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OPTIMISATION OF SPOT-WELDING PROCESS USING TAGUCHI BASED CUCKOO SEARCH ALGORITHM

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Abstract: *The present work evaluated the efficiency of a Taguchi-based Cuckoo Search (CS) algorithm for optimizing the spot-welding process. The L_9 orthogonal array of the Taguchi method is used for the conduction of required experiments. During the study input parameters are welding current (kA), hold time (cycles), welding time (cycles), and electrode pressure (kPa) while Peak Load, kN has been considered as an output parameter. The required objective function is developed through regression model formulation. Initially, CS operating parameters such as maximum number of iterations, number of nests, and probability to discover a cuckoo egg by host bird is optimized through the Taguchi method and are found as 40, 20, 0.5 respectively. That optimized CS further optimizes the spot-welding process. The maximum peak load of 34.5 kN is obtained if the welding current is 30.7 kA, welding time is 32 cycles, hold time is 20 cycles, and electrode pressure is 480 kPa respectively. Experimental validation yields a very low % error of 1.93% during optimization with an optimized CS method and while the error is substantially high if optimization is conducted using a non-optimized CS method*

Key words: Spot welding, Cuckoo Search method, Taguchi method, optimization, Peak load.

1. Introduction

Spot welding is a popular electric resistance welding process in which workpieces are held together under pressure exerted by electrodes and metal surface points in contact are get joined by the heat obtained from resistance to electric current. It is a

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quick process and enables the easier joining of even dissimilar metals. The process is widely applied in the automotive sector.

The controllable parameters of spot welding such as electrode tip diameter, weld nugget, weld current, holding time, cycle time, etc, bear a very complex relationship between them. In the recent past, researchers employed the conventional statistical design of experiment (DOE) based techniques like the Taguchi method, Response Surface Methods (RSM), Grey Relational Analysis (GRA), etc to optimize spot-welding process parameters. Attempts to optimize tensile strength for spot-welded joints of Titanium alloy [Bozkurt and Çakır (2021), Fatmahardi et al (2021)], aluminum alloys [Raheem, (2021)], dissimilar materials combining steels and composites [Neystani et al. (2019)], steels [Tyagi et al.(2022), Kumar et al. (2021), Ebrahimpour et al (2021)], have been computed through the Taguchi method [Bozkurt and Çakır (2021), Fatmahardi et al (2021), Neystani et al. (2019), Tyagi et al.(2022), Kumar et al. (2021)] and RSM [Raheem, (2021), Ebrahimpour et al. (2021)]. But such processes generally involve high mathematical complexity among operating parameters and possible experimental noise. Therefore, the application of those traditional statistical optimization methods is often found inadequate for their inability to reach global minima for the multimodal problem.

Soft computing techniques involving genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), etc can be efficiently employed for optimizing such highly non-linear problems with improved accuracy. The same has been employed already for Electric Discharge Machining (EDM) [Chinmaya et al. (2017)], Laser material processing [Chaki et al. (2012)], submerged arc welding, etc [Choudhary et. Al. (2020)]. However, limited applications of such algorithms are found in the spot-welding domain. Recently, the tensile strength of spot-welded joints for mild steel was optimized by Pattanaik et al. (2018) using L_{25} Taguchi-based GRA and GA. Cao et al. (2021) optimized spot-welded joint strength of aluminum to steel using a GA and RSM. Dhawale et al. (2019) optimized the strength of spot-welded joints using PSO and experimental validation incurred negligible error with 0.57% error. Zhao et al. (2014) optimized failure energy of spot-welded titanium alloy joints using Box–Behnken L_{17} experimental design of RSM and artificial fish swarm algorithm.

