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REVIEW

Harris hawks optimization: a comprehensive review of recent variants and applications

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Abstract
Harris hawks optimizer (HHO) has received widespread attention among researchers in terms of the performance, quality of results, and its acceptable convergence in dealing with different applications in real-world problems. This increased interest led to the emergence of many versions of HHO applied to various optimization problems in different fields. Therefore, this study aims to identify, retrieve, summarize, and analyze the critical studies related to the development of HHO. For this aim, we applied a review methodology. The applied methodology led to identified and selection of 69 related studies from different electronic sources. The review result revealed that although HHO algorithm is still in the infant stage, its superiority over several well-established metaheuristic algorithms in terms of speed and accuracy for addressing various benchmark problems and tackling several real-world optimization problems has been clearly observed. The HHO algorithm was evaluated, and its strengths and weaknesses were discussed. This review not only suggested possible future directions in this domain but also serves as a comprehensive source of information about HHO and HHO variants for future researchers due to the inclusion of charts and tabular comparison across a wide variety of attributes. A public website supports open access to this research and also source codes of the HHO in a different language and its supplementary materials at https://aliasgharheidari.com/HHO.html.

Keywords Harris hawks · Optimization · Swarm intelligence · Metaheuristic · Nature-inspired algorithm

1 Introduction

Harris hawks optimizer (HHO) is a swarm-based optimization method developed by Heidari et al. [1]. The main idea behind HHO is to mimic the action and reaction of Hawk's team collaboration hunting in nature and prey escaping to discover the solutions of the single-objective problem. In HHO, hawks chasing actions represent search agent, while prey represents the best position. HHO can play a significant role in solving different real-world optimization problems (e.g., engineering design and optimization problems, pattern recognition problems, manufacturing optimization problems, and geotechnical engineering problems, power quality problems, feature selection problem, image segmentation problems, and drug design problem). Also, the HHO can be utilized to tackle the problems with the unknown types of search space and solve the problems including discrete and continuous spaces [2], provide better solution quality [3–5], provide high accuracy in extracting the optimal parameters [6, 7]

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and enhanced the prediction performance [8, 9]. Furthermore, [10–15] ensured that HHO is a potentially powerful optimizer that helps to solve complex nonlinear problems and find the optimal solution faster, and simple computational procedure. More details about the optimization algorithms can be found in [16–18].

Therefore, due to the advantages offered by HHO, the rapid growth of the HHO studies has been noticed, which is still increasing rapidly. This increased interest led to the emergence of many applications and variants of HHO. Therefore, this study aims to review, analyze and summarize studies related to HHO. This study is significant due to its advantages of (1) identifying, categorizing and analyzing the applications of HHO in solving various optimization problems, (2) identifying the variants and versions of HHO, (3) including charts and tabular comparison across a wide variety of HHO attributes, (4) identifying strengths and weaknesses of HHO, and (5) suggesting new possible research directions.

This paper is organized into different sections as follows: In Sect. 2, we have a brief look into the basic components and concept of the HHO algorithm. This section is to make reader familiar with the structure, logic, equations and steps of the conventional version. In Sect. 3, we provide a detailed breakdown of the studied papers concerning all the applications/modifications of the selected papers. It provides a distribution of selected studies along with a visual plot, and application domains in detail followed by HHO method and versions of HHO on applied domains. These versions are presented along with problem type that utilized to tackle, HHO variants/method, method integrated with HHO, enhanced versions of HHO and the area of improvement. In Sect. 4, we present and discuss the main applications of HHO and HHO versions in engineering optimization domain, computer science, and medical domains. Section 5 summarizes the pros and cons of the illustrated HHO methods and organizes the problems in classes according to the number of variables and constraints to optimize. Section 6 presents some results of the HHO using engineering applications. Section 7 proposes as future developments a full experimental comparison of the variants presented, a guide to select the best variant for a given problem, and a theoretical study of the algorithm.

2 A look into the Harris hawks optimizer

The HHO's structure and the exploratory and exploitative trends of the conventional version were inspired by the behavior of Harris hawks during exploring prey, surprise pounce and attacking strategy. The authors tried to catch the main traits of these intricate natural patterns as much as possible. As shown in Fig. 1, the logic and the mathematical model of HHO comprised three main phases which are the exploration phase, a transition from exploration to exploitation, and exploitation phase, which are explained in the following subsequent sections.

2.1 Exploration phase

This phase describes the hawks positioning in exploring prey. It depends on two strategies. The first strategy specifies how hawks detect prey according to the positions of the real members $(X_i, i = 1, 2, 3, 4 \ldots, N)$ (where N. is the total number of hawks), which is modeled in Eq. (1). However, the second strategy specifies how hawks detect prey according to perch on a random tree (X_{rand}), which is modeled in Eq. (1)

$$X_i(t+1) = \begin{cases} X_{\text{rand}}(t) - r_1|X_{\text{rand}}(t) - 2r_2X(t)|, & q \geq 0.5 \\ \left(X_{\text{prey}}(t) - X_{\text{m}}(t) - Y\right), & q < 0.5 \end{cases} \tag{1}$$

where $X_i(t+1)$ represents the updated position of hawks in next iteration t. $X_{\text{rand}}(t)$ represents the current position of hawks, r_1, r_2, r_3, r_4, and q represents random numbers inside the set of (0, 1). ($X_{\text{prey}}(t)$ represents the position of prey. $X_{\text{m}}(t)$ represents the average of the positions for all hawks which formulated in Eq. (2)

$$X_{\text{m}}(t) = \frac{\sum_{i=1}^{\text{N}} X_i(t)}{N} \tag{2}$$

$Y = r_3(\text{LB} + r_4(\text{UB} - \text{LB})$ represents the difference between upper and lower bounds of variables.

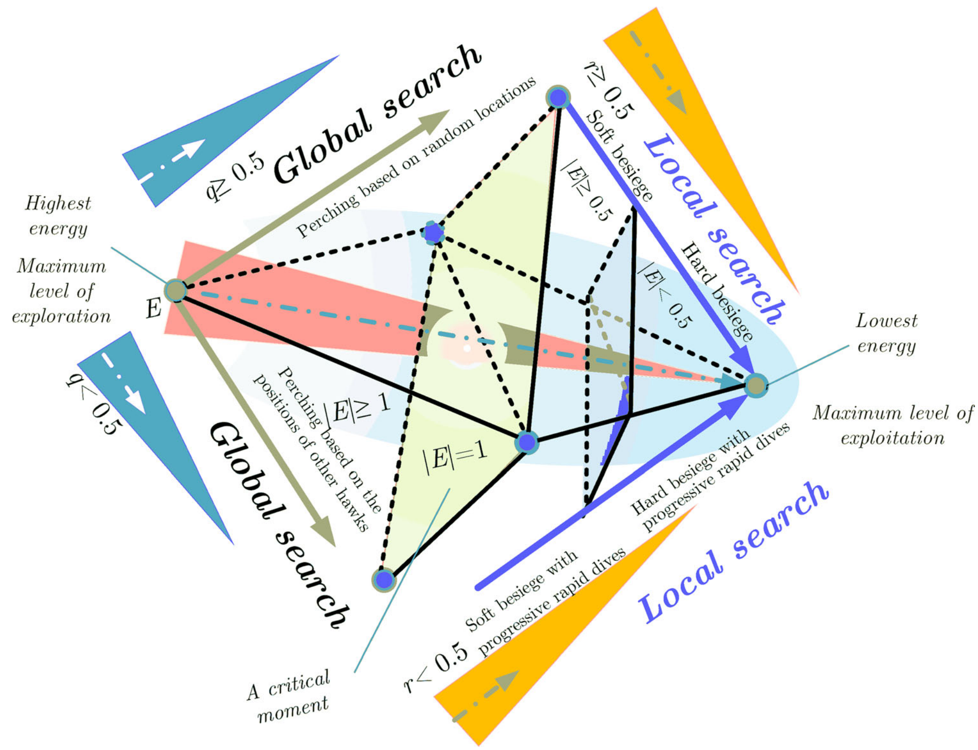
2.2 The transition from exploration to exploitation

In HHO, this phase aims to describe and model the transforming behavior of hawks from exploration to exploitation. This behavior depends on the escaping energy (E) of the prey, which is formulated in Eq. (3).

