Int. J. Simul. Multidisci. Des. Optim. **13**, 6 (2022)

https://doi.org/10.1051/smdo/2021033

IJSMDO

Available online at:
https://www.ijsmdo.org

Advances in Modeling and Optimization of Manufacturing Processes

Research Article · Open Access

Optimization of advanced manufacturing processes using socio inspired cohort intelligence algorithm

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Received: 14 June 2021 / Accepted: 28 October 2021

Abstract. The demand of Advanced Machining Processes (AMP) is continuously increasing owing to the technological advancement. The problems based on AMP are complex in nature as it consisted of parameters which are interdependent. These problems also consisted of linear and nonlinear constraints. This makes the problem complex which may not be solved using traditional optimization techniques. The optimization of process parameters is indispensable to use AMP's at its aptness and to make it economical to use. This paper states the optimization of process parameters of Ultrasonic machining (USM) and Abrasive water jet machining (AWJM) processes to maximize the Material Removal Rate (MRR) using a socio inspired Cohort Intelligent (CI) algorithm. The constraints involved with these problems are handled using static penalty function approach. The solutions are compared with other contemporary techniques such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Modified Harmony Search (HS_M) and Genetic Algorithm (GA).

Keywords: Advanced machining processes / complex problems / linear and nonlinear constraints / cohort intelligence algorithm

1 Introduction

Traditional manufacturing processes were very useful in early decades. As the world started demanding more in terms of standards and quality, it is very difficult to manufacture certain products due to its complex shape, size and quantity as it is beyond the limit of traditional manufacturing processes. Therefore, industrial sector has modified traditional manufacturing processes named as Advance Manufacturing Processes (AMP).

The real-world applications of AMPs such as Light Amplification Stimulated Emission of Radiation machining problem [1,2] which is used for cutting process. In this machine, a focused and precise laser beam is passed through the material by accomplishing cutting of material therefore other processes like wire electric discharge machining [3], electric discharge machining [3], electrochemical machining [4], electro-beam machining problem [5], ultrasonic machining [6] and more were invented for specific operations while considering human safety and standards issues. These are further classified under mechanical processes, chemical and electro chemical processes, thermal and electro thermal processes and finishing processes [7]. In these problems, precise selection of process parameters plays a key role to manufacture the product in a reasonable cost and time. Parameters such as cutting speed, cutting depth, number of passes of the wheel or table, amplitude, magnitude, volume and speed of the tool are considered under various of machining processes.

Water Jet Machining (WJM) process is a non-traditional machining process in which water at high pressure and velocity is used to cut the softer materials. An application of regression modeling and Taguchi Method were used to optimize AWJM processes parameter [8]. It has shown the great potential to improve the process parameter and to obtain the required surface roughness. The application of elasto-plastic finite element analysis used to simulate the 3D erosion in AWJM of grade 5 Titanium alloy [9]. Li and Wang [10] presented the drilling and slotting machining processes on Ti-6Al-4V alloy using AWJM. USM problem [11] was designed to maximize the MRR, which was solved using ABC, HS_M and PSO. While [12] carry forward undetermined non-conventional optimization techniques such as Gravitational Search Algorithm (GSA) and Fireworks Algorithm (FWA) on USM processes. [13] carried out the experimentation on USM using Adaptive Neuro Fuzzy Inference System (ANFIS) and Independent Component Analysis (ICA) were related together to optimize USM for multi-responses, therefore obtained data were bought together for development of mapping relationship connecting inputs and

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ANFIS. Metaheuristic algorithm such as Cuckoo Search (CS) and Chicken Swarm Optimization (CSO) were used by [14] to solve the USM problem.

