Optimization of process parameters for turning of titanium alloy (Grade II) in MQL environment using multi-CI algorithm

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Abstract

The advancement of materials science during the last few decades has led to the development of many hard-to-machine materials, such as titanium, stainless steel, high-strength temperature-resistant alloys, ceramics, refractories, fibre-reinforced composites, and superalloys. Titanium is a prominent material and widely used for several industrial applications. However, it has poor machinability and hence efficient machining is critical. Machining of titanium alloy (Grade II) in minimum quantity lubrication (MQL) environment is one of the recent approaches towards sustainable manufacturing. This problem has been solved using various approaches such as experimental investigation, desirability, and with optimization algorithms. In the group of socio-inspired optimization algorithm, an artificial intelligence (AI)-based methodology referred to as Cohort Intelligence (CI) has been developed. In this paper, CI algorithm and Multi-CI algorithm have been applied for optimizing process parameters associated with turning of titanium alloy (Grade II) in MQL environment. The performance of these algorithms is exceedingly better as compared with particle swarm optimization algorithm, experimental and desirability approaches. The analysis regarding the convergence and run time of all the algorithms is also discussed. It is important to mention that for turning of titanium alloy in MQL environment, Multi-CI achieved 8% minimization of cutting force, 42% minimization of tool wear, 38% minimization of tool-chip contact length, and 15% minimization of surface roughness when compared with PSO. For desirability and experimental approaches, 12% and 8% minimization of cutting force, 42% and 47% minimization of tool wear, 53% and 40% minimization of tool-chip contact length, and 15% and 20% minimization of surface roughness were attained, respectively.

Keywords Cohort intelligence · Multi-CI algorithm · Process parameters · Titanium alloy · Minimum quantity lubrication

1 Introduction

Machining is a major industrial activity consisting of various processes in which a raw material is cut to a desired final shape and size by a controlled material removal process. The machining system generally consists of the cutting tool, workpiece and machine tool [10]. The term machinability is broadly used to evaluate the ease with which any type of material can be cut to certain size and shape with specific tolerance, surface integrity, etc., with

minimum cost and time [8]. The reasonably good machinability of a material signifies that the material allows higher cutting rates with increased tool life, generation of lower cutting forces during machining and resulting in a satisfied surface and form tolerances. Traditional engineering materials such as steels and aluminium have higher machinability; however, to overcome challenges of the late twentieth century, along with minimizing the weight and cost of the product, improvement in the properties of the existing material also becomes more important. The

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result of this endeavour was the introduction of new generation of materials and alloys comprising of special characteristics such as higher strength-to-weight ratio, high stiffness and toughness, high heat capacity and thermal conductivity. Some of the prime examples of such new materials are titanium and its alloys, nickel and its alloys, metal matrix composites, superalloys and ceramics, etc. These advanced materials have brought new challenges such as high manufacturing cost and labour intensive process. Moreover, due to the superior characteristics of these materials such as high strength, stiffness and hardness, the manufacturing processes employed for most of the traditionally engineering materials become inefficient and may result into rapid deterioration of the cutting tools, inferior quality of quality of machined parts and may add further rework. According to Kishawy and Hosseini [21] and [10], the major reasons behind these problems are generation of high temperatures and stresses during machining these advanced materials. Hence, these materials are also referred to as difficult to cut materials.

Titanium and its alloys possess characteristics, viz. corrosion resistance, chemical stability or inertness, hot hardness, low density and desired feature such as high specific strength at elevated temperatures. Titanium offers higher strength-to-weight ratio as compared to aluminium and steel. Hence, recently aluminium and steels are being replaced with titanium alloys. Due to high thermal capacity and corrosion resistance, titanium and its alloys have made a huge impact on the petrochemical industry [25]. Automotive industry is another field of application where titanium and its alloys have been widely used. Piston connecting rods, engine valve train, valve springs are some of the examples of titanium products used in automobiles [32]. Aircraft engine parts such as fan case, compressor vanes, and compressor blades have been manufactured with titanium alloys [21]. Unalloyed titanium is used for constructing the airframe of the planes as it withstands with the cryogenic temperatures induced during the flights [18]. Titanium alloys could be machined using a variety of machining processes such as CNC End Milling [48], Abrasive Water Jet Machining (AWJM) [38], Turning [15], Micro-Scale Orthogonal Machining [33], and Laser assisted Micro-Electric Discharge Machining (EDM) [5]. Even though the titanium alloys are being widely utilized, there are several challenges associated with the manufacturing aspects of it such as shorter tool life, vibrations and chatters induced, and lower machining productivity [20, 31]. Several strategies have been developed and implemented to improve the machining efficiency of the titanium. Some notable strategies are developing tool materials and designs [7], optimization of cutting parameters and investigation of machinability [19],

