

International Journal of Intelligent Engineering & Systems

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Fossa Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Engineering Applications

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Abstract: This paper presents a novel bio-inspired metaheuristic algorithm termed the Fossa Optimization Algorithm (FOA), which emulates the natural hunting behavior of the fossa in its habitat. FOA draws its core inspiration from the two-stage hunting technique of the fossa, involving an initial attack on a spotted lemur followed by a pursuit through the trees. The theoretical framework of FOA is elaborated, and its implementation is mathematically modeled in two distinct phases: (i) exploration, which simulates the fossa's positional adjustments during the initial attack on the lemur, and (ii) exploitation, which models the positional changes of the fossa during the chase. The efficacy of FOA is tested against twenty-two constrained optimization problems from the CEC 2011 test suite, as well as four engineering design challenges. The optimization results demonstrate FOA's strong capabilities in both exploration and exploitation, maintaining a balance that facilitates convergence to optimal solutions. FOA's performance is benchmarked against twelve established algorithms, showing that it consistently outperforms its competitors by delivering superior results and ranking as the top optimizer in most of the evaluated functions. These findings indicate that FOA is highly effective in addressing optimization tasks in real-world scenarios.

Keywords: Metaheuristic, Optimization, Fossa, Exploitation, Exploration.

1. Introduction

Optimization issues are crucial in today's world, making efficient methods to handle them a significant research challenge. The primary aim is to identify the most optimal solution from a spectrum of possibilities [1]. While the ideal is to achieve the global optimum, quasi-optimal solutions are sometimes acceptable [2]. Optimization dilemmas typically involve modeling with decision variables, constraints, and an objective function, aimed at optimizing the latter by determining suitable values for the former while adhering to constraints [3]. Techniques employed to address these optimization predicaments are categorized into deterministic and stochastic approaches [4].

Deterministic algorithms always reach the same solution under the same initial conditions and are effective for simple problems and small solution spaces [5, 6]. However, they struggle with large-scale, nonlinear, and multimodal problems, often getting stuck in local optima [7, 8]. Stochastic approaches, particularly metaheuristic algorithms, offer an alternative by using random search [9]. These algorithms are popular due to their ease of

DOI: 10.22266/ijies2024.1031.78

International Journal of Intelligent Engineering and Systems, Vol.17, No.5, 2024

implementation, efficiency in complex and unknown solution spaces, and ability to handle non-convex and non-differentiable problems [10]. Despite their advantages, metaheuristic algorithms do not guarantee the global optimal solution but can provide quasi-optimal solutions close to the global optimum [11]. This has led to the development of numerous metaheuristic algorithms [12].

The No Free Lunch (NFL) theorem asserts that no single metaheuristic algorithm universally excels across all optimization problems, underscoring the imperative to innovate and develop novel algorithms [13]. The inherent stochasticity of metaheuristic algorithms and the uncertainty surrounding optimal solutions emphasize the necessity of creating fresh algorithms aimed at achieving superior solutions. These considerations serve as catalysts prompting researchers to explore and invent new metaheuristic algorithms tailored for scientific optimization tasks.

This study introduces a groundbreaking bioinspired metaheuristic algorithm known as the Fossa Optimization Algorithm (FOA), specifically developed to address complex optimization problems. The primary innovations and contributions of this research are outlined as follows:

- **Development of FOA**: The FOA is designed by drawing inspiration from the natural behaviors of the fossa, a unique predator in the wild.
- Hunting Strategy Inspiration: The FOA's conceptual framework is based on the fossa's two-phase hunting strategy, which includes an initial phase of attacking a lemur and a subsequent phase of chasing the lemur.
- **Theoretical and Mathematical Modeling**: The FOA's methodology is explained and mathematically formulated in two distinct phases:
- **Exploration Phase**: This phase models the positional changes of the fossa during its initial attack on the lemur, aiming to cover a broad search space.
- **Exploitation Phase**: This phase simulates the positional adjustments of the fossa during the chase, focusing on refining and intensifying the search around promising areas.
- **Performance Evaluation**: The effectiveness of FOA is rigorously tested on a set of twenty-two constrained optimization problems from the CEC 2011 test suite, as well as four complex engineering design problems.

• **Comparative Analysis**: The optimization results achieved by FOA are benchmarked against twelve well-established metaheuristic algorithms, providing a comprehensive comparison of performance metrics.

The outcomes of this study highlight the FOA's remarkable ability to balance exploration and exploitation throughout the search process, leading to high-quality solutions for various optimization tasks. The comparative analysis demonstrates that FOA outperforms many existing algorithms, consistently achieving superior results and securing top rankings across most benchmark functions. These findings affirm the FOA's potential as a robust tool for solving real-world optimization problems.

The paper is organized as follows: Section 2 presents the literature review. Section 3 introduces and models the proposed Fossa Optimization Algorithm (FOA). Section 4 assesses the performance of the FOA in tackling a variety of realworld optimization problems. presenting experimental results and comparative analyses to demonstrate its efficacy. Finally, Section 5 offers concluding remarks and proposes directions for future research, suggesting potential improvements and new applications for the FOA.

2. Literature review

Metaheuristic algorithms are inspired by a diverse range of natural phenomena, behaviors of living organisms, scientific principles from genetics, biology, and physics, as well as human activities and evolutionary processes. These algorithms can be broadly categorized into four groups based on their sources of inspiration: swarm-based, evolutionarybased, physics-based, and human-based approaches.

Swarm-based metaheuristic algorithms draw inspiration from the collective behaviors observed in animals, insects, birds, and other creatures. For instance, Particle Swarm Optimization (PSO) [14] mimics the movement of flocks of birds or schools of fish searching for food, where each particle (representing a potential solution) updates its position based on its own experience and that of the swarm. Ant Colony Optimization (ACO) [15] replicates the foraging behavior of ants, using pheromone trails to find the shortest path between their colony and a food source. Similarly, the Grey Wolf Optimizer (GWO) [16] models the hierarchical hunting behavior of grey wolves. Various natural behaviors inspire many swarm-based metaheuristic algorithms, including foraging, hunting, migration, and escape. Examples include Walrus Optimization Algorithm (WaOA)

[17], Gooseneck Barnacle Optimization (GBO) [18], Termite Alate Optimization Algorithm (TAOA) [19], Orca Predation Algorithm (OPA) [20], Electric Eel Foraging Optimization (EEFO) [21], and Greylag Goose Optimization (GGO) [22].

Evolutionary-based metaheuristic algorithms are grounded in principles of genetics, biology, and evolutionary theory, such as natural selection and survival of the fittest. Notable examples include Genetic Algorithm (GA) [23] and Differential Evolution (DE) [24], which emulate biological reproduction and genetic concepts such as mutation and crossover. In GA, each individual, or chromosome, represents a member of the population. Parents are selected using a selection operator, and reproduction is simulated through crossover and mutation operators. Following the survival of the fittest principle, successive generations evolve, guiding the algorithm toward the optimal solution for the problem.

Physics-based metaheuristic algorithms are inspired by principles and phenomena in physics. Simulated Annealing (SA) [25] mimics the metal annealing process, where metals are melted with heat and slowly cooled to form an ideal crystal, analogous to finding an optimal solution. Gravitational Search Algorithm (GSA) [26] models gravitational attraction between masses, where each mass represents a potential solution, moving towards better solutions based on gravitational force and Newton's laws. Spring Search Algorithm (SSA) [27] is based on Hooke's law, where weights (candidate solutions) move towards heavier weights, leading to convergence on better solutions. Momentum Search Algorithm (MSA) [28] uses collision momentum of balls, each representing a candidate solution, to move towards the best known position. Cosmological concepts inspire algorithms like Multi-Verse Optimizer (MVO) [29] and Black Hole Algorithm (BHA) [30].

Human-based metaheuristic algorithms are inspired by various aspects of human behavior, decision-making, and social interactions. Teaching-Learning Based Optimization (TLBO) [31] models the classroom learning process, where teachers and students represent candidate solutions. The best solution, the teacher, guides students toward optimal solutions during the teacher phase, and student knowledge sharing improves solution quality in the student phase. Mother Optimization Algorithm (MOA) [32] is based on a Eshrat's care and education of her children, with the mother and children as candidate solutions. The algorithm updates solutions through education, advice, and upbringing phases. Driving Training-Based Optimization (DTBO) [7] simulates driving school training, with driving applicants and instructors as candidate solutions. The algorithm updates positions through training, skill patterning, and practice phases.

Despite the extensive range of inspirations for existing metaheuristic algorithms, none have yet been designed based on the natural behaviors of the fossa, a predator native to Madagascar. The fossa's strategy of locating, attacking, and chasing lemurs through the trees exhibits intelligent and efficient hunting tactics that can be harnessed for optimization purposes. To address this gap, this paper introduces a novel metaheuristic algorithm called the Fossa Optimization Algorithm (FOA), inspired by the hunting processes of the fossa. The subsequent sections of this paper will delve into the theoretical foundation. mathematical modeling. and performance evaluation of FOA, demonstrating its potential as an effective tool for solving complex optimization problems.

3. Fossa optimization algorithm

In this section, we delve into the foundational inspiration behind the development of the proposed Fossa Optimization Algorithm (FOA). We begin by exploring the biological and behavioral characteristics of the fossa that have been emulated in the design of FOA. Following this, we present a detailed mathematical modeling of the algorithm's implementation steps, demonstrating how these natural behaviors are translated into computational procedures for optimization.

3.1 Inspiration of FOA

The fossa (Cryptoprocta ferox) is a cat-like mammal native to Madagascar, belonging to the Eupleridae family.

Among the fossa's natural behaviors in wildlife, the strategy of this animal in hunting lemurs is much more prominent. This intelligent strategy has two stages: (i) the attack of the fossa towards the location of the observed lemur and (ii) the chase process between the fossa and the lemur on the trees. Mathematical modeling of these intelligent fossa behaviors during hunting has been employed to design the proposed Fossa Optimization Algorithm (FOA) approach, which is discussed below.

3.2 Algorithm initialization

The proposed Fossa Optimization Algorithm (FOA) operates as a population-based optimization technique where each individual fossa represents a member of the population. FOA efficiently searches

for optimal solutions by mimicking the fossas' natural search behaviors within the defined problem space. In this analogy, the fossa's habitat corresponds to the problem-solving space, and the position of each fossa within this habitat represents a potential solution to the optimization problem.

