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MULTI OBJECTIVE OPTIMISATION OF ABRASIVE WATER JET MILLING USING SINE COSINE ALGORITHM

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Abstract

Abrasive Waterjet Machining (AWJM) is applied to mill the high hardness materials like Hastelloy C-276, where the conventional milling methods tend to fail. Selection of an optimal combination of process parameters for Abrasive Waterjet milling (AWJ milling) is a vital task to achieve a higher material removal rate and lower surface roughness of the milled pocket. This work aims to improve the performance of AWJ milling using the Sine Cosine algorithm (SCA). The results obtained from the SCA compared with the renowned optimisation algorithms, such as Particle swarm optimisation (PSO) and Teaching-learning-based optimisation (TLBO).

Keywords: AWJ milling, Process Parameters optimisation, Particle swarm optimisation (PSO),Teaching-learning-based optimisation (TLBO), Sine cosine algorithm (SCA), Material removal rate (MRR), Surface roughness (Ra)

NOMENCLATURE

P Water pressure (MPa), So Step over (mm), TrTraverse rate (mm/min), m_a Abrasive flow rate[AFR] (Kg/min), ND Nozle diameter (mm), SOD Stand of distance (mm), OD Orifice diameter (mm), DOC Depth of cut (mm)

1. INTRODUCTION

Machining of Nickel based alloys is difficult with conventional machining processes. This difficulty is increasingly valid for 3D featured components which are having higher Depth to be machined. Abrasive Water jet Machining (AWJM) has become famous for such complex cases. Optimisation of the AWJM process has attracted many researchers' attention because of its efficient machining capability, which means a significant contribution to the overall cost of the product. Thus, the scope of this paper presents the application of optimisation in AWJ milling process performance. Advanced optimisation techniques are receiving more attention than all the other techniques. From the era of conventional optimisation techniques to the present era of metaheuristic optimisation, the optimisation of AWJM parameters has been trending as the hot areas of research. Wolpert et. al pointed out in their study that the importance of new algorithms does not guarantee its success in solving different engineering problems have brought into learning. This remark is valid till today, even after decades. Nevertheless, the efforts to optimise the AWJM process are still going on, as the proper tuning of the machining parameters has a significant bearing on the quality of the AWJM. This research work presents the metaheuristic optimisation method Sine cosine algorithm (SCA) to optimise the AWJ milling process parameters. Section 2 critically discusses the past research on applying different metaheuristic optimisation techniques in AWJ milling and provides some direction for future research. Section 3 provides a brief outline of the following metaheuristic techniques: Particle swarm optimisation (PSO) and Teaching-learning-based optimisation (TLBO), and the Sine cosine algorithm (SCA). Section 4 provides experimental details. Section 5 provides a detailed discussion of optimisation modelling and the application of metaheuristic algorithms. The conclusion is present in Section 6.

2. LITERATURE REVIEW

Based on the studies carried by scholars over the decades, different optimisation techniques are tried for the optimisation of various AWJM parameters for machining different materials to achieve the maximum Depth of cut, Material removal rate and good surface finish etc. in Table 1.

Table 1. Literature Review

S. No	Author/year	Machining process	AWJM Process parameters	Work material	objectives	Optimisation technique(s) involved	Remarks
1.	Chakravarthy and Ramesh babu/1999. [2]	AWJ cutting	P, Tr & m_a	Granite	DOC	Fuzzy-GA	The optimum combination of process parameters achieves the expected DOC

2.	Chakravarthy and Ramesh babu/2000. [3]	AWJ cutting	P, Tr & m_a	-	DOC	Fuzzy-GA	The optimum combination of AWJM process parameters was used for cutting any material.
3.	Jain et al. /2007. [4]	AWJ cutting	P, Tr, m_a & ND	Ductile materials	MRR	GA	The optimal process parameters obtained by constraining Power consumption
4.	Srinivasu and Babu/2008.[5]	AWJ cutting	P, Tr, m_a & ND	6063-T6 Aluminium Alloy	DOC	Neuro-genetic approach	By optimising the process, parameters predicted the optimised DOC.
5.	Kolahan and khajavi/2010.[6]	AWJ cutting	P, Tr, m_a & ND	6063-T6 Aluminium Alloy	DOC	Simulated annealing (SA)	Results obtained with SA provide effective and speedy value.
6.	Rao et al. /2010.[7]	AWJ cutting	P, Tr, m_a SOD, ND & Water mass flow rate	Titanium	MRR	SA	Optimal combination of process parameters for Power consumption was considered.
7.	Zain et al. /2011.[8]	AWJ cutting	P, Tr, m_a, SOD & Abrasive grit size	Aluminium alloy 7075	Surface roughness	ANN-SA	The proposed ANN-SA integrated methods were given better results compared to experimental results. Also, it observed that better results achieve with less number of iterations compared to SA.
8.	Zain et al. /2011.[9]	AWJ machining	P, Tr, m_a, SOD & Abrasive grit size	Aluminium alloy 7075	Surface roughness	SA-GA	The proposed SA-GA approached out performed compare to single system optimisation.

