

LAB: A Leader-Advocate-Believer Based Optimization Algorithm

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Abstract

This manuscript introduces a new socio-inspired metaheuristic technique referred to as Leader-Advocate-Believer based optimization algorithm (LAB) for engineering and global optimization problems. The proposed algorithm is inspired by the AI-based competitive behaviour exhibited by the individuals in a group while simultaneously improving themselves and establishing a role (Leader, Advocate, Believer). LAB performance in computational time and function evaluations are benchmarked using other metaheuristic algorithms. Besides benchmark problems, the LAB algorithm was applied for solving challenging engineering problems, including abrasive water jet machining, electric discharge machining, micro-machining processes, and process parameter optimization for turning titanium alloy in a minimum quantity lubrication environment. The results were superior to the other algorithms compared such as Firefly Algorithm, Variations of Co-hort Intelligence, Genetic Algorithm, Simulated Annealing, Particle Swarm Optimisation, and Multi-Cohort Intelligence. The results from this study highlighted that the LAB outperforms the other algorithms in terms of function evaluations and computational time. The prominent features of the LAB algorithm along with its limitations are also discussed.

Keywords— LAB algorithm · Advanced Manufacturing Process Problems · Socio-inspired optimization

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1 Introduction

Optimization is a way of finding the best solutions to most of the problems encountered in real life. On a regular basis we encounter problems where we try to minimize efforts and maximize outcomes [1] on an action, may it be driving to work on a specific road at a specific time to minimise the time required to reach destination or decrease speed to increase mileage. Other than day-to-day implementations optimization is used on a larger scale too, such as manufacturing of cars in order to minimise wind resistance and maximise speed and handling or designing products in such a way to minimise material cost and maximise the quality and profits, etc. A variety of optimization methods inspired by nature have been developed to solve these problems[26, 58]. These algorithms can be classified into four major categories: biology-inspired/bio-inspired, swarm intelligence, socio-inspired and physics/chemistry-based[11].

1. *Bio-inspired Intelligence Techniques:* These algorithms are inspired by biological evolution and species. The most well-known and widely used bio-inspired algorithm is the Genetic Algorithm (GA)[20]. It is based on the Darwinian theory of survival of the fittest[63]. The algorithm relies on three important factors, mutation, crossover and selection to approach better quality solutions. Other examples are Covariance Matrix Adaptation Evolution (CMA-ES)[23] based on basic genetic rules, Backtracking Search Algorithm (BSA)[5], Evolutionary Strategies (ES)[2], Evolutionary Programming[14], Differential Evolution (DE)[56, 49], inspired by biological evolutionary strategies such as reproduction, mutation, recombination and selection[44]. A variety of optimization methods inspired by nature have been developed to achieve better solutions than current methods. BSA is amongst the recently proposed algorithms, which generates a trial individual using basic genetic operators (selection, mutation and crossover). Evolutionary programming is one of the first genetic algorithms developed; however evolutionary programming differs from standard GA as the focus is on the behavior of individuals, thus no crossover is used. DE is a population-based stochastic function minimizer based on iterating population towards a quality goal. JDE[4], JADE[64] and SADE[45] are recent versions of DE.
2. *Swarm Based Intelligence Techniques:* Swarm intelligence (SI) refers to a subset of bio-inspired techniques. The individuals in the swarm collectively organize themselves to achieve a common goal [24]. Particle Swarm Optimization (PSO) is one of the popular swarm intelligence methods [32]. It is inspired from the schooling of fish. In PSO, it starts with random initialisation of population and moves to search optima while updating generations. PSO uses parameters of social and individual behaviors as opposed to evolution operators used in GA. CLPSO[41] and PSO2011[47] are the updated versions of the standard PSO. Other examples of swarm-intelligence include Cuckoo Search (CS)[62], Bat Algorithm (BA)[60], Ant Colony Optimization (ACO)[8], Firefly Algorithm (FA)[61, 12], Artificial Bee Colony (ABC)[27]. ACO is based on the excretion of pheromones by ants which helps guide the way for other ants in the system. In FA, all the fireflies are unisexual and are attracted towards higher intensity(brightness) or the flash signals produced while moving towards better search space and decreasing distance between them. ABC is based on the behaviour of honey bees when discovering food sources.
3. *Physics Based Intelligence Techniques:* Some algorithms are nature-inspired but are based on principles of physics such as laws of gravitation by Newton. Existing physics-based algorithms are [55], Colliding Bodies Optimisation (CBO)[30] formulated based on Newton's law

of motion, Gravitational Search Algorithm (GSA)[50], Central Force Optimisation (CFO) [15], Space Gravitation Optimisation (SGO) [33] and [13] formulated based on Newton’s gravitational force, Big Bang–Big Crunch search (BB–BC) [25], Galaxy-based Search Algorithm [6] and Artificial Physics-based Optimisation (APO) [59] formulated based on celestial mechanics and astronomy, Ray Optimisation (RO) [29] is based on optics, Harmony Search Algorithm (HSA) [34] formulated based on acoustics, Simulated Annealing (SA) algorithm is based on thermodynamics principle [35].

4. *Socio-inspired Intelligence Techniques*: The Cultural/Social Algorithm is a subset of evolutionary-based intelligence. In a society, humans learn from one another by following them which eventually helps them evolve and achieve their goals together[37]. Based on these motives, many researchers began to develop social/socio-inspired algorithms, such as Society and Civilization Optimization Algorithm (SCO)[51], Imperialist Competitive Algorithm (ICA) [21], League Championship Algorithm (LCA) [22], Cultural Evolution Algorithm (CEA) [38], Cohort Intelligence (CI) [36], Social learning Optimization (SLO) [42], Social Group Optimization (SGO) [52] and Ideology Algorithm (IA), etc.

In this manuscript, the work is based on the competitive behaviour of individuals within a group in a competitive environment that has existed in human society for ages, may it be at an academic level or corporate level. The ultimate goal of an individual in a group is to establish his/her position also, known as rank, by competing with other individuals within the group while moving towards promising directions.

This manuscript introduces a novel socio-inspired optimization algorithm referred to as LAB: A Leader-Advocate-Believer-based optimization algorithm. The society individuals are divided into groups and are categorised into certain roles. These groups and roles help by guiding a way for the individuals to achieve their goals by competing with the individuals within the corresponding group while moving towards a promising search space. The LAB is motivated by this competitive trait of individuals in a group. Every group leader moves in a certain direction that motivates individuals to compete with it in order to lead the group towards a more promising search space. Not only does every individual compete with its associated leader but it also competes with the individuals within its group with a goal to improve and promote to a higher rank. However, the short-term goal of an individual is to reach as close as possible to its local leader. Furthermore, every local group leader always desires to be the global best leader; thus, it competes with other group leaders to become the global leader while competing with the rising individuals within its associated group. This competitive behaviour of an individual increases its chances of improving and climbing up in the group while moving towards promising search spaces is modelled here. This mechanism enabled LAB to solve several benchmark problems as well as real world problems from manufacturing domain. The performance of the LAB algorithm was better in terms of objective function as well as computational cost as compared to the existing algorithms.

The rest of the manuscript is structured as follows: Section 2 describes the methodology of the LAB algorithm with its flowchart(fig.3). Section 3 discusses the benchmark test problems, real-world machining problems. as well as individual problem formulations and a description of the processes. The performance analysis and comparison of algorithms are discussed in Section 4. In Section 5 concluding remarks and future directions are provided.

2 LAB Algorithm

List of Symbols

ϕ	approach angle
ψ^l	lower bound
ψ^u	upper bound
G	total number of groups
P	population of society
P_A	set of advocates
P_L	set of leaders
p_B^{pL}	set of believers
B_h	burr height
B_t	burr thickness
$f(\mathbf{X})$	objective function
f	feed rate
f_b	flank wear
F_c	tangential force
$kerf$	taper angle
L	tool-chip contact length
M_t	machining time
MRR	material remove rate
n	number of individuals in each group
p	individual
p_A^{pLg}	advocate associated to the leader of the g^{th} group
p_B^{pLg}	i^{th} believer associated to the leader of the g^{th} group
$p_{L_1}^*$	global best leader
p_{L_g}	leader for the g^{th} group
R_a	surface roughness

$REWR$ electrode wear rate

V_c cutting speed

V_{Bmax} tool wear

w weight

In the proposed LAB algorithm, every individual in a group competes with every other individual within the group to become the best individual. The position of the individual depends on the fitness/objective function value. The individual with the best fitness value in a group is assigned as the local group leader for the corresponding group and the individuals within the associated group will follow its direction. The second best individual is assigned as the advocate to the leader and the remaining individuals in the group are referred to as believers. The local leader also competes with all the other local leaders from corresponding groups to become the global best leader. All the other local leaders follow the direction of the global best leader while competing with one another. The local rankings motivate the group leader explore promising search spaces and the global rankings forces all the leaders to explore promising search spaces in order to remain the global best leader, while competing with other leaders. This makes every individual within the group compete with one another, thus motivating it to grow and search for better solutions.

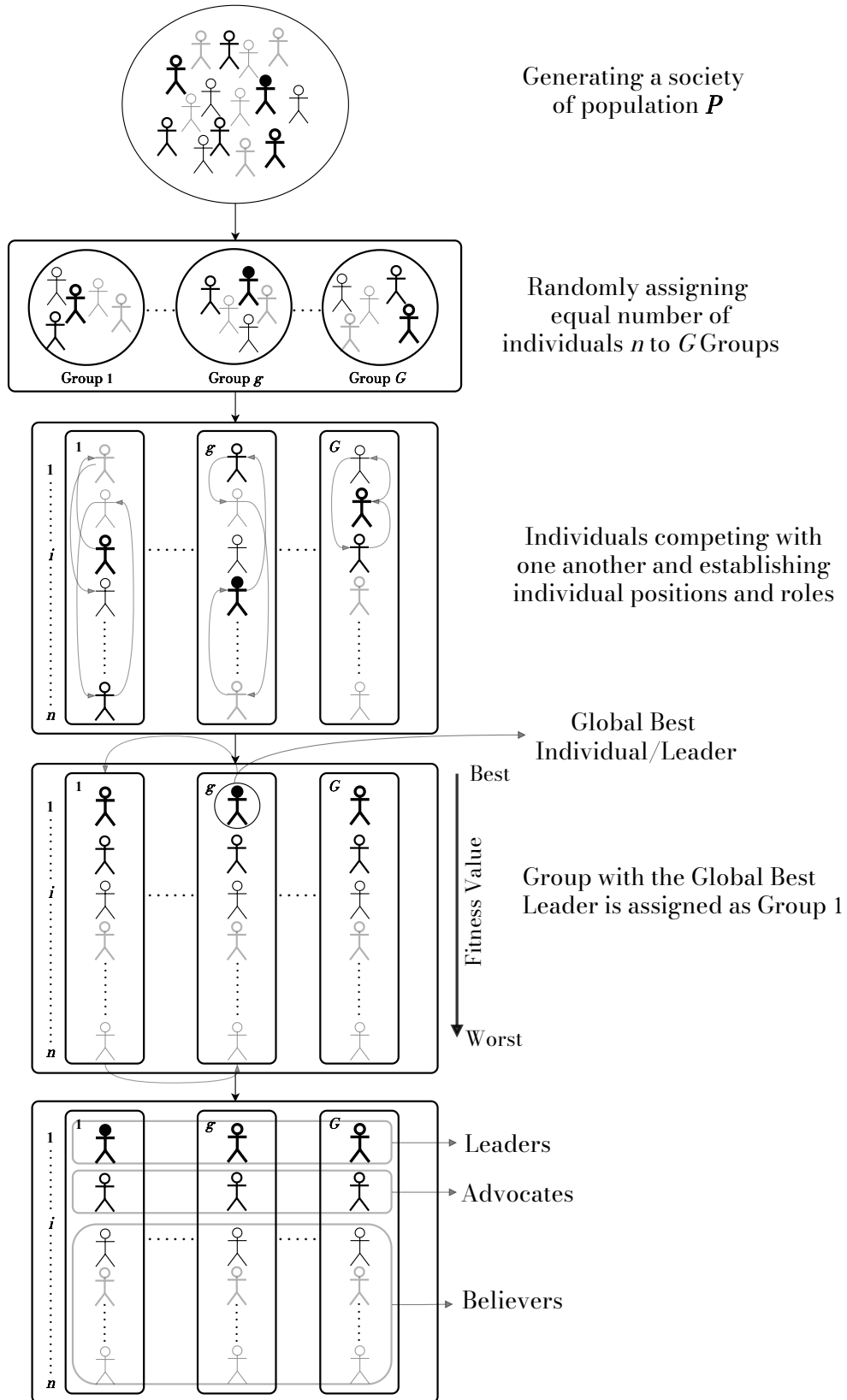


Figure 1: Visual Abstract of the LAB Algorithm

Consider a general optimization problem as follows:

$$\begin{aligned} &\text{Minimize} && f(\mathbf{X}) = f(x_1, \dots, x_i, \dots, x_N) \\ &\text{s.t.} && \psi_i^l \leq x_i \leq \psi_i^u, \quad i = 1, \dots, N \end{aligned}$$

