

Testing Related to Production Techniques

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A new neural network–assisted hybrid chaotic hiking optimization algorithm for optimal design of engineering components

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Abstract: In the era of artificial intelligence (AI), optimization and parametric studies of engineering and structural systems have become feasible tasks. AI and ML (machine learning) offer advantages over classical optimization techniques, which often face challenges such as slower convergence, difficulty handling multiobjective functions, and high computational time. Modern AI and ML techniques may not effectively address all critical design engineering problems despite these advancements. Nature-inspired algorithms based on physical phenomena in nature, human behavior, swarm intelligence, and evolutionary principles present a viable alternative for multidisciplinary design optimization challenges. This article explores the optimization of various engineering problems using a newly developed modified hiking optimization algorithm (HOA). The algorithm is inspired by human hiking techniques, such as hill climbing and hiker speed. The advantages of the modified HOA are compared with those of several famous algorithms from the literature, demonstrating superior results in terms of statistical measures.

Keywords: hiking optimization algorithm; artificial neural network; chaotic maps; real-world applications; engineering design

1 Introduction

In the era of artificial intelligence, optimization and parametric study of different systems, including engineering and structural, becomes a feasible task. The domain of artificial intelligence is comparatively more advantageous than classical optimization techniques, which realize several challenges while optimizing the constraint problems. For instance, slower convergence, challenges in handling multiobjective functions, high computational time, and unbalance between exploration–exploitation phase. However, modern trends of AI-ML may not be effective in tackling each critical design engineering problem. Hence, nature-inspired algorithms are one of the most effective options for dealing with multidisciplinary design optimization challenges. The different categories and most recently developed algorithms are indicated in Figure 1. These algorithms are developed by inspiring physical phenomena that exist in nature, human behavior, swarm intelligence, and evolutionary-based [1]–[10]. Some of the recently invented optimizers are the hiking optimization algorithm [11], the Artificial Protozoa algorithm [12], Eel and grouper optimizer [13], Greater can rat algorithm [14], Greylag goose optimizer [15], the Partial reinforcement optimizer [16], Hippopotamus optimizer [17], starfish [18], and Crayfish optimizer [19]. These algorithms are adopted in multidisciplinary fields, including but not limited to manufacturing industries, automobile system optimization, fuzzy circuit optimization, power system optimization, and structural optimization [20]–[37]. Moreover, modifications of several base algorithms have been achieved to improve the results further and realize globally optimized solutions. This being said, effective oppositional-based techniques, chaotic maps, levy flight search, multi-strategy enhancement, and hybridization of algorithms are pursued [20], [27], [28], [38]–[48]. These modified algorithms are identified to be more effective, and the results obtained are superior compared to other benchmark algorithms vis-à-vis its base version. The article studies the optimization of different engineering problems considering a newly developed hiking optimization algorithm, and modifications have

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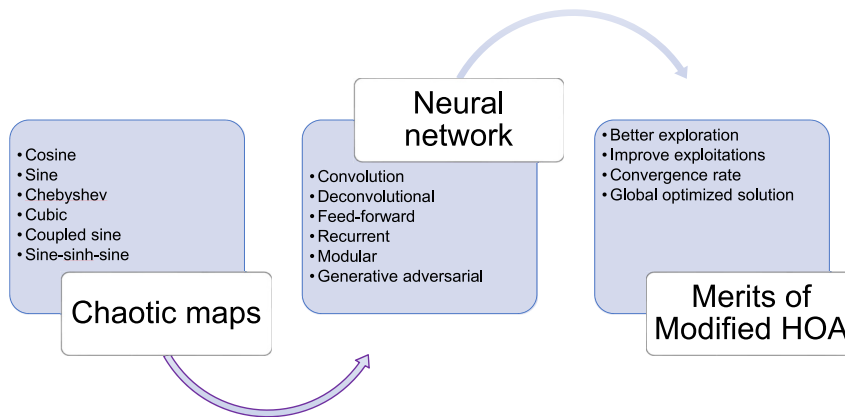


Figure 1: Chaotic maps and neural networks categories and modified algorithm's merits.

been carried out. The considered algorithm was developed on the basis of the hiking techniques of humans, including hill climbing and the speed of the hiker's. Moreover, the results of statistics were compared with the results of some of the famous algorithms in the literature [49]–[72].

