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Solving Mechanical Engineering Problems by Metaheuristic Methods

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Abstract

The goal of optimization is to create the "best" design possible given a set of prioritized conditions or constraints. These include increasing productivity, power, reliability, longevity, efficiency, and utilization. Because of their simplicity and speed in finding solutions, metaheuristic algorithms, one of the optimization techniques, have grown in importance in engineering design in recent years. This has resulted in the widespread use of metaheuristics and a growing proclivity to create new algorithms. In this study, a research was conducted on addressing real-world problems (Robot Gripper Problem, Pressure Vessel Design Problem, Rolling Element Bearing Problem, Step-Cone Pulley Problem, Tension Compression Spring Design Problem, Three-Bar Truss Beam Design Problem, Weight Minimization of Speed Reducer Problem and Welded Beam Design Problem) in the field of mechanical engineering with metaheuristic algorithms (Ant Colony Optimization, Artificial Bee Colony, Salp Swarm Algorithm and Sine Cosine Algorithm) and performing performance analyzes of these algorithms. In the experimental studies, four different scenarios were progressively determined according to various number of iterations and population parameters. Consequently, it can be confidently asserted that ACOR not only produces superior solutions but also boasts an ideal running time for efficiently solving real-world problems.

Keywords: Optimization, metaheuristics, real-world problems, engineering problems

INTRODUCTION

In the face of a growing global population, the effective utilization of existing resources stands out as a paramount concern for humanity. Engineering systems, encompassing disciplines like structural, mechanical, and industrial engineering, emerge as pivotal players in maintaining a delicate equilibrium between resources and consumption. Broadly defined, engineering design can be characterized as the skillful craft of devising systems that not only fulfill all expectations but do so with the minimal utilization of resources (Jiao et al., 2021; Martins and Ning, 2021). The term "resources" in this context spans diverse realms, including time, materials, and human labor. Within the framework of this definition, a multitude of engineering design processes can be reframed as optimization problems, necessitating the application of robust optimization techniques (Carbas et al., 2021). The landscape of real-world engineering design problems is ubiquitous, spanning industries and various research domains. While a plethora of optimization algorithms has been employed to tackle such challenges, the efficacy of these algorithms diminishes markedly as problems escalate in scale and complexity. To address this, the literature has witnessed the proposal of various iterations of optimization methods aimed at efficiently resolving intricate engineering design problems (Abualigah et al., 2022).

Optimization algorithms are made up of a randomized population of agents that act as explorers in the search space to find candidate solutions (Cayiroglu and Elen, 2012). The process begins by placing agents within the problem domain, and subsequent iterations generate potential solutions until the specified criterion is met. The algorithmic pursuit concludes with the optimal solution, identified as the most suitable candidate across all iterations (Abdullah, 2022). Surprisingly, stochastic algorithms follow a streamlined sequence that includes critical steps such as discovery and exploitation. The term "exploration" refers to the algorithm's traversal of the search space, during which candidate solutions are transformed. Concurrently, exploitation denotes the algorithm's ability to identify local optima surrounding various viable solutions (Rather and Bala, 2020).

Metaheuristic search techniques, including Ant Colony Optimization, Genetic Algorithms, and Particle Swarm Optimization, have gained popularity for their prowess in navigating complex optimization problems, drawing inspiration from natural phenomena (Braik et al., 2021). These metaheuristics exhibit versatility by accommodating both discrete and real-valued variables, offering effective solutions across a diverse spectrum of optimization challenges. In essence, trajectory and population-based metaheuristic approaches share the common goal of uncovering the global optimum within the solution space through random movements. The divergence among metaheuristics lies in their strategies for proposing the subsequent move within the solution space, compelling optimization algorithm developers to continually seek more efficient methodologies to craft resilient optimization algorithms. Nevertheless, this pursuit occasionally leads to the formulation of intricate approaches that pose challenges in comprehension and implementation (Adekanmbi and Green, 2015).

This research endeavors to address real-world engineering design challenges by employing several well-established metaheuristic optimization algorithms found in the literature, subsequently facilitating a comparative analysis of the outcomes. The algorithms under consideration in this study encompass Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Salp Swarm Algorithm (SSA), and Sine Cosine Algorithm (SCA). Throughout the experimental phase, these algorithms were applied to tackle eight distinct real-world problems, namely the Robot Gripper Problem, Pressure Vessel Design, Rolling Element Bearing, Step-Cone Pulley Problem, Tension Compression Spring Design, Three-Bar Truss Beam Design Problem, Weight Minimization of Speed Reducer, and Welded Beam Design.

In this investigation, the primary objective is to unravel the efficacy of these metaheuristic approaches across a diverse range of engineering problems, shedding light on their comparative performance and suitability for different design scenarios. The chosen problems represent a spectrum of engineering challenges, allowing for a comprehensive evaluation of the algorithms' robustness and adaptability in real-world applications.

MATERIAL AND METHODS

Metaheuristic Algorithms

Metaheuristics represent a sophisticated, problem-agnostic framework offering a set of guidelines for formulating optimization methods through heuristic approaches (Salcedo-Sanz, 2016). While drawing inspiration primarily from nature, these algorithms also integrate insights from diverse sources to enhance their adaptive capabilities and improve fitness (Wong and Ming, 2019). In the pursuit of global optima, metaheuristic algorithms emulate the collective intelligence observed in social animals and insects, exemplified by prominent methodologies like ant colony optimization, cuckoo search algorithm, particle swarm optimization, and artificial bee colony. The collaborative search of these algorithms mirrors the coordinated efforts seen in flocks, birds, fish, and other social entities.