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{3}$$

In detail, E_0 is the initial energy of the prey that randomly changing between $(-1, 1)$. If the prey energy changed from 0 to 1, this indicates the strengthening of the prey, while if the prey energy decreased from 0 to $-$ 1, this means that prey is flagging down. In Fig. 2, the dynamic behavior of E is presented during two runs and 500 iterations. This diagram in Fig. 2 applies to all the cases, and this pattern is a component of the original method. If the value of $|E| \geq 1$, then the exploration phase will remain unfinished, while if the value of $|E| < 1$, then the exploitation phase is happening.

Fig. 1 A widespread demonstration of the phases of the HHO



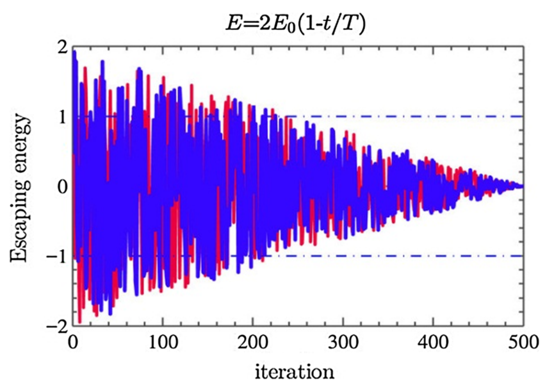


Fig. 2 Behavior of E during two runs and 500 iterations (taken from the initial paper Heidari et al. [1]

2.3 Exploitation phase

Chasing strategies of the hawks and escaping behaviors of prey are the main two elements that form this phase. Therefore, this phase aims to model the hawks surprise pounce (seven kills) behavior on the explored prey. To do so, four chasing strategies, namely (1) soft besiege, (2) hard besiege, (3) soft besiege with progressive rapid dives, and (4) hard besiege with progressive rapid dives are proposed. In HHO, switching between chasing strategies depends on two parameters which are:

Escaping energy (E)	$\|E\| \geq 0.5$ prey still has enough energy
	$\|E\| < 0.5$ prey has no enough energy
Chance of Escape r	$r \geq 0.5$. prey not successfully escaping (soft besiege is constructed)
	$r < 0.5$ prey successfully escaping (hard besiege is constructed)

The following subsequent sections describe the proposed strategies.

2.3.1 Strategy 1: soft besiege

In strategy, one soft besiege happens in the case of $|E| \geq 0.5$ and $r \geq 0.5$. This means that the prey cannot successfully escape because the energy of the prey is drained during the escape from the hawks. The rule in Eq. (4). presents the model of such behavior.

$$X_i(t+1) = \Delta X(t) - E\left|\mathrm{J}X_{\mathrm{prey}}(t) - X(t)\right| \tag{4}$$

$$\Delta X(t) = X_{\mathrm{prey}}(t) - X(t) \tag{5}$$

where, $\Delta X(t)$ represents the difference between the position vector of the rabbit and the current location in iteration t. $J = 2(1 - r_5)$ prey escaping procedure which changed randomly in each iteration. r_5 represents random number inside (0, 1).

2.3.2 Strategy 2: hard besiege

In strategy, two hard besieges happen if $|E| < 0.5$ and $r \geq 0.5$, which means that the prey cannot successfully escape because it is exhausted. In such a case, the updated positions of hawks are given by Eq. (6).

$$X(t+1) = X_{\text{prey}}(t) - E|\Delta X(t)| \tag{6}$$

2.3.3 Strategy 3: soft besiege with progressive rapid dives

This strategy model updates positions of hawks when the prey still has enough energy for successfully escaping $|E| \geq 0.5$ and hawks still construct a soft besiege $r < 0.5$. In such a case, hawks need to decide the best possible dive toward the prey. This can be done through (1) conducting several moves, (2) evaluating the new moves using Eq. (7), (3) compare the result of movement with last dive toward the prey and (4) if the comparison result does not lead to determining the best dive toward the prey, then, team rapid dives based on levy flight (LF) is performed to improve the exploitation capacity as modeled in Eq. (8).

$$Y = X_{\text{prey}}(t) - E\left|JX_{\text{prey}}(t) - X(t)\right| \tag{7}$$

$$Z = Y + S \times \text{LF}(D) \tag{8}$$

where D represents the diminution of problem. S represents random vector by size $1 \times D$. LF represents levy flight function as in Eq. (9).

$$\text{LF}(X) = \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{9}$$

where, u and v represent random values inside (0, 1). B represents a constant set to 1.5.

Therefore, in soft besiege with progressive rapid dives strategy the updated positions of hawks can be calculated by Eq. (10).

$$X(t+1) = \begin{cases} Y \text{ if } F(Y) < F(X(t)) \\ Z \text{ if } F(Z) < F(X(t)) \end{cases} \tag{10}$$

where, F is a fitness function for an optimization problem. Y and Z are calculated using Eqs. (7) and (8), respectively.

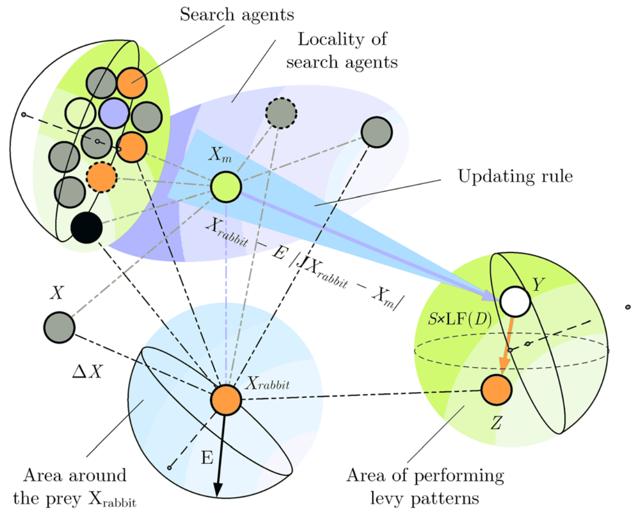


Fig. 3 Overall vectors of hard besiege with progressive rapid dives

2.3.4 Strategy 4: hard besiege with progressive rapid dives

In this strategy, prey has not enough energy to escape $|E| < 0.5$ and hawks constructed hard besiege $r < 0.5$. This strategy differs from the previous strategy (soft besiege with progressive rapid dives) that the hawks are trying to reduce the average distance of their location and the intended prey (see Fig. 3). Equation 11 is modeled this strategy according to the hard besiege.

$$X(t+1) = \begin{cases} Y' \text{ if } F(Y') < F(X(t)) \\ Z' \text{ if } F(Z') < F(X(t)) \end{cases} \tag{11}$$

where,

- Y' is obtained using Eq. (12).

$$Y' = X_{\text{prey}}(t) - E\left|\text{J}X_{\text{prey}}(t) - X_{\text{m}}(t)\right| \tag{12}$$

  $X_{\text{m}}(t)$ is obtained using Eq. (2)

- Z' is obtained using Eq. (13)

$$Z' = Y' + S \times \text{LF}(D) \tag{13}$$

Algorithm 1 presents the pseudocode of the HHO [1].

Algorithm 1 Pseudo-code of HHO algorithm

Inputs: N and T
Outputs: prey location and its fitness value
Initialize $(X_i, i = 1, 2, 3, 4 \ldots., N)$
while (stopping condition is not met) **do**
Calculate the fitness values of hawks
Set X_{prey} as the location of prey (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. (3)
      if (|E|≥ 1) **then**
        Update the location vector using Eq. (1)
      if (|E|< 1) **then**
        if (r ≥0.5 and |E|≥ 0.5) **then**
          Update the location vector using Eq. (4)
        else if (r ≥0.5 and |E|< 0.5) **then**
          Update the location vector using Eq. (6)
        else if (r < 0.5 and |E|≥ 0.5) **then**
          with progressive rapid dives
          Update the location vector using Eq. (10)
        else if (r < 0.5 and |E|< 0.5) **then**
          with progressive rapid dives
          Update the location vector using Eq. (11)
Return X_{prey}

The HHO is a population-based method with an abstract structure and low-cost computation steps, and it has several advantages and limitations as well. These abilities are also reserved in the developed variants, and almost, different works pointed to a set of advantages as explained here. As we reviewed studied papers, we observed that they have contributed to one or several of these aspects together for boosting the actual performance. First, HHO is a method that takes advantage of the time-varying components. Such a dynamic randomized time-varying trait in the escaping energy component has a very constructive impact on efficacy, and it makes the steadiness of the searching cores (diversification vs. intensification) more harmonious over the iterations. At the same time, such a characteristic helps HHO to perform a flat conversion on the mentioned phases. Second, HHO has a multiphase (extendable) exploration phase (global search) that also reflects the center of mass (average position of hawks, as in terminology of the inspiration part); this characteristic can make it more fruitful and explorative throughout the initial iterations. The third important feature is diverse levy-triggered patterns with various configurations of jumps during the exploitation phase (local search). This jumping potential has enhanced the depth of the local search and its coverage in almost all modifications of HHO and the original form. The fourth feature is because of the progressive selection scheme during the expansion of the stochastically assisted search. This ability helps search agents (hawks) to spread their access to space more and more and only select the better possible move. This also assists HHO and all variants (these features are also maintained in modifications and hybridizations) in doing a more practical search in a locality (better intensification tendencies). The multiphase construction of the HHO in the exploitation step makes it easier to reach more variety of short, sporadic patterns throughout the search. Hence, if one strategy of besieging failed, another strategy can be triggered, and at the end, the best of them is saved for the evolution in the next iteration. The next feature is because of the cleverly designed randomized jump strength, which has also contributed to more harmonization of the global and local search and local optima avoidance. All in all, these features give a high potential to HHO to run out of the local optima and show a fast-tracked convergence trend.