Each fossa's position is characterized by a vector, where each element of the vector signifies the value of a decision variable. Thus, a fossa's position encapsulates a candidate solution. The entire population of fossas, each represented by a position vector, is mathematically described by a matrix, as shown in Eq. (1). The initial positions of the fossas are assigned randomly within the problem space, according to Eq. (2).

This structured approach allows FOA to explore and exploit the search space effectively, using the fossas' dynamic positional adjustments to iteratively hone in on optimal solutions. By leveraging the inherent search capabilities of the fossas, FOA ensures a thorough examination of the problem space, leading to high-quality solutions for complex optimization problems.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,d} \cdots x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} \cdots x_{i,d} \cdots x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} \cdots x_{N,d} \cdots x_{N,m} \end{bmatrix}_{N \times m}$$
(1)

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{2}$$

In this context, X represents the population matrix of FOA, where X_i denotes the ith fossa, which is a candidate solution. $x_{i,d}$ represents the *d*th dimension of the *i*th fossa in the search space, where N stands for the number of fossas, m indicates the number of decision variables, r is a random number in interval [0,1], lb_d , and ub_d denote the lower and upper bounds of the *d*th decision variable, respectively.

As previously stated, each fossa's position denotes a potential solution for the problem and can undergo evaluation within the objective function. The resultant values from evaluating the objective function can be encapsulated in a vector, as outlined by Eq. (3).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N \times 1}$$
(3)

Here, F represents the vector of evaluated objective function values, with F_i indicating the objective function value corresponding to the *i*th fossa.

3.3 Mathematical modelling of FOA

The FOA algorithm is designed by emulating the intelligent movement strategies of fossas in nature. The positions of the FOA members within the problem-solving space are updated through two distinct phases:

Exploration Phase: This phase is inspired by the initial attack behavior of fossas when targeting a lemur. During this phase, the algorithm focuses on exploring the search space broadly to identify promising regions. The positional updates during exploration are modeled based on the changes in the fossa's position as it prepares and initiates its attack.

Exploitation Phase: This phase mimics the pursuit of the lemur through the trees, where the fossa fine-tunes its approach to home in on the target. In the exploitation phase, the algorithm intensifies the search around the identified promising areas, refining the solutions. The positional updates during exploitation are based on the dynamic adjustments made by the fossa during the chase.

The mathematical modeling and detailed explanation of each update phase in FOA are presented below.

3.3.1 Attacking and moving towards the lemur (exploration phase)

In the initial phase of the FOA, the positions of the population members within the problem-solving space are updated by simulating the fossa's attack on an observed lemur. Fossas can accurately locate lemurs using their keen sense of smell, hearing, and vision. Once the lemur's position is identified, the fossa advances toward it. This modeled displacement during the attack phase results in significant changes in the positions of the population members, thereby enhancing FOA's global exploration capabilities.

For each fossa, the positions of other population members with better objective function values are regarded as the lemurs' locations within its habitat. Consequently, the set of candidate lemurs for each fossa is determined by comparing objective function values, as described by Eq. (4):

$$CL_i = \{X_k: F_k < F_i \text{ and } k \neq i\},\$$

where $i = 1, 2, ..., N$ and $k \in \{1, 2, ..., N\}$ (4)

In this equation, CL_i represents the set of candidate lemur locations for the *i* th fossa, X_k denotes the population member with a superior

International Journal of Intelligent Engineering and Systems, Vol.17, No.5, 2024 DOI: 10.22266/ijies2024.1031.78

objective function value than the *i*th fossa, and F_k is its corresponding objective function value.

The FOA assumes that the fossa randomly selects one of these candidate lemurs in its habitat and launches an attack. Based on the fossa's positional change during the attack on the identified lemur, a new random position for each member of the FOA population is calculated using Eq. (5). If this new position yields a better objective function value, it replaces the previous position of the respective population member, as outlined in Eq. (6).

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot (SL_{i,j} - I_{i,j} \cdot x_{i,j}),$$
(5)

$$X_i = \begin{cases} X_i^{P_1}, \ F_i^{P_1} \le F_i, \\ X_i, \ else \end{cases},$$
(6)

In this context, SL_i denotes the lemur chosen by the *i*th fossa and $SL_{i,j}$ refers to the *j*th dimension of this selected lemur's position. X_i^{P1} represents the newly computed position for the *i*th fossa during the attack phase of the FOA, with $x_{i,j}^{P1}$ being its *j* th dimension. The objective function value at this new position is F_i^{P1} . The terms $r_{i,j}$ are random nvalues within the range [0, 1], and $I_{i,j}$ are random integers, either 1 or 2.

3.3.2 Phase 2: Chasing to catch lemur (exploitation phase)

In the second phase of FOA, the positions of the population members are updated by simulating the fossa's pursuit of the lemur. The fossa utilizes its exceptional climbing abilities to follow the lemur through the trees and across branches. This pursuit takes place in a confined area within the hunting ground. By modeling the fossa's movements during the chase, the algorithm introduces minor adjustments to the positions of the population members, thereby enhancing the FOA's exploitation capabilities in local search optimization.

In the FOA design, the chase process between the fossa and the lemur in nature is represented by small positional changes in the population members. The positional updates during the lemur chase are mathematically modeled, with a new position for each FOA member calculated using Eq. (7). If this new position results in an improved objective function value, it replaces the member's previous position, as outlined in Eq. (8).

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t}$$
(7)

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \le F_i \\ X_i, & else \end{cases}$$
(8)

In this context, X_i^{P2} represents the updated position computed for the *i*th f fossa during the chasing phase in the proposed FOA. Each $x_{i,j}^{P2}$ signifies the *j*th dimension of this new position, while F_i^{P2} denotes its corresponding objective function value. The variables $r_{i,j}$ are random numbers ranging from [0, 1], and *t* stands for the current iteration count.

4. Simulation studies

In this segment, the efficacy of FOA in addressing optimization challenges in practical applications is assessed. To achieve this, a total of twenty-six constrained optimization problems have been chosen. These comprise twenty-two real-world problems sourced from the CEC 2011 test suite, alongside an additional four problems from the realm of engineering design.

4.1 Evaluation of CEC 2011 test suite

In this section, we evaluate the effectiveness of FOA and its competitors in tackling the challenges posed by the CEC 2011 test suite. This test suite encompasses twenty-two distinct constrained optimization problems derived from real-world applications. Comprehensive details, including the mathematical models and descriptions of the CEC 2011 test suite, can be accessed in [33].

Table 1 presents the optimization outcomes obtained by FOA and competing algorithms on the CEC 2011 test suite. The results highlight FOA's capacity to deliver effective solutions across problems C17-F1 to C17-F22, demonstrating its adeptness in exploration, exploitation, and maintaining a balance throughout the search process. According to the findings from simulations, FOA consistently outperformed all other algorithms across all twenty-two optimization problems, positioning it as the top-performing optimizer. Statistical analyses, specifically the Wilcoxon rank sum test conducted on experimental data, further underscored FOA's significant statistical superiority over the twelve alternative algorithms in optimizing the CEC 2011 test suite.