The procedure begins with generating a society of population \mathbf{P} with individuals $p = 1, \dots, P$ randomly within its associated search space $[\psi_i^l, \psi_i^u]$ and associated objective functions are evaluated. Rest of the steps in the algorithm are explained below along with a flowchart (refer to fig.3)

Step 1 (Assigning Groups and establishing Roles) : Every group is assigned with an equal number of randomly selected individuals. Each group consists of n number of individuals,

$$\text{where } n = \frac{\text{total number of individuals}(P)}{\text{total number of groups}(G)}$$

thus making sure equal number of individuals in each group. After being assigned a group, individuals are locally ranked according to the fitness of their solution (objective function value) and arranged accordingly, i.e. individual with the best fitness quality referred to as Leader (p_L) followed by second best individual referred to as Advocate ($p_A^{p_L}$) and remaining individuals ($n - 2$, since the first two have been assigned) with worse fitness quality ($p_{B_i}^{p_L}$) referred to as Believer. Local best individuals/Leaders from corresponding groups compete with one another. The leader with the best fitness solution is assigned as Global Best Leader (p_L^*) and the associated group is assigned as Group 1, all the other leaders from the corresponding group follow it's direction. A visual representation for a society of groups with an equal number of individuals is shown below in fig.2.

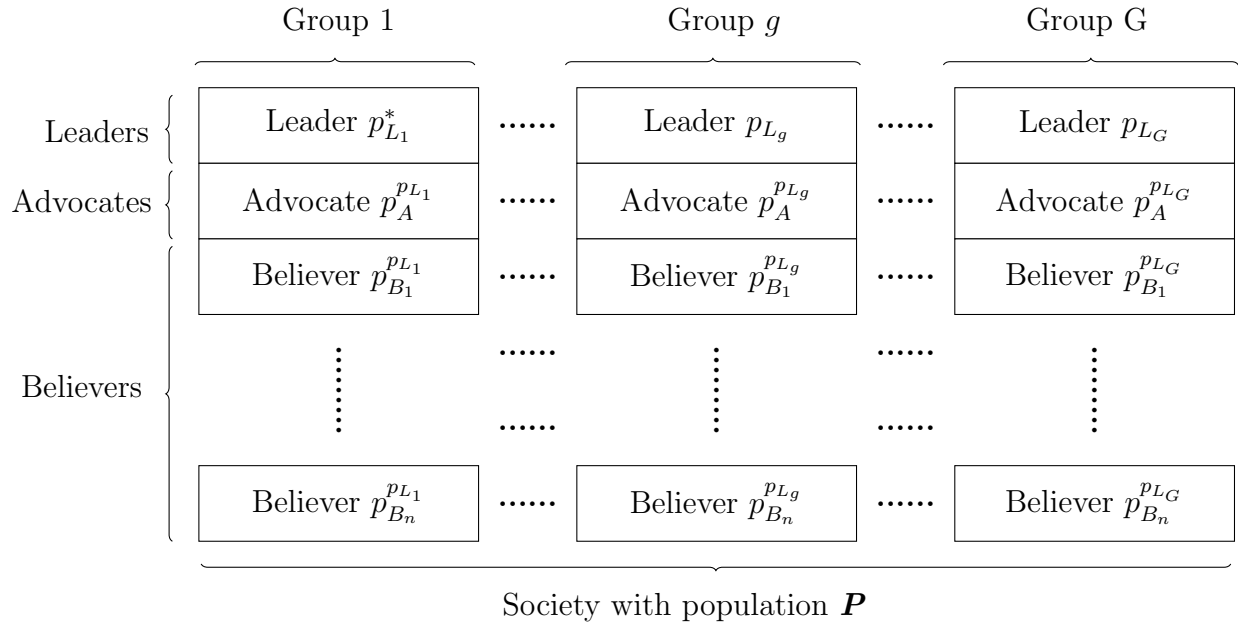


Figure 2: Visual representation of Groups and Roles of Individuals for a Society

Step 2 (Individual Search Direction) : With every iteration a new search direction for each individual is calculated, the formulation of the search direction varies as per individual's role as shown below:

- Leader : The search direction of every leader $p_L \in \mathbf{P}_L$ is influenced by the global leader $p_L^* \in \mathbf{P}_L$, the corresponding advocate individual $p_A^{p_L}$, every associated believer $p_{B_i}^{p_L} \in \mathbf{p}_B^{p_L}$ and the associated randomly generated weights such that $w_1^* > w_2 > w_3 \in [0, 1]$ and $w_1^* + w_2 + w_3 = 1$ as follows :

$$\forall x_i^{p_L} \quad x_i^{p_L} = w_1^* \times x_i^{p_L^*} + w_2 \times x_i^{p_A^{p_L}} + w_3 \times \frac{p_{B_1}^{p_L} + p_{B_2}^{p_L} + \dots + p_{B_n}^{p_L}}{n - 2}, \quad p_L \in \mathbf{P}_L$$

- Advocate : The search direction of every advocate $p_A \in \mathbf{P}_A$ is influenced by its corresponding leader $p_L \in \mathbf{P}_L$, every associated believer $p_B \in \mathbf{p}_B^{p_L}$ and the associated randomly generated weights such that $w_1^* > w_2 \in [0, 1]$ and $w_1^* + w_2 = 1$ as follows :

$$\forall x_i^{p_A} \quad x_i^{p_A} = w_1^* \times x_i^{p_L} + w_2 \times \frac{p_{B_1}^{p_L} + p_{B_2}^{p_L} + \dots + p_{B_n}^{p_L}}{n - 2}, \quad p_A \in \mathbf{P}_A$$

- Believers : The search direction of every believer $p_B \in \mathbf{P}_B$ is influenced by its corresponding leader $p_L \in \mathbf{P}_L$, advocate $p_A \in \mathbf{p}_A^{p_L}$ and the associated randomly generated weights such that $w_1^* > w_2 \in [0, 1]$ and $w_1^* + w_2 = 1$ as follows :

$$\forall x_i^{p_B} \quad x_i^{p_B} = w_1^* \times x_i^{p_L} + w_2 \times x_i^{p_A^{p_L}}, \quad p_B \in \mathbf{P}_B$$

Step 3 (Updation: Global and Local Ranking) : After corresponding search directions are calculated, individuals are updated with new search directions, individuals within each set are locally ranked and positions are assigned accordingly, followed by global ranking based on the fitness value of leaders of corresponding groups. Group with Global Best Leader (p_L^*) is assigned as Group1.

Step 4 (Convergence) : No significant improvement in the global as well as local group leaders or maximum iterations reached. Else continue to **Step 2**

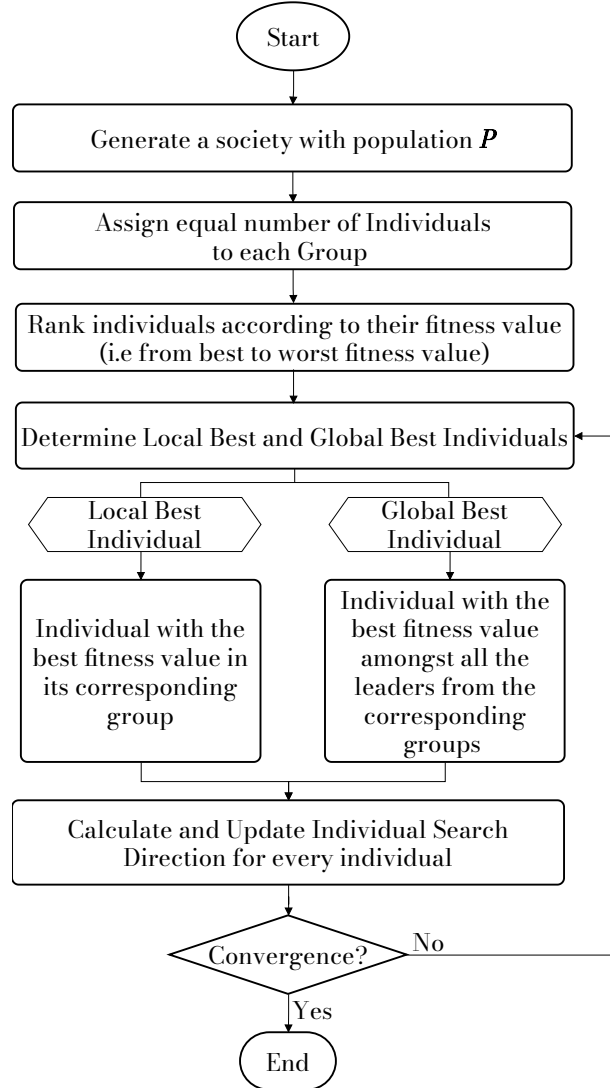


Figure 3: LAB Algorithm flowchart

3 Problem description and formulations

3.1 Benchmark Test Problems

The LAB was tested by solving 27 well-studied benchmark problems (Table 1)[27, 28]. The results are compared with contemporary algorithms.

Table 1 The benchmark test problems (Low/Lower and Up/Upper Bounds; S = Separable; U = Unimodal; N = Non-separable;M = Multimodal).

Function	Name	Type	Low	Up	Dimension
F1	Foxholes	MS	-65.536	65.536	2
F5	Ackley	MN	-32	32	30
F7	Bohachevsky1	MS	-100	100	2
F8	Bohachevsky2	MN	-100	100	2
F9	Bohachevsky3	MN	-100	100	2
F10	Booth	MS	-10	10	2
F13	Dixon-Price	UN	-10	10	30
F15	Fletcher	MN	-3.1416	3.1416	2
F16	Fletcher	MN	-3.1416	3.1416	5
F17	Fletcher	MN	-3.1416	3.1416	10
F18	Griewank	MN	-600	600	30
F19	Hartman3	MN	0	1	3
F20	Hartman6	MN	0	1	6
F21	Kowalik	MN	-5	5	4
F23	Langermann5	MN	0	10	5
F24	Langermann10	MN	0	10	10
F25	Matyas	UN	-10	10	2
F32	Quartic	US	-1.28	1.28	30
F33	Rastrigin	MS	-5.12	5.12	30
F35	Schaffer	MN	-100	100	2
F37	Schwefel_1.2	UN	-100	100	30
F38	Schwefel_2.22	UN	-10	10	30
F43	Six-hump camelback	MN	-5	5	2
F44	Sphere2	US	-100	100	30
F45	Step2	US	-100	100	30
F47	Sumsquares	US	-10	10	30
F50	Zakharov	UN	-5	10	10

3.2 Manufacturing And Machining Problems

Engineering problems are generally complex in nature and may involve several local optima. The complexity grows when the associated objective function involves coupled variables. This necessitates development of approximation algorithms, which can efficiently jump out of local optima and search for the global optimum [16, 39]. The LAB algorithm’s performance was tested by solving three types of engineering problems in the domain of machining, namely Abrasive Water Jet Machining, Electric Discharge Machining, micro-machining and Process Parameter Optimization for Turning of Alloy.

3.2.1 Abrasive Water Jet Machining (AWJM)

AWJM is an an extended version of water jet cutting, which uses water as the material to impinge on the work material to result in a cut. It can be also used for machining a heat-sensitive materials, as the heat generated is very low as well as the cut is 10x times faster than conventional methods.