Besides all advantages, there are some limitations for the original potential of the HHO, like any other stochastic population-based optimizer. Here, we also highlight those limited features. The first is that if the population of the HHO is stuck in local optima for a complicated problem, there will be a need for a proper modification to give a boost to the exploration of the algorithm. Hence, HHO cannot always escape from local optima, and in some cases, it will return immature results or will show immature convergence propensity. This limit is the most frequent reason in the literature for proposing new modifications to the HHO. Another shortcoming is that HHO cannot always keep the right poise between the cores, or it cannot find the genuine moments, or the transition is not always smooth, especially in dealing with very complicated attribute spaces. This disadvantage is also very widespread among all swarm-based optimizers as they utilize a set of random solution at first and the evolution of their quality is a very delicate process. Almost all the studied research works in this paper pointed to these two reasons to improve the convergence speed or local optima avoidance traits of the HHO in their variants.

3 Selected studies

Sixty-nine studies were selected for the review. The selected studies were identified and selected by following the methodology suggested by [19, 20]. All studies published between March 2019 and May 2020 have been retrieved. Note that the original study of HHO was available online on February 28, 2019. Next, six electronic resources (e.g., Science Direct-Elsevier, IEEE Xplore, Springer link, ACM, IMDP, and Google Scholar) were identified to include broadly related studies. The electronic search was conducted using a wide variety of keywords, alternative keywords, and keywords synonyms of HHO for solving optimization problem such as HHO, Harris hawks optimization, optimizer, algorithm, optimization, engineering, a computer since medical, drugs. Nine hundred fifty studies were retrieved from the electronic search process. Next, after reviewing the titles and abstracts of retrieved studies, 805 studies were excluded as they were beyond the scope of this review. Besides, 76 studies were excluded as they met on of the following exclusion criteria: (1) studies not focusing on the HHO, (2) studies providing only recommendations, guidelines, or principles for HHO, (3) repeated studies, and (4) studies not written in English. Finally, 69 studies related to HHO were indexed in Appendix, and each paper was read in depth.

3.1 Distribution of selected studies

Figure 4 shows three aspects (e.g., type of publications, electronic resources, and year of publication) of the distribution of the selected studies from March 2019 to May 2020. In detail, 60 studies were published as a journal, six studies as the conference, and three studies as a book chapter. The highest numbers of studies (e.g., 35 studies) were retrieved from the Science Direct online library. Subsequently, 21 studies were retrieved from IEEE Xplore, five studies from Google scholar, and three studies from MDPI online library.

3.2 HHO application domains

In this study, in order to review, analyze, and summarize studies related to HHO, data extraction form was developed and is presented in Tables 1, 2, and 3, data extraction form aims to:

1. Organize HHO studies.
2. Identify and categorize the domains and applications of HHO.
3. Identify HHO variants.
4. Identify the integrated algorithms used to improve HHO.
5. Determine the HHO area of improvement.
6. Identify the applied validation approaches of HHO (benchmark functions/performance metrics and compared algorithms).
7. Identify the results of applying HHO compared to other competitive algorithms.

As shown in Tables 1, 2, and 3 and Fig. 5, HHO was applied to three main domains (engineering, computer science, and medicine and public health) that are related to different optimization problems. A total of 49 of HHO-related studies were applied to find solutions for different engineering optimization problems. In detail, the highest number of HHO-related studies (e.g., 19 studies) was explicitly applied to optimize power system problems such as power quality problem, distribution generation allocation problem, PV reconfiguration optimization problem, power flow problem, load frequency control problem, load forecasting problem, and electrical engineering problem. Eight of HHO-related studies were conducted to enhance the traditional HHO in order to address different global and engineering optimization problems, while five of HHO-related studies were applied to optimize solar photovoltaic problems such as improving productivity active solar still, designing an optimum load frequency controller, and measuring and selecting the parameters of solar cells models). Five of HHO-related studies were conducted to optimize manufacturing industry problems such as control charts pattern problem, quality of the friction stir welding problem, milling process problem, highway guardrail design problem, manufacturing operations problem. Five of HHO-related studies were presented to optimize environmental quality problems such as geotechnical engineering problem, prediction ground vibration problem, and landslide susceptibility problem, air pollution forecasting problem. Finally, seven of HHO-related studies were applied to address different engineering problems such as stock prediction problem, entrepreneurial intention prediction problem, fuel cell stacks problem, high-

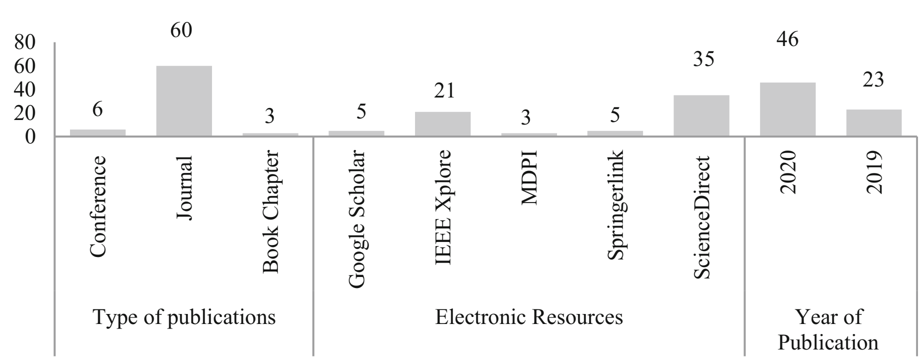


Fig. 4 Distribution of selected studies

Table 1 Data extraction form for engineering domain

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
Engineering									
[S1]	Improved HHO/To improve the performance of HHO	Global optimization problems	Hybridization HHO	QRBL	QRHHO	Exploration and exploitation phases/Increase the population diversity. Improve the convergence rate Control the balance between exploration and exploitation	23 benchmark functions/AVE, STD, BEST	HHO, OHHO, QOHHO, WOA, PSO, GWO, SCA, SSA, MVO	Find the optimal solution faster Outperform other algorithms
[S2]	Improved HHO/To maintain the balance between exploration and exploitation phases	Engineering design and optimization problems	Hybridization HHO	SCA	hHHO-SCA	Exploration and exploitation phases/control the balance between exploration and exploitation	65 benchmark functions /AVE, STD, BEST, WORST	GWO, GSA, FEP, ALO, SMS, BA, FPA, CS, FA, GA, GOA, MFO, MVO, DA, BDA, BPSO, BGSA, SCA, SSA and WOA	Solve the problems with the unknown types of search space Solve the problems including discrete and continuous types Outperform other algorithms
[S3]	Improved HHO/To maintain the balance between exploration and exploitation phases	Standard benchmark problems	Hybridization HHO	IGWO	hHHO-IGWO	Exploration and exploitation phases/Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	23 Standard benchmarked test functions/mean, STD, BEST, WORST, Median, *p*-value	GWO, ALO, DA, MVO, SCA, MFO, SSA, PSO and HHO	Find the optimal solution faster Outperform other algorithms