Swarm-based approaches, encompassing a spectrum of applications from automotive manufacturing to aerospace engineering, have garnered attention for their exceptional computational efficiency (Meng et al., 2021). Over the past two decades, research in this domain has witnessed remarkable growth, and metaheuristics can be broadly classified into three main categories: physically based algorithms, swarm algorithms, and evolutionary algorithms. Evolutionary algorithms such as Differential Evolution (DE) and Genetic Algorithm (GA) emulate nature's evolutionary principles to devise robust optimization techniques. Swarm algorithms, including Particle Swarm Optimization and Whale Optimization, replicate the collective behaviors observed in various creatures. Physically based algorithms, drawing inspiration from real-world processes such as gravity search algorithms and simulated annealing, contribute a unique perspective to the metaheuristic landscape (Abd Elaziz et al., 2021).

This investigation employed nature-inspired metaheuristic methods, namely Ant Colony Optimization, Artificial Bee Colony, Salp Swarm Algorithm, and Sine Cosine Algorithm, to assess their efficacy in solving real-world problems.

Real-world Engineering Problems

A primary hurdle faced by metaheuristic algorithms lies in their ability to deliver enhanced solutions for well-established constrained mathematical and engineering design challenges. Overcoming these challenges necessitates the utilization of robust mathematical models grounded in the foundational principles of metaheuristics (Talatahari and Azizi, 2020).

Real-world engineering design problems frequently exhibit a multitude of conflicting objectives, making it logical to conceptualize these issues as multi-objective optimization problems. Given the composite nature of engineering design problems, involving numerical simulations, analytical calculations, and catalog selections, the computation of derivatives for the objective function becomes a complex task. Consequently, gradient-free optimization techniques emerge as more suitable solutions for such intricate problems (Andersson, 2000).

This section delves into the presentation of various real-world optimization problems from the IEEE Congress on Evolutionary Computation (CEC). To gauge the efficacy of the discussed metaheuristics, eight distinct problems in Mechanical Engineering, sourced from the CEC archive, were selected for evaluation. These encompass the Robot Gripper Problem (RGP) (Savsani and Savsani, 2016), Pressure Vessel Design (PVD) (Belkourchia et al., 2019), Rolling Element Bearing (REB) (Yao et al., 2022), Step-Cone Pulley Problem (SCPP) (Zailani et al., 2021), Tension Compression Spring Design (TCSD) (Zuo et al., 2019), Three-Bar Truss Beam Design Problem (TBTDP) (Sheikhi Azqandi et al., 2020), Weight Minimization of Speed Reducer (WMSR) (Lin et al., 2013), and Welded Beam Design (WBD) (Ragsdell and Phillips, 1976). Table 1 provides details on the engineering problems utilized in experimental studies, along with their respective properties.

Table 1. Characteristics of real-world engineering problems

#	Problem	Min/Max	Dimension	Constraints	Bounds	
					Lower	Upper
1	PVD	Min	4	4	0.51	200
2	RGP	Min	7	7	0	300
3	REB	Max	10	9	0.02	150
4	SCPP	Min	5	8	0	90
5	TCSD	Min	3	3	0.05	15
6	TBTDP	Min	2	3	0	1
7	WMSR	Min	7	11	0.7	28
8	WBD	Min	4	5	0.1	10

RESULTS AND DISCUSSION

In assessing the effectiveness of the metaheuristics under consideration during experimental studies on real-world problems, the evaluation is grounded in two key metrics: the fitness value of the global best solution and the running time of the algorithm. To ensure robustness and reliability, each experiment was iterated independently 30 times, and the average fitness value of the best solutions was computed. Likewise, the running times of the metaheuristic methods were averaged to provide a comprehensive understanding of their computational efficiency. This meticulous approach to repeated experiments and subsequent averaging aims to capture the consistent performance trends and computational characteristics of the metaheuristic algorithms across diverse real-world engineering design problems.

In Case of Number of Iterations 500, Number of Populations 10

In this experiment, the number of iterations was set as 500 and the number of populations as 10. The optimisation algorithms were run 30 times for each engineering problem and the global best fitness values obtained were averaged. Table 2 shows the global best scores of the engineering problems.

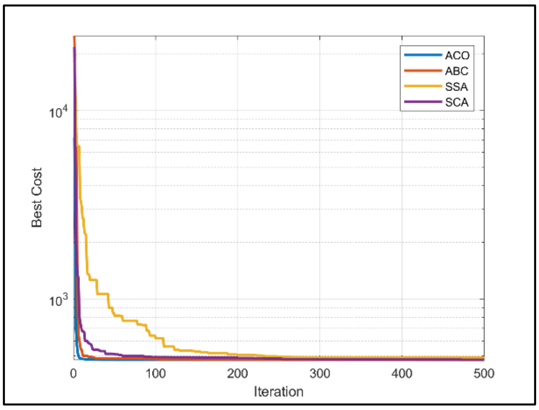
Table 2. Global-best fitness values of metaheuristic algorithms

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	476.3155	**475.6138**	490.1005	476.2735
2	RKP	**4.0583**	6.0220	5.7649	5.5061
3	MRTP	**82104.8**	81375.1	63547.5	45863.8
4	KKKP	8.2709	8.7041	**8.2416**	10.3870
5	GSYT	**0.0124**	**0.0124**	0.0128	0.0126
6	UCKKTP	**89.8504**	89.8520	**89.8504**	91.4325
7	HDAM	**2715.9872**	2718.0163	2758.7678	2875.2185
8	KKT	1.8284	1.8376	1.9119	**1.7836**

