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Use Two Kind Hybridization of the Chaotic Peafowl Algorithm with the Hummingbird Algorithm

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ABSTRACT

The wide spread of living organisms in nature and how they obtain food has prompted many scientists to form mathematical models that simulate these organisms. These models were used to solve math problems that take a long time and effort to solve, but these models were sometimes weak and required modification. In this research we used two methods to reach the optimal solution, the first method we used the Peafowl optimization algorithm (POA) with the chaos function and the chaotic tent function to reach the optimal solution and this was the first step in the work, the second method we hybridized the first step by adding the artificial hummingbird algorithm (AHA) The hybridization was of two types, the first by linking communities and the second by linking equations, and we got the optimal solution using 1000 iterations in the two steps, which resulted in producing the optimal solution.

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1. Introduction

proposed intelligent algorithms that mimic the flight and foraging behavior of organisms in nature. This simulation takes place with three types of foraging stages, which are pivotal, diagonal, and multidirectional.

Meta-Heuristic Algorithm (MHA) [1], [2] Inspired by the observation of animal species that live in flocks or live in an isolated way in nature [3-5], where researchers monitor some of these species and study their behavior in search of food [6]. Scientists created mathematical models in the form of algorithms to simulate these animals, which were then used to solve mathematical problems and improve methods of solving them to reach the best solutions.

The Peafowl Improvement Algorithm (POA) caught the attention of researchers by observing the habits and behavior of Peafowl (POA) in nature. Where males are distinguished by their long tail compared to females with short or no tail, and their behavior is divided into two parts: social behavior and spatial behavior. [7-10].

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Hummingbirds are incredible creatures and are the smallest birds on the planet. If intelligence is assessed by comparing their brain-to-body ratio, there are more than 360 species of hummingbirds worldwide. [11-14].

Chaos map has been used in many fields for the purpose of scientific research, as it has been used in several scientific fields, including mathematics, engineering, physics, biology and other sciences. Where chaos is divided into two parts: deterministic and non-deterministic chaotic systems. The first description of a chaotic process was given in 1963 by Lorenz [15] who developed a system called the Lorenz attractor, along with nonlinear differential equations [16-19].

