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SURVEY ARTICLE

Harris Hawks Optimization Algorithm: Variants and Applications

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Abstract

This paper introduces a comprehensive survey of a new swarm intelligence optimization algorithm so-called Harris hawks optimization (HHO) and analyzes its major features. HHO is counted as an example of the most effective Optimization algorithm and utilized in different problems in various domains, successfully. For example, energy and Power Flow, engineering, medical applications, networks, and image processing. This review introduces the available related works of HHO where the main topics include; HHO variants, modification, and Hybridization, HHO applications, analysis and differentiation between HHO and other algorithms in the literature. Finally, the conclusions concentrate on the existing work on HHO, showing its disadvantages, and propose future works. The review paper will be helpful for the researchers and practitioners of HHO belonging to a wide range of audiences from the domains of optimization, engineering, medical, data mining and clustering. As well, it is wealthy in research on health, environment and public safety. Also, it will aid those who are interested by providing them with potential future research.

1 Introduction

Optimization algorithms were introduced based on the behaviors of various organisms. In other words, the optimization algorithms ideas are nature-inspired. Figure 1, the main category of the optimization algorithms; (i) Heuristic approach which also known as a single solution-based, where it contains special heuristic methods. For instance, Simulated Annealing (SA) [83] and Hill-Climbing (HC) [85]. (ii) Metaheuristic algorithms which are also known as population-based methods [5, 117]. It can easily adapt to different kinds of optimization problems by using parameter tuning and modifying the operations. Metaheuristic algorithms are divided into four classes; (1) Evolutionary Algorithms (EAs), such as Genetic Algorithm (GA) [84], Genetic Programming (GP) [84], and Differential Evolution [134]. (2) human-based algorithms, such as Tabu search (TS) [58], Translation Lookaside Buffer(TLB) [106], and

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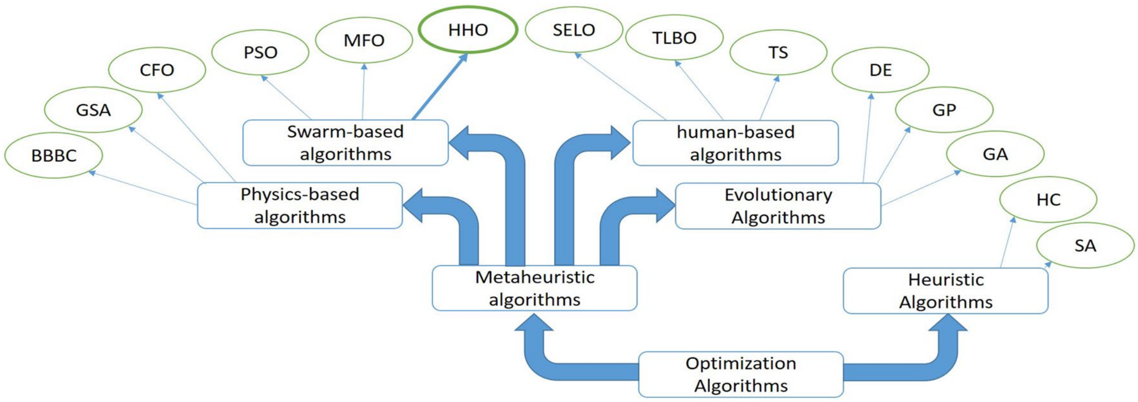

Fig. 1 Optimization algorithms

Socio-evolution and Learning Optimization (SELO) [87]. (3) Physics-based algorithms, such as Central Force Optimization (CFO) [54], Gravitational Search Algorithm (GSA) [107], and Big Bang Big Crunch (BBBC) [49]. (4) Swarm-based like cCuckoo search algorithm (CSA) [120], moth flame optimization (MFO) [93], Harris hawks optimization (HHO) [65], and others [11, 100].

Swarm-based algorithms are usually inspired by social insect colonies and animal societies [23]. Also, they emulate the behavior of swarming social insects for seasonal migrations, looking for food or safety. The main features of these methods are their robustness in achieving the solutions and flexibility in adapting the problems [12]. HHO algorithm is an example of the modern metaheuristic population-based algorithms proposed by Heidari et al. [65] in 2019, HHO inspired by the cooperative behaviors of the Harris hawks' in hunting escaping preys. Harris hawks' consider as one of the most intelligent birds.

HHO algorithms integrated between local-based and global-based searches to increase the ability to deal with exploitation and exploitation search mechanism. It's worth to mention that HHO includes four different approaches to the exploitation search mechanism (see Sect. 2). Consequently, HHO proved its efficiency in dealing with various research on health, environment and public safety. As well as different problems in various field, such as image processing [144], power energy [14], networks [133], and medical [105].

The review paper aims to provide the interested researchers with optimization algorithms by introducing a comprehensive review of the Harris hawks optimizer (HHO) algorithm, the following points show the content of this review.

- An overview of the main concept of basic HHO's to highlight the main strengths, weaknesses, and procedures of the algorithm.
- Illustrates the related works of HHO and classifies them into; Variants such as binary HHO, enhancement such as modified HHO (MHHO), and the recent applications of the HHO such as Machine learning and networks fields.
- Evaluate the efficiency of HHO compared with other algorithms in the literature.
- Introduces potential guidnesses using HHO for future works.

Based on the above, this review will aid the interested researchers and students by mentioning the major advantages and weaknesses of the HHO. Especially in swarm-based algorithms, there are many algorithms that have been introduced recently [38].

The rest sections in this review are shown as follows. Section 2 presents HHO's framework and procedures of the basic HHO algorithm. Section 3 illustrates a brief introduction of HHO algorithm. The usage of the HHO algorithm in the various fields is discussed in Sect. 4. Section 5 shows the evaluation of HHO algorithm. At the end, the conclusion and possible future directions are presented in Sect. 6.

2 Harris Hawks Optimization Algorithm

2.1 Origin

Harris hawk considered as an example of the most intelligent animal based on feeding behaviors [131]. It is known as the bird of prey and survives in groups, it's country of origin is the southern half of Arizona, USA [30]. Animal scientists noticed that the Harris hawk works cooperatively with its group, Significantly. In other words, most kinds of other raptors discovering, attacking, and eating, individually. While in Harris hawk's groups, all group members participate in the dinner banquet, which increases during the non-breeding seasons.

Fig. 2 Harris's hawk and their behaviors

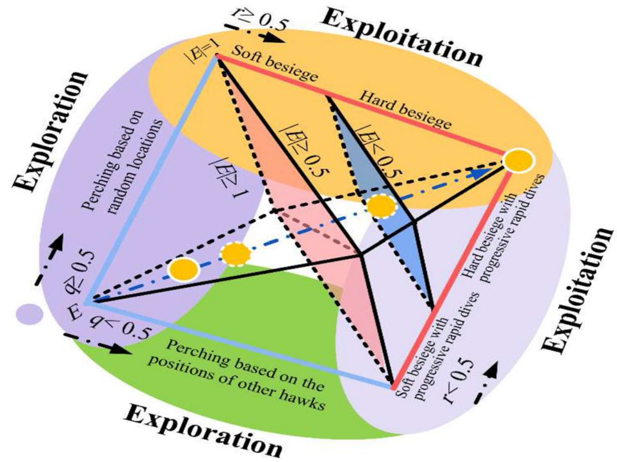

Fig. 3 Logics and steps of HHO [37]

As shown in Fig. 2, Harris hawks based on surprise pounce tactic to catch prey. This strategy also known "seven kills", where the main objective is exhaustion the prey then capture it. The success of the process includes a set of sequential steps; starts by attacking may rapidly (i.e., a few seconds) to surprise the prey. Then, members of the group take turns making multiple, short-range and rapid dives near the prey within several minutes to confuse it. After that, one of the hawks which usually has the experienced and powerful catch the tired prey easily. Finally, prey has been shared with the other members of the group.

2.2 Harris Hawks Optimization

Heidari et al. [65] proposed Harris hawks optimization (HHO) as a popular example of the population-based metaheuristic algorithms. As well as, it nature-inspired search mechanism that imitates the Harris hawks' behavior of looking and catching prey. Figure 3 presents the consuming prey energy during the escape by utilizing the HHO's strategies to grasp prey, which modeled as the following equations.

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{1}$$

$$E_0 = 2r_1 - 1 \tag{2}$$

where E indicates the flight power of the prey, t refers to the initial repetition number, T indicates the maximum number of repetition, E_0 refers to the initial prey power with a random number in [− 1, 1], and r_1 refers to a random value in [0, 1].

In each repetition, the value of E decreasing gradually because it related to the power of the prey during flight. In other words, in case the $|E| \geq 1$ the hawks looking for the prey's location in different regions, this process refers to exploration search. While if $|E| < 1$, then the hawks ready to catch the prey, this process refers to exploitation search. The following sections present more details about each search strategy (i.e., exploration and exploitation).