developing hybrid machining processes such as laser-assisted machining (LAM), minimum quantity lubrication (MQL) and cryogenic machining [17].

It is very common to use cutting fluids in machining operations for achieving higher productivity and enhanced machinability. Usually, cutting fluids are used in the machining for cooling, removal of chips and lubrication. For titanium machining, cutting fluids control the temperature while machining and yield better results in the form of enhanced machining performance and improvement in tool life. However, according to Sharma et al. [44], many cutting fluids are unsafe in the environment safety viewpoint because of their noxiousness and non-environment friendliness. There is necessity to build a sustainable lubrication method that can substitute the traditional flood cooling approach and decrease the high cutting fluid utilization. Hence, nowadays, MQL-based methods are replacing traditional flood cooling methods [36, 47]. MQL environment contains disintegration of cutting fluid, then uniformly mixed in the air and intended at the cutting edge. The flow rate in MQL system is usually regulated in the range of 50 ml/hr to 500 ml/hr [36]. The oil drops in MQL method maintain the cutting temperature by decreasing the friction at the cutting edge. On the other hand, mixed air gives the cooling action for heat dissipation via heat transfer by convection. The MQL method consumes very less quantity of cutting fluid due to its green nature and consumes less energy for pumping [36, 47].

The machining performance of titanium has been examined by Niknam et al. [31] using cutting force F_c , tool wear V_{Bmax} , surface roughness R_a and tool chip contact length L . The cutting force is directly proportional to the feed rate f , whereas it carries inverse relationship with the cutting speed V_c . The tool angle ϕ also shows significant effect on the directional cutting forces. Higher cutting forces result into increased power consumption and reduced tool life. To avoid this, cutting forces should be minimized [31]. Titanium alloys have the tendency to react with most of the cutting tool materials and that results into the poor machinability of titanium alloys. The tool failure during machining of titanium alloy is due to the flank wear and excessive chipping on the tool flank edge. Hence, it is necessary to minimize the flank wear V_{Bmax} during the machining of titanium alloy [11]. Generally low surface quality (higher surface roughness) is resulted in titanium alloys due to poor machinability, and it is important to minimize the surface roughness R_a [53]. The tool chip contact length L represents the chip formation mechanism for any machining process. As tool chip contact length increases, surface roughness also increases, and hence it is important to minimize the tool chip contact length L [31, 43].

Optimization of these machining parameters is important to achieve desired product dimensions with minimum cost yielding increased productivity. Earlier, engineers practiced trial-and-error approaches which depend on the experience and intuition to determine initial process parameter settings. However, this approach is not suitable in the context of today's manufacturing processes. Consequently, the optimization of manufacturing process parameters requires new reliable methods and approaches, based on modelling activities, in order to predict the output of the manufacturing processes or in other words to predict the behaviour of the manufacturing process [32]. In order to deliver the sustainable manufacturing approach, it is important to achieve the right combination of these process parameters for machining of titanium alloy in MQL environment. With the addition of MQL approach, the optimization problem becomes complex, and the classical techniques may not be able to optimize the process efficiently. Hence, application of evolutionary algorithms for optimization is a recent approach adopted by several researchers and scientists.

Various algorithms in the soft computing domain, especially inspired from nature such as Genetic Algorithm (GA), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO) have been applied for optimizing wide variety of engineering applications [6, 30, 39]. Similarly, the optimization techniques inspired from competition and interaction of the societal individuals are referred to as socio-inspired optimization methods. Cohort Intelligence (CI) algorithm [22] is one of such techniques and its significantly modified version is referred to as Multi-CI [46].

