Variable Tuning for Electrostatic Powder Coating Process via Elephant Herding Optimisation Algorithm on Modified Simplex Method

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***Abstract*—An iterative search process of Metaheuristic to efficiently determine the optimum depends on the parameter levels. There are various natural intelligences and inspirations and in this work, Elephant Herding Optimisation algorithm or EHO was selected to find maximal solutions of some noisy non-linear and multimodal continuous mathematical functions. Metaheuristics with their own benefits are then merged with the conventional response surface methods. An aim is to avoid the design point to be premature during the refinement of the process variables in the context of response surface methodology. The new electrostatic process is automatically used for aluminium coating on metallic alloy wheels. It is very difficult to make powder coating run under various influential process variables, resulting in significantly lower customer specification for appearance issues. This study focuses on the optimisation of electrostatic powder coating process variable level via the novel elephant herding optimisation algorithm on the modified simplex method with multiple performance measures. The experimental results suggest that the proposed levels of process variables from the proposed method seems to be more efficient on the multiple response surfaces when compared with the previous operating condition. In addition, two phases based on the response surface methodology was also applied to study the EHO parameter levels via some performance measures.**

***Index Terms*—electrostatic powder coating process, elephant herding optimisation algorithm, modified simplex method, noisy multimodal response surfaces, desirability function**

I. Introduction

Idea of stochastic algorithms based swarm intelligence is to mimic collective behaviour of natural spices. It has been a significant role of various research fields, especially hard search and optimisation problems. These systematic search procedures based on natural phenomena consist of algorithms of ant colony, firefly, monkeys, bats, cuckoo birds, spiders and counting still including elephant herding optimisation. Swarm algorithm provides its own phases and procedures. However, the main idea is to generate the set or domain of search solutions or possible agents. The best so far solution is searched by collective intelligence from its own memory, global data from swarm and randomisation. Through multiple generations, these sequential searches bring special equations to approach their optimal fitness locations.

Swarm intelligence has been successfully solved optimisation problems. Usually the algorithm starts with exploration where problem solutions widely proceed or visit new regions of a search space. Followed by Exploitation is then used where solutions visit neighborhood of previously visited design points in candidate search spaces. Their parameter values also strongly affect the quality of solutions. Determining the proper parameter levels is of importance with the requirement of expertise and information of the algorithm, the algorithmic structures, parameters and the stated problems. This paper describes how the refinement of elephant herding optimisation parameters can be automated by applying response surface method on a set of noisy multimodal continuous models.

The applications of the conventional response surface methods based on simplex design concerns the determining of optimum conditions of the processes. Many modifications of the simplex design based method include an introduction of a relation between the initial size of the simplex and the number of process variables and the size of the possible solution domain. Some cases of many variables in simple response surfaces the convergence of the modification is higher than that of the original one. Some works merge the design points from useful factorial experiments and a previous regression equation. In some procedures a vertex of the simplex can be shifted to the border of the region of variables or the design point with deteriorated responses. It is important to select appropriate levels of step size in initial vertices.

From some benefits of the metaheuristics this study proposes an evolutionary operation from the elephant herding optimisation algorithm (EHO) on the modified simplex method to avoid the simplex size extremely shrinks. Some additional study is performed to determine the effects of the EHO before implementing to the real process of electrostatic powder coating on metallic alloy wheel. The paper is organised as follows: Sections II and III give the details of the electrostatic powder coating and

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a novel algorithm which is developed by extension from the traditional modified simplex method and the elephant herding optimisation algorithm, respectively. In Section IV the simulated response surfaces in forms of noisy multimodal functions is introduced to study the effects of parameters of the elephant herding optimisation algorithm. Section V demonstrates the promising performance of the proposed method using the manufacturing problem. The conclusion and some thoughts for further studies are given in the last section.

II. Electrostatic Powder Coating Process (EPCP)

The EPCP automatically creates a durable finish on metal and some plastics without the runs and overspray. An environmentally friendly concept and sequential operations of the EPCP are simple, much more durable and perfect for on-site coating of metal items [1], [2]. A supply reservoir pneumatically feeds dry powder of pigments and resins to a spray gun with the high voltage charge. The charged powder articles are sprayed and firmly attracted to the surface of the part which is electrically grounded. They are then melted and fused into a smooth coating in the curing ovens and the powder coating will wrap around to the other side. There is no evaporation of solvents into the air or go down the drain. However, the surface of parts needs to be free from oil, sandblasting, chemical and acid pretreatments are of importance to remove dirt and rust (Fig. 1).