Four critical parameters are u_2 (in mm) as nozzle diameter, u_3 (in mm) as standoff distance, u_4 (in mm/min) as cutting head speed/traverse speed and u_1 (in mm) as workpiece thickness [31, 54, 53] for which the associated responses are surface roughness R_a and taper angle $kerf$ [7]. It is evident all the process paramters interact with one another, affecting precision of cuts. Hence, optimum combination of the above process parameters is required for optimum results. Formulated regression model of the AWJM process is adopted here[31, 53]. The function being linear nonseperable makes it complex to solve and increases the chances of getting stuck in the local minima making the problem harder and tedious to solve. The formulated regression model adopted is as shown below:

$$\begin{aligned} \text{Minimize } R_a = & -23.309555 + 16.6968u_1 + 26.9296u_2 + 0.0587u_3 + 0.0146u_4 - 5.1863u_2^2 \\ & -10.4571u_1u_2 - 0.0534u_1u_3 - 0.0103u_1u_4 + 0.0113u_2u_3 - 0.0039u_2u_4 \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Minimize } kerf = & -1.15146 + 0.70118u_1 + 2.72749u_2 + 0.00689u_3 - 0.00025u_4 \\ & +0.00386u_2u_3 - 0.93947u_2^2 - 0.25711u_1u_2 - 0.00314u_1u_3 \\ & -0.00249u_1u_4 + 0.00196u_2u_4 - 0.00002u_3u_4 - 0.00001u_3^2 \end{aligned} \quad (2)$$

where $0.9 \leq u_1 \leq 1.25$, $0.95 \leq u_2 \leq 1.5$, $20 \leq u_3 \leq 96$, $200 \leq u_4 \leq 600$

3.2.2 Electric Discharge Machining (EDM)

One of the electro-thermal non-traditional machining processes is the EDM, which uses electrical spark or thermal energy to erode unwanted material in order to create desired shape. It is a controlled metal-removal process that is used to remove metal by means of electric spark erosion. The metal-removal process is performed by applying a pulsating (ON/OFF) electrical charge of high-frequency current through the electrode to the workpiece. In the gap between the tool and the workpiece, a difference in the applied potential is formed, establishing an electric field. Due to which the loose electrons on the tool gain high velocity and energy when subjected to electrostatic forces, after which these free electrons collide with the dielectric molecules which results in ionization. More the electrons get accelerated, more positive ions and electrons get generated resulting in increase in the concentration of electrons and ions. The energy released causes electrode wear rate to take place[46, 17] resulting in case hardening of the workpiece.

In order to control surface roughness R_a process parameters: v_1 (in A) as discharge current, v_2 (in V) as gap voltage, v_3 (in μs) as pulse on-time and v_4 (in μs) as pulse off-time need to be optimized for the EDM process. The process responses for surface finish and electrode wear rate of machined

component are MRR , R_a and relative electrode wear rate $REWR$, respectively. The regression model for the above process is adopted here[53, 57]:

$$\text{Maximize } MRR = -235.15 + 39.7v_1 + 4.277v_2 + 1.569v_3 - 1.375v_4 - 0.0059v_3^2 - 0.536v_1v_2 \quad (3)$$

$$\text{Minimize } R_a = 30.347 - 0.618v_1 - 0.438v_2 + 0.059v_3 - 0.59v_4 + 0.019v_1v_4 + 0.0075v_2v_4 \quad (4)$$

$$\begin{aligned} \text{Minimize } REWR = 196.564 - 24.19v_1 - 3.135v_2 - 1.781v_3 + 0.153v_4 + 0.464v_1v_2 + 0.158v_1v_3 \\ + 0.025v_1v_4 + 0.029v_2v_3 - 0.017v_2v_4 - 0.003385v_1v_2v_3 + 0.093v_1^2 \\ + 0.001491v_3^2 + 0.005265v_4^2 \end{aligned} \quad (5)$$

where $7.5 \leq v_1 \leq 12.5$, $45 \leq v_2 \leq 55$, $50 \leq v_3 \leq 150$, $40 \leq v_4 \leq 60$

3.2.3 Micro-machining processes

The various processes of cutting raw materials into specific dimensions in a controlled removal process is termed as machining. This process of machining usually consists of a cutting tool, machine tool and a workpiece[10]. Machinability refers to evaluation of ease for cutting any type of material in minimum cost and time into a specific shape and dimension for a certain tolerance, surface quality, etc.,[3].

Micro-turning is a type of micro-machining process which uses solid micro-tools to remove material from workpiece and is almost similar to conventional turning operation. The micro-tools used to remove workpiece material have significant characteristics which significantly affect the size reduction[45].

w_1 (in m/min) as cutting speed, w_2 (in μ/rev) as feed and w_3 (in μm) as depth of cut are the process parameters for micro-turning. Performance responses are flank wear (f_b) and surface roughness (R_a). The formulated regression model for the above process is adopted here[9]:

$$\text{Minimize } f_b = 0.004w_1^{0.495}w_2^{0.545}w_3^{0.763} \quad (6)$$

$$\text{Minimize } R_a = 0.048w_1^{-0.062}w_2^{0.445}w_3^{0.516} \quad (7)$$

where $25 \leq w_1 \leq 37$, $5 \leq w_2 \leq 15$, $30 \leq w_3 \leq 70$

Process parameters x_1 (in rpm) as cutting speed, x_2 (in mm/min) as feed and process responses surface roughness R_a and machining time M_t with two milling cutters with diameters $0.7mm$ and

1mm are considered for micro-milling process [40]. The formulated regression model for the above process is adopted here:

Tool with diameter 0.7mm

$$\text{Minimize } R_a = -0.455378 + 0.00027f_1 + 0.16422f_2 - 0.000077f_1f_2 \quad (8)$$

$$\text{Minimize } M_t = 17.71644 - 0.0002f_1 - 4.8404f_2 + 0.0001f_1f_2 \quad (9)$$

Tool with diameter 1mm

$$\text{Minimize } R_a = -0.208871 + 0.000144f_1 + 0.019571f_2 \quad (10)$$

$$\text{Minimize } M_t = 20.2906 - 0.0015f_1 - 5.8369f_2 + 0.0006f_1f_2 \quad (11)$$

where $1500 \leq f_1 \leq 2500$, $1 \leq f_2 \leq 3$

B_h as Burr height and B_t as burr thickness, are performance responses for four drilling cutter diameters in micro-drilling process, 0.5mm; 0.6mm; 0.8mm and 0.9mm. Process parameters for the above are y_1 (in rpm) as cutting speed and y_2 (in mm/min) as feed. The formulated regression model of the above process is adopted here for the tools used as follows[48]

Tool with diameter 0.5mm

$$\text{Minimize } B_h = 420.94 - 0.234g_1 - 99.91g_2 + 6.55 \times 10^{-5}g_1^2 + 22.152g_2^2 \quad (12)$$

$$\text{Minimize } B_t = 90.57 - 0.049g_1 - 27.12g_2 + 1.32 \times 10^{-5}g_1^2 + 5.54g_2^2 \quad (13)$$

Tool with diameter 0.6mm

$$\text{Minimize } B_h = 369.67 - 0.028g_1 - 156.79g_2 + 6.64 \times 10^{-6}g_1^2 + 23.162g_2^2 \quad (14)$$

$$\text{Minimize } B_t = 35.34 - 0.019g_1 - 0.59g_2 + 6.44 \times 10^{-6}g_1^2 + 0.51g_2^2 \quad (15)$$

Tool with diameter 0.8mm

$$\text{Minimize } B_h = 106.116 + 0.13g_1 - 6.62g_2 + 1.49 \times 10^{-6}g_1^2 + 4.75g_2^2 \quad (16)$$

$$\text{Minimize } B_t = 59.79 - 0.024g_1 - 11.3g_2 + 7.78 \times 10^{-6}g_1^2 + 2.18g_2^2 \quad (17)$$

Tool with diameter 0.9mm

$$\text{Minimize } B_h = 450.7 - 0.09g_1 - 34.48g_2 + 2.34 \times 10^{-5}g_1^2 + 5.03g_2^2 \quad (18)$$

$$\text{Minimize } B_t = 80.07 - 0.040g_1 - 14.81g_2 + 1.516 \times 10^{-5}g_1^2 + 4.65g_2^2 \quad (19)$$

where $1000 \leq g_1 \leq 2500$, $1 \leq g_2 \leq 4$

3.2.4 Process parameter optimization for turning of titanium alloy (MQL environment)

Minimum Quantity Lubrication (MQL) has increasingly been adopted over the past few years in the manufacturing domain, due to its abilities to reduce costs and material wastes as compared with traditional methods. In MQL, a small quantity of cutting fluid such as sustainable lubricants (vegetable oil) is applied on the tool-chip surface region as well as compressed air acting as an alternative for coolant fluids. Thus cutting costs by avoiding use of huge amounts of coolant fluids, thus focusing more on the heat generated rather than using coolants to reduce surface temperatures resulting in increase in tool life[18].

k_1 (mm/rev) as Feed rate, k_2 (degrees) as approach angle, k_3 (m/min) as cutting speed are considered process parameters and the performance responses for the above are F_c as tangential force, V_{Bmax} as tool wear, R_a as surface roughness and L as tool-chip contact length. The formulated regression model of the above process is adopted here[19, 43]:

$$\text{Minimize } F_c = -202.01471 + 1.28250 \times k_3 + 3225 \times k_1 - 0.74167 \times k_2 - 9.4 \times k_3 \times k_1 \quad (20)$$

$$\text{Minimize } V_{Bmax} = -0.27368 + 0.001575 \times k_3 + 2.4 \times k_1 - 0.0010833 \times k_2 \quad (21)$$

$$\text{Minimize } R_a = -0.16294 + 0.001425 \times k_3 + 3.7 \times k_1 - 0.000416667 \times k_2 \quad (22)$$

$$\text{Minimize } L = 0.96302 - 0.00215931 \times k_3 + 0.92703 \times k_1 + 0.00152807 \times k_2 \quad (23)$$

where $200 \leq k_1 \leq 300$, $0.1 \leq k_2 \leq 0.2$, $60 \leq k_3 \leq 90$

4 Tests and Validations

The LAB algorithm was coded in Python3 on Google Collab Platform with an Intel(R) Xeon(R) @2.30 GHz Intel Core 2 Duo processor with 12 GB RAM. In the initialization step, individuals were generated and randomly assigned to groups. The selected LAB parameters are: number of groups $G = 4$, number of individuals in each group $n = 5$, max iterations = 100.

4.1 Benchmark Problems

LAB is validated by solving 27 benchmark test functions and the results are compared with other algorithms which are necessarily stochastic in nature. The criteria for comparison are mean and best solutions, standard deviation as well as runtime of the algorithms(Refer to Table 2).

A statistical analysis is performed by executing two-sided and pairwise Wilcoxon signed-rank test (Refer to Tables 3 and 4). In the two-sided comparison optimum solutions obtained from 30 independent runs solving a benchmark test problem using LAB are compared with other algorithms solving the same benchmark test problems. Significance value α was chosen as 0.05 with a null hypothesis H_0 : the median of solutions obtained by algorithms A and B are equal, in order to verify if an alternative hypothesis exists i.e. performance of algorithm B is better than algorithm A or the other way around, the size of the ranks provided by Wilcoxon signed-rank (T+ and T-values) were thoroughly examined [5].

At the bottom of the Table 3 counts of significant cases (+/-/=) are mentioned. The results obtained exhibited the superior performance of LAB algorithm as compared to the other algorithms. In the pairwise comparison, the average of the best solutions obtained by the algorithms over 30 runs for solving the benchmark test problems is compared.

The convergence plots of few selected functions namely Booth(unimodal), Hartmann6(unimodal), Matyas(multimodal) and Six-hump camelback(multimodal) are presented in Figures 4–7. These plots exhibit the competitive behaviour of individuals within a group to reach optimum solution. It is also evident from the plots that the individuals in the group follow the leader. During every iteration, group leaders from corresponding groups compete with the global best leader and are successful at times and the group associated with the global best leader is assigned as Group 1. Thus, changing the search direction of the local leaders following the global best leader. The abrupt changes in the graph exhibit this phenomena of competitiveness of individuals. The convergence highlights the significance of LAB approach by quickly reaching the optimum solution.