The literature survey indicates applications of several conventional statistical methods including Taguchi, RSM, etc to optimize the resistance spot welding processes [Bozkurt and Çakır (2021), Fatmahardi et al (2021), Neystani et al. (2019), Tyagi et al. (2021), Kumar et al. (2021)] Raheem, (2021), Ebrahimpour et al. (2021)]. However, those optimization processes have inherent limitations to stuck into local minima often resulting in faulty optimized output for multimodal problems. However, further nature-inspired algorithms like GA, PSO, SA etc. are used for solving spot welding [Pattanaik et al. (2018), Cao et al. (2021), Dhawale et al. (2019), Zhao et al. (2014)] and similar problems [Chinmaya et al. (2017), Chaki et al. (2012), Choudhury et al. (2020)] with greater accuracy where process parameters bear complex mathematical relationships among them. But, the optimization performance of those algorithms is governed by several operating parameters, whose selection is generally user-dependent. Its wrong selection often leads to inadequate optimization output. Therefore, prior optimization of those controlling parameters is necessary and if operated through an optimized parameter setting then only the best-optimized output from the algorithm may be obtained. However, such optimized nature-inspired algorithms are not employed so far for the spot-welding process. Cuckoo Search (CS) [Yang & Deb (2010)], a biologically inspired method for optimization is controlled by certain parameters like the number of nests, iterations, the probability with which the host bird discovers the cuckoo egg in nests, etc. CS is employed in the field of Time series and forecasting [Jiang et al. (2016), Xiao et al. (2017)], Data mining [Swathypriyadharsini & Premalatha (2021)], non-traditional machining [Saravanan et al. (2020), Shastri & Mohanty (2021)], Scheduling [Gu et al. (2021)] etc. Present work employed an optimized CS algorithm to optimize the spot-welding process. The Taguchi method optimized the CS algorithm during the study. Such Taguchi optimized CS is not employed earlier for optimizing the spot-welding process. Further, the performance of that optimized CS is compared with a non-optimized CS to understand the usefulness of the proposed method.

2. Methodology

A Taguchi integrated cuckoo search (CS) optimization method is employed for optimizing the RSW process using an optimized CS. The controllable input parameters in the RSW process are welding current, kA (I) 2) welding time, cycles (WT), 3) hold time, cycles (HT), and 4) electrode pressure, kPa (EP) while tensile strength is the output parameter.

Further optimization of spot welding is computed through the following steps:

i) Conduction RSW experiments using Taguchi L_9 experimental design matrix to generate an input-output dataset.
ii) Objective function formulation through developing suitable regression equation
iii) Optimization of CS parameters through Taguchi method for determining an optimized CS algorithm
iv) Optimizing the spot-welding process using that optimized CS algorithm and determining the model efficiency through experimental validation.

The outline of the process has been given in Fig.1. Detailed steps for Taguchi integrated cuckoo search (CS) optimization method are given as follows:

<u>Step A: Development of the experimental dataset</u>

I. Generate Taguchi L_9 design matrix
II. Conduct experiments following experimental design
III. Measure output characteristics
IV. Generate the input-output dataset

<u>Step B: Formulation of the objective function</u>

I. Normalize input-output dataset between 0 and 1.
II. Develop Regression model using the normalized dataset $Y = f(x_1, x_2, .., x_n) + \varepsilon$, where, $(x_1, x_2, ..., x_n)$ are n number of independent input variables, Y produces a certain response, ε represents noise or error in the response y.
III. Consider it as the objective function for the Cuckoo search (CS) algorithm.

<u>Step C: Optimization of Cuckoo search (CS) parameters</u>

I. Generate Taguchi L_9 design matrix for a) Maximum iteration numbers (I_{max}) , b) Number of nests (N), c) probability to discover a cuckoo egg by host bird (p_a)
II. For (i=1 to 9)
{
Select I_{max}, N, and p_a as CS input parameters
Call CS subroutine
Store optimum fitness function value as output for ith set of input parameters
}

III. Dataset is generated with I_{max}, N and p_a as inputs (xi's)and Fitness function as output parameter (Y_i)
IV. Compute Taguchi quality loss function and normalise for all Y_i's
V. Compute signal to noise ratio (S/N ratio)
VI. Compute level wise mean of S/N ratio for each factor
VII. Determine optimized I_{max}, N and p_a

