Fennec Adaptive Cooling Algorithm (FACA): A Novel Nature-Inspired Metaheuristic Drawn From Algerian Wildlife

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Abstract: This paper presents the Fennec Adaptive Cooling Algorithm (FACA), a novel metaheuristic inspired by the thermoregulation strategies of the Fennec fox, a species native to the Algerian desert. This algorithm leverages the adaptive cooling mechanisms of the Fennec fox to balance exploration and exploitation in the optimization process. We detail the development and implementation of FACA, showcasing its application to a warehouse location problem. The algorithm's effectiveness is demonstrated through comparative analysis with other established metaheuristics, highlighting FACA's potential in achieving optimal solutions while satisfying logistical constraints. This research not only introduces a new optimization tool but also underscores the importance of local biodiversity as a source of inspiration for solving practical problems.

Keywords: Metaheuristics, Nature-inspired Algorithms, Algerian Biodiversity, Fennec Fox, Thermoregulation, Optimization, Warehouse Location Problem.

1. INTRODUCTION

Metaheuristics, advanced methods designed to explore and exploit complex optimization spaces, have flourished over recent decades. Drawing inspiration from natural phenomena, biological systems, and animal behaviors, these algorithms harness adaptive and survival strategies found in nature. Their effectiveness surpasses traditional methods, making them pivotal in solving optimization challenges across fields like logistics and engineering. This synergy between nature-inspired metaheuristics and real-world problems underscores their importance in achieving optimal solutions efficiently.

This paper introduces the Fennec Adaptive Cooling Algorithm (FACA), a new metaheuristic inspired by the Fennec fox, a species well-adapted to the harsh conditions of the Algerian desert (Fig. 1). The Fennec fox's large ears play a crucial role in its ability to dissipate heat, a feature we emulate in our algorithm to manage the search process in optimization tasks. Our motivation for this study is to utilize local fauna as a source of inspiration, promoting biodiversity awareness and leveraging indigenous knowledge. We apply FACA to a warehouse optimization problem, aiming to minimize the distance between warehouses and customers while adhering to capacity and demand constraints. Our results indicate that FACA performs competitively with established metaheuristics, offering a new perspective in the field of Nature-inspired metaheuristics.

Figure 1. Fennec Fox: National animal of Algeria

1.1 State of the Art in Metaheuristics

Efficient optimization algorithms have evolved significantly, drawing inspiration from natural phenomena and animal behaviors. Nature-inspired metaheuristics such as Genetic Algorithms (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have emerged as robust tools for tackling complex problems (Holland, 1975; Kirkpatrick et al., 1983; Kennedy & Eberhart, 1995; Dorigo et al., 1996). These algorithms mimic biological and social behaviors: GA evolves solutions based on natural selection and genetics; SA adjusts solution acceptance criteria akin to metallurgical annealing; PSO coordinates particles through bird flocking dynamics; and ACO uses pheromone trails inspired by ant foraging.

The Firefly Algorithm (FA), developed by Yang (2008), leverages the attractiveness between fireflies to guide the search for optimal solutions. Cuckoo Search (CS), proposed by Yang and Deb (2009), simulates the brood parasitism of cuckoo birds for optimization. The Bat Algorithm (BA), introduced by Yang (2010), uses the echolocation and prey capture behavior of bats. The Grey Wolf Optimizer (GWO), developed by Mirjalili et al. (2014), models the hunting and social hierarchy of grey wolves to optimize functions, while the Artificial Bee Colony (ABC), introduced by Karaboga (2005), mimics honeybee foraging to efficiently explore and exploit food sources.

Inspired by the resilient Fennec fox, the Fennec Fox Optimization (FFA), proposed by Trojovska et al. (2022), mimics the animal's digging ability and escape strategies, showing strong performance across benchmarks and engineering problems by balancing exploration and exploitation. Additionally, the Modified Fennec Fox Algorithm (DEMFFA), introduced by Hu et al. (2024), enhances FFA with sin chaotic mapping, formula factor adjustments, Cauchy operator mutation, and differential evolution strategies. These modifications accelerate convergence and improve robustness, making DEMFFA suitable for high-dimensional and complex optimization problems.

In conclusion, nature-inspired metaheuristics continue to evolve, leveraging insights from biological systems to address increasingly complex optimization challenges.

2. Fennec Adaptive Cooling Algorithm (FACA)

2.1 Inspiration from Fennec Fox Thermoregulation

The Fennec fox, native to the deserts of North Africa, exhibits a remarkable thermoregulation process to survive the extreme heat of its environment. This small fox uses its large ears not only for acute hearing but also to regulate its body temperature and dissipate heat efficiently. This biological adaptation is the foundation for our algorithm, which emulates the Fennec fox's cooling strategy to manage the search process in optimization tasks.