Table 2 Statistical solutions of algorithms for Benchmark test problems
 (Mean= Mean solution; Std. Dev. = Standard Deviation; Best= Best Solution; Runtime= Mean Runtime in Seconds)

Problem	Statistics	PSO2011	CMAES	ABC	JDE	CLPSO	SADE	BSA	IA	LAB
F1	Mean	1.3316029265	10.074884637	0.9980038378	1.0641405484	1.8209961276	0.9980038378	0.9980038378	0.9980038690	0.9980038377
	Std. Dev.	0.9455237995	8.0277365401	0.0000000000	0.3622156830	1.6979175080	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.9980038378	0.9980038378	0.9980038378	0.9980038378	0.9980038388	0.9980038378	0.9980038378	0.9980038659	0.9980038377
	Runtime	72.52	44.78	64.97	51.10	61.65	66.63	38.12	43.53	0.05
F5	Mean	1.5214322974	11.7040011685	0.0000000005	0.0811070564	0.1863456354	0.79153682204	0.0000000010	0.0000000000	0.0000000000
	Std. Dev.	0.6617570385	9.72019615409	0.0000000003	0.31760126892	0.4389839301	0.75615934030	0.0000000034	0.0000000000	0.0000000000
	Best	0.0000000008	0.0000000000	0.0000000002	0.0000000000	0.0000000000	0.0000000000	0.0000000008	0.0000000000	0.0000000000
	Runtime	63.03	3.14	23.29	11.01	45.73	40.91	14.39	49.45	0.10
F7	Mean	0.0000000000	0.06223545337	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.13450613392	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	16.95	6.84	1.83	1.14	2.92	4.40	0.82	38.50	0.11
F8	Mean	0.0000000000	0.0072710626	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0398583252	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	17.03	2.17	1.80	1.13	2.89	4.41	0.82	39.02	0.11
F9	Mean	0.0000000000	0.0001048363	0.0000000000	0.0000000000	0.000193465	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0005742121	0.0000000003	0.0000000000	0.0000846532	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000001	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	17.13	2.12	21.71	1.12	33.30	4.30	0.82	40.89	0.11
F10	Mean	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0006063123	0.0000000000	0.0000000000	0.83463870900	0.062480783
	Std. Dev.	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0029861919	0.0000000000	0.0000000000	0.0000000000	0.054308386
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.8346387087	0.0153923338
	Runtime	17.07	1.37	22.39	1.09	28.50	4.37	0.79	39.97	0.10
F13	Mean	0.6666666667	0.6666666667	0.0000000003	0.6666666667	0.0023282134	0.6666666667	0.6444444444	0.2528116640	0.0000000000
	Std. Dev.	0.0000000002	0.0000000000	0.0000000001	0.0000000000	0.0051792841	0.0000000000	0.1217161239	0.0000000006	0.0000000000
	Best	0.6666666667	0.6666666667	0.0000000002	0.6666666667	0.0000120712	0.6666666667	0.0000000000	0.25281166341	0.0000000000
	Runtime	167.09	3.71	37.60	18.68	216.26	47.83	21.19	67.46	1.09
F15	Mean	0.0000000000	1028.39307840	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	1298.152182012	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	27.85	15.54	40.03	2.85	4.03	6.02	2.06	38.86	0.13
F16	Mean	48.7465164447	1680.34602301	0.0218688502	0.9443728655	81.751618148	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	88.8658510973	2447.4848591	0.0418109571	2.88153148270	379.924111738	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	95.35	11.94	44.57	4.71	162.94	5.76	7.78	48.26	0.08
F17	Mean	918.951849278	12340.22833264	11068149623	713.72269746	0.8530843976	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	1652.48108584	22367.16988758	9.8810950141	1710.0713074	2.9208253192	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.327465177	0.0000000000	0.0016957838	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	271.22	7.63	43.32	16.10	268.89	168.31	33.04	69.06	0.13

Table 2 Continued

Problem	Statistics	PSO2011	CMAES	ABC	JDE	CLPSO	SABE	BSA	IA	LAB
F18	Mean	0.006894369482	0.0011498935	0.0000000000	0.0048193569	0.0000000000	0.0226339327	0.000493070	0.0000000000	0.0000000000
	Std. Dev.	0.0008056520165	0.0036449414	0.0000000000	0.0133238236	0.0000000000	0.0283874288	0.0018764356	0.0000000000	0.0000000000
	Best	0.0000000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Runtime	73.89	2.64	19.07	6.91	14.86	25.85	5.75	2.71	0.76
F19	Mean	-3.862782147821	-3.7248887745	-3.8627821477	-3.8627821480	-3.8627821477	-3.8627821477	-3.8627821488	-3.8596352620	-3.6659294870
	Std. Dev.	0.0000000000000	0.5407823544	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00033967610	0.19369615340
	Best	-3.862782147821	-3.8627821477	-3.8627821477	-3.8627821477	-3.8627821477	-3.8627821480	-3.8627821479	-3.8613076574	-3.8079776928
	Runtime	19.28	21.88	12.61	7.50	17.50	24.80	6.00	46.16	0.19
F20	Mean	-3.318032067541	-3.2942534433	-3.3219951716	-3.2982165472	-3.3219951716	-3.314068962	-3.3219951757	-2.5710247593	-3.3435769166
	Std. Dev.	0.021706814827	0.05114580761	0.00000000000	0.0483702517	0.00000000000	0.0301641517	0.00000000000	0.00000000000	0.0173065935
	Best	-3.321995171585	-3.32199517157	-3.3219951716	-3.3219951716	-3.3219951714	-3.3219951716	-3.3219951757	-2.5710247593	-3.3285570654
	Runtime	26.20	7.33	13.56	8.00	20.09	33.71	6.82	59.08	0.16
F21	Mean	0.00030748599	0.0064830298	0.0004414865	0.000368320	0.000310048	0.0003074860	0.0003074860	0.0016993410	0.0388297929
	Std. Dev.	0.00000000000	0.0148565972	0.0000568391	0.0002323174	0.0000045983	0.00000000000	0.00000000000	0.00000013058	0.01149748515
	Best	0.00030748599	0.0003074860	0.0003230955	0.0003074860	0.000307486	0.0003074864	0.0003074850	0.00169899146	0.02512474121
	Runtime	84.47	13.86	20.25	7.80	156.09	45.44	11.72	48.92	0.12
F23	Mean	-1.38919922006	-0.5235864385	-1.4999990071	-1.3431399433	-1.476597274	-1.499992234	-1.4821658763	-1.5000000000	-1.499999174
	Std. Dev.	0.225719440316	0.25853307141	0.0000008441	0.2680292305	0.1281775380	0.00000000000	0.0976772648	0.00000000000	0.0000000243
	Best	-1.49999922334	-0.7977041048	-1.499992234	-1.499992234	-1.499992231	-1.499992234	-1.499992234	-1.5000000000	-1.499992011
	Runtime	33.80	17.94	37.98	20.33	42.48	36.03	18.93	41.84	0.61
F24	Mean	-0.91662067887	-0.3105076783	-0.8406348097	-0.8821752799	-0.943143280	-1.2765515662	-1.3127183562	-1.5000000000	-1.5000000000
	Std. Dev.	0.391775236745	0.20803172415	0.00000966366	0.3882445164	0.3184175871	0.3599594107	0.3158807699	0.00000000000	0.00000000000
	Best	-1.50000000000	-0.79769383560	-1.4999926801	-1.5000000000	-1.500000000	-1.5000000000	-1.5000000000	-1.5000000000	-1.5000000000
	Runtime	110.79	8.83	38.47	21.59	124.60	47.17	35.35	54.65	1.35
F25	Mean	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.0000041791	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Std. Dev.	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.0000161643	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Best	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Runtime	25.35	1.34	19.68	1.14	31.63	4.09	0.81	35.66	0.03
F32	Mean	0.00035483454	0.070161916984	0.0250163253	0.0013010315	0.0019635751	0.0016730767	0.0019953316	0.0002254250	0.00000000000
	Std. Dev.	0.00014108174	0.02887602926	0.0077209315	0.0009932080	0.0043423831	0.0007330247	0.000969894	0.0005270110	0.00000000000
	Best	0.00010143325	0.02991807014	0.0094647581	0.0001787237	0.000120645	0.0005630851	0.000608487	0.00000023800	0.00000000000
	Runtime	290.66	2.15	34.98	82.12	103.28	171.63	48.23	218.72	1.14
F33	Mean	25.63676022587	95.9799861205	0.00000000000	1127.6202656	0.6301107362	0.8622978495	0.00000000000	0.00000000000	0.00000000000
	Std. Dev.	8.294351268422	56.6919245986	0.00000000000	10688393636	0.8046401821	0.9323785264	0.00000000000	0.00000000000	0.00000000000
	Best	12.93446774222	29.8487565994	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Runtime	76.08	2.74	4.09	7.63	18.42	23.59	5.40	2.26	1.14
F35	Mean	0.00000000000	0.4651202456	0.00000000000	0.0038863640	0.00194318198	0.0006477272	0.00000000000	0.00000000000	0.00000000000
	Std. Dev.	0.00000000000	0.09333685175	0.00000000000	0.0094811744	0.00395280234	0.0024650054	0.00000000000	0.00000000000	0.00000000000
	Best	0.00000000000	0.0097159099	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000	0.00000000000
	Runtime	18.16	24.02	7.86	4.21	8.30	5.90	1.77	33.15	0.11

Table 2 Continued

Problem	Statistics	PSO2011	CMAES	ABC	JDE	CLPSO	SADE	BSA	IA	LAB
F37	Mean	0.0000000000	0.0000000000	14.5668734127	0.0000000000	6.4655746331	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0000000000	8.71284430138	0.0000000000	8.2188901352	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	4.0427699324	0.0000000000	0.1816624030	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	5.4318	3.37	1118.41	19.31	179.08	109.55	57.29	100.95	1.64
F38	Mean	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0000000000	0.0000000001	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000003	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	163.18	2.56	20.59	1.94	12.56	5.63	3.20	47.01	1.27
F43	Mean	1.0316284535	-1.004422966	-1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.03043578000	-1.0310177905
	Std. Dev.	0.0000000000	0.1490105927	0.0000000000	0.0000000000	0.0000000000	0.0000000002	0.0000000001	0.00149119000	0.0026216949
	Best	1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.0316284535	-1.03145007540	-1.0316284534
	Runtime	16.754	24.79	11.31	7.15	18.56	27.65	5.69	39.90	0.07
F44	Mean	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	159.90	2.32	21.92	1.42	14.40	5.92	3.30	17.458	1.24
F45	Mean	2.3000000000	0.0666666667	0.0000000000	0.9000000000	0.0000000000	0.0000000000	0.0000000000	0.0000538870	0.0000000000
	Std. Dev.	1.8597367259	0.2537081371	0.0000000000	3.021189535083	0.0000000000	0.0000000000	0.0000000000	0.0000000005	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.00000538861	0.0000000000
	Runtime	57.27	1.47	1.78	2.92	3.04	4.31	0.88	2.22	1.22
F47	Mean	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	564.17	2.56	24.17	1.87	15.95	6.38	4.31	31.30	1.26
F50	Mean	0.0000000000	0.0000000000	0.000000402	0.0000000000	0.0000000001	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Std. Dev.	0.0000000000	0.0000000000	0.0000002203	0.0000000000	0.0000000006	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Best	0.0000000000	0.0000000000	0.0000000002	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
	Runtime	86.36	1.86	86.45	1.41	157.84	4.93	5.70	33.37	0.46

Table 3 Statistical results for Benchmark Test problems using two-sided Wilcoxon signed-rank test ($\alpha = 0.05$)

Test Functions	CMAES vs LAB				JDE vs LAB				PSO2011 vs LAB				ABC vs LAB			
	P-value	T+	T-	Winner	P-value	T+	T-	Winner	P-value	T+	T-	Winner	P-value	T+	T-	Winner
F1	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F5	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F7	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=
F8	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=
F9	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	1	0	0	=
F10	1.6774E-06	465	0	-	1.6774E-06	465	0	-	1.6774E-06	465	0	-	1.6774E-06	465	0	-
F13	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F15	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=
F16	4.3205E-08	0	465	+	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+
F17	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F18	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F19	0.6403	255	210	-	1.3733E-06	465	0	-	0.0643	255	210	-	1.3733E-06	465	0	-
F20	1.2065E-06	0	465	+	1.2065E-06	0	465	+	1.2064E-06	0	465	+	1.2065E-06	0	465	+
F21	1.4439E-06	465	0	-	1.4439E-06	465	0	-	1.4439E-06	465	0	-	1.4439E-06	465	0	-
F23	1.1905E-06	0	465	+	1.1905E-06	0	465	+	1.1905E-06	0	465	+	1.1905E-06	0	465	+
F24	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F25	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F32	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F33	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F35	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F37	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+
F38	1	0	0	=	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+
F43	5.8021E-07	0	465	+	0.0039	45	0	-	5.8021E-07	0	465	+	0.0078	36	0	-
F44	1	0	0	=	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+
F45	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
F47	1	0	0	=	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+
F50	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+
+ / = / -																
			20/ 4/ 3				17/ 6/ 4				19/ 5/ 3				19/ 4/ 4	