2 Hiking optimization algorithm (HOA)

Researchers proposed a unique human-activity–based MH algorithm for the optimization of critical fitness functions. The algorithm is inspired by the hiker's speed, altitude of mountains, steepness, and their approach to exploring the different regions for hiking. Moreover, Tobler's hiking function is evaluated to support the identification of the various parametric calculations to attain a better solution. Furthermore, the Tobler's hiking function can be given by Equation (1) [11].

$$w_{i,t} = 6e^{-3.5|S_{i,t}+0.05|} \quad (1)$$

with i : hiker at time t and w : hiker's speed. Also, the slope of the terrain ($S_{i,t}$) can be given by Equation (2).

$$S_{i,t} = \frac{dh}{dx} = \tan \theta_{i,t} \quad (2)$$

with dh : the margin in height and dx : distance traveled by hiker. Accordingly, the present speed of the hiker can be given by Equation (3) [11].

$$w_{i,t} = w_{i,t-1} + \gamma_{i,t} (\beta_{best} - \alpha_{i,t} \beta_{i,t}) \quad (3)$$

$$\beta_{i,t+1} = \beta_{i,t} + w_{i,t} \quad (4)$$

$$\beta_{i,t} = LB + \delta (UB - LB) \quad (5)$$

with UB and LB : upper and lower bound ranges

Modifications with chaotic maps and neural network in MH optimizers: By incorporating chaotic maps and neural network techniques, the input options in the form of suggestive populations and solution options increase with the optimizer. This being said, as shown in Figure 1, neural networks improve the capability of the algorithm to examine more possible solutions and identify global solutions out of the available set of solutions. Moreover, augmenting chaotic maps improves the mathematic accuracy of the optimizer vis-à-vis and effectively improves the exploitation phase of the algorithm.

3 HOA for design of optimal engineering components

This section covers applications of a studied algorithm for the optimization of effective economic, weight, manufacturing cost, and system parameters.

3.1 Spring mass optimization using HOA

Figure 2 illustrates a computer-aided diagram of spring subjects to a tensile force, including design parameters such as wire diameter, mean coil diameter, and active coil numbers. For the optimization problem, the mass of the spring is defined as objective function, and three major constraints are considered.

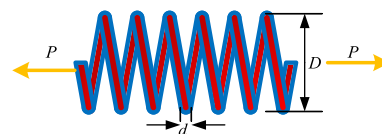


Figure 2: Computer-aided layout of spring with design variables.

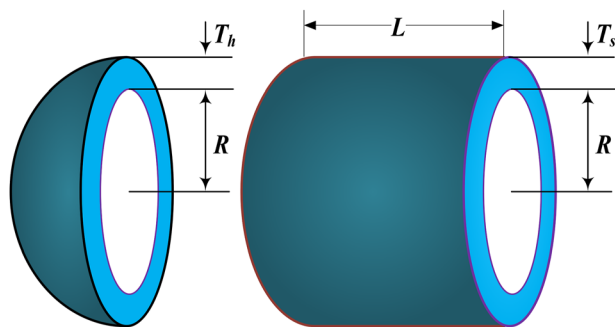
Table 1: Statistical results comparison among MHOA and other modified algorithms.