Table 1. Performance of metaheuristic algorithms on CEC 2011 test suite

			Table					argoritam		<i>C</i> 2011	iest suit			
		GA	PSO	GSA	TLBO	GWO	MVO	WOA	TSA	MPA	RSA	AVOA	WSO	FOA
	Best	20 99485	10 47427	17 97987	16 71953	1 1 3 0 6 1 1	11 58557	7 604293	16 90901	0 453935	18 45749	8 642607	14 08941	2.00E-10
	Maria	22.14945	17.20022	20.00215	17.65007	10 72522	12 50222	12.00409	17 (2112	7 719052	20.95771	12 (2970	16.05277	5.020102
	Mean	22.14845	17.20023	20.60315	17.65027	10.72532	13.59232	12.90498	17.62112	7.718053	20.85771	12.63879	16.95377	5.920103
	Median	21.54986	17.5065	21.08212	17.37924	12.49167	13.61517	13.57618	17.20423	8.845166	20.79824	12.72897	16.97953	5.687176
C11-F1	XX7 - wet	24 40024	22 21262	22.2695	10.10200	16 79722	15 55226	16.96220	10.16701	10 70704	22.27(99	16 45450	10.7(((1	12 20 000
	worst	24.49924	23.31303	22.2085	19.12309	10.78732	15.55556	10.80329	19.16/01	12.72794	23.37088	16.45459	19.70001	12.30606
	std	1.756925	6.23952	2.006092	1.188596	7.3733	2.470244	4.664845	1.157165	6.115793	2.501392	4.807401	2.952731	7.476538
	rank	13	8	11	10	3	6	5	0	2	12	4	7	1
	Talik	15	0	11	10	3	0	5	3	2	12	4	/	1
	Best	-16.1717	-24.0945	-20.9656	-13.286	-24.7265	-12.1764	-22.2907	-15.9609	-25.6183	-13.168	-21.8573	-16.597	-27.0676
	Mean	-13 9987	-22 8058	-16 3567	-12 1633	-22 7616	-10 2743	-19 1379	-12 5182	-24 9761	-12 7716	-21 3238	-15 3149	-26 3179
G11 F2	Micun	12.6400	22.0050	15.004	12.1035	22.7010	10.2745	10.2402	11.7406	25.2449	12.7710	21.3230	15.1706	26.3177
CII-F2	Median	-13.6499	-23.2107	-15.984	-12.04	-23.4923	-10.1089	-19.3403	-11./486	-25.3448	-12.7422	-21.3444	-15.1/96	-26.3856
	Worst	-12.5232	-20.7072	-12.4933	-11.2874	-19.3352	-8.70316	-15.5801	-10.6146	-23.5963	-12.4343	-20.749	-14.3035	-25.4328
	otd	1.042177	1 600267	4 174712	0.042061	2 60969	1 619709	2 606526	2 751276	1.0299	0.280212	0 577727	1 227751	0.767702
	stu	1.942177	1.000307	4.1/4/13	0.942001	2.00808	1.010700	3.090320	2.751270	1.0200	0.369213	0.377737	1.227731	0.707703
	rank	9	3	7	12	4	13	6	11	2	10	5	8	1
	Best	3 26E-06	3 26E-06	3 26E-06	3 26E-06	3 26E-06	3 26E-06	3 26E-06	3 26E-06	3 26E-06				
	Dest	3.20E 00	3.20E 00	3.20E 00	3.20E 00	3.20E 00	3.20E 00	3.20E 00	3.20E 00	3.20E 00				
	Mean	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06
C11-F4	Median	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06	3.26E-06
	Wonst	2.26E.06	2.26E.06	2 26E 06	2 265 06	2 265 06	2 265 06	2.26E.06	2 265 06	2 265 06	2.26E.06	2.26E.06	2.26E.06	2 265 06
	worst	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00	5.20E-00
	std	1.39E-16	1.40E-16	1.40E-16	7.27E-14	3.59E-15	9.22E-13	1.40E-16	2.20E-14	1.28E-15	4.62E-11	2.36E-09	2.05E-11	2.08E-19
	rank	5	2	3	0	7	10	4	8	6	12	13	11	1
	Talik	5		5	2	/	10	4	0	0	12	13	11	1
	Best	72.55129	71.10386	37.99406	58.62053	28.138/3	31.40391	38.65784	30.85337	23.23436	44.19588	26.19046	40.48998	17.74098
	Mean	74 28086	85 67926	43 4327	85 41443	29 73022	35 40336	45 08551	35 25719	26 66493	57 83315	31 42147	44 24001	22 20814
C11 E4	M I	71.20000	02.45210	44.05070	00.01(10	20.07000	24.0400	12.000001	24.54410	26.00103	55.04000	20.50202	12.045.00	21.62200
CII-F4	Median	14.25833	83.45319	44.05978	80.81618	29.87288	34.8409	43.82622	34.54418	26.20191	55.04009	30.50303	43.94568	21.62299
	Worst	75.9203	91.35037	51.37966	93.81534	31.89236	37.15296	46.47603	36.80899	28.24343	60.29817	32.97873	46.81271	24.33469
1	otd	1 951944	10 28216	6 117292	16 85201	1 74757	2 705972	3 800609	3 122015	2 32/252	8 210025	3 100126	3 505064	3 071097
1	stu	1.751044	10.20210	0.11/303	10.05201	1./+/5/	2.103012		5.123713	2.524352	0.210033	3.470420	5.505904	5.071087
	rank	11	13	9	12	3	6	7	5	2	10	4	8	1
	Best	-12,9633	-14.0945	-31,4583	-15.0617	-34,1245	-31.6367	-28.3603	-31,7808	-33,7811	-23,2641	-29.6017	-26,7142	-34,7494
	Ma	11.0745	11.102	27.0156	12.0451	21.0050	27.500	28.1602	27.7012	22.01/2	21.2004	28.50.00	25.6276	24 1074
	Mean	-11.8745	-11.103	-27.9156	-13.0451	-31.6952	-27.596	-28.1683	-27.7213	-33.2163	-21.2904	-28.5962	-25.6376	-34.1274
C11-F5	Median	-12.0577	-10.3539	-27.5065	-12.7468	-32.3842	-26.6221	-28.2	-28.0587	-33.6269	-21.4602	-28.4014	-25.6157	-34.1871
	Worst	10.4102	0.60059	25 1012	11 6251	27 9979	25 502	27.012	22 0971	21.9204	18 077	27.0904	24 605	22 2862
	worst	-10.4193	-9.00938	-23.1912	-11.0231	-27.0078	-23.303	-27.915	-22.98/1	-51.8504	-10.977	-27.9804	-24.005	-33.3802
	std	1.250673	2.30699	3.004306	1.594488	2.917966	3.142033	0.227202	3.948511	1.012393	2.411024	0.768531	0.990576	0.612958
	rank	12	13	6	11	3	8	5	7	2	10	4	9	1
	D	10.4176	7.00202	25.0106	1 005 61	00 (152	17.0125	22 7007	16.0420	25 6007	14 4770	20.05.00	15 0174	27.4200
	Best	-10.41/6	-7.99292	-25.9196	-4.88501	-22.0155	-17.8135	-22.7897	-10.9438	-25.6097	-14.4//2	-20.8568	-15.21/4	-27.4298
	Mean	-5.89114	-5.07774	-21.849	-4.30091	-19.8288	-10.7684	-20.1179	-9.00058	-22.4991	-13.9198	-19.2912	-14.8115	-24.1119
C11 E6	Median	4 52608	4 13065	21 /0/3	4 13065	10 2/185	10.6016	21.0742	6 56002	21 50/0	14 1527	10 3205	14 7852	23 0050
C11-10	Wiculan	-4.32008	-4.13003	-21.4943	-4.13003	-19.2403	-10.0010	-21.9742	-0.30902	-21.3949	-14.1327	-19.3293	-14.7832	-23.0039
	Worst	-4.09474	-4.05674	-18.4879	-4.056/4	-18.2027	-4.05674	-13.7337	-5.92048	-21.197	-12.8964	-17.6491	-14.4582	-23.0059
	std	3.318344	2.122875	3.541293	0.428562	2.28315	7.977012	4.701624	5.812291	2.296303	0.769418	1.554489	0.367927	2.415463
		11	10	2	12	5	0	4	10	2	0	(7	1
	Talik	11	12	3	15	3	9	4	10	Z	0	0	/	1
	Best	1.293914	0.854726	0.879567	1.474091	0.827545	0.841207	1.56562	1.097291	0.766328	1.608278	1.125389	1.468141	0.582266
	Mean	1 656328	1 106615	1 067479	1 636933	1.056742	0.890619	1 65915	1 265574	0 933894	1 816199	1 249677	1 536587	0.860699
C11 E7	Madian	1 742515	1 110592	1.066024	1 656959	1.065555	0.97712	1 620522	1 102451	0.077272	1.920225	1.244005	1 522509	0.01775
C11-17/	wieuran	1.742313	1.119362	1.000934	1.030838	1.005555	0.87712	1.030322	1.165451	0.977372	1.639323	1.244903	1.525596	0.91775
	Worst	1.846369	1.332569	1.25648	1.759925	1.268311	0.967026	1.809935	1.598104	1.014501	1.977866	1.383506	1.63101	1.025027
	std	0 272084	0 265478	0 186178	0 139852	0 197138	0.066569	0 114757	0 246191	0 125447	0 167329	0 152119	0.076051	0.219737
	510	0.272004	0.205470	0.100170	0.157052	0.177150	0.000507	0.1147.57	0.240171	0.125117	0.107525	0.102117	0.070051	0.217757
	rank	11	6	5	10	4	2	12	8	- 5	13	/	9	1
	Best	220	245.9004	220	220	220	220	242.6022	220	220	278.3859	224.0273	255.2005	220
	Maan	222 7130	443 6161	244.049	224 1316	227.048	224 1316	261 6804	253 8425	222 6734	314 7225	238 70/7	278 5874	220
	Wiedii	222.7139	445.0101	244.049	224.1310	227.040	224.1310	201.0804	233.8423	222.0734	514.7225	230.1941	278.3874	220
C11-F8	Median	220.5788	497.1932	234.7096	220.3934	226.9554	220.9722	250.2866	226.9554	222.5807	313.1747	238.3086	274.4072	220
	Worst	229.6981	534,1777	286.7768	235,7397	234.2814	234.582	303.5461	341.4594	225.5322	354.1547	254.5343	310.3349	220
	otd	5 110295	149 666	24 50719	9 460409	0 000007	7 626272	20 72647	64 19600	2 275126	22.07946	14 22104	26 45290	0
	sta	5.119565	148.000	54.59/18	8.400498	0.000007	1.020212	30.73047	04.18099	5.575120	33.97840	14.55194	20.43289	0
	rank	3	12	7	4	5	4	9	8	2	11	6	10	1
	Best	1669561	779171.2	633837.2	305005.7	17992.06	70020 37	187100	46780 75	11358 35	623943.8	303703.8	336624.4	5457 674
	Maria	1741(00	071660.5	720742.2	269500 6	41227.10	1000007	228205 ((2107.06	20011 10	052252.7	241407	501590	9790 296
	Mean	1/41009	9/1009.3	139143.3	308399.0	41557.18	122209.7	558205.0	02107.90	20911.18	935555.7	541467	301389	0/09.200
C11-F9	Median	1726937	958802.2	765168.3	348439.9	37918.27	117413.7	297579	61996.84	21185.22	1035051	348103.4	546223.3	7828.591
	Worst	1843000	1180002	794700 2	472513	71520.11	183001.2	570564.2	77657 41	20015.02	1110360	366037.4	577285	14042 20
	worst	1043000	1109903	794799.3	472313	24506.0	103391.2	100504.2	14:00.2	29915.95	1119309	300037.4	1000-1	14042.29
	std	92744.64	239797	/8603.68	80205.77	24690.8	51444.35	190694.6	14680.84	8914.331	244/08.1	29948.31	123361	4040.59
	rank	13	12	10	8	3	5	6	4	2	11	7	9	1
	Best	-11 8777	-12 1302	-14 1377	-12.00	-14 0635	-20.8400	-13 0637	-18 7065	-19 2772	-13 2432	-17 2126	-15/1171	-21 8200
1	M	11.5777	12.1372	10 (10)	11.0715	14.4020	15.0275	10.0007	14.7400	10.0000	10.0412	17.2120	14.0700	21.3279
1	Mean	-11./99/	-12.0639	-15.6434	-11.9/47	-14.4933	-15.0277	-15.3928	-14./489	-18.8938	-12.8612	-17.0117	-14.5738	-21.4889
C11-F10	Median	-11.8093	-12.0602	-13.7626	-11.974	-14.7956	-13.5846	-13.3078	-13.8074	-18.8929	-12.7759	-17.0947	-14.1093	-21.669
1	Worot	11 7024	11.006	12 0100	11 9606	13 /192	12 0015	12 0010	12 6742	18 5122	12 6409	16 6447	13 9507	20 7979
1	worst	-11./024	-11.790	-12.9109	-11.0000	-13.4103	-12.0913	-12.9919	-12.0/43	-10.5122	-12.0498	-10.044/	-13.0397	-20./0/0
1	std	0.082719	0.0703	0.657711	0.116756	0.796964	4.308425	0.446373	2.968027	0.431168	0.292805	0.287749	0.774897	0.518028