Table 3 Continued

Test	SADE vs LAB				IA vs LAB				CLPSO vs LAB				BSA vs LAB				
	P-value	T+	T-	Winner	P-value	T+	T-	Winner	P-value	T+	T-	Winner	P-value	T+	T-	Winner	
F1	1	0	0	=	1.6699E-06	0	465	+	4.3205E-08	0	465	+	1	0	0	=	
F5	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	
F7	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F8	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F9	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F10	1.6774E-06	465	0	-	1.6774E-06	0	465	+	1.6774E-06	465	0	-	1.6774E-06	465	0	-	
F13	4.3205E-08	0	465	+	1.7084E-06	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	
F15	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F16	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F17	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F18	4.3205E-08	0	465	+	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	
F19	1.3733E-06	465	0	-	2.8269E-06	460	5	-	1.3733E-06	465	0	-	1.3733E-06	465	0	-	
F20	1.2065E-06	0	465	+	1.2065E-06	0	465	+	1.2065E-06	0	465	+	1.2065E-06	0	465	+	
F21	1.4439E-06	465	0	-	1.5068E-06	465	0	-	1.4439E-06	465	0	-	1.4439E-06	465	0	-	
F23	2.2247E-06	6	459	+	4.6458E-04	231	22	-	1.1905E-06	0	465	+	1.1905E-06	0	465	+	
F24	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	4.3205E-08	0	465	+	
F25	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F32	4.3205E-08	0	465	+	1.7344E-06	0	465	+	4.3205E-08	0	465	+	4.3205E-08	0	465	+	
F33	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F35	4.3205E-08	0	465	+	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F37	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
F38	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F43	0.0039	45	0	-	3.7037E-05	35	430	+	0.0039	45	0	-	0.0039	45	0	-	
F44	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F45	1	0	0	=	1.7311E-06	0	465	+	1	0	0	=	1	0	0	=	
F47	1	0	0	=	1	0	0	=	1	0	0	=	1	0	0	=	
F50	1	0	0	=	1	0	0	=	4.3205E-08	0	465	+	1	0	0	=	
+ / = / -		15 / 8 / 4				9 / 14 / 4				7 / 16 / 4				8 / 16 / 3			

Table 4 Statistical pairwise comparison.

Other Algorithms vs LAB	p-value	T+	T-	Winner
PSO vs LAB	0.0151	21	115	LAB
CMAES vs LAB	0.0010	21	210	LAB
ABC vs LAB	0.1074	55	135	LAB
JDE vs LAB	0.0129	24	129	LAB
CLPSO vs LAB	0.218	38	152	LAB
SADE vs LAB	0.1909	26	65	LAB
BSA vs LAB	0.3221	32	46	LAB
IA vs LAB	0.2061	18	48	LAB

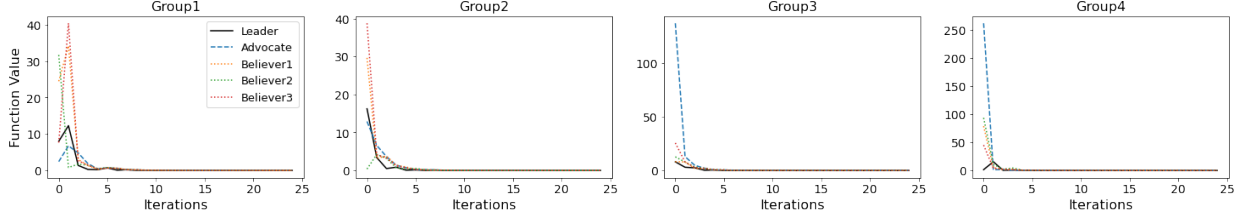


Figure 4: Convergence: Booth Function(F10)

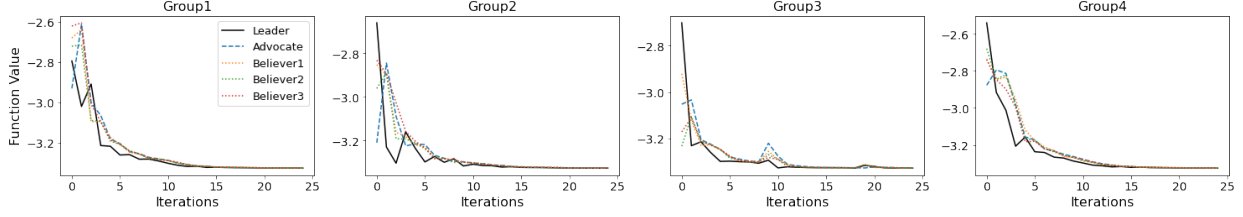


Figure 5: Convergence: Hartmann6 Function(F20)

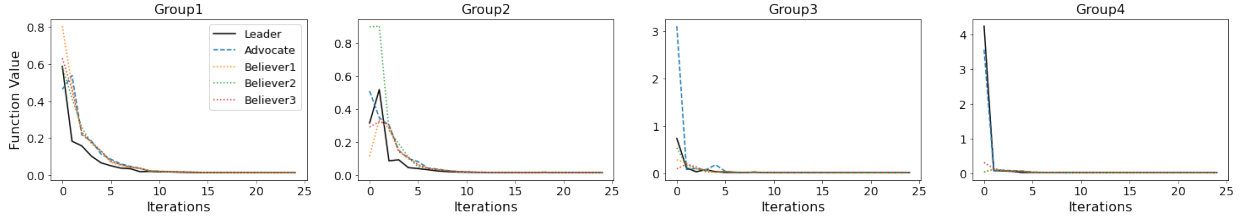


Figure 6: Convergence: Matyas Function(F25)

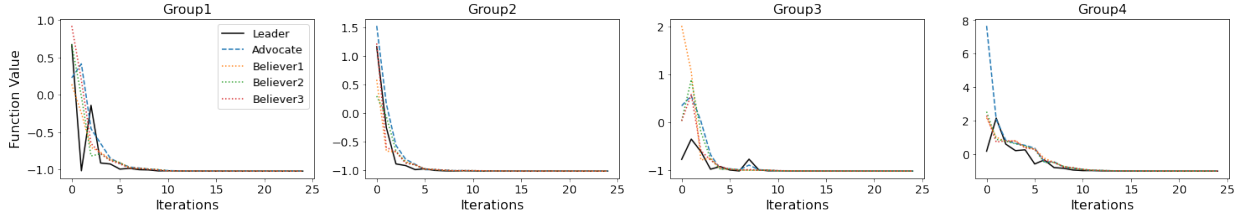


Figure 7: Convergence: Six-hump Camelback Function(F43)

4.2 Solutions to AWJM and EDM

Table 5 contains best and mean solutions along with their associated standard deviation obtained for R_a and $kerf$ of AWJM using LAB, Multi-CI, GA, SA and PSO and comparison with the variations of CI is shown in Table 6. In LAB approach, individuals are randomly assigned the group and the associated leader in the first iteration. For every following iteration, the individuals follow the local best individual/leader and the local best individual/local leader also follows the global best individual/Global Leader, helps to explore better solutions due to which individuals avoided local minima. Hence, LAB yielded in better solutions as compared with FA, experimental, regression approach and PSO for $kerf$.

LAB was able to outperform RSA, BPNN, FA, f_{best} , f_{better} and alienation in the matter of quality of solution for solving MRR for EDM problems due to its strong exploration and exploitation

mechanism evident from Table 7.

It is evident in Table 5, the results shown for LAB are less robust as compared to GA and Multi-CI. As compared to SA and PSO, LAB outperformed by achieving 8% and 23% minimization of $kerf$ in AWJM as is evident in Tables 5 and 6. Compared to f_{best} , f_{better} and alienation, LAB achieved 78%, 79% and 47% maximization of MRR for EDM as is evident in Table 7.

Table 5 Solutions to R_a and $kerf$ of AWJM

Function	SA	Multi-CI	PSO	GA	LAB
R_a					
Mean	4.86	4.38	4.39	4.43	5.35
SD	0.12	0.00	0.22	0.03	0.22
Best	4.61	4.38	4.75	4.38	4.81
Run time	2.63	4.63	1.78	1.62	0.13
$kerf$					
Mean	0.41	0.33	0.43	0.33	0.33
SD	0.04	0.01	0.00	0.01	0.04
Best	0.36	0.33	0.43	0.33	0.23
Run time	2.8	3.89	1.52	1.48	0.12

Table 6 Overall solutions to R_a and $kerf$ of AWJM

Problem	FA Shukla and Singh (2017)	Experimental (Kechagias, 2012)	Regression (Kechagias, 2012)	fbest	roulette wheel	alienation	fbetter	Multi-CI	GA	PSO	SA	LAB
	Gulia and Nargundkar(2019)											
R_a	4.44	5.80	5.41	4.38	4.38	4.38	4.38	4.38	4.38	4.39	4.61	5.35
$kerf$	0.37	0.85	0.90	0.34	0.34	0.34	0.34	0.33	0.33	0.43	0.35	0.33

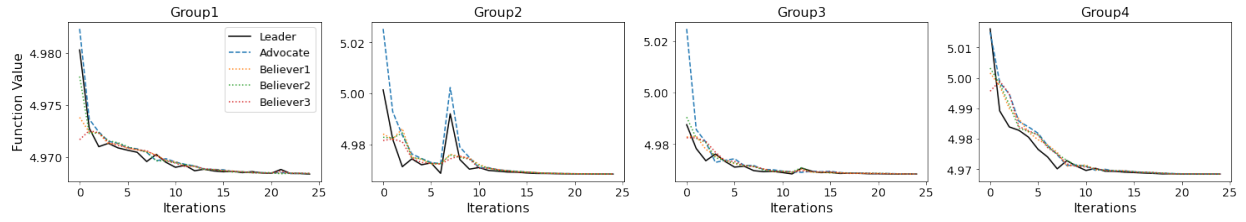
Best solution plots in every iteration of LAB for solving AWJM and EDM problems are exhibited in Fig. 8 and Fig. 9 a-c respectively, as well as the solution comparison is exhibited in Table 6.