9.	Pawar and Rao/2013.[10]	AWJ machining	P, Tr, m_a, SOD, ND,OD & Water mass flow rate	Titanium	MRR	TLBO	The TLBO algorithm performance accuracy outperformed and superior to some of the well-known optimisation techniques.
10.	Pandu et al. /2012.[11]	AWJ cutting	P, Tr, m_a, & ND	6063-T6 aluminium alloy	DOC	GA-Fuzzy logic	GA has been used to optimise the database and rule base of the FL-system.
11.	Yusup et al. /2013.[12]	AWJ Cutting	P, Tr, m_a, SOD & Abrasive grit size	Aluminium 7075 alloy	Surface roughness	Artificial bee colony (ABC) algorithm	ABC has given better results than the results obtained with GA and SA.
12.	Aich et al. /2014.[13]	AWJ cutting	P, Tr, m_a & SOD	Borosilicate Glass	DOC	Particle swarm optimisation (PSO)	The optimum combination of process parameters was obtained using PSO.
13.	Aich et al./ 2014.[14]	AWJ cutting	P, Tr, m_a & SOD	Borosilicate Glass	DOC & MRR	Simulated annealing and Particle swarm optimisation	The optimum combination of process parameters was obtained using SA and PSO.
14.	Murugabalaji et al/2014.[15]	AWJ cutting	P, Tr, m_a & Abrasive Mesh size	Graphite	DOC & Surface Roughness	Particle swarm optimisation	A multi objective optimisation carries using the PSO algorithm to get better quality of cutting.
15.	Azizah et al. /2015.[16]	AWJ cutting	P, Tr, ma, SOD & Abrasive grit size	Aluminium 7075-T6 alloy	Surface roughness	Cuckoo algorithm (CA)	The cuckoo algorithm has used to find minimum surface roughness.

16.	Huang et al. /2015.[17]	AWJ cutting	P, Tr, m_a, ND, abrasive diameter & Water flow rate,	---	MRR	TLBO based cuckoo search	The integrated TLBO based cuckoo search algorithm was given Maximum MRR compared to GA, SA, TLBO and CS.
17.	Aich et al. /2016.[18]	AWJ cutting	P, Tr, m_a & SOD	Borosilicate Glass	DOC & MRR	PSO	Support vector machine parameters tuned by using PSO to get good predictive accuracy.
18.	Mellal et al. /2016.[19]	AWJ cutting	P,Tr, m_a, SOD & Abrasive grit size	Aluminium alloy 7075	Surface roughness	Cuckoo optimisation algorithm (COA) and Hoop heuristic optimisation (HHO)	HHO has the same results as the artificial bee colony algorithm and performed better than GA and COA
19.	Shukla et al. /2017.[20]	AWJ cutting	Tr, SOD & ND	TRIP sheet steels	Kerf , Surface Roughness (R_a)	Firefly algorithm (FA)	FA algorithm was adopted to compare results obtained by previous researchers.
20.	Shukla et al. /2017.[21]	AWJ cutting	Tr, SOD & m_a	AA631 -T6	Kerf top width & Taper angle	PSO, FA, ABC, SA, Black hole, Bio-geography based, Cuckoo search algorithm and NSGA	BBO algorithm outperformed other algorithms.
21.	Purusothaman et al. /2017.[22]	AWJ cutting	P, Tr, m_a & SOD	Al-Ni-Ti and Al-Ni-Ti-nano SiC composites	Surface roughness & kerf angle	Gravitational search algorithm (GSA)	The optimum value of minimum kerf angle and surface roughness has searched through the GSA.