2.2.1 Exploration Phase

This section describes the initial phase of the hunting process, which contains monitoring, tracking, and then detecting the prey. In HHO, this stage indicates the exploration mechanism. In nature, Harris hawks may stay several hours to discover the prey. Thus, the probability of finding the prey (i.e., target) is based on the Harris hawks (i.e., candidate solutions). Consequently, the best candidate solution is intended to prey the nearest one to it. Harris hawks follow two strategies when waiting for prey; either waiting in locations with their family members' locations to be close together at the time of the attack or waiting in random positions like tall trees. Both cases are modeled in the following equation.

$$X(t+1) = \begin{cases} X_{rand}(t) - r_2\left|X_{rand}(t) - 2r_3X(t)\right| & q \geq 0.5 \\ (X_{prey}(t) - X_m(t)) - r_4(LB + r_5(UB - LB)) & q < 0.5 \end{cases} \tag{3}$$

where $X(t+1)$ indicates the new hawks' positions based on iteration t, X_{prey} is the location of the prey, X_m refers the average of the initial population's position, X_{rand} refers to hawk determined randomly from the search space, $X(t)$ refers to the initial hawks' locations, which is calculated as shown in Eq. 4. r_2, r_3, r_4, r_5, and q are random values in between the interval (0,1), its worth to mention that these random numbers upgraded in each repetition t.

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \tag{4}$$

where X_i refers to the position of hawk in repetition t and N is the total amount of hawks.

2.2.2 Exploitation Phase

This stage starts after discovering the prey in the exploration (i.e., wide search). Harris hawks try to pounce on prey suddenly. On other hand, the prey tries to escape from which called seven kills [30]. HHO modeled four potential approaches for hunting's strategies and escaping's behaviors. Where that was proposed r as a random number to refer the opportunity of prey in successfully flight ($r < 0.5$), in contrast ($r \geq 0.5$) in the event of failure. Also, the hawks will be based on a soft or hard blockade to capture the prey based on the prey power E. For instance, if the blockade is soft the representation will be $|E| \geq 0.5$, otherwise $|E| < 0.5$.

1. *Soft besiege* As mentioned above, when the values of $|E| \geq 0.5$ with $r \geq 0.5$. Thus, the prey has sufficient energy to flight from hawks by following random ways and misleading jumps. Unfortunately, it will fail because the harris hawks exhaust its energy by encircling it, and then surprise attack. Equation 5 shows the modeled of this behavior.

$$X(t+1) = \Delta X - E\left|JX_{prey}(t) - X(t)\right| \tag{5}$$

$$\Delta X(t) = X_{prey}(t) - X(t) \tag{6}$$

$$J = 2 \times (1 - r_6) \tag{7}$$

where ΔX indicates the distinction's location amidst the preys and the initial location in repetition t, r_6 is a random value in (0,1), and J refers to the prey's random jump, where it (i.e.,J) alterations randomly to mimic the nature of prey motions.

2. *Hard besiege* In this case, $E < 0.5$ and $r \geq 0.5$. Thus, there is no energy for the prey to escape. Moreover, the hawks are ready to encircle the prey and perform the surprise attack, hardly. Equation 8 illustrates the updating of the current positions of this situation.

$$X(t+1) = X_{prey}(t) - E|\Delta X(t)| \tag{8}$$

3. *Soft besiege with progressive rapid dives* This case is more complicated than the previous cases, where it uses when the $|E| \geq 0.5$ and $r < 0.5$. Thus, the prey has sufficient power to escape, successfully. On the other hand, the hawks still execute many rapid dives to enforced the prey to change its path and distracting it. The process continues until chosen the best time to catch the prey. The following equation describes the hawks' decision to move for implementing the soft encircle.

$$Y = X_{prey}(t) - E\left|JX_{prey}(t) - X(t)\right| \tag{9}$$

If the hawks feel that the prey preforms misleading movements and it almost escape, they will increase the abrupt, irregular, and rapid dives. The new hawks' technique depends on levy flights (LF) as shown in the following equation.

$$Z = Y + S \times LF(D) \tag{10}$$

where D indicates the dimension of the issue, S refers to a random vector by size $1 \times D$, and LF is calculated as the following equation.

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \tag{11}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right) \tag{12}$$

where u and v refer to a random value in (0,1), β indicates the fixed variable set to 1.5. Consequently, the mathematical model for upgrading the hawks' locations in the soft encircle stage is shown as the following equation.

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & if\ F(Z) < F(X(t)) \end{cases} \tag{13}$$

where Y and Z are found in Eqs. 9 and 10, respectively.

4. *Hard besiege with progressive rapid dives* In the last case, the values of $r < 0.5$ and $|E| < 0.5$. That means the prey doesn't have sufficient power to escape. At the same time, hawks try to minimize the space with the prey before the surprise pouncing to hunt the prey. The following equation shows the updating of hawks' positions.

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & if\ F(Z) < F(X(t)) \end{cases} \tag{14}$$

$$Y = X_{prey}(t) - E\left|JX_{prey}(t) - X_m(t)\right| \tag{15}$$

$$Y = X_{prey}(t) - E\left|JX_{prey}(t) - X_m(t)\right| \tag{16}$$

where $X_m(t)$ is found in Eq. 4. The summary of the HHO algorithm's procedures is presented as the follows pseudo-code.

Algorithm 1 Harris Hawks optimization algorithm

Input: The population size N and maximum number of iteration T
Outputs: The location of rabbit and its fitness value initialize the random population $X_i = (i = 1, 2, ..., N)$
while stopping condition is not met **do**
  Calculate the fitness values of hawks
  Set X_{rabbit} as the location of rabbit (best location)
  for each hawk x_i **do**
    Update the initial energy E_0 and jump strength J. $E_0 = 2rand() - 1$, $J = 2(1 - rand())$
    Update the E using Eq.1
    if $|E| \geqslant 1$ **then**
      Update the location vector using Eq. 3
    end if
    if $|E| < 1$ and $r \geq 0.5$ and $|E| \geq 0.5$ **then**
      Update the location vector using Eq. 5
    else
      if $r \geq 0.5$ and $|E| < 0.5$ **then**
        Update the location vector using Eq. 8
      end if
    else
      if $r < 0.5$ and $|E| \geq 0.5$ **then**
        Update the location vector using Eq. 13
      end if
    else
      if $r < 0.5$ and $|E| < 0.5$ **then**
        Update the location vector using Eq. 14
      end if
    end if
  end for
end while
Return X_{rabbit}

3 Different Variants of HHO

Although the age of the HHO algorithms around two years, the researchers introduced many variants (i.e., versions) by developing it to be compatible for solving different kinds of problems. In this review paper, the materials have been collected based on using the HHO as a keyword through two stages. Firstly, the published HHO papers are obtained from highly-reputed publishers such as Elsevier, Springer, and IEEE as well, from other journals which were searched using Google Scholar. Second, the search results are classified and distributed into various fields as shown in this section. Figure 4 shows the percentage of the number of published articles in each categories. It can be noticed that the hybridization category outperformed the other category based on the number of articles which refers that the researchers are interested to increase the HHO's capability and efficiency. As well as, it has a simple structure that enables to merge it with other techniques and algorithms. At the end of this section, a summary of the HHO's variants is shown in Table 1.

3.1 Binary

Real-world optimization problems have, by nature, discrete search spaces rather than continuous. Therefore, binary version of HHO has been introduced. Thaher and Arman [135] presented an Enhanced Binary HHO algorithm (EBHHO) augmented with the Adaptive Synthetic Oversampling (ADASYN) to improve feature selection (FS) for Software Fault Prediction (SFP). K-nearest neighbors (kNN), Decision Trees (DT), and Linear Discriminant Analysis (LDA) classifiers were used to evaluate the efficiency of the introduced algorithm [16]. The experimental illustrated that the introduced model produce better solutions compared to basic HHO and to other optimization algorithms in the literature, especially for the LDA classifier.

Zhang et al. [158] introduced an enhanceed HHO (IHHO) for FS tasks by combining the salp swarm algorithm (SSA) and the basic HHO to enhance the update stage in the HHO optimizer. The experiment results showed that IHHO