Sahu and Mahapatra [42] used grey relation-based firefly algorithm for optimization titanium alloy with EDM. Pramanik et al. [37] investigated and minimized geometrical errors produced by Wire EDM of titanium alloy. [1] employed GA for multi-objective optimization of shape memory alloy with Wire EDM. [15] modelled the process through response surface methodology (RSM) and particle swarm optimization (PSO) technique was used for optimizing the machining associated parameters. Revuru et al. [41] experimentally optimized process parameters for tool wear, cutting forces, and surface roughness of titanium machining under varying lubricating scenarios such as dry machining, cutting fluid with and without micro-graphite and cutting fluid based on soybean, with and without graphite. The investigation of turning performance of Inconel 825 alloy using physical vapour deposition-titanium nitrate inserts has been carried out by Tamang et al. [52] focusing sustainable machining. Three aspects of sustainability, viz. cutting power consumption, tool wear, and surface roughness, have been investigated employing dry and MQL machining environment. Three cutting parameters such as cutting speed, cutting feed and depth

of cut have been considered. MQL environment has been proved to be the favourable environment for reducing the tool wear and power consumption. Furthermore, multi-objective GA is applied for the simultaneous optimization of cutting power consumption, tool wear and surface roughness. For the application in manufacturing industry, an explicit grid of optimized cutting parameters for obtaining the desired surface finish with minimum tool wear and power consumption is discussed. The milling of Ti-6Al-4 V alloy also referred to as titanium grade V is analysed by Kumar et al. [23] under three different cooling systems, viz. dry, wet and cryogenic using coated AlCrN /TiAlN tool. The Liquid Carbon Dioxide (LCO₂) has been employed as a cryogenic coolant considering the economical aspect. Furthermore, Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) approach has been adopted for optimizing the machining conditions to optimize the surface roughness and tool flank wear. According to the authors, it has been concluded that optimal machining takes place under LCO₂ conditions along with low level of speed and feed rate. Osman et al. [34] analysed the properties of various concentrations of hexagonal boron nitride nanoparticles in MQL system for the process improvements of slot-milling of titanium alloy. Furthermore, PSO algorithm has been applied to improve energy-efficiency of the process. Gupta et al. [13] investigated nano-fluid-based MQL system for the machining of titanium alloy in order to improve the surface roughness of generated product. Also, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied to predict the response. The machining performance of textured carbide tool in terms of tool wear, tool life, and surface roughness while turning of Ti-6Al-4 V alloy under three different lubrications, viz. dry turning, MQL turning using canola oil, and NMQL turning using graphene (1 wt%) mixed in canola oil is investigated experimentally by Singh et al. [51]. The effect of cutting speed has been analysed. The various tool-wear forms, surface roughness, and lubrication tendency of graphene are examined by using tool maker's microscope, surface roughness analyser, Confocal Raman spectroscopy, SEM equipped with an energy-dispersive X-ray spectrometer (EDS), and optical microscope. It is reported that the use of graphene along with canola oil improved the performance of the textured tool and resulted in enhanced tool life simultaneously improving the surface finish. Singh et al. [49, 50] applied multi-attribute decision-making methods (MADM) such as Analytic Hierarchy Process (AHP), TOPSIS, and Simple Additive Weighting (SAW) to optimize the turning of titanium alloy. Singh et al. [49, 50] employed the evolutionary algorithms such as PSO, Bacteria Foraging Optimization (BFO) and Teaching–Learning-Based Optimization (TLBO) to optimize the turning of titanium with upgraded MQL environment. Gupta et al. [14] applied

Taguchi method with TOPSIS to optimize the turning of titanium alloy. Mishra et al. [28] experimentally investigated the performance of turning of Ti6Al4V alloy with laser textured tools under three different machining environments, viz. dry, vegetable oil-based MQL, and alumina suspended water-based nano-MQL. Four responses such as cutting forces, contact length, tool wear and chip adhesion over the rake face have been analysed. The results of plain and textured tools with the same machining parameters have been compared. It is observed that the textured tools along with the MQL environment have resulted in reduction of cutting forces, contact length, tool wear and chip adhesion over the rake face. It is reported that the limited advantage of using nano-fluids as nanoparticles get accumulated in the textured space. Mia et al. [27] applied six sigma methodology for finding out the optimized process parameters of the turning of hardened steel under various cooling considerations such as dry, flood cooling, MQL, and solid lubrication with compressed air condition. RSM methodology has been applied for designing and analysing the experiments. Furthermore, regression equations are developed for finding out the optimum surface finish, keeping the process temperature minimum. It is reported that the improved quality surface is generated with dry cutting condition; however the process temperature is dispersive. The reduction in temperature is achieved with the MQL cutting conditions.