	rank	13	11	8	12	6	4	9	5	2	10	3	7	1
	Deet	5677042	107(15)	1255754	4074510	2470200	707421 5	1010070	1619960	1605025	7909244	022660.6	5170050	260927.0
	Best	30/1943	40/0150	1555/54	46/4318	3479200	191431.5	1212878	4048869	1005925	1698344	933009.6	5170959	200837.9
	Mean	5715298	4909100	1503283	4899197	3668455	1411326	1328293	5556217	1724848	8161789	1127735	5428932	571712.3
C11 E11	Median	5710274	4911323	1494330	4896975	3602463	1080007	1309812	5450789	1720208	8204838	1140258	5389551	598725.2
CII-FII	M	5710274	4027500	1660716	4020222	20002403	1007997	1400 572	667110	1050046	0204050	1006756	5567551	000720.2
	Worst	5762701	4937598	1668/19	4928322	3989695	2667880	1480672	6674421	1853049	8339135	1296753	5765667	828560.9
	std	39470.81	31430.76	140055.5	30459.3	243250.4	927121.6	123049	912761.6	127928.3	204150.5	175849.4	298944.6	271080
	rank	12	0	5	8	7	4	3	11	6	13	2	10	1
	D	12	,	5	0	10.5550	4	107-007	11	1010-11	13	2	10	1
	Best	12985236	2075391	5069911	12214423	1267206	1204649	4976933	4413862	1212610	11129535	3073561	7330982	1155937
	Mean	13101652	2218684	5325393	12957822	1423395	1337048	5347886	4645979	1289778	11980897	3167584	7650391	1199805
C11 E12	Madiar	13000441	2109262	5365007	13042669	1/25105	1340014	5111050	4702610	1200570	12022002	3170057	7669000	1106065
C11-F12	wieulan	13099001	2190202	5505007	13042008	1455195	1340014	J444638	4702019	12003/8	12032002	31/963/	/008092	1190903
1	Worst	13222048	2402821	5501647	13531529	1555984	1463515	5524894	4764815	1369345	12730048	3237059	7934399	1249353
	std	106367	148202.6	203566.6	603530.0	130905 5	116064.8	277918.8	179484 8	74652.8	716923 /	77855 9/	272018.8	48993 46
1	Sid	100507	170292.0	200000	12	130903.3	110004.8	211710.0		, 10,52.0	110923.4	11055.74	10.0	+0775.40
L	rank	13	5	8	12	4	3	9	7	2	11	6	10	1
	Best	15461.56	15473.13	84613.22	15610.79	15491.54	15486.67	15490.35	15479.1	15461.74	15849.47	15449.72	15650.7	15444.19
	Mean	28468 14	15488.02	116417.0	15884.56	15498 11	15504.10	15528.85	15488 35	15464.19	16221.86	15450.61	15816.09	15444.2
~	Micall	20400.14	15466.92	110417.9	15004.50	15490.11	15504.19	15520.05	15468.55	15404.18	10221.00	15450.01	15610.98	15444.2
C11-F13	Median	15619.13	15480.19	110751.1	15769.62	15495.75	15495.83	15521.86	15487.34	15463.33	15945.42	15450.75	15698.87	15444.2
	Worst	67172.77	15522.16	159556.3	16388.19	15509.41	15538.42	15581.33	15499.63	15468.33	17147.14	15451.22	16219.49	15444.21
	044	28177 61	24 47421	26915 07	284.045	8 626120	26 22076	16 1251	10 80610	2 170962	670 1700	0.707511	205 2020	0.000445
	sta	20177.01	24.47431	30645.87	364.045	8.030126	20.33876	40.4354	10.80619	3.179862	079.1709	0.707511	293.8929	0.009445
	rank	12	5	13	10	6	7	8	4	3	11	2	9	1
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Median 9908.06 1002.56 1012.76 27610.27 1910.03 1903.31 1925.35 1925.40 1925.35 1925.40 1925.35 1925.41 1925.15 1925.41 1925.15 1925.41 1915.35 1925.41 1915.35 1925.41 1915.35 1925.41 1915.35 1925.41 1915.31 1923.42 1915.31 1917.31 1917.31 1917.33 1917.32 1917.32 1917.32 1917.32 1917.32 1917.33 <t< td=""><td></td><td>Mean</td><td>19077.55</td><td>19088.96</td><td>19059.83</td><td>280023.5</td><td>19185.03</td><td>19352.06</td><td>19178.82</td><td>19452.19</td><td>18626.04</td><td>206926.2</td><td>18546.95</td><td>102602.5</td><td>18295.35</td></t<>		Mean	19077.55	19088.96	19059.83	280023.5	19185.03	19352.06	19178.82	19452.19	18626.04	206926.2	18546.95	102602.5	18295.35
Word 1923.631 1923.685 5386.55 1932.94 1991.15 1870.04 1972.92 184.12 1472.12 183.85 mark 5 6 4 13 8 9 7 10 5 12 2 11 1 mark 5 6.6 4 13 8 9 7 10 5 12 2 11 1 Mem 710722 3323.23 2377.58 2307.58 2209.01 836153 9662.23 3388.43 3287.58 2209.01 836153 9662.23 3388.43 3287.58 2209.01 836153 9662.23 100.43 3281.84 400.54 11 7 10 1 7 10 11 7 10 11 7 10 11 11 7 10 11 11 7 10 11 11 11 11 12 10 11 7 11 12 11 11 <td< td=""><td></td><td>Median</td><td>19068.96</td><td>19095.56</td><td>19102.76</td><td>276190.7</td><td>19169.03</td><td>19362.31</td><td>19195.3</td><td>19319.71</td><td>18631.88</td><td>188733.6</td><td>18547.18</td><td>94586.94</td><td>18275.87</td></td<>		Median	19068.96	19095.56	19102.76	276190.7	19169.03	19362.31	19195.3	19319.71	18631.88	188733.6	18547.18	94586.94	18275.87
std 2291445 129.364 120.344 2071627 152.115 135.154 367.0078 767.007 372.12 2 11 1 Bear 3227130 3323.773 200949.8 23023.56 3300.93 3300.47 33417.85 32075.8 32075.4 23287.58 200041 42110.22 3383.11 3283.11 3283.11 3283.11 3283.11 3283.11 3283.11 3283.11 3208.13 3208.13 3218.31 447387.3 3288.33 3228.31 3288.31 3288.31 331.34 2383.14 447387.7 300.68 3288.31 331.43 331.43 3318.31 447387.7 300.66 237.7 300.67 300.42 3288.31 330.28 3288.31 330.28 318.31 44730.7 307.84 3289.35 3289.31 3288.31 330.28 330.28 330.28 330.28 3288.31 330.28 3288.31 330.28 3288.31 330.20 3288.31 330.20 328.31 4473.22 128.10 128.10 128.10		Worst	19353.51	19226.62	19236.88	538663.5	19358.95	19432.94	19294.4	19951.15	18700.84	297329.2	18641.62	142712.3	18388.08
mak 5 6 4 0 3 8 9 0 7 100 3 2 2 2 1 10 12 2 2 1 10 11 12 2 2 1 10 11 12 12 2 2 1 11 13 14 13 13 13 14 13 14 10 14 10 14 10 14 10 14 13 14 13 13 </td <td></td> <td>std</td> <td>239 1445</td> <td>129 5361</td> <td>210 3944</td> <td>267168.7</td> <td>152 4139</td> <td>84 72372</td> <td>133 1554</td> <td>367.0078</td> <td>76 74049</td> <td>70641.04</td> <td>98 64241</td> <td>31350.13</td> <td>74 38679</td>		std	239 1445	129 5361	210 3944	267168.7	152 4139	84 72372	133 1554	367.0078	76 74049	70641.04	98 64241	31350.13	74 38679
Best 32371 32 32197 32 32197 32 32197 32 32197 32 3217 32		rank	5	6	4	13	8	9	7	10	3	12	2	11	1
Mean 710702 3322.55 71871.5 1387265 21828.58 2001.85 1717.53 1000.00 81431.8 23283.58 Word 1217091 3313.24 92928.8 20588.88 3301.23 3384.07 28836.7 11005.49 3218.44 32956.46 Main 447737 129.34 287527 1209.01 12381.12 1398.07 28836.7 11004.9 3218.47 2107.42 20275.42 20277.42 20277.42 20277.42 20277.42 20277.42 20277.42 20277.42 12079.11 1107.7 1107.1 <		Best	3237130	33247 73	240949.8	2895904	33032.56	33005.93	33000.47	33047.85	32875 58	720290.4	42110.22	338511.1	32782 17
Challin Openation Openation Openation Openation Openation Openation Openation Openation Openation C11-F18 Mores 12170293 3531.23 25202.02 05088353 3331.23 3338.02 25383.57 110054.0 3331.81 447779 104779.4 204757.6 32921.52 05087.65 3321.83 144779.07 10477.67 204756.6 32956.46 3329.125 10475.6 1295.05 20521.65 705541.6 20931.75 10470.65 1295.05 1317.22 1171.821 11491.6 14191.65 14191.65 14191.6		Moon	7107022	22222 55	271972.5	12007659	22124 41	22154.22	100218 4	52258.2	22019.30	1717624	100060.8	916422.9	22002.50
C11-F18 Microal Database Database <thdatabase< th=""> <thdatabase< th=""> <th< td=""><td></td><td>Modion</td><td>6507622</td><td>22264 50</td><td>276807.7</td><td>15872046</td><td>22101 02</td><td>22112.49</td><td>240022.2</td><td>22165.02</td><td>22000.01</td><td>926157.2</td><td>06682.82</td><td>420929.2</td><td>22805.50</td></th<></thdatabase<></thdatabase<>		Modion	6507622	22264 50	276807.7	15872046	22101 02	22112.49	240022.2	22165.02	22000.01	926157.2	06682.82	420929.2	22805.50
Work 1211929 53312.6 24924.8 201012 33344.0 23384.0 23384.0 24382.0 11054.9 321286 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116 1041.6 20116	C11-F15	Weulan	12170202	22512.29	2/0807.7	13872940	22201.22	22284.02	240023.2	110054.0	32990.01	4477020	90082.82	439626.3	32897.80
Side 4417(2) 159-348 2037/3-8 153-20 129 day 17/3281 12/3281 42/3058 32/308 3		worst	121/9295	120.249	292928.8	20388838	120 (200	177.0201	283820.7	110034.9	150 5020	4477930	72064.12	2047308	52950.40
Inits Li 3 4 5 4 5 6 0 0 1 / 1 <td></td> <td>std</td> <td>44//3//</td> <td>139.348</td> <td>26377.34</td> <td>8/8522/</td> <td>129.6209</td> <td>1/7.9281</td> <td>123599.1</td> <td>42004.12</td> <td>159.5038</td> <td>2012667</td> <td>72064.12</td> <td>899537.6</td> <td>19.94256</td>		std	44//3//	139.348	26377.34	8/8522/	129.6209	1/7.9281	123599.1	42004.12	159.5038	2012667	72064.12	899537.6	19.94256
Best 55289603 5894654 892065 7/564482 14/2005 1538554 14/08.04 4380546 14/08.5 21/2149 1533550 C11+F16 Median 65400467 7/2143701 16774448 18/97204 153000.1 577356.7 133257.5 Wordt 14/03522 1230851 1000371 102430.4 4704.14 410400.7 14101.9 14101.9 14101.9 14100.19 14105.2 15000.6 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 15610.8 21/8373 1471.4 15610.9 24/91.0 21/8101 12/81.10 162.10 10/91.10 22/91.7 15610.8 588.00 10/92.06 152.00 13/8371 13/81-10 20/81.00 19/92.05 13/92.00 13/81.10 13/92.10 12/81.10 10/81.10 19/92.05 11/92.10 11/92.10 11/92.10 11/92.10 11/92.10 11/92.10	-	rank	12	5	9	13	3	4	8	6	2	11	/	10	1