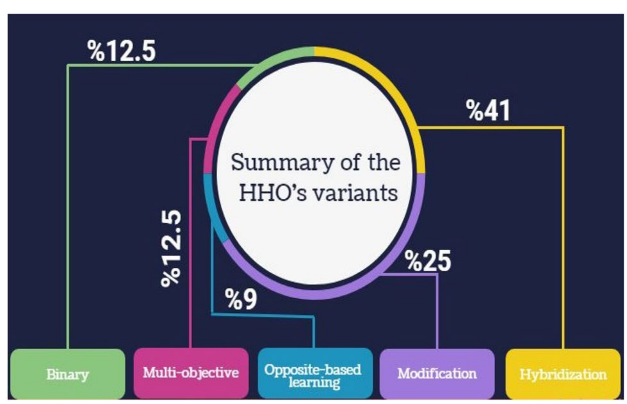

Fig. 4 Summary of the HHO's variants

Table 1 HHO's variants

Application	Abbreviation	Description	Area	References
Binary	EBHHO	Using EBHHO Software fault prediction based on a wrapper feature selection and the Adaptive Synthetic Oversampling (ADASYN)	Software fault prediction	Thaher and Arman [135]
	IHHO	Combining the salp swarm algorithm (SSA) and the original HHO for feature selection tasks	Feature selection	Zhang et al. [158]
	BHHO and QBHHO	QBHHO and BHHO algorithms are presented to find optimal feature selection	Feature selection	Too et al. [137]
Multi-objective	HHMO	combining GWMO with HHO to solve desired reference points problem	Reference point problem	DeBruyne and Kaur [40]
	IHHO and MOIHHO	Improving HHO by using new location strategy and using grey relation analysis	Distribution systems	Selim et al. [115]
Opposite-based learning	m-HHO	Using m-HHO four strategies: nonlinear power variable for the power of prey, various tuning for rapid dives, a greedy selection scheme, and opposition-based learning	Optimization problems	Gupta et al. [62]
	NCOHHO	The neighborhood centroid is used to with the opposite-based learning to enhance the efficiency of HHO	Optimization problems	Fan et al. [52]
	IHHO	Elite opposite-based learning is used to improve HHO. Mutation, mutation neighborhood search, and rollback are used to enhance search	Feature selection	Sihwail et al. [128]
Modification	MHHO	Improve the HHO accuracy using six strategies to update escaping energy of prey	HHO modification, enhancement, and variant	Zhang et al. [159]
	MHHO	Combine HHO with chaotic Singer map and LF	CCHP system	Zhao et al. [160]
	IHHO	Improve HHO by using crossover operation of the AT algorithm	SAR and stock market index prediction	Hu et al. [70]
	AHHO	Improve HHO combines adaptive cooperative foraging and dispersed foraging strategies	HHO modification, enhancement, and variant	Zhang et al. [157]
	CMDHHO	combining three strategies: chaos strategy, topological multi-population, and DE	HHO modification, enhancement, and variant	Chen et al. [36]
	MHHO	Utilizing the SSA with HHO to enhance the local search in order to find optimal solutions	machine scheduling	Jouhari et al. [78]
	MHHO	Using LF and randomly shrinking exponential function	Photovoltaic systems	Yousri et al. [150]
	EHHO	Enhanced HHO used chaotic Tent map to find the chaotic positions of the prey	HHO modification, enhancement, and variant	Zheng-Ming et al. [161]

Table 1 (continued)

Application	Abbreviation	Description	Area	References
Hybridization	HHOBSA	Using HHOA to improve the search behavior and to avoid fall into a local optimum	Feature selection	Abdel-Basset et al. [3]
	HHOSA	Using HHOSA to optimize the design parameters for highway guardrail systems	Parameter tuning	Kurtuluş et al.[88]
	HHOSA	Using HHOSA for job scheduling in cloud computing	Job scheduling	Attiya et al. [25]
	H-HHONM	Applying H-HHONM for designing and manufacturing optimization problems	Parameter tuning	Yıldız et al. [149]
	HHO-SVM and HHO-kNN	Using HHO-SVM and HHO-kNN to achieve high classification accuracy of drug design and discovery	Feature selection	Houssein et al. [68]
	CHHO-CS	Proposing CHHO-CS to avoid getting stuck in a local minimum and to control the balance between intensification and diversification	Feature selection	Houssein et al. [67]
	MOHHO	Using MOHHO to tune the parameters of ELM model with high prediction accuracy and stability, which is then used to predict the air pollutant concentration	Parameters optimization	Du et al. [46]
	ANN-HHO	Utilizing ANN-HHO to optimize the parameters of ANN to develop deep scouring prediction models	Parameters optimization	Sammen et al. [112]
	MSCAHHO	introducing MSCAHHO to optimize the SVM parameters, thereafter the best model of SVM was applied to classify the rolling bearing fault in industrial production	Parameters optimization	Fu et al. [55]
	HHO-ANN	Using HHO-ANN to predict the coefficient of soil compression	Parameters optimization	Moayedi et al. [96]
	hHHO-IGWO	Applying hHHO-IGWO approach to improve the extent of exploitation and exploration capabilities	Numerical optimization	Moayedi et al. [96]
	HHOMPA	Utilizing HHOMPA to improve the efficiency of search procedure	Numerical and engineering optimization	Barshandeh et al. [29]
	HHO-HGSO	Using HHO-HGSO to solve numerical benchmark functions and real-world engineering problems	Numerical and engineering optimization	Xie et al. [145]

converge speed is faster with equation between exploitation and exploration. as well as, the authors constructed a binary IHHO for a FS wrapper. The results showed that the binary IHHO is more accurate compare to other wrapper-based FS methods.

In the same line. Too et al. [137] introduced a binary HHO (BHHO) to fix the FS problem. To convert the continuous variable to a binary variable, BHHO utilizes the either V-shaped or S-shaped transmit function. Furthermore, the authors proposed another algorithm called quadratic BHHO(QBHHO) to improve the efficiency of BHHO. The experimental results show that the QBHHO work more effectively and outperform other algorithms, for instance binary MVO (BMVO), binary SSA (BSSA), binary DE (BDE), and binary FPA (BFPA) in terms of categorization efficiency, fitness values, and feature size.

3.2 Multi-objective

DeBruyne and Kaur [40] introduced HHO Objective Optimizer (HHMO) to solve reference point multi-objective issues. The model combines the grey wolf multi-objective optimization (GWMO) by modeling the hunting behaviors of the Harris's Hawk. The results showed that the HHMO out preformed the other algorithms in terms of fitness value and convergence time. HHMO located solutions' clusters at the desired reference points or near it.

Selim et al. [115] proposed both improved single-objective HHO (IHHO) and multi-objective improved HHO algorithms (MOIHHO) to fix the problem of radial distribution systems, in particular, finding the optimal size and position of distribution production. IHHO improves the performance of the traditional HHO by utilizing the rabbit position alternatively of the random position. On the other hand, MOIHHO uses grey relation analysis to identify the optimal solution of the Pareto solutions. The results illustrated the efficiency of both IHHO and MOIHHO in finding the optimal allocation of distribution generation compared with conventional HHO and other optimization techniques in terms of finding best solutions.

3.3 Opposite-Based Learning

Gupta et al. [62] introduced m-HHO, a MHHO to improve the search-efficiency and provide premature convergence problems. In order to achieve this goal, m-HHO uses four different strategies. First, a non-linear power variable for the power of prey is used. Second, various tunings are used to improve rapid dives. Third, applying a greedy selection scheme to express all hawks. Fourth, opposition-based learning is employed. The experimental results on 33 benchmark problems showed the superiority of m-HHO comparing with the basic HHO and state of the art optimization algorithms.

Fan et al. [52] introduced neighborhood centroid opposite-based learning HHO algorithm (NCOHHO) to enhance performance of HHO. The neighborhood centroid generates the opposite particle utilizing the opposite-based learning, while other operation conditions (e.g., the diversity of the population) are kept unchanged which enhance probability of determining the best solution. Experimental results showed that NCOHHO outperform the basic HHO algorithm and the current algorithms. For instance, PSO, CAS, Harmony Search (HS), Gbest-guided Gravitational Search Algorithm (GGSA), differential evolution algorithm (DE). Moreover, the experimental results confirmed efficiency of using NCOHHO for training feed-forward neural network (FNN).

In [73] the authors presented an alternative version of HHO to boost HHO's convergence speed while avoiding local optima. The presented algorithm combines HHO with three different techniques, chaotic local search (CLS), self-adaptive technique (ST), and opposition-based learning (OBL). The CLS is applied to allow the best agent to conduct a second search in the nearby area. The ST allows updating individual solutions. The OBL technique is used to improve the randomly initialized initial solutions. The proposed approach was evaluated against ten state-of-the-art algorithms using a variety of numerical and engineering benchmark problems.

Sihwail et al. [128] utilized elite opposite-based learning and proposed an improved HHO (IHHO) and a new search mechanism. IHHO avoids local optima trapping, improves population diversity, accelerates convergence rate, and increases computational accuracy. IHHO also utilized number of strategies such as mutation, mutation neighborhood search, and rollback to enhance its search mechanism capabilities. The experiment results show superiority of IHHO comparing with other algorithms. For instance, Generic algorithm (GA), Grasshopper Optimization Algorithm (GOA), Ant Lion Optimizer (ALO), Bat Algorithm (BA), Butterfly Optimization Algorithm (BOA), and Grey Wolf Optimization (GWO) by focusing on the selected features, the accuracy of the classification, and fitness value on twenty benchmark datasets.

3.4 Modification

A MHHO algorithm is proposed in [159] to improve the solutions' accuracy, speed up the convergence rate, and improve the local optimal avoidance. The paper introduced six strategies to update and adjust the critical variables escaping energy (EE) of prey. The strategies are: straight linear decreasing strategy, power-based non-linear decreasing strategies with downward bend, power-based non-linear reducing techniques with upward bend, convex-concave sin strategy, concave-convex sine strategy, and exponential reducing techniques [7]. The experiment showed that exponential decreasing strategy is superior and outperforms other best strategy. Moreover, the results also showed that MHHO has a remarkable search performance compared with the conventional HHO and with other optimization technologies such as MFO, GA, TLBO, HS, and PSO.

Zhao et al. [160] introduced MHHO algorithm to optimize Combined Cooling, Heating, and Power (CCHP) system to increase its efficiency. In order to reduce premature convergence in HHO, chaotic Singer map is utilized to convert random parameter to regular values. Moreover, the conventional LF mechanism, which is used in the exploration part, is utilized and is modeled using new equations. Simulation outcomes showed that MHHO algorithm outperform the basic HHO algorithm and the other algorithms in the literature.