The applicability of several evolutionary algorithms to solve the complex problems of machining of titanium alloy in MQL environment is clearly evident from the above review. The manufacturing processes have become extremely complex owing to the recent technological advances. Today's manufacturing industry is trying to address the challenges such as growing needs for safety, reduced time-to-market that implies minimal manufacturing costs through the efficient use of the resources, and expected quality of highly customized products. Determining optimal process parameter settings critically influences productivity, quality, and cost of production. In order to avoid rework and to achieve the desired dimensions with the set tolerances, surface finesses, etc., the optimization of the process parameters is foremost important. Several problems of advanced manufacturing processes such as AWJM, EDM, and micro-machining have been already solved with contemporary algorithms, viz. firefly and PSO. The same problems have been solved with the socio-inspired algorithms such as CI [46] and its significantly modified version referred to as Multi-CI [46]. It has been observed that these algorithms performed

exceedingly better as compared with the contemporary algorithms. Therefore, the performance of these algorithms can also be exploited for solving real-world optimization problem of turning of titanium alloy (Grade II) in MQL environment. Its several variations and significantly modified version referred to as Multi-CI have been successfully applied for solving real-world optimization problem of Titanium alloy under MQL Environment. The performance responses such as tangential force F_c , tool wear V_{Bmax} , surface roughness R_a and tool-chip contact length L have been successfully optimized. The novelty and contribution of the current work is as follows: 1. The suitability of variations of CI and Multi-CI algorithms for optimization of process parameters of turning of titanium alloy in MQL environment is successfully demonstrated and validated. 2. The solutions using variations of socio-inspired Cohort Intelligence (CI) algorithm and Multi-CI are robust with reasonable computational cost. 3. Multi-CI solutions are comparable with other variations of CI; however, it could yield minimum of 8% and maximum of 53% improvement as compared to contemporary algorithms, desirability and experimental approaches.

Rest of the paper is structured as follows: Sect. 2 in detail describes four problems of turning of titanium alloy in MQL environment, viz. minimization of cutting force F_c , surface roughness R_a , tool wear V_{Bmax} , and tool chip contact length L . It includes importance of the problems and mathematical formulations. In Sect. 3, the solution methodologies are discussed and in Sect. 4 the results and comparison amongst several algorithms have been presented. Conclusions and future directions are provided at the end.

2 Problem description and formulations

Gupta et al. [16] performed turning of titanium alloy (Grade II) with cubic boron nitride tool in MQL environment. Cutting speed V_c (m/min), feed rate f (mm/rev) and approach angle ϕ (degrees) were considered as process parameters, while tangential force F_c , tool wear V_{Bmax} , surface roughness R_a and tool-chip contact length L were process responses (refer to Fig. 1. A generic MQL schematic for turning process is presented in Fig. 1.

The cutting force F_c depends on the depth of cut and feed rate f . The value of F_c is directly proportional to the feed rate f , and is inversely proportional to the cutting speed V_c . The directional cutting forces also depend on the tool entering angles used [31]. As mentioned earlier, increase in the cutting forces is directly proportional to