22.	Mali et al. /2017.[23]	AWJ cutting	P, Tr, SOD & m_a	GFRP	Kerf top width, Taper angle & Surface roughness	NSGA-II	The optimum combination parameters were obtained using a Multi-objective NSGA-II.
23.	Pawar et al. /2018.[24]	AWJ cutting	P, Tr, SOD & m_a	Marble	Kerf width, Kerf taper & Depth of striation	Artificial bee colony algorithm	The optimum combination parameters were obtained using the Multi-objective Artificial bee colony algorithm.
24.	Tamilarasan et al. /2018.[25]	AWJ cutting	P, Tr, m_a & SOD	Ceramic Tile	Surface roughness	Crow search algorithm	The optimum condition of the control parameter setting has been searched using Crow search algorithm.
25.	Shankar Chakraborty & Ankan. Mitra/2018.[26]	AWJ cutting	P, Tr, m_a, Water flow rate & Nozzle diameter	Titanium	MRR & Surface roughness	Grey wolf optimiser (GWO)	The GWO algorithm outperformed over SA, GA, and TLBO.
26.	Zhengrong et al. /2018.[27]	AWJ Cutting	P, Tr, m_a, OD, ND Mixing chamber diameter, Mixing chamber length, Nozzle length, Particle delivery angle, &	---	Nozzle erosion rate, output energy	Cuckoo search (CS) algorithm	The optimum combination was obtained using a Multi-objective CS algorithm for better performance and less computing time.
27.	Rao et al. /2019.[28]	AWJ cutting	P, Tr, m_a, SOD, ND Material thickness, & Tilt angle,	---	Kerf top width Taper angle, DOC & Surface roughness	Jaya algorithm	The Jaya algorithm performance provided superior results than other algorithms.

28.	Vikas et al. /2019. [29]	AWJ cutting	SOD, Tr & ND	TRIP steels	Kerf width, Surface roughness	Cohort intelligence	Demonstrated successful application of Cohort intelligence for optimisation of AWJM process.
29.	Durga Prasada Rao et al./2019.[30]	AWJ cutting	Tr, m_a & SOD	CFRP GFRP CGFRP	MRR Kerf width & Surface roughness,	NSGA	NSGA approach has produced better results in CGFRP composite Compared to GFRP and CFRP.

3. METAHEURISTIC ALGORITHMS

A brief overview of PSO, TLBO and SCA presents here.

3.1 Particle swarm optimisation

Particle swarm optimisation is a simple but powerful optimisation technique, which utilises a search algorithm based on an information-sharing model used by a school of fish or a flock of birds to locate its prey or food. Birds use the so-called intricate hunting or foraging strategies to alert the neighbouring birds and the flock about the target. This technique helps them in reducing the energy required in foraging by cooperating. Fishes too synchronise their swimming patterns depending on the signals and movements from other fish and the school towards food source based on the information shared. By this, they are helping them to coexist with each other and save time. This level of intelligence is not achievable by an individual, but together as the group (i.e., using communication, learning from information shared, and searching for better options) is how birds and fish find the best food for consumption. These patterns and strategies have been observed and studied by researchers to implement them with relevance in finding minima in an optimisation problem of given data. The population of individuals and group solutions are the swarm of particles within the search space (i.e., all possible solutions) considered here in this algorithm. The swarm of particles (data points) has two vectors, a Position vector being the possible solution of the objective function and a Velocity vector being the change in position (magnitude and direction) required to arrive at minima. Position vectors move in the search space with a velocity looking for the best solution. For '*n*' number of particles, they move in an *n*-dimensional search space. The following equation gives the updated value of the new position acquired by a particle concerning the given best solution at an instance.

$$Xi(t+1) = Xi(t) + Vi(t+1) \qquad (1)$$

Where *Xi (t)* shows the position of *the i*th particle at *t*th iteration and *Vi (t+1) is the updated direction and magnitude* that the *i*th particle at (*t+1)*th iteration has moved. The significant component in the above equation to update the position is the velocity term, which contains three main terms: the inertial term, the cognitive component, and the social component.

Inertial term

The current velocity *Vi (t)* of the particle at *t*th instance, multiplied by the inertial factor *ω,* determines the tendency to maintain the previous velocity.