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S4]	Improved HHO/To maintain the balance between exploration and Exploitation phases	Real-world problems	Chaotic HHO	CS, MPS, DE	CMDHHO	Exploration and exploitation phases/Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	30 Standard benchmark functions & Eight selected real-world benchmark problems/AVE, STD	SaDE, jDE, ALCPSO, CLPSO, BLPSO, RCBA, CDLOBA, CBA, CMSSA, ESSA, CSSA, HHO, GWO, and WOA,	Prevented falling into local optimum Enhanced the basic global and local search capacities of HHO Outperform other algorithms
[S5]	Improved HHO/To maintain the balance between exploration and exploitation phases	Engineering design problems	Modifications HHO	NEP-E, PRD, OBL, GSM	m-HHO	Exploration and exploitation phases/Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	33 benchmark problems /BEST, WORST, median, mean, STD	GWO, OBGWO, SCA, OBSCA, SSA, PSO, FA, TLBO, OBTLBO	Decrease number of opposite solutions Avoid the LO Increase the convergence rate Outperform other algorithms
[S6]	Improved HHO/To improve the performance of HHO	N/A	Chaotic HHO	CS	CHHO	Exploration phase	18 benchmark functions/None	HHO	Find the optimal solution faster
[S7]	Information exchange/For maintaining the balance between exploration and exploitation phases	Constrained optimization engineering problems	Chaotic HHO	NEP-E, CS	IEHHO	Exploration and exploitation phases/Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	Four benchmark functions, five CEC-2017 problems, and seven practical engineering problems/STD BEST, WORST, Mean	BA, CS, CSA, JADE, FPA, GWO, PSO, TLBO, and HHO	Provide better solution quality and faster convergence speed Improve optimization search process Sufficient the global exploration ability Avoid falling into a local optimum

Table 1 (continued)

ID	Study objective	Problem type	Variant/method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/performance metrics	Compared algorithms	Results
[S8]	Improved HHO/To improved multi-verse optimizer	Engineering problems	Chaotic HHO	MVO chaotic maps	CMVHHO	None	15 benchmark functions/STD, BEST, MFV	MVO, ALO, SCA, PSO, GA, BAT, DA, MFO,	HHO helps to improve maintaining MVO population HHO helps to speed up MVO searching, premature convergence
[S9]	Environmental quality/To propose air pollutant prediction model	Multi-objective optimization	Hybridization HHO	ELM	MOHHO	To overcome the shortcomings of single-objective optimization HHO	Four multiobjective functions, namely ZDT/MAE RMSE, MAPE, U1, U2, IA, r	MOGOA, MOPSO and MSSA	Achieved high accuracy and stability for air pollutant concentrations prediction
[S10]	Stock Prediction/To model SAR target recognition & predict stock market	Classification and prediction problems	Hybridization HHO	ATA, SVM, ELM	IHHO-SVM	Exploration phase To add velocity into the exploration phase	23 benchmark functions/AVE, STD	ALO, DA, DE, GA, GWO, MFO, SCA, WOA, PSO, AT, HHO	Improve position vectors of HHO Find the optimal solution faster Increase the convergence rate
[S11]	Entrepreneurial intention prediction/To predict the students' entrepreneurial intention on self-employment	Real-world problem	Hybridization HHO	KELM, GB	GBHHO-KELM	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	30 CEC 2014 benchmark functions/*p*-value, STD, Mean, AVE	MFO, FA, GWO, HHO, WOA, ACWOA, OBSCA OBLGWO, SCADE	Achieve smaller fitness and variance Obtain better parameter combinations and feature subset

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S12]	Fuel cell stacks/To obtain the accurate operating parameters of PEMFC	PEMFC problem	Chaotic HHO	Chaos strategy	CHHO	Exploration phase	Ten chaotic functions/STD, BEST, WORST, MAE, RMSE, RE, Median, Mean	HHO, GWO, CS-EO, SSO	They achieved high accuracy in extracting the optimal parameters of PEMFC Outperform other algorithms
[S13]	High-dimensional reliability analysis/To extract the global optimal solutions for high dimensional problems	High-dimensional engineering problem	Hybridization HHO	FORM	HHO-FORM	None	5 explicit and implicit performance functions/STD, BEST, Average, Mean	PSO-FORM, jHLRF, GWOFORM, iHLRF, SSA-FORM, DA-FORM, SQP, HLRF	Increase the convergence rate
[S14]	Microchannel heat sink/To enhance the performance of microchannel heat sinks	Engineering problem	Conventional HHO	None	HHO	None	Two dimensionless parameters/None	PSO, BeA, DA, WOA, GOA	Outperform other algorithms in less CPU time
[S15]	Manufacturing industry/Control charts pattern for monitoring the production process	Pattern recognition problems	Hybridization HHO	ConvNet	HHO-ConvNet	None	Nine CCPs recognition/STD, BEST, WORST, Mean	MLPNN, RBFNN, ANFIS, RF, and SVM	Outperform other algorithms in terms of classification accuracy
[S16]	Manufacturing industry/To maximize the quality and strength of the friction stir welding	Engineering Design Optimization	Hybridization HHO	ANFIS	ANFIS-HHO	None	Experimental dataset/R2, RMSE, MRE, MAE, COV	ANFIS	HHO effectively selects optimal ANFIS model with the most appropriate parameters.
[S17]	Manufacturing industryTo optimize the process parameters in milling operations	Manufacturing optimization problem	Hybridization HHO	Nelder-Mead	H-HHONM	None	Three benchmark Problems/None	HHO, MVO, GOA, MFO, SSA, ALO, MBA, CS, DEDS, PSO-DE, Ray and Sain, Tsa	Outperform other algorithms in terms of selecting the best machining parameters.

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S18]	Manufacturing industry/To select the best design parameters of highway guardrail systems	Manufacturing optimization problem	Hybridization HHO	Simulated annealing	HHOSA	None	Three benchmark Problems/None	HHO, MVO, GOA, MFO, SSA, ALO, MBA, CS, DEDS, PSO-DE, Ray and Sain	Outperform other algorithms
[S19]	Manufacturing industry/To optimize the process parameters for manufacturing operations	Manufacturing optimization problem	Hybridization HHO	GOA and MVO	HHO, GOA and MVO	None	Three benchmark Problems/None	GA, ACO, CA, DEA, PSO, SA, ABC, HS, IDE, HPSA, TLO, CS, FSA	Outperform other algorithms
[S20]	Environmental quality/To optimize the prediction of blast-induced ground vibration	Engineering problems	Hybridization HHO	RF	HHO-RF	None	137 datasets and seven variables of blast-induced ground vibration/ RMSE, R2, MAE	RF	Enhanced the prediction performance of the RF model
[S21]	Environmental quality/To optimize the prediction of the soil compression coefficient	Geotechnical engineering problem	Hybridization HHO	ANN and GOA	HHO-ANN and GOA-ANN	None	12 critical factors of soil/R2, RMSE, and MAE	ANN	Outperform ANN
[S22]	Environmental quality/To examine the bearing capacity in the position of a classification issue	Geotechnical engineering problem	Hybridization HHO	None	HHO-MLP	None	Seven settlement key factors/MSE, and MAE	DA-MLP	DA-MLP Outperform HHO-MLP in terms of consistency and obtain desired classification values
[S23]	Environmental quality/To landslide susceptibility analysis	Engineering problems	Hybridization HHO	ANN	HHO–ANN	None	14 landslide conditioning factors/AUROC, MSE, and MAE	ANN	HHO effectively improved the performance of ANN

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S24]	Fault diagnosis/To diagnose the faults in rolling bearings	Engineering problems	Hybridization HHO	MSCA	MSCAHHO	None	Nine benchmarking functions/STD, Mean	SCA, HHO, PSO, BPNN	MSCAHHO outperforms PSO and BPNN for improving the performance of SVM
[S25]	Stability performance/To optimize the prediction accuracy of slope stability conditioning factors	Engineering problems	Hybridization HHO	ANN	HHO–ANN	None	75 dataset of four slope stability conditioning factors/RMSE, MAE, R2	MLR	HHO increases the prediction accuracy of the ANN Outperform MLR
[S26]	Solar still/To optimize productivity prediction accuracy of active solar still	Engineering problems	Hybridization HHO	ANN	HHO-ANN	None	Dataset of 72 experiments with five variables performed for 3 solar cell cases/ RMSE, MAE, MRE, EC, R2, CRM, OI	ANN and SVM	HHO_ANN has optimal prediction accuracy over ANN and SVM
[S27]	Solar photovoltaic/ To measure the parameters of the single diode photovoltaic model	Real-world optimization problems	Modification of HHO	None	BHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	Experimental data of a Kyocera KC120-1 multicrystalline PV module form for seven weather conditions/ RMSE, *R*2, STD, AE,TS, MSE	HHO, WOA, FPA, FA, ER-WCA, MVO, MFO, SSA, BOA, ABC, CS, EM, Rcr-IJADE, IADE, PDE, PSO,	Provide high consistently converges comparing to other methods
[S28]	Solar photovoltaic/ To design an optimum controller for load frequency control in the microgrid	Real-world design engineering problems	Conventional HHO	None	HHO	None	5 transfer functions /None	GOA, CSA, GA	Outperform other algorithms in term of less overshoot and minimum settling time