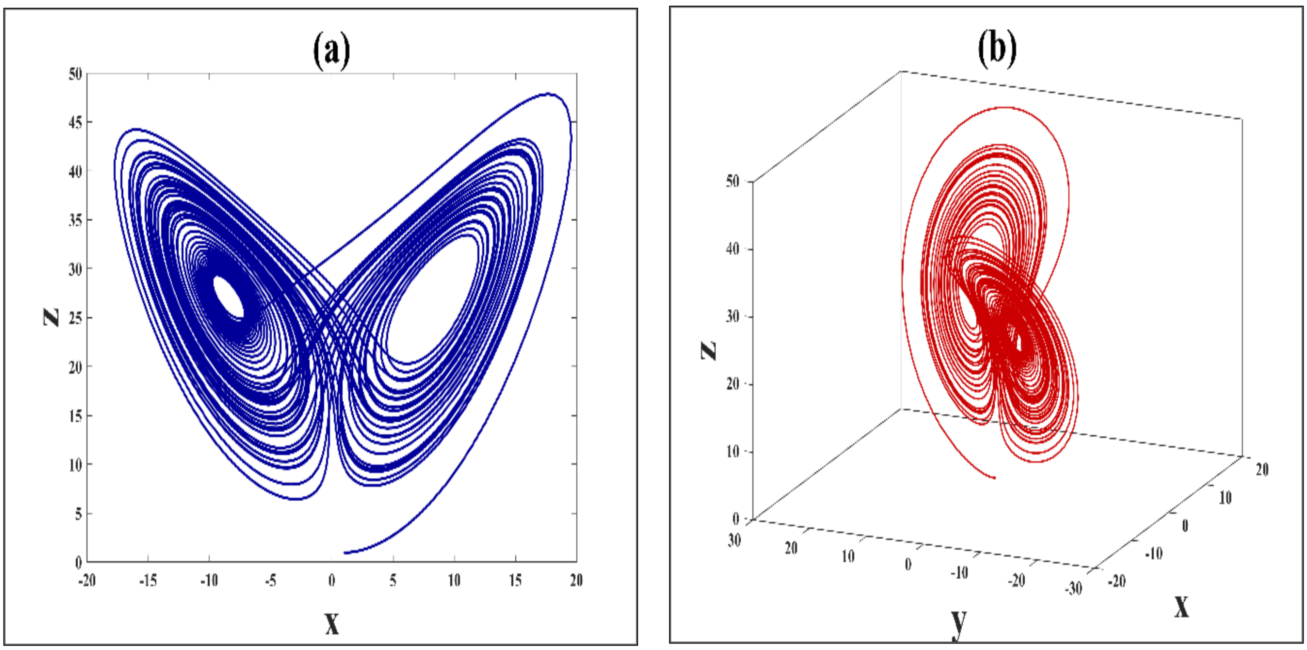

Figure 1. Chaotic attractors.

In this paper we used the chaos method with the Peafowl algorithm (POA) as a first step, then we hybridized it with two types of hybridization, the first through the community and the second through equations, using the artificial hummingbird algorithm (AHA), which represents the second step to obtain the results that represent the solution optimum.

2. Artificial Hummingbird Algorithm (AHA)

Hummingbirds are incredible creatures and they are the smallest birds on the planet. There are more than 360 species of hummingbirds around the world. Like the bee hummingbird, it is the smallest of the hummingbirds, measuring 5.4 cm in length and 1.84 g in weight on average. This bird eats a lot of flower nectar [20] - [23].

The three core components of an algorithm (AHA):

Food: Hummingbirds look for food in the wild based on the qualities of the food. They favor nectar from flowers. The characteristics of these sources are taken into consideration by the bird in terms of the quantity and frequency of nectar replenishment. The value of functional fitness, The higher the fitness rating, the quicker the nectar replaces the food supply.

Hummingbird: A particular food source is designated for each hummingbird. bird could consider the location and rate of nectar replenishment for a certain food source and share that knowledge with the rest of the group. The amount of time that has passed since a hummingbird last visited a particular food source is another thing, they may keep track of.

Figure 2. The hummingbird.

The AHA algorithm's pseudo code is shown in Figure.

START
Initialization
While
The stop requirement is not satisfied
Foraging with a guide
Foraging on a territorial scale
Foraging during migration
END

2.1. Algorithm and mathematical model

The hummingbird algorithm is expressed mathematically", as shown below:

$$m_i = \mathrm{L} + \mathrm{p} \cdot (\mathrm{U} - \mathrm{L}) \quad \mathrm{i} = 1, \ldots, \mathrm{k} \quad (1)$$

where (L) and (U) are the upper and lower limits for a d-dimensional problem, p is a random vector in [0, 1], and m_i is the location of the ith food source that provides the answer to a given problem. The visit table of food sources was first initialized as follows:

$$VT_{i,j} = \begin{cases} 0 & if \quad i \neq j \\ null & \quad\quad i = j \end{cases} \quad i = 1, \ldots, \mathrm{k}; \mathrm{j} = 1 \ldots, \mathrm{k} \quad (2)$$

where $for\ i = j\ \ VT_{i,j}$= null implies that each hummingbird is consuming food from its own source; for $i \neq j$, $VT_{i,j}$= 0 indicates that the ith hummingbird in the current iteration has just visited the j th food source.

2.2. Food with a guide

The target food should have a high rate of nectar replenishment and a long period of visits for that hummingbird since each hummingbird instinctively seeks the food source with the highest volume of nectar. This hummingbird may fly to its preferred food source once it has found it. The AHA approach successfully enhances and defines three flight capabilities: omnidirectional, radial and pivot flights. This is done by providing a vector that switches direction while foraging. This vector defines which directions can be reached in two-dimensional space. Diagonal flight, on the other hand, enables the hummingbird to fly between any two of the three coordinate axes, hummingbirds may move along any coordinate axis. Any direction of flight can be projected onto any of the three coordinate axes. Thanks to multi-directional flight, only hummingbirds have the ability to fly axially and diagonally, although all birds are capable of flying in all directions. To expand on these flight patterns, use the following axial flight definition.d-D space:

$$\mathrm{H}^{\mathrm{i}} = \begin{cases} 1 & \text{if} \quad \mathrm{i} = \mathrm{rand}([1,\mathrm{h}]) \\ 0 & \text{else} \end{cases} \quad \mathrm{i} = 1,\ldots,\mathrm{h} \tag{3}$$