In [70] the authors added the velocity to the HHO exploration phase and proposed the Improved HHO (IHHO) algorithm. IHHO is based on the crossover operation of the bionic optimization algorithm Artificial Tree (AT) [The artificial tree (AT) algorithm] to improve the position vectors of soft and hard besiege in the attacking stages of the traditional HHO algorithm. IHHO are compared with many different algorithms. The experimental results showed that the IHHO is superior finding solutions.

Zhang et al. [157] proposed an enhanced HHO to overcome some weaknesses of HHO (e.g., single search method and low population diversity) and thus enhance the global search performance. The proposed algorithm, called ADHHO, combines adaptive cooperative food and sparse food techniques. At the first stage, adjusted cooperating food techniques is used to randomly chosen three Harris hawk individuals to cooperatively update positions and thus enhances the diversity of solutions [118]. At the second stage,sparse food technique is used to force some hawks to quit their existing location and move to new positions to find possible prey and thus obtain improved candidate solutions. The efficiency of the introduced ADHHO algorithm perform better than HHO and swarm intelligence algorithms in terms quality of solution, avoid local optimum, stability, and convergence accuracy. However, ADHHO convergence speed is slow.

To overcome HHO shortcomings such as convergence problems and local optima problem, Chen et al. [36] introduced a variant of HHO by combining three different strategies: chaos strategy which is used to enhance the HHO exploitation capabilities. Topological multi-population technique is utilized to equation the local and global search ability. Differential evolution (DE) technique is used to enhance the solutions' quality. The introduced model, called CMDHHO, showed excellent performance compared with original HHO and other algorithms. The simulation results demonstrated that CMDHHO avoided the local optimum and substantially increased the convergence speed.

Jouhari et al. [78] proposed a modified HHO, called MHHO, to address the machine scheduling problems. The new optimization method aims to enhance HHO performance, decrease computation time, avoid local optima and premature convergence. This is achieved by utilizing the SSA enhance the mechanism of HHO in the local search in order to find optimal solutions. The evaluation results indicated the superiority of the MHHO compared with both SSA and HHO in convergence to the optimal solution.

A chaotic map was used in which the parameters of the HHO algorithm are optimized and the population diversity enhanced in [57, 132]. The authors used ten distinct chaotic map approaches on numerical benchmark functions with various features and other design engineering problems. The authors claim that the changes they made improve the algorithm's exploration and exploitation capabilities.

Yousri et al. [150] developed a novel MHHO algorithm to find the optimal reconfiguration of the photovoltaic modules. The Modified Harris hawks optimizer (MHHO) aims to improve exploration stage to avoid premature convergence and local solutions problems. MHHO used Le'vy flight to emulate the zigzag motion of the prey. Moreover, the random exponential task is utilized to express the prey escape energy instead of the linear deciding function used in traditional HHO. The MHHO produced a better results compared with total-cross-tied, competence square, PSO, and GA using several metrics.

Enhance HHO by employing chaotic Tent map has been introduced in [161]. The main objective of the proposed algorithm is finding the chaotic positions of the prey. The experiments results demonstrated that Tent map HHO outperform the HHO in terms of convergence rate and the scalability.

Rajendran et al. [103] proposed a big data classification approach based on CPIO chaotic pigeon inspired optimization (CPIO) and HHO. The CPIO method is used to choose a relevant subset of features, and the HHO is utilized as a classifier to provide appropriate class labels. The HHO approach helps to improve classification performance by tuning the hyperparameters of the deep belief network (DBN) model. The suggested algorithm outperforms other state-of-the-art algorithms, according to the authors' findings.

3.5 Hybridization

Hybridization mechanism is one of the most popular way used by researchers, in various optimization fields, to improve the search capabilities of a various of optimization algorithms.

A hybrid approach of HHOA and SA was applied to solve different types of optimization issues. The major goal of this hybridization is to enhance the efficiency of HHOA and to avoid fall into a local traps during the search mechanisms. Abdel-Basset et al. [3] introduced a hybrid method for FS problem. The mutation operation was modified to eliminate Undesirable features from the best solution. Authors applied the method on a combination of standard and artificial datasets characterized by large dimension sizes. Significant results were observed for the introduced algorithm compared to a range of optimization algorithms including binary CSA, Binary Bat Algorithm, and Discrete Firefly algorithm. Another hybridized method of HHOA and SA was presented by Kurtuluş et al. [88] to find the best design of variables highway guardrail techniques. The proposed algorithm showed the ability to solve various types of engineering problems in an efficient manner compared to basic HHO algorithm and the other optimization algorithms in the literature.

Also, Attiya et al.[25] presented a hybrid HHA-SA algorithm for job scheduling in cloud computing. The efficiency of the introduced algorithm was compared with other job scheduling algorithms. All compared algorithms were implemented on the CloudSim toolkit with standard and synthetic workloads to examine their performances. Results showed that the hybridized algorithm realized significant reductions in makespan of the job scheduling problem.

In [149] the authors introduced a hybrid algorithm that integrates the HHOA and Nelder-Mead local search algorithm for designing and manufacturing optimization problems. Authors applied the hybrid algorithm to find the optimal process variables in milling procedures [17]. Several benchmark problems were used to investigate the algorithm's performance including cantilever beam, three bar truss, and welded beam problems. The introduced algorithm illustrated high efficiency compared other optimization algorithms including cuckoo search (CS), traditional HHO, SA, artificial bee colony algorithms.

To achieve high classification accuracy of drug layout and detection, Houssein et al. [68] hybridized HHOA with two classification methods, namely, Support Vector Machines (SVM) and the k-NN to extract the high-level features. Experimental results were performed on two different datasets, namely, MonoAmine Oxidase and QSAR Biodegradation. The proposed HHO-SVM method illustrated better performance in obtaining the best features compared to the efficiency of other popular optimization algorithms. For instance, CSA, Dragonfly Algorithm (DA), and SA. Later, Houssein et al. [67] applied another hybrid method to solve the same problem. The hybrid method employed the operators of CS and chaotic maps to HHO algorithm. The objectives of employed operators are to avoid getting stuck in a local minimum and to control the equation between diversity and intensity. The experimental results on different datasets illustrated that the introduced algorithm achieved solutions that are much more preferred than the competing algorithms in the literature.

ÇetınbaŞ et al. [34] offer a hybrid strategy combining HHA and arithmetic optimization algorithm to improve solution quality by maintaining high solution diversity during the search iterations. The proposed strategy was tested for sizing optimization capacity planning of an off-grid microgrid and showed that accuracy, computation time, and overall performance all improved. The proposed method is evaluated on a microgrid that includes numerous power systems and generators. In comparison to alternative systems, the authors claim that the developed microgrid is reliable, cost-effective, and eco-friendly.

Another hybrid approach was provided by Du et al. [46] to improve the efficiency of predicting the air pollutant concentration. The hybrid approach combined multi objective HHO with extreme learning machine (ELM) and enhanced complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN). Time series data consists of six air pollutant concentrations were utilized to estimate the introduced hybrid algorithm. The experimental results illustrated that the introduced algorithm got a high level of prediction accuracy.

A hybrid of ANN and HHO algorithms was offered by Sammen et al. [112] to predict the depth of scour downstream of ski spillway jumping. The HHO algorithm was used to find the optimal parameters of ANN to develop deep scouring prediction models. Results showed better performance of the introduced algorithm compared to other hybrid algorithms including ANN-PSO, conventional NN, ANN-GA, and Wu Model.

Fu et al. [55] applied sine cosine algorithm (SCA) and HHO to optimize the SVM parameters, thereafter the best model of SVM was applied to classify the rolling bearing fault in industrial production. The proposed algorithm was validated on nine benchmark functions with an outstanding performance compared with another three algorithms (PSO, HHO, and SCA algorithms) by focusing on the fitness's solution and convergence rate. Moreover, authors assessment their proposed algorithm using data collected from bearings data center of case western reserve university. The results illustrated an advantage performance for the proposed algorithm compared to fine-sorted dispersion entropy and multiscale dispersion entropy methods, in terms the accuracy of the classification [15].

Hybridization algorithm has been introduced in [96] which is combining ANN with GOA and HHO algorithm to predict the coefficient of soil compression. The dataset represents real-world survey and laboratory tests consisting of 496 samples. 80% of the samples were selected randomly to train the proposed algorithm, whereas the remaining 20%

of the samples were used for testing. The hybrid ANN-HHO showed better performance than hybrid ANN-GOA in both learning and testing stages.

Dhawale and Kamboj [42] presented a combined approach of HHO and Improved GWO (IGWO) algorithms for numerical optimization problems. The IGWO algorithm is followed the HHO algorithm in the proposed approach to improve the extent of exploitation and exploration capabilities. The introduced method was examined using 23 numerical benchmark functions and the results illustrated better performance for the hybrid approach compared to the performance of ten optimization algorithms including PSO, IGWO, HHO, Ant-lion Optimizer (ALO), and DE in terms of convergence behavior.

Another hybridization method of HHO and artificial ecosystem-based optimization (AEO) was applied by Barshandeh et al. [29] to solve engineering problems. Authors validated their proposed method on fifty numerical examine functions with various properties and compared the results with other well-known algorithms like spotted hyena optimizer (SHO), farmland fertility algorithm (FFA), and SSA. Also, the introduced method was effectively employed to fix seven real-world engineering problems.