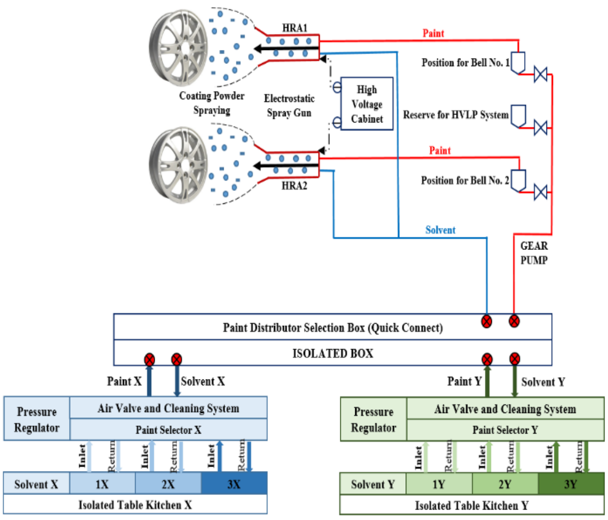

Figure 1. Electrostatic powder coating process.

TABLE I. Process Variables of the EPCP

Process Variables	Symbol
Paint Resistance	x_1
Electrostatic Charging	x_2
Paint Viscosity	x_3
Paint Flow Rate for Spray Gun Station 1	x_4
Ring Air Pressure for Spray Gun Station 1	x_5
Paint Flow Rate for Spray Gun Station 2	x_6
Ring Air Pressure for Spray Gun Station 2	x_7

There are only some important parameters to be tested to avoid excessive complication of experiments. These are determined by comparing the changes in the response caused by a change in level of each of the parameters upon expert systems. Then there are 7 variables of the EPCP in this implementation. The first three process variables are from metallic coating materials and the remaining are from twin spray gun stations (Table I). The pressure of regulator for solvent, paint inlet and return are set at 3, 6 and 5 bars, respectively. There are four simultaneously controlled specifications or process responses based on the metallic thickness in each position of the wheel as shown in Table II.

TABLE II. Customer Specifications on Coded Thickness

Reference Position	Coded Metallic Thickness		
	Lowest	Target	Highest
Outboard spoke	150	225	300
Inboard spoke	150	225	300
Window between spoke	100	175	250
Window outboard	10 0	175	250

III. Proposed Algorithm

A. *Modified Simplex Method (MSM)*

Process optimisation system consists in such a selection of the controllable variables. These selected parameters enable a certain state-dependent variable or response to achieve the most beneficial levels. A classical algorithm for determining the optimal conditions is a one-variables-at-a-time (OVAT) optimisation procedure. An aim is to refine such a level of the given variable, which can provide the most preferable result of the experiment. However, there are some OVAT disadvantages other methods have been proposed with more information and less time consumption such as the steepest ascent technique by Box and Wilson, Various optimisation methods have been developed to achieve the smallest number of experiments needed and the simplicity of calculations. One among them is the algorithm involving geometric solids referred to as simplexes. The simplex method (SM) has been first introduced by Spendley and team. Every system applying the SM reacts to changes in the level of the response by changing the given set of values of the process variables. If the number of process variables is n, the simplex is a geometric figure defined by a number of points higher by one compared with or $(n+1)$ dimensional [3].

Process optimisation of the SA consists in finding the coordinates or values of the process variables that optimise the response. According to the basic principles of searching for an optimum by the SM the simplex is moved in the variable space depending on the experimental results in all the simplex vertices. After performing experiments for all the vertices the vertex corresponding to the worst response is decided to discard and reflect in the opposite face in order to generate the new vertex. Various procedures that enables to avoid the premature in searching within a local optimum have been proposed to increase the efficiency of searches for optima. Nelder and Mead have proposed a modified simplex method (MSM) to include an expansion and contraction of the simplex. These rules of such a movement guarantee that even if for a new vertex the corresponding response is worse than that corresponding to the discarded one, the movement of the simplex toward the space of the optimum continues. There is always a possibility, that there are more than one response of the process. It is impossible to establish the overall performance measure via the desirability function technique.