Mean 6840642 7124370 16774448 799005 142383 141600.4 141918.6 144500.4 137885.4 179800.4 152865.3 80740.2 133357.5 Worst 87492894 85131824 30336734 81887274 150609.3 149252.3 14710.4.1 146100.7 124365 12000.1 577936.5 133357.5 133357.5 133357.5 133357.5 133357.5 133357.5 133357.5 14357.5 13355.5 13355.5 13355.5 <td></td> <td>Best</td> <td>55289650</td> <td>58934654</td> <td>8526963</td> <td>77564482</td> <td>142909.8</td> <td>133833.5</td> <td>136624.1</td> <td>141930.9</td> <td>135804.4</td> <td>438659.6</td> <td>134084.5</td> <td>2/3214.9</td> <td>1313/4.2</td>		Best	55289650	58934654	8526963	77564482	142909.8	133833.5	136624.1	141930.9	135804.4	438659.6	134084.5	2/3214.9	1313/4.2
C11-F16 Median 652-163 14371.1 14457.3 144797.1 144500.7 112403.6 13600.0 15793.6.7 133257.5 work 1403222 12330851 10298312 1978328 397.8.9 7018.439 477.445 2214.617 144510.62 161.67.54 884983.8 2485.329 mak 11 12 10 13 7 4 5 6 3 9 2 8 1 Mean 1.968-10 1.888+10 1.058+10 2.0841 1022207 700367 1.158-00 6289305 1.388+10 9.026.015 9.888-09 1.268+10 2.088+00 1.268+00 1.268+00 1.268+00 1.268+00 1.268+00 1.268+00 1.268+00 1.268+00 1.268+00 1.269.01 1.438+10 2.071+00 8.988+00 1.261.01 1.066+0 1.212318 3.288+00 1.261.02 1.261.01 1.066+0 1.271.03 3.279.09 1.261.02 1.261.02 1.261.02 1.261.02 1.261.02 1.261.02		Mean	68406462	71243770	16774448	79596055	145238.3	141600.4	141918.6	144570.6	137885.4	1759603	135665.3	860740.2	133550
Worst 8742894 85131823 3033734 8187274 [150605, 149253.4] [14610.7] 144610.7] 45516.6 1201805 [116774] 85948.2 2214.617 2825.563 121850 [116774] 85948.2 2845.32 rank 11 12 10 13 7 4 5 6 3 9 2 8 1 Rest 18381-10 1058-10 8848-00 1.158-10 62998.6 1.398+10 2.088+09 1.028+10 2.081+09 8.081+09 1923612 Worst 2.128+10 2.168+10 1.068+10 7.358+00 7.358 3.3722.7 2.466+09 2.086+08 1123218 3.288+09 1.868+08 9.958+08 12470.83 3.3722.7 2.466+09 2.068+08 112318 3.288+09 1.861+08 9.598+08 1.928+10 1.928+109 1.928+109 1.921428 3.288+109 1.864+08 9.591+08 1.4270.83 3.035804 9.4147.5 1.421418 1.016148 5.751016 3.932450 1.116148	C11-F16	Median	65421652	70454300	14117049	79466231	143717.1	141657.3	141973	145080.4	137067.7	1124036	136090.1	577936.7	133257.5
std 1498222 12330831 1102 10 13 7 4 5 6 3 9 2 8 1 Best 1.85E-10 1.65E+10 1.85E+10 1.65E+10 1.85E+10 1.65E+10 1.85E+10 1.65E+10 1.85E+10 1.65E+10 1.85E+10 1.65E+10 1.85E+10		Worst	87492894	85131824	30336734	81887274	150609.3	149253.4	147104.1	146190.7	141601.9	4351682	136396.6	2013873	136310.8
rank 11 12 10 13 7 4 5 6 3 9 2 8 1 Rest 1.83E+01 1.65E+10 8.84E+00 192E+10 6297236 6601966 1.15E+00 620965 1.23E+10 2.08E+00 8.03E+00 1926455 C11+F17 Medin 1.83E+10 1.05E+10 1.62E+10 1.05E+00 8.28E+00 1.12E+00 6208731 1.43E+10 2.27E+00 8.98E+00 19242685 wors 2.21E+10 2.01E+10 8.98E+00 1.23E+00 1.86E+08 1.27E+08 8.1E+08 1.24E+08 1.202975 9.9122.8 8682456 1.91790 976570.8 1.06E+08 5.93303 3.9252.7 7.330553 3.61220 3.395804 9.3416.2 Median 1.05E+04 1.24E+08 1.060664 2.129764 1.027916.3307990 2.22171 1.		std	14938222	12330851	10298312	1978328	3947.89	7018.439	4767.445	2214.617	2825.563	1921850	1161.754	854983.8	2485.329
Best 1.85E+10 1.65E+10 1.87E+10 1.29E+10 222110 9.98E+20 1.38E+200 1.89E+200 1.88E+200 1.88E+200<		rank	11	12	10	13	7	4	5	6	3	9	2	8	1
Mean I.96E+10 I.87E+10 IE+10 2E:10 692237 700503 8.68E+09 I.17E+06 6059317 I.33E+10 20.8E+09 102312 Worst 2.11E+10 2.16E+10 1.06E+10 2.09E+10 922301 7403570 1.15E+10 1.23E+00 7488320 1.7E+10 2.27E+00 8.9E+00 1247083 rank 12 11 9 13 3 4 5 2 10 6 7 14 Best 9886808 1.01E+08 1538917 2210160 968293.4 971576.3 3730553 1066+08 573105 330249 942057.5 Median 1.03E+08 1.24E+08 10020993 2900053 990122.8 1802490 240721 1036728 1.21E+08 5040957 942057.5 5033053 3933024 942057.5 5033053 953033 94255.5 5033053 5033053 5053057 504672 1.21E+08 5044956 5533053 505008 574472 124151 1064145		Best	1.83E+10	1.65E+10	8.84E+09	1.92E+10	5297236	6661968	6.19E+09	9.49E+08	5224908	9.98E+09	1.89E+09	6.84E+09	1916953
C11-F17 Median L88E+10 L38E+10 L38E+10 L38E+10 L38E+10 L38E+10 L38E+10 L32E+10 L32E+10 <thl32e+10< th=""> <thl32e+10< th=""> <thl3< td=""><td></td><td>Mean</td><td>1.96E+10</td><td>1.87E+10</td><td>1E+10</td><td>2E+10</td><td>6922237</td><td>7005034</td><td>8.68E+09</td><td>1.15E+09</td><td>6269965</td><td>1.39E+10</td><td>2.08E+09</td><td>8.03E+09</td><td>1926615</td></thl3<></thl32e+10<></thl32e+10<>		Mean	1.96E+10	1.87E+10	1E+10	2E+10	6922237	7005034	8.68E+09	1.15E+09	6269965	1.39E+10	2.08E+09	8.03E+09	1926615
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11-F17	Median	1.89E+10	1.83E+10	1.03E+10	1.99E+10	6583310	6977244	8.5E+09	1.17E+09	6198317	1.43E+10	2.07E+09	8.18E+09	1923412
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Worst	2.21E+10	2.16E+10	1.06E+10	2.09E+10	9225091	7403679	1.15E+10	1.32E+09	7458320	1.7E+10	2.27E+09	8.9E+09	1942685
rank 12 11 9 13 3 4 8 5 2 10 6 7 1 Best 9886898 1.01E+08 7538917 2210160 968293.4 97757.3 3739361 1707773 95355.4 73305536 3631280 339840.4 94207.5 C11-F18 Median 1.03E+08 1.24E+08 10026993 2900053 990555.5 99407.6 17882971 1906769 57999.8 1.15E+08 504456 5004307 944706.9 94705.9 1006761.0 1036729 1.21E+08 1079466 5009007 94470.6 240661.2 43947.61 2445003 3329758 11321428 2882.138 rank 11 13 8 9 4 3 7 5 2 2 0 10 1 1131428 2882.138 rank 1.01 1.44E+08 1038108 155206 1390531715715 1027181 1016129 970700 571138 450532 2 <		std	1.89E+09	2.51E+09	8.93E+08	7.35E+08	1909349	357222.7	2.46E+09	2.06E+08	1123218	3.28E+09	1.86E+08	9.95E+08	12470.83
Best 9888689 1011-08 7538917 22101606 9682934 977576.3 3793961 1707773 953554.7 73305536 3631280 33958804 93416.2 C11-F18 Mean 1.03E+08 1.21E+08 10066604 27859754 1029725 99122.8 8682456 1941970 9976570.8 1.06E+08 5975105 49330249 942057.5 Worst 1.06E+08 1.24E+08 12681053 30136132 1189417 99162.8 1516920 2246712 1036729 1.21E+08 10179946 56096087 944706.9 att 3364918 155984910 2208023 2206071 1135171 1065265 2121670 1035410 1445269 697977.7 Mean 1.03E+08 1.55E+08 5739020 3199158 1448953 1450839 9224616 2343471 147559 104E+08 6088032 48581106 102571 Mean 1.03E+08 1.54E+08 591645 32337561 1979533 16696406 22242701 1163544343		rank	12	11	9	13	3	4	8	5	2	10	6	7	1
Mean 1.03E+08 1.21E+08 10068634 27859754 1029725 99122.8 8682456 1941970 976570.8 1.06E+08 5975105 49330249 942057.5 C11-F18 Median 1.03E+08 1.24E+08 10026993 22600639 980595.5 994076.1 7882971 1036729 121E408 10179946 550630678 944706.9 rank 11 13 8 9 4 3 7 5 2 12 6 0 1 rank 11 13 8 9 4 3 7 5 2 12 6 0 1 Best 1E408 1.4E+08 2281906 22432725 122267 1135717 1906955 2110354 1075570 89781843 5585104 4146269 967927.7 Mean 103E+08 1.5E+08 5739023 381756 13279758 1062140 233247 1147559 1.04E+08 6088032 48551106 1025341		Best	98886898	1.01E+08	7538917	22101606	968293.4	977576.3	3793961	1707773	953554.7	73305536	3631280	33958804	938416.2
C11-F18 Median 1.03E+08 1.24E+08 1026993 2960033 980595.5 994076.1 7882971 1906696 957999.8 1.15E+08 5044596 53633053 942553.5 Worst 1.06E+08 1.34E+08 12681633 30136132 118417 999162.8 15161062 437471 12472 2828138 rank 11 13 8 9 4 3 7 5 2 12 6 10 1 Best 1.4E+08 1.4E+08 528109 210354 107570 89781843 558104 41462669 967927.7 Meain 1.03E+08 1.5E+08 6591645 32831756 1320751 1979515 1696406 234247 1147559 1.04E+08 680802 48581106 1025341 Vort 1.06E+08 1.798008 105214 1139405 9207210 131E+08 594077103 5711338 4556652 9831945.0 1025341 C11-F19 Median 1.03E+08 1.4920		Mean	1.03E+08	1 21E+08	10068634	27859754	1029725	991222.8	8682456	1941970	976570.8	1.06E+08	5975105	49330249	942057 5
Worst 1.062408 1.34E+08 123412 120322 120322 1203233 120323 1203233 120323 1203233 120323 120334 1005323 120334 1005323 120334 1005323 120334 1005323 120334 1005323 110334 120333 110334 120334 101334 120334 101334 120334 1103433 110354 103334 110354 103334 110354 103334 110354 101334 101334 101334 101334 101334 101334 101334	C11-F18	Median	1.03E+08	1 24F+08	10026993	29600639	980595 5	994076.1	7882971	1906696	957999.8	1.15E+08	5044596	53633053	942553.5
std 3363/16 1593/20 200/20 </td <td>011110</td> <td>Worst</td> <td>1.05E+08</td> <td>1.24E+00 1.34E+08</td> <td>12681633</td> <td>30136132</td> <td>1189417</td> <td>999162.8</td> <td>15169920</td> <td>2246712</td> <td>1036729</td> <td>1.13E+08 1.21E+08</td> <td>10179946</td> <td>56096087</td> <td>944706.9</td>	011110	Worst	1.05E+08	1.24E+00 1.34E+08	12681633	30136132	1189417	999162.8	15169920	2246712	1036729	1.13E+08 1.21E+08	10179946	56096087	944706.9
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		etd	3364018	15984910	2508023	4209691	116531.1	10532.68	5246107	280616.2	13947.61	24445003	3320758	11321428	2882 138
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		ronk	11	13984910	2308023	4209091	110551.1	2	7	200010.2	4 <i>39</i> 47.01	12	5529150	10	1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Bost	1E+08	1.4E+08	2281006	22/32725	1222677	1135717	1060505	2110354	1075570	80781843	5585104	41462669	067027 7
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Moon	1.02E+08	1.4E+08	5720620	21001581	12/2077	1450802	0276615	2224247	11/7550	1.04E+09	6088032	49581106	1025241
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11 E10	Madian	1.03E+08	1.55E+08	6501645	22921756	1222796	1204055	9270013	2334247	114/339	07677002	5711229	46561100	0021466
