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APPLICATION ARTICLE

Chemical reaction optimization algorithm for machining parameter of abrasive water jet cutting

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Abstract

Abrasive water jet cutting is one of the most prominent technique for the cutting of wide range of materials. Selection of the input process parameter with optimized condition determines the productivity and process applicability. Present paper describes the nature inspired meta-heuristic chemical reaction optimization (CRO) algorithm for the selection of input process parameter for the most favorable material removal rate (MRR). In the present paper ductile material model for the MRR is considered by CRO for the solution approach. Five input variables namely water jet pressure, diameter of nozzle, feed rate of nozzle, mass flow rate of abrasive and mass flow rate of water were considered for the material removal rate in abrasive water jet machining. It was found that CRO algorithms delivers improved performance compare to different algorithms such as genetic algorithm, cuckoo search, teaching learning-based optimization and teaching learning based cuckoo search algorithm. The predicted results can be used for the identification of the input process parameter to enhance outcome at the acceptable range for machining.

Keywords Chemical reaction optimization · Meta-heuristics · Material removal rate · Parameter optimization · Abrasive water jet · Machining

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1 Introduction

In the global world, the advanced manufacturing process plays an important role in industrial evolutions. The abrasive water jet machining process (AWJM) is one of the most used processes among other advanced manufacturing process such electro discharge machining (EDM), laser beam machining (LBM), wire cut electro discharge machining (WEDM) etc., due to its unique capabilities of cutting any material from soft to hard and ductile to brittle over a wide range of material system. The cutting capability of the material depend upon the nature (i.e., ductile and brittle) to large extent. Further, the particle distributions, orientation of the grains and dislocations determine the amount of cutting energy. AWJM uses high intensity water along with hard abrasive to cut material with high impact energy on the work surface. The main functional unit AWJM process is illustrate in the Fig. 1. The AWJM mainly consist of high intensity pressure unit, abrasive hopper, nozzle head, catcher tank and controller unit. The material removal process in AWJM can be explained by the numerous actions such as erosion, fatigue, melting and brittle fracture which act together to remove the unwanted material [1–5]. The stated process is taking place due to striking of the high velocity water jet pressure along with hard abrasive particle which are responsible for the main cutting action during machining. The final product quality and system reliability are in direct relationship with the type of process parameter adopted for machining. However, consideration of optimized process parameter gives the overall aspect of machining, cost and productivity of

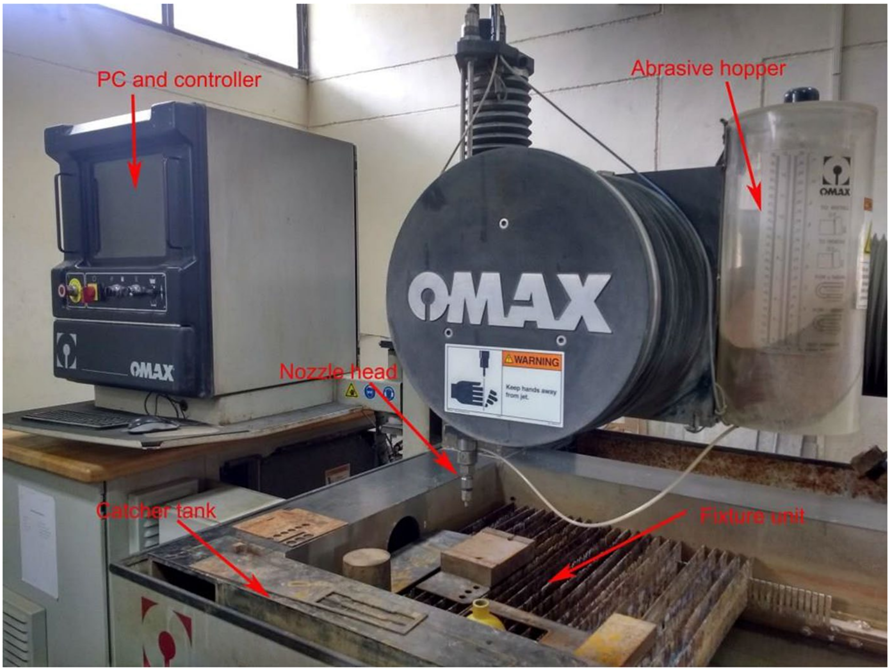

Fig. 1 Different functional unit in abrasive water jet machining (AWJM)