Table 7 Solutions to R_a , MRR , $REWR$ of EDM

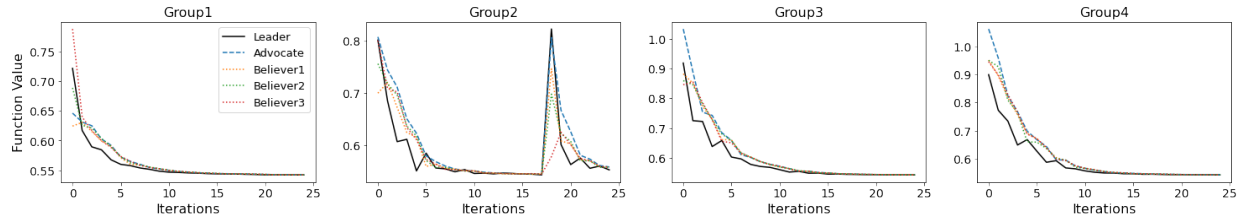
Function	GA	SA	PSO	Multi-Cl	Roulette Wheel	fbest	fbetter	Alienation	LAB
MRR	183.37	182.03	183.37	183.37	183.26	38.98	38.24	96.45	183.87
S.D.	0.00	2.21	0.00	0.00	0.11	0.69	0.71	23.21	2.33
Best	183.37	183.09	183.37	183.37	183.35	39.63	39.52	144.32	187.60
Run Time	1.41	2.61	1.81	1.81	0.35	0.59	0.64	0.51	0.12
Mean	3.55	3.67	3.55	3.55	3.61	3.60	3.61	5.99	4.99
S.D.	0.00	0.16	0.05	0.00	0.03	0.02	0.03	1.76	0.54
Best	3.55	3.58	3.55	3.55	3.55	3.55	3.55	4.06	3.95
Run Time	1.45	2.69	1.89	1.89	0.38	0.6	0.63	0.53	0.13
Mean	1.30×10^{-8}	6.82×10^{-4}	3.73×10^{-9}	1.85×10^{-8}	8.53×10^{-5}	2.96×10^{-5}	7.90×10^{-6}	2.37×10^{-7}	2.39×10^{-5}
S.D.	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Best	1.22×10^{-7}	1.36×10^{-2}	8.95×10^{-9}	9.50×10^{-9}	2.43×10^{-4}	1.49×10^{-4}	4.15×10^{-5}	9.79×10^{-7}	6.23×10^{-7}
Run Time	1.7	2.8	1.42	1.93	0.42	0.62	0.66	0.57	0.13

Table 8 Overall solutions to R_a , MRR , $REWR$ of EDM

Problem	GA	RSM Tzeng and Chen (2013)	Multi Cl	FA Shukla and Singh (2017)	PSO	roulette wheel	fbest	fbetter	alienation	BPNN Tzeng and Chen (2013)	
										SA	LAB
MRR	183.35	157.39	183.37	181.67	183.37	183.35	39.63	39.52	144.32	159.70	183.09
R_a	3.55	7.38	3.55	3.67	3.55	3.55	3.55	3.55	4.06	7.04	3.58
$REWR$ %	1.22×10^{-7}	7.63	9.50×10^{-9}	6.32×10^{-5}	1.85×10^{-9}	2.43×10^{-4}	2.96×10^{-5}	7.90×10^{-6}	9.79×10^{-7}	6.21	2.43×10^{-4}
											2.39×10^{-5}

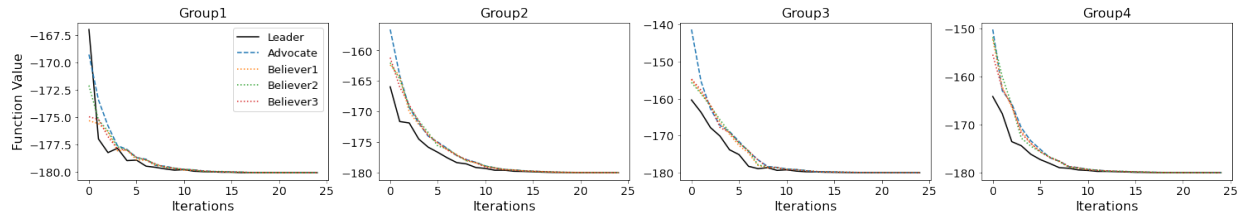


(a) R_a

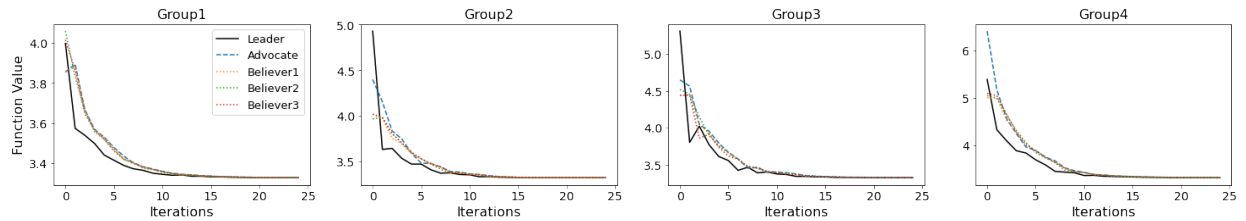


(b) $ker f$

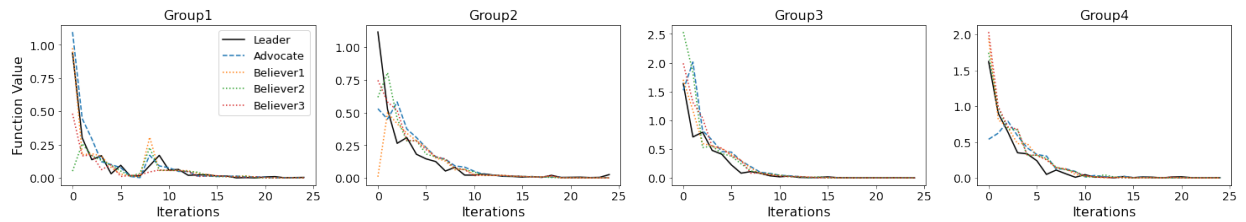
Figure 8: Convergence: AWJM



(a) MRR



(b) R_a



(c) $REWR$

Figure 9: Convergence: EDM

4.3 Solutions to Micro-machining problems

Comparison Tables 9, 10 and 11 exhibit solutions consisting of mean and best solution along with standard deviation for 30 trials of each objective function of algorithms for solving micro-turning, micro-milling and micro-drilling processes. For micro-drilling processes, LAB obtained comparable results with Multit-CI, GA, SA and variations of CI as well as outperforming GA, SA and PSO in convergence rate. However, for micro-turning and micro-milling with $0.7mm$ and with $1mm$ tool diameter for machining time (M_t) LAB could compete with other algorithms but could not produce superior results.

Table 9 Solutions to Micro-Turning processes

Cutter Diameter	Objective Function	Algorithms Applied									
		SA	Multi-CI	PSO	Variations of CI			GA	LAB		
					roulette wheel	fbest	fbetter			alienation	
0.2mm Nose Radius	R_a	Mean	0.45	0.46	0.46	0.46	0.45	0.45	0.46	0.45	0.55
		S.D.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
		Best	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.47
	f_b	Run Time	2.80	0.39	1.21	0.04	0.03	0.04	0.10	1.64	0.09
		Mean	0.64	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.88
		S.D.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10
		Best	0.64	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.69
Run Time	2.78	0.38	0.89	0.06	0.04	0.04	0.10	1.42	0.10		

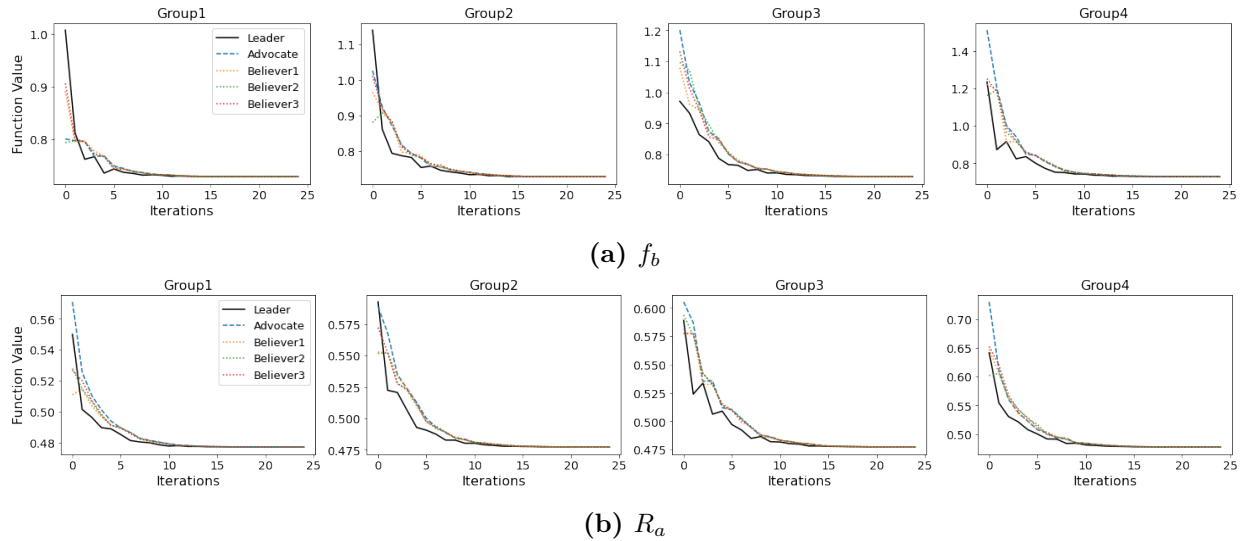
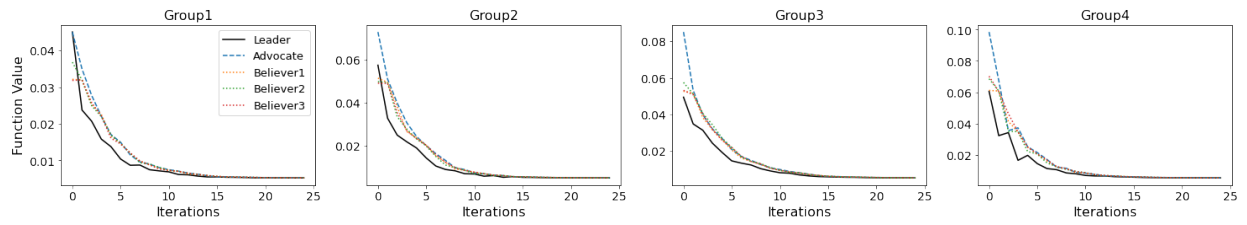


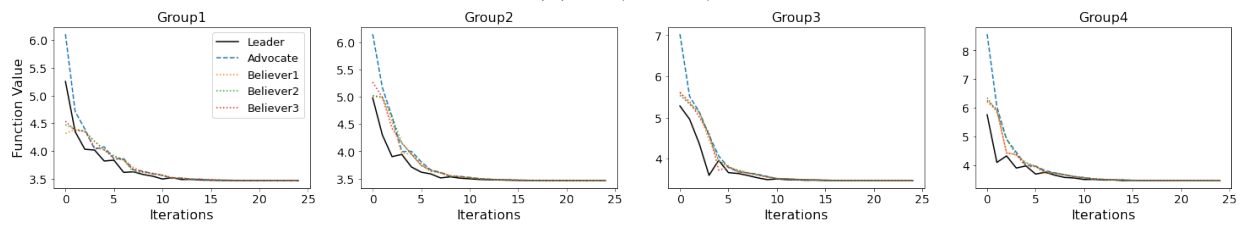
Figure 10: Convergence: Micro-Turning

Table 10 Solutions to Micro-Milling processes

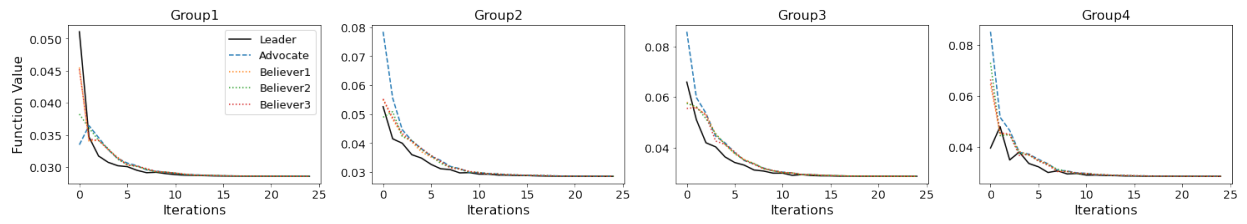
Cutter Diameter	Objective Function	Algorithms Applied									
		GA	Multi-CI	SA	Variations of CI				PSO	LAB	
					roulette wheel	fbest	fbetter	alienation			
0.7mm	R_a	Mean	0.00	0.00	0.13	0.00	0.12	0.19	0.00	0.00	0.03
		S.D.	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
		Best	0.00	0.00	0.13	0.00	0.09	0.19	0.00	0.00	0.00
		Run Time	1.40	0.21	2.60	0.06	0.05	0.06	0.14	1.12	0.07
	M_t	Mean	3.35	3.35	3.42	3.35	3.35	3.35	3.35	3.34	3.60
		S.D.	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.12
		Best	3.35	3.35	3.42	3.35	3.35	3.35	3.35	3.35	3.37
		Run Time	1.44	0.16	2.62	0.04	0.04	0.04	0.10	0.74	0.06
1mm	R_a	Mean	0.03	0.03	0.16	0.03	0.11	0.21	0.03	0.03	0.03
		S.D.	0.00	0.00	0.00	0.01	0.02	0.00	0.01	0.00	0.00
		Best	0.03	0.03	0.15	0.03	0.06	0.21	0.03	0.03	0.03
		Run Time	1.78	0.39	2.76	0.06	0.05	0.06	0.11	0.98	0.06
	M_t	Mean	3.23	3.23	3.47	3.23	3.23	3.23	3.23	3.23	3.58
		S.D.	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.15
		Best	3.23	3.23	3.44	3.23	3.23	3.23	3.23	3.23	3.36
		Run Time	1.72	0.37	2.77	0.05	0.06	0.05	0.10	1.07	0.06