Step D: Process optimization with optimized CS algorithm

I. Set, I_{max}, N and p_a, at optimized value as determined in Step C
II. Call CS subroutine
III. Determine optimized fitness function value
(# such as maximum tensile strength or Peak Load of RSW joint in present work)

Cuckoo Search (CS) subroutine

Begin
Set, the objective function using the regression equation developed in step B
Maximum iteration numbers (I_{max})
Number of nests (N)
Probability to discover a cuckoo egg by host bird (pa)

Iterate:
generate randomly a cuckoo (i) from lev́y flight
Evaluate fitness function value (F_i)
randomly select nest j and determine fitness function value (F_j)
if ($F_i < F_j$)
replace j using the new solution
end
Abandon worst nests by a fraction p_a
Randomly generate new solution from all cuckoos
Fitness evaluated
Keep the Better solutions
Current best is found through ranking
Continue (until Iteration > I_{max})

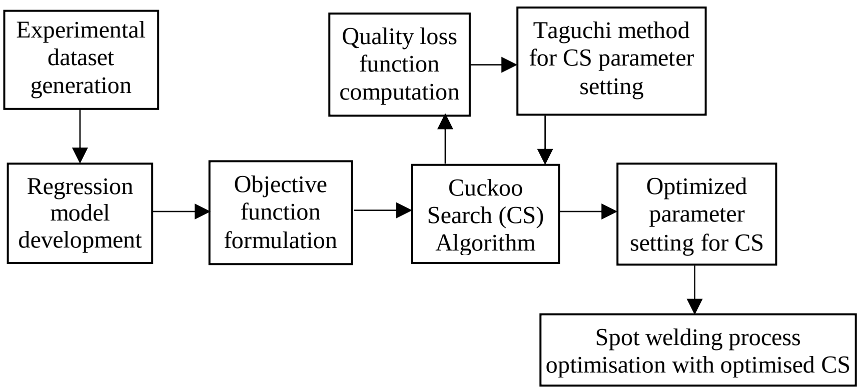

Figure 1. Outline of the Taguchi based cuckoo search algorithm

2.1. Experiment

A resistance spot welding setup (manufactured by Electro Weld Industries) operated by AC (50 Hz) 200 KVA rating (@ 50% duty cycle) is used for conducting experiments using 3 levels, 4-factor experimental design on mild steel (IS 2062, Gr. B) having block dimensions 100mm x 25mm x3mm. The experimental setup used is given in Fig.2.