the system [6]. A number of heuristic and meta-heuristic optimization methods are available which includes a number of conventional and non-conventional optimization techniques such as taguchi based, factorial based, response surface methodology (RSM) based, genetic algorithms (GA), stimulated annealing methods (SA), particles swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC) etc., are effective methods to solve the optimization [7–14]. Several attempts have been made by the researchers in the time span to get optimized and enhanced output with different combination of input condition utilizing traditional and non-traditional optimization techniques. The main influencing factor in AWJM can be classified into hydraulic abrasive, mixing, and cutting parameter, which directly in relation with output response of the process [11, 15–17]. The different processing parameters which affect the performance and overall product quality of the AWJM can be clearly seen in the Fig. 2. The main process conditions include hydraulic, abrasive, mixing, cutting conditions and work piece which directly related with the overall machining performance during machining.

Wang [18] proposed neural network approach to solve multi-objective machining parameters which provides a global measure of input interaction with the response. Chakravarthy and Babu [19] presented fuzzy logic based genetic algorithm to solve the multi criteria optimization in the AWJM, which provides maximized output with lower power consumptions. Their predicted value for depth of cut was found to deviate within a range of 10%. Meta-heuristic optimization cuckoo search algorithms were applied by Gandomi et al. [12] for the solution of structural optimization problem and found to superior from other traditional approaches in the existing literature. In the recent year, a number of non-traditional approaches has been developed and used by several researchers in search of global and local optimum solution in various machining process. In order to meet the specific requirement as per customer demand many hybrid and new algorithms were utilized by the several author playing with the standard input process environment for enhanced product quality in the AWJM [7, 20–22]. For the titanium based alloy material a set of process variable is utilized by Muthuramalingam et al. [21], where they described the SOD is the

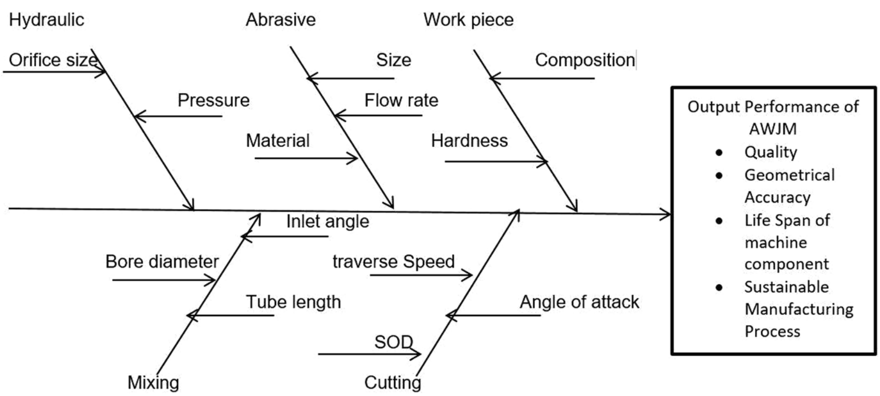

Fig. 2 Cause and effect diagrams for abrasive water jet machining (AWJM)

most influencing process parameter for the machining performance. Jain et al. [23] utilized ductile material model for AWJM with genetic algorithm (GA) optimization method. Their study obtained the material removal rate in the optimum range with defined variable bounds for input parameter. Further, Mellal and Williams [16] optimize the AWJM with cuckoo algorithms with a smaller number of function evaluation and in a faster way. The obtained results in the cuckoo algorithm was better compared to GA. Pawar et al. [15] demonstrate the teaching learning-based optimization (TLBO) for ductile material model in AWJM. They observed that TLBO was proved to be efficient way of finding the optimum solution with less computational time compared to previous work of optimization.