B. Elephant Herding Optimisation Algorithm

Elephant herding optimisation algorithm (EHO) is a swarm optimisation algorithm proposed by Wang et al., in 2012 [4]. EHO was based on the social behaviour of elephant clans. There two herding rules on the EHO. On the exploitation, whole population of elephants contains some fixed number of clans or subgroups. The elephants in the clans move under the leadership of a matriarch. On the exploration, in each generation a fixed number of elephants leave their own clan and live alone. The following conclude the set of functions that control the herding of elephants in the search space.

The EHO is defined as follows. Suppose, there is a complete elephant population and they are divided into *C* clans. There are *P* elephants in each clan. The position of ith elephant in jth clan is represented as $X_{i,j}$. In each clan updating operator, the current position of all elephants is updated as given below:

$$\text{New } X_{i,j} = X_{i,j} + \alpha \times \text{rand} \times (X_{BEST,j} - X_{i,j})$$

The new position of elephant (New $X_{i,j}$) is updated from the old position ($X_{i,j}$) to the best or matriarch location ($X_{BEST,j}$) and $\alpha \in [0, 1]$ is a matriarch scale factor determining the influence on clan. The parameter rand$\in[0, 1]$ is a random number. The best elephant which represents the matriarch cannot be updated the previous equation. The matriarch movement is then updated by the following equation.

$$X_{BEST,j} = \beta \times X_{CENTRE,j}$$

where $\beta \in [0, 1]$ is the EHO factor controlling an influence of the center location of the herd as followed:

$$X_{CENTRE,j} = \frac{1}{P}\sum_{j=1}^{P} X_{i,j}$$

In each clan there is the exploration of some elephants with the worst values of the objective function moving away from the clan or the worst position ($X_{WORST,j}$). The worst position is updated to the new positions according to the following equation:

$$X_{WORST,j} = X_{MIN} + \text{rand} \times (X_{MAX} - X_{MIN} + 1)$$

where X_{MIN} and X_{MAX} represent, the lower and upper levels of the feasible solutions, respectively. The parameter rand$\in[0, 1]$ is random number chosen from uniform distribution. These sequential procedures continue until termination criterion meets. The pseudo code of the EHO is shown in Fig. 2 below [5]-[12].

```
Procedure EHO Metaheuristic()
Begin;
Initialise all EHO parameters
Define the fitness function
Set generation counter = 1
Set the maximal generation or MaxGen
Initialise the population and
Repeat
    Sort all the elephants according to their fitness level
    For all clans j in the population do
        For all elephants i in the clan j do
            Update X_{i, j} and generate New X_{i, j}
            If X_{i, j} is the best then
                Update X_{i, j} and generate X_{BEST, j}
            End if
        End for
    End for
    For all clans ci in the population do
        Replace the worst elephant in clan j by X_{WORST, j}
    End for
    Evaluate population by the newly updated positions
Until stop criteria=FALSE
Return the best solution among all population
End procedure
```

Figure 2. Pseudo Code of the EHO Algorithm.

IV. Preliminary Study of EHOMS

In this work, to test our proposed method or the novel elephant herding optimisation algorithm on modified simplex method (EHOMS) we used a C++ computer program and experiments were done on the platform with A Laptop computer DV2000 HP Pavilion. We tested the EHOMS on four standard benchmark functions with noisy and multimodal natures. Parameters of EHO algorithms were population size, clans, α, and β. Lower and upper bounds are provided in the previous section of multimodal response surfaces.

There are various multimodal benchmark functions available in the literature. However, these functions are relatively simple and various algorithms can efficiently solve them. There is also a lack of noisy multimodal problems. In this paper, there are four noisy non-linear response surfaces used to determine the performance measures of the proposed metaheuristic for searching the optimal solutions. The functions, F1-F4, including its ranges are illustrated as follow [13].

