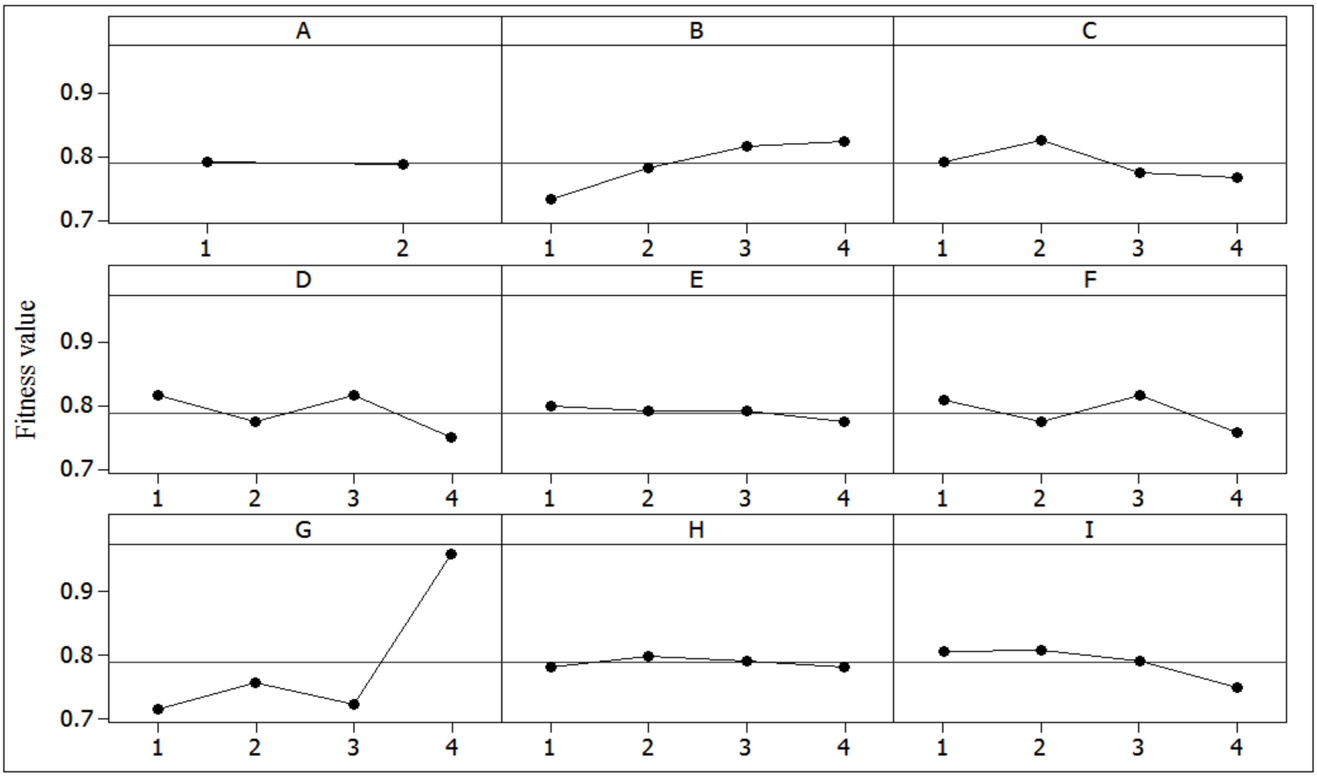

Fig. 2: Main-effect chart

Table 5: Selected solver parameter set for solving the case study problem

Migration direction	Population size	Fitness scaling function	Selection function	Elite count	Crossover fraction	Mutation function	Crossover function	Hybrid function
Forward	200	Rank	Roulette	1	0.7	Gaussian	Two point	None

