Enhancing Laser Welding Process via a Constrained Response Surface Optimisation Model Embedded with ACO

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***Abstract*—In this research, a novel constrained response surface optimisation model (CRSOM) with the incremental solution constructions via the metaheuristic of ant colony optimisation is introduced to determine the preferable levels of industrial process parameters. They are developed in two forms including both linear (LCRSOM) and nonlinear (NLCRSOM) regression models for estimation of influential parameter coefficients. Then, in order to compare the accuracy of the proposed algorithm, a comparison is made on a laser welding process of the electronic industry. On the current situation of the head support and suspension, assembly it has been found that shear strength is quite higher than customers' specification. During an inspection, the sample size and frequency are set at high levels. Other quality characteristics include welding diameter and depth as well. The proposed method is having a provision to include both explicit constraints of influential process parameters as well as implicit constraints of customer specifications. From experimental results, the mean absolute errors of the CRSOM on ACO are better and the best so far solutions are provided by nonlinear form (NLCRSOM) due to fluctuations of responses affected by the influential parameters. The selected levels of influential process parameters have been successfully implemented for all three responses. The advantage of the incremental solution constructions via both metaheuristics in each type of CRSOM is that all the experimental data are simultaneously collected and analysed to obtain a final operating condition. When industrial problems are large and complicated, finite instructions from the proposed approach are effective. Setting industrial parameters is more useful, systematical and practical.**

***Index Terms*—constrained response surface optimisation, ant colony optimisation, laser welding process**

I. Introduction

Optimising product and process parameters is crucial for manufacturing industries. It always takes a relatively long time regardless of levels of a process variation including variation in use or from deterioration. Only with the application of applied response surface methodology, firms can perfect product and process characteristics, reduce related design cost, and plan manufacturing processes more efficiently and systematically. Noisy environment may give rise to various inaccurate consequences of robust product or process. Robust design and analysis is determined as a realistic and effective identification of expected future performance characteristics via parameter values while minimising the effect of noise. However, the mean received actual responses were little statistically significant when applying conventional response surface methods in some processes. Recently, response surface methods embedded with metaheuristics has received notable attention from the designer to understand these potential sources of variation and take additional sequential procedures to desensitise the product or process to these potential sources of variation [1]. For many metaheuristic methods, scientists or practitioners have used the intelligent design to improve the accuracy of optimal parameter levels.

The algorithm of ant colony optimisation (ACO) first introduced by Marco Dorigo and colleagues [2]. The ACO is simulated with the behavior of the real ants. These ants have the capability to find the shortest path from the food source to the nest or their destination. Ants communicate each other via the chemical substance or pheromones in their immediate environment. They are capable of searching a new shortest path when the old one is no longer feasible because of an obstacle. Robust design and analysis via a novel constrained response surface optimisation method can be achieved through embedded ACO metaheuristic. Via the proposed method, the designers would understand and declare crucial product or process design parameters affecting performance characteristics. They also could be capable to determine the optimal levels to those parameters while minimising all related variation. This article presents the novel response surface method. It applies the incremental solution constructions from the ACO for estimating potential process or product parameter coefficients to generate a constrained response surface optimisation model (CRSOM). The proposed method has both linear and nonlinear forms.

An objective of this research is to determine preferable process parameter levels to maximise shear strength of a head support and suspension assembly while customer

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specifications in terms of welding diameter and depth are satisfied. This new settings could bring lower levels of the processing cost from higher levels of quality inspections. In the second section, the related process is briefly described. The fundamental ACO algorithm is included in section “Constrained response surface optimisation model embedded with the ACO (CRSOM-ACO).” In section “Numerical results and analysis” results obtained by the CRSOM on both linear and nonlinear programming models embedded with ACO are presented. Finally, the conclusions and discussions of the research and the suggestions for further studies are given in section “Conclusions and discussions.”