The combination of different algorithms provides superior outcomes at the investigated environments. However, the complexity in the process does not count the all the material properties and input process conditions simultaneously. From the extensive literature work it was observed that no efforts were made towards the use of chemical reaction optimization (CRO) in AWJM. In the present investigation an attempt has been made to examine the effect of material properties, input process conditions and their behavior with respect to the material removal rate in AWJM. Present study involves the use of CRO and the evaluation of the material removal rate for the set of process condition which directly affects the overall performance of the machining. The use of CRO provides the better outcomes compare with other newly developed optimization algorithms [24]. CRO is used to search the global values, which satisfy the objective and provide a better solution of the problem. CRO is a variable population-based meta-heuristic algorithm which is based on the interaction of the molecules in every iteration process [25].

2 Problem formulation

The abrasive water jet machining uses the high velocity water jet and hard abrasive particle for removal of material for the target surface. The machine is capable of machining diverse class of material ranging for extreme brittle to ductile material. The process is having unique capability of cutting the material without the generation of heat at the machining zone which protects the work material from different thermal damage to the cutting zone [6, 17]. In support of cutting mechanism several researchers propose the different material model for the prediction of material removal rate, surface roughness, kerf profile during the cutting action. The material removal in case of ductile material takes place due to plastic deformation and cutting wear. The indentation rapture, crack propagation is the main responsible factor for the material removal in case of brittle material. For the ductile material Hashish [26] proposed the mathematical model for the material removal process by the neglecting the kerf wall drags in the different cutting zone. The different affecting process parameter in case of AWJM shown in the Fig. 2. The main process variables which affect the performance can be classified in terms of hydraulic parameter, abrasive parameter, mixing and nozzle variable and the work material which is targeted for the cutting action. Now-a-days use of evolutionary algorithms to optimize the advanced machining process parameter is continuously growing because most of the problem belong to non-deterministic Polynomial- time

(NP)hard category. In order to obtained exact solution of this NP-hard problem is very cumbersome so, evolutionary algorithms provide near exact solutions [11, 14, 27–31]. For AWJM a number of optimization techniques were adopted by different researchers to generate the optimum solution. The present paper formulates the solution approach by the use of CRO meta-heuristic approach for the determination of material removal rate. The solution approach and detailed description of the adopted algorithms is discussed in the later section.

2.1 Mathematical model

In the present case the ductile material model is utilized for the solution of material removal rate in AWJM. Present case utilizes the material removal model for the ductile material for the MRR. The different input process variable is given in the Table 1.

2.2 Decision variables

In the present case five following variables are taken as the decision variables for the solution of the developed model.

P_w:	Water jet pressure (MPa)
d_{awn}:	Abrasive water jet nozzle diameter (mm)
f_n:	Feed rate of nozzle (mm/s)
M_w:	Mass flow rate of water (Kg/s)
M_a:	Mass flow rate of abrasive particles (Kg/s)

Table 1 Input process parameter for AWJM

Parameters	
$\rho_a =$	Density of abrasive particles (Kg/mm^3)
$v_a =$	Poisson ratio of abrasive particles
$E_{Ya} =$	Modulus of elasticity of abrasive particles (MPa)
$f_r =$	Roundness factor of abrasive particles
$f_s =$	Sphericity factor of abrasive particles
$\eta_a =$	Proportion of abrasive grains effectively participating in machining
$v_w =$	Poisson ratio of work material
$E_{Yw} =$	Modulus of elasticity of work material (MPa)
$\sigma_{ew} =$	Elastic limit of work material (MPa)
$\sigma_{fw} =$	Flow stress of work material (MPa)
$C_{fw} =$	Drag friction coefficient of work material
$\xi =$	Mixing efficiency between abrasive and water
$P_{\max} =$	Allowable power consumption value (KW)

2.3 Objective function

In the present case the objective function is selected as the maximization of the material removal rate (MRR). The objective function can be given by the Eq. 1 which is dependent upon the decision variables and their selected range. The material removal rate is the function of water jet pressure, abrasive water jet nozzle, feed rate of nozzle, mass flow rate of water and abrasive which is directly linked with the indentation depth due to cutting wear and deformation wear [32].