Cognitive component

It consists of the Personal best term *Pi(t)*, which is the best position acquired closer to the solution, an acceleration component C1, which determines the extent with which the cognitive component influences the velocity and a random multiplier r1, which randomly distributes the particle (0,1) in the search space since PSO has a stochastic optimisation technique. The difference between the Personal best and current position Xi*(t)* multiplied by C1 and r1 gives the extent to which the particle has moved towards the personal best (i.e., local minima). This component called 'Cognitive' because it accounts for a bird's intelligence by recalling the best position and diverting its course to a new location.

Social Component

It consists of the Global best term *G(t),* which is the common best position of all the particles amongst the swarm of particles in search space, an acceleration component C2, which determines the extent with which the Social component influences the velocity, and a random multiplier r2, which randomly distributes the particle in the search space since PSO is a stochastic optimisation technique. Difference between the Global best and current position *Xi (t)* multiplied by C2, and r2 giving the extent with which the particle had moved towards the Global best (i.e., Global minima) including the Social component converges the solution of particles towards one point.

With these three components, the next position of a particle defined by the updated velocity vector, given by Eq. (2): -

$$V_i(t+1) = \omega V_i(t) + C1r1\left(P_i(t) - X_i(t)\right) + C2r2\left(G(t) - X_i(t)\right) \qquad (2)$$

In the well-considered PSO version, ω decreases linearly from 0.9 to 0.4, proportional to the number of iterations. The parameters C1 and C2 are both set to 2.

3.2 Teaching–learning-based optimisation

The Teaching Learning Based Optimisation algorithm was introduced by Rao et al. [31] in 2011. It works on the teacher teaching process effect's effect on the learner's performance in the class. The algorithm works on two types of phases. These are the teacher phase and the learner phase. The learning of the student in the teacher phase is through the teacher. The learner phase works on knowledge sharing between the students or knowledge sharing between the learner and another learner. In this algorithm, learners are the population, the subjects are the variables, and the student or learner's result was the fitness value or the function.

Teacher Phase

In the teacher phase, the teacher tries to increase the class's mean result according to their ability. However, a teacher is generally considered the most learned person who trains learners to achieve better results. The algorithm identifies the teacher, who is the best learner among learners. The difference between the existing mean results of each subject was given by Eq. (3).

$$\text{Difference\_Mean} = r_1 (X_{best} - T_F M) \tag{3}$$

where X_{best} is the result of the best learner, TF is the teaching factor either 1 or 2. An updated solution in the teacher phase is followed by Eq. (4).

$$X'_{best} = X_{best} + \text{Difference\_Mean} \tag{4}$$

All function values accepted at the end of the teacher phase are input to the learning phase because the learning phase depends on the teacher phase.

Learner Phase

The learner phase is the 2nd and last phase of the TLBO algorithm, in which the learners enhanced their knowledge by sharing their knowledge. Randomly select two learners, A and B, such that $X'_{total\text{-}A} \neq X'_{total\ B.}$ where, $X'_{total\text{-}A}$ and $X'_{total\text{-}B}$ are the updated values of the end of teacher phase is followed by Eq.(5) and Eq.(6).

$$X''_{\text{Final value}} = X'_A + r_i(X'_A - X'_B), \text{If} X'_{total-A} < X'_{total-B} \tag{5}$$

$$X''_{\text{Final value}} = X'_A + r_i(X'_B - X'_A), \text{If} X'_{total-B} < X'_{total-A} \tag{6}$$

3.3 Sine cosine Algorithm

The Sine cosine algorithm (SCA) is a new stochastic population-based optimisation algorithm based on a set of random solutions on the sine and cosine functions [32]. It has exploration and exploitation phases. In the first phase, the SCA optimisation algorithm generates random solutions with high randomness to find better search space solutions. In the second stage, the changes in solutions and random variations are considerably lesser than in the former stage. The two equations proposed to balance both the stages and update the search space positions.

$$X_j^{t+1} = X_j^t + r_1 \times sin(r_2) \times \left| r_3 P_j^t - X_j^t \right| \tag{7}$$

$$X_j^{t+1} = X_j^t + r_1 \times \cos(r_2) \times \left| r_3 P_j^t - X_j^t \right| \tag{8}$$