II. Laser Welding Process (LWP)

This research focuses on laser welding which is the logical processing solution to accomplish joining and cutting needs of hard disk drive (HDD) applications. There are various HDD parts such as a platter, an actuator and a head support and suspension assembly (HSSA). While the HSSA stores the information of a magnetic disk drive, it moves and positions the recording head (Fig. 1). Various production processes of the HSSA consist of etching, forming, gimbal aperture cutting, laser beam welding assembly, gram forming, separation, and aqueous precision cleaning including a gram load and static attitude adjustment [1]. Improving undesirable HSSA quality measures at the design stage are actually aimed to remove the processing variations. Particularly, this research focuses on a deformation of a load beam and a gimbal while joining these components together. A laser welding process possibly brings the shear strength at lower levels. Mechanical fastening and moving towards a technology are of interest to avoid suffering thermal distortion and degradation of metallurgical properties. In a laser, welding process the heat with the high density is obtained from the application of a concentrated coherent light beam via hard optics or a fibre optic cable. It is striking and impinging upon the surfaces of the metalwork pieces to be joined. After the weld pool is formed and cooled the joint becomes stronger.

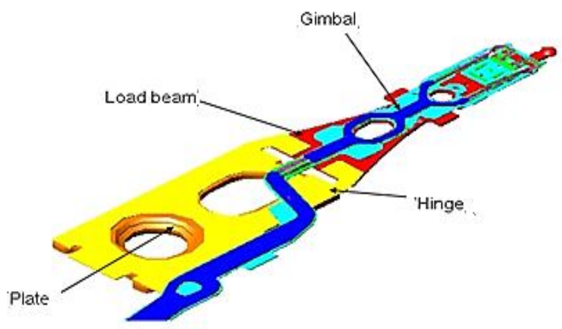

Figure 1. Head support and suspension assembly (HSSA) [3].

However, in a laser welding process (LWP) there are many parameters and sub-processes concerning some physical defects. These unsuccessful weld results consist of burning, incorrect welding depth and diameter. Therefore, a primary goal of this study is to identify the appropriate levels for the processing parameters in order to manage both the stability and the reproducibility of the overall process. Currently, an important concern includes a variation in the HSSA shear strength. Throughout the development have been inspected, both sample size and frequency could be performed at higher levels to accurately obtain the desired responses or welding properties The most important and efficient procedures of the designed experiments are deemed to yield valid and objective conclusions. Based on an expert system the process parameters consist of a compressive fixture spring force after applying the LWP, laser energy, gas flow rate and the pulse width to heat through the metal (Fig. 2). A series of structured experimental tests are designed so that planned changes are made to the process parameters and the interesting effects can be investigated. Both the governing parameters from LWP mechanics and the crucial primary and secondary responses to be discussed are defined in advance. The parameter choice is usually based on both literature and experience on similar processes [4].

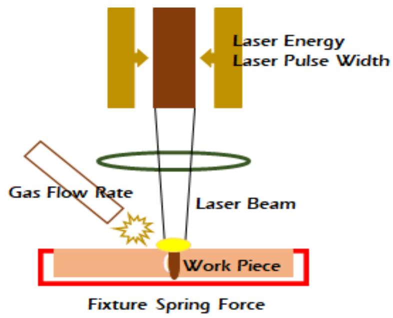

Figure 2. Laser Welding Process (LWP).

III. Constrained Response Surface Optimisation Model with Embedded ACO (CRSOM-ACO)

Response surface methodology (RSM) collects mathematical and statistical tools for building an empirical model via a series of experimental designs. The objectives are to optimise a response influenced by several parameters and identify the reasons for changes in the response. However, measurement errors or noises cause an inaccuracy in physical experiments. Low-order polynomials such as the first or second-order functions are widely used to approximate the structure of the unknown relationship between the responses and the related parameters of the system. In the first phase of the steepest ascent (descent) path a sequence of linear approximation is applied to rapidly search the direction of optimal improvement when there is no curvature effect the move continues in linear searches. Otherwise, the second phase replaces by generating a second-order or quadratic polynomial regression model. In this section, the empirical model and its variants are suggested in details. A proposed approach using particle swarm [5]-[10] and ant colony optimisation is embedded in the constrained response surface optimisation model. This can possibly generate alternatives of the estimated coefficients of the models. From various approximation structures as part of the solutions it leads to the advantage of the proposed approach. An aim is to determine a function structure with the best possible quality measure. Additionally, the complexity is not limited to the linear function but there is the inclusion of various interaction effects between parameters, depending on the understanding of the engineering systems.