Table 2 illustrates the global-best fitness values attained by various metaheuristic algorithms across eight different engineering design problems. In the context of the Robot Gripper Problem (BKT), ACO_R and SCA exhibit closely comparable fitness values, surpassing ABC and SSA. For the Pressure Vessel Design (RKP), ACO_R stands out with the lowest fitness value, while ABC and SSA demonstrate similar performance. In the Rolling Element Bearing problem (MRTP), SSA emerges as the most successful algorithm, yielding the lowest fitness value compared to its counterparts. For the Step-Cone Pulley Problem (KKKP), ACO_R and SSA deliver similar fitness values, outperforming ABC and SCA. The Global Sensitivity and Yielding Tendency problem (GSYT) showcases minimal differences in fitness values among all algorithms. In the Three-Bar Truss Beam Design Problem (UCKKTP), ACO_R and SSA once again exhibit comparable performance, outperforming ABC and SCA. For the Heat Exchanger Design and Manufacturing problem (HDAM), SSA outshines others with the lowest fitness value, while ACO_R and ABC follow closely. Lastly, in the Welded Beam Design problem (KKT), ACO_R secures the lowest fitness value, outperforming ABC, SSA, and SCA. The running times of the metaheuristics were measured in seconds for each problem as shown in Table 3. SSA was the fastest algorithm in all experiments.

Table 3. Execution times of metaheuristic algorithms (in sec)

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	185.1463	96.4975	**37.8228**	41.7797
2	RKP	4684.4399	3329.4593	**1373.3508**	2873.5159
3	MRTP	358.6466	144.3775	**61.7456**	72.8864
4	KKKP	247.3981	121.2473	**48.8588**	54.8794
5	GSYT	169.6356	97.5699	**36.0501**	39.1379
6	UCKKTP	142.3768	106.8492	**32.9257**	34.4966
7	HDAM	264.2581	134.8877	**47.8286**	55.9821
8	KKT	187.2139	114.2081	**37.6670**	42.5511



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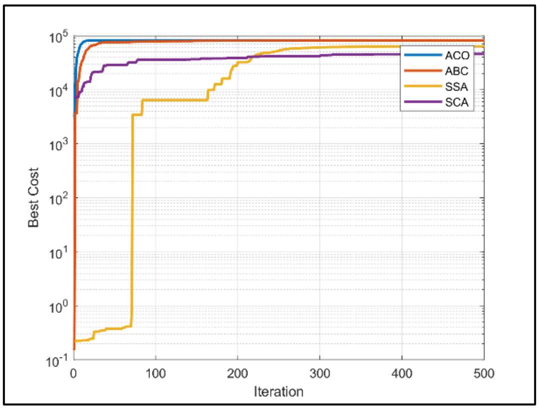

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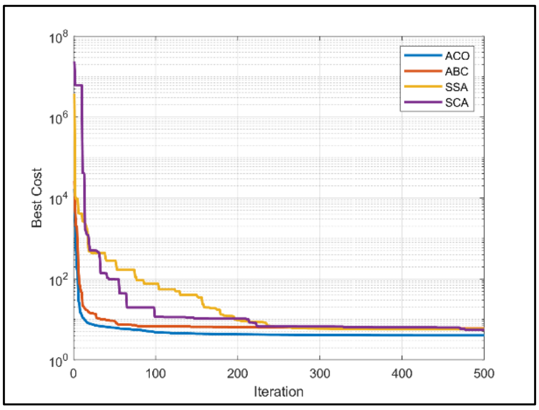

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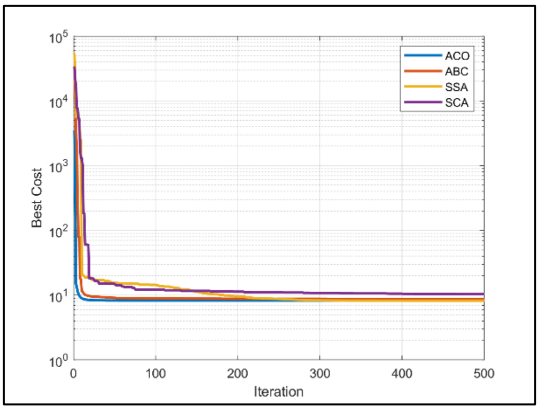

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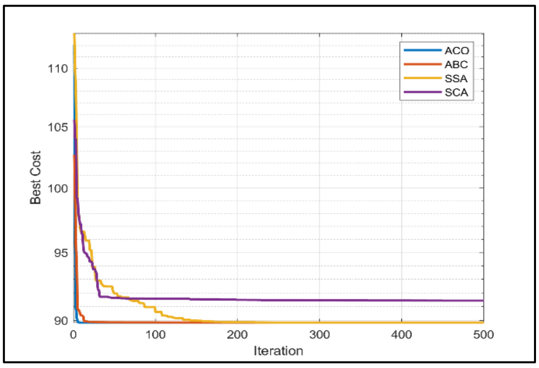
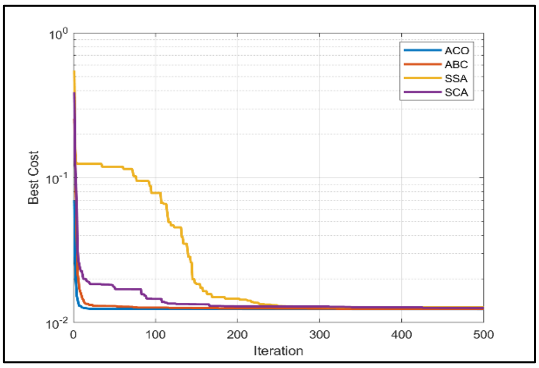