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S29]	Solar photovoltaic/ To select the unknown parameters of the three-diode photovoltaic model	Real-world engineering problems	Conventional HHO	None	HHO	None	Experimental dataset of 9 electrical parameters of TDPV model of KC200GT and CS6K280 M PV modules/None	MLE, WOA, SFO, GA, SA	HHO has a smaller error HHO can be used to find the electrical parameters of any PV panels
[S30]	Solar photovoltaic/ To measure the parameters of solar cells models of the three-diode photovoltaic model	Real-world engineering problems	Chaotic HHO	OBL mechanism and CLS strategy	EHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	Experimental dataset of 3 manufacturer's datasets/BEST, WORST, STD, RMSE	BLPSO, CLPSO, IJAYA, and GOTLBO	Improve search space and decrease stagnation Enhance the population intensification Outperform other algorithms
[S31]	Power systems/To address the directional overcurrent relays coordination problem	Real-world engineering problems	Conventional HHO	None	HHO	None	4 test systems 3-bus, 4-bus, 8-bus, and 9-bus/ STD	GA, GA-LP, BBO, BBO-LP, Jaya	Outperform other algorithms
[S32]	Power systems/To enhance multi-step short-term wind speed forecasting	Real-world engineering problems	Hybridization HHO	Mutation-based GWO	MHHOGWO	None	9 Benchmark functions/RMSE, MAE, MAPE	PSO, ALO, SCA, MFO, WOA, GWO, HHO	HHO can effectively achieve the simultaneous realization of parameters optimization and FS
[S33]	Power systems/To enhance the performance of ANFIS for online voltage stability assessment	Real-world engineering problems	Conventional HHO	None	HHO	None	3 test systems IEEE standard 39-bus, 118-bus and 300-bus/RMSE, STD	LS + BP, GS + MLPNN, RWT + PCA + RBFNN	HHO algorithm effectively improved the performance of ANFIS

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S34]	Power systems/To enhance power system performance by extracting the optimal parameters of load frequency control	Real-world engineering problems	Conventional HHO	None	HHO	None	4 Controller Parameters/None	None	HHO algorithm effectively improved the performance of the power system
[S35]	Power systems/To optimize the damping oscillations controller design	Real-world engineering problems	Modification of HHO	None	MHHOS	Exploration phase Increase the population diversity	5 Control parameters of PSS STATCOM/ None	ALO, WOA, HHO	Outperform other algorithms in terms of maximizing the minimum damping ration
[S36]	Power systems/To enhance the power quality indicators by optimizing the design and control of MMC STATCOM	Power quality (PQ) problems	Hybridization HHO	HHO	HHO-ASO	None	The objective function of THD/ None	ASO, HHO, PSO	HHO obtained the optimal solution in less time
[S37]	Power systems/To optimize harmonic overloading of frequency-dependent components	Power quality (PQ) problems	Conventional HHO	None	HHO	None	3objective functions of C-type harmonic filter/BEST, WORST, Mean, STD	SSA, CSA, PSOGSA,	HHO outperform other algorithms in terms of finding The minimum power loss and harmonic overloading level of The frequency-dependent components
[S38]	Power systems/To enhance power system performance by determining the gains of the PID	Automatic generation control problem	Conventional HHO	None	HHO	None	2 area interconnected power system based nine parameters and three transfer functions /ISE	SOS, ABC	Outperform other algorithms in terms of tuning parameters of PSS and STATCOM

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S39]	Power systems/To optimize the solution for solving the optimal power flow problem	Optimal power flow problem	Hybridization HHO	DE	HHODE	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	13 benchmark functions of CEC2005 and CEC2017/None	HHO, GA, BBO, DE, PSO, CS, TLBO, BA, BAT, FPA, FA, GWO, MFO	Outperform other algorithms Maintained trade-off balance between exploration and exploitation
[S40]	Power systems/To optimize high dimensionality of power flow problems by minimizing fuel cost, emission, and power loss	Optimal power flow problems	Modification of HHO	LM long-term memory	LMHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	29 benchmark functions of CEC'17/P-value, STD, Mean	PSO, FPA, MFO, FA, WOA, SOS, Jaya, GWO, BSA	LMHHO improved search efficiency LMHHO did not lose exploration ability throughout iterations LMHHO maintained trade-off balance between exploration and exploitation LMHHO also generated superior results than the competitive methods

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S41]	Power systems/To improve the heating ventilation and air conditioning system	power quality (PQ) problems	Hybridization HHO	MLP	HHO-MLP	None	Dataset of heating load the cooling load/RMSE, MAE	EHO-MLP, ACO-MLP	HHO-MLP has mostly underestimated the cooling load values HHO-MLP perform more accurately between the cooling load and input factors
[S42]	Power systems/	Power quality (PQ) problems	Modification of HHO	Logarithmic function	LogHHO	The transition from exploration to exploitation: Improve the convergence rate	Dataset of power system with VSC-Based STATCOM/None	HHO, GWO, and MFO	LogHHO effectively finds optimal control parameters
[S43]	Power systems/To select the best allocation of DG units in the radial distribution system	Distribution generation allocation problem	Multi-objective of HHO	Grey relation decision making	IHHO and MOIHHO	Enhanced the random location Best compromise solution among the non-dominated solutions	3 objective functions of (power loss, VD, and VSI) IEEE 33-bus and IEEE 69-bus/ BEST, AVERAGE, WORST	PSO, MOPSO, LSF, fuzzy-IAS, BSOA, BFOA, TLBO, QOTLBO, SIMBO-Q, QOSIMBO-Q HHO, GA, GA/PSO, TM, MOTA, MOHHO	HHO algorithm effectively improved algorithms for Optimal allocation of DG in the radial distribution system Reduce the total power and voltage deviation Improve the overall voltage profile
[S44]	Power systems/To optimize sitting and sizing of RES-DG units in distribution systems	Distribution generation allocation problem	Hybridization HHO	POS	HHO-PSO	None	3 radial distribution systems (RDSs)/ BEST, WORST, Mean, STD	POS, HHO, BSOA, KHA, SKHA	Outperform other algorithms by maximizing the techno-economic benefits of the distribution systems

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S45]	Power systems/To define the best interconnection for the modules in the considered PV array during PSC	PV reconfiguration optimization problem	Modification of HHO	None	MHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	23 CEC2005 benchmark functions/STD, Mean	TCT, CS, GA, HHO	Reduce the total power and voltage deviation Improve the overall voltage profile Solve the multi-peak issue in the PV characteristics
[S46]	Power systems/To extract the optimal parameters of solar cells and PV modules effectively and accurately	PV reconfiguration optimization problem	Chaotic HHO	OL, GOBL	EHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	Two datasets of RTC France photovoltaic cell and Photowatt-PWP 201 photovoltaic Module/RMSE	HHO, CPSO, PS, LMSA, ABC, ABSO, GOTLBO, GOFPANM	HHO algorithm effectively estimates unknown parameters in different solar cells and PV modules
[S47]	Power systems/To estimate the best parameters of the Proportional–Integral (PI) controller	Load frequency control problem	Conventional HHO	None	HHO	None	Two interconnected systems connected to the PV module/ Wilcoxon signed-rank test	ALO, GWO, SCA, MVO	HHO algorithm effective in designing LFC
[S48]	Power systems/To reduce the prediction error by enhancing the performance of FNN	Load forecasting problem	Hybridization HHO	FNN	HHO-FNN	None	Dataset of weather data of the Queensland region/MAPE, SMAPE, D	PSO-ANN, PSO-LSSVM, and BPNN	HHO algorithm effectively used for optimizing the weight and basis of neurons

Table 1 (continued)

ID	Study objective	Problem type	Variant/ method	Integrated Method	HHO improved version	Area of improvement	Benchmark functions/ performance metrics	Compared algorithms	Results
[S49]	Electrical system/To optimize solutions of getting the best of nonlinear VdP dynamic heart model	Electrical Engineering Problem	Hybridization HHO	IPA	HHO-IPA	None	MAD, ENSE, RMSE, GbMAD, GbENSE, GbRMSE	RNS	Outperform other algorithms

dimensional problems, microchannel heat sinks, diagnose the problem of the fault, and stability performance problem.

