Tribology and Materials
Vol. 3, No. 1, 2024, pp. 44-50

ISSN 2812-9717
https://doi.org/10.46793/tribomat.2024.004

# Swarm intelligence algorithms for optimising sliding wear of nanocomposites

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**Keywords**
swarm intelligence
sliding wear
nanocomposites
optimisation

**History**
Received: 14-01-2024
Revised: 24-03-2024
Accepted: 29-03-2024

**Abstract**

This paper presents simulation results obtained by a set of modern algorithms adhering to swarm intelligence for minimising wear rate in the case of A356/$Al_2O_3$ nanocomposites produced using a compocasting process. Grey wolf optimisation (GWO) algorithm, moth-flame optimisation (MFO) algorithm, dragonfly algorithm (DA) and whale optimisation algorithm (WOA) were the algorithms under examination. A full quadratic regression equation that predicts wear rate, as the optimisation objective by considering reinforcement content, sliding speed, normal load and reinforcement size as the independent process parameters, was utilised as the objective function. Simulation results obtained by the selected algorithms were quite promising in terms of fast convergence and global optimum result arrival, thus prompting to further investigation of applying swarm intelligence to general problem-solving aspects related to tribology.

## 1. Introduction

Metal matrix composites (MMCs) have been investigated over the years owing to their physical, mechanical and tribological properties compared to other engineering materials. Metallic materials like magnesium, zinc and aluminium are some of the materials applied to composites owing to their low density, lightweight, superior performance (i.e. hardness, strength and stiffness) and outstanding behaviour in real-world applications. Based on this concept, research has shown that significant improvements can be obtained referring to matrix materials when adding a relatively small amount of several elements as reinforcement [1-3]. Nevertheless, MMCs reinforced with ceramics have a major drawback; that of poor ductility. This shortcoming of MMCs is related to low yield that restricts their plastic deformation. Poor ductility is a result of hard yet brittle ceramic reinforcement phases and the undesired formation of micron-size reinforcements as these materials are processed. To compensate this drawback, inclusions of light metal matrix nanocomposites (MMnCs) have been tested by several researchers under varying amounts and sizes to reach the desired outcome and maintain adequate ductility [4-8].

Sekar et al. [9] examined the mechanical and tribological properties of A356 alloy reinforced with $Al_2O_3$ nanoparticles and $MoS_2$ microparticles. The authors maintained the percentage of $Al_2O_3$ at 1 wt. % whilst $MoS_2$ varied from 0.5 to 2 wt. % with an interval of 0.5 %. After conducting a series of tribological experiments they concluded that hybrid MMC containing 0.5 and 1 wt. % of $MoS_2$ and $Al_2O_3$ (1 wt. %) exhibited the highest flexural strength, reduced wear and friction coefficient. Li et al. [10] investigated the effect of in-situ γ-$Al_2O_3$ particles and heat treatment on the microstructure and mechanical properties of A356 alloy. Xu et al. [11] managed to fabricate the nanometer in-situ γ-$Al_2O_3$ particles reinforced aluminium matrix composites by the A356 aluminium alloy and $Co_3O_4$ powder at 850 °C using in-situ reaction in the high-temperature melt. Thereby the authors studied in detail the effects of γ-$Al_2O_3$ particles and cobalt element on the microstructure and properties of the composites. Several other contributions have adopted similar concepts towards the characterisation and reinforcement of MMCs and MMnCs using various reinforcement particles under aluminium matrices and different fabrication methods [12-17].

Experiments related to tribology are established by determining the settings for their process parameters as they occur in any engineering problem. Therefore, specifying the settings for parameters involved by means of intelligent optimisation methodologies constitutes a vital activity for reducing experimental costs and time-consuming operational efforts [18-20]. To this concept, several intelligent systems have been implemented to optimise tribological aspects. König et al. [21] monitored and classified the multi-variant wear behaviour of sliding bearings. They implemented acoustic emission (AE) to a test rig for sliding bearings. Signals obtained were evaluated with machine learning methods in order to detect anomalies from a hydrodynamic bearing operation. Thereby, a deep learning approach based on convolutional neural networks was adopted for multi-class classification into three different wear failure modes. Cavaleri et al. [22] implemented an artificial neural network (ANN) to predict the tribological performance of three highly alloyed tool steel grades. Their experiments involved plane-contact sliding tests under unlubricated conditions on a pin-on-disk tribometer. Wear maps generated via ANN modelling were quite promising in terms of the presentation of wear-related information as regards the determination of areas under steady-state wear. Sardar et al. [23] implemented an artificial neural network (ANN) and a genetic algorithm (GA), which were integrated to model tribological characteristics of stir-cast Al-Zn-Mg-Cu matrix composites under two-body abrasion considering large numbers of experimentally generated results. Tribological responses of wear rate, coefficient of friction and abraded surface roughness were assessed under a wide range of input parameters. Shabani et al. [24] conducted factor optimisation during the semi-solid processing of the nanocomposite with the A360 aluminium alloy matrix and TiC nanoparticles. An adaptive neuro-fuzzy inference system was applied to compute the problem's objective function which was finally minimised through the application of particle swarm optimisation (PSO) algorithm.