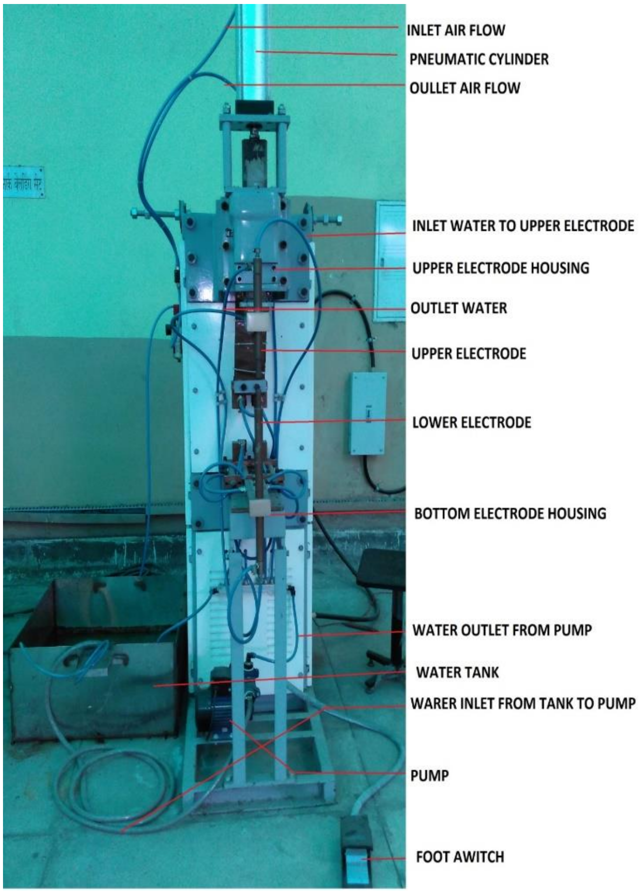

Figure 2. Experimental setup

Table 1 specifics the values of control factors at different levels. The possible variations of control factors for Table1 have been determined through pilot experiments. Altogether nine experiments are conducted using Taguchi L_9 experimental design. The input parameters considered during experimentation are, 1) welding current, kA (I) 2) welding time, cycles (WT), 3) hold time, cycles (HT), and 4) electrode pressure, kPa (EF). For welded joints, the output parameter is the ultimate tensile strength which is the maximum force required to tear the spot joints from each other. A Universal Testing machine measured it through peak load, kN (L). Table 2 furnishes the experimental dataset. Input and output parameters are as follows:

$$\mathrm{X} = [\mathrm{I} \quad \mathrm{WT} \quad \mathrm{HT} \quad \mathrm{EP}], \quad Y = [PL]$$

(a) Before

(a) After

Figure.3. Job specimen before and after resistance spot welding

Table 1. Control factors with their levels

Control Factors	Symbol	Level of Control Factors		
		Level 1	Level 2	Level 3
Welding Current, kA	I	29.5	30	30.7
Welding Time, cycles	WT	25	28	32
Welding Hold time, cycles	HT	20	25	30
Electrode pressure, kPa	EP	480	550	620

2.2. Development of regression model

A first-order regression model with interaction effects is developed to determine the approximate relationship between four input variables and the output variable. The experimental dataset is normalized prior development of the model to ensure better optimization performance. The input and output variables are normalized as follows before modeling:

$$\mathrm{X_{nor}} = \frac{\mathrm{X} - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}}$$

$$\mathrm{Y_{nor}} = {}^{\mathrm{Y}}\!/_{\mathrm{Y_{max}}} \quad (2)$$

Where X_{max} and X_{min} represent the maximum and minimum values of the input parameters and Y_{max} represents the maximum value of the output parameter.

The model is developed using Minitab16 software has been given below:

$$PL = 0.592122 + 0.387324 \times \mathrm{I} + 0.307468 \times \mathrm{WT} + 0.521117 \times \mathrm{HT} - 0.117952 \times \mathrm{EP} - 0.0806291 \times \mathrm{I} \times \mathrm{WT} - 0.430832 \times \mathrm{I} \times \mathrm{HT} - 0.556653 \times \mathrm{WT} \times \mathrm{HT} \quad (3)$$

The model is evaluated by the regression coefficient (R-square) value. R^2 and R^2 (adjusted) values obtained are 0.9715 and 0.7731 respectively. Near unity R^2 and R^2 (adjusted) value indicates the developed model is adequate.

Table 2. Input design matrix and experimental details

Trial No.	Input parameters				Output parameter
	Welding current, kA	Welding Time, cycles	Welding Hold time, cycles	Electrode Pressure, kPa	Peak Load KN
	I	WT	HT	EP	PL
1	29.5	25	20	480	17.15
2	29.5	28	25	550	21.55
3	29.5	32	30	620	21.5
4	30	25	25	620	23.8
5	30	28	30	480	28.5
6	30	32	20	550	28.25
7	30.7	25	30	550	28.6
8	30.7	28	20	620	27.15
9	30.7	32	25	480	27.6
Maximum value	30.7	32	20	480	28.6
Minimum value	29.5	25	30	620	-

2.3. Formulation of objective function

It is intended to maximize the tensile strength of the joint in terms of peak load. The objective functions along with constraints are given below:
The objective functions:

Maximize PL (I, WL, HT, EP)

Subject to constraints:

$29.5 \leq I \leq 30.7$

$25 \leq WT \leq 32$

$20 \leq HT \leq 30$

$$480 \leq EP \leq 620 \qquad (4)$$

However, as the CS algorithm is inherently developed for minimization problems, the –ve sign is incorporated before the output variable to convert it into a maximization problem. Along with, as regression model is formed with normalized dataset the objective function and constraints have been reduced into the following form:

Minimize:

$$PL = -(0.592122 + 0.387324 \times \mathrm{I} + 0.307468 \times \mathrm{WT} + 0.521117 \times \mathrm{HT} - 0.117952 \times \mathrm{EP} - 0.0806291 \times \mathrm{I} \times \mathrm{WT} - 0.430832 \times \mathrm{I} \times \mathrm{HT} - 0.556653 \times \mathrm{WT} \times \mathrm{HT})$$

Subject to constraints:
$$0 \leq I, WT, HT, EP \leq 1 \qquad (5)$$

2.4. Cuckoo Search Algorithm

Cuckoo search (CS) [Yang & Deb (2010)] is a nature-inspired metaheuristic algorithm based on the brood parasitism characteristics observed in cuckoo species by which it can lay its eggs in the nests of other host birds (often other species). Upon discovering the eggs do not belong to them, the host bird will remove those eggs from nests, or move to another nest leaving that nest. The probability of discovering the egg laid by a cuckoo by the host bird is $p_a \in [0, 1]$. Here, each nest refers to one egg that also refers to one cuckoo. During optimization, n numbers of host nests (x_i, i=1,….,n) are randomly selected as the initial population and fitness value (F_i) of eggs of host nests are computed. Further, the new nest is randomly generated by a cuckoo(i) through levy flight using the equation, ${x_i}^{t+1} = {x_i}^{t} + \alpha \oplus L\acute{e}vy(\lambda)$ where, where α > 0 indicates the step size of steps, t represents iteration number, and random walk-through Lévy flight (λ) is accomplished by a Lévy distribution of $L\acute{e}vy{\sim}u = t^{-\lambda}$, (1 < λ ≤ 3). Further, corresponding to updated solution points (nests) fitness value (F_j) of eggs is computed. Upon comparing with the initial fitness value (F_i), if improvement in fitness value is observed, the updated solution is accepted. During computation, the p_a fraction of the worst nests is abandoned. Repetition of the above process is continued till stopping criteria are achieved. Here, controllable parameters are the maximum number of iterations, number of nests, and probability to discover a cuckoo egg by host bird (p_a).

2.5. Taguchi Method for optimization of CS parameters

Taguchi's method studies the entire factor space through a limited set of experiments based on an orthogonal array. The method designates the desirable value of output as 'signal' and the undesirable value as 'noise'. The term 'signal-to-noise ratio' or S/N ratio is an indicator of the deviation of output from the desired value. L_9 orthogonal array, based on three levels three factors experimental design is used. Factors are the maximum iteration numbers (I), the number of nests (N), and the value of p_a respectively. The numeric value of variables at different levels is furnished in Table 3. For a specific set of factor values, CS computes optimized objective function value PL and employs it for computing loss function. For maximization of PL higher-the-better quality characteristic is required and the loss function (f_i) can be given as:

$$f_i = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2} \tag{6}$$

Where, y_i is the observed output at the i[th] trial, and n is the number of trials. Quality loss functions obtained are normalized and signal to noise ratio or S/N ratio (SNR) is calculated corresponding to i[th] trial condition as:

$$\mathrm{SNR}_i = -10\log_{10}(f_i) \tag{7}$$

3. Results and Discussion

3.1. Optimization of CS parameters using Taguchi method

The Taguchi design matrix with control parameter settings of CS has been shown in Table 3. A program code for CS is developed in MATLAB2010 using the objective function developed (Eq.5). Further, the program is run for each parameter setting of CS given in Table 4 to find the corresponding objective function value (PL). It is further evaluated for determining the quality loss function, its normalization, and signal-to-noise ratio using Eq. (6) - Eq. (7) and shown in Table 4.