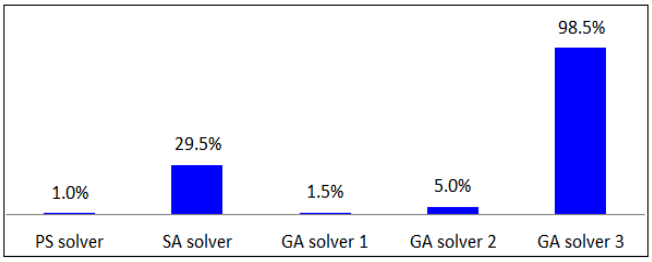

Fig. 3: Success probability comparison

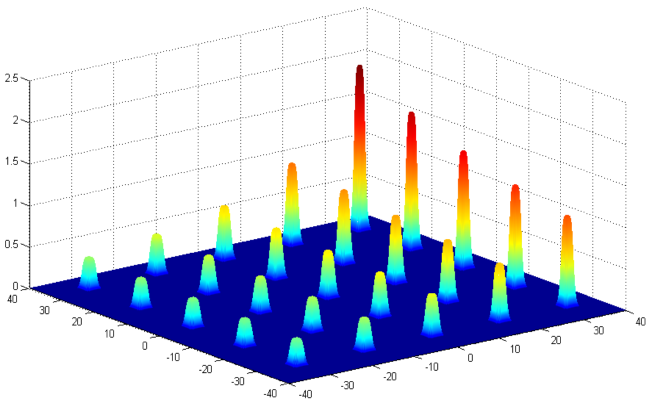

Fig. 4: Shekel Foxholes function

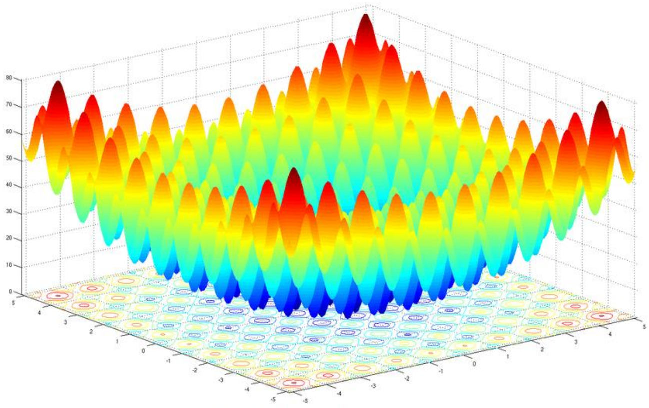

Fig. 5: Rastrigin function

3.2. Large-Scale Problem

To further evaluate the robustness of the proposed approach, four large-scale case study problems were considered herein. Each problem has a known global optimal solution with 15 dimensions. Details of the problems are shown in Table 7. The proposed approach was applied to tune the parameters of the GA solver for solving the four large-scale problems. The related experiment layout and data are shown in Tables 8-11 in Appendix. It is noted that for the sake of comparison with optimisation algorithms available in the literature, the termination criterion used in these four problems was the number of objective function evaluations, as indicated in Tables 8-11.

After conducting ANOVA analysis, the parameter set of the GA solver for solving different problem was selected as shown in Table 12. It is noted that for the sake of simplicity, the further tuning process as mentioned in Step 4 in Section 2 was not used in selecting the parameters in Table 12. In addition, the parameter of the GA solver, namely hybrid function, was not used here to make a fair comparison with three optimisation algorithms available in the literature; which means that level 1 of this parameter was guaranteed to be selected. Performance of the GA solver tuned by the proposed approach in solving the four large-scale problems will be discussed in the next Section.

- *Results and Discussions*

Quality of the solutions to the four large-scale problems, obtained by four different optimisation algorithms, is shown in Table 13. Performances of the first three algorithms, i.e. Spiral Dynamic Algorithm (SDA), Bacterial Foraging Algorithm (BFA) and Hybrid Spiral-Dynamic Bacteria-Chemotaxis algorithm (type R) named HSDBC-R, in solving the four problems, have been published in the research of Nasir & Tokhi [22]. To make a fair comparison, the termination criterion of the GA solver in this article was set exactly the same as in the publication of Nasir & Tokhi [22], i.e. 80000 objective function evaluations as indicated in Table 13; and the GA solver, like the other algorithms, was independently run for 30 times.