F1: Himmelblau's function

$f(x_1, x_2) = 200 - (x_1^2 + x_2 - 11)^2 - (x_1 + x_2^2 - 7)^2$

Range: $-6 \le x_1, x_2 \le 6$

F2: Six-Hump Camel Back's function

$f(x_1, x_2) = -4[(4-2.1x_1^2 + \frac{x_1^4}{3})x_1^2 + x_1x_2 + (-4+4x_2^2)x_2^2]$

Range: $-1.9 \le x_1 \le 1.9$

$-1.1 \le x_2 \le 1.1$

F3: Shekel's Foxholes function

$$f(x_1, x_2) = 500 - \frac{1}{0.002 + \sum_{i=0}^{24} \frac{1}{1 + i + (x_1 - a(i))^6 + (x_2 - b(i))^6}}$$

where $a(i) = 16(i \bmod 5) - 2$ and

$b(i) = 16\left(\frac{i}{5}\right) - 2$

Range: $-65.536 \le x_1, x_2 \le 65.535$

F4: Inverted Shubert's function
$f(x_1, x_2) = -\prod_{i=1}^{2} \sum_{j=1}^{5} j cos[(j+1)x_i + j]$
Range: $-10 \le x_1, x_2 \le 10$

Apart from the original function above in the context of response surface methodology, the process responses also apply the noise on all four multimodal functions. The noise is normally distributed with the mean of zero and standard deviation levels of 0, 1, 2 and 3. In a response surface method, screening designed experiments are performed in the early stages of the process to determine large effects of influential EHO parameters on the response for further investigation. An approximation model via a two-level factorial approach is built to determine the main and interaction effects among four parameters. The low and high levels of each of four parameter of the EHO need to be defined as shown in Table III. There are 200 realisations performed for each of the four functions and three noise levels. The results showed that the population size statistically affected the response when there was noise on the response at 95% confidence interval. All parameters, except α, affected the response when there was no noise on the response at 10% significance level (Table IV).

TABLE III. EHO PARAMETERS AND THEIR LOW/HIGH LEVELS

Parameter	Low	High
Population size (P)	50	100
Clan (C)	5	10
α	0.6	0.7
β	0.005	0.05

TABLE IV. INFLUENTIAL PARAMETERS AND THEIR P-VALUES

Parameter	Noise	F1	F2	F3	F4
P	0	0.012	0.009	0.021	0.001
	1	0.035	0.042	0.021	0.032
	2	0.048	0.029	0.033	0.045
	3	0.032	0.020	0.007	0.028
C	0	0.056	0.023	0.072	0.096
	1	0.021	0.073	0.092	0.008
	2	0.058	0.094	0.052	0.092
	3	0.056	0.023	0.022	0.013
α	0	0.124	0.233	0.103	0.376
	1	0.523	0.246	0.179	0.686
	2	0.408	0.233	0.103	0.376
	3	0.332	0.208	0.115	0.256
β	0	0.075	0.098	0.011	0.041
	1	0.019	0.042	0.053	0.074
	2	0.088	0.076	0.060	0.042
	3	0.008	0.059	0.073	0.092

A second-order model can be constructed efficiently with the central composite design (CCD) of three parameters by fixing α at its proper level of 0.8. This designed experiment allowed estimation of the tuning parameters of the EHO. From the second phase of designed experiments, parameters of EHO algorithms were recommended as follows. Population size was 100 and it was divided into 5 clans. Parameter α was set to 0.7 and β was 0.005. For each function, the computational run using each method was repeated 100 realisations using different random seed numbers. The experimental results obtained from each phase including the best so far, worst, mean responses and its standard deviation (Stdev) as shown in Table V were compared for all four testing functions described in the previous section.

TABLE V. COMPARISON OF PERFORMANCE MEASURES OF THE EHOMS AFTER TWO PHASES OF DESIGNED EXPERIMENTS WITHOUT NOISE

Surface	Performance Measure	1st Phase	2nd Phase
F1	Best so far	-7.300	-1.905
	Worst	-20.221	-5.886
	Mean	-13.236	-3.762
	Stdev	3.794	1.235
F2	Best so far	-2.715	-0.780
	Worst	-10.074	-2.626
	Mean	-6.006	-1.749
	Stdev	2.044	0.621
F3	Best so far	-21.357	-1.690
	Worst	-40.695	-3.654
	Mean	-29.795	-2.582
	Stdev	6.587	0.576
F4	Best so far	-14.302	-2.661
	Worst	-21.094	-11.057
	Mean	-17.879	-5.761
	Stdev	2.232	2.388