A. Constrained Response Surface Optimisation Method (CRSOM)

Practically, a first-order or linear polynomial model will be used to generate the path of steepest ascent (or descent). When there is no significant effect on pure quadratic curvature from the lack of fit test, the new design points will be located via a preset step length from the current operating condition until there is no further improvement in the response. However, in the complex problems there are various associated responses. The most important will be determined as the primary response and others are assigned as secondary responses [11]-[13]. A constrained response surface optimisation model (CRSOM) is then generated to determine preferable levels of k parameters of the system. These levels bring the optimal primary response (Y_P) and satisfy all other secondary response constraints (Y_S). Moreover, feasible regions of influential parameters are also included in the proposed model. An aim is to provide suitable design points without an extrapolation. A regression analysis is used to establish primary ($\widehat{Y_P}$) and associated secondary responses ($\widehat{Y_S}$) of the CRSOM. Linear (LCRSOM) and nonlinear (NLCRSOM) programming models are formulated subject to the lower (LB) and upper (UB) bounds of secondary responses and influential parameters (X), namely:

Optimise $\widehat{Y_P}$

Subject to

$$\mathrm{LB} \leq \widehat{Y_S} \leq \mathrm{UB}$$

$$\mathrm{LB} \leq X \leq \mathrm{UB}$$

The CRSOM for estimating the preferable parameter levels in both linear (LCRSOM) and nonlinear (NLCRSOM) form can be expressed as follows:

$$\mathrm{S_{Linear}} = \beta_0 + \sum_{i=1}^{4} \beta_i x_i + \varepsilon_{ij}$$

$$S_{Quadratic} = \beta_0 + \sum_{i=1}^{4} \beta_i x_i + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 + \beta_{11} x_1^2 + \beta_{12} x_2^2 + \beta_{13} x_3^2 + \alpha_{14} x_4^2 + \varepsilon_{ij}$$

The proper parameter settings are selected by minimising the mean absolute error (MAE) between the actual (Y_P^{Act}) and estimated (Y_P^{Est}) values of primary response [14].

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |(Y_P^{Act}(i) - Y_P^{Est}(i))|$$

B. Ant Colony Optimisation (ACO)

An ant colony optimisation is a technique that based on the foraging behavior of the real ants to find the incremental solution development. If ants find their food source, then they move some food to their nest and leave a chemical pheromone trail on the ground [15]-[17]. When others smell pheromone, they tend to choose paths marked by strong pheromone amount. The quality and quantity of the source discovered can well define the concentration of the pheromone on the ground. At each iteration of the construction procedure, m ants concurrently build solutions. Ants leave pheromone trails when they make a transition and trails are used in prioritising transition. The quantity of the pheromone is deepened near the best response level. After each iteration, pheromone evaporation will be applied on all solutions as follow:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}$$

For ACO, each ant represents the design point. For the optimisation via the ACO the following procedures are applied to determine the appropriate coefficient values. First, there are m ants or design points to be constructed based on state transition rule. Next, the updated amount of pheromone follows the global updating rule. Both heuristic and pheromone information are used to guide the new design point corresponding to the best response. The algorithmic procedures are carried out until the termination rule via a cycle counter is met. On the state transition rule, the probability of the candidate s with the parameter i set at level j at time t or $P_{jl}^s(T)$ is applied for each design point.

