Testing Related to Production Techniques

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Optimum design of electric vehicle battery enclosure using the chaotic metaheuristic algorithms

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Abstract: Metaheuristic algorithms are optimization techniques inspired by natural processes, widely used to solve complex real-world problems. Traditional methods like swarm-based established optimizers often face challenges like premature convergence and high computational costs. The aim of this research is to develop a new optimization method for optimizing electric vehicle components and real-world problems. This research introduces a new chaotic fishing cat optimization algorithm (CFCO), a new optimization algorithm based on recent fishing cat optimization algorithm and chaotic maps. The chaotic maps are integrated into FCO to improve the balance between exploration and exploitation. This research is the first application of the CFCO to the optimum design of electric vehicle components in the literature. The algorithm is applied to various industrial design optimization problems, including structural optimization of cantilever beams, weight optimization of a coupling with a bolted rim, optimization of side profile of an electric vehicle battery enclosure, and heat exchanger economic optimization. The results demonstrate that the developed CFCO outperforms existing recent metaheuristic techniques, achieving superior efficiency and accuracy in industrial applications.

Keywords: electric vehicles; battery enclosure; chaotic maps; optimum design; fishing cat optimizer; industrial optimization problems

1 Introduction

Metaheuristic algorithms are advanced optimization techniques designed to tackle complex real-world problems where traditional methods struggle due to their computational limitations. Accordingly, these optimizers are inspired by natural phenomena that occur in nature, such as swarm behavior, physics, and human cognition, to explore vast and intricate search spaces efficiently. Their ability to provide near-optimal solutions within reasonable computational time has led to their widespread adoption in various domains, including routing and charging scheduling of electric vehicles, optimization of li-ion battery state of health prediction, optimal placement of electric vehicle charging stations, crashworthiness optimization of battery enclosures, optimization of lattice-based battery enclosure, optimization of shell and tube heat exchangers, optimum design of clutch diaphragm spring, manufacturing optimization, shape optimization, optimal gear design for automotive transmissions, healthcare, finance, and logistics [1]–[36].

The increasing complexity of modern problems has necessitated continuous advancements in metaheuristic algorithms. While traditional optimization techniques have proven effective, they often face premature convergence, local optima trap, and high computational time. To address these issues, researchers have been developing novel metaheuristic algorithms that enhance optimization performance through improved exploration–exploitation balance, adaptive learning mechanisms, and hybridization techniques. The Firefighter Optimization Algorithm is inspired by the strategic and collaborative approaches firefighters use during emergencies. It combines principles of swarm intelligence and evolutionary computation to adjust search strategies based on environmental conditions dynamically. Extensive benchmarking has demonstrated its superior performance in handling multimodal and high-dimensional problems, outperforming classical techniques in speed and accuracy[16]. The Halfway Escape Optimization (HEO) Algorithm is a quantum-inspired metaheuristic algorithm designed to navigate complex optimization landscapes with high efficiency [32]. Puma Optimizer (PO) and Walrus Optimizer (WO) Inspired by the hunting and survival strategies of pumas and walruses, these bio-inspired metaheuristic algorithms introduce novel search mechanisms that mimic adaptive predation and movement behaviors [34], 35.

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The newly developed metaheuristic algorithms have shown significant improvements in solving complex real-world problems across multiple domains. Metaheuristics are widely applied in structural design, power systems optimization, and robotic path planning, where traditional mathematical models fail due to high-dimensional search spaces. Moreover, metaheuristic techniques enhance feature selection, neural network training, and hyper-parameter tuning, improving model accuracy and computational efficiency. These algorithms are used for medical image processing, disease diagnosis, and drug discovery by optimizing classification and predictive models. Furthermore, metaheuristics help optimize stock portfolio selection, risk management, and economic forecasting, enabling better decision-making in uncertain environments. Moreover, they improve route optimization, vehicle scheduling, and warehouse management, leading to cost reductions and efficiency enhancements.

2 Chaotic fishing cat optimizer (CFCO)

The FCO algorithm is a new meta-heuristic algorithm inspired by the behavior of biological groups whose agent group is mainly composed of distinctive "fishing cat" entities. More details about the mathematical background of the algorithm can be found in [31].