Apart from these, there are several socio-inspired optimization algorithms proposed so far, such as PC [15], SOS [16], Teaching Learning Based optimization (TLBO) [17], so on and so forth. The CI algorithm is also one of the socio inspired algorithm proposed by [18]. It models the learning behavior of the candidates such as following, interacting, cooperating and competing with every other candidate in the cohort. It was modified to solve constrained problems and applied to solve combinatorial NP-hard 0-1 Knapsack problem with the number of items varying from 4 to 75 [19]. The probability-based constraint handling techniques was used to handle the constraints. Similar approach was also applied for solving real world combinatorial problems from healthcare and logistics domains and large sized complex problems from the Cross-Border Supply Chain domain [20], Traveling Salesman Problem (TSP) [21] and several benchmark problems [18]. A self-adaptive Cohort Intelligence (SACI) algorithm [22] was proposed using tournament mutation operator and a self-adaptive scheme to update the sampling interval. It is tested on several benchmark problems and obtained promising results. The static and dynamic penalty function approach is incorporated in CI (CI-SPF and CI-DPF) for solving several test problems and manufacturing engineering problems [23]. The multi-CI [24] and variations of CI [25] were used to solve the AWJM problem for minimization of surface roughness. The CI-SPF is adopted for solving complex problems from truss structure and mechanical engineering domain [26, 27]. Being observed the limitation in CI-SPF, the CI is incorporated with Self Adaptive Penalty Function (SAPF) approach [28]. Further, some intrinsic properties of CI and Colliding Bodies Optimization (CBO) are combined to formed a new hybrid metaheuristic CI-SAPF-CBO. Using CI-SAPF and CI-SAPF-CBO, 40 problems from truss structure domain, design engineering domain, linear and nonlinear problems and real-world manufacturing domain problems [28].

In this paper, very first time a socio inspired Cohort Intelligence (CI) algorithm is validated by solving AMPs problems such as abrasive water jet machining and ultrasonic machining problems. These problems are associated with linear and nonlinear constraints which are handled using static penalty function approach. The constrained version of CI algorithm [26] is used to investigate these problems. The solutions obtained using CI algorithm are compared with other contemporary algorithms and results are discussed.

The paper is organized as follows: The CI algorithm along with its characteristics are described in Section 2. The framework of CI and its flowchart is presented in Section 2.1. Section 3 demonstrates the constraint handling SPF approach. Section 4 discussed the AMP problems, in the same section the results comparison with contemporary algorithms and its analysis is discussed. Finally, the conclusion is presented in Section 5.

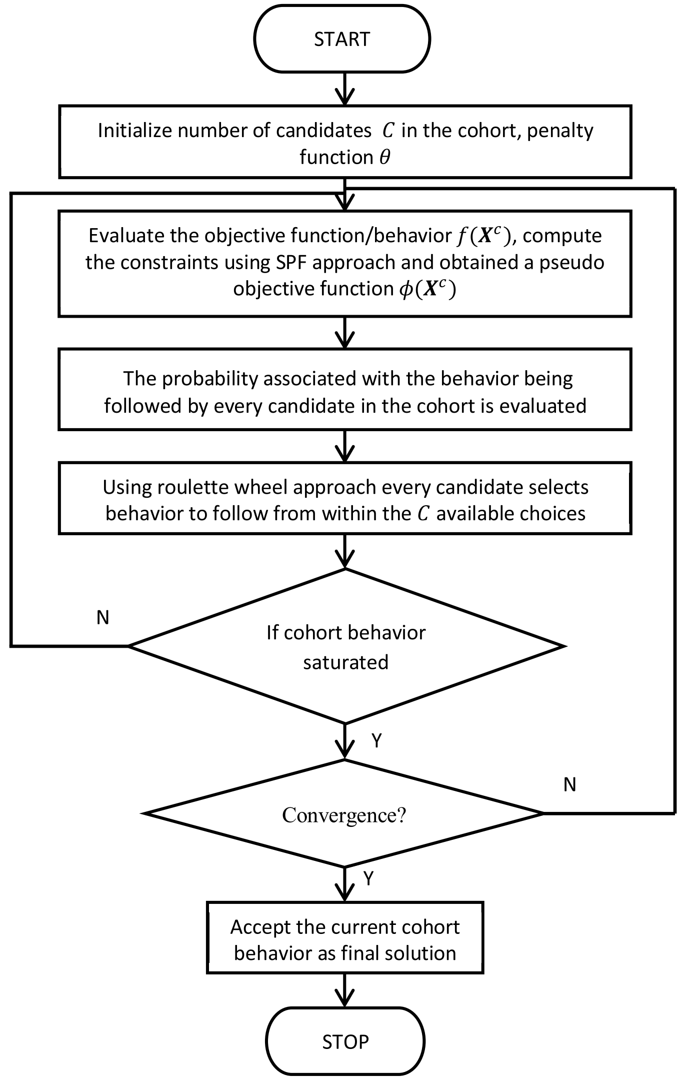

Fig. 1. Flowchart of CI algorithm.