In the computer science domain, seven of HHO-related studies conducted to discover solutions for image thresholding optimization problem such as multilevel image segmentation problem and finding the improved parameters of the thresholding functions. Also, five of HHO-related studies were applied to optimize problems related to networking and distributed system such as web service composition problem, distribution network reconfiguration problem, large-scale wireless sensor networks deployment problem, complex combinatorial optimization problem, and visible-light communications problem. However, four of HHO-related studies were introduced to optimize data mining and data processing problems such as job scheduling problem, data clustering problem, and feature selection problem. Finally, two studies used HHO to optimize some of software engineering problems such as regression testing expense problem and predicting the faulty components in a software project.

Also, HHO was applied in medicine and public health domain. It was utilized for drug design chemical descriptor selection problem. Also, one study applied HHO to handle the problem of feature selection for breast mass classification problem.

3.3 HHO and versions of HHO

Figure 6 shows the number of conventional HHOs and improved versions of HHO that were applied in the engineering domain. For example, nine studies applied conventional HHO. At the same time, 40 studies proposed different improved versions of HHO. These versions were categorized into four categories which are chaotic HHO, hybridization HHO, modification of HHO and multiobjective HHO. In chaotic HHO category, four studies [S4, S7, S30 and S46] proposed chaotic HHO to improve the exploration and exploitation phases of HHO which aimed to increase the population diversity, improve the convergence rate, and control the equilibrium between exploration and exploitation phases. Two studies [S6 and S12] developed chaotic HHO to improve the exploration phase. Also, the new version of HHO was integrated with MVO and chaotic maps in [S8] to improve the exploitation phase of MVO. Next, a total of 26 hybrid HHOs are proposed, which are distributed as follows. Firstly, the highest number of studies (19 studies) is developed in hybrid HHO in order to improve the performance of other algorithms or to increase the accuracy of the proposed solution [S13, S15, S16, S17, S18, S19, S20, S21, S22, S23, S24, S25, S26, S32, S36, S41, S44, S48 and S49]. Secondly, five studies [S1, S2, S3, S11, and S39] proposed hybrid HHO in order

Table 2 Data extraction form for computer science domain

ID	Study objective	Problem type	Variant/Method	Integrated Method	HHO Improved Version	Area of improvement	Benchmark functions/Performance metrics	Compared Algorithms	Results
Computer Science									
[S50]	Task scheduling/to optimize the solution of scheduling jobs in the cloud computing environment	Job scheduling problem	Hybridization HHO	SA	HHOSA	Exploration phase To improve the convergence rate To improve local search	Two standard parallel Workloads (NASA Ames iPSC/860 and HPC2N)/ Makespan, PIR	SSA, MFO, PSO, FA, HHO,	Outperform other scheduling algorithms in terms of achieving near-optimal performance
[S51]	Data clustering/To determine the best position vectors of centroids that are the best representative of clusters	Data clustering problem	Chaotic HHO	LCM	CHHO	Exploration phase To avoid the problem of local entrapment	12 benchmark datasets of the UCI machine learning repository/ Friedman test and Iman–Davenport test	HHO, GWO, BOA, MVO SCA, SSA	Outperform other algorithms in terms of position vectors that are best representative of clusters
[S52]	Data mining/To optimize feature selection tasks	Feature selection problem	Hybridization HHO	SSA	IHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	23 benchmark functions/ Mean, STD	HHO, DE, GWO, WOA, SSA, MFO, SCA, PSO, MVO, ALO, GOA	Provide better solution quality and faster convergence speed Improve optimization search process Sufficient global exploration ability Avoid falling into a local optimum
[S53]	Data mining/To optimize feature selection tasks	Feature selection Problem	Binarization HHO	None	BHHO	None	9 dataset datasets/ Wilcoxon rank-sum	BGSA, BSSA, GA, BPSO, BBA, BALO	HHO algorithm effectively handles the problem of dealing with high-dimensional real-world datasets that have a low number of samples
[S54]	DNA storage/To estimate the optimal constrained DNA-sequence lower bound	Complex combinatorial optimization problem	Chaotic HHO	NCPS, ROBLS	NOL-HHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	23 widely used benchmark functions/ Wilcoxon rank-sum test	HHO, GA, PSO, BBO, FPA, GWO, BAT, FA, MFO, DE	Provide better solution quality and faster convergence speed Improve optimization search process Sufficient the global exploration ability Avoid falling into a local optimum

Table 2 (continued)

ID	Study objective	Problem type	Variant/ Method	Integrated Method	HHO Improved Version	Area of improvement	Benchmark functions/ Performance metrics	Compared Algorithms	Results
[S55]	Visible light communications/ To optimize the sum rate of ground users subject to constraints on power allocation	Real-world optimization problem–power allocation problem	Hybridization HHO	None	HHOFNN	None	GRPA, RandP, Conventional OFDMA [1. 46]/None	PSO, ES, GA	Outperform other algorithms in terms of optimization problem–power allocation problem
[S56]	Image thresholding/To determine the optimum thresholds of color image	Image segmentation problems	Hybridization HHO	DE	HHO-DE	Exploration Phase To enhanced the necessary global and local search capacities	Ten benchmark Images/ AFV, STD, PSNR, SSIM, FSIM,	HHO, DE, SCA, BA, HSO, PSO, and DA	Outperform other algorithms in terms of determining the optimum thresholds of color image
[S57]	Image thresholding/To optimize the solution for multi-level image segmentation	Image segmentation problems	Hybridization HHO	SSA	HHOSSA	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	36 IEEE CEC 2005 benchmark functions and 11 natural grayscales/Wilcoxon's rank-sum test	HHO, GWO, WOA, SCAOBL, SSA, LSHADE, SCA, MSADE, SHO, ABC, BSOMFO, MFO, MVO	Outperform other algorithms in terms of: Optimize solution for multi-level image segmentation Achieves a more stable performance
[S58]	Image thresholding/To optimize the solution for multi-level image segmentation	Image segmentation problems	Hybridization HHO	DEA	DEAHHO	Exploration phase To control parameter E (escaping energy)	23 benchmark test functions And 500 images/PSNR, SSIM, FSIM	HHO, CS, PSO, FA, WDO, STOA, DE	Outperform other algorithms in terms of optimizing solution for multi-level image segmentation Could be used in the segmentation of biomedical images
[S59]	Image thresholding/To optimize the solution for multi-level image segmentation	Image segmentation problems	Hybridization HHO	MCET	MCET-HHO	Exploration phase To improve the convergence rate To improve local search	Three sets of benchmark images/STD, PSNR, RMSE, SSIM, FSIM, G, PC, PRI, VoI, GCE	HHO, PSO, FFO, DE, HS ABC, SCA, *K* -means and Fuzzy IterAg	Outperform other algorithms in terms of optimizing solution for multi-level image segmentation. Could be used in the segmentation of biomedical images

Table 2 (continued)