Compared optimizers	Superior values	Average values	Worst values	SD-standard deviations	Evaluations numbers
Marine predators algorithm	0.01266835	0.01302	0.019963	1.25369E-04	15,000
Salp swarm algorithm [73]	0.0126684	0.01311	0.019625	1.2691E-03	18,000
Multi-verse optimizer [73]	0.0126934	0.0159	0.018075	1.8089E-03	18,000
Moth flame algorithm [73]	0.0126780	0.01430	0.01777	1.6344E-03	18,000
Equilibrium optimizer [73]	0.0126677	0.01315	0.017773	1.3810E-03	18,000
MHOA	0.0126665	0.012935	0.013021	8.1009E-08	15,000

Table 1 shows a statistical comparison among 17 algorithms published in a research paper for the present case. Well-known algorithms such as marine predators, salp swarm optimizer, moth flame optimizer, equilibrium optimizer, and multiverse optimizers were compared with a modified hiking optimization algorithm for each case. The MHOA is able to tackle global best values effectively.

3.2 Study of the cylindrical pressure vessel for economic optimization using HOA

A cylindrical pressure vessel selected to be optimized in terms of total cost is shown in Figure 3. Accordingly, shell thickness, cylindrical section length, heat thickness, and internal radius of the cylinder are selected as design variables. Table 2 records the statistical results, as well as the mean and deviations for MHOA and other compared algorithms. Moreover, MHOA provides more effective results than the rest of the algorithms.

**Figure 3:** Cylindrical pressure vessel cross-sectional view with design variables.

3.3 Structural design optimization of three-bar truss by weight optimization

In this study, three elementary truss designs have been optimized for sustaining maximum stress as a condition with minimum system weight as a fitness function. Figure 4 shows the arrangement of each truss element with the cross-sectional area as a design parameter. Table 3 shows results obtained from the MHOA algorithm with a chaotic version and other well-known MH results from the literature. The comparison indicates the dominance of MHOA over other optimizers vis-à-vis algorithm realized minimum functional evaluations with the least deviations.

3.4 Optimization of volume capacity for piston-lever design assembly

Figure 5 represents the computer-aided design of the piston-lever assembly that is used to transfer reciprocating motion to rotational by traversing the crankshaft from 0° to 45°.

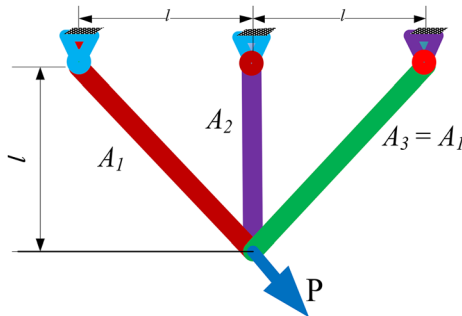
Accordingly, height, width, diameter, and stroke are considered decision parameters, with stress and load acting over these systems as constraints. Table 4 records the statistical data of MHOA with other compared optimizers. Again, in this case, MHOA realized effective results with dominance over the other MHs in terms of best values of fitness function and least standard deviations. However, MPA and SSA pursued competitive results with MHOA.

3.5 Weight optimization of spur gear design

Spur gears are generally used in mechanical industries and automobile systems to transfer motion at a regular speed ratio. The speed can be reduced or improved by identifying an adequate gear ratio, as shown in Figure 6.

Table 2: Results for MHOA and other MHs algorithms.

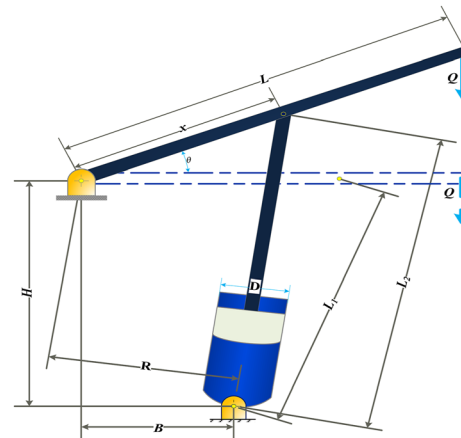
Compared optimizers	Superior values	Average values	Worst values	SD-standard deviations	Evaluations numbers
Marine predators algorithm	6,061.587963	6,398.259875	6,870.973	223.8965	5,000
Multiverse optimizer [73]	6,068.511494	6,465.615946	7,335.97353	341.336	25,000
EBO [73]	6,092.567106	6,501.053179	6,830.72863	260.008	25,000
ES [73]	6,059.715421	6,617.432326	7,800.53185	471.316	25,000
MHOA	6,059.714335	6,089.5362	6,108.7	57.356	15,000