The Fennec fox's large ears provide a significant surface area, allowing for better heat dissipation. These ears are rich in blood vessels, allowing heat to be released through the skin and dissipated into the surrounding air as blood flows through them. This mechanism is similar to how elephants use their large ears to regulate their body temperature. Additionally, the Fennec fox's ears are positioned to maximize exposure to cooling breezes while minimizing direct exposure to the sun, further aiding in temperature regulation.

This natural thermoregulation process, where the large ears function as radiators to dissipate excess heat, inspired the development of our optimization algorithm. By mimicking the cooling strategy of the Fennec fox's biological adaptation for heat management, the algorithm dynamically adjusts its search parameters to prevent premature convergence and maintain diversity in the population. This approach leverages biological efficiency to tackle complex problems by balancing exploration and exploitation, ensuring robust performance in finding optimal solutions.

2.2 Mathematical Modeling of the Fennec Adaptive Cooling Algorithm (FACA)

The Fennec Adaptive Cooling Algorithm (FACA) is designed as a metaheuristic optimization method. It employs an analogy to the cooling process observed in the Fennec fox's thermoregulation mechanism, adapted to guide the search for optimal solutions. Below is a structured mathematical model of the algorithm:

- **Initialization:**

Population Size (P): Number of solutions in the population.

Max Iterations (MaxIter): Maximum number of iterations.

Initial Temperature (T_0): Initial metaphorical temperature.

Cooling Factor (α): Factor by which temperature is reduced.

- **Solution Representation:**

Each solution S_{i} in the population represents a set of positions for the problem-specific entities.

- **Fitness Evaluation:**

The fitness of a solution is evaluated based on the objective function $f(S_{\mathrm{i}})$:

$$f(S_{\mathrm{i}}) = evalute_{fitness(S_{\mathrm{i}})} \tag{1}$$

Where $evalute_{fitness(S_{\mathrm{i}})}$ computes the fitness of solution S_{i} specific to the problem.

- **Mutation:**

Mutation perturbs solutions slightly:

$$S'_{\mathrm{i}} = mutate(S_{\mathrm{i}}, \mathrm{T}) \tag{2}$$

Where $mutate(S_{\mathrm{i}}, \mathrm{T})$ adjusts solution S_{i} based on the current temperature T.

- **Cooling Schedule:**

The temperature T decreases in each iteration:

$$T_{t+1} = \alpha \cdot T_t \tag{3}$$

- Selection (Tournament Selection):

Selection uses tournament selection to form the next generation of solutions:

$$next_{generation} = tournament_{selection(population)} \tag{4}$$

Where $tournament_{selection(population)}$ selects solutions from the population based on their fitness through a tournament process.

2.3 Repetitions Process, Pseudo-Code, and Flowchart of FACA.

The Fennec Adaptive Cooling Algorithm (FACA) iteratively updates solution positions through mutation and fitness evaluation until it reaches the specified maximum iterations T. It adjusts a metaphorical temperature T to balance exploration and exploitation, employing tournament selection to choose the best solutions. This process continues until convergence or the maximum iterations are reached, ultimately yielding the best solution found for the optimization problem. The FACA implementation steps are presented as a flowchart in Figure 2, and its pseudo-code is in Algorithm 1.

Algorithm 1 Pseudo-Code of the Fennec Adaptive Cooling Algorithm (FACA).

Start FACA.

1. Input problem-specific information and set algorithm parameters.

- Population Size (P)

- Max Iterations ($MaxIter$)

- Initial Temperature (T_0)

- Cooling Factor (α)

2. Initialize population of solutions with random positions.

3. Evaluate fitness of initial population.

4. For $t = 1$ to $MaxIter$:

5. For each solution S_i in the population:

6. Mutate solution S_i based on current temperature T.

7. Evaluate fitness of mutated solution.

8. Reduce temperature T using cooling factor α.

9. Select next generation of solutions using tournament selection.

10. Save the best solution found so far.

11. Output the best solution found by the algorithm.

End FACA.

