MEKATRONIKA
e-ISSN: 2637-0883
VOL. 5, ISSUE 2, 32 – 40
DOI: https://doi.org/10.15282/mekatronika.v5i2.9754

ORIGINAL ARTICLE

Application of Modified Adaptive Bats Sonar Algorithm with Doppler Effect and Levy Flight (MABSA-DELF) to Optimize Mechanical Engineering Problems

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ABSTRACT – This paper describes the application of the Modified Adaptive Bats Sonar Algorithm with Doppler Effect and Levy Flight (MABSA-DELF) to mechanical engineering design optimization issues. MABSA-DELF is a new algorithm that employs Doppler Effect and Levy Flight theory to improve the position of the transmitted bats' beam. This project served as a showcase for the superior performance of MABSA-DELF. The computer simulation method employed in the creation of the software is based on the MATLAB platform. The MABSA-DELF framework exhibited a heightened proficiency in addressing engineering design challenges within the domains of business, mechanical/manufacturing engineering, and electrical engineering. MABSA-DELF's result are compared to those of other established algorithms.

ARTICLE HISTORY
Received: 15th Sept 2023
Revised: 12th Oct 2023
Accepted: 8th Oct 2023
Published: 24th Oct 2023

KEYWORDS
Doppler effect
Design problems
Levy Flight
MABSA-DELF
Mechanical engineering
Optimization

INTRODUCTION

The process of engineering design involves the application of a range of methodologies and scientific ideas to precisely specify a device, process, or system with enough precision to enable its physical implementation. Real-world engineering design problems frequently involve multiple competing objectives. Hence, it is inherent to perceive the engineering design challenge as a singular or many objective optimisation problem. The occurrence of several, often contradictory, and unresolvable goals is a prevalent attribute observed in real-world engineering design challenges. [1]. As computers' computational capabilities increase, the use of optimization in engineering is increasing daily. A few years ago, calculations required significantly more time than it do today. Consequently, the number of numerical optimization applications has increased dramatically.

According to Antoniou and Lu [2], optimisation theory looks at the best ways to solve a problem. It includes techniques, methods, processes, and algorithms. Most fields have to deal with the optimisation problem. As an engineer, you may have to deal with modelling and characterization, designing tools, instruments, and equipment, designing structures and buildings, planning and scheduling production, keeping track of quality, inventory, and processes, and maintaining and fixing equipment or systems. [2].

With the current swarm intelligence algorithms, it is still impossible to optimize mechanical engineering design problems with the highest degree of accuracy and precision. In addition, the algorithm's exploration and exploitation processes must be well-balanced in order for mechanical engineering design problems to be optimized to the greatest extent possible. A new method called Modified Adaptive Bats Sonar method with Doppler Effect and Levy Flight (MABSA-DELF) is proposed in this study as a way to solve mechanical engineering design problems.

The rest of the content of this paper is laid out as follows: the second section provides a concise summary of existing methods for optimizing mechanical engineering design problems. The third section will be the methodology used to develop the MABSA-DELF followed by the mechanical engineering design issues. Next, in section four, it regarding the testing results as well as the discussion and lastly a conclusion have been made at the fifth section.

RELATED WORK

This section provides a summary of existing methods for optimizing mechanical engineering design, followed by the creation of the Modified Adaptive Bats Sonar Algorithm with Doppler Effect and Levy Flight (MABSA-DELF).

Over the past two decades, numerous scholarly works addressing mechanical engineering design problems have been published. The Particle swarm optimisation (PSO) algorithm has gained significant popularity as a widely used method for addressing multi-objective optimisation issues. According to Moore and Chapman [3], they were the pioneers in adapting the PSO method from single objective optimisation issues to address the challenges posed by multi-objective optimisation problems. In PSO, a swarm of agents searches for the global optimal solution by updating the velocity and its position according to the agent's current position, personal best, and the swarm's global best. Eventually, it arrives at the optimal solution by moving towards particles with higher fitness value.