ID	Study objective	Problem type	Variant/ Method	Integrated Method	HHO Improved Version	Area of improvement	Benchmark functions/ Performance metrics	Compared Algorithms	Results
[S60]	Image thresholding/To extract boundaries, locate objects and separate regions in high-resolution satellite images	Multilevel color image segmentation problem	Chaotic HHO	DCPS & DE/best/2	DHHO/M	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	Eight satellite images/ AFV, STD, PSNR, MSE, SSIM, FSIM, ACT	HHO, TLBO, IDSA, BDE, MGOA, MABC, MFPA, GWO,	Improve the quality of the result for satellite images in terms of objective function value practicality and feasibility
[S61]	Image thresholding/To process the de-noised image data for finding the improved parameters of the thresholding functions	Image De-Noising problem	Hybridization HHO	JADE	HHO-JADE	None	Six satellite images/ PSNR, MSSIM	JADE, BM3D, WNNM	HHO algorithm performs much better than other algorithms visually and quantitatively
[S62]	Image thresholding/To process the de-noised image data for finding the improved parameters of the thresholding functions	Image De-Noising problem	Hybridization HHO	SSBS	HHO-SSBS	None	Three satellite images/ None	JADE, Sahraeian's TNN, Noorbakhsh-TNN, Sahraeian-HHO Noorbakhsh–HHO	HHO algorithm performs much better than other algorithms visually and quantitatively
[S63]	Service Composition/to address the QoS-aware web service composition problem	QoS-aware Web Service Composition problem	Chaotic HHO	LCSDP strategy	CHHO	Exploration phase To improve local search	QWS2.0 Datasets [42]/ Friedman test and Wilcoxon signed-rank test	HHO, ESWOA, mABC	Outperform other algorithms in terms of performance especially in large-scale scenarios
[S64]	Distribution network reconfiguration/To allocate distributed generations (DGs) along with DNR	Distribution Network Reconfiguration problem	Conventional HHO	None	HHO	None	83-node practical distribution system/ None	N/A	Improve loss minimization Enhance its voltage stability
[S65]	Wireless sensor networks/To optimize the network lifetime	Large-scale wireless sensor networks deployment problem	Conventional HHO	None	HHO	None	12 parameter of LSWSNs/ Mean, STD, BEST, WORST	PSO, FPA, GWO, SCA, MVO, WOA	Achieve the best solutions with the lowest energy consumption and localization error
[S66]	Software testing/to select the best test cases	Minimize regression testing expense problem	Conventional HHO	None	HHO	None	Five different objects of SIR/Mean STD	HS	Outperforms other algorithms in terms of the fault coverage

Table 2 (continued)

ID	Study objective	Problem type	Variant/ Method	Integrated Method	HHO Improved Version	Area of improvement	Benchmark functions/ Performance metrics	Compared Algorithms	Results
[S67]	Software testing/to optimize the solution for predicting the faulty components in a software project	Feature selection problem	Binarization HHO	EB	EBHHO	Exploration and exploitation phases/ Increase the population diversity Improve the convergence rate Control the balance between exploration and exploitation	15 well-regarded SFP datasets/None	ESBHHO EVBHHO BGSA BGOA WOA BBA GA2 bALO	Outperform other algorithms when used with LDA classifier

to improve the population diversity, the convergence rate, and maintain the balance between exploration and exploitation phases. Finally, two [S9 and S10] studies were developed in hybrid HHO to improve the exploration phase of HHO.

In the category of modification of HHO, six studies proposed different modified versions of HHO. For instance, studies [S40, S45, S5, and S43] proposed different modified versions of HHO, which aimed to increase the population diversity, improve the convergence rate, and control the balance between exploration and exploitation phases of HHO. At the same time, the study introduced by [S35] developed a modification of the HHO algorithm to improve the exploration phase of HHO. In [S42], modified version of HHO was proposed to improve the convergence rate in the transition from exploration to exploitation phase.

In the domain of computer science, three categories of HHO versions are considered, such as binarization of HHO, hybrid HHO, and chaotic HHO. In the binarization category, two binary HHO algorithms are proposed. For example, the study introduced by [S67] developed binary HHO algorithm in order to improve the exploration and exploitation phases of HHO (e.g., increase the population diversity, improve the convergence rate and control the balance between exploration and exploitation), while the study proposed by [S53] implemented binarization HHO algorithm to adapt the feature selection problem. However, the remaining studies [S64, S65, and S66] used conventional HHO to solve the optimization problems in this domain.

In medicine and public health domain, two versions of HHO are proposed, which are hybrid HHO developed by [S68] and chaotic HHO [S69]. In [S68], HHO was integrated with SVM in order to extract the best features with accuracy, while in [S69] chaotic HHO was proposed to improve the exploration phase of HHO. However, a summary of the main variants of HHO is reported in Tables 1, 2, 3. Also, details of the main variants of HHO are discussed in the following section.

4 Applications and variants of the Harris hawks optimizer

4.1 Engineering optimization

In engineering optimization domain, different versions of HHO (e.g., chaotic HHO, hybrid HHO, modification of HHO, and multiobjective HHO) were applied to handle various types of engineering problems. Tables 1, 2, 3 present these versions along with problem type that was used to tackle HHO variants/method, method integrated with HHO, improved versions of HHO, and the area of

Table 3 Data extraction form for medicine and public health domain

ID	Study objective	Problem type	Variant/ method	Integrated method	HHO improved version	Area of improvement	Benchmark functions/ Performance metrics	Compared Algorithms	Results
Medicine & public health									
[S68]	Drug design and discovery/Feature selection for achieving high classification accuracy of chemical descriptor selection and chemical compound activities	Drug design-chemical descriptor selection problem	Hybridization HHO	SVM and KNN	HHO-SVM and HHO-kNN	None	Two chemical datasets (MonoAmine Oxidase (MAO) and QSAR Biodegradation)/mean, BEST, WORST, STD	GWO, DA, SCA, HHO, SSA, BOA, MFO, PSO, SA	Outperform other algorithms in terms of obtaining the optimal features
[S69]	Mammogram images classification/ Feature selection in breast masses classification	Feature selection-breast mass classification problem	Chaotic HHO	opposition based	OHHO	Exploration phase	7 benchmark functions/ mean, STD	PSO, SCA, GWO, HHO	Outperform other algorithms in terms of feature selection in breast masses classification

improvement. Besides, the following sections present and discuss the main applications of HHO and HHO versions in engineering optimization domain.

4.1.1 Improved HHO

The work in [S1] proposed a hybrid algorithm called QRHHO that is comprised of HHO and QRBL. Hybrid QRHHO algorithm aims to address global optimization problems. The proposed algorithm aims to enhance the performance of HHO in terms of increasing the population diversity, improving the convergence rate and to control the balance between exploration and exploitation phases. The experiment study involved 23 benchmark functions and used three measurement metrics (e.g., AVE, STD, BEST) to validate the performance of the proposed algorithm. The proposed algorithm was compared with nine state-of-the-art algorithms which are HHO, OHHO, QOHHO, WOA, PSO, GWO, SCA, SSA, and MVO. The analysis result shows that the proposed QRHHO can find the optimal solution faster, and it outperforms other algorithms.

To solve engineering design and optimization problems, the work in [S2] developed hHHO-SCA algorithm. It aims to maintain and control the balance between exploration and exploitation phases. The improved hybrid algorithm comprised two main algorithms which are HHO and SCA. To evaluate the performance of hHHO-SCA, 65 benchmark functions and four main measurement metrics (e.g., AVE, STD, BEST, and WORST) were applied in the experimental study. Also, it was compared with other 20 algorithms, namely GWO, GSA, FEP, ALO, SMS, BA, FPA, CS, FA, GA, GOA, MFO, MVO, DA, BDA, BPSO, BGSA, SCA, SSA, and WOA. The analysis results revealed that the proposed algorithm was able to (1) solve the problems with the unknown types of search space, (2) solve the problems including discrete and continuous types, and (3) outperform other algorithms.

In [S3], the authors introduced the hybrid HHO called hHHO-IGWO—the proposed algorithm is comprised of HHO and IGOW. HHO-IGWO algorithm aims to enhance the balance between exploration and exploitation phases for standard benchmark problems by increasing the population diversity, improving the convergence rate, and controlling the balance between exploration and exploitation phases. Twenty-three standard benchmarked test functions were used to validate the effectiveness of the hHHO-IGWO algorithm. Moreover, the performance of the hybrid algorithm was compared with nine state-of-the-art algorithms which are GWO, ALO, DA, MVO, SCA, MFO, SSA, PSO, and HHO concerning six different measurement criteria (e.g., mean, STD, BEST, WORST, median, and p value). The analysis result found that the proposed hHHO-IGWO

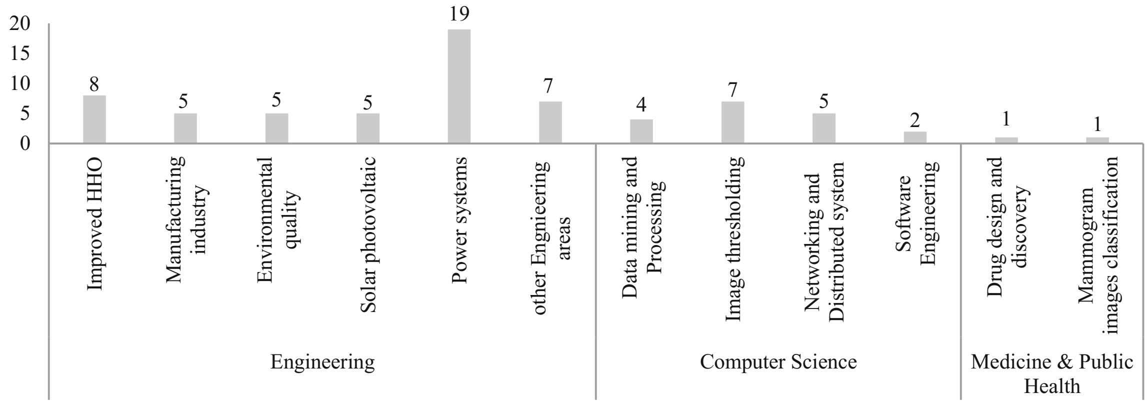


Fig. 5 HHO applications

can find the optimal solution faster, and it provides competitive results compared to other algorithms.