$$f(P_w, d_{awn}, f_n, M_w, M_a) = d_{awn} f_n (h_c + h_d) \tag{1}$$

2.4 Constraints

$$1 - \frac{M_w P_w}{P_{\max}} \geq 0 \tag{2}$$

$$\begin{aligned} h_c = & \left(\frac{1.028 \times 10^{4.5}\xi}{C_k \rho_a^{0.4}}\right)\left(\frac{d_{awn}^{0.2} M_a^{0.4}}{f_n^{0.4}}\right)\left(\frac{M_w P_w^{0.5}}{M_a + M_w}\right) \\ & - \left(\frac{18.48 K_a^{2/3} \xi^{1/3}}{C_k f_r^{0.4}}\right)\left(\frac{M_w P_w^{0.5}}{M_a + M_w}\right)^{1/3} \text{ when } \alpha_t \leq \alpha_0 \end{aligned} \tag{3}$$

$$h_c = 0 \text{ when } \alpha_t \geq \alpha_0 \tag{4}$$

$$h_d = \frac{\eta_a d_{awn} M_a \left[K_1 M_w P_w^{0.5} - (M_a + M_w) v_{ac}\right]^2}{\left(1570.8\sigma_{fw}\right) d_{awn} f_n (M_a + M_w)^2 + \left(K_1 C_{fw} \eta_a \left[K_1 M_w P_w^{0.5} - (M_a + M_w) v_{ac}\right] M_a M_w P_w^{0.5}\right)} \tag{5}$$

$$\alpha_t = \left(\frac{0.389 \times 10^{-4.5} \rho_a^{0.4} C_k}{\xi}\right)\left(\frac{d_{awn}^{0.8} f_n^{0.4} (M_a + M_w)}{M_{a^{0.4}} M_w P_w^{0.5}}\right) \text{(degrees)} \tag{6}$$

$$\alpha_0 = \left(\frac{0.02164 C_k^{1/3} f_r^{0.4}}{K_a^{2/3} \xi^{1/3}}\right)\left(\frac{M_w P_w^{0.5}}{M_a + M_w}\right)^{1/3} \text{(degrees)} \tag{7}$$

$$V_{ac} = 5\pi^2 \frac{\sigma_{cw}^{2.5}}{\rho_a}\left[\frac{1 - v_a^2}{E_{Ya}} + \frac{1 - v_w^2}{E_{Yw}}\right]^2 \text{(mm/ sec)} \tag{8}$$

$$K_1 = 2^{0.5} \times 10^{4.5} \xi \tag{9}$$

$$C_k = \left(\frac{3000\sigma_{fw} f_r^{0.6}}{\rho_a} \right)^{1/2} \text{(mm/s)} \tag{10}$$

$$50 \leq \leq 400\ (MPa) \tag{11}$$

$$0.5 \leq \leq 5(\text{mm}) \tag{12}$$

$$0.2 \leq \leq 25\ (\text{mm/s}) \tag{13}$$

$$0.02 \leq \leq 0.2(\text{kg/s}) \tag{14}$$

$$0.0003 \leq 0.08\ (\text{kg/s}) \tag{15}$$

Constraint 2 exhibit the maximum input power available in the abrasive water jet machining process. Equation 3 shows the indentation depth (h_c) due to cutting action when impingement angle at the top of the machine surface α_t is less than or equal to critical angle α_0 and similarly Eq. 4 resemble the indentation depth when impingement angle at the top of the machined surface α_t is greater than critical angle α_0. The cutting depth due to deformation wear (h_d) is given in the Eq. 5. Equation 6 and 7 represents the impingement angle at the top of the machined surface α_t and critical angle α_0 at which maximum erosion occurs during cutting action. The critical velocity (V_{ac}) of the abrasive particles is given in Eq. 8. The effect of mixing efficiency on the cutting performance is depicted in the Eq. 9. The Eq. 10 shows the characteristics velocity which combines the material and particle characteristics. The parameter C_k (Eq. 10) depends upon the flow stress of the work material, roundness factor for the abrasive particle and density of the work material. The bound for the input variables is given in the Eqs. 11–15. The description for the various symbols is given in the Table 1.