Xie et al. [145] presented a hybridized algorithm of the Henry Gas Solubility Optimization (HGSO) and HHO algorithms to solve numerical common benchmark functions and real-world problems. The HHO algorithm was used to enhance the mechanism of behavior of HGSO. The presented algorithm was validated on CEC2005 and CEC2017 benchmark functions, as well as used successfully for fixing four real engineering design problems.

Khan et al. [82] developed a soft computing approach to analyze the mathematical model of heartbeat dynamics. The developed approach applies the HHO and Interior Point Algorithm (IPA) technique for finely tuning unknown weights. The results of numerous situations show that the proposed method is well-conditioned, according to the authors. In all solution scenarios, the accuracy is determined by achieving the lowest residual errors.

4 Harris Hawks Optimization Applications

This section includes hot topics of the applications that have been solved by using HHO. Also, showed brief comparisons to show the strengths and weaknesses of the performance of the HHO algorithm with other algorithms in the literature. At the end of this section, a summary of the HHO's applications is shown in Table 2.

4.1 Machine Learning

Tikhamarine et al. [136] integrated Multi-Layer Perceptron (MLP) neural network and Least Squares Support Vector Machine (LSSVM) with HHO to predict the changes in rainfall-runoff relationship. The results illustrated the efficiency of the introduced model outperformed the other integrated models like LSSVM with PSO.

In [39] the authors introduced an improved Machine-Learning approach for COVID-19 prediction using HHO with feature analysis utilizing SHapely adaptive exPlanations (SHAP) values. The proposed method and HHO-based eXtreme gradient boosting (HHOXGB) have been applied to publicly available big COVID 19 data and yielded a prediction accuracy of 92.38% for the proposed method while HHOXGB achieved 92.23%. Moreover, the experimental results illustrated that the proposed method outperformed the other traditional algorithms and other ML-based methods.

Wei et al. [140] introduced a hybrid model called GBHHO-KELM to forecast students' intentions towards self-employment. Gaussian barebone (GB) is used to equation HHO global and local search capabilities and to strengthen the kernel extreme learning machine (KELM). The experiment illustrated that proposed method has higher prediction and classification accuracy and stability than other optimization algorithms and machine learning algorithms on 30 CEC2014 benchmark problems.

A binary HHO with specular reflection learning method was utilized as a classification tool to find the critical features for the early accurate assessment of COVID-19 from a blood sample dataset. Various swarm intelligence feature selection approaches are compared to the proposed method. The proposed algorithm, according to the authors, achieves superior results in terms of accuracy, sensitivity, specificity, and time consumption [71].

4.2 Networks

Harris hawks optimization has been used in different areas and various domains such as the telecommunications and network area, especially in Wireless Sensor Networks (WSN) field.

Houssein et al. [69] used HHO to fix the problem of selecting the location of basin intersection sensor in Large-Scale Wireless Sensor Network (LSWSN). The results of a simulation demonstrated that HHO performed better than other optimization techniques such as PSO, GWO, FPA and WOA in terms of prolong wireless sensor network lifetime, low localization error and minimum energy consumption evaluation metrics.

In the same line, Srinivas and Amgoth [133] proposed an optimized model to minimize energy consumption and consequently prolong WSN lifetime. In details, the authors

Table 2 The applications of HHO

Field	Abbreviation	Description	Area	References
Machine learning	HHO	Integrated MLP-NN and Least Squares Support Vector Machine (LSSVM) with HHO	Hydrology	Tikhamarine et al. [136]
	ensemble model	An Improved ML using HHO and Feature Analysis Using SHAP	COVID-19	Debjit et al. [39]
	GBHHO-KELM	Integrate HHO with Gaussian barebone (GB) and kernel extreme learning machine (KELM)	Entrepreneurial intention	Wei et al. [140]
Networks	HHO	Find location of sink node in Large-Scale WSN	WSN management	Houssein et al. [69]
	HH-SS	Select cluster head (CH) and discovers optimal route from mobile sink (MS) to the CHs	WSN management	Srinivas and Amgoth [133]
	HHO-AM	Enhance the accuracy and reduce errors of estimating sensors nodes location in WSN	WSN management	Bhat and Venkata [31]
	CHHO	Compose web service in large-scale networks based on QoS	Service Composition	Li et al. [89]
	HHO-RDDI	Reliable and secure data aggregation and diffusion	IoT management	Seyfollahi and Ghaffari [116]
	HHOLS	Energy aware fog computing task scheduling using HHO	Fog computing	Abdel-Basset et al. [4]
	FHHO	processing data collected from wearables devices to monitor patients	Wearables devices	Ding et al. [45]
Benchmark	QRHHO	Proposing a combination of HHO and QRBL technique	Global optimization	Fan et al. [53]
	hHHO-SCA	Using sine-cosine algorithm in the exploration process	Numerical and engineering optimization	Kamboj et al. [79]
	HHMV	Merging HHO with Multi-verse Optimizer to enhance converges tardily	industrial engineering	Abualigah et al. [9]
	IEHHO	Using information exchange and chaotic perturbation to improve the convergence rate	MRI images	Qu et al. [102]
Image processing	DEAHHO	Using a hybridization between selection operators and differential concepts to improve HHO	Multi-level image thresholding	Wunnava et al. [144]
	HHO-DE	Using a hybridization between HHO and DE to achieve better balance between exploration and excitation	Multi-level image thresholding	Bao et al. [28]
	AHHO	Using an adaptive HHO based on modified parameters and enhanced 2D grey gradient	Multi-level image thresholding	Wunnava et al. [143]
	HHOSSA	Using SSA as a competitive method with HHO to find the best solution	Multi-level image segmentation	Abd Elaziz et al. [2]
	MCET-HHO	Using a minimization of cross-entropy as a objective function for HHO method	Multi-level image segmentation	Rodríguez-Esparza et al.[109]

Table 2 (continued)

Field	Abbreviation	Description	Area	References
	DHHO-M	Using a dynamic strategy for control parameter associated with mutation technique	Satellite image segmentation	Jia et al. [75]
	HHO-PCNN	Using HHO method to optimize PCNN searching parameters	Image segmentation	Jia et al. [76]
	CMDHHO	Proposing a multi-population differential evolution assisted HHO	Satellite image noise removal	Golilarz et al. [60]
	HHO	Proposing the use of HHO with an adaptive technique and AGGD	Satellite image noise removal	Golilarz et al. [59]
Energy and power flow	HHO	Applied HHO on of two-Area interconnected power system with DFIG based wind turbine	Load frequency control	HA et al. [63]
	MHHOS	Improve the operation of power system and enhance the dynamic stability by means of AGC of the interconnected power systems	AGC problem	Sobhy et al. [130]
	LMHHO	Utilizing HHO to minimize the loss of power, emission, and fuel cost	Optimal power flow problem	Hussain et al. [72]
	HHO	Using HHO to minimize of generator fuel cost, active power loss, voltage profile improvement, emission, and quadratic fuel cost with valve-point loadings	Optimal power flow problem	Akdag et al. [13]
	HHO	Using HHO to minimize generation cost and power losses	Optimal power flow problem	Islam et al. [74]
	HHO	Determine the optimal parameter identification for Proportional-Integral (PI) controller	Load frequency control	Yousri et al. [151]
	BHHO	using BHHO to equation between exploitation and exploration	PV models	Ridha et al. [108]
	HHO	Extract the optimal parameters of a maximum power point tracking MPPT controller under partial shading conditions	Load frequency control	Mansoor et al. [91]
	HHO	Utilizing HHO to choose the optimal parameters of a TIDF controller	Load frequency control	Sahoo and Panda [110]
	EHHO	Orthogonal Learning and OL and GOBL is added to the basic HHO in order to increase convergence speed and the accuracy of the solution	PV models	Jiao et al. [77]
Engineering	HHO	Using HHO method to optimize the performance of ANN in predicting FOS of the soil slope	Soil slopes	Moayedi et al. [95]
	HHO-ANN	Using a new model to enhanced productivity prediction of active solar	Solar	Essa et al. [50]
	HHO-BLDC	Using HHO, GOA and GA methods to Control Of BLDC Motor	Electrical vehicle	Saravanan et al. [113]

Table 2 (continued)

Field	Abbreviation	Description	Area	References
	ANFIS-HHO	Proposing ANFIS-HHO method to predict the FSW's mechanical properties	Friction stir welding process	Shehabeldeen et al. [127]
	HHO	Using HHO to minimize the entropy generation	Micro channel heat sinks	Abbasi et al. [1]
	EHHO	Proposing EHHO method to find the best performance of solar photovoltaic cells	solar photovoltaic cells	Jiao et al. [77]
	CMVHHO	Using MCOHHO method to determine the most suitable map and to solve engineering problems	Engineering-chaotic maps	Ewees and Abd Elaziz [51]
	HHO	Choosing Harmonic Elimination for Light-Rail Transportation Motor Drives Using HHO	Engineering-transportation	Nalcaci et al. [98]
Natural	HHO-ANN	HHO coupled ANN to overcome the computational shortcomings in spatial modeling of landslide susceptibility mapping	Landslide	Bui et al. [33]
	HHO-RF	Proposing the HHO-RF model, a hybrid approach for ground vibration prediction.	Ground vibration	Yu et al. [153]
	HHO-ANN	HHO coupled ANN to overcome the computational shortcomings in spatial modeling of landslide susceptibility mapping	Landslide	Bui et al. [32]
	HHO	Using HHO to optimize water supply networks	Water supply networks	Khalifeh et al. [81]

proposed a hybrid optimization algorithm based on HHo and salp swarm (Hybrid HH-SS) to select cluster head (CH) in a clustered network, then adaptive ant colony optimization (AACO) algorithm is used to discovers an optimal route from mobile sink (MS) to the CHs. The simulation results illustrated that proposed model enhances WSN energy efficiency in terms of network lifetime, packet delivery rate, average throughput, packet loss rate, energy consumption, and end-to-end delay.

