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COMPARISON OF CHOSEN METAHEURISTIC ALGORITHMS FOR THE OPTIMIZATION OF THE ABRASIVE WATER JET TREATMENT PROCESS

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Abstract

Abrasive waterjet machining (AWJ) is characterized by significantly better efficiency and better precision for difficult-to-machine materials than conventional machining technologies. However, the larger number of control parameters characterizing this process needs optimization. The study compares the performance of three nature-inspired metaheuristic algorithms, ALO, GWO, and MFO for optimizing the abrasive water jet (AWJ) treatment. The Response Surface Methodology was used to determine the cost function. The study evaluates the convergence and computational cost of the algorithms to aid future developments in this field. The study aims to maximize the cutting thickness by predicting the optimal water-abrasive cutting parameters (nozzle diameter, abrasive concentration, feed speed). For all three algorithms, the maximum cutting depth was determined to be 87.47 mm, which differs only less than 3% from the actual value. The results highlight the potential of ant-lion optimization (ALO), grey wolf optimizer (GWO), and (MFO) moth-flame optimization algorithms for resolving optimization issues in AWJ machining.

Keywords:

meta-heuristic algorithms; ALO; GWO; MFO, Abrasive Water Jet; AWJ

1 INTRODUCTION

Conventional machining technologies are insufficiently effective to provide the necessary degree of performance and precision when cutting materials that are challenging to process. Abrasive Water Jet (AWJ) processing is a modern separation technology that has started to compete efficiently with standard methods of separating materials in recent years. This is primarily directly to its versatile nature, ensuing from the broad possibilities of machining various materials, including composite and multilayer materials [Szatkiewicz et al. 2023], as well as cutting out complex shapes with high-quality or carried out in extraordinary surroundings (fire risk, explosion hazard, possibility of use in work up to 6000 m underwater, etc.). It is a special, 'on cold condition' machining process. A coherent, high-velocity jet may be produced with a small-diameter nozzle at pressures of up to 600 MPa at speeds of up to 1000 m/s, and even over 1000 MPa in the special devices [Perec et al. 2021a]. These are the benefits of AWJ over other machining technologies: minimal machining forces, high flexibility, high machining adaptability, and lack of thermal deformations [Perec et al. 2021].

Because there are many more control parameters characterized the abrasive waterjet machining (AWJ) than ordinary separation techniques, it requires optimization. Advanced production processes are described by a lot of control factors that have a significant impact on their efficiency [Perec 2021], [Srivastava et al. 2019], [Madić et al. 2024]. AWJ cutting process is widely used in numerous industries [Perec, Kawecka, et al. 2023], due to its ability to cut hard [Perec et al. 2022], [Radomska-Zalas 2023a], and thick materials with high quality [Valicek et al. 2007], [Hreha et al. 2014 Optimization of the cutting control factors like nozzle diameter, garnet concentration, and traverse speed is crucial to achieving efficient and effective cutting [Kawecka 2023], [Perec 2023], [Radomska-Zalas 2023b]. An optimization algorithm finds the best solution [Perec and Musial 2021] among possible solutions to a given issue. Finding the best settings to achieve maximization or minimization of a given cost function is the aim [Kawecka et al. 2024]. Optimization algorithms are used to search for optimal answers to challenging issues by iteratively exploring the solution space and selecting the best option among multiple possibilities. An optimization problem involves finding the input variables that satisfy a set of constraints while minimizing a given objective function. The constraints specify the allowable values for the variables, while the objective cost function evaluates the quality or performance of the solution. Single-criteria optimization consists of minimizing or maximizing a previously defined objective function, subject to various constraints, equality, and inequality constraints. Solving the optimization problem consists of finding the best (lowest or highest) value of a given objective function for a variable $f(x)$ $x = [x_1, x_1, \ldots, x_D]$ with the following restrictions:

$$L_i \leq x_i \leq U_i, \tag{1}$$

$$i = 1, 2, \ldots, D, \tag{2}$$

where:

D – the size of the solution search space,

x – decision variable defining the space of solutions

$[L_i, U_i]$ – boundaries of search areas of – this size i.

Optimization methods can be broadly categorized into exact [Radomska-Zalas 2024] and metaheuristic methods [Rawicki and Podhajecki 2024]. Exact methods, such as dynamic programming, constraint programming, A* search, and branch and bound, aim to obtain the optimal answer by exploring the solution space.