Fig. 1 Generic MQL schematic

the feed rate f , whereas it carries inverse relationship with the cutting speed V_c . The tool angle ϕ also shows significant effect on the directional cutting forces. Higher cutting forces results into increased power consumption, and reduced tool life. To avoid this, cutting forces should be minimized. The relationship is as presented in Eq. 1. Titanium is a highly reactive metal. It is the major cause of poor machinability of titanium alloys. Flank wear V_{Bmax} and excessive chipping on the tool flank edge are the major causes of the tool failure. Hence, to reduce the tool wear, low cutting speed V_c is preferred [11]. According to Ghani et al. [12] cutting speed V_c and depth of cut were the major causes for the failure of the cutting tools. The higher values of the cutting speeds, depth of cut and sharp tool angle ϕ increase the loading conditions on the tool. This increases the tool load, ultimately micro-cracks are developed and tool fails with the brittle fracture. Equation 2 defines the objective function of tool wear V_{Bmax} . The machining of titanium alloys results in the poor machinability and hence finishing processes must be employed. It is observed that the surface roughness R_a for titanium alloys is a result of complexities involved in the machining associated with the built up edge formation, geometry and tool wear, temperature, tool coating, feed rate f , cutting speed V_c , approach angle ϕ , and depth of cut [53]. Also, sub-effects like material phase transformations, and mechanical and thermal deformations during the machining processes have an impact over surface roughness R_a which is directly proportional to the feed rate and inversely proportional to the cutting speed and depth of cut [31]. In order to achieve the better surface quality of machined titanium product, it is required to minimize the surface roughness R_a . Equation 3 describes the associated mathematical function. The effect of chip formation mechanism on the machining process is characterized by tool chip contact length L .

The chip and segmented chips have been observed [31]. In the literature, a strong correlation has been observed between the cutting forces V_c , the tool damage types, and the workpiece surface roughness. This confirms the relationship of the cutting parameters such as speed V_c , feed f , and the insert geometry such as tool angle ϕ on the tool condition and surface finish [43]. Hence it is important to minimize the tool chip contact length L . Equation 4 defines the associated mathematical formulation.

As stated above, in order to achieve better product quality with increased productivity and minimum cost, process parameters such as cutting speed V_c , feed rate f and approach angle ϕ should be optimized for the turning of titanium alloy (Grade II) which may yield into optimal values of cutting force F_c , tool wear V_{Bmax} , surface roughness R_a and tool-chip contact length L [13]. Gupta et al. [13, 14] performed the parametric optimization of the turning Titanium (Grade-II) alloys for F_c , V_{Bmax} , R_a , and L using PSO and desirability analysis. In addition, confirmation experiments have also been performed. According to Gupta et al. [13, 14] the RSM technique has been used for analysis and design of experiments. The Box–Behnken design (BBD) approach has been adopted for developing the response models using RSM along with a total of seventeen experiments under MQL condition using Cubic Boron Nitride (CBN) cutting tool. The range of input parameters was selected such that higher material removal rate can be achieved. Based on the experimental data, the best fit equations to relate the responses, viz. F_c , V_{Bmax} , R_a , and L with cutting parameters as V_c , f and ϕ have been developed by method of regression analysis with the design expert software. The final regression equations (mathematical models) developed by Gupta et al. [15, 16] are given in Eqs. 1–4. These objective functions have been adopted in the current work

$$\text{Minimize } F_c = -202.01471 + 1.28250 \times V_c + 3225 \times f_c - 0.74167 \times \emptyset - 9.4 \times V_c \times f \quad (1)$$

$$\text{Minimize } V_{\text{Bmax}} = -0.27368 + 0.001575 \times V_c + 2.4 \times f - 0.0010833 \times \emptyset \quad (2)$$

$$\text{Minimize } R_d = -0.16294 + 0.001425 \times V_c + 3.7 \times f - 0.000416667 \times \emptyset \quad (3)$$

$$\text{Minimize } L = 0.96302 - 0.00215931 \times V_c + 0.92703 \times f + 0.00152807 \times \emptyset \quad (4)$$

The upper and lower limits for the each of the process parameters are as follows:

$$200 \leq V_c \leq 300,$$

$$0.1 \leq f \leq 0.2,$$

$$60\emptyset \leq 90$$

3 Solution methodologies

There are several nature inspired optimization algorithms which are broadly classified into bio-inspired, physics-based and socio-inspired methods. The notable socio-inspired methods are Ideology Algorithm [17], Election Algorithm [9], The League Championship Algorithm [19], Soccer League Competition Algorithm [29], Teaching Learning-Based Optimization [40], Cultural Evolution Algorithm [24], Social Learning Optimization [26], Anarchic Society Optimization [2] and CI [22]. Recently, algorithm of CI and its hybridized versions have been applied for solving several complex problems. Few of them are from domains such as healthcare [3], feature selection [4], etc. The framework of CI [22], and Multi-CI [45] methodologies have been concisely discussed here.