$$P_{jl}^s(T) = \frac{[\tau_{jl}(T)]^\alpha [\varphi_{jl}(T)]^\beta}{\sum_s^{si} [\tau_{js}(T)]^\alpha [\varphi_{js}(T)]^\beta}$$

where τ_{jl} is the pheromone intensity and φ_{jl} is the heuristic information between parameter i and level j. In addition, α and β are the relative importance of the trail and the heuristic information, respectively. From the improvement process of the ACO, an ant may choose the new design point violating explicit constraints of process parameter levels and implicit constraints of secondary responses. Amount of pheromone is then deposited at higher levels if the generated design point is feasible. In contrast, it is deposited at low levels if the generated design point is infeasible. The amount of explicit and implicit constraint violations reflect in forms of penalties. The trail intensity can be then updated as the following function.

$$\tau_{ij}(new) = \rho \tau_{ij}\,(\text{old}) + \Delta\tau_{ij}$$

where ρ is a coefficient such that (1- ρ) means the evaporation of the trail. $\Delta\tau_{ij}$ is given below [18]-[20].

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$$

where m is the number of design points and $\Delta\tau_{ij}^{k}$ is given by:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1 \text{ if the k design point choose level j for parameter} \\ 0 \text{ otherwise} \end{cases}$$

IV. Numerical Results and Analysis

In this study, the numerical results of linear and nonlinear CRSOM are introduced in details. The LWP has two types of the customer specifications. Iterative strategies apply shear strength (Y_P) as a primary response. Secondary responses (Y_S) form physical constraints of the LWP. They consist of two customer specifications of welding depth and diameter (Table I). The initial CRSOM is generated to optimise the primary response subject to both implicit and explicit constraints. The parameter levels are controlled within their feasible ranges via explicit constraints. ACO metaheuristic is used to determine alternatives of regression coefficients to form two secondary responses or implicit constraints. The establishment of the CRSOM is based on four influential parameters. Metaheuristic algorithm of ACO optimised coefficients of the four influential parameters (x_i; i = 1, 2, 3, 4). These parameters consist of laser energy ($x_1: volt$), laser pulse width ($x_2: ns$), gas flow rate ($x_3: l/min$) and fixture spring force ($x_4: mm$). The performance measures of various models are determined via the minimum of the mean absolute error function measured by the difference between the observed and estimated values of primary response. The LCRSOM and NLCRSOM models are developed to the process refinement. The optimal parameter settings are of importance for the ACO. In this study these parameters are selected from the literatures. Five sequential procedures of the CRSOM are shown as follow.

TABLE I. Types of Responses and Their Feasible Coded Levels

Types	Responses	Feasible coded levels
Primary (Y_P)	Shear strength	> 4.60
Secondary 1 (Y_{S1})	Welding depth	< 1.02
Secondary 2 (Y_{S2})	Welding diameter	1.8-2.6

Step 1: Generate a 2^k factorial design points, where k is the number of parameters, close to the current operating condition of the LWP.

Step 2: Perform a principle of least squares via the statistic software (SS) including the ACO to estimate predicted regression coefficients (β) on both types of process responses.

Step 3: Minimise the mean absolute error (MAE) between the observed and estimated values of primary response to establish both linear (NLCRSOM) as shown below and nonlinear (NLCRSOM) constrained response surface optimisation models. From both models, estimate the new operating condition from the CRSOM via the generalised reduced gradient algorithm and go to Step 4.

$$\text{Maximise: } \widehat{Y_P} = \hat{\beta}_0^P + \hat{\beta}_1^P x_1 + \hat{\beta}_2^P x_2 + \ldots + \hat{\beta}_k^P x_k$$

Subject to

$$\widehat{Y_{S1}} \text{ or } \hat{\beta}_0^{S1} + \hat{\beta}_1^{S1} x_1 + \hat{\beta}_2^{S1} x_2 + \ldots + \hat{\beta}_k^{S1} x_k \leq \text{UB}$$

$$\text{LB} \leq \widehat{Y_{S2}} \text{ or } \hat{\beta}_0^{S2} + \hat{\beta}_1^{S2} x_1 + \hat{\beta}_2^{S2} x_2 + \ldots + \hat{\beta}_k^{S2} x_k \leq \text{UB}$$

$$\text{LB} \leq x_i \leq \text{UB};\ i = 1, 2, \ldots, k$$

Step 4: If CRSOM design points are feasible, replace the previous one by the new condition from the CRSOM.