Where X_j^(t+1) is the position of the current solution in j-th dimension and t- th iteration. r_1, r_2 and r_3 are the random numbers generated for a solution in a search space during each iteration. The combined equation is expressed as follows,

$$X_j^{t+1} = \begin{cases} X_j^t + r_1 \times sin(r_2) \times \left| r_3 P_j^t - X_j^t \right|, & r_4 < 0.5 \\ X_j^t + r_1 \times cos(r_2) \times \left| r_3 P_j^t - X_j^t \right|, & r_4 \geq 0.5 \end{cases} \tag{9}$$

Where r_4 is the random number between 0 and 1

r_1, r_2, $r_{3\ \text{and}}$ r_4 are main parameters in the sine cosine algorithm.

r_1 – Helps for movement direction.

r_2 - Indicates how far the movement should be.

r_3 – Helps to bring random weight to the destination.

r_4 – Helps to switch the components in sine cosine.

In order to get promising results of the search space to converge global optimum, balancing are needed in both exploration and exploitation stages. Thereby, the Eq. (7) and Eq. (8) are changed accordingly based on the following equation.

$$r_1 = a - t\frac{a}{T} \tag{10}$$

Where t' is the current iteration, T is the maximum iteration and *a* is the constant.

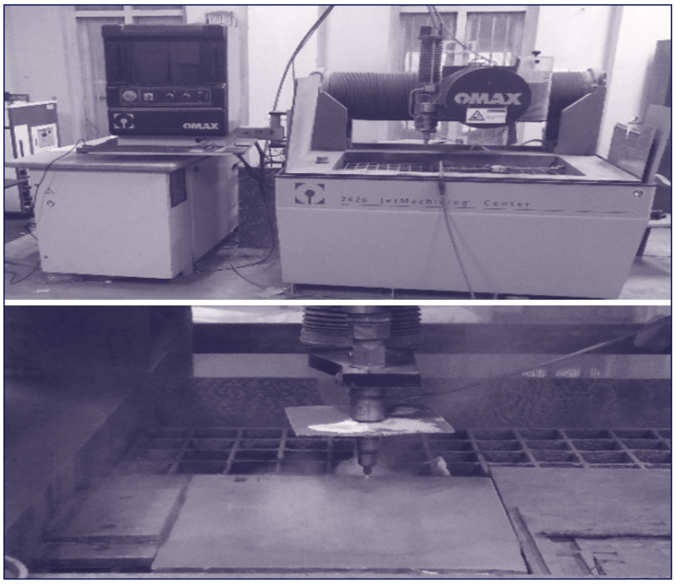
4. EXPERIMENTAL DETAILS

The experimental runs are used in the present study as shown in Table 2. The machining parameters are set to the pre-defined levels according to the design of experiments for each experimental run. Response surface methodology was used to design experimental work. OMAX 2626 AWJ Machining center was used to mill 20 mm × 10 mm 3D features and the Hastelloy C-276 as a test specimen, as shown in Figure 1. The milled pockets are shown in Fig 2. All machining was done in single-pass machining. Some of the AWJ milling parameters were kept as constant during the experiment. These parameters are nozzle diameter (0.76 mm), nozzle length (101.6 mm), orifice diameter (0.35 mm) and impact angle (90°). The garnet of 85 mesh size is used as abrasive for all the experiments. In this work, MRR and Ra were considered as a Multi-objective optimisation problem. The Multi-objective optimisation problem of the AWJ milling process is solved using the PSO, TLBO and SCA algorithm, respectively. The computer program for the above algorithms is built in MATLAB R2016a.

5. OPTIMISATION MODEL

Formulation of the optimisation model in AWJ milling is the most critical task in the optimisation process. It involves identifying decision variables, expressing the objective functions and setting up the bounds for decision variables, and finally expressing the optimisation problem as a mathematical model. The AWJ milling process optimisation model is formulated in the present work is based on the experimental work carried by Gopichand et. al [33]. The decision variables considered for this model are Water pressure (P) (MPa), Step over (So) (mm), Traverse rate (Tr) (mm/min) and Abrasive flow rate (m_a) (kg/min). The following objective functions are generated using response surface methodology (RSM) in Design expert software.