V. RESULTS AND DISCUSSIONS ON THE EPCP

In this research the procedure for simultaneous optimisation of the four responses is a modification of the desirability function method developed by Derringer and Suich [14]-[17]. Each predicted response, $\hat{y}$, is transformed to a dimensionless partial desirability function (d_i). This method considers the researcher's priorities and desires when building the optimisation procedure of the specific process. In the EPCP refinement the response i is to be the-nominal-the best: The desirability function for the case of the nominal-the-best can be written as:

$$d_i = \begin{cases} \left[\frac{\hat{y}-A}{T-A}\right]^{s_i}, A \le \hat{y} \le T, s_i \ge 0 \\ \left[\frac{\hat{y}-B}{T-B}\right]^{t_i}, T \le \hat{y} \le B, t_i \ge 0 \\ 0, Otherwise \end{cases} \quad , i = 1,2,3,4$$

In the quantity d_i above, A and B are the lower and the lower bounds obtained for the response i, respectively. The value of $\hat{y}$ is required to achieve a specific target T. When the $\hat{y}$ equals to T, the desirability level is 1; if the departure of $\hat{y}$ excesses a particular level from the target, the desirability level is 0. Parameters of s_i and t_i are the weights in each response. d_i ranges between 0, for a completely undesired response, and 1, for a fully desired response. In both weight parameters, d_i can vary non-linearly while approaching the desired value. However, in this study a weight is set at 1, d_i then varies linearly. In this work we chose weights equal to 1 for all four responses. The individual desirability functions (d_i) are then merged into a single composite response, the so-called overall desirability function (D). It is defined as the geometric mean of the different d_i levels:

$$D = [d_1 \times d_2 \times \ldots \times d_n]^{1/n}$$

When all responses are near their target values simultaneously with the D level close to 1, the combination of the different criteria is globally optima.

The design parameter levels of all parameters (x_1, x_2, x_3, x_4, x_5, x_6, x_7) are currently set at (90, 50, 9.8, 75, 2.3, 75, 2.5), respectively. The coded levels of lower and upper bounds of operation on x_1, x_2, x_3, x_4, x_5, x_6, and x_7 is given as [75, 100], [35, 65], [9, 10], [50, 70], [2, 2.5], [50, 70] and [2.5, 3], respectively. The aim of this study is to collect all benefits from the mentioned strategies to form the novel Elephant Herding Optimisation algorithm on the Modified Simplex method (EHOMS) for multiple response surface optimisation. This algorithm is applied to the EPCP and an aim is to simultaneously optimise all four customer specifications or process responses via the proper levels of influential variables. Firstly, the starting treatments from the MSM will be applied to moves toward the optimum. All four responses are measured by the overall desirability. The size and position of the initial simplex is determined from preliminary experiments.

For all the vertices the coordinates of all seven variables may be calculated from the step size of individual variables and from the initial design point selected in the variable space. The new vertices of the conventional MSM such as the reflected, passive and negative contraction are generated in order to achieve the better overall desirability level. The response surface is sometimes confined to such boundaries of admissible range of variables, which result from process conditions. If the vertex of a simplex moves outside this region or the simplex excessively shrink the realisation of the experiment becomes impossible. The simplest solution to this problem is to hybridise with the EHO to escape from the current solution to continue the search for the optimum. The proposed algorithm has been proposed used for controlling the shape of the simplex to avoid its massive contraction and thus ending the search for the optimum. After three main evolutionary MSM operators, the EHO generated four vertices and the vertex of EHO3 led to the preferable level of overall desirability. Moreover, some design points of C2- and C3- went outside the upper and lower bound of the process variables. The search for optimum by the EHOMS terminates after a certain value of an accepted criterion has been reached. In this implementation the search for a target was completed when the overall desirability reaches a level considered to be optimum by the experimenter. There were three iterations of the EHOMS as shown in Table VI and Fig. 3. The first experimental result applied successfully via the MSM operator of the reflected vertex. From the second cycle the reflected vertex deteriorated in the overall desirability the additional contraction was then performed to achieve the better result at C2+. However, in the third iteration there was no improvement via the MSM the evolutionary operation from the EHO was used for further improvement. Currently, the best so far solution (BSF) is **x*** = (x_1*, x_2*, x_3*, x_4*, x_5*, x_6*, x_7*) = (75, 60, 9.27, 67, 2, 67, 2.8). At the BFS individual corresponding desirability levels of d_1, d_2 d_3 and d_4 are 0.983, 0.777, 0.623, and 0.544, respectively. To validate the outcome from the EHOMS, the new design point were carried out with targeted responses of outboard spoke, inboard spoke, window between spoke and window outboard of about 223.75, 241.67, 146.75 and 140.83, respectively, on average.