The following are the details of a diagonal flight:

$$\mathrm{H}^{\mathrm{i}} = \begin{cases} 1 & \text{if} \quad \mathrm{i} = \mathrm{O(j)}, \mathrm{j} \in [1,\mathrm{H}], \mathrm{O} = \mathrm{randperm(d)}, \mathrm{d} \in [2, \lceil \mathrm{r1}.(\mathrm{H}-2) \rceil + 1 \\ 0 & \text{else} \end{cases} \tag{4}$$

Flying in an omnidirectional manner is defined as:

$$\mathrm{H}^{\mathrm{i}} = 1 \qquad \mathrm{i} = 1,\ldots,\mathrm{h} \tag{5}$$

where Rand perm(d) produces a random integer permutation between the numbers 1 and h, where r1 is a random number. in (0, 1], and Randi ([1, h]) produces a random integer between 1 and d. Any coordinate axis from 2 to d-1 can be used to define a hyperbolic rectangle. This demonstrates that mathematical models of flying abilities may imitate hummingbird search behaviors in three-dimensional and multi-dimensional settings. The humming (AHA) visits the target food source, resulting in the receipt of a supply filter food. As a result, the food source is updated in relation to the target food source selected from the previous source, all of the available sources. The mathematical formula for simulating directed foraging behavior and a prospective food source is given below:

$$v_n(l+1) = x_{n,tbr}(l) + b.D.\left(x_{n(l)} - x_{n,tbr}(l)\right) \tag{6.}$$

$$b \sim B(0{,}1) \tag{7}$$

where $x_{n(l)}$ shows where the ith food supply is at any given time. t, $x_{n,tbr}(l)$ represents the position of the targeted target food source for the ith hummingbird, and a denotes a directed factor that fits the normal distribution. A variety of flying patterns with a mean of 0 and a standard deviation of 1 are used by hummingbirds to participate in directed foraging, as stated by b (0,1) Eq. (6.) It enables each existing food source to change where it is in relation to the desired food source. The most recent location information for the ith food source is as follows:

$$x_n(\mathrm{l}+1) = \begin{cases} x_n(l) & f(x_n(l)) \leq f(v_n(l+1)) \\ v_n(l+1) & f(x_n(l)) > f(v_n(l+1)) \end{cases} \tag{8}$$

where the function's fitness value is indicated by f (.) If the candidate food source's rate of nectar replenishment is greater than the existing one, according to Eq. (8), the hummingbird will leave its current feeding location and feed at the candidate food source (6).

3. Peafowl optimization algorithm (POA)

parts of China, unlike the blue Peafowl, which is widely distributed in Southeast Asia. Male Peafowl are famous for their long tails and luxurious plumage, unlike females, which have short or no tails. The Asian species engage in courtship rituals that involve the use of a "tail" or "row" of concealed feathers. Depending on their activity, males roam around females and flaunt their beautiful plumage to show their dominance and entice females. to mate. If a male is more attractive than other males, more females may flock to him. Peafowl can be classified into groups that breed, search for food, be social, and move in space. Foraging is one of the most important aspects of bird behavior and one of the most important actions of birds. It also gives us a solid basis for investigating how environmental factors influence flocks. Peafowl open their plumage when they locate a food source and spin dance routines to extend their range and attract females. There are two alternating dance positions: circling around the site and around the food source. Figure (3) of the Peafowl [24] - [27].