In comparison to gradient optimization methods, for example (Newton's method), metaheuristic algorithms use stochastic methods. Metaheuristic optimization algorithms are also divided into two parts: local search-based optimization methods (single candidate solution) and population-based optimization methods (multiple solutions). Local search-based optimization methods operate with a single answer and try to increase a single answer using a 'neighborhood' mechanism, such as simulated annealing and hill-climbing methods [Jaddi and Abdullah 2020], [Morales-Castañeda et al. 2019].

The main advantage of these optimization techniques, therefore, is faster exploration. In contrast, the main drawback is their focus on exploration (global search) rather than exploitation (local search) search, resulting in an increased probability of local optimum trapping. The meta-heuristic algorithms are classified based on different inspirations in four classes [Rajakumar et al. 2016]: Evolutionary Algorithm (EA), Physics Based Algorithm (PhA), Human Based Algorithm (HBA), and Swarm Intelligence (SI) algorithm.

The phenomenon of evolution in nature inspires the evolutionary algorithms [Michalak 2015], [Ganovska et al. 2016]. An initial random solution evolved to undertake optimization. A new population is generated by the combining and mutation of individuals from the preceding generation. The newly created individuals have a higher probability of forming a new population, which should be better than the initial and previous generations. Over some generations, the initial random population will be optimized.

Algorithms based on physics are motivated by physical phenomena in the surroundings but not by living organisms. They were created by imitating some physics and chemistry laws and transforming them into mathematical and computational models. There were few references to the usage of these routines in manufacturing. In the future research works can be carried out to use these algorithms in the field of manufacturing.

Human-based algorithms were put out, drawing inspiration from the social behaviors of people [Bai et al. 2023].

Swarm intelligence is a soft biomimetic of natural swarms, i.e. it imitates the collective organizations and interactions of the swarm rather than the particular structure in usual artificial intelligence [Shah et al. 2016]. An example of a swarm intelligence population-based method is Teaching Learning Based Optimization (TLBO) introduced by Rao et al., [Rao et al. 2011] uses the impact of a teacher on learners. This algorithm belongs to the population-based group, and the method advances to the global solution by using a population of solutions.

Other examples of swarm-based optimization methods (algorithms) are Ant Lion Optimization Algorithm (ALO), Gray Wolf Optimizer Algorithm (GWO), Moth-Flame Optimization Algorithm (MFO), Bat Algorithm (BA), Artificial Bee Colony Algorithm (ABC), Krill Herd Algorithm (KH) and Cuckoo Search Algorithm (CSA). The ant lion optimization algorithm tries to reflect the behavior of ants in their life cycle, which consists of two periods: larval and adult. The grey wolf algorithm exploits the behavior and hierarchy of the grey wolf. The month flame algorithm utilizes a swarm of months circulating to the flame.

In the exploration of the global best (near-optimal) answer, meta-heuristic algorithms require numerous fitness evaluations [Gad 2022].

Process control variables including water pressure, abrasive flow rate, traverse speed, and standoff distance have a big impact on the effectiveness of AWJ machining. Optimizing these parameters is crucial to improving cutting performance and efficiency. Meta-heuristic algorithms like Grey Wolf Optimizer (GWO), Ant Lion Optimizer (ALO), and Moth Flame Optimization (MFO) are used in process parameter optimization on account of their high potential to look for close to optimal answers in elaborate search areas.

Okokpujie et al., [Okokpujie and Tartibu 2023] demonstrated a single optimization problem solved to separately optimize the cutting force and surface roughness using an optimizer using the Ant lion algorithm. A multi-criteria optimization problem was also solved using the metaheuristic Ant lion algorithm which was applied to obtain non-dominated or Pareto optimal solutions.

Rajamani et al., compared MFO with additional algorithms and found it superior in conditions of speed alignment and answer quality. for AWJM applications The optimal performance of AWJC was derived by using a moth flame optimization (MFO) metaheuristic algorithm to increase the quality of treatment. The performance of MFO was also compared with other algorithms like the genetic algorithm, particle swarm algorithm, dragonfly algorithm, and gray wolf algorithm. MFO was identified to have better results in conditions of the most important efficiency parameters, including fast convergence, diversity, spacing, and hyper-volume values, among the compared algorithms [Rajamani et al. 2023].