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11-1-19	Weulan	1.05E+08	1.3E+08	7402105	20070000	1522760	1394033	9220230	2240793	1202400	97077003	7244240	43300332	963140.0
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		worst	1.06E+08	1.79E+08	7493195	39870088	120076.6	18/9/45	10090400	2729050	1302409	1.51E+08	/344349	0020707	102555.5
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		sta	2552248	18224008	2582122	8246265	139970.0	339655.7	/5/6039	296442.5	113940.5	20772114	919788	9980797	103555.5
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		rank	11	13	6	9	5	4	8	5	2	12	/	10	1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Best	98348523	1.3E+08	8591082	303/55/1	9/9533.8	965606.1	6245290	15/4189	961236.8	98191740	4/55991	45431180	936143.2
$ \begin{array}{c} \mbox{C11-F20} & \mbox{Median} & \mbox{1.04E+08} & \mbox{1.43E+08} & \mbox{11224473} & \mbox{31026530} & \mbox{9998114} & \mbox{974995.6} & \mbox{655891} & \mbox{1685079} & \mbox{964071} & \mbox{1.09E+08} & \mbox{5357579} & \mbox{4997379} & \mbox{4009552} & \mbox{9409553} & \mbox{940640} & \mbox{1.33E+08} & \mbox{6046402} & \mbox{61111371} & \mbox{946866.6} & \mbox{1.33E+08} & \mbox{6046402} & \mbox{61111371} & \mbox{946866.6} & \mbox{9408333} & \mbox{14919097} & \mbox{538754} & \mbox{641381.5} & \mbox{1594597} & \mbox{9334779} & \mbox{410649.8} & \mbox{227709.2} & \mbox{2403.706} & \mbox{16376455} & \mbox{584973.9} & \mbox{729408} & \mbox{5208.733} & \mbox{73} & \mbox{73} & \mbox{73} & \mbox{73} & \mbox{75} & \mbox{24037} & \mbox{21.25222} & \mbox{66.651} & \mbox{1.212522} & \mbox{66.651} & \mbox{1.212522} & \mbox{4.866645} & \mbox{12.71443} & \mbox{10.1547} & \mbox{12.5232} & \mbox{4.866645} & \mbox{12.71443} & \mbox{12.12523} & \mbox{4.866645} & \mbox{12.71443} & \mbox{13.1547} & \mbox{13.8644} & \mbox{10.70104} & \mbox{1.04376} & \mbox{13.45401} & \mbox{24.24733} & \mbox{29.48577} & \mbox{18.42639} & \mbox{87.6601} & \mbox{23.12498} & \mbox{5.251248} & \mbox{12.95425} & \mbox{12.95425} & \mbox{13.8644} & \mbox{10.1547} & \mbox{12.8298} & \mbox{5.251248} & \mbox{14.97499} & \mbox{14.97499} & \mbox{14.97499} & \mbox{13.4298} & \mbox{33.429023} & \mbox{29.88577} & \mbox{18.4639} & \mbox{87.6601} & \mbox{23.12498} & \mbox{5.51228} & \mbox{2.250654} & \mbox{11.5013} & \mbox{14.9743} & \mbox{13.82957} & \mbox{18.42643} & \mbox{14.1077} & \mbox{13.8293} & \mbox{14.1097} & \mbox{14.1297} & \mbox{14.1097} & \mbox{16.12513} & \mbox{14.1097} & \mbox{14.1297} & \mbox{14.1097} & \mbox{14.1097} & \mbox{14.12613} & \mbox{43.24257} & \mbox{11.2384} & \mbox{14.24253} & \mbox{16.667671} & \mbox{1.588698} & \mbox{1.52856} & \mbox{14.1097} & 14.2$	G11 500	Mean	1.03E+08	1.43E+08	12880053	31054116	9981/5.3	9/5145.4	6622515	1/3942/	963984.7	1.12E+08	53/9388	51622517	941250.4
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11-F20	Median	1.04E+08	1.43E+08	11524473	31026530	999801.4	974999.6	6559891	1685079	964071	1.09E+08	535/5/9	499/3/59	940995.9
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Worst	1.07E+08	1.55E+08	19880187	31787834	1013565	984976.4	7124987	2013362	966560.1	1.33E+08	6046402	61111371	946866.6
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		std	4043353	14919097	5387546	641381.5	15945.97	9334.779	410649.8	227709.2	2403.706	16376455	584973.9	7296408	5208.733
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		rank	11	13	8	9	4	3	7	5	2	12	6	10	1
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		Best	54.60476	83.80605	34.18591	45.26357	20.14849	23.76096	33.88851	25.41455	14.00337	53.05298	19.85679	39.1355	9.974206
$ \begin{array}{c} \mbox{C11-F21} \\ \mbox{Median} & 103.2593 & 97.69051 & 39.02586 & 94.17921 & 21.62156 & 26.43952 & 36.22601 & 29.53327 & 16.06672 & 70.33024 & 21.01376 & 46.55892 & 12.95425 \\ \hline \mbox{Worst} & 113.8644 & 107.0104 & 41.04376 & 134.5401 & 24.24733 & 29.48409 & 40.09472 & 29.83577 & 18.42639 & 87.66401 & 23.12498 & 55.21246 & 14.97499 \\ \hline \mbox{std} & 30.11547 & 12.6295 & 3.297139 & 39.95036 & 20.08403 & 3.429023 & 2.988624 & 2.320265 & 2.250136 & 16.67677 & 1.538698 & 7.551228 & 2.506594 \\ \hline \mbox{rank} & 12 & 13 & 8 & 11 & 4 & 5 & 7 & 6 & 2 & 10 & 3 & 9 & 1 \\ \hline \mbox{Best} & 84.01881 & 82.03603 & 37.2219 & 61.58839 & 23.72063 & 24.30535 & 37.80818 & 27.11712 & 16.46137 & 43.54151 & 21.82335 & 38.765 & 11.50133 \\ \hline \mbox{Mean} & 85.1019 & 97.6976 & 44.00065 & 94.08526 & 24.56654 & 31.10542 & 43.68071 & 30.96559 & 19.27119 & 50.04216 & 26.76287 & 44.11097 & 16.12513 \\ \hline \mbox{Median} & 84.84462 & 100.4589 & 43.42257 & 101.7697 & 24.65206 & 32.16406 & 44.42632 & 31.66513 & 19.61731 & 62.42624 & 26.8069 & 44.23459 & 16.72317 \\ \hline \mbox{Worst} & 86.69957 & 107.8366 & 51.93637 & 111.2133 & 25.24143 & 35.7882 & 48.062 & 33.41497 & 21.38878 & 67.77466 & 31.61431 & 49.20969 & 19.55286 \\ \hline \mbox{std} & 1.242318 & 12.64539 & 6.634157 & 24.32807 & 0.710153 & 5.511919 & 5.075941 & 2.956052 & 2.556775 & 11.66582 & 5.059597 & 4.902887 & 4.36122 \\ \hline \mbox{rank} & 11 & 13 & 8 & 12 & 3 & 6 & 7 & 5 & 2 & 10 & 4 & 9 & 1 \\ \hline \mbox{Mean} \mbox{rank} & 234 & 210 & 165 & 233 & 99 & 123 & 151 & 150 & 56 & 240 & 112 & 198 & 22 \\ \hline \mbox{Mean} \mbox{rank} & 10.63636 & 9.545455 & 7.5 & 10.59091 & 4.5 & 5.59099 & 6.863663 & 6.818182 & 2.554555 & 10.90909 & 9 & 9 & 1 \\ \hline \mbox{Mean} \mbox{rank} & 12 & 10 & 8 & 11 & 3 & 5 & 7 & 6 & 2 & 13 & 4 & 9 & 1 \\ \hline \mbox{Mean} \mbox{rank} & 12 & 10 & 8 & 11 & 3 & 5 & 7 & 6 & 2 & 13 & 4 & 9 & 1 \\ \hline \mbox{Mean} \mbox{rank} & 12 & 10 & 8 & 11 & 3 & 5 & 7 & 6 & 2 & 13 & 4 & 9 & 1 \\ \hline \mbox{Mean} \mbox{rank} & 12.2188 & 6.28E-19 & 2.11E-18 & 1.32E-18 & 1.75E-18 & 9.84E-16 & 4.24E-19 & 9.03E-19 & 1.75E$		Mean	93.74696	96.54937	38.32035	92.04052	21.90974	26.53102	36.60882	28.57921	16.1408	70.34437	21.25232	46.86645	12.71443
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11-F21	Median	103.2593	97.69051	39.02586	94.17921	21.62156	26.43952	36.22601	29.53327	16.06672	70.33024	21.01376	46.55892	12.95425
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Worst	113.8644	107.0104	41.04376	134.5401	24.24733	29.48409	40.09472	29.83577	18.42639	87.66401	23.12498	55.21246	14.97499
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		std	30.11547	12.62395	3.297139	39.95036	2.008403	3.429023	2.988624	2.320265	2.250136	16.67677	1.538698	7.551228	2.506594
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		rank	12	13	8	11	4	5	7	6	2	10	3	9	1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	C11-F22	Best	84.01881	82.03603	37.22109	61.58839	23.72063	24.30535	37.80818	27.11712	16.46137	43.54151	21.82335	38.765	11.50133
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		Mean	85.1019	97.6976	44.00065	94.08526	24.56654	31.10542	43.68071	30.96559	19.27119	59.04216	26.76287	44.11097	16.12513
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Median	84.84462	100.4589	43.42257	101.7697	24.65206	32.16406	44.42632	31.66513	19.61731	62.42624	26.8069	44.23459	16.72317
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	1	Worst	86.69957	107.8366	51.93637	111.2133	25.24143	35.7882	48.062	33.41497	21.38878	67.77466	31.61431	49.20969	19.55286
rank 11 13 8 12 3 6 7 5 2 10 4 9 1 Sum rank 234 210 165 233 99 123 151 150 56 240 112 198 22 Mean rank 10.63636 9.545455 7.5 10.59091 4.5 5.590909 6.863636 6.818182 2.545455 10.90909 9 1 Total rank 12 10 8 11 3 5 7 6 2 13 4 9 1 p-value 1.32E-18 6.28E-19 2.11E-18 1.32E-18 1.75E-18 9.84E-16 4.24E-19 9.03E-19 1.75E-18 4.24E-19 -	1	std	1.242318	12.64539	6.634157	24.32807	0.710153	5.511919	5.075941	2.956052	2.556775	11.66582	5.059597	4.902887	4.36122
Sum rank 234 210 165 233 99 123 151 150 56 240 112 198 22 Mean rank 10.63636 9.545455 7.5 10.59091 4.5 5.590909 6.863636 6.818182 2.545455 10.90909 5.090909 9 1 Total rank 12 10 8 11 3 5 7 6 2 13 4 9 1 p-value 1.32E-18 6.28E-19 2.11E-18 1.32E-18 1.75E-18 9.84E-16 4.24E-19 9.03E-19 1.75E-18 4.24E-19 -	1	rank	11	13	8	12	3	6	7	5	2	10	4	9	1
Mean rank 10.63636 9.545455 7.5 10.59091 4.5 5.590909 6.863636 6.818182 2.545455 10.90909 9 1 Total rank 12 10 8 11 3 5 7 6 2 13 4 9 1 p-value 1.32E-18 6.28E-19 2.11E-18 1.32E-18 1.75E-18 9.84E-16 4.24E-19 9.03E-19 1.75E-18 4.24E-19 -	Sum	rank	234	210	165	233	99	123	151	150	56	240	112	198	22
Total rank 12 10 8 11 3 5 7 6 2 13 4 9 1 p-value 1.32E-18 6.28E-19 2.11E-18 1.32E-18 1.75E-18 9.84E-16 4.24E-19 9.03E-19 1.75E-18 4.24E-19 2.41E-18 4.24E-19 -	Mean rank		10.63636	9.545455	7.5	10.59091	4.5	5.590909	6.863636	6.818182	2.545455	10.90909	5.090909	9	1
p-value 1.32E-18 6.28E-19 2.11E-18 1.32E-18 1.75E-18 9.84E-16 4.24E-19 9.03E-19 1.75E-18 4.24E-19 2.41E-18 4.24E-19 -	Total	rank	12	10	8	11	3	5	7	6	2	13	4	9	1
	p-value		1.32E-18	6.28E-19	2.11E-18	1.32E-18	1.75E-18	9.84E-16	4.24E-19	9.03E-19	1.75E-18	4.24E-19	2.41E-18	4.24E-19	-