A cohort is a group of learning candidates. These candidates attempt to achieve the best possible individual behaviour through interaction and competition with other candidates in the cohort. This learning drives the candidates to evolve. The entire cohort is assumed to have saturated once when most of the candidates exhibit the similar behaviour and further learning from another is not possible. The CI algorithms model the interactive and competitive behaviour of the candidates. The behaviour of every candidate is modelled as problem objective function associated. Every candidate iteratively attempts to achieve the best value of the objective function. This way the candidates evolve the objective function value and eventually the cohort. The cohort is assumed to be converged once all the candidates have the similar objective function

Fig. 2 Cohort intelligence (CI) flowchart [22]

value and further learning is not possible. The best objective function value from the converged cohort is accepted as the final solution. The flowchart of the CI algorithm is presented in Fig. 2. For detailed mathematical formulation refer to Kulkarni et al. [22]. Different variations of CI algorithm have been proposed by Patankar and Kulkarni [35] based on the learning mechanism adopted. In the follow best approach, the candidate attempts to learn from the

one which has the best objective function value, in the follow better approach candidate attempts to learn from any of the other candidates with better function value. The Roulette wheel approach exploits the associated probabilistic rule and the alienation approach employs following any candidates excluding an isolated candidate.

It is important to mention that the CI algorithm [3, 4, 22] models the behaviour of the candidates in single cohort. Shastri and Kulkarni [45] proposed Multi-Cohort Intelligence (Multi-CI) Algorithm in which interaction and competition among different cohorts is modelled. This intra- and inter-cohort learning behaviour helped the cohorts explore the search space more efficiently as well as local search. The probabilistic selection of the candidates from a pool of best objective function value candidates chosen from within all the cohorts along with the pool of every cohort is at the heart of the Multi-CI algorithm. The step-by-step procedure with illustrative example is given in Shastri and Kulkarni [45]. The detailed flowchart is shown in Fig. 3.

4 Results and discussion

The variations of CI and Multi-CI algorithm were coded in MATLAB R2017 on Windows Platform with an Intel Core i3 processor and 4 GB RAM. The control parameters associated with the Multi-CI and variations of CI for solving the turning of titanium in MQL environment problem are listed in Table 1. These parameters are chosen based on the initial trials of the algorithms. Every problem was solved 30 times. In Table 2, best and mean solutions for Cutting Force F_c , Tool Wear V_{Bmax} , Surface Roughness R_a and Tool Chip Contact Length L along with associated standard deviation and run time obtained using variations of CI, and Multi-CI are shown. These solutions have been compared with experimental work, desirability approach and PSO algorithm as shown in Table 3. Optimum values of cutting speed V_c , feed f , and the tool angle θ associated with the best values (refer Table 3 for variations of CI, and Multi-CI algorithms are presented in Table 4.

In the method of PSO, a swarm of solutions modify their positions in the search space. Every particle has certain velocity with which it moves in the search space based on the local best solution in the close neighbourhood as well as the global best solution in the entire swarm. According to [15, 16, 45], the algorithm of PSO may not be efficient for solving inseparable, nonlinear real-world problems. It is evident from Eq. 1 that the considered problem is inseparable, multimodal and nonlinear in nature and hence algorithm needs balanced exploration and exploitation abilities to find

Fig. 3 Multi-CI algorithm flowchart [15]

Table 1 Parameter setting for multi-CI and variations of CI

Solution methodology	Parameter	Stopping criteria
Multi-CI	No. of Cohorts = 3 No. of candidates = 5 Value of Reduction factor = 0.99 Behavioural Variations for best candidates = 5 and for rest of the candidates = 10	Function value less than 10^{-16}
Variations of CI	No. of candidates = 5 Value of Reduction factor = 0.99	