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MABSA is another method for optimizing mechanical engineering design issues. MABSA is introduced by Yahya and Tokhi [4] as an improvement to the Adaptive Bats Sonar Algorithm (ABSA) which being developed by Yahya et al., [5]. MABSA draws inspiration from the echolocation abilities exhibited by bats, which use sonar to locate the prey. The ABSA algorithm was examined as an enhanced iteration of the original Bats Sonar Algorithm (BSA) for addressing unconstrained single objective optimisation problems. Nevertheless, in order to resolve a constrained single-objective optimisation problem, the crucial issue of incorporating inequality and equality constraints with the objective function must be addressed. The performance of ABSA in addressing this particular problem is suboptimal, indicating that an algorithmic approach may not be a direct and effective answer.

The task of finding a solution inside the possible zones delimited by limitations can often provide difficulties when employing a direct approach [6]. In order to tackle this matter, the creation of MABSA involves the redefinition of specific parts within ABSA and the reformulation of a significant component inside BSA. The MABSA system will possess the ability to provide a solution that effectively fulfils all imposed constraints. The objective of MABSA is to effectively address and resolve optimisation problems that are subject to constraints [4].

In 2005, X. S. Yang [7] established the virtual bee algorithm (VBA), which simulated the social honey bee swarm interactions. The process of honey-seeking bees, as described by the VBA, can be summarised as follows: an individual bee locates a food source and subsequently returns to the hive to deposit the collected honey. Through the performance of a behaviour known as the "waggle dance," the returning bee communicates the location and distance of the food source to other bees in the hive. These recruited bees then acquire knowledge of the distance and direction to the food source from the information conveyed through the dance. Consequently, they proceed to forage from the same food source, establishing it as the preferred path for subsequent honey-seeking activities. A genetic algorithm (GA) and VBA were used to compare how well they worked to improve both De Jong's test function and Keane's multi-peaked bumpy test function. Because the method works in parallel, the results showed that VBA is better than GA [7].

Moreover, during 2009, a cuckoo search (CS) algorithm was created by X. Yang and Deb [8]. It was based on the fact that some species of cuckoo are forced to feed on other cuckoos' eggs. There is also the Levy flight behaviour of some birds and fruit flies built into this programme. The CS algorithm is based on three rules that were inspired by how cuckoos breed. The reproductive behaviour of cuckoos involves the deposition of a single egg in a nest chosen at random. The nest that possesses the highest-quality eggs is subsequently inherited by future generations. It is important to note that the number of suitable host nests is limited. The CS method was evaluated and contrasted with GA and PSO on 10 common benchmark test functions for single objective optimisation. The findings from the simulation indicate that CS exhibited superior performance compared to existing algorithms, particularly when dealing with multimodal objective functions [8].

METHODOLOGY

Development of MABSA-DELF

MABSA-DELF's *beam length (L)* is initialized similarly to MABSA by Yahya and Tokhi [4] during its development. The solution range is the value between the limit of *upper search space,* SS_{Max} and the *lower search space,* SS_{Min} limit as below:

$$L = Rand \times \left(\frac{SS_{size}}{10\% \times Bats}\right) \tag{1}$$

$$SS_{size} = SS_{Max} + SS_{Min} \tag{2}$$

The solution range is partitioned into micron sizes, specifically accounting for 10% of the overall bat population within the search space. The percentage denotes the magnitude of the potential search area for sound emission by individual bats, while ensuring avoidance of collisions with their counterparts. Each dimension *(Dim)* is associated with its own set of limitations, sometimes referred to as dimension constraints. Every iteration has a different value of L. In the MABSA-DELF algorithm, a momentum term *(μ)* is incorporated to effectively manage the danger of converging to a local optimum. This term can be mathematically represented as follows:

$$L_{new} = L_{old}(1 \pm \mu) \tag{3}$$

Where,

$$0 < \mu < 1$$

Beam number of increment (*BNI*) is incorporated into the MABSA-DELF to demonstrate the actual echolocation of bats. The BNI is characterised by two parameters, namely the *maximum number of beams* ($NBeam_{Max}$) and the *minimum number of beams* ($NBeam_{Min}$):

$$BNI = \left(\frac{NBeam_{Max} - NBeam_{Min}}{MaxIter}\right) \times iter \tag{4}$$