Chakraborty et al. [Chakraborty and Mitra 2018] used the Grey Wolf Optimizer (GWO), to optimize the AWJM process minimizing the kerf inclination angle and maximizing the target removal degree using GWO particle swarm optimization (PSO), genetic algorithm (GA), and simulated annealing (SA). The results demonstrate that the GWO algorithm is better than the other algorithms in conditions of convergence rate, computational effectiveness, and precision.

Overall, the literature review indicates that nature-inspired metaheuristic algorithms can effectively optimize the water-abrasive cutting process parameters. The purpose of research is to fill up this gap by comparing three recently proposed metaheuristic techniques, namely ant lion optimization (ALO), grey wolf optimizer (GWO), and (MFO) Moth-flame optimization algorithm evaluating their performance in optimizing the process parameters of water-jetting processes.

These algorithms were chosen because of their unique search processes, which successfully strike an equilibrium between the search area's investigating and exploiting, the potential to locate global solutions, and the avoidance of early convergence. Furthermore, they demonstrate various methods: ALO emulates lion ant predation, GWO simulates grey wolf hunting, and MFO mimics moth navigability. Additionally, these algorithms were chosen to compare how well they will work for the water jet cutting process optimization problem.

2 MATERIALS AND METHODS

2.1 Cutting material

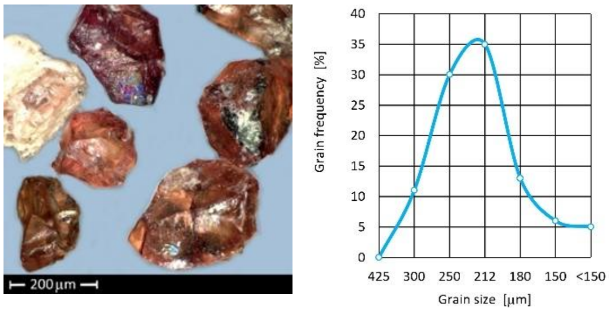
Marble was selected as the target for cutting. It is a heterogeneous rock material whose features vary depending on its origin. Marble is a crystalline rock, with calcite grains making up the majority. This rock was initiated as a result of the limestone conversion. Marble is a worthy material for ornamental and construction purposes. It is frequently applied for sculpting, as a structural material, and for different other building purposes. Marble appears in a diversity of hues: white, cream, red, and gray. The rock utilized in the research comes from the Nanutarra White Marble Quarry, Western Australia. This rock is durable, attractive, and has high luster. The ensuing characteristics are density: 2730 kg/dm^3, compression strength: 45 - 48 MPa, hardness: 7 (Mohs).

2.2 Abrasive material

In this test, almandine garnet was used as the abrasive. Due to its unique properties, it is widely applied as an abrasive material [Młynarczuk et al. 2014]. Very good properties, i.e. characterize it:

- Hardness of 7 to 8 on the Mohs scale, making it efficient in abrasive applications.
- High resistance to high-speed impacts without cracking.
- Low dust generation: Garnet produces minimal dust during abrasive processes.
- High recycling potential, which enables the recovery of grains after processing up to five times.
- Chemically inert and does not react with most materials, ensuring the ability to tool a broad scope of materials.

J80A garnet was utilized in the research. This abrasive comes from the Jinhong Mining deposit, in China. Its detailed properties are presented in Tab. 1. Its grain forms and distribution are shown in Fig. 1.



a) b)

Fig. 1. Garnet J80A grains: a) forms, b) size distribution

Tab. 1: Chosen characteristic of J80A abrasive.

Mineral Content [%]						
Amandine	Ilmenite	Omphacite	Rutile	Quartz	Hornblende	Free Silica
90-96	1.0	1.5	0.6	<0.1	<0.5	<0.5%
Chemical Composition [%]						
`Fe_2O_3	SiO_2	Al_2O_3	FeO	CaO	MgO	MnO
17	39	21	8	9.5	5	0.4

2.3 Meta-heuristic algorithms

In this paper, for the optimization problem parameters of the AWJ cutting process, the ALO, GWO, and MFO were used. In meta-heuristic algorithms, the process of finding a solution is divided into two parts: exploration and exploitation. The exploration phase addresses the process of exploring the area of the search space as widely as possible. The algorithm for this phase requires stochastic operators to search the space randomly and globally. The exploitation is the process of finding local maxima around the solution space in the surroundings of the local optimal values obtained in the exploration phase.