Step 5: Check for the termination of the CRSOM via the curvature effect. If there is no evidence, continue and repeat Step 1.

In the course of an iterative optimisation process modelled by the CRSOM, a new scheme for the design and analysis of experiments has been formulated with the following procedures. A single designed experiment focuses on examining four parameters on three specifications of a laser welding process. Actually, in order to receive the highest information level, a general full factorial design is required to contain all possible combinations of parameters and levels. This design is available to take reasonable account of any interaction of two parameters. With many experimental design points in this research the two level factorial designs are applied to consider only effects of all parameters and their interactions. Because of the confidential data, the (low, high) levels in the natural parameters for x_1, x_2, x_3 and x_4 are all coded as (195, 205), (350, 500), (10, 30) and (4, 8), respectively. In the early phases of the process improvement when it is likely that there are many process parameters, various screening designed experiments are traditionally applied to remove some parameters with little or no effect on the response. An aim is to identify the influential process parameters that have large effects for further investigation. Moreover, in multiple response surface optimisation, these design points will be also used to analyse the best so far of average primary responses under satisfactory levels of all constraints of secondary responses including all feasible parameter levels. A normal probability plot of effects showed that influential parameters of x_1, x_2, and x_4 including the $x_1x_2x_3x_4$ interaction statistically affected the primary response of shear strength (Fig. 3). In addition, all process parameters affect statistically to the secondary responses of welding depth and diameter at the approximate 5% significance level throughout. The data were also used to validate the models.

The mathematical models and its performance were established. According to the previous operating conditions, it can be concluded that the linear function fits a relationship between four process parameters and shear strength. However, the linear model also contains many limitations because the relationship of parameters and two remaining secondary responses are nonlinear. Consequently, the CRSOM based on four parameters was modeled using both forms in this research. The CRSOM is developed in two forms including both Linear (LCRSOM) and Nonlinear (NLCRSOM). In addition, particle swarm and ant colony optimisation algorithms are used to compare their accuracy via the different

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estimated regression coefficient levels. Tables II and III provide the coefficients of linear and nonlinear models including the relative errors between estimated and observed data (MAE). The comparison between statistic software (SS), and ACO exposes that the ACO is providing better-fit estimation than SS whether in linear or nonlinear forms. However, there is only a statistically significant evidence of a difference in means on the nonlinear form from an analysis of variance (ANOVA) at the confidence interval of 95%.

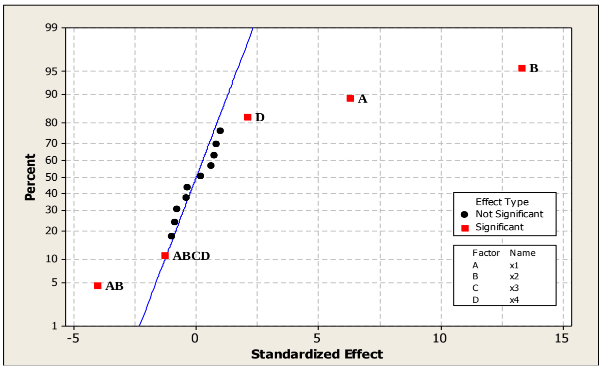

Figure 3. Normal probability plot of effects on a primary response of shear strength.