The quality of the obtained solutions in terms of the best fitness value (called Best), average fitness value (called Mean) and standard deviation of the fitness values (called Std.dev.) is shown in Table 13. For problem F1, all four optimisation algorithms are capable of finding a solution which is very close to the global solution. In other words, the performances of the four algorithms in solving problem F1 are about the same. For problems F2-F4, the GA solver in this article outperforms the other optimisation algorithms available in the literature. More specifically, the GA solver always found the global solution to problem F2, with fitness value of 0.00 in 30 independent runs; while fitness values, on average, obtained by SDA, BFA and HSDBC-R are 2.76, 17.22 and 0.47, respectively. It should be noted that all four problems herein are minimum optimisation problems. The results in Table 13 reveal that problems F3-F4 seem to be harder than problems F1-F2, since none of the four algorithms could find solutions which are very close to the global solutions. However, on average, the solution to problem F3, obtained by the GA solver in this article, is 97.2, 75.3 and 41.0% better, compared to those obtained by SDA, BFA and HSDBC-R, respectively; for problem F4, these figures are 86.5, 89.4 and 83.0%, respectively. In terms of consistency, the GA solver in this article is also better than SDA, BFA and HSDBC-R, as shown in Table 13.

IV. Conclusion

In this paper, a systematic and comprehensive approach based on Taguchi experimental design has been proposed to support users of Matlab GA solver in selecting the solver parameters to maximise its performance. The effectiveness of the proposed approach has been demonstrated through a "hard" two-dimensional problem in which the success rate of finding the global optimal solution of the GA solver with parameters tuned by the proposed approach was 98.5%, in comparison with the rates of 1.5 and 5.0% of the two conventional GA solvers. In addition, the success rates of two other commercial optimisation solvers, namely PS solver and SA solver, were only 1.0 and 29.5%, respectively. In addition, the effectiveness of the proposed approach has been evaluated through solving four large-scale case study problems, in which the GA solver tuned by the proposed approach could provide the solutions with much better quality in comparison with the solutions obtained by three optimisation algorithms, i.e. SDA, BFA and HSDBC-R, available in the global optimisation literature.

In future work, the authors would test and evaluate the robustness of the proposed approach in solving highly constrained optimisation problems.

Table 7: Large-scale problems (adapted from [22, 23])

No.	Name	Dimension	Equation	Range	Global minimum
1	Sphere (F1)	n = 15	$f_1(x) = \sum_{i=1}^{n} x_i^2$	$(-5.12, 5.12)^n$	0.00
2	Ackley (F2)	n = 15	$f_2(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + \exp(1)$	$(-15, 30)^n$	0.00
3	Dixon & Price (F3)	n = 15	$f_3(x) = (x_1 - 1)^2 + \sum_{i=2}^{n} i\left(2x_i^2 - x_{i-1}\right)^2$	$(-10, 10)^n$	0.00
4	Rastrigin (F4)	n = 15	$f_4(x) = \sum_{i=1}^{n}\left[x_i^2 - 10cos(2\pi x_1) + 10\right]$	$(-5, 5)^n$	0.00

Table 12: Selected parameter set of GA solver for solving different problem

Problem	Migration direction	Population size	Fitness scaling function	Selection function	Elite count	Crossover fraction	Mutation function	Crossover function	Hybrid function
F1	Forward	100	Top	Tournament	10	0.9	Constraint dependent	Arithmetic	None
F2	Both	200	Shift linear	Tournament	5	0.3	Adaptive feasible	Scattered	None
F3	Forward	150	Top	Tournament	10	0.9	Constraint dependent	Arithmetic	None
F4	Both	200	Rank	Stochastic uniform	15	0.9	Uniform	Scattered	None

Table 13: Performance comparison

No.	Test function	Dimension	Global minimum	No.of.obj.fun. evaluations	Fitness value	SDA [22]	BFA [22]	HSDBC-R[22]	GA solver
1	Sphere (F1)	15	0.00	80000	Best	0.00	0.06	0.00	0.00
					Mean	0.05	0.15	0.00	0.13
					Std.dev.	0.10	0.04	0.00	0.14
2	Ackley (F2)	15	0.00	80000	Best	0.16	14.24	0.00	0.00
					Mean	2.76	17.22	0.47	0.00
					Std.dev.	1.55	0.85	0.59	0.00
3	Dixon & Price (F3)	15	0.00	80000	Best	0.67	1.52	0.67	0.01
					Mean	21.21	2.41	1.01	0.59
					Std.dev.	37.11	0.78	0.58	0.59
4	Rastrigin (F4)	15	0.00	80000	Best	22.06	42.49	22.03	4.75
					Mean	56.23	71.77	44.53	7.57
					Std.dev.	21.41	10.05	14.00	1.98

APPENDIX

Table 8: Experiment layout and data (Problem F1)