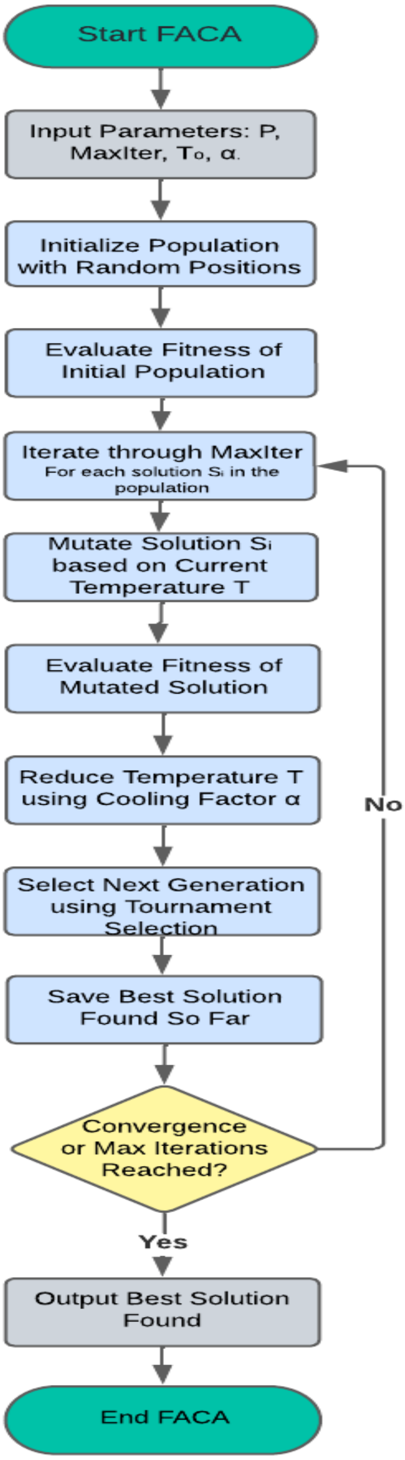

Figure 2. Flowchart of FACA.

3. Optimization Case Study: Warehouse Location Problem

3.1 Problem Description

The warehouse optimization problem aims to minimize transportation costs by strategically placing warehouses to meet customer demands while respecting warehouse capacity constraints. Each warehouse can serve multiple customers, but each customer can only be served by one warehouse.

The objective is to allocate customers to warehouses such that the total distance traveled (and thus the total cost) is minimized, taking into account each warehouse's capacity limitations.

3.2 Mathematical Formulation

Objective Function: Minimize the total cost, defined as the sum of distances multiplied by customer demands, between warehouses and customers (5).

Minimize total_cost where:

$$total_{cost} = \sum_{j=1}^{C} \left(\min_{i \in \{1,\ldots,w\}} \left(distance(w_i, c_j)\right) \cdot d_j \right) \qquad (5)$$

And the distance between warehouse and customer in 2D space is calculated using the Euclidean norm (6):

$$distance(w_i, c_j) = \|w_j - c_j\| \qquad (6)$$

subject to $\sum_{j=1}^{C} (x_{ij} \cdot d_j) \leq c_i \quad \forall i \in \{1, \ldots, w\}$ (7)

$$\sum_{i=1}^{W} x_{ij} = 1 \qquad \forall j \in \{1, \ldots, C\} \qquad (8)$$

Equation (7) is the warehouse capacity constraint: Each warehouse i must not exceed its maximum capacity c_i.

Equation (8) is the customer assignment constraint: Each customer j must be assigned to exactly one warehouse i.

With x_{ij} is a binary decision variable indicating whether customer j is assigned to warehouse i (9).

$$\begin{cases} x_{ij} = 1 \; if \; customer \; j \; is \; assigned \; to \; warehouse \; i \\ x_{ij} = 0 \quad if \; not \end{cases} \qquad (9)$$

Variables:

- W: Number of warehouses.
- C: Number of customers.
- w_i: Position of warehouse i in 2D space.
- c_j: Position of customer j in 2D space.
- d_j: Demand of customer j.

Parameters:

- c_i: Capacity of warehouse i.

3.4 Example of Implementation of FACA for Warehouse Problem

Inputs:

- Number of Warehouses (W): 3
- Number of Customers (C): 5
- Capacities: [50, 70, 80] (maximum capacities of the warehouses)
- Demands: [20, 30, 10, 25, 15] (demands of the customers)
- Positions of Customers: Customer 1: (0.2, 0.3), Customer 2: (0.4, 0.6), Customer 3: (0.7, 0.4), Customer 4: (0.5, 0.2), Customer 5: (0.8, 0.1)
- Penalty for exceeding capacity: 1000

Handling Constraints: In this implementation, constraints such as warehouse capacities are enforced by adding a penalty to the objective function. If a warehouse exceeds its capacity when serving customers, a penalty is incurred. This penalty is an additional cost added to the total distance traveled by the warehouses, aiming to discourage solutions that violate capacity constraints. This approach ensures that the optimization process respects the practical limitations imposed by warehouse capacities while minimizing the overall transportation costs.