2 Cohort intelligence algorithm

The CI algorithm [18] models the social tendencies of learning candidates of a cohort. Every candidate in the cohort iteratively attempts to achieve a goal which is common to all. For this, every candidate employs roulette wheel approach and selects another candidate to follow which may result in the improvement of its own behavior. This makes every candidate learn from one another and helps the overall cohort behavior to evolve. The cohort behavior could be considered saturated, if for considerable number of learning attempts the behavior of every candidate does not improve considerably and becomes almost same. The flowchart is presented in Figure 1 [26]. The characteristics of CI algorithm [28] are as follows:

– It models the learning mechanism of cohort candidates. Every candidate has inherently common goal to achieve the best behavior by improving its qualities. The interaction and competition are the two natural instincts of every cohort individual. These are achieved through

roulette wheel selection and further sampling in the close neighborhood of the selected (being followed) candidate. For details refer to [18,21].
- Every candidate observes itself and every other candidate in the cohort to improve its individual behavior and associated qualities.
- In CI algorithm, at the end of every learning attempt every candidate independently updates its search space.
- The problem with large number of variables and constraints can be efficiently handled [20,26].

2.1 Framework of CI

In the context of CI candidate follows other candidate which is probabilistically chosen from the cohort using roulette wheel approach. The CI algorithm [18] is mathematically expressed as follows:

Step 1: Consider a cohort with C number of candidates; every individual candidate $c\,(c = 1, 2, \ldots, C)$ contains a set of attributes/variables $\boldsymbol{X}^c = \left(X_1^c, X_2^c, \ldots, X_i^c \ldots, X_n^c\right)$ which makes the behaviour of an individual candidate $f(\boldsymbol{X}^c)$. The initial solution is randomly generated similar to the other population-based technique as follows:

$$\boldsymbol{X}^c = \Psi^{\text{lower}} + \left(\Psi^{\text{upper}} - \Psi^{\text{lower}}\right).r \text{ and } (1, n).s \tag{1}$$

Step 2: A static penalty function (SPF) approach is incorporated to handle the constraints and obtained pseudo objective function $\varphi(\boldsymbol{X}^c)$ (refer Sect. 3).

Step 3: The probability of selecting behavior $f(\boldsymbol{X}^c)$ of every associated candidate $c\,(c = 1, 2, \ldots, C)$ is calculated as follows:

$$p^c = \frac{1/_{\phi}(\boldsymbol{X}^c)}{\sum_{c=1}^{C} 1/_{\phi}(\boldsymbol{X}^c)} \tag{2}$$

Step 4: Every individual candidate $c\,(c = 1, 2, \ldots, C)$ generates a random number $r\varepsilon\,[0, 1]$ and using roulette wheel approach decides to follow the corresponding behaviour and associated attributes.

Step 5: Every candidate $c\,(c = 1, 2, \ldots, C)$ shrinks the sampling interval $\Psi_i^c, i = 1, \ldots, n$ associated with every variable $X_i^c, i = 1, \ldots, n$ to its local neighborhood. This is done as follows:

$$\Psi_i^c \varepsilon \left[X_i^c - (\Psi_i/2), X_i^c + (\Psi_i/2)\right] \tag{3}$$

Where $\Psi_i = \Psi_i \times R$; R is sampling space reduction factor.

Each candidate $c\,(c = 1, 2, \ldots, C)$ samples their qualities from within the updated sampling interval Ψ_i^c and computes the function values. This makes the cohort is available with C updated behaviors represented as $F^C = \{f(\boldsymbol{X}^1), \ldots, f(\boldsymbol{X}^c), \ldots, f(\boldsymbol{X}^C)\}$.