Experiment	Parameter of GA solver									No.of.obj.fun.	Fitness value				
	A	B	C	D	E	F	G	H	I	evaluations	Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	1	1	1	1	1	1	1	80000	0.1473	0.1543	0.1661	0.1421	0.1651
2	1	1	2	2	2	2	2	2	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
3	1	1	3	3	3	3	3	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
4	1	1	4	4	4	4	4	4	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
5	1	2	1	1	2	2	3	3	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
6	1	2	2	2	1	1	4	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
7	1	2	3	3	4	4	1	1	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
8	1	2	4	4	3	3	2	2	1	80000	0.0000	0.0000	0.0000	0.0000	0.0000
9	1	3	1	2	3	4	1	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
10	1	3	2	1	4	3	2	1	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
11	1	3	3	4	1	2	3	4	1	80000	0.0000	0.0000	0.0000	0.0000	0.0000
12	1	3	4	3	2	1	4	3	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
13	1	4	1	2	4	3	3	4	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
14	1	4	2	1	3	4	4	3	1	80000	0.0090	0.0091	0.0114	0.0236	0.0144
15	1	4	3	4	2	1	1	2	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
16	1	4	4	3	1	2	2	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
17	2	1	1	4	1	4	2	3	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
18	2	1	2	3	2	3	1	4	1	80000	0.0388	0.0272	0.0140	0.0223	0.0487
19	2	1	3	2	3	2	4	1	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
20	2	1	4	1	4	1	3	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
21	2	2	1	4	2	3	4	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
22	2	2	2	3	1	4	3	2	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
23	2	2	3	2	4	1	2	3	1	80000	0.0000	0.0000	0.0000	0.0000	0.0000
24	2	2	4	1	3	2	1	4	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
25	2	3	1	3	3	1	2	4	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
26	2	3	2	4	4	2	1	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
27	2	3	3	1	1	3	4	2	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
28	2	3	4	2	2	4	3	1	1	80000	0.0000	0.0000	0.0000	0.0000	0.0000
29	2	4	1	3	4	2	4	2	1	80000	0.2224	0.1355	0.0716	0.2677	0.0642
30	2	4	2	4	3	1	3	1	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
31	2	4	3	1	2	4	2	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
32	2	4	4	2	1	3	1	3	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 9: Experiment layout and data (Problem F2)

Experiment	Parameter of GA solver									No.of.obj.fun.	Fitness value				
	A	B	C	D	E	F	G	H	I	evaluations	Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	1	1	1	1	1	1	1	80000	2.2231	1.7789	2.2309	3.1140	2.6101
2	1	1	2	2	2	2	2	2	2	80000	0.9313	0.0000	0.0000	0.0000	0.0000
3	1	1	3	3	3	3	3	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
4	1	1	4	4	4	4	4	4	4	80000	1.8997	0.0003	0.0002	0.0001	0.0001
5	1	2	1	1	2	2	3	3	4	80000	3.7857	0.0000	3.2225	3.2225	3.9826
6	1	2	2	2	1	1	4	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
7	1	2	3	3	4	4	1	1	2	80000	1.8997	1.8997	2.4959	1.6462	1.6462
8	1	2	4	4	3	3	2	2	1	80000	0.0000	0.0001	0.0000	0.0000	1.3404
9	1	3	1	2	3	4	1	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
10	1	3	2	1	4	3	2	1	4	80000	1.3404	2.3168	2.1201	2.3168	0.9313
11	1	3	3	4	1	2	3	4	1	80000	0.0001	0.0001	0.0001	0.0001	0.0001
12	1	3	4	3	2	1	4	3	2	80000	0.0000	1.6462	0.0000	2.1201	0.9313
13	1	4	1	2	4	3	3	4	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
14	1	4	2	1	3	4	4	3	1	80000	2.8706	2.7623	1.7891	2.4643	3.4506
15	1	4	3	4	2	1	1	2	4	80000	0.0002	0.0001	0.0000	0.0000	0.0001
16	1	4	4	3	1	2	2	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
17	2	1	1	4	1	4	2	3	2	80000	0.0000	3.2225	3.5742	4.0762	1.3404
18	2	1	2	3	2	3	1	4	1	80000	1.5884	1.3948	0.8612	1.0986	1.5010
19	2	1	3	2	3	2	4	1	4	80000	3.3451	1.6462	1.6462	0.0003	2.3168
20	2	1	4	1	4	1	3	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
21	2	2	1	4	2	3	4	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
22	2	2	2	3	1	4	3	2	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
23	2	2	3	2	4	1	2	3	1	80000	0.0010	0.0001	2.1201	0.0001	0.0001
24	2	2	4	1	3	2	1	4	2	80000	0.0002	0.0001	0.0001	0.0002	0.0002
25	2	3	1	3	3	1	2	4	4	80000	1.6462	1.3404	0.0000	2.6602	3.3449
26	2	3	2	4	4	2	1	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
27	2	3	3	1	1	3	4	2	2	80000	2.8144	2.8138	3.7856	2.3168	3.4620
28	2	3	4	2	2	4	3	1	1	80000	0.0001	0.0001	0.0001	0.9313	0.0001
29	2	4	1	3	4	2	4	2	1	80000	1.4321	1.4830	2.6738	2.4011	2.4819
30	2	4	2	4	3	1	3	1	2	80000	0.0000	0.0000	0.0000	0.0000	0.0000
31	2	4	3	1	2	4	2	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
32	2	4	4	2	1	3	1	3	4	80000	0.0001	0.0003	0.0001	0.0001	0.0002