2.1 Chaotic map-assisted fishing cat optimizer

Chaotic maps are fundamentally multimodal mathematical functions that enable the optimizer to explore the search domain efficiently. Moreover, each function contains unique characteristics that can enhance the algorithm's capabilities to

Table 1: Equations of different chaotic maps.

Chaotic map	Equation	Number
Chebyshev map	$x_{k+1} = \cos\ (k \cos^{-1}(x_k))$	(1)
Circular-shaped map	$x_{k+1} = x_k + b - (a - 2\pi)\sin\ (2\pi x_k) \bmod (1)$	(2)
Gauss/Mouse map	$x_{k+1} = \begin{cases} \varepsilon + x_k + cC_k^n, & 0 < x_k \le P \\ \dfrac{X_k - P}{1 + P}, & P < x_k < 1 \end{cases}$ $\dfrac{1/1}{x_k\ \mathrm{mod}(1)} = \dfrac{1}{x_k} - \left[\dfrac{1}{x_k}\right]$	(3)
Iterative map	$X_{k+1} = \sin\left(\dfrac{a\pi}{X_k}\right)$	(4)
Logistic map	$X_{k+1} = a\, X_k\, (1 - X_k)$	(5)
Piecewise map	$f(x) = \begin{cases} \dfrac{x_k}{P} & 0 \le x_k < P \\ \dfrac{x_p - P}{0.5 - P} & P \le x_k < \dfrac{1}{2} \\ \dfrac{1 - P - X_k}{0.5 - P} & \dfrac{1}{2} \le x_k < 1 - P \\ \dfrac{1 - X_k}{P} & 1 - P \le x_k < 1 \end{cases}$	(6)
Sine map	$x_{k+1} = \dfrac{a}{4}\sin\ (\pi x_k)$	(7)
Singer-based map	$x_{k+1} = \mu\left(7.86x_k - 23.31x_k^2 + 28.75x_k^3 - 13.3028.75x_k^4\right)$	(8)
Sinusoidal-based map	$x_{k+1} = ax_k^2 \sin\ (\pi X_k)$	(9)
Tent-based map	$X_{k+1} = \begin{cases} \dfrac{X_k}{0.7}, & X_k < 0.7 \\ \dfrac{10}{3}(1 - X_k), & X_k \ge 0.7 \end{cases}$	(10)

balance the exploration and exploitations. In the present study, the various chaotic maps, as shown in Equations (1–10), are augmented with the DRO for further improvement, and the results of the suited chaotic map are tabulated in the subsequent section. The same chaotic maps mathematical models are recorded in Table 1.

3 Applications of chaotic fishing cat optimization algorithm for industrial design optimization

This section covers the application of a chaotic fishing cat optimization algorithm for industrial components. For instance, mechanical engineering design components, electric vehicle components, and industrial heat exchanger optimization. The statistical results are effectively utilized to check the potential optimizer. Moreover, the results of the developed optimizer were compared with the well-known results from the literature.

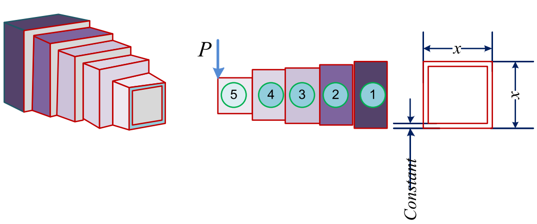

Figure 1: CAD layout of the cantilever beam.

3.1 Structural optimization of a cantilever beam using CFCOA

Figure 1 shows the stepped cantilever beam. The reduction of the beam's structural mass is the goal function. These cross-sectional characteristics, or the widths and heights of the beam elements, are the design variables of stepped beams [5].

Table 2 provides a comparison between the best results from CFCOA and those from the literature. It is demonstrated that CFCOA produces superior results than those seen in the literature. 1.33995 is the lowest weight that was attained. CFCOA needs 5000 function evaluations to find the optimal design.-CFCOA requires 5000 function evaluations to find the optimal design. However, the shiprescue(9000), crayfish(10000), and backtracking search algorithms(12000) require many more function evaluations to reach the global optimum. This demonstrates CFCOA's success in achieving globally optimal designs.