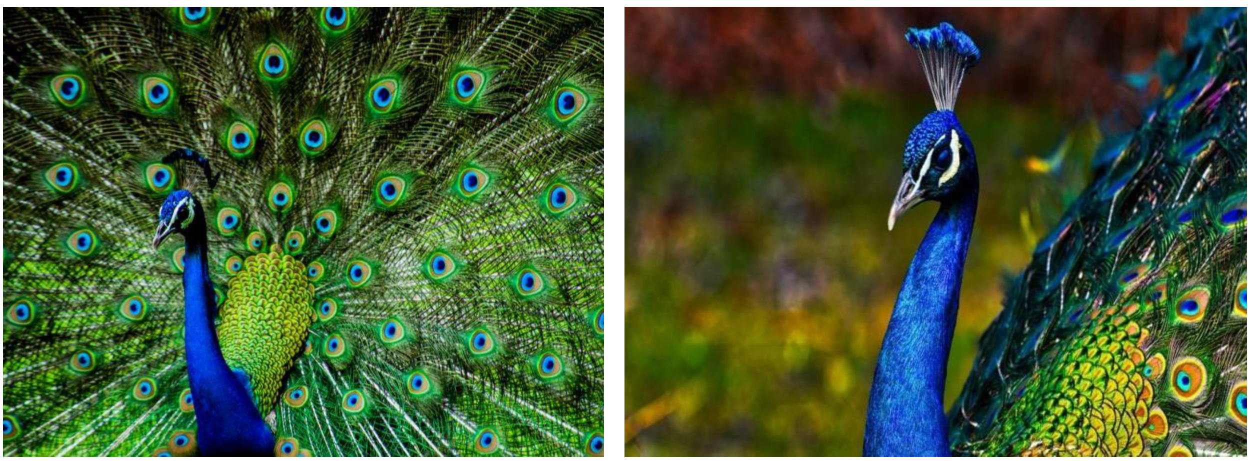

Figure 3. The Peafowl.

3.1. Algorithm and mathematical model

This section presents mathematical models of several cognitive processes of Peafowl. Then the basic operations of the POA are explained. To create an appropriate mathematical model for the various individual behaviors of a Peafowl flock, such as courtship, foraging, and chasing, the Peafowl community is divided into three roles: adult Peafowl, young Peafowl, and Peafowl juvenile. Each Peafowl is evaluated according to how valuable it is.. Peafowl 1, Peafowl 2, Peafowl 3, Peafowl 4 and Peafowl 5 which are identified as Mature Peafowl are the top five answers to the optimization challenges. The first 30% of individuals are classified as adult Peafowl, leaving the remaining 70% as juvenile. Both adult and juvenile peafowl display distinct behaviors that are strongly influenced by adult peafowl. In order to ensure compliance (POA), it is also necessary to redistribute tasks among individuals depending on their fitness values after each iteration. This is because, unlike natural populations, the role of each individual in a peafowl flock may change over time. peafowl engage in courtship behaviors such as circling around a food source to show off in an attempt to attract females and increase the likelihood of mating. Males adopt an exquisite dance posture when approaching females, spreading their tails which is a sign of courtship. Some estranged courtship behaviors, including flapping, flapping of feathers, and tail extension, have three main phases. They cycle from 0 to 15 circles around the female, rising and spreading their tail feathers like fans, the male wagging the tail intermittently, quickly, and at a high frequency to produce a swishing sound that attracts the female's attention during the tail-showing phase. The proposed technique focuses on turning behaviors that may actually lead to changes in fitness value over the course of repetition in order to describe the activities of peafowl using mathematical language and an accurate and cost-effective mathematical model. It is important to keep in mind that the rotational behaviors of male peafowl may involve either circling on site or circling around a food source after extending their tails. The only criterion used to choose between the two spinning behaviors is their fitness values. peafowl with higher levels of fitness are more likely to circle the food source in a wider circle, while peafowl with lower levels of fitness are more likely to circle the food source in a smaller circle radius. But the following can be done to develop such a mathematical model

$$x_{uc1} = x_{uc1}(t) + 1.R_s.\frac{x_{o1}}{\|x_{o1}\|} \qquad (9)$$

$$x_{uc2} = \begin{cases} x_{uc2}(t) + 1.5.R_s.\frac{x_{o2}}{\|x_{o2}\|} & , r_1 < 0.9 \\ x_{uc2}(t) & , \quad \text{otherwise} \end{cases} \qquad (10)$$