Where,

$$NBeam_{Max} = 200$$

$$NBeam_{Min} = 20$$

Then, *NBeam* expressed as:

$$NBeam = NBeam_{Min} + BNI \tag{5}$$

For each bat, the equilibrium point between the current iteration's *(t)* pos_{SP}, pos_{LB}, and pos_{RB} and the pos_{GB} of the most recent F_{GB} who will be appointed as the new pos_{SP} for the following iteration *(t + 1)* is calculated using the arithmetic mean. The arithmetic mean's first level is reached by finding the average of the current iteration's pos_{SP}, pos_{LB}, and pos_{RB} values for each bat. The second level of arithmetic mean then establishes the centre tendency between the position value obtained by the first level and pos_{GB}.

As a result, at the beginning of each new iteration, each bat will initiate a fresh set of beam transmissions from the pos_{SP} that has been determined by taking into account the optimal compromise between the F_{SP}, F_{LB}, F_{RB}, and F_{GB}. Here is the expression for the two sorts of arithmetic mean:

$$pos_{SP}(t+1) = \frac{\left(\frac{pos_{SP}(t)+pos_{LB}(t)+pos_{RB}(t)}{3}+pos_{GB}\right)}{2} \tag{6}$$

Each MABSA-DELF transmitted beam's *end point position* (pos_i) is determined by the formula:

$$pos_i = (lf \times pos_{SP}) + de \times (cos[\theta_m + (i-1)\theta])^{\omega} \tag{7}$$

Equation 7 above, *lf* and *de* are the elements of Levy Flight and Doppler Effect respectively. Element *lf* is incorporated with random walk characteristics and will ensure that each bat can quickly adjust to the new pos_{SP}, which is derived from the previous pos_{SP}, pos_{LB}, pos_{RB} and pos_{GB}. The principal purposes of element *de* are twofold: firstly, to avoid the occurrence of beam overlap or collision with other bats' beams, and secondly, to serve as a guidance device that directs the transmitted bat beams to more appropriate placements.

The *beam tuning constant (ω)*, often known as the acceleration constant, is equal to 2. The aforementioned constant will enhance the *de*, resulting in the deflection of the transmitted beam to the newly specified angle inside the authorised search space.

MECHANICAL ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Pressure vessel design

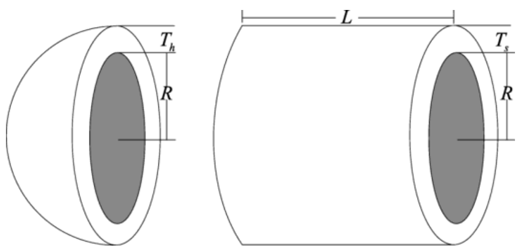

Figure 1. Pressure vessel design.

Gear train design

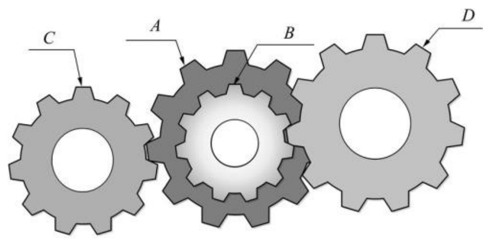

Figure 2. Gear train design.

Speed reducer design

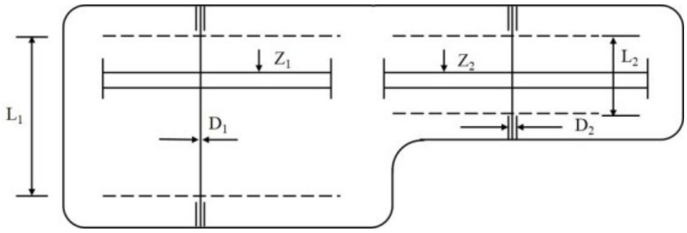

Figure 3. Speed reducer design.

Three-truss bar design.