This paper investigates the performance of four modern swarm intelligence algorithms in minimising the mathematical relationship among the independent variables of normal load (N), sliding speed (m/s), reinforcement content (wt. %) and reinforcement size (nm) and the optimisation objective of wear rate ($mm^3$/m) in the case of A356/$Al_2O_3$ nanocomposites fabricated using the compocasting method. The four algorithms selected were the grey wolf optimisation (GWO) algorithm, moth-flame optimisation (MFO) algorithm, dragonfly algorithm (DA) and whale optimisation algorithm (WOA). As a fitness function for the antagonising algorithms tested, a full quadratic regression model previously developed [18] was selected. Competitiveness among these algorithms was based on indications such as minimum result, convergence rate and quality of convergence curve. The major scope is to implement the selected algorithms to optimisation problems related to tribology and assess their operational behaviour as well as their quality in optimisation performance. The algorithms are tested for the first time in the broader literature of tribology.

## 2. Design of experiments and objective function definition

To conduct the optimisation simulations for minimising wear in the case of A356/$Al_2O_3$ nanocomposites, the full quadratic regression equation presented in [18] was applied. Block-on-disk contact geometry was used with three different $Al_2O_3$ contents, namely 0.2, 0.3 and 0.5 wt. %. The sliding distance was set equal to 1000 m whereas the determined sliding speeds were 0.5 and 1.0 m/s. The experimental values for applied normal loads were 40 and 100 N. These levels for block-on-disk process parameters were assigned to a response surface experiment (RSM) to determine the number of experimental runs. Table 1 presents the experimental design and the results obtained; wear rate *WR* ($mm^3$/m) is the key objective whilst normal load *NL* (N), sliding speed *SS* (m/s), reinforcement content *RC* (wt. %) and reinforcement size *RS* (nm) were considered as the independent tribological parameters.

The optimisation problem formulated is focused on minimising the wear rate ($mm^3$/m) of A356/$Al_2O_3$ nanocomposites with respect to the boundaries determined by the original experimental design for all independent parameters presented in [18]. As an objective function for the problem, the full quadratic regression equation corresponding to the experimental design of Table 1 was considered. The regression model was examined for its validity and prediction quality through analysis of variance (ANOVA) and it was found to have a good correlation among experimental and predicted results. This was justified by the resulting indication for coefficient of determination $R^2$ that explains the overall variation of wear rate as a response ($R^2 = 95.31\ \%$). The model was also found to adhere to normal distribution when examining the residuals.

**Table 1.** Design of experiments and corresponding results for wear rate

| Process parameter | | | | Response objective |
|---|---|---|---|---|
| *NL*, N | *SS*, m/s | *RC*, wt. % | *RS*, nm | $WR \times 10^{-4}$, $mm^3/m$ |
| 40 | 0.25 | 0.2 | 30 | 1.088 |
| 40 | 0.25 | 0.2 | 100 | 0.506 |
| 40 | 0.25 | 0.3 | 30 | 0.970 |
| 40 | 0.25 | 0.3 | 100 | 0.450 |
| 40 | 0.25 | 0.5 | 30 | 0.914 |
| 40 | 0.25 | 0.5 | 100 | 0.345 |
| 40 | 1.00 | 0.2 | 30 | 0.533 |
| 40 | 1.00 | 0.2 | 100 | 0.320 |
| 40 | 1.00 | 0.3 | 30 | 0.228 |
| 40 | 1.00 | 0.3 | 100 | 0.036 |
| 40 | 1.00 | 0.5 | 30 | 0.089 |
| 40 | 1.00 | 0.5 | 100 | 0.003 |
| 100 | 0.25 | 0.2 | 30 | 3.404 |
| 100 | 0.25 | 0.2 | 100 | 1.123 |
| 100 | 0.25 | 0.3 | 30 | 2.530 |
| 100 | 0.25 | 0.3 | 100 | 0.783 |
| 100 | 0.25 | 0.5 | 30 | 2.165 |
| 100 | 0.25 | 0.5 | 100 | 0.689 |
| 100 | 1.00 | 0.2 | 30 | 0.844 |
| 100 | 1.00 | 0.2 | 100 | 0.711 |
| 100 | 1.00 | 0.3 | 30 | 0.623 |
| 100 | 1.00 | 0.3 | 100 | 0.095 |
| 100 | 1.00 | 0.5 | 30 | 0.542 |
| 100 | 1.00 | 0.5 | 100 | 0.013 |