UCKKTP



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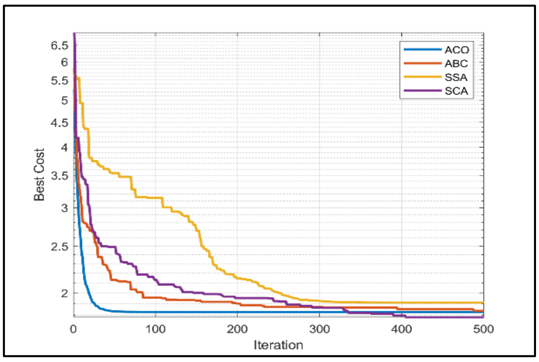
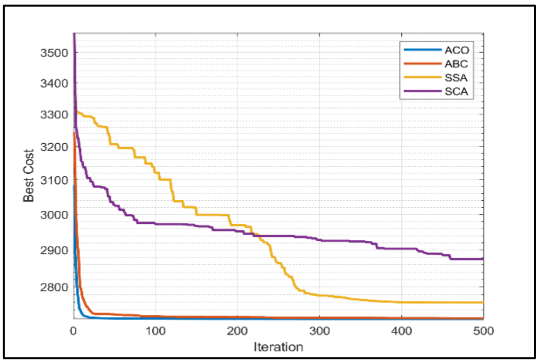


KKT



HDAM

Figure 1. Convergence of metaheuristic algorithms

Table 3 displays the execution times of various metaheuristic algorithms in seconds for eight different engineering design problems. In the context of the Robot Gripper Problem (BKT), SSA exhibits the fastest execution time at 37.8228 seconds, followed by ABC, ACO_R, and SCA. For the Pressure Vessel Design problem (RKP), ABC displays the quickest execution time at 3329.4593 seconds, outperforming ACO_R, SCA, and SSA. In the Rolling Element Bearing problem (MRTP), SSA once again demonstrates the fastest execution time at 61.7456 seconds, followed by ACO_R, ABC, and SCA. The Step-Cone Pulley Problem (KKKP) showcases ABC as the fastest algorithm at 121.2473 seconds, surpassing ACO_R, SSA, and SCA. For the Global Sensitivity and Yielding Tendency problem (GSYT), SSA stands out with the quickest execution time at 36.0501 seconds, followed by ACO_R, ABC, and SCA. In the Three-Bar Truss Beam Design Problem (UCKKTP), SSA demonstrates the fastest execution time at 32.9257 seconds, outperforming ACO_R, ABC, and SCA. The Heat Exchanger Design and Manufacturing problem (HDAM) highlights SSA as the fastest algorithm at 47.8286 seconds, followed by ACO_R, ABC, and SCA. Lastly, in the Welded Beam Design problem (KKT), SSA once again exhibits the fastest execution time at 37.6670 seconds, followed by ACO_R, ABC, and SCA.

In Case of number of iterations 500, number of populations 10, the convergence graphs of the engineering problems are given in Figure 1.

In Case of Number of Iterations 500, Number of Populations 50

In this experiment, the number of iterations was set as 500 and the number of populations as 50. The optimisation algorithms were run 30 times for each engineering problem and the global best fitness values obtained were averaged. Table 3 shows the global best scores of the engineering problems.

Table 4. Global-best fitness values of metaheuristic algorithms

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	474.8162	**474.4043**	479.5544	475.2589
2	RKP	**3.6755**	4.1950	3.9235	4.3033
3	MRTP	**82125.8**	82125.4	72505.3	57620.9
4	KKKP	**8.1885**	**8.1885**	**8.1885**	9.7711
5	GSYT	**0.0123**	0.0124	0.0126	0.0124
6	UCKKTP	**89.8504**	**89.8504**	**89.8504**	89.8529
7	HDAM	**2715.9872**	**2715.9872**	2737.2328	2792.5970
8	KKT	**1.6305**	1.6363	1.7253	1.7271

The provided numerical values represent the global-best fitness scores obtained by different metaheuristic algorithms for various engineering design problems. In the context of the Robot Gripper Problem, ACO_R achieves a fitness score of 474.8162, slightly outperforming ABC, SSA, and SCA. For the Pressure Vessel Design problem, ACOR secures a fitness score of 3.6755, displaying superior performance compared to ABC, SSA, and SCA. In the Rolling Element Bearing problem, ACO_R and ABC attain identical fitness scores of 82125.8, while SSA outperforms both with a score of 72505.3, and SCA trails behind. For the Step-Cone Pulley Problem, minimal differences exist in fitness scores among ACO_R, ABC, and SSA, with SCA demonstrating a slightly higher value. In the Global Sensitivity and Yielding Tendency problem, all algorithms showcase extremely close fitness scores, emphasizing their similar performance. The Three-Bar Truss Beam Design Problem highlights uniform fitness scores among ACO_R, ABC, and SSA, slightly surpassing SCA. In the Heat Exchanger Design and Manufacturing problem, ACOR and ABC exhibit similar fitness scores, with SSA achieving a slightly lower value, while SCA lags behind. Finally, in the Welded Beam Design problem, ACO_R secures the lowest fitness score, outperforming ABC, SSA, and SCA. The running times of the algorithms were measured in seconds for each problem as shown in Table 5. SSA was the fastest algorithm in all experiments except problem 2.

Table 5. Execution times of metaheuristic algorithms (in sec)

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	583.9117	495.6912	**188.9991**	210.1969
2	RKP	**5355.4662**	14563.1065	7639.6609	16795.6691
3	MRTP	789.6234	792.5244	**320.5342**	377.8640
4	KKKP	661.0245	630.3324	**251.7666**	287.8837
5	GSYT	573.6928	504.4589	**186.1982**	200.7379
6	UCKKTP	537.8684	560.0184	**168.3947**	175.5711
7	HDAM	677.5585	691.0457	**238.9354**	282.4484
8	KKT	587.6973	588.5523	**191.0540**	210.7186

In Case of number of iterations 500, number of populations 50, the convergence graphs of the engineering problems are given in Figure 2.