4.2 Evaluation of engineering design problems

In this section, we assess the efficacy of FOA and rival algorithms in tackling four distinct engineering optimization tasks. These challenges encompass pressure vessel design, speed reducer design, welded beam design, and tension/compression spring design. Pressure vessel design aims primarily at minimizing construction costs within real-world engineering applications. Detailed mathematical models and comprehensive information on pressure vessel design can be found in reference [34]. Similarly, speed reducer design focuses on minimizing the weight of the speed reducer, with detailed models and information available in references [35, 36]. Welded beam design aims to reduce fabrication costs, and its detailed mathematical model is outlined in reference [37]. Lastly, tension/compression spring design aims to minimize the weight of these components, with detailed models also available in reference [37].

Table 2 presents the implementation results and performance of competing algorithms in optimizing these engineering challenges. FOA has demonstrated significant achievements in each design scenario:

Table 2. Performance of metaheuristic algorithms on engineering design problems

DP		FOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
TCS	x 1	0.051689	0.051737	0.051257	0.050326	0.05169	0.051073	0.051233	0.050326	0.051924	0.052324	0.054699	0.052053	0.051888
	x2	0.356718	0.357867	0.346439	0.319486	0.356738	0.342104	0.345876	0.324558	0.362385	0.372754	0.430976	0.366437	0.362179
	x3	11.28897	11.22211	11.92786	14.29026	11.2879	12.22009	11.96323	13.56401	10.96935	10.81158	8.238095	11.25212	11.33667
	OF	0.012665	0.012665	0.01267	0.013099	0.012665	0.01268	0.01267	0.01274	0.01267	0.012783	0.013024	0.012792	0.012752
	x1	0.778027	0.77803	0.778152	1.194252	0.778029	0.779498	0.911327	0.834505	0.778847	0.908547	1.129191	0.933719	0.886017
	x2	0.384579	0.384583	0.384653	0.639897	0.384581	0.385818	0.450989	0.416446	0.386002	0.628703	1.155857	0.641424	0.557939
WB	x3	40.31228	40.31245	40.3187	60.51195	40.31237	40.38643	46.22319	43.22087	40.34048	42.75299	44.1012	44.05702	43.02611
	x4	200	199.999	199.9263	48.28486	200	200	133.9229	163.8891	199.7992	182.9717	190.8091	168.7006	176.7552
	OF	5882.901	5882.941	5883.219	7756.095	5882.934	5909.346	6270.268	6004.221	5891.301	7762.927	11970.25	7816.691	7181.082
	x1	3.5	3.500037	3.500004	3.581054	3.500014	3.511351	3.576922	3.502079	3.500663	3.50624	3.520229	3.506347	3.50428
	x2	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.700726	0.70242	0.700726	0.700484
	x3	17	17	17	17	17	17	17	17	17	17.09734	17.32445	17.09734	17.06489
SD	x4	7.3	7.3	7.30074	8.110958	7.3	7.3	7.3	7.3	7.304521	7.491246	7.757514	7.545238	7.47249
ы	x5	7.8	7.800502	7.800076	8.205554	7.800498	8.205554	7.984485	8.036471	7.8	7.823629	7.878762	7.823629	7.815752
	x6	3.350215	3.350249	3.350272	3.355059	3.350215	3.350501	3.360247	3.367261	3.362298	3.366437	3.401692	3.367212	3.361677
	x7	5.286683	5.286693	5.286703	5.4595	5.286687	5.289792	5.286754	5.286861	5.288556	5.313197	5.373942	5.313517	5.304633
	OF	2996.348	2996.378	2996.386	3160.309	2996.367	3011.773	3033.212	3006.84	3000.933	3043.037	3148.787	3043.958	3028.259
	x1	0.886017	0.20573	0.205728	0.205044	0.19779	0.205728	0.20438	0.212751	0.205952	0.205601	0.228928	0.283135	0.228904
	x2	0.557939	3.470489	3.470516	3.485375	3.526928	3.470516	3.492384	3.346984	3.465724	3.473457	3.273343	2.812744	3.273462
\mathbf{PV}	x3	43.02611	9.036624	9.036654	9.036704	9.817037	9.036654	9.060873	8.981482	9.043723	9.036264	8.612117	7.617417	8.61337
	x4	176.7552	0.20573	0.20573	0.205729	0.216335	0.20573	0.206105	0.219144	0.206017	0.205792	0.232667	0.295529	0.232664
	OF	7181.082	1.724852	1.724862	1.725806	1.945043	1.724862	1.732763	1.809626	1.727966	1.725466	1.819821	2.040803	1.819994

- For pressure vessel design, FOA yielded optimal design variable values of (0.7780271, 0.3845792, 40.312284, 200) and an objective function value of 5882.8955.
- In speed reducer design, FOA achieved superior results with design variable values of (3.5, 0.7, 17, 7.3, 7.8, 3.3502147, 5.2866832) and an objective function value of 2996.3482.
- For welded beam design, FOA obtained optimal design variable values of (0.2057296, 3.4704887, 9.0366239, 0.2057296) and an objective function value of 1.7246798.
- In tension/compression spring design, FOA produced optimal design variable values of (0.0516891, 0.3567177, 11.288966) and an objective function value of 0.0126019.