## 3. Wear rate optimisation using swarm intelligence algorithms

Swarm intelligence algorithms mimic the social behaviour of natural species and have already been implemented in almost every scientific field related to engineering, manufacturing and general industrial problem-solving applications [25]. Noticeable swarm intelligence metaheuristics that have been recently developed and applied to several areas of engineering science are the grey wolf optimisation (GWO) algorithm [26], the moth-flame optimisation (MFO) algorithm [27], the dragonfly algorithm (DA) [28] and the wale optimisation algorithm (WOA) [29] among others. However, these algorithms are yet to be implemented for optimisation problems related to tribology. These algorithms exhibit different operational behaviour whilst each of them simulates the major physical aspects of living species considered as search agents.

In general swarm intelligence algorithms present essential benefits when applied to optimisation problems from the perspective that they manage to maintain information from the search domain over iterative evaluations and they do it so by handling fewer algorithm-related operators when compared to evolutionary algorithms. As a result, their implementation is facilitated when it comes to practical applications.

Grey wolf optimisation algorithm mimics the social behaviour of natural grey wolves. Emphasis is given to their strict leadership, social dominant hierarchy and pack hunting. Major algorithmic functions involve mathematical models that simulate discrete steps namely prey tracking, prey pursuing/encircling and finally attacking the prey. In computational terms, the leader grey wolf is considered the fittest solution or best score. Thereby, the next two grey wolves in the hierarchy (2nd and 3rd) play the role of best scores after the "optimal" one (fittest score). The rest of the hypothetical wolf pack plays the role of the rest of the solutions that follow the first three in the hierarchy. Finally, the hunting process (optimisation) is guided by the first three "optimal" values for a given problem until the maximum number of algorithmic iterations has been reached. The rest of the algorithmic functions involve operations related to the algorithm's exploration and exploitation capabilities (global and local search) [26]. Search agents (grey wolves) update their positions as the optimisation process evolves having the first three solutions as a reference.

Moth-flame optimisation algorithm considers natural moths as its search agents. Consequently, a problem's independent parameters are assumed to be the positions of moths in the search domain. Based on the problem's characteristics these positions are iteratively updated until the algorithm concludes the predetermined simulations. The best positions found by moths in each evaluation are represented by the flames. Flames can be assumed to be pins or flags dropped by moths while searching the solution domain [27]. Thus, each moth investigates a flag and updates it if a better solution than the current one has been found. This facilitates maintaining the best solution. A random population of moths is first created and then moths are moved towards the search domain. As the optimisation process evolves, the positions of moths are updated with regard to flames. The updating process referring to moths and flames facilitates the exploitation mechanism of the algorithm provided that a logarithmic spiral-type type of path will be programmed to maintain the major update mechanism.

Dragonfly algorithm simulates natural dragonflies as predators that hunt all other smaller insects found in the natural environment. Dragonflies exhibit a unique swarming behaviour owing to the need for hunting and migration. The former constitutes static behaviour whereas the latter constitutes dynamic behaviour [28]. Static swarm of dragonflies is characterised by its small groups and restricted search regions (local search). In addition, small dragonfly swarms may abruptly alter their flying path towards haunting by performing back-and-forth trajectories. In the case of dynamic dragonfly swarms, all dragonflies are prompted to migrate towards a new long-distance direction. Despite this noticeable difference between the two swarm behaviours, the exploration and exploitation phases are quite similar. Static swarms of dragonflies fly over several regions by formulating sub-swarms. This simulates exploration. On the contrary, dynamic swarms fly towards one direction in bigger swarms which facilitates exploitation. By determining the algorithm-related parameters of the dragonfly algorithm, a variety of different exploitative-explorative strategies can be programmed for problem-solving.

Whale optimisation algorithm simulates the social behaviour and prey-attacking mechanism of humpback whales [29]. The prey-attacking mechanism of humpback whales involves two discrete operations: the random search or best search referring to the simulated algorithm's agents and the implementation of a spiral-type path for representing the "bubble-net" attaching mechanism by humpback whales. The "bubble-net" attacking mechanism constitutes a foraging technique with two approaches: upward-spiral bubbled paths and double-loops. Further mathematical modelling and algorithmic development refer to the operators for "prey encircling", "bubble-net" attacking (exploitation phase) and prey searching (exploration phase). The development of the whale optimisation algorithm is based on vectors and closed intervals to represent search agents and current positions towards the higher scope of finding the global optimal solution. The algorithm switches between the exploration and exploitation phases by using a probability according to the problem's technical nature and particularities. Further aspects and development attributes concerning the detailed description of WOA can be found in [29].