Outputs:

- Best warehouse positions
- Best Fitness (total distance + penalty)

4. Experimental Findings and Discussion

4.1 Experimental Setup

Computational Environment:

The experiments were conducted using Python version 3.12.3 on an Intel Core i5 8th Gen processor. Computational tasks were facilitated by the NumPy library for efficient numerical computations.

Metaheuristic Algorithms Used for The Comparative Analysis:

We utilized a selection of advanced metaheuristic algorithms to address the warehouse optimization problem, each recognized for its robust optimization capabilities. Our study compared the performance of the Fennec Adaptive Cooling Algorithm (FACA) against established methods including Genetic Algorithms (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Firefly Algorithm (FA). Each algorithm was evaluated based on its ability to minimize operational costs, integrating factors such as distance traveled and warehouse capacity constraints. Furthermore, we analyzed the computational efficiency of each algorithm in terms of execution time, providing insights into the comparative effectiveness of FACA and its counterparts for warehouse optimization tasks.

4.2 Results and Discussion

We conducted a comparative evaluation of the Fennec Adaptive Cooling Algorithm (FACA) against several established metaheuristic algorithms for optimizing warehouse placement. The objective was to minimize the total cost associated with distance and capacity constraints. The table below presents the objective function values and execution times obtained from each algorithm:

Table 1. Comparative Evaluation of Metaheuristic Algorithms for Warehouse Placement Optimization

Algorithm	Objective Function Value	Execution Time (sec)	Discussion
GA	3008.1099	03.11	The GA produced a solution with a total cost of 3008.1099 units. It operated effectively but showed a relatively longer execution time compared to other algorithms.
SA	3009.1272	02.10	SA achieved a solution value of 3009.1272 units, slightly higher than GA. It demonstrated faster convergence, completing in 02.10 sec.
FA	3008.8197	28.86	The FA delivered a solution close to the GA and SA with a value of 3008.8197 units. However, its execution time was notably longer at 28.86 seconds, indicating slower convergence.
PSO	1025.5366	01.67	PSO achieved a significantly lower objective function value of 1025.5366 units, suggesting superior optimization. It also had a fast execution time of 01.67 sec.
ACO	3012.3041	01.53	ACO resulted in the highest solution value of 3012.3041 units, with an execution time of 01.53 sec, performing competitively in speed.
FACA	**2031.0049**	**01.68**	**FACA achieved a solution value of 2031.0049 units, demonstrating competitive performance against established algorithms. Its execution time was 01.68 seconds, comparable to other efficient algorithms.**

Discussion:

Solution Quality: FACA achieved a solution value of 2031.0049 units, showcasing its effectiveness in minimizing the objective function that combines distance and capacity constraints. This performance is notably competitive compared to other algorithms like ACO, SA, FA, and GA.

Execution Efficiency: With an execution time of 01.68 seconds, FACA demonstrated efficient convergence, comparable to effective algorithms like PSO and ACO. This efficiency is crucial for real-time decision-making and scalability to larger problem instances.

Comparison with Other Algorithms: While PSO achieved the lowest objective function value of 1025.5366 units, indicating strong optimization capabilities, FACA's performance is commendable given its competitive solution quality and efficient execution time. Algorithms such as GA and SA, while effective, showed slightly higher solution values and longer execution times in this context.

Advantages and Suitability: FACA employs adaptive cooling techniques inspired by natural systems, which facilitate a dynamic balance between exploration and exploitation in optimization tasks. This innate adaptability enhances FACA's performance across diverse problem complexities, ensuring robust outcomes. The algorithm excels in addressing warehouse placement optimization challenges, delivering superior solution quality with efficient computational execution. Comparative evaluations against algorithms like GA and SA demonstrate FACA's competitive advantage and potential applicability in real-world applications.

5. CONCLUSIONS

The Fennec Adaptive Cooling Algorithm (FACA), inspired by the thermoregulation strategies of the Fennec fox, represents a significant advancement in nature-inspired metaheuristics. Its competitive performance against well-established algorithms like Genetic Algorithms (GA) and Simulated Annealing (SA) demonstrates its potential for addressing real-world optimization challenges effectively. Furthermore, integrating FACA with hybrid algorithms or applying it to diverse real-world applications could unlock new avenues for leveraging nature-inspired metaheuristics in practical settings. This research not only introduces a new algorithm but also highlights the importance of biodiversity conservation and local knowledge in developing innovative solutions for complex logistical problems.

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