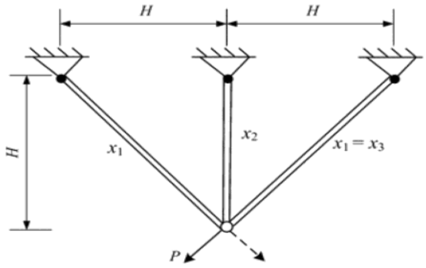

Figure 4. Three-truss bar design

Welded beam design

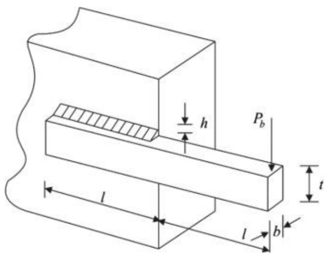

Figure 5. Welded beam design.

Tension/compression spring design

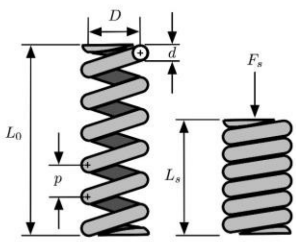

Figure 6. Tension/compression spring design.

TESTING RESULTS

There are six design optimisation problems in the field of mechanical engineering. These include the pressure vessel design optimisation problem, the gear train design optimisation problem, the speed reducer design optimisation problem, the three-truss bar design optimisation problem, the welded beam design optimisation problem and the tension/compression spring design optimisation problem—were looked at and tested to show that the MABSA-DELF was better. A total of 30 iterations were conducted for each engineering design optimisation challenge. The findings for each of the proposed engineering design optimisation challenges were compared with data from the relevant literature to demonstrate that MABSA-DELF performs better than three other well-known methods. Notably, no re-simulation experiments were done using the known algorithms. MABSA [4], mine blast algorithm (MBA) [9] and particle swarm optimization with differential evolution (PSO-DE) [10] are the algorithms that have been thought about.

Pressure vessel design

Table 1. Statistics-based evaluation of several optimisation techniques applied to the challenge of pressure vessel design ('n/a" means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	**2483.5601**	**2328.3870**	**1858.8623**	**2664.2560**	875.1374	70000
PSO-DE	6059.7143	n/a	6059.7143	6059.7143	$\mathbf{1.000e^{-10}}$	42100
MBA	6200.6477	n/a	5889.3216	6392.5062	160.3400	70650
MABSA	5607.7972	5618.6387	5167.333	6092.8908	252.3335	80227

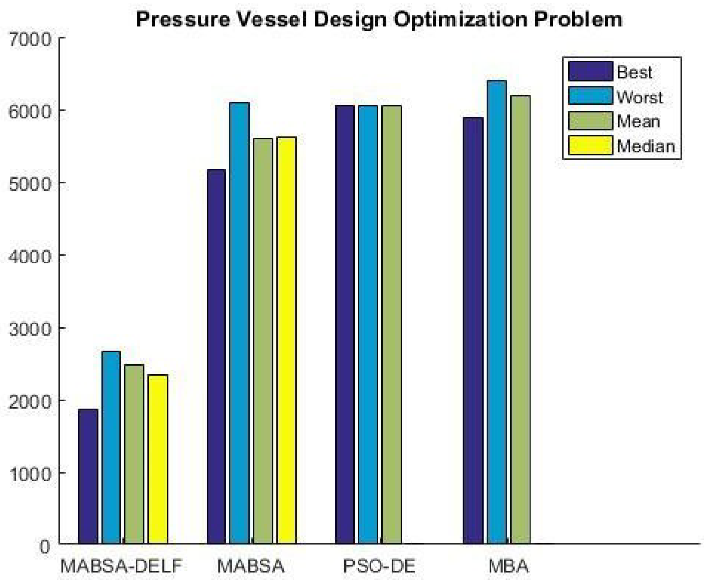

Figure 7. Bar plot of statistical results for pressure vessel design optimization problem.