All metaheuristic algorithms have specific control parameters, such as the annealing temperature in the simulated annealing algorithm, the update of the pheromone level as a parameter in the ant algorithm, and the mutation rate in the genetic algorithm. These parameters are required to be properly tuned to achieve effective optimization. In general, it is essential to fine-tune the control parameters by a trial-and-error method in every optimization problem.

The objective function, characterizing the abrasive water jet cutting process, was established using the Response Surface Methodology (RSM). [Fajdek-Bieda et al. 2021].

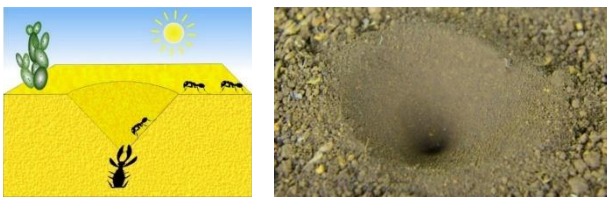
Population-based metaheuristic algorithms start by selecting a fixed number of search agents, and then randomly generating their initial positions in the exploration area. These algorithms then explore the search space by updating the locations of the search agents based on their cost function values [Kawecka 2024].

For example, in Ant Lion Optimizer [Mirjalili 2015a] and other metaheuristic algorithms based on certain populations, like Grey Wolf Optimizer [Mirjalili et al. 2014], and Moth-Flame Algorithm [Kawecka and Puzio 2024], the initial population is determined by the number of objects as grey wolves, ant lions, or moth-flames, respectively [Mirjalili 2015b], [Gupta et al. 2015].

Ant Lion Optimization Algorithm

Ant Lion Optimization algorithm is a nature-inspired meta-heuristic algorithm that uses two populations [Kawecka 2024]. The first population is ants, and the second population is ant lions. Ant lions in their larval form hunt ants by digging holes in the sand in a desert area (Fig. 2a). This can cause an ant to fall into the hole towards the center, where an ant lion is waiting to catch it. If an ant enters the trap, the ant lions try to get it down towards the center of the hole. (Fig. 2b).

The algorithm models the behavior of these two populations. The algorithm uses vectors and matrices to represent the ant lions and ants and their distance from each other. The ants are search agents used to find the optimal answer. By updating the positions of the ants to the highly ranked ant lions, based on the value of the cost function, the algorithm converges to the optimal answer.



a) b)

Fig. 2. a) Ant lion hunting schematic, b) Ant lion trap view

The ants are search agents, using random walking to explore the search area. A random walking of ants takes place in the area between the boundaries of the area occupied by the ant lions.

The ant lions represent solutions to the optimization problem. If an ant enters the trap, the ant lions try to get it down towards the center of the hole. (Fig. 2b).

In the algorithm, the highest-level ant lions are selected. The ant search paths are influenced by these selected best-ranking ant lions introducing elitism in the algorithm.

The ants and ant lions with the highest ranking are randomly chosen using a roulette wheel, and those with the highest ranking, are selected more frequently, with higher probability. Ants random search and selection of ant lions ensure finding the global minimum and avoids situations when algorithm stagnation in local optima.

The ant lion is steered towards the center of the ant trap by reducing the size of the hypersphere so that the ant can explore and search space around the trap. This is achieved by applying a ratio to the lower and upper bounds of the ant's orbit. As the algorithm runs over time, the area will decrease. In this way, we control the area of exploration of the search area that takes place.

Random ant walks in search space ensure a high level of solution space exploration. In addition, a random search of the search space by ants and a random selection of ant lions. The exploration of the search area is ensured by decreasing the intensity of random walking with time, ensuring the convergence of the algorithm. The algorithm can be implemented with various parameter settings to achieve optimal performance.

The number of ants (search agents) in the swarm, the dimensionality of the issue, the maximum number of iterations, and the algorithm's sorting and updating of ant positions during each iteration are some important variables that affect the ALO algorithm's computational complexity [Roeva et al. 2023]. The parameters of ALO algorithm are the number of ants (search agents) in the population, the maximum number of iterations, and the number of variables or dimensions in the optimization problem to solve.

Gray Wolf Optimization Algorithm

Grey Wolf Optimization (GWO) is a metaheuristic algorithm inspired by dominance order and the hunting procedure of grey wolves [Mirjalili et al. 2014]. Grey wolves have a hierarchical system in which wolves are ranked according to strength and power. All members of the pack have a specific rank, there are alpha, beta, delta, and omega wolves. GWO imitates the behavior of alpha, beta, and delta wolves in a pack, which coordinate and communicate to hunt their prey.