Step 6: The cohort behavior could be considered saturated, if there is no significant improvement in the behavior $f(\boldsymbol{X}^c)$ of every candidate.

If either of the two criteria listed below is valid, accept any of the C behavior from current set of behavior in the cohort as the final objective function values as final solution and stop, else continue to Step 1.
- If maximum number of attempts exceeded.
- The cohort reaches a saturation state. There is no significant improvement in the further learning attempts.

3 Static penalty function (SPF) approach

In general, the constrained optimization problem is expressed as follows:

$$\text{Minimize } f(\boldsymbol{X}) = f(X_1, X_2, \ldots, X_i, \ldots, X_n) \tag{4}$$

$$\text{Subject to } g_i(\boldsymbol{X}) \leq 0, \qquad i = 1, 2, \ldots, p$$

$$h_i(\boldsymbol{X}) = 0, \qquad i = 1, 2, \ldots, m$$

$$\Psi_i^{\text{lower}} \leq X_i \leq \Psi_i^{\text{upper}}$$

An exterior Static Penalty Function (SPF) constraint handling approach was widely used [29]. It is expressed as follows:

$$PF = \theta \times \left(\sum_{i=1}^{p} g_i(\boldsymbol{X}) + \sum_{i=1}^{m} h_i(\boldsymbol{X})\right) \tag{5}$$

where θ is a penalty parameter and $\left(\sum_{i=1}^{p} g_i(\boldsymbol{X}) + \sum_{i=1}^{m} h_i(\boldsymbol{X})\right)$ is summation of the violated constraints. The value of θ needs to be chosen arbitrary.

For the validation of proposed CI algorithm, the problems considered here are from advanced manufacturing domain. The CI algorithm is coded in MATLAB (R2019a) and the simulations are run on Windows 10 platform using an Intel Core i5, 2.5 GHz processor speed and 8GB RAM. Furthermore, both the problems are solved 30 times. The solutions obtained from CI algorithm and comparison with other contemporary algorithms are discussed in the following sections.

4 Advanced manufacturing processes (AMP) problems

The CI algorithm is applied to solve AMP problems such as AWJM problem and USM problem. The objective is to maximize the MRR. The constraints are handled using a static penalty function approach. Similar problems were also solved using different techniques such as ABC, HS_M and PSO [11] and GA [30] with different objective function.

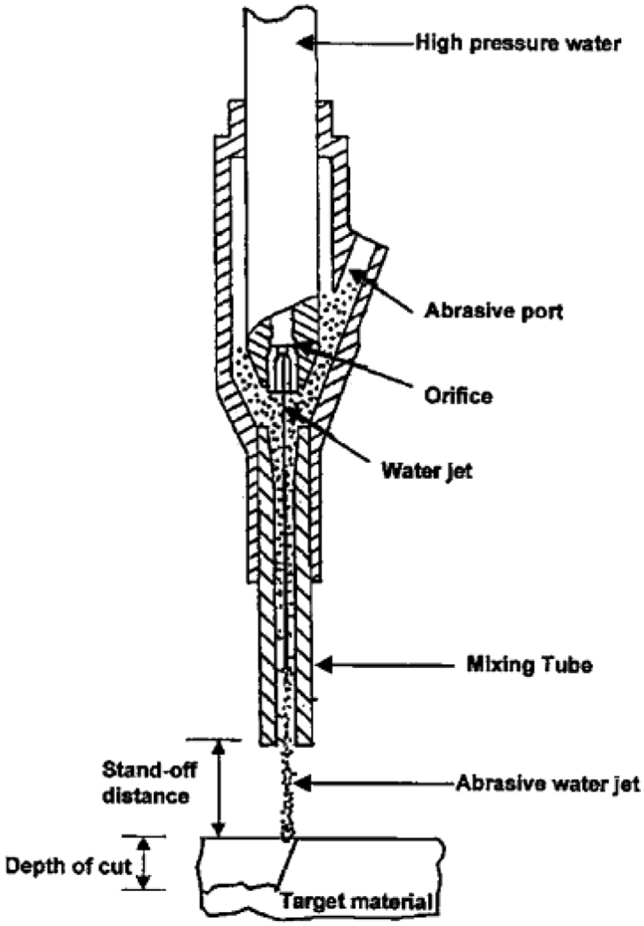

Fig. 2. Abrasive Water Jet Machining process [31].