Table 3. CS parameters with different levels

Symbol	CS parameters	Level 1	Level 2	Level 3
I_{max}	Maximum iteration numbers	20	30	40
N	Number of nests	10	20	30
p_a	Probability to discover a cuckoo egg by host bird	0.1	0.3	0.5

Table 4. Quality loss values with S/N ratio using L_9 orthogonal array

Exp no.	Coded Input Parameters			Output Parameter	Quality Loss	Normalized Quality Loss	SNR (dB)
	Imax	N	Pa	Objective Fn (PL)			
1	1	1	1	-1.1848	0.7124	1.0000	0.0000
2	1	2	2	-1.1892	0.7071	0.9926	0.0322
3	1	3	3	-1.2042	0.6896	0.9680	0.1411
4	2	1	2	-1.1922	0.7036	0.9876	0.0541
5	2	2	3	-1.2053	0.6884	0.9663	0.1490
6	2	3	1	-1.1951	0.7002	0.9828	0.0752
7	3	1	3	-1.2029	0.6911	0.9701	0.1317
8	3	2	1	-1.2021	0.6920	0.9714	0.1259
9	3	3	2	-1.1885	0.7079	0.9938	0.0271

Further, from the influence of controlling parameters of CS on the S/N ratio (Table 5) the optimized level of CS parameters is determined as follows:

Maximum number of iterations (level 3): 40

Number of nests (level 2): 20

Probability to discover a cuckoo egg by host bird, p_a (level 3): 0.5

Comparison between optimized CS parameter setting with initial parameter setting indicates reasonable improvement in SNR (i.e. 0.1562) and provided in Table 6.

3.2. Optimization of spot-welding process parameters

Finally, the spot-welding process is optimized through an optimized CS with the above-mentioned controlling parameter setting. Fig.2 shows the nature of variation of the best function value with iterations leading to convergence.

Table 5. Effect of factors on S/N ratio

Factor	Mean of S/N ratio (dB)			Maximum - Minimum	Rank
	Level 1	Level 2	Level 3		
Maximum iteration numbers (Imax)	0.1733	0.2783	0.2847[a]	0.1114	2
Number of nests (N)	0.1858	0.3071[a]	0.2433	0.1213	3
probability to discover a cuckoo egg by host bird (p_a)	0.2011	0.1134	0.4218[a]	0.3084	1

[a] Optimum level

Table 6. Improvement in performance at the optimum parameter level

	Initial Parameter Setting	Optimal CS parameters
Level	$I_1N_1p_{a1}$	$I_3N_2p_{a3}$
PL	-1.1848	-1.2063
MSNR (dB)	0	0.1562
Improvement of SNR (dB)		0.1562

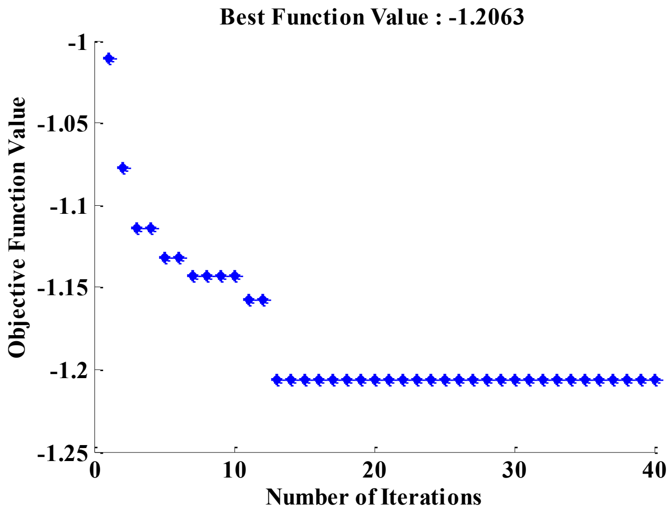

Figure 4. Performance of optimized CS during optimisation

The optimized (maximum) value of PL is found as 1.2063. The optimized value peak load (PL) after denormalization is 34.5 kN with corresponding operational input parameter welding current (I), welding time (WT), hold time (HT), and electrode pressure (EP) values as, 30.7 kA, 32 cycles, 20 cycles, and 480 kPa respectively.