Fig. 1 OMAX 2626 AWJ Machining Centre



Objective function: $MRR = 151.79244 + 4.45950 \times P - 920.26433 \times So - 0.094421 \times Tr - 1399.29628 \times m_a - 1.23100 \times P \times So - 1.08137E - 003 \times P \times Tr + 11.26587 \times P \times m_a + 0.048515 \times So \times Tr - 663.85000 \times So \times m_a - 0.18129 \times Tr \times m_a - 6.18654E - 003 \times P^2 + 1556.77583 \times So^2 + 5.29090E - 005 \times Tr^2 + 384.1133 \times m_a^2$ (11)

Fig 2. Milled pockets in Hastelloy C-276 workpiece (G. Gopichand.et.al.[33])

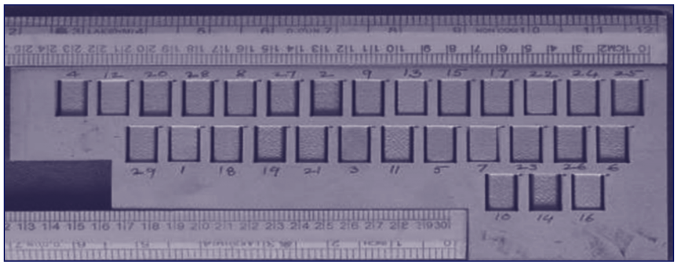


Table 2.Experimental runs (G.Gopichand.et.al [33])

AWJ milling Process parameters					Output responses	
S. No.	P (MPa)	So (mm)	Tr (mm/ min)	m_a (kg/ min)	MRR (mm^3/min)	R_a (μm)
1	150	0.2	2000	0.32	217.70	2.966
2	190	0.2	2000	0.32	362.12	3.600
3	150	0.4	2000	0.32	157.96	6.061
4	190	0.4	2000	0.32	292.54	6.871
5	170	0.3	1500	0.22	282.25	5.220
6	170	0.3	2500	0.22	190.68	5.840
7	170	0.3	1500	0.42	350.561	3.760
8	170	0.3	2500	0.42	222.739	5.503
9	150	0.3	2000	0.22	178.734	5.180
10	190	0.3	2000	0.22	270.886	6.136
11	150	0.3	2000	0.42	151.898	3.586
12	190	0.3	2000	0.42	334.177	4.300
13	170	0.2	1500	0.32	349.375	3.920
14	170	0.4	1500	0.32	289.552	6.506
15	170	0.2	2500	0.32	228.301	4.986
16	170	0.4	2500	0.32	178.181	7.220
17	150	0.3	1500	0.32	231.46	3.096
18	190	0.3	1500	0.32	387.865	4.560
19	150	0.3	2500	0.32	148.767	3.800
20	190	0.3	2500	0.32	261.917	5.505
21	170	0.2	2000	0.22	267.176	5.443
22	170	0.4	2000	0.22	213.559	8.400
23	170	0.2	2000	0.42	332.035	3.673
24	170	0.4	2000	0.42	251.864	6.223
25	170	0.3	2000	0.32	242.025	4.616
26	170	0.3	2000	0.32	236.962	4.410
27	170	0.3	2000	0.32	238.734	4.180
28	170	0.3	2000	0.32	245.569	4.830
29	170	0.3	2000	0.32	243.037	4.540

$$\mathrm{Ra} = -13.58386 + 0.35574 \times \mathrm{P} - 35.71883 \times \mathrm{So} - 3.46945\mathrm{E} - 003 \times \mathrm{Tr} - 46.03093 \times m_a - 0.022000 \times \mathrm{P} \times \mathrm{So} - 6.02500\mathrm{E} - 006 \times \mathrm{P} \times \mathrm{Tr} - 0.030250 \times \mathrm{P} \times m_a + 1.76000\mathrm{E} - 003 \times \mathrm{So} \times \mathrm{Tr} - 10.17500 \times \mathrm{So} \times m_a + 5.61500\mathrm{E} - 003 \times \mathrm{Tr} \times m_a - 9.95667\mathrm{E} - 004 \times P^2 + 87.77333 \times So^2 + 5.35433\mathrm{E} - 007 \times Tr^2 + 55.23583 \times {m_a}^2 \quad (12)$$

Parameter bounds for the four process variables are as follows.