4.1 Problem 1: Abrasive water Jet machining (AWJM) problem

Abrasive Water Jet machining (AWJM) process (refer Fig. 2) [32], in which velocity of water jet is increased and abrasive mixture is used to erode the workpiece. It uses the mixture of water and abrasive substance which mixed in a separate chamber and then pressurized towards nozzle for the cutting process. This process is used to cut wide variety of objects having complex dimensions. Hard materials such as metal, granite, wood, rubber, silicon, etc. are machined [32].

The AWJM problem was earlier solved using GA [33], PSO and ABC [31]. The objective is to maximize the MRR subject to power. The five decision variables considered for this model are: water jet pressure at the nozzle exit (P_w), diameter of AWJ nozzle d_{awn} feed rate of nozzle (f_n), mass flow rate of water (M_W) and mass flow rate of abrasives (M_a). The constants and parameters associated to this problems are illustrated in Table 1. The problem is formulated as follows:

Maximize $MRR = (d_{awn} \times (F_n(h_c + h_d)))$

where,

$$h_d = \frac{\eta_a d_{awn} \dot{M}_a \left[K_1 \dot{M}_w P_{w^{0.5}} - (\dot{M}_a + \dot{M}_w) v_{ac}\right]^2}{(1850.8\sigma_{fw\cdot}) d_{awn^2} f_n (\dot{M}_a + \dot{M}_w)^2 + (K_1 C_{fw} \eta_a)} \left[K_1 \dot{M}_w P_{w^{0.5}} - (\dot{M}_a + \dot{M}_w) v_{ac}\right] (\dot{M}_a \dot{M}_w P_{w^{0.5}}) \quad (6)$$

$$h_c = \left(\frac{1.028 \times 10^{4.5}\zeta}{C_k \rho_{a^{0.4}}}\right)\left(\frac{d_{awn^{0.2}} \dot{M}_a^{\ 0.4}}{f_n^{\ 0.4}}\right)\left(\frac{\dot{M}_w P_{w^{0.5}}}{\dot{M}_a} + \dot{M}_w\right) - \left(\frac{18.48 K_{a^{0.67}} \zeta^{\left(\frac{1}{3}\right)}}{C_{k\left(\frac{1}{3}\right)} f_r^{\ 0.4}}\right)\left(\left(\frac{\dot{M}_w P_{w^{0.5}}}{M_a} + \dot{M}_w\right)^{\left(\frac{1}{3}\right)}\right) \quad (7)$$

If $\alpha_t \leq \alpha_o$, then $h_c = 0$

$$\text{Subject to } 1.0 - \left(\frac{P_w \times M_w}{P_{max}}\right) \geq 0 \text{ (Surface Roughness)}. \quad (8)$$

The bounds for the five variables are as follows:

$$50 \leq P_w \leq 400 \text{ (Mpa)}$$

$$0.2 \leq F_n \leq 25.0 \text{ (mm/s)}$$

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

$$0.5 \leq d_{awn} \leq 5.0 \text{ (mm)}$$

$$0.01 \leq M_w \leq 0.2 \text{ (kg/s)}.$$

For AWJM problem, CI algorithm has obtained better solution (maximum MRR) as compared GA [34], PSO and ABC [31] (refer Tab. 2). The best, mean and worst solutions obtained form 30 trials using CI algorithm are 97.7921 mm^3/s, 93.1370 mm^3/s and 90.9787 mm^3/s with standard deviation 1.4686. The average function evaluations are 591 and average computational time is 0.81 s. The other computational details are presented in Table 5. The convergence plot is presented in Figure 3. It is observed that, the MRR obtained from PSO and ABC is 230.50 mm^3/s and 218.49 mm^3/s, respectively. However, MRR for PSO and ABC is recalculated using the obtained decision variables by [31] where the MRR found to be 90.54 mm^3/s and 88.66 mm^3/s, respectively. From that it is observed that CI has found better solution than GA [34], PSO and ABC [31].