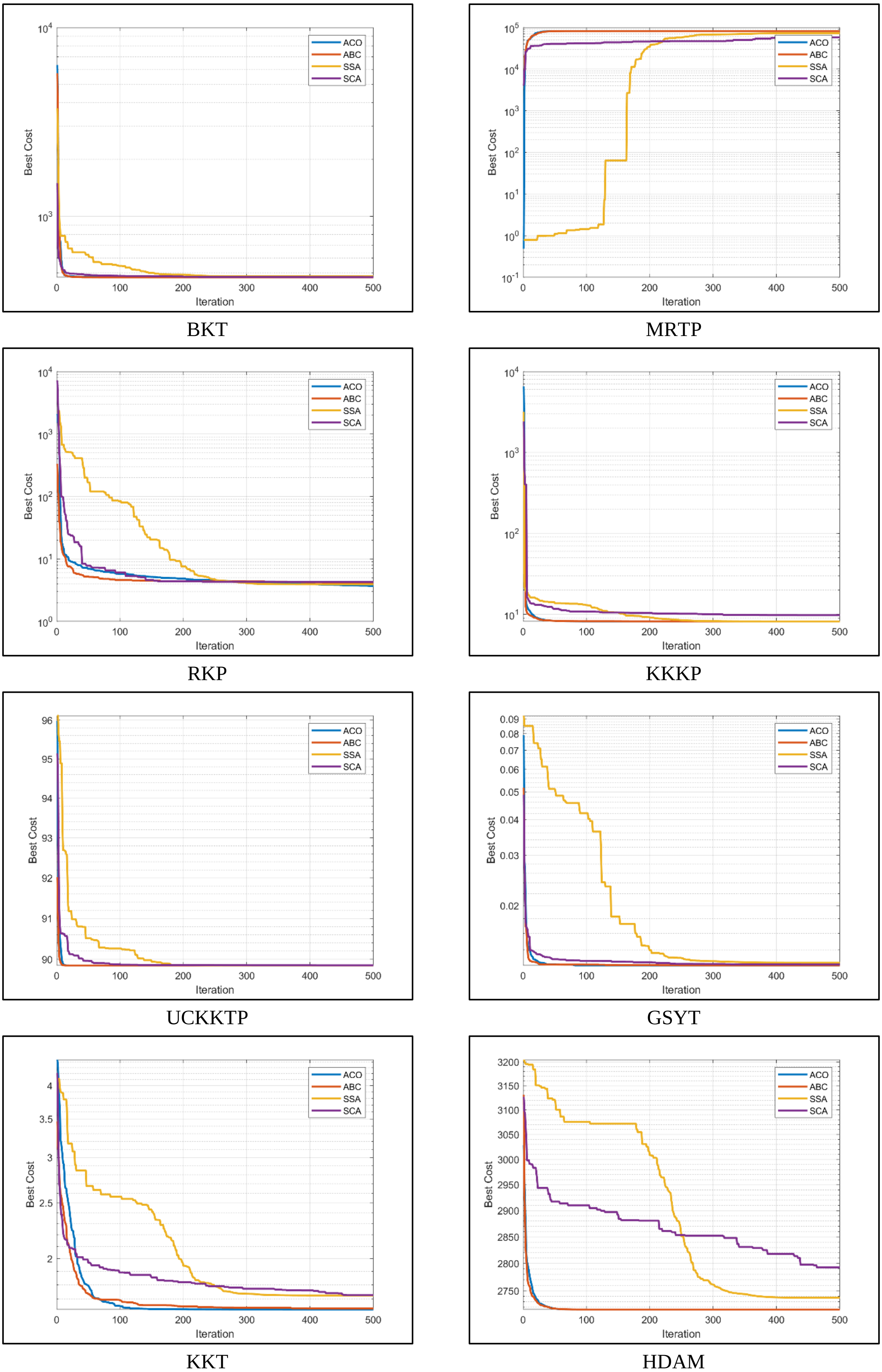


Figure 2. Convergence of metaheuristic algorithms

In Case of Number of Iterations 1000, Number of Populations 10

In this experiment, the number of iterations was set as 1000 and the number of populations as 10. The optimisation algorithms were run 30 times for each engineering problem and the global best fitness values obtained were averaged. Table 6 shows the global best scores of the engineering problems.

Table 6. Global-best fitness values of metaheuristic algorithms

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	479.2746	**475.6983**	485.9391	476.3926
2	RKP	**3.5151**	5.1948	4.4472	4.7548
3	MRTP	81246.5	**81448.9**	74084.7	50245.7
4	KKKP	8.2382	8.6117	**8.1983**	15648.9397
5	GSYT	0.0125	**0.0124**	0.0130	0.0125
6	UCKKTP	**89.8504**	89.8512	**89.8504**	94.5728
7	HDAM	**2715.9872**	2717.8021	2734.0179	2832.8562
8	KKT	**1.6970**	1.8126	1.7037	1.7253

The ACO algorithm obtained the best score in all experiments except for problems 1, 3, 4 and 5. ABC ranked second with the best score in three experiments and SSA ranked third with the best score in two experiments. The provided numerical values represent the global-best fitness scores obtained by different metaheuristic algorithms for various engineering design problems. In the context of the Robot Gripper Problem, ACO_R achieves a fitness score of 479.2746, outperforming ABC, SSA, and SCA. For the Pressure Vessel Design problem, ACOR secures a fitness score of 3.5151, displaying superior performance compared to ABC, SSA, and SCA. In the Rolling Element Bearing problem, ACO_R and ABC attain similar fitness scores around 81246.5, while SSA outperforms both with a score of 74084.7, and SCA trails behind. For the Step-Cone Pulley Problem, minimal differences exist in fitness scores among ACO_R, ABC, and SSA, with SCA demonstrating a notably higher value. In the Global Sensitivity and Yielding Tendency problem, all algorithms showcase subtle variations in fitness scores, reflecting their comparable performance. The Three-Bar Truss Beam Design Problem highlights uniform fitness scores among ACOR, ABC, and SSA, slightly surpassing SCA. In the Heat Exchanger Design and Manufacturing problem, ACO_R and ABC exhibit similar fitness scores, with SSA achieving a slightly lower value, while SCA lags behind. Finally, in the Welded Beam Design problem, ACO_R secures the lowest fitness score, outperforming ABC, SSA, and SCA. The running times of the optimisation algorithms were measured in seconds for each problem as shown in Table 7. SSA was the fastest running algorithm in all experiments.