3 Solution approach

Combination of different input process variable leads to complex formulation and expensive solution for machining process. The prime consideration in the optimization problem is to enhance the productivity and sustainability of the process by virtue of utilizing best input combination for desired outcomes without compromising the quality [9, 11, 23, 31]. In this paper, we have proposed a mixed integer non-linear problem (MINLP) model to capture the abrasive jet water jet machining process (AWJM) with various constraints. The AWJM non-traditional machining process is NP hard problem having complex and large terms for output [33]. In the similar context Jain et al. [23] explored the (GA) for finding the best possible combination in advanced machining operation. Mellal and Williams [16] used the cuckoo search (CS) and hoopoe heuristic for optimization of advanced machining operation. On a similar note TLBO [15], CS and teaching learning based cuckoo search (TLCS) [34], fuzzy logic based optimization [14, 35], adoptive wavelet neural network [36] were implemented to extract the best possible input parameter for higher material removal and enhanced product quality during AWJM. In the present work Meta-heuristic approach i.e. CRO have been used to determine the optimal MRR. Recently, CRO was utilized by Bargaoui et al. [37] to solve the distributed permutation flow shop scheduling problem with makespan criterion. CRO is a novel meta-heuristic method to solve complex optimization problem. On a similar note Mogle et al. [27] solve the bulk wheat transportation and storage problem in a public distribution system with two stage supply chain network with CRO. The author further implemented the Tabu-search along with CRO to solve the complexity of the distribution and storage of wheat. It was observed that hybridization of Tabu-search in CRO reduces the computational work for all problem sizes. Looking at the earlier research it was observed that CRO was not applied for the optimization of the AWJM. Hence, an attempt is made in the current work to apply the CRO algorithm for machining parameter optimization. Further, the comparative assessment was done with the other advanced algorithms in terms of final optimum solution.

3.1 Chemical reaction optimization (CRO)

Meta-heuristic approach i.e., Chemical reaction optimization (CRO) is used to solve the objective function. CRO is based on the interaction of molecule in the search domain to find out the best possible optimum value [38]. The CRO is based on the basic two law of thermodynamics which can be explained as (1) the total energy of the system can only be transferred it cannot be created nor destroyed, it remains constant. (2) The reactant system releases the energy by minimizing the potential energy to increase the system stability. In the CRO the energy is obtained by the conversion of potential energy into kinetic energy and by the transfer of the energy to the molecules [24]. The energy profile of the reactant is a representation of single energetic pathways with the co-ordinates and the final product is shown in the Fig. 3

3.2 Description of the CRO

CRO is polpulation bsed meta-heuristic approach to solve the problem. The size of the population depends upon the total number of iteration and size of the molecule interacting with each other during. the synthesis and decomposition are controlledby the factor β and α respectively. The different attributes of the CRO can be explained as: The molecular structure capture the solution of in the specific format such as a number, vector or matrix. In the current situation we are dealing with the maximization of material removal in the AWJM process.The objective function value of the corresponding solution can be explained by the potential energy of the molecules. The kinetic energy of the molecule is the non-negative number and tolerance of the system to accept the solution of the objective function. When the molecule undergoes collosion one elementry reaction causes the changes in the molecular structure of the system. The minimum potential energy which a molecule attain is the min

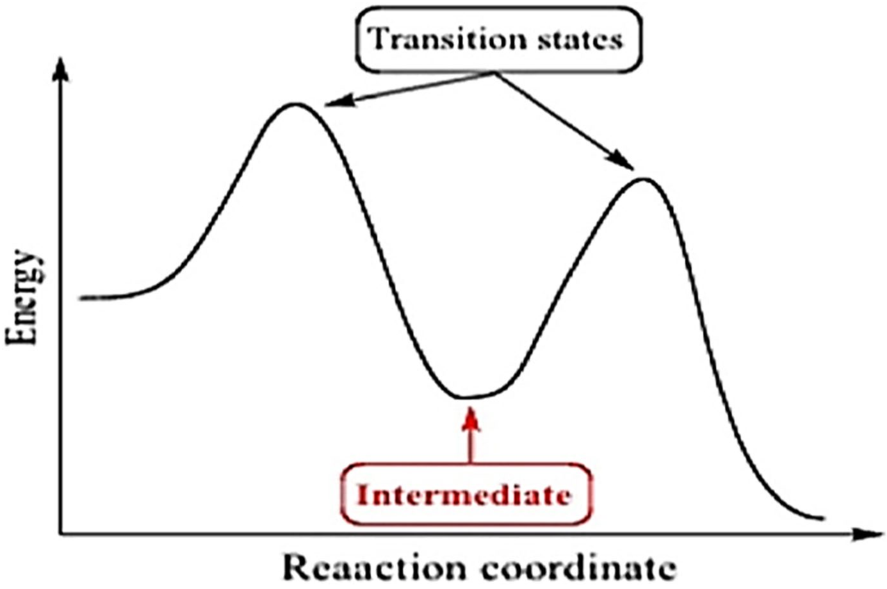

Fig. 3 Energy profile of reactants

structure similarly the minPE is when the molecule attains its min potential energy. The loss in kinetic energy during synthesis of the molecule is determined by the parameter KELoss rate. There are four kind of elementry reaction which occur during CRO process.