In order to enhance the accuracy and reduce errors of estimating sensors nodes location in WSN, Bhat and Venkata [31] proposed a method called HHO based localization with Area Minimization (HHO-AM). The experimental results proved the superiority of proposed model in terms of localization error and performance stability over other models such as DV-Hop, DV-maxHop, and other equivalent models.

WSNs applications face many critical challenges (e.g., heterogeneity of sensor hardware). SOC and SOA are seen as solutions for WSN applications challenges [20]. Optimization algorithm has been successfully used for SOC and SOA services composition [21] and in the wider domain of web service composition. For instance, Li et al. [89] proposed combination between logical chaotic sequence and HHO, named CHHO, for Quality of Service (QoS) aware web service composition in large-scale networks. The experiments illustrated that the CHHO achieved high performance than the other algorithms when solving web service composition problems.

Seyfollahi and Ghaffari [116] proposed enahnced HHO to fix the issue of reliable and secure data aggregation, diffusion, and routing in the Internet of Things (IoT). The proposed model has improved energy consumption, packet transmission distance, delivery ratio, end-to-end delay, reliability, and computational overhead compared with other approaches.

The rapid advanced in IoT area has led to new computing paradigm called Fog computing which serves as intermediate processing layer between the Cloud and the IoT smart objects. The major challenge in Fog counting is power consuming on Fog devices which is effected by task scheduling.

Abdel-Basset et al. [4] proposed HHO algorithm based on a Local Search strategy (HHOLS) which is an energy aware fog computing task scheduling model based on the standard HHO and local search strategy. The proposed model produced superior results compared with other models in terms of energy consumption, carbon dioxide emission rate, cost, makespan, and flow time.

IoT technologies (e.g., smart wearables) have found its way in healthcare domain introducing smart healthcare systems which are able to monitor and track patients. HHO was utilized to fix optimization issues in smart healthcare and wearable devices. For example, Ding et al. [45] proposed a model for monitoring cardiomyopathy patients by processing their vital signs collected from wearable devices and sensors they wear. The proposed model called Fuzzy Harris hawks optimizer (FHHO) hybridized HHO and Fuzzy Logic (FL) to increase the coverage percentage of patients by repositioning wearable sensors that ultimately reduces numbers of needed sensors. The results proved the efficiency of FHHO in increasing patients' coverage percentage and significantly reduced the number of requires wearable sensors compared with other optimization techniques.

Diaaeldin et al. [44] employed HHO algorithm to optimize Distribution Network Reconfiguration (DNR) and allocate Distributed Generations (DGs) based smart inverters optimally. The experimental results showed that using HHO algorithm enhanced voltage stability and minimized the total active losses.

4.3 Benchmark

Fan et al. [53] introduced an enhanced HHO algorithm called quasi-reflected HHO (QRHHO) to tackle global optimization missions. The authors introduced a combination of HHO and quasi-reflection-based learning (QRBL) technique. QRBL technique was used in two phases: in the initial phase to increase the diversification and in the update stage to improve the convergence rate. To evaluate the proposed method performance, twenty-three different benchmark functions have been used [8]. The experimental results revealed that QRHHO has a better and faster performance against other HHO variations and swarm-based optimizers.

In order to accelerate the global searching process of HHO method, Kamboj et al. [79] proposed a hybrid HHO sine-cosine algorithm (hHHO-SCA). The suggested method aimed to find the optimum solution for numerical and engineering optimization problems. hHHO-SCA utilized a sine-cosine algorithm in the exploration process. To validate this method, sixty-five benchmark problems have been used in the verification process. It has been observed that the hHHO-SCA method achieved high efficiency than other optimizers in the field of meta-heuristic problems.

Qu et al. [102] proposed an enhanced HHO based on information exchange called IEHHO. The purpose of this method was to tackle numerical and practical engineering problems. IEHHO works by determining the sufficient amount of information exchange between harris hawks while the exploration process to improve the convergence rate. Moreover, chaotic perturbation has been used with the EE factor to gain an equation between exploitation and exploration. The proposed method has been outperformed other optimization algorithms regarding stability, robustness, convergence curves, and precision. However, IEHHO suffers from some limitations in parameters settings and general random search.

In [9] the authors used classical and CEC2019 benchmark functions with several dimensions size to evaluate the performance of the proposed new version of HHO. The aim of this version to enhance the converges tardily and slowly to the optimal solution of the basic HHO by merging it with Multi-verse Optimizer, called HHMV. The results illustrated that HHMV is outperformed the other algorithms published in the literature.

4.4 Image Processing

Wunnava et al. [144] introduced a new DE adaptive HHO (DEAHHO) method. In the proposed method, HHO perching and escaping strategies were replaced by a hybridization of differential location hypothesis and selection factors. Moreover, the authors proposed a new 2-D practical Masi entropy function for multilevel image thresholding. DEAHHO has been validated using several benchmark functions and compared to other optimizers such as basic HHO, PSO, DE, CS [148], firefly algorithm (FA) [146], and sooty tern optimization algorithm (STOA) [43]. It has been shown an improved convergence rate for the proposed method against other optimization methods.

Bao et al. [28] introduced a hybrid approach for multilevel image thresholding depend on both HHO and DE methods. The proposed method called HHO-DE. Firstly, the initial population was divided into two subpopulations between HHO and DE methods. Thereafter, both methods participated equivalently in the update process. Extensive experiments have been done to evaluate HHO-DE approach. The results showed a competitive performance for this approach against other approaches in the literature.

An adaptive Harris hawks optimizer (AHHO) was introduced in [143] to treat multi-level image thresholding. In AHHO, HHO parameters were modified especially the EE and perching control parameters to achieve better convergence results. The authors also suggested an enhanced 2D grey gradient (I2DGG) to avoid edge non-uniformity problem. The proposed method has been achieved superior results with a reasonable computational complexity in comparison to other methods such as HHO, PSO, DE, CS, FA, and crow search algorithm (CSA) [24].

Abd Elaziz et al. [2] introduced an enhanced HHO called HHOSSA based on salp swarm algorithm (SSA) to tackle multi-level image segmentation task. SSA method was used as a competitive method with HHO during the update process to determine the optimal solution. The proposed HHOSSA achieved better performance in different measures for global optimization compared to the state-of-the-art optimization algorithms. For instance basic HHO, SSA, and other methods.

A new metaheuristic HHO method called MCET-HHO was proposed by Rodríguez-Esparza et al.[109]. The proposed method aimed to treat multilevel image segmentation task. MCET-HHO optimized the searching capability of HHO based on minimum cross-entropy technique as a fitness function. In order to validate MCET-HHO, several experiments have been done to test the segmented image quality and optimization capability. MCET-HHO showed a robust performance with different benchmark datasets. Moreover, it has been noticed that conditions like threshold amount and histogram gray level could boost the performance.

Jia et al. [75] presented a hybrid HHO method (DHHO-M) to treat satellite image segmentation task. The proposed method was based on a dynamic strategy for controlling parameters associated with the mutation technique. This method aimed to improve the HHO searching efficiency and avoid the probability of falling in a local optimum problem. Several experiments have been conducted to evaluate DHHO-M method which proved its efficiency in terms of statistical test, image segmentation effect, and fitness function evaluation.

In [76], HHO method has been used to optimize pulse coupled neural network (PCNN) parameters for image segmentation task. The proposed method called HHO-PCNN. The authors utilized the capability of HHO method to reduce the number of searching parameters. Thereafter, they have employed an interactive information entropy and image entropy as fitness functions. HHO-PCNN efficiency was compared with other hybrid PCNN algorithm and achieved the best segmentation results. This method could be also applied to object segmentation in different situations.

Another application of HHO was introduced by Golilarz et al. [60] for satellite image noise removal task. The proposed method was a multi-population differential evolution assisted HHO (CMDHHO). Three main changes have been applied to the standard HHO: multi-population, differential evolution, and chaos. Several experiments have been carried out to compare CMDHHO with other optimizers like DE, PSO, SSA, HHO, and whale optimizer algorithm (WOA) [94]. Experiments showed that CMDHHO has better qualitative and quantitative performance.

HHO was deployed by Golilarz et al. [59] with an adaptive technique to solve noise removal task. The proposed method used HHO capability to obtain the optimal parameters for the threshold function. Moreover, the authors suggested an adaptive generalized Gaussian distribution (AGGD) which has the ability to work without the need for shape tuning parameter. The proposed method results have been compared to JADE optimizer [154] and outperformed it quantitatively and visually.