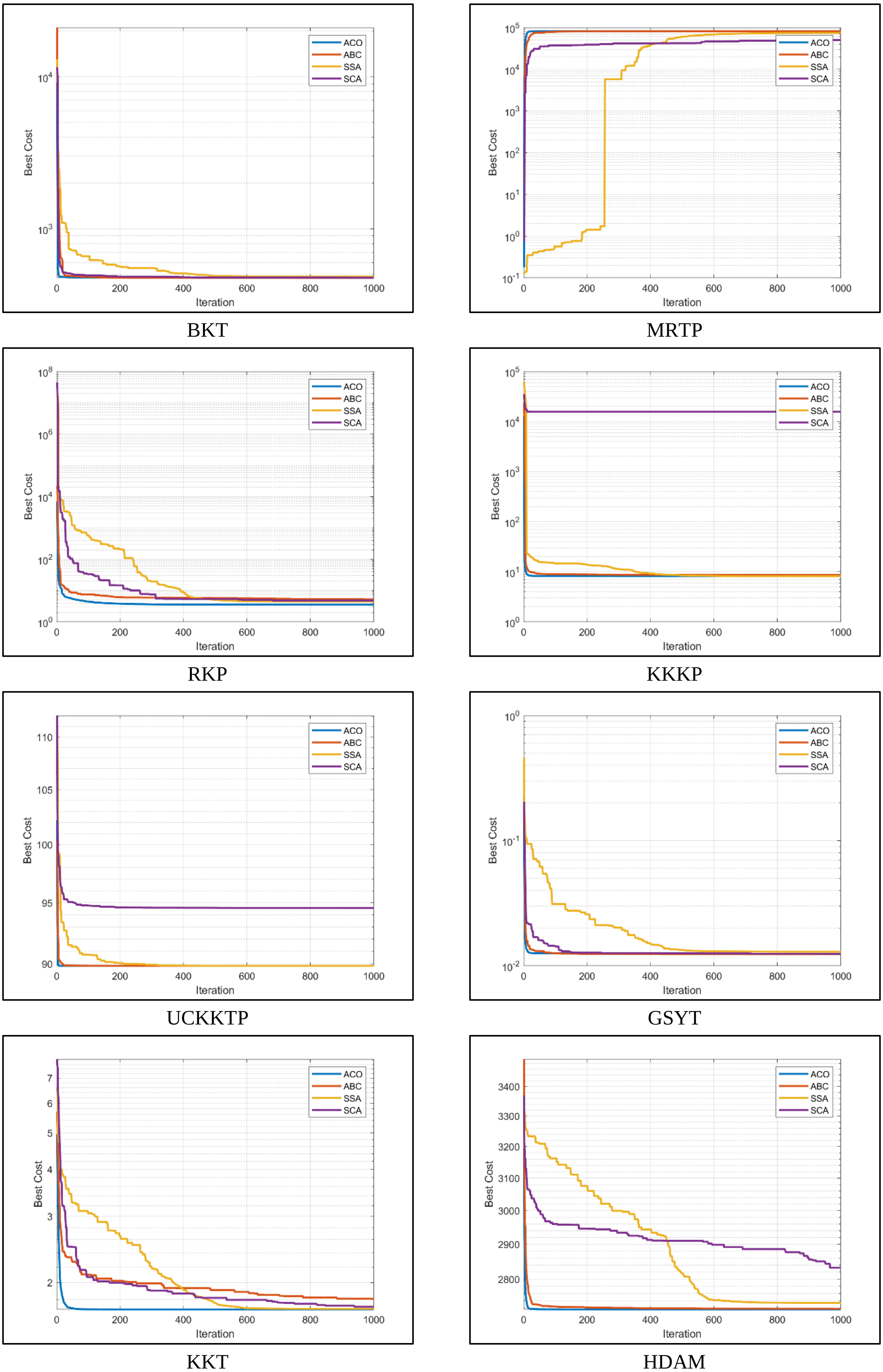


Figure 3. Convergence of metaheuristic algorithms

In Case of number of iterations 1000, number of populations 10, the convergence graphs of the engineering problems are given in Figure 3.

Table 7. Execution times of metaheuristic algorithms (in sec)

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	352.0897	181.5402	**71.0167**	80.6726
2	RKP	8387.5331	6156.2643	**2590.1573**	5740.1892
3	MRTP	682.1775	269.4687	**115.8177**	139.6405
4	KKKP	472.4440	228.0231	**92.5395**	104.7709
5	GSYT	327.2195	188.0169	**69.6981**	75.1521
6	UCKKTP	273.9899	199.5363	**62.6357**	65.8694
7	HDAM	496.2187	245.1594	**88.3884**	105.0990
8	KKT	357.4127	217.2282	**70.8474**	79.4123

In Case of Number of Iterations 1000, Number of Populations 50

In this experiment, the number of iterations was set as 1000 and the number of populations as 50. The optimisation algorithms were run 30 times for each engineering problem and the global best fitness values obtained were averaged. Table 8 shows the global best scores of the engineering problems.