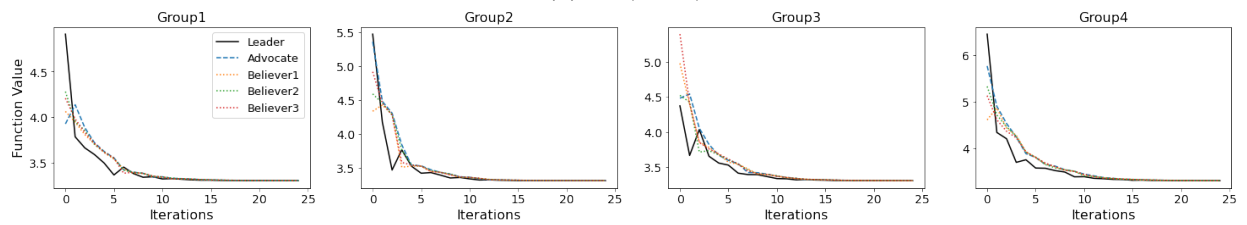
(a) $R_a(0.7mm)$



(b) $M_t(0.7mm)$



(c) $R_a(1mm)$



(d) $M_t(1mm)$

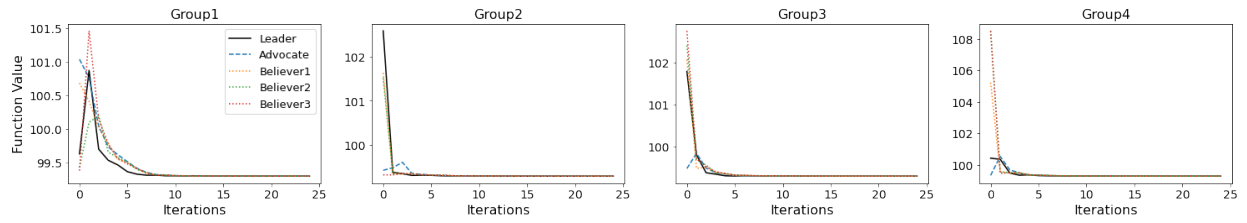
Figure 11: Convergence: Micro-Milling

Table 11 Solutions to Micro-Drilling processes

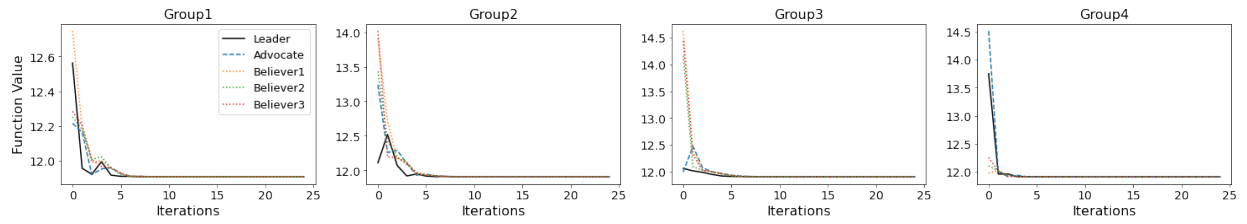
Cutter Diameter	Objective Function	Algorithms Applied									
		GA	Multi-CI	SA	Variations of CI				PSO	LAB	
					roulette wheel	fbest	fbetter	alienation			
0.5mm	B_h	Mean	99.29	99.29	134.13	99.29	99.29	99.29	99.29	99.29	99.29
		S.D.	0.00	0.00	1.30	0.00	0.00	0.00	0.00	0.00	0.00
		Best	99.29	99.29	131.79	99.29	99.29	99.29	99.29	99.29	99.29
		Run Time	1.47	0.14	2.60	0.04	0.04	0.04	0.08	1.14	0.06
	B_t	Mean	11.91	11.91	21.13	11.91	11.91	11.91	11.91	11.90	11.91
		S.D.	0.00	0.00	1.22	0.00	0.00	0.00	0.00	0.00	0.01
		Best	11.91	11.91	18.14	11.91	11.91	11.91	11.91	11.90	11.90
		Run Time	1.43	0.15	2.62	0.04	0.04	0.04	0.08	0.87	0.06
0.6mm	B_h	Mean	74.83	74.81	75.30	74.81	74.81	74.81	74.81	74.81	74.81
		S.D.	0.04	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00
		Best	74.81	74.81	74.91	74.81	74.81	74.81	74.81	74.81	74.81
		Run Time	1.62	0.14	2.65	0.04	0.04	0.04	0.08	0.76	0.06
	B_t	Mean	21.25	21.25	22.65	21.25	21.25	21.25	21.25	21.25	21.32
		S.D.	0.01	0.00	1.91	0.00	0.00	0.00	0.00	0.00	0.03
		Best	21.25	21.25	21.25	21.25	21.25	21.25	21.25	21.25	21.26
		Run Time	1.64	0.14	2.66	0.04	0.04	0.05	0.01	1.23	0.06

Table 11 Continued

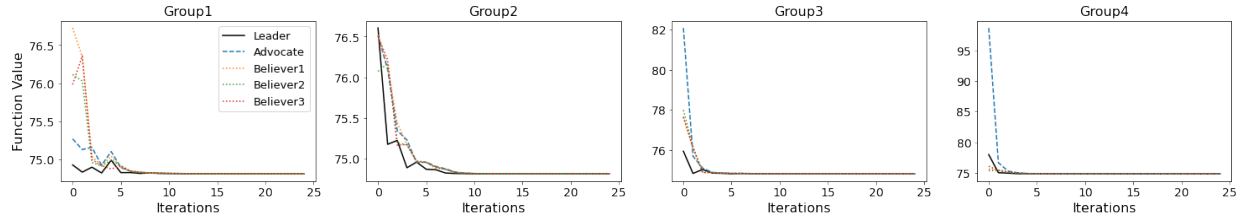
Cutter Diameter	Objective Function	Algorithms Applied								
		GA	Multi-CI	SA	Variations of CI				PSO	LAB
					roulette wheel	fbest	fbetter	alienation		
0.8mm	B_h Mean	235.78	235.74	235.73	235.74	235.74	235.74	235.74	235.74	255.56
	S.D.	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.83
	Best	235.74	235.74	235.73	235.74	235.74	235.74	235.74	235.74	238.70
	Run Time	1.73	0.17	2.67	0.06	0.05	0.06	0.12	1.34	0.06
	B_t Mean	26.64	26.64	32.90	26.64	26.64	26.64	26.64	26.64	26.63
	S.D.	0.00	0.00	0.6	0.00	0.00	0.00	0.00	0.00	0.00
	Best	26.64	26.64	31.70	26.64	26.64	26.64	26.64	26.64	26.63
	Run Time	1.68	0.16	2.71	0.035	0.036	0.04	0.076	0.88	0.07
0.9mm	B_h Mean	305.07	305.07	305.07	305.07	305.07	305.07	305.07	307.74	305.07
	S.D.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.46	0.01
	Best	305.07	305.07	305.07	305.07	305.07	305.07	305.07	305.39	305.07
	Run Time	1.42	0.08	1.12	0.04	0.03	0.03	0.07	2.60	0.06
	B_t Mean	41.89	41.89	41.89	41.89	41.89	41.89	41.89	43.09	41.89
	S.D.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00
	Best	41.89	41.89	41.89	41.89	41.89	41.89	41.89	43.01	41.89
	Run Time	1.47	0.10	0.96	0.04	0.03	0.04	0.07	2.64	0.07



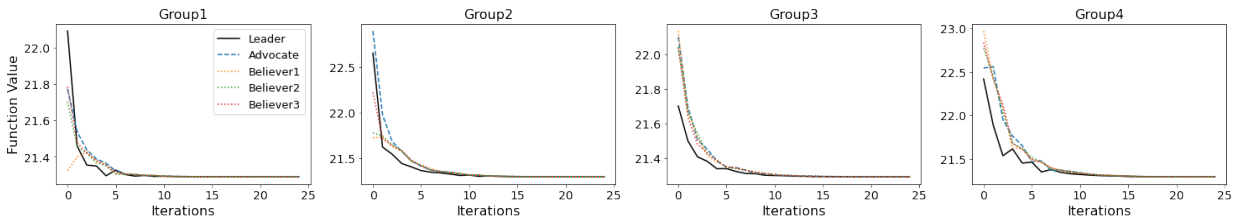
(a) $B_h(0.5mm)$



(b) $B_t(0.5mm)$



(c) $B_h(0.6mm)$



(d) $B_t(0.6mm)$

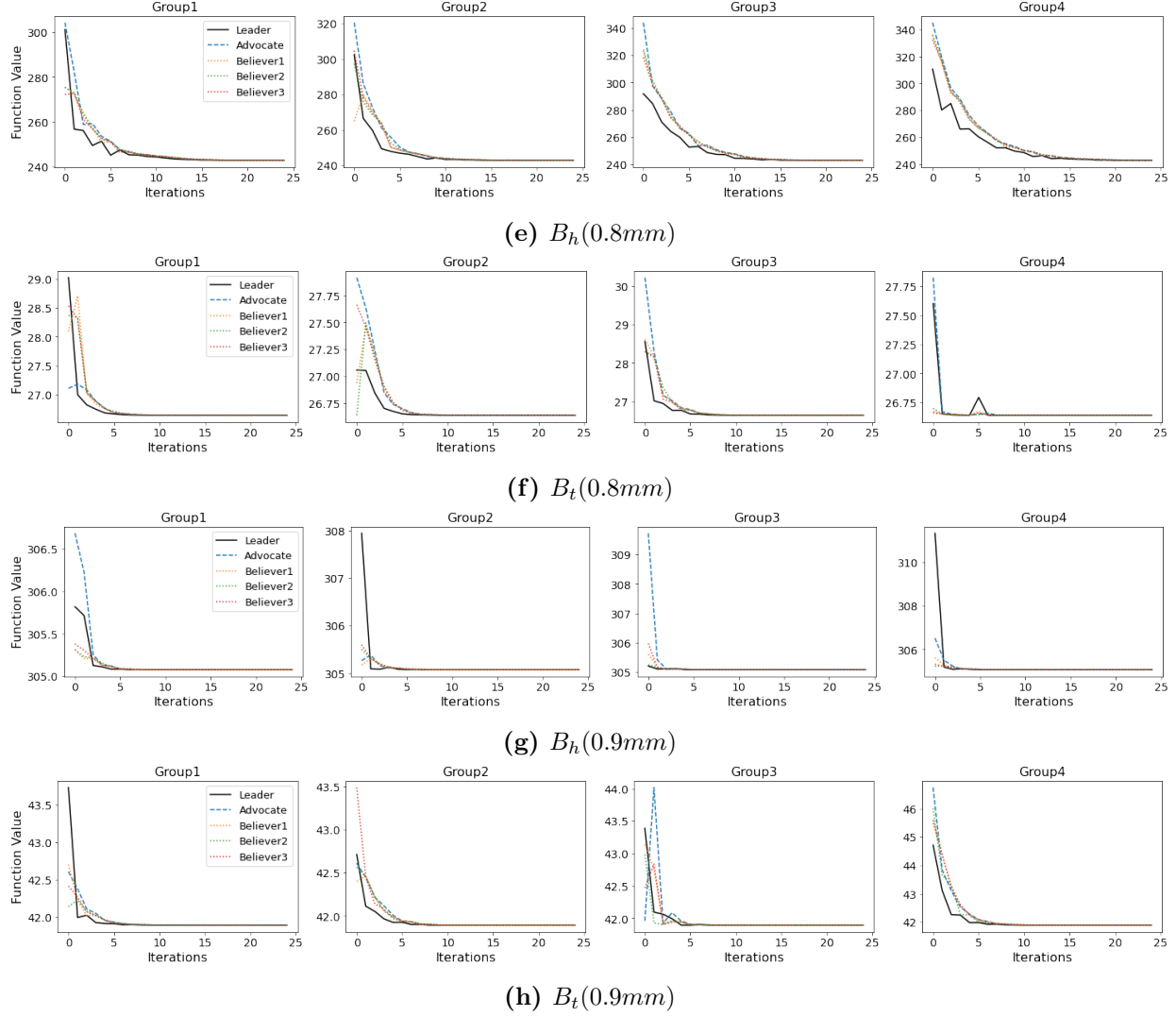


Figure 12: Convergence: Micro-Drilling

The LAB solutions exhibited higher standard deviation for micro-turning (Table 9), micro-drilling (Table 10) and micro-milling (Table 11) problems, for convergence plots refer to Fig. 10, 11 and 12, respectively. This is because the individuals in LAB are updated at every iteration after computing individual search directions, to simultaneously obtain updated solutions and rankings. This iterative individual updating process after computing individual search direction i.e local ranking as well as global ranking, thus resulting less robustness and higher standard deviation.