First in rank is the Alpha wolf stays at the top of the hierarchy and leads the pack. Second in the hierarchy is the beta wolf, his role is supporting the alfa wolf to maintain discipline in the pack. Last in the hierarchy is the omega wolf. The omega wolf is furthermore responsible for taking care of the younger wolves. The hunting strategy of a wolf pack involves the following stages. First is approach, tracking, and chasing the prey. The second one is to chase, harass, and circle the victim until it ceases to move. The third is attacking the prey when it is exhausted (Fig. 3).

Applying the wolf behavior to our optimization problem, each step of the algorithm evaluates the three appropriate solutions by alpha, beta, and delta, respectively, and the remaining solutions by omega. Essentially, this means that the optimization process follows the flow of the three appropriate solutions obtained so far. Finally, the prey will be the optimal solution of the optimization.

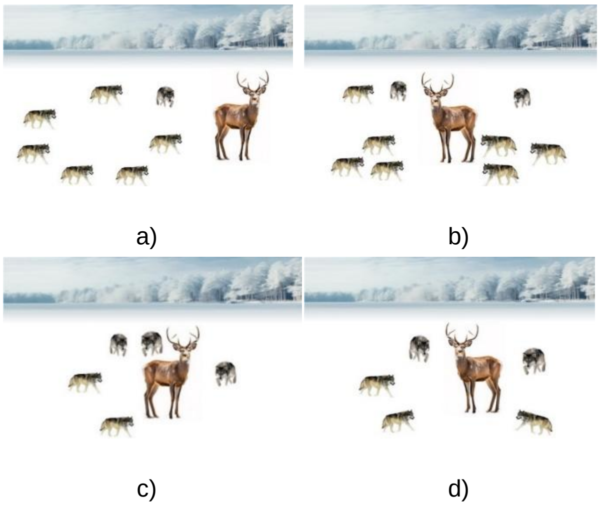


Fig. 3. Hunting procedure by grey wolves: a), b) pursue and track victim, c) encircling prey, d) attacking prey

There are two parameters of the algorithm. The first parameter of the algorithm, vector A, controls the trade-off between exploration and exploitation of the search area by changing values from 2 to 0 in successive iterations of the algorithm. The second parameter defined by vector C adds a component of randomness, necessary to ensure that search agents do not get stuck in the local minimum. Since we do not know the actual position of the optimal solution, the direction of the search and the update of the location of the search agents depend on the top three solutions. The position of the wolf will be updated according to the three best wolves from the previous iteration.

In a mathematical model reflecting the behavior of a wolf pack, the discrete positions of all individuals at successive time steps are determined.

The position of the i-th wolf in the j -th time step X_k^i is determined in the algorithm according to the relation:

$$X_k^i = X_{k-1}^p - A_k |C_k X_{k-1}^p - X_{k-1}^i| \quad (1)$$

where:
k- time step number, X_{k-1}^p- the position of the victim (optimal point) at the previous time step.

At each time step, the parameters A and C are calculated as follows:

$$A_k = 2a_k r_2 \ ,$$

$$C_k = a_k r_1 .$$

Where: r_1, r_2 - random numbers in the range (0, 1), a- coefficient determining the extent of movement of wolves in the search area of the optimization problem.

In the case of a large value of the parameter, a individuals can move in all the search areas of the task. However, in case a small value of the parameter a makes the optimal point searched for in the finest individual wolf's nearest environs. In the algorithm, the value of the parameter A is varied in the range [0, 2].

Based on the hunting techniques used by grey wolves the phase of encirclement of the potential prey), the algorithm assumes that the optimal point is between the best-adapted individuals in the pack, wolf α, β, γ.

To determine the position in the next iteration step for the *i*-th individual, the determination of the distance of this individual from the best individuals in the pack is used.

$$D^{\alpha} = \left|C_1 X^{\alpha}_{k-1} - X^{i}_{k-1}\right|,\ D^{\beta} = \left|C_1 X^{\beta}_{k-1} - X^{i}_{k-1}\right|, \tag{2}$$

The algorithm's time intricacy of the calculation is determined by on the number of iterations, the number of agents, and the size of the search area. During the search process, the position of each wolf is updated iteratively using a combination of exploration and exploitation strategies. The position of each wolf is defined and grounded on the locations of the alpha, beta, and delta wolves, considering a certain degree of randomness.