Table 8. Global-best fitness values of metaheuristic algorithms

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	474.4144	**474.3841**	475.6687	475.0677
2	RKP	**3.0242**	4.3005	3.9888	4.2147
3	MRTP	**82125.8**	**82125.8**	75858.2	61754.5
4	KKKP	**8.1885**	**8.1885**	**8.1885**	9.3204
5	GSYT	**0.0123**	0.0124	0.0125	0.0124
6	UCKKTP	**89.8504**	**89.8504**	**89.8504**	89.8510
7	HDAM	**2715.9872**	**2715.9872**	2734.6323	2792.6272
8	KKT	**1.6293**	1.6334	1.7144	1.7184

ACO algorithm obtained the best score in all experiments except problem 1. ABC ranked second with the best score in five experiments and SSA ranked third with the best score in two experiments. The running times of the optimisation algorithms were measured in seconds for each problem as shown in Table 9. SSA was the fastest running algorithm in all experiments except problem 2.

In Case of number of iterations 1000, number of populations 50, the convergence graphs of the engineering problems are given in Figure 4.

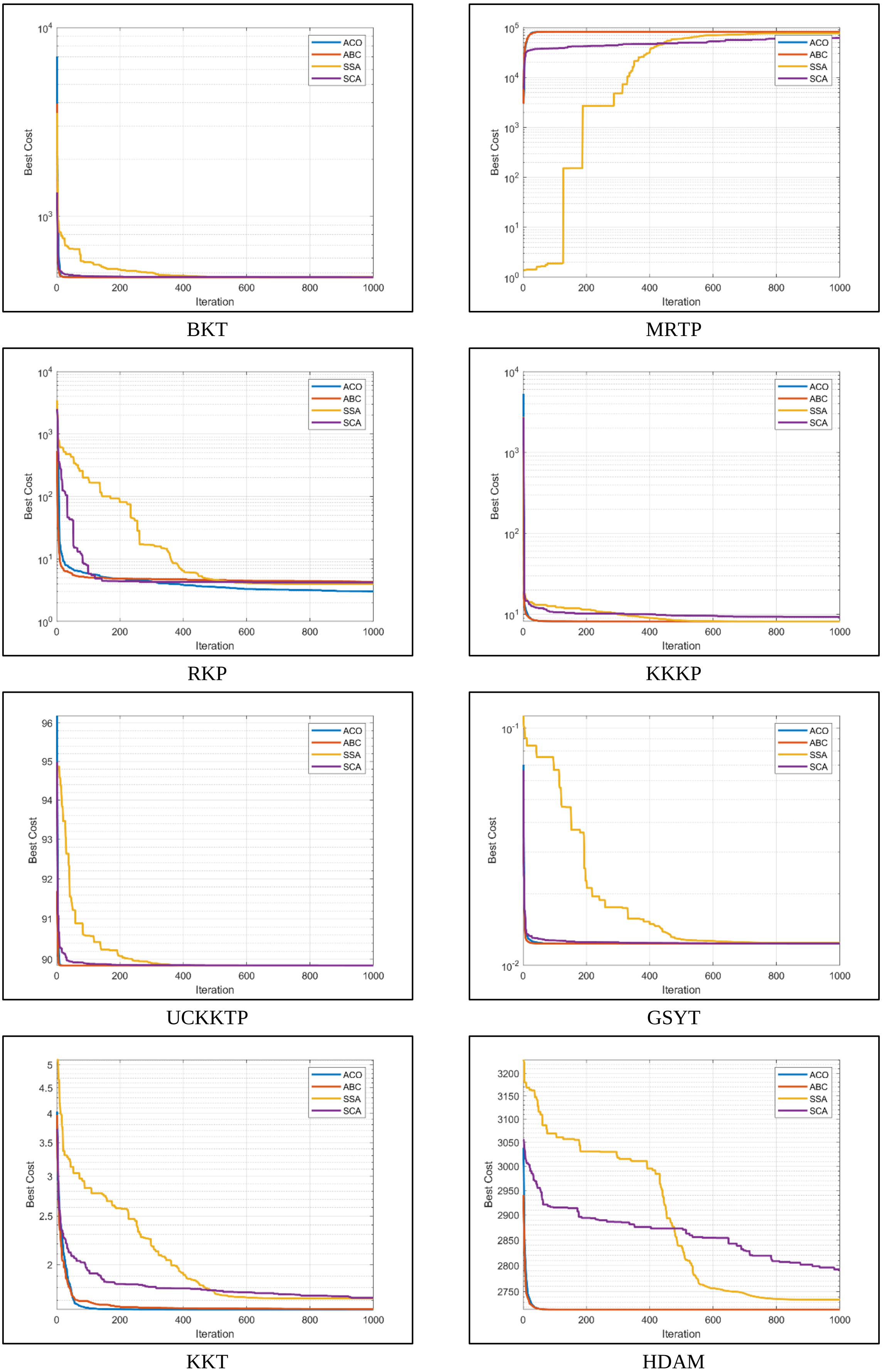


Figure 4. Convergence of metaheuristic algorithms

Table 9. Execution times of metaheuristic algorithms (in sec)

No	Problem	ACO_R	ABC	SSA	SCA
1	BKT	2441.3257	2415.4573	**894.9065**	990.4625
2	RKP	**19048.2559**	46736.6988	26368.7637	56895.9064
3	MRTP	3780.1957	4075.2605	**1606.6733**	1825.5777
4	KKKP	3010.9504	3246.5425	**1288.2404**	1388.2759
5	GSYT	2631.3144	2696.4627	**944.1845**	1044.4299
6	UCKKTP	2518.8396	2902.1494	**914.8963**	974.2277
7	HDAM	3170.5489	3335.9925	**1159.1721**	1332.0030
8	KKT	2736.5262	3004.2976	**1015.2128**	1100.6511