TABLE II. COEFFICIENT ESTIMATES OF LINEAR MODEL

Coef	$\widehat{Y_P}$		$\widehat{Y_{S1}}$		$\widehat{Y_{S2}}$	
	SS	ACO	SS	ACO	SS	ACO
$\widehat{\beta_1}$	0.03318	0.19423	0.01231	0.00784	0.01178	0.02017
$\widehat{\beta_2}$	0.07031	-0.1113	0.01831	0.08993	0.01484	0.01062
$\widehat{\beta_3}$	0.00437	-0.151	-0.0001	-0.0197	-0.0002	0.00855
$\widehat{\beta_4}$	0.01106	0.13026	-0.0018	0.0287	-0.0006	0.01726
MAE	0.1317	0.0843	0.036	0.0427	0.0623	0.0383

CRSOM models (LCRSOM and NLCRSOM) are developed to set new expected operating condition of the LWP. From the literatures, it is important to perform the metaheuristic algorithm ACO under their optimal parameter settings. According to a preliminary study the proper levels of ants (n) are 40; maximum iterations are 100,000. Following CRSOM (linear and nonlinear) equations are obtained for empirical model building. In the linear form, coefficients obtained by the ACO are given in the LCRSOM below:

$$\text{Maximise } \widehat{Y_P} = 0.19423x_1 - 0.1113x_2 - 0.1510x_3 + 0.13026x_4$$

Subject to

$$0.00784x_1 + 0.08993x_2 - 0.0197x_3 + 0.0287x_4 \le 0.102$$

$$0.18 \le 0.02017x_1 + 0.01062x_2 + 0.00855x_3 + 0.01726x_4 \le 0.26$$

$$\text{LB} \le x_i \le \text{UB};\ i = 1, 2, 3, 4$$

The coefficients obtained by the ACO on the NLCRSOM were given below:

$$\text{Maximise}\widehat{Y_P} = -0.08383x_1 + 0.05992x_2 + 0.04564x_3 - 0.12511x_4 - 0.03859x_1x_2 + 0.04296x_1x_3 - 0.15988x_1x_4 - 0.20932x_2x_3 + 0.18138x_2x_4 - 0.16014x_3x_4$$

Subject to

$$0.099x_1 + 0.00937x_{21} + 0.06477x_3 - 0.0491x_4 - 0.01732x_1x_2 + 0.00264x_1x_3 + 0.0742x_1x_4 - 0.02921x_2x_3 - 0.05695x_2x_4 + 0.01178x_3x_4 \le 0.102$$

$$0.18 \le 0.02429x_1 + 0.03512x_2 + 0.00273x_3 - 0.0125x_4 - 0.0146x_1x_2 + 0.01207x_1x_3 + 0.02114x_1x_4 + 0.0178x_2x_3 - 0.00359x_2x_4 - 0.00256x_3x_4 \le 0.26$$

$$\text{LB} \le x_i \le \text{UB};\ i = 1, 2, 3, 4$$

The process constructing response surface models is iterative with the goodness-of-fit. If there is no satisfactory result, the iterative process is restarted and approximated. Further experimental designed points are then included. In each of these three settings in each model, five applicable replicates are executed. The average of shear strength will serve as the objective for the preferable process settings. These alternatives are subject to all desirable levels of constraints. On the LCRSOM the estimated settings for all scenarios of SS, and ACO were impractical whereas the NLCRSOM-ACO gave the new setting of influential parameters with the highest average shear strength. In the first iteration, the parameter settings from the NLCRSOM could be used as the new operating condition of the LWP for a specific time period. A new experimentation continues to determine the better settings.