Upon comparing the operational input parameter setting with corresponding level values provided in Table 1 it has been found that the maximum peak load indicator of ultimate tensile strength of the joint will be obtained at high welding current, high welding time, Low hold time, and low electrode pressure. A validation experiment is conducted with optimized parameter setting and compared with optimized output for evaluating the accuracy of the optimized CS algorithm and furnished in Table 7. The optimized CS method can predict optimized output with an absolute % error of 1.93%. Computation has been conducted using a Pentium IV, 3 GHz, and 512 MB PC.

Table 7. Results of spot-welding optimization using optimized CS and experimental validation

	Operational Input Parameters				Output Parameter
	Welding current	Welding Time	Welding Hold time	Electrode Pressure	Peak Load
	kA	cycles	cycles	kPa	KN
Normalised Value	1	1	0	0	1.2063
Denormalised Value	30.7	32	20	480	34.50
Experimental Value	30.7	32	20	480	35.18
Absolute % Error					1.93

4. Conclusion

Present work aimed to develop a Taguchi-based CS algorithm for enhanced optimization performance and employed to optimize spot welding process. The process is intended to maximize the peak load leading to a maximum tensile strength of the welded joint. The conclusions are as follows:

(i) Taguchi method determined the optimum value of controllable parameters of CS algorithm such as the number of iterations (I_{max}), number of nests (N), and probability to discover a cuckoo egg by host bird (p_a). An optimum combination of CS parameters with I_{max}, N, and p_a values as 40, 20, and 0.5 respectively will yield the best optimization result for the spot-welding problem under study.

(ii) The performance of the CS algorithm is improved considerably with the optimized CS parameter combinations. On comparing that performance with a non-optimized initial parameter setting, an improvement of 0.1562 dB is measured in terms of SNR.

(iii) Finally, optimization of spot welding with the optimized CS yields a maximum peak load of 34.5 kN for 30.7 kA welding current, 32 cycles welding time, 20 cycles hold time and 480 kPa electrode pressure.

(iv) The maximum peak load for the welded joint is found at high welding current, high welding time, Low hold time, and low electrode pressure.

(v) Experimental validation of the optimized result indicates a low error of 1.93% which signifies the accuracy of the model.

(vi) The Taguchi-based CS algorithm may be used effectively for any other process. The process may be further extended to optimize operating parameters of other popular algorithms like the water cycle algorithm, krill herd algorithm, mine blast algorithm, interior search algorithm, etc.

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References

Bozkurt, F., & Çakır, F.H. (2021). An experimental design of spot welding of Ti6Al4V sheets and numerical modeling approach. Welding in the World, 65, 885–898.

Cao, X., Li, Z., Zhou, X., Luo, Z., & Duan, J., (2021). Modeling and optimization of resistance spot welded aluminum to Al-Si coated boron steel using response surface methodology and genetic algorithm. Measurement, 171, 108766.

Chaki, S., Ghosal, S., & Bathe, R.N., (2012). Kerf quality prediction and optimisation for pulsed Nd: YAG laser cutting of aluminium alloy sheets using GA-ANN hybrid model. International Journal of Mechatronics and Manufacturing Systems, 5, 263-279.

Choudhary, A., Kumar, M., Gupta, M.K., Unune, D.K., & Mia, M., (2020). Mathematical modeling and intelligent optimization of submerged arc welding process parameters using hybrid PSO-GA evolutionary algorithms. Neural Computing & Applications, 32, 5761–5774.