Table 10: Experiment layout and data (Problem F3)

Experiment	Parameter of GA solver									No.of.obj.fun. evaluations	Fitness value				
	A	B	C	D	E	F	G	H	I		Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	1	1	1	1	1	1	1	80000	11.5219	4.1338	7.7140	12.5320	8.6989
2	1	1	2	2	2	2	2	2	2	80000	0.6667	0.0000	0.0000	0.6667	0.6667
3	1	1	3	3	3	3	3	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
4	1	1	4	4	4	4	4	4	4	80000	0.6667	0.6667	0.6667	0.6667	0.6667
5	1	2	1	1	2	2	3	3	4	80000	0.6667	0.6667	0.6667	0.6667	0.6667
6	1	2	2	2	1	1	4	4	3	80000	0.6667	0.6667	0.6667	0.6667	0.6667
7	1	2	3	3	4	4	1	1	2	80000	0.6667	0.6667	0.6667	0.6667	0.6667
8	1	2	4	4	3	3	2	2	1	80000	0.0001	0.0354	0.0000	0.0463	1.2614
9	1	3	1	2	3	4	1	2	3	80000	0.6667	0.0000	0.6667	0.6667	0.0000
10	1	3	2	1	4	3	2	1	4	80000	0.6667	0.0000	0.0000	0.6667	0.0000
11	1	3	3	4	1	2	3	4	1	80000	0.0025	0.0015	0.0002	1.3344	0.0003
12	1	3	4	3	2	1	4	3	2	80000	0.6667	0.6667	0.6667	0.6667	0.6667
13	1	4	1	2	4	3	3	4	2	80000	0.0000	0.0000	0.0000	0.0000	0.6667
14	1	4	2	1	3	4	4	3	1	80000	1.1909	0.9481	3.2526	0.8862	1.1974
15	1	4	3	4	2	1	1	2	4	80000	0.6667	0.0000	0.6667	0.6667	0.6667
16	1	4	4	3	1	2	2	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
17	2	1	1	4	1	4	2	3	2	80000	0.6667	0.6667	0.6667	0.6667	0.6667
18	2	1	2	3	2	3	1	4	1	80000	2.0499	3.1522	8.7104	2.0991	2.7156
19	2	1	3	2	3	2	4	1	4	80000	0.6667	0.6667	0.0000	0.6667	0.6667
20	2	1	4	1	4	1	3	2	3	80000	0.0000	0.0000	0.6667	0.0000	0.0000
21	2	2	1	4	2	3	4	1	3	80000	0.6667	0.6667	0.6667	0.6667	0.0000
22	2	2	2	3	1	4	3	2	4	80000	0.6667	0.0000	0.0000	0.0000	0.6667
23	2	2	3	2	4	1	2	3	1	80000	0.0005	0.0439	0.6680	0.0344	0.1173
24	2	2	4	1	3	2	1	4	2	80000	0.6667	0.6667	0.6667	0.6667	0.6667
25	2	3	1	3	3	1	2	4	4	80000	0.0000	0.6667	0.0000	0.0000	0.0000
26	2	3	2	4	4	2	1	3	3	80000	0.6667	0.6667	0.6667	0.6667	0.6667
27	2	3	3	1	1	3	4	2	2	80000	0.6667	0.6667	0.6667	0.6667	0.6667
28	2	3	4	2	2	4	3	1	1	80000	0.7932	0.6667	0.6725	0.8990	0.6829
29	2	4	1	3	4	2	4	2	1	80000	5.1998	8.1264	11.9071	12.1126	8.5254
30	2	4	2	4	3	1	3	1	2	80000	0.0000	0.6667	0.6667	0.0000	0.0000
31	2	4	3	1	2	4	2	4	3	80000	0.6667	0.0000	0.0000	0.6667	0.0000
32	2	4	4	2	1	3	1	3	4	80000	0.6667	0.0000	0.0000	0.6667	0.6667