TABLE III. COEFFICIENTS OF NONLINEAR MODEL

Response	Coefficients	SS	ACO
Y_P	$\widehat{\beta_1}$	0.03319	-0.08383
	$\widehat{\beta_2}$	0.07031	0.05992
	$\widehat{\beta_3}$	0.00438	0.04564
	$\widehat{\beta_4}$	0.01106	-0.12511
	$\widehat{\beta_5}$	-0.02131	-0.03859
	$\widehat{\beta_6}$	0.00525	0.04296
	$\widehat{\beta_7}$	0.00319	-0.15988
	$\widehat{\beta_8}$	-0.00463	-0.20932
	$\widehat{\beta_9}$	-0.00419	0.18138
	$\widehat{\beta_{10}}$	0.00400	-0.16014
	MAE	0.0617	0.0227
Y_{S1}	$\widehat{\beta_1}$	0.01231	0.09900
	$\widehat{\beta_2}$	0.01831	0.00937
	$\widehat{\beta_3}$	-0.00019	0.06477
	$\widehat{\beta_4}$	-0.00181	-0.04910
	$\widehat{\beta_5}$	-0.00881	-0.01732
	$\widehat{\beta_6}$	-0.00006	0.00264
	$\widehat{\beta_7}$	-0.00081	0.07420
	$\widehat{\beta_8}$	0.00231	-0.02921
	$\widehat{\beta_9}$	0.00081	-0.05695
	$\widehat{\beta_{10}}$	0.00094	0.01178
	MAE	0.0237	0.0073
Y_{S2}	$\widehat{\beta_1}$	0.01178	0.02429
	$\widehat{\beta_2}$	0.01484	0.03512
	$\widehat{\beta_3}$	-0.00028	0.00273
	$\widehat{\beta_4}$	-0.00066	-0.01250
	$\widehat{\beta_5}$	0.00672	-0.01460
	$\widehat{\beta_6}$	0.00059	0.01207
	$\widehat{\beta_7}$	0.00109	0.02114
	$\widehat{\beta_8}$	-0.00109	0.01780
	$\widehat{\beta_9}$	0.00128	-0.00359
	$\widehat{\beta_{10}}$	0.00053	-0.00256
	MAE	0.0167	0.0223

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As general rule for a process refinement to be effectively portrayed, a series of structured experimental tests are designed so that planned changes of all the referred results are made to all process parameters. Since the parameter settings were met in each model of the designed experimental plan, they were fed with all of the operating conditions. Statistical significance was not adequate for some regression coefficients, so some corresponding models were neglected. Furthermore, low significance resulted the melted work piece occurred after changing the predicted levels of all influential parameters except gas flow rate according to the numerical results from the LCRSOM. The resulting P-values to assess significance and reliability of each model are focused. A deeper statistical analysis is worth performing considering the proposed models for the parameters to be involved in the process refinement.

In the second and third refinements, unsatisfactory results in welding work pieces from the LCRSOM had been enhanced by adding more replicates of designed experiments centred at the previous operating condition. The new settings of the process parameters via the LCRSOM and NLCRSOM led to the better levels of all three performance measures when compared to the previous refinement (Table IV). In the forth iteration, additional design points were included for the factorial experiments. Models for both the LCRSOM and NLCRSOM were produced involving parameter interactions among the process parameter and the corresponding P-values from the ANOVA were considered as significance indicators. The optimisation procedure was then carried out. The first four iterative solutions as suggested when simultaneously considering the shear strength, welding depth and diameter are given in Table IV. Considering the nonlinear model of the CRSOM, the best so far combination achieved by GRG and their coded levels was a laser energy of 227.92, a laser pulse width of 212.12, a gas flow rate of 20 and a fixture spring force of 8. It is also considerably robust without significant variation both in the three responses. The condition was actually tested in the experimental plan as the iteration number 4. There was no melted work piece found via the LWP (Fig. 4).

TABLE IV. PROCESS OPTIMISATION ON THE LWP VIA LCRSOM AND NLCRSOM

Iteration	Alternatives	(x_1, x_2, x_3, x_4, Actual Y_P, Y_{S1}, Y_{S2})
1	LCRSOM	(87.70,2832.3,20, 8, -, -, -)
	NLCRSOM	(217.45,202.65,20,8,6.48,0.99,2.04)
2	LCRSOM	(216.72,198.92,20,8,6.02,1.02,1.94)
	NLCRSOM	(218.07,203.27,20,8,6.08,0.98,2.23)
3	LCRSOM	(217.98,202.18,20,8,6.58,0.96,2.09)
	NLCRSOM	(218.02,204.36,20,8,6.38,0.99,1.80)
4	LCRSOM	(216.67,206.54,20,8,6.19,0.94,2.25)
	NLCRSOM	(227.92,210.12,20,8,6.81,0.93,2.23)