## 4. Results and discussion

The optimisation problem formulated in this paper has been based on the experimental design and corresponding results presented in [18] as regards the wear rate ($mm^3/m$) in the case of $A356/Al_2O_3$ nanocomposites. Process parameters as well as their upper and lower bounds were determined the same as those presented in [18]. Thus reinforcement content $RC$ (wt. %), sliding speed $SS$ (m/s), normal load $NL$ (N) and reinforcement size $RS$ (nm), are the independent parameters whilst wear rate $WR$ ($mm^3/m$) is considered as the objective to be minimised. Based on the original full quadratic regression model presented, the objective function for the four algorithms tested is expressed by Equation (1).

$$\begin{aligned}\min WR &= 0.1873 - 0.761 \cdot RC - 0.1204 \cdot SS + \\ &+ 0.004052 \cdot NL - 0.001101 \cdot RS + 0.973 \cdot RC^2 + \\ &+ 0.030 \cdot RC \cdot SS - 0.00197 \cdot RC \cdot NL + \\ &+ 0.00064 \cdot RC \cdot RS - 0.001778 \cdot SS \cdot NL + \\ &+ 0.001744 \cdot SS \cdot RS - 0.000018 \cdot NL \cdot RS. \end{aligned} \tag{1}$$

The bounds for independent parameters are presented as follows:

$$0.2 \le RC \le 0.5, \tag{2}$$

$$0.25 \le SS \le 1.0, \tag{3}$$

$$40 \le NL \le 100, \tag{4}$$

$$30 \le RS \le 100. \tag{5}$$

To provide a rigorous comparison among the four algorithms tested in this paper as well as the original results reported in [18], algorithm-related parameters were properly determined to match the original settings of algorithm-related parameters. The number of search agents in all algorithms was set to 10 and the maximum number of iterations was set to 100. It should be mentioned that the number of iterations is of high importance when it comes to algorithmic simulations since it affects the overall performance. The number of iterations establishes the algorithm's termination criterion and influences the ability to track beneficial (optimal) solution regions within a search space. As expected, an increased number of iterations will lead to an increased simulation time and thus computational cost. Consequently, the settings of algorithm-specific parameters (including the number of iterations) are of paramount importance for achieving a fast convergence rate (reduced number of iterations needed), increasing computational efficiency and ensuring the quality of proposed optimal solutions.

All four algorithms tested, needed less than 10 seconds to complete the simulations. Simulations were performed in an Intel® core™ i3-4160 CPU 3.60 GHz 8GB RAM 64bit operating system. The algorithms were coded in MATLAB environment [26-29]. The resulting convergence curves obtained by GWO, MFO, DA and WOA algorithms are summoned and presented in Figure 1.

All algorithms managed to arrive at the lowest fitness score equal to – 0.132 based on the original regression model presented in [18]. Note that the result of – 0.132 refers to the lowest fitness score based on the regression model that plays the role of objective function and not to wear rate *WR* ($mm^3/m$). However, this result should correspond to positive values for independent process parameters that will deliver the lowest outcome for the wear rate. The best position for the lowest fitness score in terms of the independent process parameters corresponds to 0.44 wt. % for reinforcement content, 1.0 m/s for sliding speed, 100 N for normal load and 100 nm for reinforcement size. These are in agreement with the optimal values found in [18] by implementing genetic algorithm (GA) and particle-swarm optimisation (PSO). However, convergence curves differ in terms of the iteration number where the best fitness scores were obtained. GWO algorithm obtained its lowest fitness score in the 35th iteration, MFO in the 27th iteration, DA in the 52nd iteration and WOA in the 13th iteration. By observing the convergence evolution of the algorithms tested, it is noticeable that all of them stacked at local regions from where they rapidly managed to escape. By examining Figure 1 it is observed that most local regions are found in MFO and WOA algorithms. Compared to GWO, MFO and WOA algorithms DA algorithm exhibited the largest fitness score in the early stage of the fitness function evaluation process.