3.2.1 On-wall ineffective collision

In this collison the main motive is to transfer the kinetic energy by means by collioding the particles inside the closed conatiner or system. The transffered energy is added to the central buffer system. Let the current energy for the molecule having low potenetial energy is say a random number $a \in [KELoss, 1]$ then (Eq. 16 and 17 shows the on wall effective collision process numerically).

$$\mathrm{KE}_w = \left(\mathrm{PE}_w + \mathrm{KE}_w - \mathrm{PE}_w\right) \times a \tag{16}$$

The remaining transffered energy to the buffer can be given as

$$\text{buffer} = \text{buffer} + \left(\mathrm{PE}_w + \mathrm{KE}_w - \mathrm{PE}_w\right) \times (1 - X) \tag{17}$$

3.2.2 Decomposition

The decomposition process leads to the development of the new molecule in the exploration of the search space. The decomposition process develops the new molecule with the collision of the external agent ($w \to w_1' + w_2'$). During the decomposition process the required energy loss is obtained from the buffer. In the search space the conservation of the energy can be given by the following equation when the molecule kinetic energy of the two different molecules is δ_1 and δ_2 are the random numbers, $\varepsilon(0,1)$. Equation 18–20, represents the different behavior observed during decomposition process.

$$\mathrm{E} = \mathrm{PE_w} + \mathrm{KE_w}\delta_1 \times \delta_2 \times \mathrm{buffer} - \mathrm{PE'_{w_1}} + \mathrm{PE'_{w_2}} \tag{18}$$

$$\mathrm{buffer} = \mathrm{buffer}\left(1 - \delta_1 \times \delta_2\right) \tag{19}$$

$$\mathrm{KE^n_{w_1}} = \mathrm{E} \times \delta_1 \text{ and } \mathrm{KE^n_{w_2}} = \mathrm{E} \times \delta_2 \tag{20}$$

3.2.3 Inter molecular ineffective collision

In the present case the larger number of molecules are collide similar to uni-molecular collision. However, the larger number of collosion of moelcules generates the better propbabilty for the exploration of the search space. If the potential energy of the new molecules obtained from searching the neighbors follows $\mathrm{E} > 0$ where the energy E can be given by the equation 21.

$$\mathrm{E} = \mathrm{PE_{w_1}} + \mathrm{KE_{w_1}} + \mathrm{PE_{w_2}} + \mathrm{KE_{w_2}} - \mathrm{PE'_{w_1}} - \mathrm{PE'_{w_2}} \tag{21}$$

Here the energy conservation in the total reactio process can be stated as the following stated expresion with (in the equation 22-23).

$$\mathrm{KE_{w_1}} = \mathrm{E} \times \delta_3 \text{ and } \mathrm{KE_{w'_2}} = \mathrm{E} \times \left(1 - \delta_4\right) \tag{22}$$

$$\mathrm{PE_{w_1}} = \mathrm{PE_{w'_1}} \text{ and } \mathrm{PE_{w_2}} = \mathrm{PE_{w'_2}} \tag{23}$$

3.2.4 Synthesis

In this process more than two molecule unit for the formation of the new molecule. The process generate new molecule which is hiving higher tendencies to create the new solution due to explosion of higher energy. The kinetic energy of the developed molecule can be expressed as (equation 24):

$$\mathrm{KE_{w'}} = \left(\mathrm{PE_{w_1}} + \mathrm{KE_{w_1}} - \mathrm{PE_{w_2}} + \mathrm{KE_{w_2}} - \mathrm{PE'_{w}}\right) \tag{24}$$

4 Prediction results

In this paper, we have implemented CRO algorithim to solve proposed mathematical model and maximize the material removal rate, simultaneously optimize the process paramaters of AWJM (Abrasive water jet machining). We have run the program in MATLAB 2015 b and performed the computation experiment on Intel (R) core (TM) i-5 5200U CPU @ 2.20 GHz with RAM 8 GB in windows 10 environment (Table 2).