**Figure 4:** Computer-aided design model of truss structure.

Accordingly, mass minimization of the system is kept as an objective function with five design variables: module, pinion teeth, face width, pinion diameter, and shaft diameter. Moreover, Table 5 shows recorded data from a computational study regarding statistics best, mean, worst, and standard deviation. Hence, MHOA pursued the best value for the fitness function as the minimum weight of the spur gear system with minimum functional evaluations. However, MPA and other optimizers have shown competitive results with MHOA in the present case.

3.6 Structural optimization of automobile components using MHOA

Structural optimization of vehicle components for obtaining effective efficiency has been carried out using MHOA. In this case study, the objective function is to reduce the weight using structural and volume reduction optimization

**Figure 5:** Computer-aided layout of piston-lever assembly.

concepts. However, the element is subjected to several critical constraints as given by Equations (6)–(8).

Objective function: minimum mass of the element

$$F(y) = f_1(a) \quad (6)$$

Constraint:

$$g(y) \leq 300 \text{ N/mm}^2 \quad (7)$$

$$a_i^l \leq a_i \leq a_i^u, i = 1, \text{NDV} \quad (8)$$

with, y^u and y^l : upper and lower variables limits, respectively.

Moreover, the operating range of the six considered decision parameters are $6.2 < a_1 < 13.9$, $35.2 < a_2 < 45$, $25.2 < a_3 < 35.6$, $18.2 < a_4 < 26.4$, $18.2 < a_5 < 26.4$, and $6.3 < a_6 < 13.8$. Accordingly, the initial computer graphics are shown in Figure 7.

Table 3: Results comparison of MHOA with other optimizers.

Compared optimizers	Superior values	Average values	Worst values	SD-standard deviations	Evaluations numbers
MPA [73]	263.9863023	263.9986	264.8976	0.135693	5,000
MBA [73]	263.8958522	263.897996	263.915983	3.93E–03	13,280
CS [73]	263.97156	264.0669	–	0.00009	15,000
MHOA	263.8958522	263.897863	263.9123651	2.89E–04	4,500

Table 4: Results comparison of MHOA with other optimizers.

Compared optimizers	Superior values	Average values	Worst values	SD-standard deviations	Evaluations numbers
MPA [73]	8.4369853	198.8963	224.5369	58.36599	20,000
SSA [73]	8.4220378	276.9405	653.4973	121.4145	25,000
MVO [73]	8.4289960	138.4470	356.2368	138.5046	25,000
MFO [73]	8.4126983	91.12391	167.4727	80.27315	25,000
ASO [73]	213.83459	346.0264	778.6031	115.1357	25,000
HSOGA [73]	8.4127155	128.0854	230.0218	84.22322	25,000
MHOA	8.4126981	8.556963	8.5896321	5.2369854	15,000

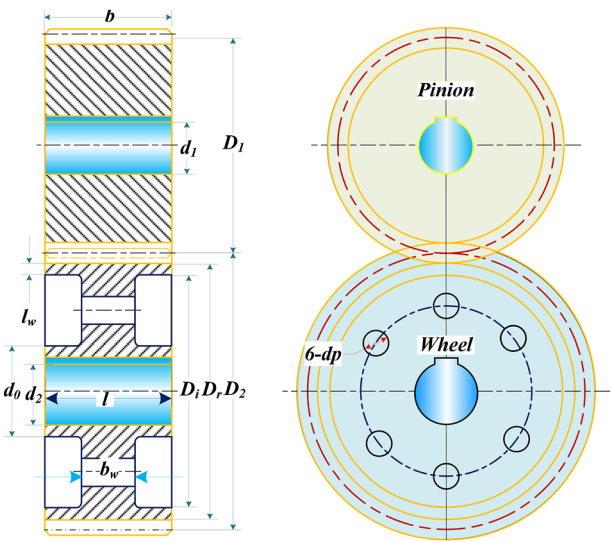


Figure 6: Computer-aided layout of spur gear design.