Table 2: Results attained by competitive algorithms and studied algorithm.

Optimizers	Optimized decision parameters					Objective	NFE
	x_1	x_2	x_3	x_4	x_5		
CFCOA	6.02	5.31	4.49	3.50	2.16	1.33995	5,000
Ship rescue optimization algorithm	6.02	5.31	4.49	3.50	2.16	1.34	9,000
Crayfish optimization algorithm	6.01	5.31	4.48	3.50	2.16	1.34	10,000
Backtracking search algorithm	5.98	5.32	4.50	3.51	2.16	2.16	12,000

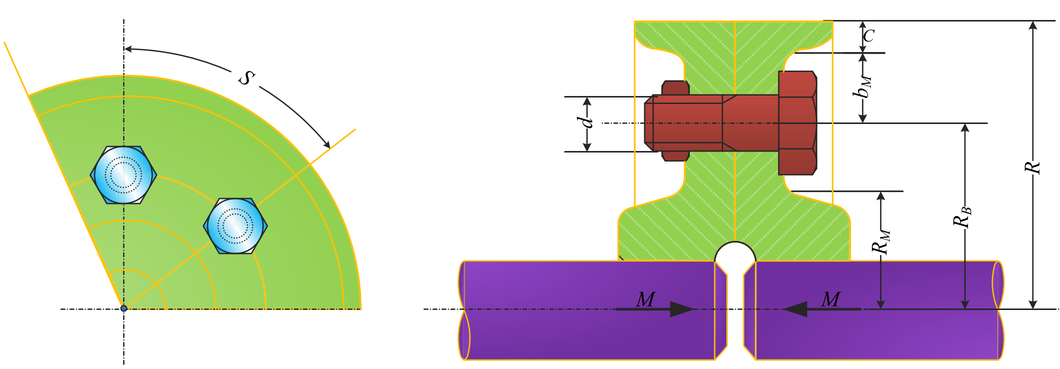

Figure 2: Layout of the studied mechanical system with decision parameters.

3.2 Weight optimization of a coupling with a bolted rim

When designing a mechanical component coupling that is attached to a bolted rim, the primary goal is to minimize mass, which is subject to 11 limitations imposed by inequalities. Additionally, this study's decision factors are radius, bolt diameters, shaft torque, and the total number of bolts (N). Figure 2 shows a geometric illustration of the CWBR (coupling with a bolted rim).

Additionally, the CFCOA results were examined using well-known MHs, as shown in Table 3. According to Table 3, which compiles the statistical findings from the test optimizers. Consequently, the CFCOA realizes the best value for the objective function with the Chebyshev map. The function's best fitness function, as (3.48000000), and worst mean (3.48000000702) values are supplied by CFCOA. The CFCOA with the Chebyshev map, on the other hand, obtained a minimum standard deviation (SD) of 1.1003 E−09. As a result, CFCOA can achieve better results for the current design issue.

3.3 Structural optimization of electric vehicle battery box side profile using CFCOA

One of the most important components of an electric heicle is the electric vehicle battery box side profile. However, structural optimization of the electric vehicle battery box side profile is encouraged to reduce the vehicle's overall weight and, hence, lower emissions. The electric vehicle battery box side profile's location in the entire system is displayed in Figure 3.

The 3D image of the electric vehicle battery box side profile (BP) under various stress circumstances and design variables is shown in Figures 4 and 5, respectively. The accompanying mathematically modeled Equations (11)–(14), which include boundary conditions, constraints, design variables, and goal function, provide insight into the detailed problem formulation.