Analysis of simulation results indicates that FOA consistently outperforms competing algorithms in solving these engineering design challenges. Its capability to effectively explore, exploit, and maintain balance throughout the search process underscores its robust performance in real-world optimization applications.

5. Concluding remarks and future works

This study introduced the Fossa Optimization Algorithm (FOA), a newly developed metaheuristic inspired by the hunting strategies of fossas in the wild. FOA was designed to emulate the fossa's approach to hunting lemurs, which involved initial attacks followed by strategic pursuits through trees. The algorithm was meticulously explained and mathematically modeled to optimize exploration and exploitation during these distinct phases. To evaluate its efficacy, FOA was tested on twenty-two challenging optimization problems sourced from the CEC 2011 test suite, alongside four practical engineering designs. Results highlighted FOA's capability in achieving optimal solutions by effectively balancing exploration, exploitation, and search management. Comparative assessments against twelve prominent metaheuristic algorithms consistently demonstrated FOA's superiority across diverse benchmarks.

Future research directions include developing binary and multi-objective versions of FOA and applying it across diverse scientific and practical domains.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, T.H, B.B, G.B, and F.W; methodology, TH, M.D, and K.E; software, K.E, B.B, and F.W; validation, K.E, M.D, G.B., and Z.M; formal analysis, Z.M, M.D, and K.E; investigation, B.B, Z.M, and F.W; resources, T.H, Z.M, B.B, and G.B; data curation, K.E, G.B, and F.W; writing original draft preparation, M.D, T.H, and F.W; writing—review and editing, F.W, Z.M, B.B, G.B, and K.E; visualization, K.E; supervision, M.D;

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DOI: 10.22266/ijies2024.1031.78

project administration, K.E, T.H, and Z.M; funding acquisition, K.E.

References

- [1] A. Taheri *et al.*, "Partial reinforcement optimizer: An evolutionary optimization algorithm", *Expert Systems with Applications*, Vol. 238, p. 122070, 2024, doi: 10.1016/j.eswa.2023.122070.
- [2] S. Barua and A. Merabet, "Lévy Arithmetic Algorithm: An enhanced metaheuristic algorithm and its application to engineering optimization", *Expert Systems with Applications*, Vol. 241, p. 122335, 2024, doi: 10.1016/j.eswa.2023.122335.
- [3] N. Singh, X. Cao, S. Diggavi, and T. Başar, "Decentralized multi-task stochastic optimization with compressed communications", *Automatica*, Vol. 159, p. 111363, 2024, doi: 10.1016/j.automatica.2023.111363.
- [4] D. A. Liñán, G. Contreras-Zarazúa, E. Sánchez-Ramírez, J. G. Segovia-Hernández, and L. A. Ricardez-Sandoval, "A hybrid deterministicstochastic algorithm for the optimal design of process flowsheets with ordered discrete decisions", *Computers & Chemical Engineering*, Vol. 180, p. 108501, 2024, doi: 10.1016/j.compchemeng.2023.108501.
- [5] H. Qawaqneh, "New contraction embedded with simulation function and cyclic (α, β)-admissible in metric-like spaces", *International Journal of Mathematics and Computer Science*, Vol. 15, No. 4, pp. 1029-1044, 2020.
- [6] T. Hamadneh, N. Athanasopoulos, and M. Ali, "Minimization and positivity of the tensorial rational Bernstein form", In: Proc. of 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology, pp. 474-479, 2019.
- [7] M. Dehghani, E. Trojovská, and P. Trojovský, "A new human-based metaheuristic algorithm for solving optimization problems on the base of simulation of driving training process", *Scientific Reports*, Vol. 12, No. 1, p. 9924, 2022, doi: 10.1038/s41598-022-14225-7.
- T. Hamadneh and R. Wisniewski, "The Barycentric Bernstein Form for Control Design", In: *Proc. of* 2018 Annual American Control Conference (ACC), pp. 3738-3743, 2018, doi: 10.23919/ACC.2018.8431599.
- [9] F.-A. Zeidabadi, M. Dehghani, P. Trojovský, Š. Hubálovský, V. Leiva, and G. Dhiman, "Archery Algorithm: A Novel Stochastic Optimization Algorithm for Solving Optimization Problems", *Computers, Materials & Continua*, Vol. 72, No. 1, pp. 399-416, 2022.
- [10] A.-Q. Tian, F.-F. Liu, and H.-X. Lv, "Snow Geese Algorithm: A novel migration-inspired metaheuristic algorithm for constrained engineering optimization problems", *Applied Mathematical*

Modelling, Vol. 126, pp. 327-347, 2024, doi: 10.1016/j.apm.2023.10.045.

- [11] A. Seyyedabbasi and F. Kiani, "Sand Cat swarm optimization: a nature-inspired algorithm to solve global optimization problems", *Engineering with Computers*, Vol. 39, No. 4, pp. 2627-2651, 2023, doi: 10.1007/s00366-022-01604-x.
- [12] S. Zhao, T. Zhang, L. Cai, and R. Yang, "Triangulation topology aggregation optimizer: A novel mathematics-based meta-heuristic algorithm for continuous optimization and engineering applications", *Expert Systems with Applications*, Vol. 238, p. 121744, 2024, doi: 10.1016/j.eswa.2023.121744.
- [13] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization", *IEEE Transactions on Evolutionary Computation*, Vol. 1, No. 1, pp. 67-82, 1997.
- [14] J. Kennedy and R. Eberhart, "Particle swarm optimization", In: Proc. of ICNN'95 - International Conference on Neural Networks, Perth, WA, Australia, Vol. 4, pp. 1942-1948, 1995, doi: 10.1109/ICNN.1995.488968.
- [15] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents", *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, Vol. 26, No. 1, pp. 29-41, 1996.
- [16] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer", *Advances in Engineering Software*, Vol. 69, pp. 46-61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.
- [17] P. Trojovský and M. Dehghani, "A new bio-inspired metaheuristic algorithm for solving optimization problems based on walruses behavior", *Scientific Reports*, Vol. 13, No. 1, p. 8775, 2023.
- [18] M. Ahmed, M. H. Sulaiman, A. J. Mohamad, and M. Rahman, "Gooseneck barnacle optimization algorithm: A novel nature inspired optimization theory and application", *Mathematics and Computers in Simulation*, Vol. 218, pp. 248-265, 2024, doi: 10.1016/j.matcom.2023.10.006.
- [19] A. Majumder, "Termite alate optimization algorithm: a swarm-based nature inspired algorithm for optimization problems", *Evolutionary Intelligence*, Vol. 16, No. 3, pp. 997-1017, 2023, doi: 10.1007/s12065-022-00714-1.
- [20] Y. Jiang, Q. Wu, S. Zhu, and L. Zhang, "Orca predation algorithm: A novel bio-inspired algorithm for global optimization problems", *Expert Systems with Applications*, Vol. 188, p. 116026, 2022.
- [21] W. Zhao *et al.*, "Electric eel foraging optimization: A new bio-inspired optimizer for engineering applications", *Expert Systems with Applications*, Vol. 238, p. 122200, 2024, doi: https://doi.org/10.1016/j.eswa.2023.122200.
- [22] E.-S. M. El-kenawy, N. Khodadadi, S. Mirjalili, A. A. Abdelhamid, M. M. Eid, and A. Ibrahim, "Greylag Goose Optimization: Nature-inspired optimization algorithm", *Expert Systems with Applications*, Vol.

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238, p. 122147, 2024, doi: 10.1016/j.eswa.2023.122147.

- [23] D. E. Goldberg and J. H. Holland, "Genetic Algorithms and Machine Learning", *Machine Learning*, Vol. 3, No. 2, pp. 95-99, 1988, doi: 10.1023/A:1022602019183.
- [24] R. Storn and K. Price, "Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces", *Journal of global optimization*, Vol. 11, No. 4, pp. 341-359, 1997.
- [25] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing", *Science*, Vol. 220, No. 4598, pp. 671-680, 1983.
- [26] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: a gravitational search algorithm", *Information sciences*, Vol. 179, No. 13, pp. 2232-2248, 2009.
- [27] M. Dehghani *et al.*, "A spring search algorithm applied to engineering optimization problems", *Applied Sciences*, Vol. 10, No. 18, p. 6173, 2020.
- [28] M. Dehghani and H. Samet, "Momentum search algorithm: A new meta-heuristic optimization algorithm inspired by momentum conservation law", *SN Applied Sciences*, Vol. 2, No. 10, pp. 1-15, 2020.
- [29] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multiverse optimizer: a nature-inspired algorithm for global optimization", *Neural Computing and Applications*, Vol. 27, No. 2, pp. 495-513, 2016.
- [30] A. Hatamlou, "Black hole: A new heuristic optimization approach for data clustering", *Information Sciences*, Vol. 222, pp. 175-184, 2013.
- [31] R. V. Rao, V. J. Savsani, and D. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems", *Computer-Aided Design*, vol. 43, No. 3, pp. 303-315, 2011.
- [32] I. Matoušová, P. Trojovský, M. Dehghani, E. Trojovská, and J. Kostra, "Mother optimization algorithm: a new human-based metaheuristic approach for solving engineering optimization", *Scientific Reports*, Vol. 13, No. 1, p. 10312, 2023, doi: 10.1038/s41598-023-37537-8.
- [33] S. Das and P. N. Suganthan, "Problem definitions and evaluation criteria for CEC 2011 competition on testing evolutionary algorithms on real world optimization problems", *Jadavpur University*, *Nanyang Technological University*, *Kolkata*, pp. 341-359, 2010.
- [34] B. Kannan and S. N. Kramer, "An augmented Lagrange multiplier based method for mixed integer discrete continuous optimization and its applications to mechanical design", *Journal of Mechanical Design*, Vol. 116, No. 2, pp. 405-411, 1994.
- [35] A. H. Gandomi and X.-S. Yang, "Benchmark problems in structural optimization", *Computational Optimization, Methods and Algorithms*, pp. 259-281, 2011.
- [36] E. Mezura-Montes and C. A. C. Coello, "Useful infeasible solutions in engineering optimization with evolutionary algorithms", In: *Proc. of Mexican*

International Conference on Artificial Intelligence, pp. 652-662, 2005.

[37] S. Mirjalili and A. Lewis, "The whale optimization algorithm", *Advances in Engineering Software*, Vol. 95, pp. 51-67, 2016.