4.2 Ultrasonic machining (USM) problem

The Ultrasonic Machining (USM) process (refer Fig. 4) is used in ceramics, semiconductors and glass industries. It is a material removal process which erode material in the

Table 1. Constants used in Abrasive Water Jet Machining problem.

Constants	Details	Value
ρ_a	Abrasive particles Density	3.95×10^{-6} kg/mm^3
v_a	Velocity of abrasive particles	0.25 mm/s
E_{ya}	Youngs Modulus of elasticity of abrasive particles	350000 MPa
f_r	Roundness factor of abrasive particle	0.35
f_s	Sphericity factor of abrasive particle	0.78
η_a	Proportionality of abrasive grains effectively	0.7

Table 2. Comparison of results for solving Abrasive Water Jet Machining problem.

Algorithms	$dawn$	fn	Mw	pW	Ma	$\alpha 0$	αt	hc	hd	MRR $\frac{mm^3}{s}$
GA [34]	3.726	23.17	0.141	398.3	0.079	0.384	0.572	0	1.04	90.257
PSO [31]	3.242	13.08	0.140	400	0.080	0.385	0.384	3.31	2.12	230.50 (90.54)
ABC [31]	3.062	9.158	0.143	386	0.08	0.386	0.310	3.11	218.49	218.49 (88.66)
CI	**3.1477**	**13.2607**	**0.0201**	**50.183**	**0.04621**	**0.1116**	**0.6214**	**0**	**1.0088**	**97.7921**

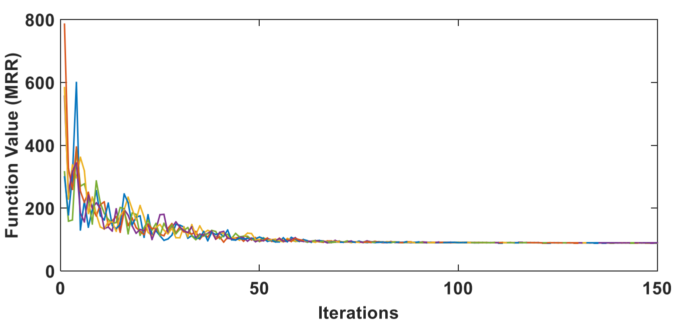

Fig. 3. Convergence plot for Abrasive Water Jet Machining (AWJM) problem.

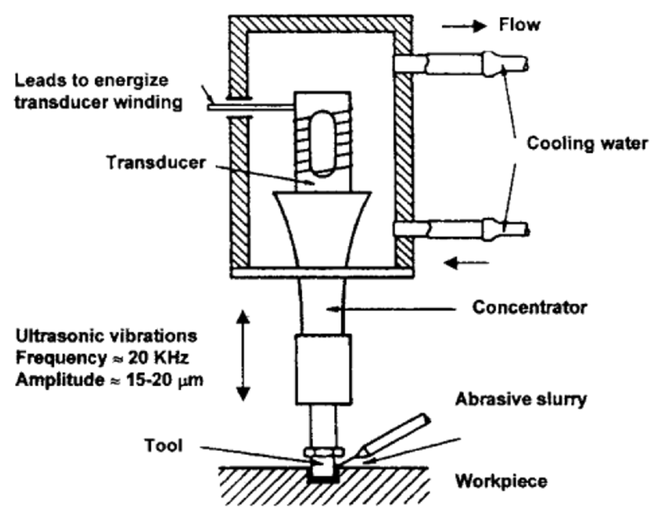

Fig. 4. Ultrasonic Machining process [31].

form of fine holes and cavities. It works on small amplitude and high frequency typically in the range of 10 micro meter at 20 kHz [35] and material removal rate (MRR) will take place in the form of fine grains by shear deformation.