$150 \leq \mathrm{P} \leq 190$ (MPa) (13)

$0.2 \leq \mathrm{So} \leq 0.4$ (mm) (14)

$1500 \leq \mathrm{Tr} \leq 2500$ (mm/min) (15)

$0.22 \leq m_a \leq 0.42$ (kg/min) (16)

Two objectives considered in this work, i.e., Material removal rate (MRR) and surface roughness (Ra) to find the right combination of process parameters that satisfy desired objectives, a multi objective function is formulated using the priori approach procedure, and equal weight is applied to the two objectives. In this way, the multi objective function is express by Eq. (17).

$$MinimizeZ = w_1\left(\frac{R_a}{R_a^*}\right) - w_2\left(\frac{MRR}{MRR^*}\right) \quad (17)$$

Ra* is the minimum value of surface roughness obtained by solving Eq. (12) in single objective optimisation individually. Similarly, MRR* is the maximum value of material removal rate obtained by solving Eq. (11) in single objective optimisation individually.

Therefore, to solve this problem with desired constraints, three algorithms have been used, such as PSO, TLBO, and SCA algorithm. For a fair comparison of results, the same number of function evaluations used in the present work with the population size of 20 and a maximum number of generations of 60. The results obtained for an individual objective are report in Table 3 and Table 4. In the case of individual objective functions, the results obtained by all algorithms are the same, but in this situation, the performance of the algorithms can be compared using the computational time and the number of generations Rao et al. [31]. In this way, the SCA algorithm performed better than the remaining two algorithms.

Single objective optimisation

The optimum AWJ milling process parameter values for MRR are P=190 MPa, So=0.2mm Tr=1500 mm/min and m_a = 0.42 kg/min as shown in table 3. However, the results obtained by PSO, TLBO and SCA are the same. The SCA algorithm converges in fewer generations as shown in Fig.3; the computational time is also lesser than the PSO and TLBO, which shows that the SCA algorithm is much more effective than the PSO and TLBO.

Table 3. Optimised results of PSO, TLBO and SCA for MRR

Name of Algorithm	Process Parameters				Objective Function MRR (mm^3/min)	Number of Generations	Computational time (Seconds)
	P MPa	So mm	Tr Mm/min	m_a Kg/min			
PSO	190	0.2	1500	0.42	500.0746	8	9.509
TLBO	190	0.2	1500	0.42	500.0746	4	2.569
SCA	190	0.2	1500	0.42	500.0746	***3**	**0.167**

Fig. 3 Convergence graph of MRR

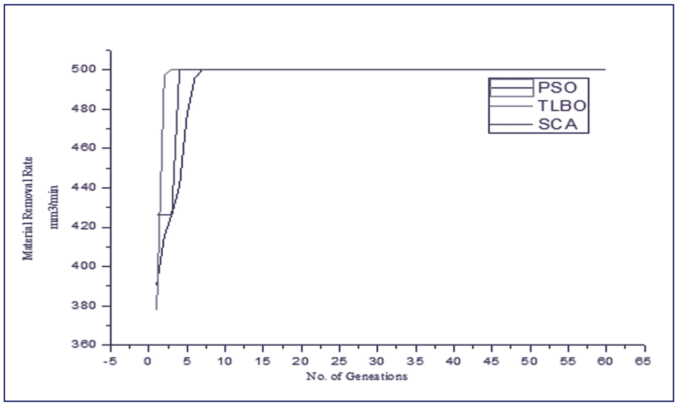


Table 4 shows that the optimum AWJ milling process parameter values for R_a. The PSO, TLBO and SCA algorithms obtained the same results. However, the PSO algorithm converged at 10 generations and TLBO algorithm converged at 9 generations and SCA algorithm converged only at 6 generations for the optimal solution as shown in Fig.4. The time required for PSO, TLBO and SCA algorithm is 9.617s, **7.59**s and **0.273s** to perform same function evaluations. The robustness of the above algorithms is evaluated by running the three algorithms 30 times independently of the same functional evaluation value with a random initial population in each run. The same solution for all 30 runs was achieved with PSO, TLBO and SCA algorithms