Fitness function:

$$f(x) = \text{mass}(x) \tag{11}$$

$$\sigma_{\max} \le \sigma_{\text{permissible}} \tag{12}$$

$$y_i^l \le y_i \le y_i^u, \quad i = 1\, to\, 5, \tag{13}$$

$$\begin{array}{l} 5 < y_1 < 15 \\ 5 < y_2 < 15 \\ 5 < y_3 < 15 \\ 5 < y_4 < 15 \\ 5 < y_5 < 15 \end{array} \tag{14}$$

This is combined with a comparison with the traditional MHs as ship rescue optimizers and backtracking search optimization algorithms. Table 4 provides details on the superior design derived from the CFCOA. Accordingly, the CFCOA has achieved the most notable weight reduction with maximum stress (lowest mass: 234 g, stress: 300 MPa) compared to the original design (mass: 280 g, stress: 189 MPa). The final optimized design can be depicted in Figure 6.

Table 3: Statistical results comparison for the studied algorithm.

Optimizers	Best	Mean	Worst	Std	NFE
CFCOA	3.48000000000	3.48000000005	3.48000000702	1.1003E-09	5,000
Ship rescue optimization algorithm	3.48000000005	3.48000001122	3.48000004014	7.6005E-05	5,000
Crayfish optimization algorithm	3.48000000022	3.48000001429	3.48000008551	8.7896E-05	5,000

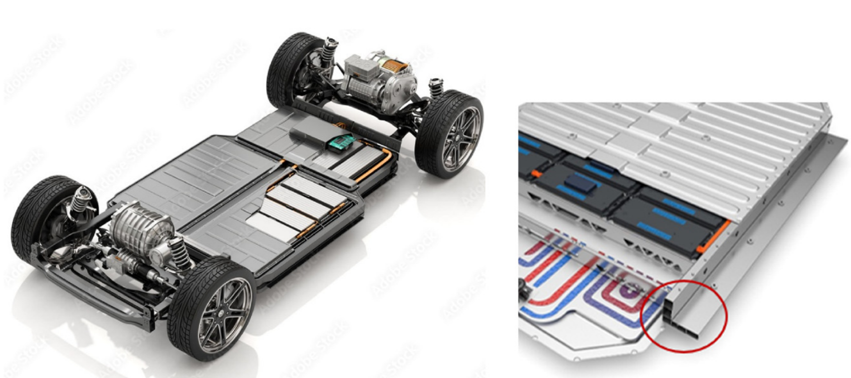

Figure 3: Electric vehicle battery box side profile weight optimization and orientation in an automobile [37].

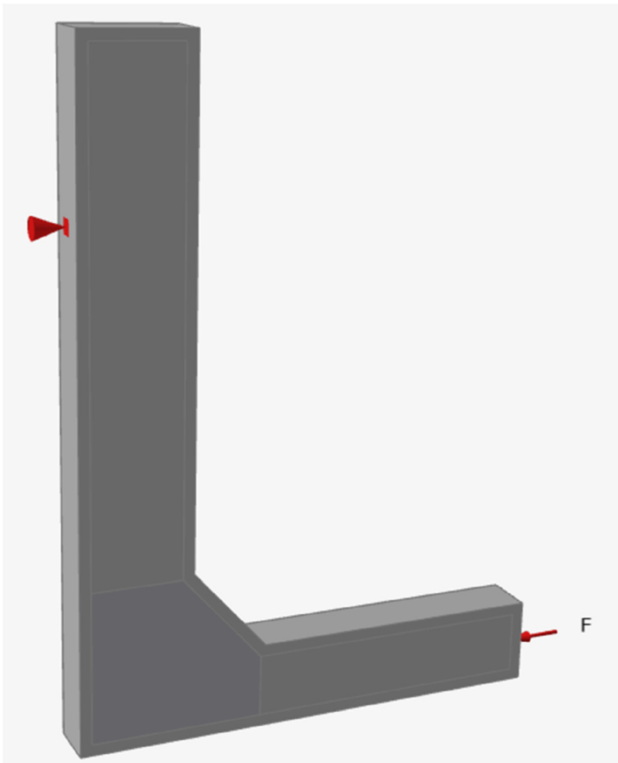

Figure 4: Capacity constraints of the electric vehicle battery box side profile.