The location of the *i*-th wolf at succeeding time step X_k^i is determined by the algorithm according to the following equation:

$$X_k^i = \frac{X_1 + X_2 + X_3}{3} \tag{3}$$

where:

$$X_1 = X^{\alpha}_{k-1} - A^{\alpha}_k D^{\alpha},\ X_1 = X^{\beta}_{k-1} - A^{\beta}_k D^{\beta},\ X_1 = X^{\delta}_{k-1} - A^{\delta}_k D^{\delta} \tag{4}$$

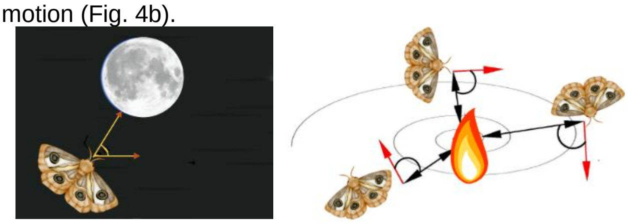
Additionally, the straightness, and ease of application of GWO make it an attractive optimization algorithm in different applications.

The computational intricacy of the GWO algorithm is determined by the number of wolves, the number of variables, the maximum iteration count, and the sorting procedure for wolves at each iteration. The most important parameters of GWO algorithm are the population size of wolves (N) (search agents) in the population, the maximum number of iterations, and the variables or dimensions of the optimizing problem [Alsheikh and Munassar 2023]. It controls the trade-off between exploration and exploitation.

Moth-Flame Optimization Algorithm

Moths fly around a light source at night, giving the impression that they want to get closer to the source light. The Moth Flame Optimization (MFO) algorithm is inspired by the natural world [Mirjalili 2015b]. The algorithm uses a spiral movement of the moths around the light source. Moths fly around a light source at night and moth behavior is a consequence of their natural navigation strategy used to fly in a straight line. The moth tries to keep the light source at a constant angle to itself. In the absence of unnatural light, this is usually the moon (Fig. 4a). When natural and artificial light sources are close the moths keep a constant angle to a closer light source which causes the moths to circle around the flame or lamp.

This is an algorithm based on the population that the moths represent, represented by a matrix. The best solutions obtained so far are represented by the flame matrix. The flames are points around which the search agents, i.e. the moth population, will circulate in a spiral motion (Fig. 4b).



a) b)

Fig. 4. a) Transverse orientation b) Spiral flying path around close light sources.

The moth and flame have an additional vector storing the values of the cost function. The moths fly around the best answer obtained so far, the flames and moths try to approach them using movement like a logarithmic spiral. The formula for this trajectory depends on the distance between the moth and the corresponding flame and it depends on user parameters and random variables which reduces the range of the spiral with time.

The paradigm of population-based metaheuristic optimization algorithms is to ensure a balance between the two phases of the algorithm, called exploration and exploration of the search area. If the number of flames were fixed during the running of the algorithm, this could lead to insufficient exploration of the best solutions obtained so far. To avoid this situation, the number of flames is changed and decreases with the duration of the algorithm. This provides the best solutions received from a total exploration of its area. Solutions to the optimization issue are found under the influence of the best solution (flames) on the search process performed by the population. The flames are the best answer received so far, ranked applied to the ranking of the cost function.

The maximum iteration level, the number of variables, the number of moths (search agents) in the population, and the sorting process for moths at each iteration all affect how computationally complicated the MFO algorithm is [Mirjalili 2015b].

The population size of moths (N), the maximum number of iterations, the number of variables or dimensions of the optimization problem, and the parameter logarithmic spiral constant, which defines the spiral's form and affects convergence behavior, are this algorithm's key parameters [Abderazek et al. 2020.

3 OPTIMIZATION OF THE AWJ CUTTING PROCESS

Abrasive water jet machining uses a high-pressure water jet and abrasive particles mixed in a special cutting head. The abrasive water jet thus created is directed towards the processed material. It is an advanced production technique because the process is characterized by many more control parameters than other machining processes using a traditional cutting tool (turning tool, milling cutter, or grinding wheel). It is necessary to evaluate the algorithm's speed and precision. This can be performed by considering the rate at which the fitness function is called, the running time of the algorithm, the number of iterations, and the speed at which the calculations are completed. Usually, a shorter duration is preferred.