Fig. 4 Convergence graph of Ra

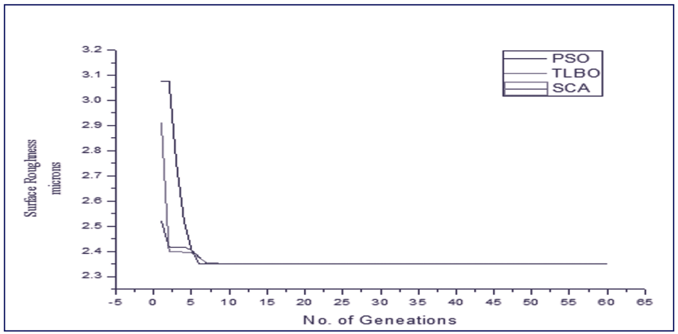


Table 4. Optimised results of PSO, TLBO and SCA for Ra

Name of the Algorithm	Process Parameters				Objective Function Ra **(µm)**	Number of Generations	Computational time (Seconds)
	P MPa	So mm	Tr mm/min	m_a Kg/min			
PSO	150	0.223016	1500	0.40204	2.349086	10	9.617
TLBO	150	0.223016	1500	0.40204	2.349087	9	7.59
SCA	150	0.223016	1500	0.40204	2.349087	***6**	**0.273**

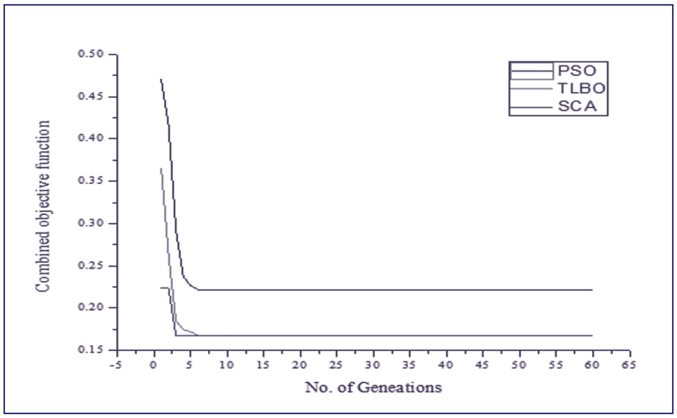
Multi-objective optimisation:

In the multi (combined) objective function, the PSO algorithm required 17 generations, the TLBO algorithm required 6 generations and the SCA algorithm requires only 3 generations to achieve convergence. The time required for PSO, TLBO and SCA10.008s, 2.166s and 0.208s respectively to perform same number of function evaluations. The number of generations required by the SCA algorithm was lower than the number of generations needed by the PSO and TLBO algorithms. The combined objective function value obtained by the SCA and TLBO algorithms (i.e. 0.16736) referred to in Table 5 is better than the combined objective function value obtained by the PSO algorithm (i.e. 0.221802) referred to in Table 5. As shown in Figure 5, the convergence graph of SCA, TLBO and PSO algorithms. The obtained number of generations and computational time by the SCA compared with the TLBO and PSO obtained is very less. The SCA performs better than the TLBO and PSO as written in the bold refer from Tables 3 to 5.

Table5. The combined objective results obtained using PSO, TLBO and SCA for AWJ Milling

Name of the Algorithm	Process Parameters				Minimise Z	MRR	Ra	Number of Generations	Computational time (Seconds)
	P MPa	So mm	Tr mm/min	m_a Kg/min					
PSO	150	0.20566	1500	0.408792	0.221802	285.202612	2.379227	17	10.008
TLBO	190	0.2	1500	0.42	0.167368	**500.074587**	**3.135411**	**6**	**2.166**
SCA	190	0.2	1500	0.42	0.167363	**500.074587**	**3.135411**	***3**	**0.208**

Fig. 5 Convergence graph for combined objective of MRR & R_a



6. CONCLUSIONS

Single objective optimisation and Multi objective optimisation aspect of AWJ milling process consider in this work. SCA, TLBO and PSO algorithms are applied to optimise the singleobjective optimisation of MRR and Ra, also multi objective optimisation of AWJ milling process optimisation problem. The SCA algorithm performance compares with the TLBO and the PSO algorithm for optimisation of AWJ milling is considered in this work, based on computational time and generations. It is observed that the optimised values of process parameters achieved by SCA and TLBO algorithms are better than the PSO algorithm. The computational time and number of generations achieved by the SCA algorithm are lesser than the computational time and number of generations achieved by TLBO and PSO algorithms for the AWJ milling process. The SCA algorithm is a fast, robust and convenient algorithm for solving the AWJ milling process optimisation problems. The SCA algorithm can also be applied to solve the optimisation problems of other machining processes, such as conventional and unconventional machining processes.

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