Table 2 Statistical solutions to problems using variations of CI and multi-CI

Mechanical machining process	Objective function	Algorithms applied				Multi-CI
		Variations of CI				
		Roulette wheel	Follow best	Follow better	Alienation	
Turning in MQL environment	F_c					
	Mean	122.34	122.35	122.24	122.27	122.23
	SD	0.05	2.95	0.00	0.01	0.01
	Best	122.28	122.24	122.24	122.25	122.23
	Run time (Sec)	0.32	0.27	0.57	1.07	0.64
	V_{Bmax}					
	Mean	0.18	0.19	0.18	0.18	0.18
	SD	0.00	0.01	0.00	0.00	0.00
	Best	0.18	0.18	0.18	0.18	0.18
	Run time (Sec)	0.49	0.28	0.58	1.40	0.59
	L					
	Mean	0.49	0.49	0.49	0.49	0.49
	SD	0.00	0.00	0.00	0.00	0.00
	Best	0.49	0.49	0.49	0.49	0.49
	Run time (Sec)	0.32	0.27	0.57	1.17	0.57
	R_a					
	Mean	0.46	0.46	0.46	0.46	0.46
	SD	0.00	0.00	0.00	0.00	0.00
	Best	0.45	0.46	0.45	0.45	0.45
	Run time (Sec)	0.54	0.27	0.58	1.32	0.58

Mean mean solution, SD standard-deviation of mean solution, Best best solution, runtime mean runtime

Table 3 Comparison of Algorithms

Objective Function	PSO Gupta et al. [15]	Desirability Gupta et al. [15]	Experimental Gupta et al. [15]	Roulette Wheel	Follow Best	Follow Better	Alienation	Multi-CI
F_c	132.52	138.68	133.45	122.28	122.24	122.24	122.25	122.23
V_b	0.31	0.38	0.34	0.18	0.18	0.18	0.18	0.18
L	0.793	0.853	0.811	0.49	0.49	0.49	0.49	0.49
R_a	0.53	0.60	0.56	0.45	0.46	0.45	0.45	0.45

Table 4 Optimum Values of V_c , f , and ϕ for variations of CI and Multi-CI

Mechanical machining process	Objective function	Algorithms applied				Multi-CI
		Variations of CI				
		Roulette wheel	Follow best	Follow better	Alienation	
Turning in MQL Environment	F_c					
	V_c	200.10	200	200	200	200
	f	0.1	0.1	0.1	0.1	0.1
	$\emptyset$	89.99	89.99	89.99	89.99	89.99
	V_{Bmax}					
	V_c	200.00	200	200.00	200.00	200
	f	0.1	0.1	0.1	0.1	0.1
	$\emptyset$	89.99	89.99	89.99	89.99	89.98
	L					
	V_c	299.99	300	300	300	300
	f	0.1	0.1	0.1	0.1	0.1
	$\emptyset$	60.07	60.01	60	60	60.02
	R_a					
	V_c	200	200	200	200	200
	f	0.1	0.1	0.1	0.1	0.1
	$\emptyset$	83.71	83.12	83.69	83.71	86.02

global optimum solution. It is evident from Table 3 that the Multi-CI algorithm outperformed PSO in terms of solution quality as Multi-CI has intra- as well as inter-group learning mechanism which makes the algorithm stronger in exploitation. Multi-CI solutions are more robust with less standard deviation when compared with the follow best and roulette wheel approach of variations of CI (refer Table 2). In addition, the run time for alienation approach is more when compared with other variations of CI and Multi-CI. In addition, Multi-CI outperformed experimental and desirability approach (refer Table 3). For cutting force F_c , tool wear V_{Bmax} , tool-chip contact length L and surface roughness R_a , the best solutions in every learning attempt for each cohort of Multi-CI and variations of CI are plotted in Fig. 4 (a), (b), (c) and (d), respectively.