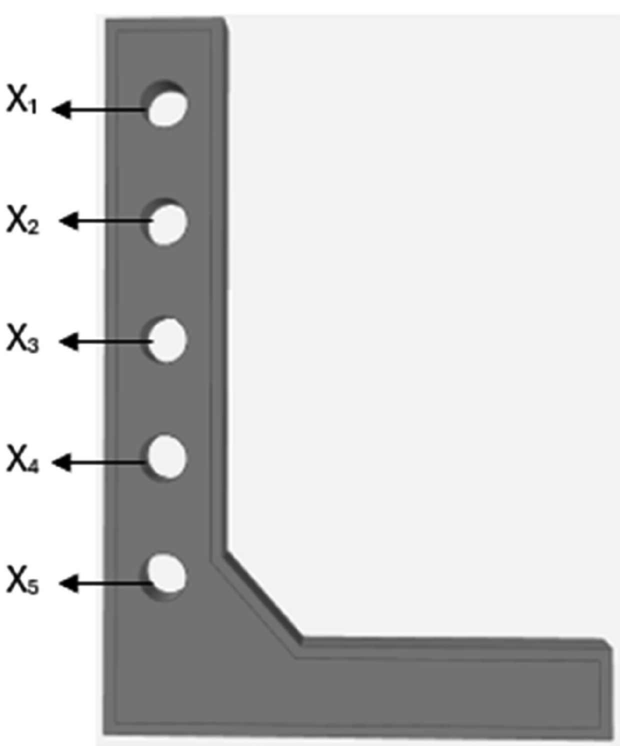

Figure 5: Design variables of the electric vehicle battery box side profile.

3.4 Cost-effective optimization of thermal heat exchanger

With a broad heat duty capability, heat exchangers (HEs) are well-known heat recovery machines utilized in several sectors. The fluid temperatures, heat transfer coefficients, and operating circumstances are taken into consideration when designing these HEs. Additionally, FTHE's expanded surface area over the cylindrical tube increases the rate of heat transmission. FTHEs are typically composed of stainless steel and aluminum. Both longitudinal and transverse augmentations are possible for the fins. The FTHE is specifically used in industry for process heating purposes. Figure 7 displays a crisp three-dimensional view of FTHE. The optimization of the FTHE takes into account the particular application, which is to lower the temperature of the water-processed air. Inlet water and hot air temperatures (40 °C and 104 °C) and the predicted air temperature (51 °C) at the output are the particular parametric circumstances. Air and water volumetric flows are kept at 58 kg s^{-1} and 39 kg s^{-1}, respectively.

The main obstacle facing the heat recovery units and companies is the whole cost of the FTHE. However, when designing the heat exchanger, thermal-hydraulic considerations are equally crucial. The heat exchanger's overall cost is optimized and chosen as the goal function at this point. Therefore, the FTHE's initial cost, as well as any maintenance or handling costs, are considered when calculating the final economic factors.

The following is an explanation of the mathematical model for cost optimization under consideration [2]:

The economics optimization of the FTHE was examined in this article using a unique optimizer CFCOA. Additionally, the results obtained were contrasted with a few benchmark algorithms published in the literature to guarantee the CFCOA's performance level. The statistical findings from the CFCOA and three other MHs that were compared are shown in Table 5. Table 5 shows that CFCOA achieves the best outcomes (at the lowest cost) with a noteworthy success rate. Additionally, it can be verified that the CFCOA's target standard deviation is significantly lower than that of the findings of the FTHE problem.

4 Conclusions

Optimization of electric vehicle components is a crucial issue. This research is dedicated to the optimization of the electric vehicle battery enclosure. For this aim, a new chaotic fishing cat optimization algorithm (CFCO) is developed. After the CFCO is validated with benchmark engineering problems

Table 4: Electric vehicle battery box side profiles optimized results in the form of statistics.