For the adopted model, the simulation results of CRO shows better other methods reported in the literature such as GA, CS, TLBO and TLCS for the material removal rate in AWJM. The optimum parameter found by the number of iterations of the formulated model using CRO algorithms. In case of meta-heuristic, the solution obtained in near optimal solution not the exact optimal value. In case of CRO each run produces a new optimal set of conditions with respect to associated process variable so here we have considered a set of 25 run and average of all the simulated run is compared with closed approximated solution obtained during simulation process to get near optimal solution of the tested situations. It was observed that with the use of CRO the computational time reduced and the results obtained is superior as compared to other techniques. Table 3 represents the comparative results of the different optimization used for the AWJM process. In the present case the solution obtained by the synthesis of input process

Table 2 Value of the constant and used parameters in Abrasive water jet machining process [15]

Notations	Value	Notations	Value	Notations	Value
ρ_a	$3.95\times10^{-4.5}$	f_s	0.78	σ_{ew}	883
v_a	0.25	η_a	0.07	σ_{fw}	8,142
E_{Ya}	350,000	v_w	0.20	C_{fw}	0.002
f_r	0.35	E_{Yw}	114,000	ξ	0.8
$P_{\max}$	56				

Table 3 Comparative results of the different process parameters obtained from different algorithms

Method/ Ref	P_w(MPa)	d_{awn}(mm)	f_n (mm/s)	M_w(kg/s)	M_a(kg/s)	MRR (mm^3/s)	P_{max} (Kw)
GA [Jain et al. 2007] [23]	398.3	3.726	23.17	0.141	0.079	90.257	56
TLBO [Pawar et al. 2013][15]	400	5.0	5.404	0.141	0.07	239.54	56
CS [Haung et al. 2015][34]	398.4552	4.9168	10.7346	0.1403	0.08	305.76	56
TLCS [Haung et al. 2015][34]	400	5	10.4468	0.140	0.08	307.87	56
CRO (Current work)	344.012	3.1835	20.9168	0.1816	0.0605	316.12	56

GA-Genetic algorithms, TLBO-Teaching–learning based optimization, CS-Cuckoo search, TLCS-Teaching–learning-based cuckoo search, CRO-Chemical reaction optimization parameter using CRO is better compared to reported value by different algorithms in the literature [11, 15, 23].

5 Effectiveness and managerial implications of CRO

The research work identifies the optimal input process conditions for maximum material removal rate in abrasive water jet machining for a ductile material. Machining of ductile material is a challenging task due to continuous chip formation and rapid tool wear. Thus, the use of evolutionary algorithms in the machining process can be utilized to enhance productivity. In the present work, the use of CRO in AWJM can be helpful to a machinist to find out the higher material removal with available resources in the competitive environment. Table 3 confirms the CRO algorithm has given an improved value of material removal rate compared to established evolutionary algorithms such as GA, TLBO, CS and TLCS. The understanding obtained in this work would be helpful for the researchers and industrial personal to plan and to facilitate effective decision in the machining operation.

6 Conclusion and future work

This paper represents CRO based meta-heuristic approach to optimize the process parameter in AWJM. The approximate solution obtained in CRO is higher compared to the earlier reported value for material removal rate. Based on the result of the present study it was proved that CRO algorithm is proficient in giving higher material removal rate. There are many output responses such as surface roughness, kerf quality, jet lag, etc. which can be optimized further using CRO. The research in the direction of CRO and machining processes can be used for the convergence of faster solutions and better results Consideration of other output parameters and optimized conditions for kerf angle, surface roughness, and cost of production per sheet can be implemented using CRO algorithms for machining applications in future. In the current work, basic version of CRO meta-heuristics was utilized for AWJM. The combination of different evolutionary algorithms, new and adaptive version and Tabu-Search algorithm with CRO can be implemented to enhance productivity and overall sustainability in machining operation.

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