The optimum brake pedal design is carried out using the MHOA algorithm, as shown in Figure 6. A minimum mass of 1081.7 g is found with the MHOA, as presented in Table 6.

Figure 8 shows an optimum design of the brake pedal. Moreover, Table 6 shows the statistical results that were compared to show the dominance of the MHOA over the ship rescue optimizer and the crayfish optimization algorithm.

Table 5: Results comparison of MHOA with other optimizers.

Compared optimizers	Superior values	Average values	Worst values	SD-standard deviations	Evaluations numbers
MPA	1,538.9986	1,546.1023	1,559.1519	11.02536	20,000
MVO [73]	1,538.9537	1,539.0275	1,539.1666	0.047911	25,000
ASO [73]	1,624.2236	1,713.7505	1,827.0782	49.41359	25,000
MHOA	1,538.94468	1,538.9450	1,538.9462	0.000318	15,000

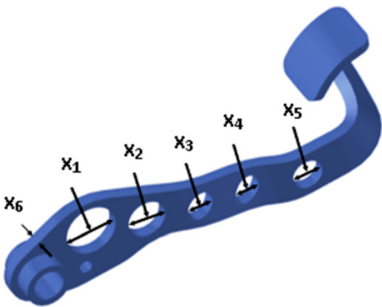


Figure 7: Computer-aided design of automobile component.

3.7 Optimization of plate and fin heat exchanger using MHOA

Many industries use different types of heat exchangers to process or heat off fluids in space. The most important examples include but are not restricted to solar-thermal applications, heat recovery devices, power plants, and cryogenics [48]. Using efficient surface areas like fins, ribs, the heat exchanger’s primary job is to move heat from one medium to another. The literature provides a full description of the thermal design [50]. The dense aluminum used to assemble the fin plate heat exchanger has a density of about 2700 kgm^{−3} [47]. Figure 9 and Table 7, respectively, identify the parametric and the 3-D picture. Furthermore, the study focuses on minimizing the cost of fin plate heat exchanges using the cheetah optimizer.

Table 6: Optimum results for the brake design.

Compared optimizers	Optimized weight in gram	Mean values	Worst values	Standard deviation	Stress (MPa)
Initial design	1,583				187
Ship rescue optimizer	1,122.5	1,138.2	1,154.0	4.31	298
Crayfish optimizer	1,096.6	1,125.6	1,136.0	4.23	297
MHOA	1,081.7	1,098.7	1,105.6	1.06	299

**Figure 8:** Optimized design of vehicle brake pedal using MHOA.

Equation (9) [23] provides the mathematical model for the heat exchanger's initial cost.

$$C_{\text{ini-PFHE}} = C_{\text{PFHE}} * \left(\frac{SA}{N_{\text{PFHE}}} \right)^{n_1} \quad (9)$$

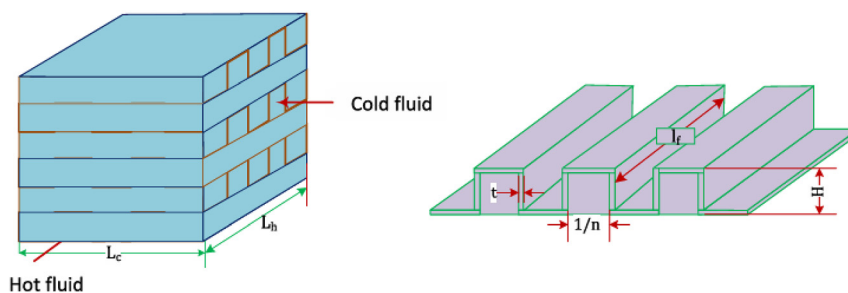
$$C_{\text{oc-FPHE}} = (P_{\text{pump}} + P_{\text{compressor}}) \times t_{\text{op}} \times \text{COE} \quad (10)$$