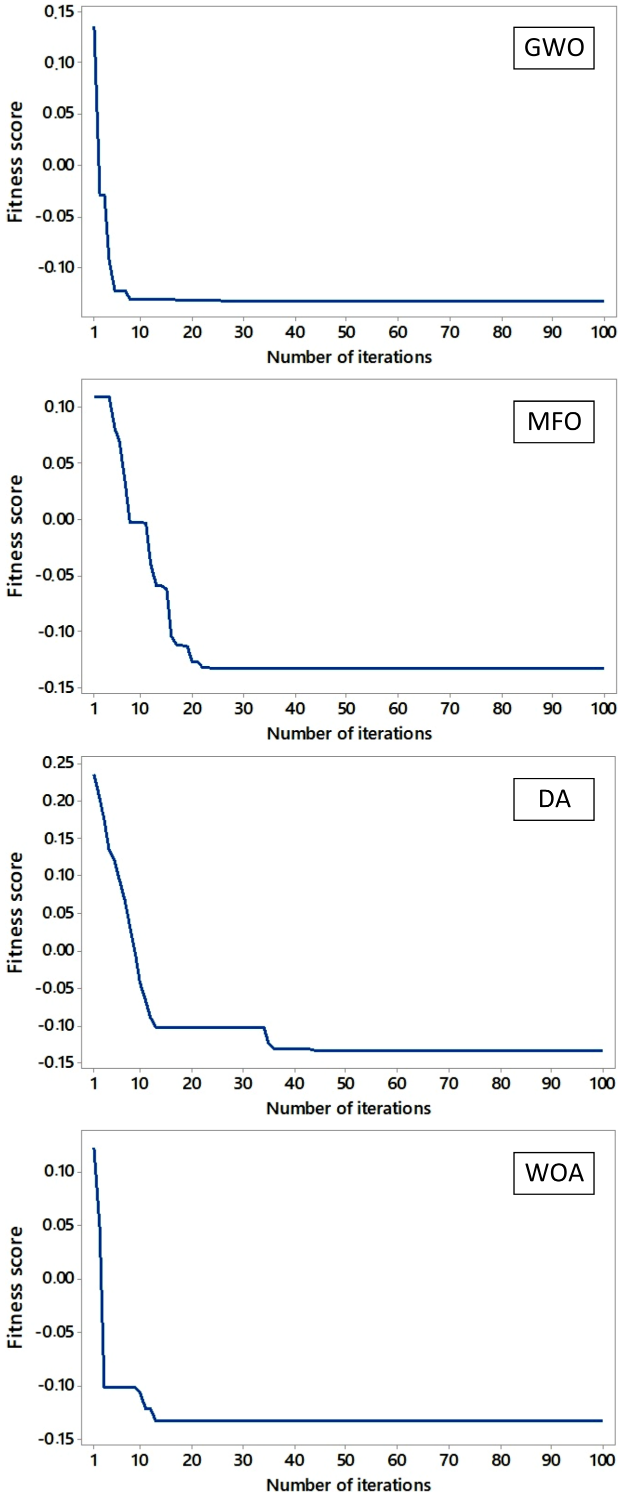


**Figure 1.** Convergence curves of algorithms for minimising wear rate ($mm^3/m$) of $A356/Al_2O_3$ nanocomposites

## 5. Conclusion

This paper examines the beneficial implementation of different swarm intelligence algorithms on minimising wear rate ($mm^3/m$) of $A356/Al_2O_3$ nanocomposites as a typical optimisation problem related to the scientific field of tribology. The problem's optimisation domain was adopted by selected research available in the literature. The optimisation problem examined considers reinforcement content (wt. %), sliding speed (m/s), normal load (N) and reinforcement size (nm) as the independent variables whereas wear rate ($mm^3/m$) was determined as the optimisation objective.

The work has been motivated by the successful application of swarm intelligence metaheuristics in solving optimisation problems related to almost all aspects of engineering, manufacturing and industry. The results obtained by simulation experiments revealed that swarm intelligence algorithms not only manage to solve tribological optimisation problems but they achieve it by maintaining low computation time as well.

According to the results obtained WOA algorithm was found to be the most prominent against GWO, MFO and DA algorithms in terms of its faster convergence to an earlier iteration number and global optimum result finally obtained for wear rate. Even though all algorithms showed encouraging results for minimising wear rate WOA appeared the most promising for tribology-related optimisation problems. However, this depends on the nature of objective function representation (i.e. regression model, neural network, customised programming environment for fitness score evaluations, etc).

Future research intends to examine the potentials of swarm intelligence algorithms to other tribology-related optimisation problems with an emphasis on multi-objective optimisation.

## Acknowledgement

The authors wish to thank colleagues B. Stojanović, S. Gajević, N. Kostić, S. Miladinović and A. Vencl for providing the original experimental results.

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