$$x_{uc3} = \begin{cases} x_{uc3}(t) + 2.R_s.\frac{x_{o3}}{\|x_{o3}\|} & , r_2 < 0.8 \\ x_{uc3}(t) & , \quad \text{otherwise} \end{cases} \qquad (11)$$

$$x_{uc4} = \begin{cases} x_{uc4}(t) + 3.R_s.\frac{x_{o4}}{\|x_{o4}\|} & , r_3 < 0.6 \\ x_{uc4}(t) & , \quad \text{otherwise} \end{cases} \qquad (12)$$

$$x_{uc5} = \begin{cases} x_{uc5}(t) + 5.R_s.\frac{x_{o5}}{\|x_{o5}\|} & , r_4 < 0.3 \\ x_{uc5}(t) & , \quad \text{otherwise} \end{cases} \qquad (13)$$

$$x_o = 2.\text{rand}\,(1, \text{Dim}) - 1 \qquad (14)$$

where x_{uci} represents the location vector of the male peafowl,$i = 1,2, \dots ,5$; R_s represents the radius of rotation it X_o represents a random vector ; X_o refers to modules of X_o ; o_1 , o_2 , o_3 , o_4 a set of four random integers with a consistent distribution$(0, 1)$; Dim denotes the number of variables. Furthermore it, rotation R_s With each cycle, the radius is supposed to alter dynamically., It can be explained as

$$R_s(t) = R_{so} - (R_{so} - 0).\left(\frac{t}{t_{max}}\right)^{0.01} \qquad (14)$$

where t and t_{max} reflect the number of iterations that have already occurred and the maximum number of iterations; R_{so} represents a starting Using the search space of the optimal problem, the rotation radius vector may be calculated as follows:

$$R_{so} = C_v . (X_U - X_L) \qquad (15)$$

Where X_U and X_L signify the searching space's upper and lower limits; C_v It is possible to establish the visibility factor of peafowls circling at 0.2.

4. Chaotic Map

The chaotic map is a mathematical model that has been applied and used in many intelligence algorithms in order to improve them and get the best solutions. Chaos is associated with dynamic systems that are sensitive to starting conditions, because every change in them has an effect on the final outcome. Chaotic systems show unpredictable behavior, and random maps create chaotic sequences. This section contains a variety of chaotic maps. It will be used to improve the performance of the algorithm [28] - [30].

4.1. Tent Chaotic Map

The chaos map has many types, including the tent, which is described mathematically as follows: [31] - [33].

$$x_{n+1} = \begin{cases} 2x_n & x_n < \frac{1}{2} \\ 2(1 - x_n) & x_n \geq \frac{1}{2} \end{cases} \qquad (16)$$

Where x_n Tent map produces chaotic sequences in the range of 0 to 1.

4.2. Gauss Map

Another well-known and frequently used map for producing chaotic sequences is the Gauss map[34]–[36]:

$$x_{n+1} = \begin{cases} 0 & x_n = 0 \\ \frac{1}{x_n} \mathrm{mod}(1), & \text{otherwise} \end{cases} \qquad (17)$$

5. Working Idea

The work is divided into two main stages: the first use of the chaotic map with the Peacock algorithm, which approaches the optimal solution, and the second stage is the hybridization of the first stage by adding the artificial hummingbird AHA. It is based on the creation of a two-part hybrid. The first hybridization is by linking communities, where the basis of its work is to take the best community from the first algorithm and place it as an initial community for the second algorithm, and the second hybridization is by linking the equations by taking the speed equation for the first algorithm and linking it to the equations of the second algorithm in order to improve them and obtain results that represent the optimal solution. Compare the results with the original algorithms and the first step. As shown in Table 1, 2, and, 3, which represents using a Gauss Chaotic map with POA and then cross-hybridizing it [37] - [40]:

Table 1 - represents the minimum value functions:

0	Name	Function	D	Range

F1	sphere	$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100,100]
F2	Schwefel 2.22	$f_2(x) = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	30	[−10,10]
F3	Schwefel 1.2	$f_3(x) = \sum_{i=1}^{n} (\sum_{j=1}^{n} x_j)^2$	30	[−100,100]
F4	Schwefel 2.21	$f_4(x) = -\sum_{i=1}^{n} (x_i \sin\left(\sqrt{\|x_i\|}\right))$	30	[−500,500]
F5	Step	$f_5(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[−100,100]
F6	Quartic	$f_6(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	30	[−1.28,1.28]
F7	Rastrigin	$f_7(x) = -\sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[−5.12,5.12]
F8	Ackley	$f_8(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right.$	30	[−32,32]
F9	Griewank	$f_9(x) = \frac{1}{4000}\sum_{i=1}^{n}(x_i - 100)^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i - 100}{\sqrt{i}}\right) + 1$	30	[−600,600]
F10	Penalized	$f_{10}(x) = \frac{\pi}{2}\{10 sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2 \times [1 + 10 sin^2(\pi y_i + 1)] + (y_n - 1)^2\} + \sum_{i=1}^{30} u(x_i, 10,100,4)$	30	[−50,50]

Table 2 - the use of the Tent Chaotic Map with POA and then its crossbreeding.

No.	Function	POA	TPOA	TPOA_AHA1	TPOA_AHA2
F1	sphere	3.6721 e-07	0	0	0
F2	Schwefel 2.22	3.3368 e-07	1.2251 e-122	1.2603e-272	0
F3	Schwefel 1.2	2.1389 e-07	3.113e-175	0	0
F4	Schwefel 2.21	0.0088	5.1981e-107	3.2641e-260	0
F5	Step	3.5318e-07	0.0034	0	0
F6	Quartic	0.0076	1.4316 e-04	2.9069e-05	0
F7	Rastrigin	15.9193	0	0	0
F8	Ackley	1.908	4.4409e-15	8.8818e-16	0
F9	Griewank	0.1003	0	0	0
F10	Penalized	0.3101	6.7528 e-06	4.4861e-23	0

Table 3 - represents the use of the Gauss Chaotic Map with POA and then its crossbreeding

No.	Function	POA	GPOA	GPOA_AHA1	GPOA_AHA2
F1	Sphere	3.1618 e-07	0	0	0
F2	Schwefel 2.22	3.8645 e-07	2.3615 e-197	1.99e-287	0
F3	Schwefel 1.2	0.19404	3.3125e-281	0	0
F4	Schwefel 2.21	1.2693	1.2605 e-199	2.3127e-272	0
F5	Step	2.9135e-07	0.0038	0	0
F6	Quartic	0.0012	1.3456 e-04	4.6226e-05	0
F7	Rastrigin	3.6813	0	0	0
F8	Ackley	1.8998	1.9540 e-15	8.8818e-16	0
F9	Griewank	0.0116	0	0	0
F10	Penalized	0.2808	8.4094 e-06	9.4416e-06	0

6. Conclusion

This paper proposed a POA method using Chaotic Map to increase the algorithm's performance and achieve the best result. We saw that we didn't get the best result in several functions, so we enhanced them by utilizing a second algorithm AHA and cross-breeding it with the first. By comparing the first and second tables, we can see that the cross-over led us to the best answer.

References

[1] M. A. A. Alhafedh and O. S. Qasim, “Two-stage gene selection in microarray dataset using fuzzy mutual information and binary particle swarm optimization,” *Indian J. Forensic Med. Toxicol.*, vol. 13, no. 4, pp. 1162–1171, 2019.

[2] Y. A. Fattah Hamoodi and S. A. M Ramadhan, “Identification of Biometrics based on a Classical Mathematical Methods in Forensic Medicine.,” *Indian J. Forensic Med. Toxicol.*, vol. 13, no. 3, 2019.

[3] S. Desale, A. Rasool, S. Andhale, and P. Rane, “Heuristic and meta-heuristic algorithms and their relevance to the real world: a survey,” *Int. J. Comput. Eng. Res. Trends*, vol. 351, no. 5, pp. 2349–7084, 2015.

[4] B. Yang *et al.*, “Comprehensive overview of meta-heuristic algorithm applications on PV cell parameter identification,” *Energy Convers. Manag.*, vol. 208, p. 112595, 2020.

[5] A. Kaveh and M. Khayatazad, “A new meta-heuristic method: ray optimization,” *Comput. Struct.*, vol. 112, pp. 283–294, 2012.