TABLE VI. ITERATIVE PROCEDURES OF THE EPCP REFINEMENT VIA THE EHOMS

Vertex	x_1	x_2	x_3	x_4	x_5	x_6	x_7	D
Current	90	50	9.27	70	2.3	65	2.5	0.329
R1	82	45	9.23	55	2.5	65	2.5	0.401
R2	78	48	9.54	58	2.5	65	2.5	0.376
C2-	81	46	9.62	60	2.5	66	3.5	Na
C2+	79	47	9.37	58	2.5	68	2.5	0.432
R3	81	43	9.27	55	2.5	68	2.5	0.291
C3-	80.5	46	9.26	47	2.5	68	2.5	Na
C3+	81	47	9.27	55	2	65	2.5	0.275
EHO1	80.5	48	9.47	50	2.5	60	2.5	0.483
EHO2	100	50	9.54	70	2	70	2.5	0.542
EHO3	75	60	9.27	67	2	67	2.8	0.713
EHO4	80.5	46	9.58	57	2.2	65	3	0.677

The current and new operating conditions were tested to determine the differences between group means via an analysis of variance (ANOVA) at the 95% confidence interval. It can be concluded that there was no statistical significance on both scenarios. However, the statistical results suggested that the EHOMS scenario provided the slightly better performance in terms of the average the coded thickness for all customer requirements.

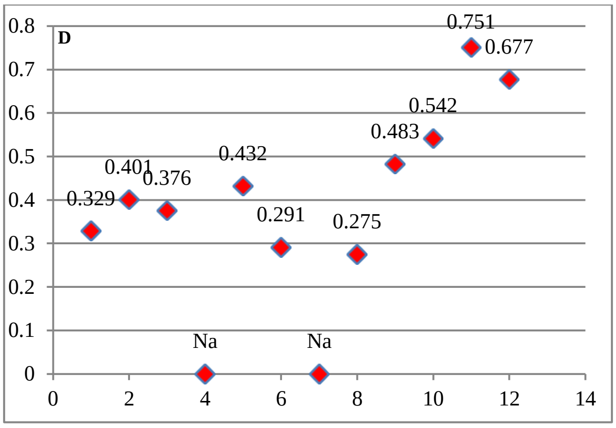

Figure 3. Sequential Performance of the EHOMS on the EPCP.

VI. CONCLUSIONS

In this paper, elephant herding optimisation algorithm was adapted to find optimal solutions of four noisy multimodal response surfaces. A series of designed experiments were conducted to ease the difficulty of choosing proper parameter levels of the metaheuristic when solving multimodal optimisation problems. Performance measures consist of the best so far solutions, mean and standard deviation. Based upon the number of peaks and the noise levels, population size, one among various important factors in maximising multimodal functions, has influences on the formation of stable subpopulations. With a small population the algorithm is not able to fully explore the solution space, thus miss local optima. In contrast, a large population size takes longer to converge to the optimum after improving individuals' experience and forming stable groups around local optima. The hybridisation of the elephant herding optimisation algorithm to the response surface method called the modified simplex method is proposed to fine tuning of the variable levels of the automatic electrostatic powder coating process. The experimental results show that with the overall desirability level increases from 0.329 to 0.713.

Seven variables of paint resistance, electrostatic charging, paint viscosity, paint flow rate for spray gun station 1, ring air pressure for spray gun station 1, paint flow rate for spray gun station 2 and ring air pressure for spray gun station 2 should be set at 75, 60, 9.27, 67, 2, 67, and 2.8, respectively. Therefore, this proposed method based on the conventional MSM and the evolutionary operation from the EHO metaheuristic is able to enhance the responses of the production process effectively, fast and economically. This metaheuristic can avoid the premature of the simplex and search further feasible levels of influential variables during the variable refinement. However, its parameter levels are sensitive to different problems. The additional procedure is needed to determine the proper levels of metaheuristic parameters. In future work, other metaheuristics would be considered to enhance the performance of the conventional response surface methods. Moreover, additional study includes their algorithmic procedures, especially the related parameters. Additionally, more complex and dimensional benchmarking functions will be considered to compare the performance measures of the algorithms when optimizing the manufacturing processes.

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