Table 11: Experiment layout and data (Problem F4)

Experiment	Parameter of GA solver									No.of.obj.fun. evaluations	Fitness value				
	A	B	C	D	E	F	G	H	I		Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	1	1	1	1	1	1	1	80000	16.0838	5.5842	6.1145	9.2199	11.5298
2	1	1	2	2	2	2	2	2	2	80000	0.0000	10.9445	1.9899	0.0000	1.9899
3	1	1	3	3	3	3	3	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
4	1	1	4	4	4	4	4	4	4	80000	4.9748	1.9899	2.9849	4.9748	8.9546
5	1	2	1	1	2	2	3	3	4	80000	11.9395	9.9496	25.8689	19.8992	27.8588
6	1	2	2	2	1	1	4	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
7	1	2	3	3	4	4	1	1	2	80000	9.9496	3.9798	9.9496	8.9546	1.9899
8	1	2	4	4	3	3	2	2	1	80000	11.9395	5.9697	4.9748	5.9698	10.9445
9	1	3	1	2	3	4	1	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
10	1	3	2	1	4	3	2	1	4	80000	7.9597	6.9647	11.9395	17.9092	10.9445
11	1	3	3	4	1	2	3	4	1	80000	0.0000	0.0000	0.0000	0.0000	0.0000
12	1	3	4	3	2	1	4	3	2	80000	34.8235	37.8084	34.8235	19.8991	27.8587
13	1	4	1	2	4	3	3	4	2	80000	0.0000	0.0000	0.0000	0.9950	0.0000
14	1	4	2	1	3	4	4	3	1	80000	19.2426	8.9190	12.2462	11.4618	16.1837
15	1	4	3	4	2	1	1	2	4	80000	0.0000	0.0000	0.0000	0.0000	0.0000
16	1	4	4	3	1	2	2	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
17	2	1	1	4	1	4	2	3	2	80000	9.9496	3.9798	8.9546	9.9496	4.9748
18	2	1	2	3	2	3	1	4	1	80000	2.5846	3.2491	4.3576	1.6338	1.0394
19	2	1	3	2	3	2	4	1	4	80000	11.9395	33.8285	3.9798	31.8386	17.9093
20	2	1	4	1	4	1	3	2	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
21	2	2	1	4	2	3	4	1	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
22	2	2	2	3	1	4	3	2	4	80000	1.9899	4.9748	0.9950	0.9950	0.9950
23	2	2	3	2	4	1	2	3	1	80000	2.9849	6.9647	5.9698	3.9798	4.9748
24	2	2	4	1	3	2	1	4	2	80000	0.0000	1.9899	0.9950	0.0000	0.0000
25	2	3	1	3	3	1	2	4	4	80000	14.9244	8.9546	17.9092	20.8941	19.8992
26	2	3	2	4	4	2	1	3	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
27	2	3	3	1	1	3	4	2	2	80000	22.8840	32.8336	15.9193	25.8689	52.7326
28	2	3	4	2	2	4	3	1	1	80000	0.9950	1.9899	0.0000	0.0000	0.0000
29	2	4	1	3	4	2	4	2	1	80000	8.7401	9.1765	7.6401	7.0909	6.3953
30	2	4	2	4	3	1	3	1	2	80000	0.0000	1.9899	13.9294	1.9899	0.9950
31	2	4	3	1	2	4	2	4	3	80000	0.0000	0.0000	0.0000	0.0000	0.0000
32	2	4	4	2	1	3	1	3	4	80000	0.9950	0.0000	0.0000	0.0000	1.9899

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