[6] M. A. El Aziz, A. A. Ewees, and A. E. Hassanien, “Hybrid swarms optimization based image segmentation,” in *Hybrid soft computing for image segmentation*, Springer, 2016, pp. 1–21.

[7] P. Kenekayoro, “A Meta-Heuristic Search Algorithm based on Infrasonic Mating Displays in Peafowls,” *arXiv Prepr. arXiv2106.14487*, 2021.

[8] E. Asyabi, A. Bestavros, E. Sharafzadeh, and T. Zhu, “Peafowl: In-application cpu scheduling to reduce power consumption of in-memory key-value stores,” in *Proceedings of the 11th ACM Symposium on Cloud Computing*, 2020, pp. 150–164.

[9] J. Wang *et al.*, “Novel phasianidae inspired peafowl (Pavo muticus/cristatus) optimization algorithm: Design, evaluation, and SOFC models parameter estimation,” *Sustain. Energy Technol. Assessments*, vol. 50, p. 101825,

2022.

[10] K. Sun, K. A. Meiklejohn, B. C. Faircloth, T. C. Glenn, E. L. Braun, and R. T. Kimball, "The evolution of peafowl and other taxa with ocelli (eyespots): a phylogenomic approach," *Proc. R. Soc. B Biol. Sci.*, vol. 281, no. 1790, p. 20140823, 2014.

[11] M. A. S. Ali, F. R. PP, and D. Salama Abd Elminaam, "A Feature Selection Based on Improved Artificial Hummingbird Algorithm Using Random Opposition-Based Learning for Solving Waste Classification Problem," *Mathematics*, vol. 10, no. 15, p. 2675, 2022.

[12] B. S. Yildiz, P. Mehta, S. M. Sait, N. Panagant, S. Kumar, and A. R. Yildiz, "A new hybrid artificial hummingbird-simulated annealing algorithm to solve constrained mechanical engineering problems," *Mater. Test.*, vol. 64, no. 7, pp. 1043–1050, 2022.

[13] Yahia, W. B., Al-Neama, M. W., & Arif, G. E. (2020). PNACO: parallel algorithm for neighbour joining hybridized with ant colony optimization on multi-core system. *Вестник Южно-Уральского государственного университета. Серия: Математическое моделирование и программирование*, *13*(4), 107-118.

[14] A. Fathy, "A novel artificial hummingbird algorithm for integrating renewable based biomass distributed generators in radial distribution systems," *Appl. Energy*, vol. 323, p. 119605, 2022.

[15] E. N. Lorenz, "Deterministic nonperiodic flow," *J. Atmos. Sci.*, vol. 20, no. 2, pp. 130–141, 1963.

[16] Z. Hua, Y. Zhou, and H. Huang, "Cosine-transform-based chaotic system for image encryption," *Inf. Sci. (Ny).*, vol. 480, pp. 403–419, 2019.

[17] S. F. Al-Azzawi and Z. S. Al-Talib, "Generalized function projective synchronization via nonlinear controller strategy," *J. Interdiscip. Math.*, pp. 1–13, 2022.

[18] Q. Lai, "A unified chaotic system with various coexisting attractors," *Int. J. Bifurc. Chaos*, vol. 31, no. 01, p. 2150013, 2021.

[19] M. Alawida, A. Samsudin, J. Sen Teh, and R. S. Alkhawaldeh, "A new hybrid digital chaotic system with applications in image encryption," *Signal Processing*, vol. 160, pp. 45–58, 2019.

[20] A. M. Sadoun, I. R. Najjar, G. S. Alsoruji, M. S. Abd-Elwahed, M. A. Elaziz, and A. Fathy, "Utilization of improved machine learning method based on artificial hummingbird algorithm to predict the tribological behavior of Cu-Al2O3 nanocomposites synthesized by in situ method," *Mathematics*, vol. 10, no. 8, p. 1266, 2022.

[21] M. A. Hamida, R. A. El-Sehiemy, A. R. Ginidi, E. Elattar, and A. M. Shaheen, "Parameter identification and state of charge estimation of Li-Ion batteries used in electric vehicles using artificial hummingbird optimizer," *J. Energy Storage*, vol. 51, p. 104535, 2022.