$$C_{\text{total-FPHE}} = C_{\text{in-FPHE}} \frac{i(1 + \text{IR})^n}{(1 + \text{IR})^n - 1} + C_{\text{oc-FPHE}} \quad (11)$$

The objective function can be calculated using Equations (12) and (13), [23].

$$\text{Minimization of } f(y) = C_{\text{total-FPHE}} + \sum_{j=1}^m z_j \bar{g}_j(y) \quad (12)$$

$$z_j = \frac{|\bar{C}_{\text{total-FPHE}}|}{\sum_{j=1}^m [\bar{g}_j(y)]^2} \quad (13)$$

**Table 7:** Considerations of parameters and constraints.

	Parameters to be optimized	Min. values	Max. values	Range
	Hot fluid side length (10^{-3}m)	100	1,000	–
	Cold fluid side length (10^{-3}m)	100	1,000	–
	Fin height (10^{-3}m)	2	10	–
	Fin thickness (10^{-3}m)	0.1	0.2	–
	Fin pitch (/m)	100	1,000	–
	Placing of fin (10^{-3}m)	1	10	–
Critical constraints	Difference in pressure at hot fluid side (Pa)	–	–	$\leq 9.5\text{E} + 03$
	Difference in pressure at cold fluid side (Pa)	–	–	$\leq 8\text{E} + 03$
	FPHE overall weight	–	–	$< 350\text{ kg}$
	Measured effectiveness	–	–	$\geq 88\%$

Table 8: Results in terms of statistics.

Optimizers	Best	Worst	Mean	SD	SR
MHOA	1,570.64	1,570.01	1,570.46	0.00119	100
ES [22]	1,570.97	1,576.84	1,572.72	2.49	75
SOS [22]	1,570.97	1,571.62	1,571.05	0.172	100
AF [22]	1,570.97	1,571.15	1,571.1	0.0112	100
PVS [22]	1,570.97	1,576.91	1,573.24	1.87	40
SS [22]	1,571.21	1,576.89	1,574.40	2.45	35
GWO [22]	1,570.97	1,571.03	1,570.98	0.0445	100
GOA [22]	1,570.97	1,571.15	1,570.98	0.0428	100
ALO [22]	1,572.08	1,576.82	1,573.29	1.63	55

Table 8 and 9 can be used to perform statistical analysis by comparing a number of parameters that the MHOA algorithm has achieved, including best, worst, mean, and standard deviation values.

Table 9: Optimized results pursued by MHOA.

Optimized parameters	Results
The overall HE weight	350 kg
Loss of hot-side fluid pressure	0.67 kPa
The overall HE cost	1,570.64 (\$)

Figure 9: Optimization of PFHE.

4 Conclusions

This study successfully demonstrates the application and efficacy of the modified hiking optimization algorithm (MHOA) in optimizing various engineering components. The MHOA, inspired by human hiking behavior and enhanced by hiking function, has proven to be effective in solving complex optimization problems. The algorithm was tested on several engineering optimization cases, including spring mass optimization, cylindrical pressure vessel cost optimization, three-bar truss structural optimization, piston-lever design optimization, spur gear weight optimization, heat exchanger, and structural optimization of automobile components. MHOA outperformed other well-known algorithms in each case, achieving superior best values, mean values, and standard deviations. The results indicate that MHOA is a robust and efficient optimization tool capable of addressing multidisciplinary design challenges with improved accuracy and computational efficiency. The success of MHOA in these applications suggests its potential for broader adoption in various engineering optimization problems.

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