The USM problem was previously solved using GA [34], PSO, ABC and HS_M [31]. The objective is to maximize the MRR. Figure 4 represents the USM process. The decision variables are amplitude of vibration A_v (mm); frequency of vibration f_v(Hz); mean diameter of abrasive grain d_m (mm); columetric concentration of abrasive particles in slurry C_{av}, and static feed force F_s (N). K_u Is a constant of proportionality (mm^{-1}) relating mean diameter of abrasive grains, and diameter of projections on an abrasive grain$\left(= K_u d_m^2\right)$, the constant values associated with this problem is presented in Table 3

$$\text{Maximize } MRR = \left(\left(\frac{\left(4.963\left(A_t{}^{0.25}\right)\left(K_{usm}{}^{0.75}\right)\right)}{\left(\sigma_{fw}(1+\lambda)\right)^{0.75}}\right) \times F_s{}^{0.75} A_v{}^{0.75} C_{av}{}^{0.25} d_m f_v\right) \tag{9}$$

$$\text{Subject to } 1.0 - \left(\left(\frac{1154.7}{\left(At \times \sigma_{fw}(1+\lambda)\right)^{0.5} \times (R_a)_{max}}\right) \times \left(\frac{F_s \times A_v \times d_m}{C_{av}}\right)^{0.5}\right) \geq 0 \tag{10}$$

The bounds for the five variables are as follows:

$$0.005 \leq A_v \leq 0.1\,(\mathrm{mm})$$

$$0.007 \leq d_m \leq 0.15\,(\mathrm{mm})$$

$$4.5 \leq F_s \leq 45.0\,(\mathrm{N})$$

$$10,000 \leq f_v \leq 40,000\,(\mathrm{Hz})$$

$$0.05 \leq C_{av} \leq 0.5.$$

Table 3. Constant value used in Ultrasonic Machining problem.

Constant	Details	Value
A_t	Cutting tools Cross sectional	20 mm^2
σ_{fw}	Abrasive particle Flow stress	6900 MPa
K_{usm}	Constant of proportionality relating mean diameter of abrasive grains and diameter of projection on an abrasive grain	$0.1\,\mathrm{mm}^{-1}$
$R_{\max}$	Surface roughness allowable value	$0.8\,\mu\mathrm{m}$

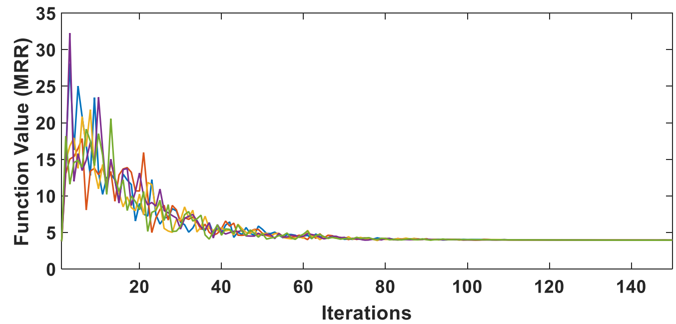

Fig. 5. Convergence plot for Ultrasonic Machining (USM) problem.

For USM problem, CI algorithm has obtained better solutions as compare to GA [34] and HS_M [31] and precisely similar as compared, PSO and ABC [31]. The best, mean and worst reported solutions obtained form 30 trials using CI algorithm are 3.9375 mm^3/s, 3.9373 mm^3/s and 3.8391 mm^3/s with standard deviation 0.0868. The average function evaluations are 1209 and average computational time is 0.47 s. The other computational details are illustrated in Table 5. The convergence plot is presented in Figure 5.

5 Result analysis and discussion

The non-traditional single objective, multi variable nonlinear constrained AWJM problem and USM problem [31, 34] were successfully solved using constrained version of CI algorithm. CI algorithm was run for 30 times to

Table 4. Comparison of results for solving Ultrasonic Machining problem.

Techniques	Av	fv	dm	Cav	Fs	MRR $\frac{\mathrm{mm}^3}{s}$
GA [34]	0.0263	39,333.9	0.133	0.479	10.8	3.553
ABC [31]	0.0167	40,000	0.15	0.5	16.4	3.941
HS_M [31]	0.0582	40,000	0.15	0.5	4.5	3.870
PSO [31]	0.06	40,000	0.15	0.5	4.5	3.950

Table 5. Solutions of CI algorithm.