Optimizers	Best Mass (gram)	Average	Outclass	Stress (MPa)	Evaluations
Initial design	280	–	–	189	–
Ship rescue optimizer	253	258	265	300	3,000
Backtracking search algorithm	248	252	260	300	3,000
CFCOA	234	238	240	300	3,000

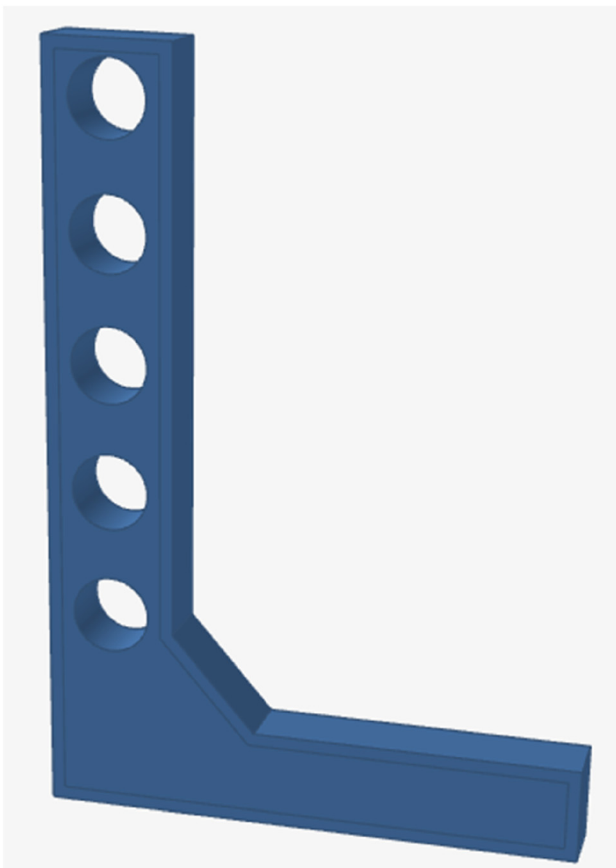

Figure 6: Final optimized design of electric vehicle battery box side profile system.

Table 5: Results for the fin tube heat exchanger realized by a chaotic fishing cat optimizer.

Optimizers	Best	Worst	Mean	SD
CFCOA	3,466.97	3,469.93	3,468.63	1.03
Ship rescue optimizer	3,466.97	3,470.93	3,468.63	1.17
Backtracking search algorithm	3,466.97	3,471.48	3,467.78	1.2
Crayfish optimization algorithm	3,466.98	3,465.24	3,467.42	1.14

from literature, it is used for optimization of the side profile of the electric vehicle battery enclosure. The CFCO has been potentially applied to a range of industrial optimization problems, demonstrating its robustness and efficiency. Compared to existing metaheuristic algorithms, CFCO consistently delivers improved solutions with higher accuracy and efficiency. The integration of chaotic maps further enhances its performance by maintaining an optimal balance between exploration and exploitation. Experimental results show that CFCO achieves significant improvements in production cost reduction, structural weight minimization, and heat exchanger efficiency. Overall, the research confirms that CFCO is a promising optimization technique with wide applicability in electric vehicle component design, optimal design of engineering structures, and complex real-world problems.

Research ethics: Not applicable.
Informed consent: Not applicable.

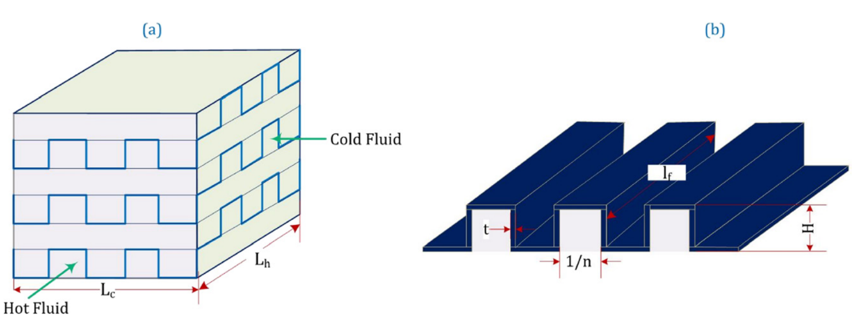

Figure 7: Computer-based design and layout of heat exchanger.

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Conflict of interest: The author states no conflict of interest.
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