4.5 Energy and Power Flow

In this context, HHO has been applied namely in optimal parameter selection or identification for the various devices and controllers of power systems to improve performance. Modeling these parameters becomes‘ an optimization task either to maximize or minimize the parameters according to a certain objective; such as power output, reduce operation cost, flow regulation, and load balancing, etc. The HHO algorithm has become an attractive choice due to the efficiency of searching nonlinear data which is the nature of these parameters and superior ability to avoid as much as possible being stuck at local minima. It is worth mentioning that the topic of energy holds the highest number of publications and applications on HHO, this is due to the prolific interest in renewable energy in recent years and also the fact that the original paper was initially published about HHO was applied on PV sytems [64].

In [48], the basic HHO has been used to improve the frequency reply of a two-area integrated energy system. By optimizing controller parameters in order to dampen the oscillation of frequency at both areas and tie-line power for enhanced system performance. Simulations performed using Matlab confirm that this method solves the load frequency control (LFC) problem under step load perturbation (SLP) by 2% and that oscillation of frequency at both areas and tie-line are effectively damped.

Similarly, a MHHO algorithm is proposed in [41] to identify optimal parameters for the power system osculation damping devices to improve the stability of power system. The modification of the basic HHO algorithm consists of replacing the original linear EE equation with the squared decay rate. The study shows that this modification (compared to the original HHO) enhances exploration and exploitation capabilities when higher levels of escaping energies are present. The modified version has adopted maximizing the minimum damping ratio of the system as the objective function for identified tuning parameters. The proposed method is run using samples of different permutations (between heavy and light load conditions) on a simulated system, static synchronous compensator (STATCOM), as a power oscillation damping device. The Results are comparing with ALO, WOA, and basic HHO. Results demonstrate that the tuned parameters derived exhibit improved damping characteristics.

There exist other applications using HHO algorithm regarding the regulation of power flow in overall power systems. Such work as in [130] which employs HHO to optimize power system procedure and enhance the system stability. The HHO technique is used to optimize the gains of the PID controllers that are utilized in power system load frequency regulation. The MATLAB/SIMULNK simulations of a two-area system with thermal producing units were taken under different conditions by considering the: load disturbance, step load perturbations, generation rate constraints (GRC). The empirical simulation shows an effective and superior performance of the proposed method compared to other optimization algorithms.

Hussain et al. [72] presented another version of HHO by adding an extra user-defined parameter Memory Length (ML) to the optimization problem, which shows the previous experiences the population can recall at a time, named long-term memory HHO (LMHHO). This is intended to overcome premature optimal convergence, where it allows the individuals to select the next move based on their previous experiences. The cost of fuel, loss of power, and emission are all minimized in the optimization problem. The experiments on numerical benchmark and optimal power flow problems showed considerable improvement for the most part compared to popular and recently introduced metaheuristic techniques.

In [13], the authors applied seven different random distribution functions to choose the selection position in the diversification step of basic HHO; instead of the uniform random function typically used. The intention of this modification is to create an enhanced searching strategy for a stochastic optimization problem. Moreover, the distribution function may be switched during the optimization cycle according to the state of the problem to provide flexibility. The 5 test cases; minimization of generator fuel cost, active power loss, voltage profile improvement, emission, and quadratic fuel cost with valve-point loadings. Results show that ND-HHO using normal distribution yielded better optimization capabilities than basic HHO.

Also in [74], authors applied basic HHO to minimize the generation cost and power losses. Experiments were simulated on MATLAB with IEEE-30 bus system benchmark and the results are compared against well-known meta-heuristic algorithms, including GWO, ALO, SSA, WOA, MF, and BF.The revealed results showed reasonable and consistent effectiveness of the introduced algorithm than the other algorithms.

Yousri et al. [151] used HHO to optimize the controller of Proportional-Integral (PI) based on LFC parameters. In addition to conventional thermal power plants, the system under investigation has PI controllers included in a multi-interconnected system with renewable energy sources (RESs) such as photovoltaic (PV) panels and wind production systems. The objective function is the integral time absolute error (ITAE) of the frequency and tie-line power. Three cases of different interconnected systems from multiple energy sources were considered in MATLAB/SIMULINK simulations to evaluate efficiency when different load disturbances occur. The findings show that modifying the parameters of a PI controller-based LFC via HHO results in more stable frequency and tie-line power responses with load fluctuation in any multi-interconnected system with acceptable overshoots and settling times. Furthermore, the proposed method PI controller achieves an oscillation with quick damping using settings determined from the proposed HHO.

In [108], Enhancements to the originally published HHO algorithm, focus to achieve a more steady equation between exploitation and exploration; it aid to avoid getting stuck at local trap and early convergence to suboptimal solutions. Multiple modifications have been incorporated to achieve this objective. First, the EE is boosted by employing two various intervals to allow a better seeking paths. Second, the variety of the search space is enhanced through employing random procedures inspired by FPA that uses the LF mechanism. Third, the mutation technique of the DE is combined with the 2-Opt algorithm to accelerate the convergence and determine the optimal and worst solutions for replacement. Lastly, in each iteration, a scaling factor (F) in mutation is used to maintain equation between exploitation and exploration capabilities. The modifications are inspired by the flower pollination algorithm and DE. The first alteration is intended to increase diversity of the solution. The first stage is replaced by reproduction probability, as inspired by flower constancy, Which corresponds to the two flowers similarity involved rather than random selection. The second stage is replaced by DE as a mutation scheme. This alternation is intended to speed convergence and ensure escaping from local minima. The efficiency of the introduced algorithm is achieved by contrasting the real testing data with the actual results. The experimental results show that the proposed algorithm achieves better accuracy and reliability compared to the traditional algorithm and other well-known algorithms. Statistical analysis was conducted under real data consisting of different temperature and sunlight values on a single diode model.

To observe maximum power from a PV module under partial shading settings, Mansoor et al. [91] used HHO to extract the optimal parameters of a maximum power point (MPP) tracking controller. The results are compared with perturb and observe algorithm, dragonfly optimizer, CS, practical swarm optimization, and grey wolf optimization. Four distinct cases were taken into consideration with different degrees of irradiance versus shading. Results show that there is a 10–30% faster tracking time of the MPP for a PV system compared to other methods. Moreover, robustness is evaluated by two characteristics; tracking time and settling time. The exploration phase in HHA is used to find the global maxima hence resulting in the least time between tracking and settling time among the other algorithms.

In [110], the authors used HHO to choose the optimal parameters of a tilt-integral derivative with derivative filter (TIDF) controller to solve the LFC problem to maintain a better balance between load demand and generation within Microgrids. The case study considered for load frequency analysis is a model of an isolated microgrid consisting of solar photovoltaic, wind turbine, biogas, biodiesel generators, flywheel, and battery storage system. Experiments compare a conventional PID controller and a cascaded PI-TIDF controller using multiple heuristic algorithms including the basic HHO version to extract optimal parameters. Results show that out of all the methods used the HHO tuned PI-TIDF attains minimum Integral of Time multiplied Absolute Error (ITAE) value. Moreover, the frequency deviance response of the proposed PITIDF controller achieves a better dynamic response with less overshoot,settling time and undershoot compared to PIDF and TIDF controllers.

Ramachandran et al. [104] introduced new hybrdizing algorithm that combining the Modified Grasshopper Optimization Algorithm (MGOA) and the Improved Harris Hawks Optimizer (IHHO), called MGOA-IHHO for achieving a better balance between the exploration and exploitation search mechanisms. MGOA-IHHO has been applied on four real world problems in the Combined Heat and Power Economic Dispatch (CHPED). The experimental results proved the efficiency of MGOA-IHHO comparing with its variants and optimization algorithms introduced in the literature.

In [77] the authors proposed an enhanced version of HHO. The authors incorporated two methods, General Optimization-Based Learning GOBL and Orthogonal Learning (OL). Orthogonal Learning has been shown to be effective in predicting the best solution. It is intended to increase convergence speed and the accuracy of the solution. After that GOBL is applied to increase the diversity of the population where in each iteration the opposite solution (reverse population) is generated and compared against the current population via a fitness function to determine an updated population with optimal individuals. The enhanced HHO algorithm was simulated in MATLAB to be compared with measured data single-diode/double-diode cells and a photovoltaic module. Comparisons of the cases based on the average Root Mean Square Error RMSE show that the enhanced HHO algorithm has faster convergence and is a more accurate solution than that of the original.

4.6 Engineering

Ewees and Abd Elaziz [51] proposed a modified Multi-Verse Optimizer (MVO) method called Chaotic Multi-Verse HHO (CMVHHO). CMVHHO is used to decide the most appropriate map and the optimal parameter values of the MVO. CMVHHO method was used in two stages: applying chaos theory and through the HHO operators. To assess the proposed technique performance, ten different chaos maps have been applied. The experimental results show that CMVHHO has a high performance in terms of convergence and statistical analysis than the other algorithms in the literature.

In [77] the authors developed a technique that depends on Combines HHO, orthogonal learning (OL) and general opposition-based learning (GOBL) called Enhanced Harris Hawk Optimization (EHHO). The proposed method is used to recognize the optimal performance of solar photovoltaic cells and to approximate the parameters effectively and accurately. EHHO mechanism verifies anonymous parameters identification problems in SDM, DDM of several types of solar cell, and different PV models. The results indicated the efficiency of EHHO as a stochastic optimizer.