When compared with other algorithms for solving micro-machining problems LAB resulted in lower run time as compared to other algorithms but showed less robustness. However, LAB outperformed SA, f_{best} and f_{better} by achieving 76%, 85% and 75% minimization of R_a respectively for micro-milling with 0.7 mm tool diameter. LAB achieved 81%, 72%, 85% minimization of R_a when compared to SA, f_{best} and f_{better} for 1 mm tool diameter. LAB also achieved 24% and 34% minimization of B_h and B_t as compared to SA for micro-drilling with tool diameter 0.5 mm. For tool diameter 0.8 mm and 0.9 mm, 16% and 3% minimization of B_t , respectively, were achieved as compared to SA (exhibited in Tables 9, 10, 11).

4.4 Solution to Turning of Titanium Alloy

Table 12 includes best solutions obtained for Cutting Force F_c , Tool Wear V_{Bmax} , Tool Chip Contact Length L and Surface Roughness R_a produced by variations of CI, Multi-CI and LAB with their corresponding mean solutions, standard deviation and run time. Table 13 contains additional comparison of solutions by algorithms namely experimental work, desirability approach and PSO. In Table 14 optimum values yielded by variations of CI, Multi-CI and LAB for cutting speed V_c , feed f and the tool angle ϕ are shown. The algorithm needs more balanced exploration and exploitation abilities to find global optimum solution as it is quite evident from Eq. 20 it is inseparable, multimodal and nonlinear in nature. Plots in Fig.13a, 13b, 13c and 13d represent the best solutions of LAB for cutting force F_c , tool wear V_{Bmax} , tool-chip contact length L and surface roughness R_a respectively. Efforts of the individuals in climbing up the rankings by competing to be the best are evident in Fig. 13.

Table 12 Comparison of statistical solutions for Turning in MQL environment

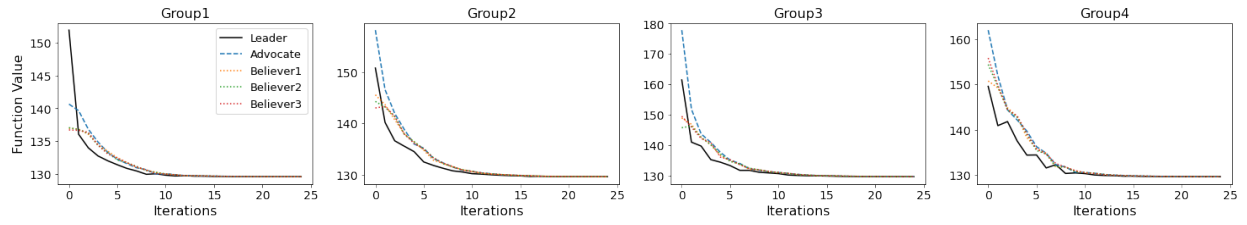
Objective Function		Multi-CI	Variations of CI				LAB
			Follow best	Roulette wheel	Alienation	Follow better	
F_c	Mean	122.23	122.35	122.34	122.27	122.24	145.18
	SD	0.01	2.95	0.05	0.01	0.00	7.20
	Best	122.23	122.24	122.28	122.25	122.24	129.80
	Runtime	0.64	0.27	0.32	1.07	0.57	0.09
V_{Bmax}	Mean	0.18	0.19	0.18	0.18	0.18	0.25
	SD	0.00	0.01	0.00	0.00	0.00	0.02
	Best	0.18	0.18	0.18	0.18	0.18	0.20
	Runtime	0.59	0.28	0.49	1.40	0.58	0.09
L	Mean	0.49	0.49	0.49	0.49	0.49	0.52
	SD	0.00	0.00	0.00	0.00	0.00	0.02
	Best	0.49	0.49	0.49	0.49	0.49	0.48
	Runtime	0.57	0.27	0.32	1.17	0.57	0.09
R_a	Mean	0.46	0.46	0.46	0.46	0.46	0.55
	SD	0.00	0.00	0.00	0.00	0.00	0.02
	Best	0.45	0.46	0.45	0.45	0.45	0.50
	Runtime	0.58	0.27	0.54	1.32	0.58	0.09

Table 13 Comparison of algorithms

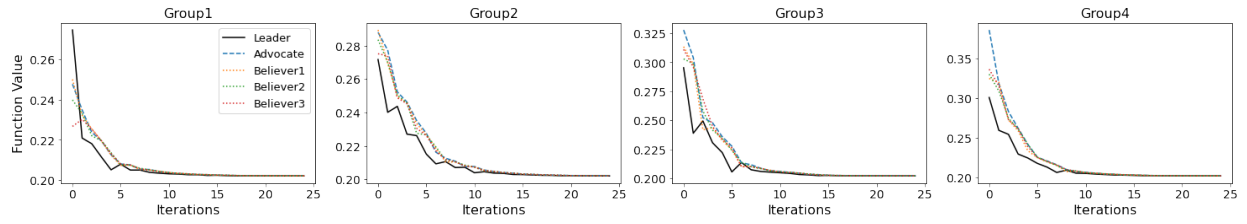
Objective Function	Multi-CI	Desirability	Roulette Wheel	PSO	Follow Best	Experimental	Follow Better	Alienation	LAB
F_c	122.23	138.68	122.28	132.52	122.24	133.45	122.24	122.25	145.18
V_b	0.18	0.38	0.18	0.31	0.18	0.34	0.18	0.18	0.25
L	0.49	0.853	0.49	0.793	0.49	0.811	0.49	0.49	0.52
R_a	0.45	0.60	0.45	0.53	0.46	0.56	0.45	0.45	0.55

Table 14 Comparison of optimum values for the solutions of V_c , f , and ϕ

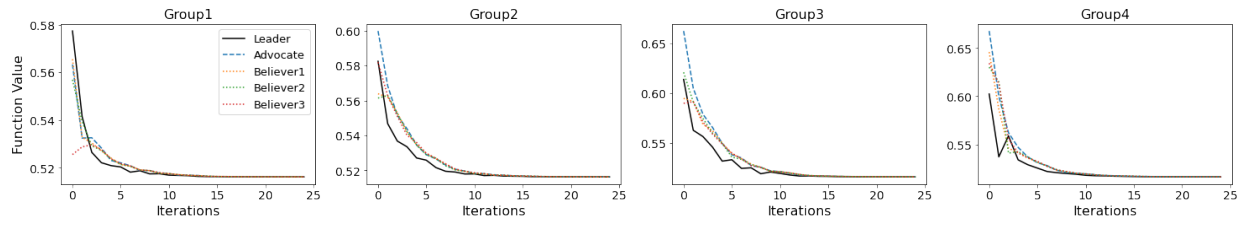
Function	Multi-CI	Variations of CI				LAB
		Fbest	Alienation	Fbetter	Roulette wheel	
F_c	k_1	200	200	200	200.10	200.98
	k_2	0.1	0.1	0.1	0.1	0.1
	k_3	89.99	89.99	89.99	89.99	86.41
V_{Bmax}	k_1	200	200	200.00	200.00	201.79
	k_2	0.1	0.1	0.1	0.1	0.1
	k_3	89.99	89.99	89.99	89.99	71.15
L	k_1	300	300	300	299.99	293.64
	k_2	0.1	0.1	0.1	0.1	0.1
	k_3	60.02	60.01	60	60.07	61.11
R_a	k_1	200	200	200	200	237.10
	k_2	0.1	0.1	0.1	0.1	0.1
	k_3	83.02	83.12	83.71	83.71	84.08



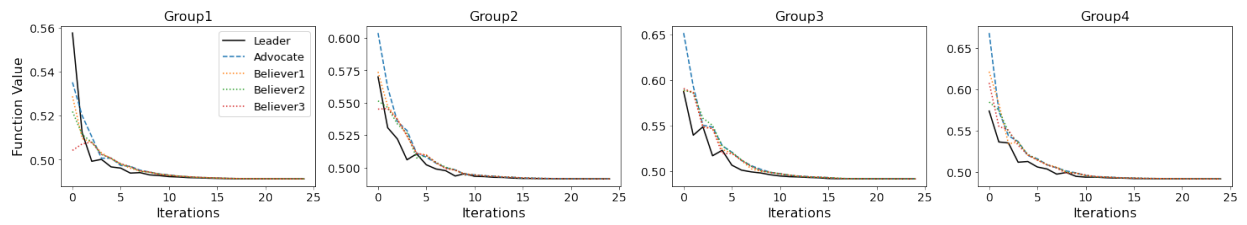
(a) F_C



(b) V_{Bmax}



(c) L



(d) R_a

Figure 13: Convergence Plots for optimal values of F_C, V_{Bmax}, L, R_a

5 Conclusions and future directions

In this manuscript, a novel socio-inspired algorithm is introduced, named the LAB algorithm, based on how individuals in a group with certain personality traits follow, make decisions and compete within the group in society. The proposed algorithm was examined by solving 27 benchmark test problems from CEC 2005 and a statistical comparison using Wilcoxon-signed rank test was conducted. LAB was able to perform slightly better when compared in terms of best solution, mean solution, robustness and computational time when compared to CMAES and IA and was able to outperform PSO2011, CMAES, ABC, JDE, CLPSO, and SADE in computational time. LAB demonstrated low robustness but exceedingly low computational time.

The algorithm was also validated by solving 23 real-world problems consisting of AWJM, EDM, Parameter tuning of turning titanium alloy and Advanced manufacturing processes problem to compare exploitation, exploration, computation cost and convergence rate with other well-known and recent algorithms: Experimental (Kechigas, 2012), Regression (Kechigas, 2012), FA, Variations of CI (roulette wheel, f_{best} , f_{better} , alienation), GA, SA, PSO, Multi-CI.

Problems for minimization of surface roughness R_a for AWJM, EDM and micro-machining processes namely micro-turning and micro-milling for Advanced Manufacturing Processes were solved. Minimization of burr thickness B_t and burr height B_h , relative electrode wear rate $REWR$ for EDM and taper angle $kerf$ for AWJM in micro-drilling was executed. In micro-turning process flank wear f_b and in micro-milling processes machining time M_t were minimized. Micro-drilling process utilized four drilling cutter diameters: $0.5mm$; $0.6mm$; $0.8mm$ and $0.9mm$. In the micro-milling processes, two cutter diameters: $0.7mm$ and $1mm$, were utilized. The results of LAB were then compared with multiple algorithms consisting of variations of CI, Multi-CI algorithm, experimental results and also with relatively modern algorithms such as SA, PSO, GA, BPNN, RSM and FA.

LAB was able to perform exceedingly well when compared to FA, SA, PSO, experimental results and solutions using regression for solving $kerf$ of AWJM problem in terms of solution quality. LAB results were comparable with GA and PSO for solving EDM and micro-machining problems. LAB was able to outperform variations of CI, regression, RSM, FA, SA, BPNN approaches in terms of solutions obtained. The run time of LAB is quite lower as compared to other algorithms for majority of the problems, because in LAB all the individuals simultaneously compete and interact with one another and individuals are updated at every iteration helps it gain more exploration and exploitation capabilities; however, it resulted in higher standard deviation which exhibited its low robustness.

Several enhancements can be done in the algorithm for better and faster computation in order to solve complex and higher dimension problems easily, by introducing a method of triggering the algorithm when stuck at local minima, which may help LAB solve a wider range of higher dimension complex real-life problems. Moreover, LAB algorithm can be modified to solve multi-objective problems making the competitive groups to handle different objectives.

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