Gear train design

Table 2. Quantitative analysis of the performance of several optimisation techniques used to the gear train design problem ("n/a"means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	$\mathbf{2.9748e^{-21}}$	$\mathbf{7.0109e^{-22}}$	$\mathbf{1.1329e^{-23}}$	$\mathbf{3.0307e^{-20}}$	$\mathbf{7.0765e^{-21}}$	70200
MBA	$2.4716e^{-9}$	n/a	$2.7009e^{-12}$	$2.0629e^{-8}$	$3.9400e^{-9}$	1120
MABSA	$4.7837e^{-13}$	$3.4364e^{-13}$	$2.7473e^{-16}$	$1.8761e^{-12}$	$5.3938e^{-13}$	91007

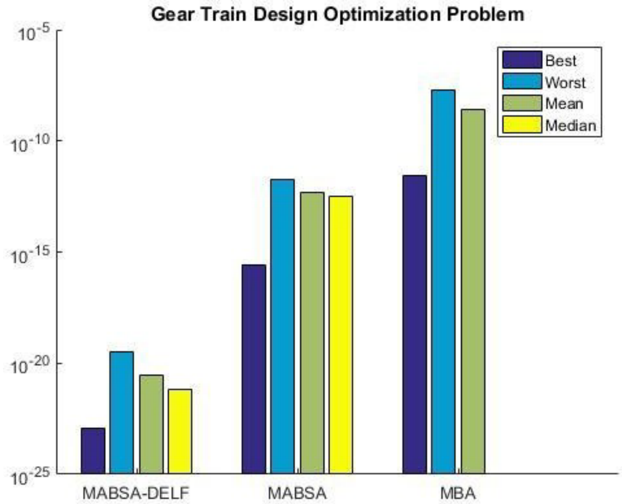

Figure 8. Bar plot of statistical results for gear train design optimization problem.

Speed reducer design

Table 3. Quantitative analysis of the performance of several algorithms used to the challenge of optimising speed reducer designs ("n/a" means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	**2616.0274**	**2621.9903**	**2452.7015**	**2740.1660**	58.3625	70000
PSO-DE	2996.3482	n/a	2996.3482	2996.3482	$\mathbf{1.0000e^{-7}}$	70100
MBA	2996.769	n/a	2994.4825	2999.6524	1.5600	6300
MABSA	2939.3242	2932.6487	2903.4328	2992.6411	29.2630	90433

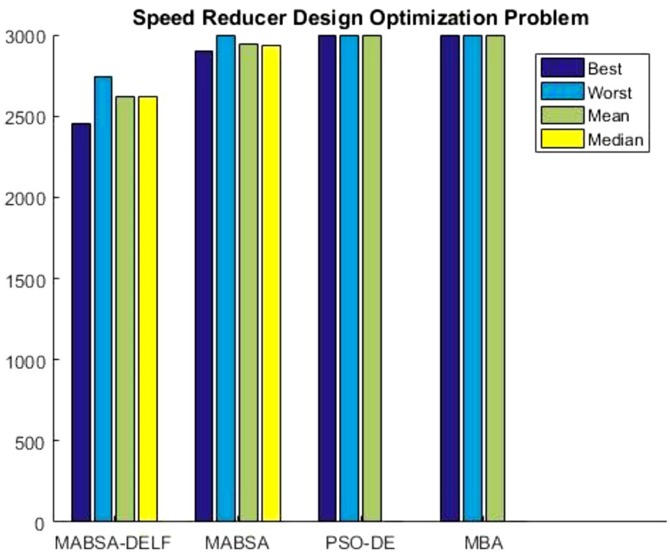

Figure 9. Statistics bar plot for speed reducer design optimisation.

Three-truss Bar Design

Table 4. Comparison of statistical results with different algorithms for three-truss bar design optimization problem.("n/a" means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	**218.8352**	**219.0023**	**217.9985**	**219.0024**	0.3737	70000
PSO-DE	263.8958	n/a	263.8958	263.8958	$\mathbf{1.2000e^{-10}}$	17600
MBA	263.898	n/a	263.8959	263.916	$3.9300e^{-3}$	13280