Another application of HHO algorithm was introduced by Abbasi et al. [1] to reduce the generation of entropy on microchannel heat sinks. Five main powerful algorithms have been studied and compared to the standard HHO; GOA, PSA, BEA, WOA, and DA. The simulation results proved that HHO algorithm achieved high performance in fixing various real problems. The proposed algorithm also showed an outstanding performance compared to others in terms of CPU time reduction, due to its robust exploration and search behavior.

HHO was applied by Nalcaci et al. [98] to support the harmonic elimination in a traction motor drive depending on the voltage source inverter. The HHO results have been compared to grey wolf optimizer (GWO) and outperformed it in terms of stability, robustness, convergence curves, and precision through using MATLAB Simulink simulation tests.

In [95], the authors employed HHO algorithm as a new combination method to increase the efficiency of ANN in identifying FOS of soil descent while also addressing ANN's computational challenges. They used four aspects of slope stability; slope angle, rigid foundation position, soil strength, and applied surcharge. The results indicated that the efficiency of ANN became more robust in learning and identifying the slope failure pattern.

To improve productivity detection of active solar, Essa et al. [50] proposed a novel model called HHO-ANN. The proposed model is intended to recognize productivity and to avoid costly time-consuming experiments. To confirm this model, the authors applied three models, including HHO-ANN, SVM, and basic ANN. The three models are used to predict the productivity of three desalination components (condenser, active and passive solar still). The results showed that HHO-ANN is the best prediction model compared to the other models.

The electrical vehicle is the upcoming technology in the automobile industry. Saravanan et al. [113] proposed the BLDC motor model by using the nature-based such as Grasshopper Optimization Algorithm (GOA), HHO, and GA through MATLAB. The developed model is intended for real-time automobile applications with the maximum set speed of 2000 rpm via a wireless network. The simulation results showed that the proposed model has reduced errors compared to other methods.

Shehabeldeen et al. [127] presented a novel integrated method that combines adaptive neuro-fuzzy inference system (ANFIS) and HHO called ANFIS-HHO. The main goal of this technique is to be an alternative way to recognize Friction Stir Welding (FSW) properties and to decide the appropriate decisions. HHO is employed to find the best ANFIS model with the most suitable properties. The performance results indicated that the proposed model provides a feasible choice for modeling the process of FSW and observing the optimal solutions.

In [129] the authors applied a novel combining method contains HHO and Salp Swarm Algorithm (SSA) called (HSSAHHO) on six engineering design optimization problems. As well as, 29-standard IEEE CEC 2017, 10-standard IEEE CEC 2020 benchmark test problems. HSSAHHO considered as a good choice for this purpose to solve these issues, where SSA used for exploitation phase and HHO for exploration phase in uncertain environment. The results illustrated that the HSSAHHO is outperformed comparing with other meta-heuristics approaches.

4.7 Natural

In China, Yu et al. [153] Folan developed a hybrid detection approach, named HHO-RF, to detect ground vibration. the proposed approach employs RF, Monte Carlo simulation, and HHO. The authors build a database consists of 137 datasets from different places. Thereafter, seven variables were used as the income, with the high particle speed variable as the outcome. The findings demonstrated that blast-induced ground vibration may be correctly predicted and that blast design can be improved prior to a blast operation.

Landslides are serious ecological hazards that should be mimicked using nonlinear analysis. In Western Iran, in [32] the authors combined HHO and ANN to deal with computational shortcomings in spatial modeling of landslide susceptibility mapping. The performance of the proposed model was improved through setting parameters tuning [139]. The experimentals indicated the efficiently of HHO in decreasing learning error of the ANN. The landslide susceptibility map showed that HHO-ANN was better performed that ANN map within discovering the unseen landslide events.

In Iran, Bui et al. [33] employed the HHO algorithm to optimize water distribution in network systems. The results showed that the HHO algorithm performs better in terms of the optimal design of the water supply network, and the optimization rate was about 12%.

5 Evaluation of HHO

Since its introduction in 2019, the HHO was employed widely to tackle a various of real problems across multiple domains, as described in the preceding sections. Similar to many other optimization algorithms, flexibility, simple in nature and easily implemented are Clear indications of increased use of the HHO by the researchers. Moreover, there are particular features of HHO. For instance, bypassing local optimal, which leads to raising the effectiveness of HHO to find the optimal solutions in various fields, especially when a fast solution is required. However, HHO faces some drawbacks and limitations.

One of the common theories in the optimization domain called no free lunch. The main idea of this theory is summarized that there is no basic optimization algorithm can be employed to solve different problems with optimal solutions [156]. Thus, HHO needs some improvements to be suitable for solving different kinds of optimization problems. HHO suffers loos diversity and weak its capability in the global search [70, 159].

In the community discovery problems, HHO proved its efficiency for soft problems. For hard problems, however, the efficiency of HHO is not effective enough as well as could be degraded compared with the performance of other algorithms, which leads to increased computational time [78]. Also, HHO based on the random parameters in its attack strategies. Thus, it may not escape to the local optima trap [157].

Finally, Table 3 shows the comparisons between the HHO and the other algorithms based on many features such as introduced date, time complexity, rate of convergence, number of parameters, and algorithm's strengths and shortcomings. It's worth noting that the algorithms were chosen from a variety of evolutionary algorithms (such as GA and HS), swarm-based algorithms (such as CSA and PSO), and trajectory-based algorithms (such as TS) [122].

6 Conclusion and Possible Future Directions

About a hundred research articles have been reviewed to produce this review article. The HHO algorithm's features, robustness, and weaknesses have all been investigated and

Table 3 Comparison between basic HHO and other algorithms

Attributes	Algorithm					
	HHO	CAS	GA	PSO	HS	TS
Algorithm	Heidari et al. [65]	Yang and Deb [147]	Holland [66]	Kennedy [80]	Geem et al. [56]	Glover [58]
Variables	3 [152]	3 [120]	3 [97]	5 [101]	3 [35]	4 [155]
Complexity	$O(N \times (T + TD + 1))$ [65]	$O(n.D.t_{max})$ [111]	$O(m^2)$ [10]	$O(nm^2)$ [126]	$O(HMS \times M + HMS \times log(HMS))$ [138]	$O(mn^2)$ [19]
Convergence	Speed convergence rate [53]	Normal convergence rate [123]	Speed convergence rate [141]	High speed converge [90]	Premature convergence rate[61]	High speed converged [22]
Strength	Equation between exploration and exploitation [102]	Equation with intensification and diversification [99]	Deal with the complex fitness landscape [27]	Don't have overlapping and mutation calculation [26]	High diversity [92]	Avoid local trap [18]
Weaknesses	Searching performance is conventional [159]	Fall in a local optimum [124]	Eestimation is comparatively expensive [162]	Has a problem from partial optimism [6]	Suffers from local optima [92]	Needs huge memory resources [86]

analyzed in this research article. Thus, it can provide aid for interested students and researchers in this domain. It's worth to mention that the authors collected the articles related to the HHO algorithm since it proposed in March 2019 until May 2022. The collected articles have been categorized into different topics, based on the domain in which the HHO algorithm was used. For example, Machine learning, Networks, Image processing, Energy, Engineering, and Medical applications. Moreover, variants of HHO algorithms, modifications, and hybridizations were added to increase the scientific value of the review paper.

Although the HHO algorithm is one of the recent algorithms. It considers a promising algorithm where proved its efficiency to solve problems in different fields. The HHO algorithm's features aided in its success, such as the simplicity of its structure where it divides into the diversification phase and intensification phase which contains hard besiege, soft besiege, hard besiege with progressive rapid dives, and soft besiege with progressive rapid dives. Moreover, it has a few parameter settings compared with other algorithms. In contrast, as mentioned previously, the random mechanism in the attack strategies, may lead to get stuck in a bad local optima [157]. Also, it suffers from a weakness in solving large-size problems which cause to increase computational time [78]. Therefore, it can be noticed in Sect. 3 the researchers tried to improve the HHO algorithm's capability to bypass these weaknesses.

As mentioned above, HHO's advantages over other optimization algorithms include its simplicity, fewer parameters compared with other algorithms, and ease of hybridization with other optimization algorithms. However, HHO lacks the mathematical analysis. It does not have a theoretical analysis similar to other algorithms, such as PSO [114] and GA [142]. This difference can be observed with the difficulty of understanding when and why the algorithm works. Additionally, how does the performance of the algorithm improve compared to other search techniques Parameter tuning is also considered an important part of research [47], where the values and settings of the parameters govern the HHO performance.

In the end, this review paper provides some suggestions which may useful for future works. For instance, there are common selection schemes can be replaced with the current selection scheme (i.e., random selection) such as Truncation Selection Scheme, Proportional Selection Scheme, and Greedy-based Selection Scheme [125]. Also, to prevent the occurrence of rapid convergence as well as ensure that you do not get stuck in bad local optima, it can take the advantages of the HC algorithm which proved its efficiency to solve this issue [119, 121].

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Declarations

Conflicts of interest The authors declare that they have no conflicts of interest.

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