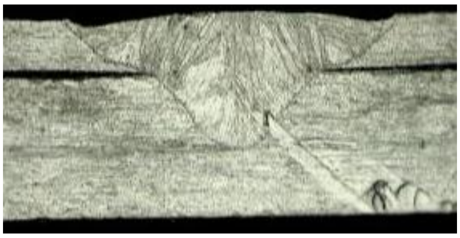

Figure 4. No melted work piece found via the new operatingcondition.

A deeper analysis has been performed on mathematical models. The regression coefficients estimated by the method of least squares and its variants from the ACO is now worth performing considering the models to be involved in the process parameter refinement. The primary response of shear strength is shown in the contour plot with the secondary responses (Fig. 5). A higher shear strength level in the numerical optimisation was awarded subject to the constraints involving the welding depth and diameter within their specifications. Additionally, to compensate the shortcomings of actual response surfaces of process parameters and each response, the relationship is estimated to draw the useful information of the better levels of parameters. In summary, when there is an increase in parameter levels the shear strength and welding diameter increase, but welding depth decreases.

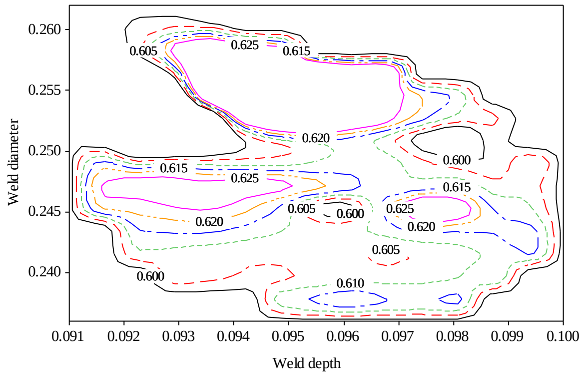

Figure 5. Contour plot of shear strength against secondary responses.

V. CONCLUSIONS AND DISCUSSIONS

In a context of product and process development, accurate process parameter refinement is of importance in the manufacturing industry. With the evolution of artificial intelligence, metaheuristics based on applied statistics and operational research strategies have been popular fast convergent to determine more appropriate operating conditions. Therefore, in this research, both linear and nonlinear types were applied to a system refinement with a CRSOM including the coefficients selection from the ACO evolutionary elements. There are a lot of parameters affecting both classes of responses of the LWP. After a screening designed experiment, four key parameters considered in this research consist of laser energy, laser pulse width, gas flow rate and fixture spring force. In order to meet the fluctuations of process responses, both linear and quadratic forms of the CRSOM

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developed with undesirable levels of P-Values. The availability and advantages of metaheuristics, all standardised regression coefficient belonging to all the influential parameters and their interaction effects are collected and modeled. The actual previous data are calculated to validate the accuracy of results.

The ACO method is compared via two forms of the CRSOM to show the capability in providing a robust model. Based on the statistical results the accuracy of the proposed ACO on the LCRSOM is acceptable. This would allow the practitioner to move toward the optimum faster. LCRSOM and NLCRSOM have their own advantages and disadvantages. The best strategy will rely on the particular experimental circumstances, the initial operating condition used, the true response shape, experience and statistical results from previous designed experiments. Although there have been two models to be considered in the study of parameter refinement, further research on the hybridisations of different metaheuristics is necessary. In addition, there is no statistically significant process parameters of the model proposed, so the suggestion for next work is to take the differences of coefficient estimates into consideration to the process refinement. Moreover, changing the parameter levels may affect others on multiple response surfaces. Therefore, it is important to efficiently collect and analyse all of the responses at one time via the desirability function.

Conflict of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Author Contributions

P. LUANGPAIBOON contributed to the design and implementation of the research, to the analysis of the results and to the whole writing of the manuscript.

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