Problems	CIBest Meanworst	Standard deviation	Average number of function evaluations	Average Computational time (sec)	% improvement over the best reported solution	Parameters
AWJM	97.7921 93.1370 90.9787	1.4686	591	0.81	8.0098	$C=5$ $R=0.95$
USM	3.9375 3.9373 3.8391	0.0868	1209	0.47	0.3164*	$C=5$ $R=0.95$

analyse the effectiveness and robustness of algorithm. The statistical results for both the problems are presented in Table 5. It represents the best, mean and worst function values, average function evaluations, average computational time, closeness to the reported solution and the set of parameters required to run the CI algorithm. The constrained involved with these problems were handled using static penalty function approach. For maximization of MRR, AWJM problem was previously solved using GA [34], PSO and ABC [31]; however, CI obtained 8.0098% better solutions about with less computational time and function evaluations (refer Tab. 5). For USM problem, CI solution is 0.3164% worse than PSO [31]; whereas, HS_M [31] and GA [34] were slightly worst as compare to CI algorithm. The probabilistic roulette wheel approach provided the possible choices to follow the best candidate in the cohort which assist the algorithm to escape the solution from local minima. Furthermore, the CI algorithm is depended on two parameter such as number of candidates C and sampling space reduction factor R which need to be tuned to obtain the better convergence within less computational cost.

6 Conclusion

The AWJM and USM problems are complex in nature and may not be able to solve using traditional gradient based optimization techniques. In this paper, a stochastic based CI algorithm is successfully applied to solve AWJM and USM problems for maximization of MRR. These problems are associated with linear and nonlinear constraints, a penalty function approach is used to handle the constraints. The solutions obtained from CI algorithm are successfully validated and obtained better solutions as comparing with GA, PSO, ABC and HA_M. CI is incorporated with roulette wheel approach which make available to follow the best possible choices which helps the CI algorithm to obtained the better solution. In the near future CI algorithm can be applied for solving similar real-world application form advance manufacturing domain problem, complex healthcare and logistic domain problem.

Abbreviations

ABC	Artificial Bee Colony Algorithm
AMP	Advance Machining Process
ANFIS	Adaptive Neuro Fuzzy Inference System
AWJM	Abrasive Water Jet Machining
BSA	Binary Search Algorithm
CI	Cohort Intelligent Algorithm
CLPSO	Comprehensive Learning Particle Swarm Optimizer
COA	Cuckoo Optimization Algorithm
CSO	Chicken Swarm Optimization
FW	Fireworks Algorithm.
GA	Genetic Algorithm
GSO	Gravitational Search Optimization
HH	Hoopoe Heuristic
HS_M	Modified Harmony Search
ICA	Independent Component Analysis
MRR	Material Removal Rate
PSO	Particle Swarm Optimization
SA	Simulated Annealing
SFL	Shuffled Frog Leaping
SPF	Static Penalty Function approach
TLBO	Teaching Learning Based Optimization
USM	Ultrasonic Machining
WJM	Water Jet Machining

Nomenclature

h_c	Indentation depth due to cutting wear
h_d	Indentation depth due to deformation wear
σ_{fw}	Flow stress of the work material
A_t	Cutting tool Cross-sectional area
A_v	Amplitude of vibration
C_{av}	Abrasive grains volumetric concentration in slurry
F_s	Static feed force
M_W	Water Mass flow rate
M_a	Abrasives Mass flow rate
P_W	Water jet pressure at the nozzle exit
$Ra_{\max}$	Allowable surface roughness value
d_{awn}	Abrasive-water jet nozzle Diameter
d_m	Mean diameter of abrasive grains
f_n	Nozzle traverse or feed rate
f_v	Frequency of vibration
r_m	Mean radius of abrasive particles
v_a	Velocity of abrasive particles
α_0	Angle of impact at which erosion peaks
α_t	Angle of impact at top of cutting surface
ρ_a	Abrasive particles Density
ρ_w	Density of work material
σ_{ft}	Abrasive particles Flow stress
α	Angle of impact

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Cite this article as: Ishaan R. Kale, Mayur A. Pachpande, Swapnil P. Naikwadi, Mayur N. Narkhede, Optimization of advanced manufacturing processes using socio inspired cohort intelligence algorithm, Int. J. Simul. Multidisci. Des. Optim. **13**, 6 (2022)