Dhawale, P.A., & Ronge, B.P., (2019). Parametric optimization of resistance spot welding for multi spot welded lap shear specimen to predict weld strength. Materials Today: Proceedings, 19, 700-707.

Ebrahimpour, A., Mostafapour, A. & Nakhaei, M.R., (2021). Application of response surface methodology for weld strength prediction in FSSWed TRIP steel joints. Welding in the World, 65,183–198.

Fatmahardi, I., Mustapha, M., Ahmad, A., Derman, M.N., Lenggo Ginta, T., & Taufiqurrahman, I., (2021). An Exploratory Study on Resistance Spot Welding of Titanium Alloy Ti-6Al-4V. Materials, 14, 2336.

Jiang, P., Liu, F., Wang, L.Z., & Song, Y.L., (2016). Cuckoo search-designed fractal interpolation functions with winner combination for estimating missing values in time series. Applied Mathematical Modelling, 40, 9692–9718.

Kumar, R., Chohan, J.S., Goyal, R. & Chauhan, P., (2021). Impact of process parameters of resistance spot welding on mechanical properties and microhardness of stainless steel 304 weldments. International Journal of Structural Integrity, 12, 366-377.

Mohanty, C.P., Mahapatra, S.S., & Singh, M.R., (2017). An intelligent approach to optimize the EDM process parameters using utility concept and QPSO algorithm. Engineering Science and Technology, an International Journal, 20, 552-562.

Neystani, R., Beidokhti, B., & Amelzadeh, M., (2019). Fabrication of dissimilar Fe-Cu-C powder metallurgy compact/steel joint using the optimized resistance spot welding, Journal of Manufacturing Processes, 43, 200-206.

Pattanaik, A.K., Panda, S.N., Pal, K., & Mishra, D.A., (2018). Comparative Investigation to Process Parameter Optimization for Spot Welding Using Taguchi Based Grey Relational Analysis and Metaheuristics. Materials Today: Proceedings, 5, 11408-11414.

Raheem Al-Sabur. (2021) Tensile strength prediction of aluminium alloys welded by FSW using response surface methodology – Comparative review. Materials Today: Proceedings, 45, 4504-4510.

Saravanan, M., Thiyagarajan, C., & Somasundaram, S., (2020). Parametric optimization of wirecut-electrical discharge machining through cuckoo search algorithm. Materials Today: Proceedings, 22, 681-687.

Shastri, R.K., & Mohanty, C.P., (2021). Sustainable Electrical Discharge Machining of Nimonic C263 Superalloy. Arabian Journal for Science and Engineering, 46, 7273–7293.

Swathypriyadharsini, P., & Premalatha, K. (2021). Hybrid cuckoo search with clonal selection for triclustering gene expression data of breast cancer. IETE Journal of Research, 1-9.

Tyagi, A., Kumar, G., Kumar, M., & Wahid, M.A., (2022). Analysis the effect of process parameters on robot spot welding of JSC 590RN mild steel using Taguchi based GRA. Materials Today: Proceedings, 51, 1211-1216.

Wenbin, G., Li, Z., Dai, M., & Yuan, M., (2021). An Energy-Efficient Multi-Objective Permutation Flow Shop Scheduling Problem Using an Improved Hybrid Cuckoo Search Algorithm. Advances in Mechanical Engineering, 13, 1–15.

Xiao, L., Shao, W., Yu, M., Ma, J., & Jin C., (2017). Research and application of a hybrid wavelet neural network model with the improved cuckoo search algorithm for electrical power system forecasting. Applied Energy, 198, 203–222.

Yang, X-S., & Deb, S, (2010). Engineering Optimisation by Cuckoo Search. Int. J. Mathematical Modelling and Numerical Optimisation, 1,330–343.

Zhao, D., Wang, Y., Wang, X.,Wang, X., Chen, F., & Liang, D., (2014). Process analysis and optimization for failure energy of spot-welded titanium alloy. Materials & Design, 60, 479-489.