[22] S. Haddad, B. Lekouaghet, M. Benghanem, A. Soukkou, and A. Rabhi, "Parameter Estimation of Solar Modules Operating Under Outdoor Operational Conditions Using Artificial Hummingbird Algorithm," *IEEE Access*, 2022.

[23] Yahia, W. B., Al-Neama, M. W., & Arif, G. E. (2020). A Hybrid Optimization Algorithm of Ant Colony Search and NeighbourJoining Method to Solve the Travelling Salesman Problem. *Advanced Mathematical Models and Applications*, *5*(1), 95-110.

[24] O. W. Khalid, N. A. M. Isa, and H. A. M. Sakim, "Emperor penguin optimizer: A comprehensive review based on state-of-the-art meta-heuristic algorithms," *Alexandria Eng. J.*, 2022.

[25] R. Chaudhary and H. Banati, "Peafowl Algorithm," in *2019 IEEE Congress on Evolutionary Computation (CEC)*, 2019, pp. 2331–2338.

[26] T. SAWANGTHAM and A. WIWEGWEAW, "Genetic diversity of green peafowl (Pavo muticus) in northern

Thailand based on mitochondrial DNA control region sequences," *Trop. Nat. Hist.*, vol. 18, no. 1, pp. 11–23, 2018.

[27] L. G. C. Vithakshana and W. Samankula, "IoT based animal classification system using convolutional neural network," in *2020 International Research Conference on Smart Computing and Systems Engineering (SCSE)*, 2020, pp. 90–95.

[28] A. Kanso and H. S. Own, "Steganographic algorithm based on a chaotic map," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 8, pp. 3287–3302, 2012.

[29] C. Pak and L. Huang, "A new color image encryption using combination of the 1D chaotic map," *Signal Processing*, vol. 138, pp. 129–137, 2017.

[30] C. Han, "An image encryption algorithm based on modified logistic chaotic map," *Optik (Stuttg).*, vol. 181, pp. 779–785, 2019.

[31] C. Li, G. Luo, K. Qin, and C. Li, "An image encryption scheme based on chaotic tent map," *Nonlinear Dyn.*, vol. 87, no. 1, pp. 127–133, 2017.

[32] S. Kanwal *et al.*, "An Effective Color Image Encryption Based on Henon Map, Tent Chaotic Map, and Orthogonal Matrices," *Sensors*, vol. 22, no. 12, p. 4359, 2022.

[33] F. Kuang, Z. Jin, W. Xu, and S. Zhang, "A novel chaotic artificial bee colony algorithm based on tent map," in *2014 IEEE congress on evolutionary computation (CEC)*, 2014, pp. 235–241.

[34] J. A. de Oliveira, H. M. J. de Mendonça, V. A. Favarim, R. Carvalho, and E. D. Leonel, "Boundary crises and supertrack orbits in the Gauss map," *Eur. Phys. J. Spec. Top.*, pp. 1–4, 2022.

[35] E. Güler, H. H. Hacısalihoğlu, and Y. H. Kim, "The Gauss map and the third Laplace-Beltrami operator of the rotational hypersurface in 4-space," *Symmetry (Basel).*, vol. 10, no. 9, p. 398, 2018.

[36] Younis, Y. S., Ali, A. H., Alhafidhb, O. K., Yahia, W. B., Alazzam, M. B., Hamad, A. A., & Meraf, Z. (2022). Early diagnosis of breast cancer using image processing techniques. *Journal of Nanomaterials*, *2022*.

[37] X.-S. Yang, "Test problems in optimization," *arXiv Prepr. arXiv1008.0549*, 2010.

[38] S. Arora and S. Singh, "Butterfly algorithm with levy flights for global optimization," in *2015 International conference on signal processing, computing and control (ISPCC)*, 2015, pp. 220–224.

[39] X.-S. Yang and S. Deb, "Engineering optimisation by cuckoo search," *arXiv Prepr. arXiv1005.2908*, 2010.

[40] X.-S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *arXiv Prepr. arXiv1003.1409*, 2010.