MABSA	263.8955	263.8955	263.8955	263.8955	$3.7757e^{-8}$	87650

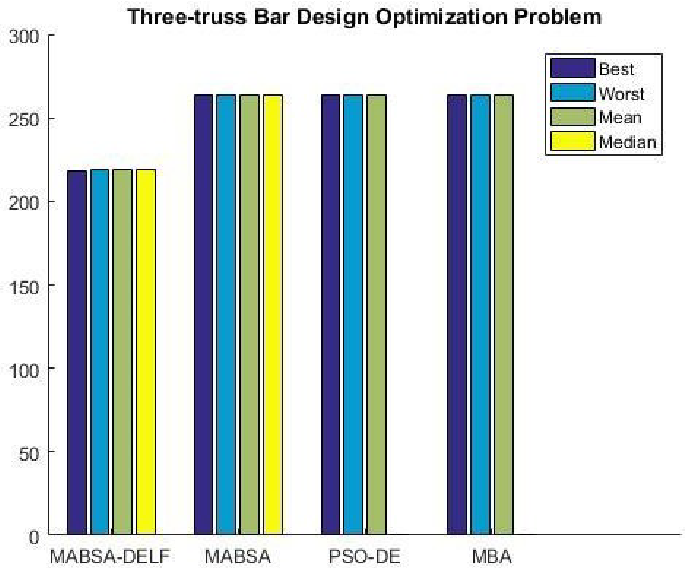

Figure 10. Statistics bar plot for three-truss bar design optimization problem.

Welded beam design

Table 5. Comparison of statistical results with different algorithms for welded beam design optimization problem.("n/a" means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	**1.3118**	**1.3245**	**1.1284**	**1.4979**	$1.1462e^{-1}$	70000
PSO-DE	1.7249	n/a	1.7249	1.7249	$6.7000e^{-16}$	66600
MBA	1.7249	n/a	1.7249	1.7249	$\mathbf{6.9400e^{-19}}$	47340
MABSA	1.6776	1.6800	1.6308	1.7241	$2.8858e^{-2}$	86113

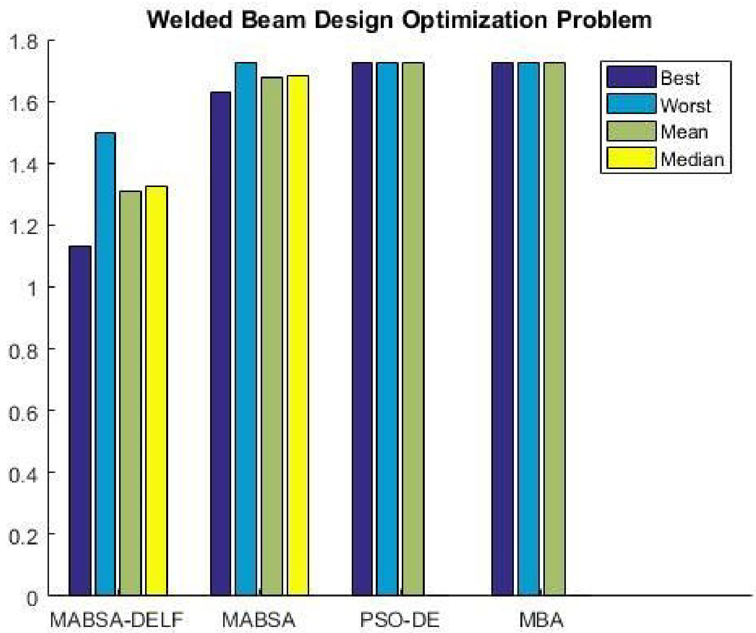

Figure 11. Statistics bar plot for welded beam design optimization problem.

Tension/compression spring design

Table 6. Comparison of statistical results with different algorithms for tension/compression spring design optimizationproblem. (“n/a” means not available, bolded value shows the most superior for each statistical criterion).