The measurement of the time required to solve a problem of a certain size is one method of comparison of algorithms. This can help to identify which method is more effective in terms of computation time and running time. Moreover, the precision of each algorithm can be determined by counting the number of times the evolution function or the matching function is used during the implementation of the algorithm. Another essential element is the number of iterations needed to find an answer. Algorithms that are less likely to be iterative tend to be more accurate than iterative algorithms that require more iterations. By analyzing the results of each algorithm's answer, it is possible to assess how accurate the algorithm is. The algorithm's precision, however, can vary depending on the problem being solved. A simpler algorithm is often regarded as better. This is because the simpler algorithms are easier to understand and evaluate and may be less prone to implementing errors or other problems. Moreover, simpler algorithms often operate faster and use fewer computing resources, which can be a key factor in some applications. The number of parameters, the number of times a step is required, and the amount of computing resources required to execute an algorithm are major factors when it comes to comparing the two algorithms' complexity.

The results presented in the paper were obtained using the Simulink software, which is part of the MATLAB numerical package by MathWorks [A Matlab 2024]. With the program, users may simply way input the goal function, upper and lower boundaries for the variables, number of variables, maximum iterations, number of search agents, and number of variables [Mirjalili 2015a]. The specific settings suggested by the algorithm's developers were kept for each algorithm's particular parameters [Abderazek et al. 2020], presented in Tab. 2.

For analyzed topics, the input data and their ranges are as follows:

x_1 – the first parameter is water nozzle diameter in the range [0.25, 0.33],

x_2 – the second parameter is abrasive concentration [%], range [15, 22.5],

x_3 – the third parameter is traverse speed in the range [2.0, 6.0].

Tab. 2: Parameters of ALO, GWO and MFO algorithms

Name	Parameter	Value
ALO	*np* and t_{max}	[0, 1]
GWO	Parameter *a*	[2, 0]
MFO	Logarithmic spiral constant *b*	1

The cost function obtained using the RSM response surface method [Perec, Radomska-Zalas, et al. 2023], [Perec et al. 2024] has three variables and has the following form:

$$C = 13.7 - 663x_1 + 14.14x_2 - 3.06x_3 + 1499x_1^2 - 0.37x_2^2 - 0.38x_3^2 \quad (5)$$

The maximum value of the cutting depth corresponded to the cost function had the lowest value of -87.2856 was equal to x_1 = 0.33, x_2 = 19.3434, x_3 = 2.
Figure 5 shows a comparison of all three algorithms studied for the problem under consideration in the chart form of the impact of the number of iterations, and the number of search agents on the calculated value of the cost function. For the GWO and MFO algorithm for the number of search agents greater than m=10, all three solutions converge after just five iterations. The ALO algorithm requires more search agents to obtain a more accurate solution. For more search agents, the MFO algorithm converges to a solution just as fast as the GWO algorithm. However, the differences are not significant, and all algorithms work with sufficient accuracy and speed. Considering fewer iterations, the GWO algorithm is more accurate than the ALO algorithm. For the number of iterations greater than m=30, the results are identical. The extremum values for each algorithm are shown in Tab. 3.

Tab. 3: Comparison of extremum calculation effects.

Algorithm	Number of iterations	Nozzle Diameter [mm]	Abrasive Concentration [%]	Traverse Speed [m/s]	Cost function [mm]
ALO	100	0.33	19.3434	2	-87.47378
GWO	100	0.33	19.3425	2	-87.47376
MFO	100	0.33	19.3423	2	-87.47375