In follow best approach, candidates randomly select the behaviour and the associated characteristics in the first attempt. For every following learning attempt, the candidates follow the behaviour of the best candidate and at the same time best candidate also explores the better solution due to which candidates do not get trapped in local minimum and gives better mix of exploration and exploitation. This behaviour can be clearly seen from Fig. 4. It is an important observation that follows better variation of CI converged to optimum solution; however, the fluctuating pattern highlighted the multimodality of every function. The efforts of the candidates in jumping out of the local minima are evident from Fig. 4. Because of intra- and inter-learning group

mechanisms, Multi-CI could exhibit faster convergence for every cohort as compared to other approaches. In follow best approach, candidates follow the best candidate from the cohort. So, there is a possibility of solutions getting trapped in local minima. It could be observed in the convergence plot given in Fig. 4. As learning progresses, the best candidate jumps out of local minima and eventually for all candidates the global minimum is obtained. It is important to mention that for turning of titanium alloy in MQL environment, Multi-CI achieved 8% minimization of cutting force F_c , 42% minimization of tool wear V_{Bmax} , 38% minimization of tool-chip contact length L , and 15% minimization of surface roughness R_a when compared with PSO. For desirability and experimental approaches, 12% and 8% minimization of cutting force F_c , 42% and 47% minimization of tool wear V_{Bmax} , 53% and 40% minimization of tool-chip contact length L , and 15% and 20% minimization of surface roughness R_a were attained, respectively (refer Table 3).

As stated in Sect. 2, it is important to find out the optimum combination of cutting speed V_c , feed f , and the tool angle ϕ for minimizing the cutting force F_c , tool wear V_{Bmax} , tool-chip contact length L and surface roughness R_a . It is clear from Eq. that there exists nonlinear relation and inter-relation between the parameters affecting the responses. This makes the problem complex. It is critical in the manufacturing industry to achieve the required level of surface roughness. Furthermore, nowadays the industry is adopting the sustainable manufacturing approach keeping the impact on the environment minimum. In the present

Fig. 4 Convergence plots of best solutions

study, the optimum combination of parameters for the sustainable manufacturing approach, resulting in the significantly improved results as compared with the existing literature solution, has been achieved (refer Table 4). The industry can directly adopt these parameters for achieving the desired surface finish, keeping the cutting forces and tool wear minimum. However, to make the problem more realistic and industry oriented, real-world constraints on productivity, machining time, desired material removal rate, cutting power consumption, etc., could be considered. Also, multi-objective optimization approach could be adopted.

5 Conclusions and future directions

This paper presents the application of socio-inspired optimization techniques, viz. CI and its variations as well as Multi-CI for solving real-life machining optimization problem of titanium alloy (Grade II) in MQL environment. The objective functions are minimization of cutting force F_c , tool wear V_{Bmax} , tool-chip contact length L and surface roughness R_a . The solutions obtained using follow better, follow best, alienation & roulette wheel approaches of CI, and Multi-CI algorithms have been compared with the experimental results reported in the literature as well as with contemporary evolutionary algorithm PSO. Multi-CI successfully outperformed experimental results,

desirability approach and PSO in terms of solution quality. Since in Multi-CI, several cohorts interact and compete with one another, it is observed that the computational time for variations of CI is lower as compared to Multi-CI algorithm. However, the solution quality using Multi-CI is better as compared to PSO and experimental approach. In addition, the standard deviation of Multi-CI was comparatively lower which exhibited its robustness. This is because Multi-CI exhibits better exploration and exploitation capabilities as every candidate competes with its individual local best solution along with the best solution chosen from the other cohorts. It is important to mention that for turning of titanium alloy in MQL environment, Multi-CI achieved 8% minimization of cutting force F_c , 42% minimization of tool wear V_{Bmax} , 38% minimization of tool-chip contact length L , and 15% minimization of surface roughness R_a when compared with PSO. For desirability and experimental approaches, 12% and 8% minimization of cutting force F_c , 42% and 47% minimization of tool wear V_{Bmax} , 53% and 40% minimization of tool-chip contact length L , and 15% and 20% minimization of surface roughness R_a were attained, respectively.

In the future, the optimized parameters could be directly adopted by the manufacturing industry for achieving the desired surface finish, keeping the cutting forces and tool wear minimum. Furthermore, real-world constraints on productivity, machining time, desired material removal rate, cutting power consumption, etc., could be considered. In addition, constrained handling methods could be incorporated in CI as well as in Multi-CI to solve hard constrained mixed variable problems from the sustainable manufacturing domain.

Compliance with ethical standards

Conflict of interest All authors have declare that they have no conflict of interest.

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