CONCLUSION

The goal of this study was to use metaheuristic algorithms to solve real-world problems, followed by a comprehensive performance analysis of these algorithms. The findings shed light on the suitability of each method for solving mechanical engineering design problems, taking into account both fitness value and processing time. The metaheuristic algorithms were subjected to 30 independent runs for each problem subjected to experimental studies, and the average global best scores were computed. In addition, the average running times of each algorithm were compared to determine its computational efficiency. The experiments were carried out in two stages, each with a different population size, yielding the following results. Upon a comprehensive evaluation of the experimental studies, it becomes evident that the ACO_R algorithm consistently outperforms its competitors in addressing real-world engineering design problems. The optimization algorithms can be ranked in order of success as ABC, SSA, and SCA. A careful examination of the algorithms' running times reveals that SSA stands out as the overwhelmingly fastest method. On the other hand, the SCA algorithm holds the lowest ranking in the experiments concerning execution time. Consequently, it can be confidently asserted that ACO_R not only produces superior solutions but also boasts an ideal running time for efficiently solving real-world problems.

REFERENCES

Abd Elaziz, M., Elsheikh, A.H., Oliva, D., Abualigah, L., Lu, S., Ewees, A.A. 2021. Advanced metaheuristic techniques for mechanical design problems. Archives of Computational Methods in Engineering, 1–22.

Abdullah, E. 2022. A complete solution to exam scheduling problem: A case study. Journal of Scientific Reports-A, 049: 12–34.

Abualigah, L., Elaziz, M.A., Khasawneh, A.M., Alshinwan, M., Ibrahim, R.A., Al-Qaness, M.A., Mirjalili, S., Sumari, P., Gandomi, A.H. 2022. Meta-heuristic optimization algorithms for solving real-world mechanical engineering design problems: A comprehensive survey, applications, comparative analysis, and results. Neural Computing and Applications, 1–30.

Adekanmbi, O., Green, P. 2015. Conceptual comparison of population based metaheuristics for engineering problems. The Scientific World Journal, 1-9.

Andersson, J. 2000. A survey of multiobjective optimization in engineering design. Department of Mechanical Engineering, Linktjping University. Sweden.

Belkourchia, Y., Azrar, L., Zeriab, E.S.M. 2019. A hybrid optimization algorithm for solving constrained engineering design problems. 2019 5th International Conference on Optimization and Applications (ICOA), 25-26 April, p: 1–7.

Braik, M., Sheta, A., Al-Hiary, H. 2021. A novel meta-heuristic search algorithm for solving optimization problems: Capuchin search algorithm. Neural Computing and Applications, 33: 2515–2547.

Carbas, S., Toktas, A., Ustun, D. 2021. Introduction and overview: Nature-inspired metaheuristic algorithms for engineering optimization applications. Nature-Inspired Metaheuristic Algorithms for Engineering Optimization Applications. ISBN: 978-981-33-6773-9. Springer, Singapore. p: 1–9.

Cayiroglu, I., Elen, A. 2012. A heuristic optimization approach for a real-world university timetabling problem. Advances in Computer Science and Engineering, 9(2).

Jiao, R., Commuri, S., Panchal, J., Milisavljevic-Syed, J., Allen, J.K., Mistree, F., Schaefer, D. 2021. Design engineering in the age of industry 4.0. Journal of Mechanical Design, 143(7): 070801.

Lin, M.H., Tsai, J.F., Hu, N.Z., Chang, S.C. 2013. Design optimization of a speed reducer using deterministic techniques. Mathematical Problems in Engineering, 1-7.

Martins, J.R., Ning, A. 2021. Engineering design optimization. 1st ed. Cambridge University Press.

Meng, Z., Li, G., Wang, X., Sait, S. M., Yıldız, A.R. 2021. A comparative study of metaheuristic algorithms for reliability-based design optimization problems. Archives of Computational Methods in Engineering, 28: 1853–1869.

Ragsdell, K.M., Phillips, D.T. 1976. Optimal design of a class of welded structures using geometric programming.

Rather, S.A., Bala, P.S. 2020. Swarm-based chaotic gravitational search algorithm for solving mechanical engineering design problems. World Journal of Engineering, 17(1): 97–114.

Salcedo-Sanz, S. 2016. Modern meta-heuristics based on nonlinear physics processes: A review of models and design procedures. Physics Reports, 655: 1–70.

Savsani, P., Savsani, V. 2016. Passing vehicle search (PVS): A novel metaheuristic algorithm. Applied Mathematical Modelling, 40(5–6): 3951–3978.

Sheikhi Azqandi, M., Delavar, M., Arjmand, M. 2020. An enhanced time evolutionary optimization for solving engineering design problems. Engineering with Computers, 36(2): 763–781.

Talatahari, S., Azizi, M. 2020. Optimization of constrained mathematical and engineering design problems using chaos game optimization. Computers & Industrial Engineering, 145: 106560.

Wong, W.K., Ming, C.I. 2019. A review on metaheuristic algorithms: Recent trends, benchmarking and applications. 2019 7th International Conference on Smart Computing & Communications (ICSCC), 28-30 June, p:1–5.

Yao, J., Sha, Y., Chen, Y., Zhao, X. 2022. A Novel ensemble of arithmetic optimization algorithm and Harris hawks optimization for solving industrial engineering optimization problems. Machines, 10(8): 602.

Zailani, Z.A., Zaibi, N.M., Hamidon, R., Harun, A., Bahari, M.S., Zakaria, S. 2021. Improvement on the surface quality in machining of aluminum alloy involving boron nitride nanoparticles. Intelligent Manufacturing and Mechatronics. ISBN: 978-981-16-0866-7. Springer, Singapore. p: 351–363.

Zuo, W., Zhao, C., Zhou, L., Guo, G. 2019. Comparison of gradient and nongradient algorithms in the structural optimization course. International Journal of Mechanical Engineering Education, 47(3): 275–290.