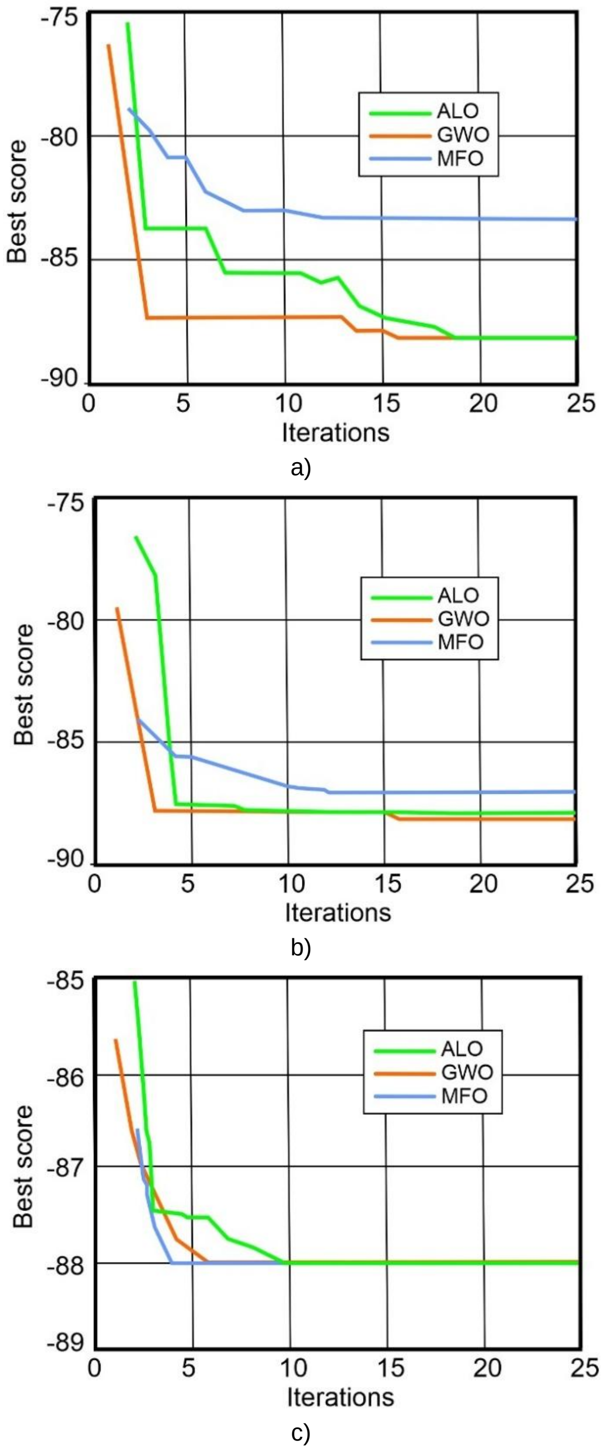


Fig. 5. The example results of influence iteration number on the cost function value for the following search agent numbers: a) m=5, b) m=10, c) m=30

4 CONCLUSIONS

It may be inferred from the comparison of the simulation results with the findings of earlier studies that the chosen algorithms have good efficiency in solving the problem of optimizing parameters for the process of cutting materials by abrasive water jet. The analysis of the results found the optimal set of control factors process to the achievement of higher cutting depth:

- water nozzle diameter: 0.33 mm,
- abrasive concentration: 19.34%,
- traverse speed: 2.0 mm/s.

The depth of the cut surface with such process parameters reaches the value of 87.47 mm. The accuracy of the algorithm ALO and GWO for the small number of agents is better in comparison to the MFO algorithm.

All considered algorithms achieved optimal cutting performance but differed in accuracy and convergence speed. The Grey Wolf Optimizer and Ant Lion Optimization outperform MFO in precision, especially with smaller agent populations. GWO offers the best trade-off between convergence speed and computational cost, performing well with fewer iterations and search agents. MFO performs similarly to GWO but requires fewer evaluations in some cases, making it computationally efficient. ALO has a higher computational cost due to slower convergence, but it excels in avoiding local optima with more search agents.

The calculations of the selected algorithms were considered by listing the function costs for each, examined by the data of the iteration step values. Grounded on the effects of the analysis, it can be determined that all selected algorithms pose a basis for individual effectiveness in the case study. All these algorithms are metaheuristic population-based, making it difficult for the algorithm to get stuck in a local optimum. Similar optimization results were achieved using other metaheuristic algorithms [Kawecka 2023].

All the used algorithms: the Ant Lion Optimization (ALO) algorithm, Gray Wolf Optimization (GWO), and Moth Flame Algorithm (MFO) are all good additions to optimization tools. The algorithm is simple to use due to the small number of factors that can be changed and to be tuned to obtain a good solution. The algorithm is also easy to understand and implement.

In future research, the integration of a constraint-handling technique is necessary with the optimizer to solve the limitations of the external penalty method (death penalty) used in the algorithm. Among the constraint-handling methods known from the literature [Mirjalili 2015a], the following are considered: hybrid approaches, repair algorithms, punishment functions, special operators, and the division of goals and restrictions.

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