Algorithm	Mean	Median	Best	Worst	Standard Deviation	NFEs
MABSA-DELF	**0.0083**	**0.0080**	**0.0079**	**0.0104**	$5.8785e^{-4}$	100000
PSO-DE	0.0127	n/a	0.0127	0.0127	$\mathbf{4.9000e^{-12}}$	42100
MBA	0.0127	n/a	0.0127	0.0129	$6.3000e^{-5}$	7650
MABSA	0.0125	0.0125	0.0123	0.0127	$1.4195e^{-4}$	89680

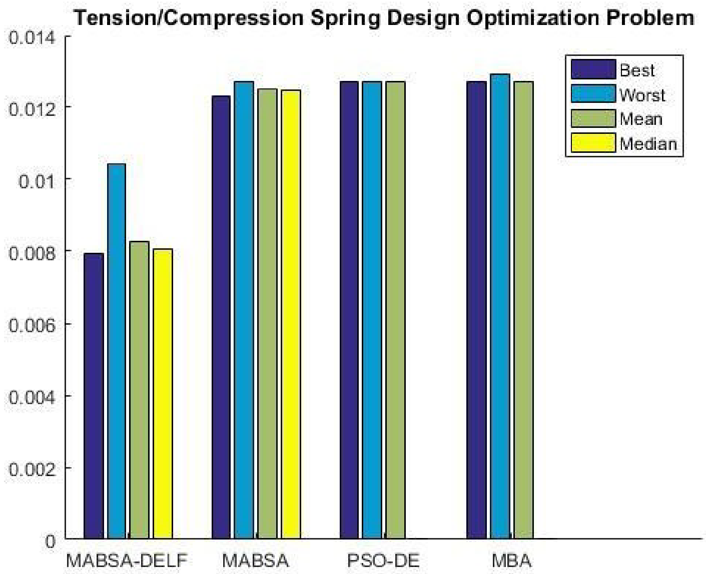

Figure 12. Statistics bar plot for tension/compression spring design optimization problem.

Overall comparison of all considered algorithms

To rank all algorithms under consideration, the mean absolute error (MAE) of each algorithm is calculated using the expression below. MAE is a statistical criteria that measures outcomes deviation from real values.

$$MAE = \frac{\sum_{z}^{i=1} |m_i - h_i|}{z} \quad (8)$$

Where,
m_i = mean of optimum achieved results
h_i = global optimum value
z = number of test function

The methods evaluated for mechanical engineering design optimisation issues are rated as presented in Table 7. On the other hand, only MABSA-DELF, MABSA, and MBA were evaluated in comparison to all six test functions, z of mechanical engineering design optimization problems, while PSO-DE were compared to only five test functions due to the unavailability of results from previous study.

Table 7. Rank of algorithms designed to solve optimisation problems in mechanical engineering design.

Algorithms	*z*	*MAE*	*Rank*
MABSA-DELF	6	-301.0260	1
PSO-DE	6	-84.8000	2
MBA	5	-0.0008	3
MABSA	6	23.5588	4

Based on the table above, without considering the value of the test functions that have been done, MABSA-DELF still ranks first among the other algorithms. Also, by looking at the result for mean absolute error, MABSA-DELF came out with the least value, which indirectly shows that MABSA-DELF is capable of optimizing the mechanical engineering design problems, especially all six engineering design problems that have been studied in this project.

CONCLUSION

Modified Adaptive Bats Sonar Algorithm with Doppler Effect and Levy Flight (MABSA-DELF) has been setup in this project to optimize the mechanical engineering design problems. The Modified Adaptive Bats Sonar Algorithm (MABSA), the Mine Blast Algorithm (MBA), and the Particle Swarm Optimisation with Differential Evolution (PSO-DE) have all been used to compare the proposed method to their respective performance on six distinct mechanical engineering design problems.

This study provides evidence supporting the superiority of MABSA-DELF over several statistical criteria, including the best, worst, mean, and median. The proposed optimization technique had the highest standard deviation values, indicating that it is the algorithm with the least robustness. It demonstrated high efficiency and superiority in optimizing the six mechanical engineering design optimization problems considered despite this. MABSA-DELF is a robust optimization tool that can effectively solve complex mechanical engineering design problems, but its high variability may render it unsuitable for some applications.

ACKNOWLEDGEMENT

The authors express their gratitude to Universiti Malaysia Pahang Al-Sultan Abdullah for the financial support provided by the UMP Internal Grant (Grant No. RDU210370). Additionally, the authors would like to acknowledge the Faculty of Manufacturing and Mechatronic Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, for granting access to laboratory facilities.

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