To address real-world problems, the work in [S4] improved HHO algorithm by combining CS, MPS, and DE algorithms. The introduced chaotic HHO algorithm is called CMDHHO. It aims to maintain the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate. The study used 30 standard benchmark functions and eight selected real-world benchmark problems to evaluate and validate the proposed algorithm. To measure the performance, the chaotic algorithm CMDHHO was compared to 14 different algorithms involved, SaDE, jDE, ALCPSO, CLPSO, BLPSO, RCBA, CDLOBA, CBA, CMSSA, ESSA, CSSA, HHO, GWO, and WOA. Besides, AVE, STD are two measurement metrics obtained to identify the accuracy of the proposed algorithm. The experiment results indicate that CMDHHO plays an essential role in preventing HHO from falling into local optimum, enhancing the necessary global and local search capacities of HHO, and it outperforms other algorithms.

The work in [S5] modified HHO to be used for general engineering design problems. The modification version of HHO called m-HHO, which was modified according to NEP-E, PRD, OBL, GSM algorithms. The m-HHO aims to preserve the balance between exploration and exploitation phases and enhance the performance of HHO in terms of increasing the population diversity and improving the convergence rate. To endorse the effectiveness of the m-HHO algorithm, 33 benchmark problems were applied. The m-HHO was compared to nine different algorithms involved, GWO, OBGWO, SCA, OBSCA, SSA, PSO, FA, TLBO, and OBTLBO. The performance result was validated using multiple measurement metrics (e.g., BEST, WORST, median, mean, STD). Overall results showed that m-HHO is significant in (1) decreasing the number of opposite solutions; (2) avoiding the LO; (3) increasing the convergence rate; and (4) outperforming over other algorithms.

The work in [S6] proposed CHHO chaotic algorithm that aims to enhance the performance of HHO. It combines a tent map chaos strategy. Eighteen benchmark functions were used to validate the new CHHO algorithm. Results found that the proposed CHHO can find the optimal solution faster in the exploration phase.

In [S7], to address constrained optimization engineering problems, chaotic HHO algorithm called IEHHO that combined NEP-E and CS was implemented. The proposed algorithm aims to exchange information, increase the population diversity, improve the convergence rate, and control the balance between exploration and exploitation. To validate the IEHHO algorithm, four benchmark functions, five CEC-2017 problems, and seven practical engineering problems were adopted. The improved algorithm was compared to BA, CS, CSA, JADE, FPA, GWO, PSO, TLBO, and HHO algorithms where the compression results were validated using four criteria (e.g., STD, BEST, WORST, and Mean). The analysis results found that IEHHO chaotic algorithm (1) provides better solution quality and faster convergence speed, (2) is able to improve the optimization search process, (3) is sufficient in the global exploration ability, and (4) is able to avoid falling into a local optimum.

The work in [S8] has proposed a chaotic CMVHHO algorithm that aims to improve and modify the multi-verse optimizer method in the context of engineering problems. It combines two main algorithms: MVO, chaotic maps, and HHO. Fifteen benchmark functions were used to validate the new CMVHHO algorithm, in addition to multiple measurement metrics (STD, BEST, and MFV). The improved algorithm was compared to eight algorithms (e.g., MVO, ALO, SCA, PSO, GA, BAT, DA, MFO). The analytical results have shown that HHO helps to maintain MVO population and to speed up MVO searching and premature convergence.

4.1.2 Manufacturing industry

To solve pattern recognition problems, [S15] developed HHO-ConvNet algorithm. It aims to control charts pattern for monitoring the production process. The improved hybrid algorithm is comprised of two main algorithms which are HHO and ConvNet. To evaluate the performance of HHO-ConvNet, Nine CCPs recognition methods were used. Also, it was compared with the other five algorithms, namely MLPNN, RBFNN, ANFIS, RF, and SVM. Four main criteria, namely STD, BEST, WORST, and Mean, are obtained to identify the accuracy of the proposed algorithm. The study revealed that HHO-ConvNet algorithm was able to outperform other algorithms in terms of classification accuracy.

In terms of engineering design optimization, the work in [S16] used HHO algorithm to improve the performance of ANFIS. The hybridized algorithm was named as ANFIS-HHO. The main goal of ANFIS-HHO is to maximize the quality and strength of the friction stir welding. The experimental dataset was developed to evaluate ANFIS-HHO's effectiveness. Also, to measure ANFIS-HHO performance, the algorithm was compared to ANFIS by assessing the values of R2, RMSE, MRE, MAE, and COV measurement metrics. Results of the analysis revealed that HHO algorithm successfully improved the performance of ANFIS and effectively selected optimal ANFIS model with the most appropriate parameters.

In the context of manufacturing optimization, the work in [S17] proposed H-HHONM, which hybridizes HHO algorithm and Nelder-Mead method that aims to optimize the process parameters in milling operations. Three benchmark function problems were used to validate the algorithm. Moreover, the improved H-HHONM was compared to 13 various algorithms, namely HHO, MVO, GOA, MFO, SSA, ALO, MBA, CS, DEDS, PSO-DE, Ray, and Tsa and Sain. Results prove the superiority of H-HHONM over other algorithms in terms of selecting the best machining parameters.

A hybrid of HHO, along with simulated annealing, was presented in [S18] to select the best design parameters of highway guardrail systems, which is known as HHOSA. Three benchmark function problems were used to validate the algorithm. The improved HHOSA was compared to 12 various algorithms (e.g., HHO, MVO, GOA, MFO, SSA, ALO, MBA, CS, DEDS, PSO-DE, and Ray and Sain). Results have shown that HHOSA outperforms other algorithms virtually.

In work by authors in [S19], hybrid HHO algorithm comprised of HHO, GOA, and MVO algorithms is proposed to address the manufacturing optimization problem. The proposed algorithm was used to optimize the process parameters for manufacturing operations. To validate the algorithm, three benchmark functions were used. The integrated algorithm was compared to GA, ACO, CA, DEA, PSO, SA, ABC, HS, IDE, HPSA, TLO, CS, and FSA algorithms. The analysis results show that the hybrid of HHO, GOA, and MVO algorithms outperforms other algorithms.

4.1.3 Environmental quality

In the context of air pollution forecasting, the research in [S9] proposed air pollution prediction model known as MOHHO, which hybridizes ELM and HHO algorithms. The proposed MOHHO aims to overcome the shortcomings of single-objective optimization HHO. Different multiobjective functions (e.g., ZDT/MAE, RMSE, MAPE, U1, U2, IA, r) were used to validate the model. Moreover, the improved MOHHO was compared to three various algorithms, which are MOGOA, MOPSO, and MSSA. The experimental results show that MOHHO achieved high accuracy and stability for air pollution concentrations prediction.

The work in [S20] introduced hybrid HHO that is comprised of HHO and RF algorithms. HHO-RF aims to optimize the prediction of blast-induced ground vibration. One hundred thirty-seven datasets and seven variables of blast-induced ground vibration were used to measure the effectiveness of HHO-RF method. To estimate HHO-RF performance value, it was compared to the RF algorithm by evaluating the values of RMSE, R2, and MAE measurement metrics. The statistical analysis results ensure that the HHO algorithm effectively enhanced the prediction performance of the RF model.

To optimize the prediction of the soil compression coefficient, a hybrid HHO along with ANN and GOA algorithms was suggested [S21]. Twelve critical factors of soil were used to validate the algorithm. The hybridized algorithm was compared to the ANN algorithm to evaluate its performance using measurement metrics (e.g., R2, RMSE, MAE). Results have shown that the proposed algorithm was effectively outperforming over the ANN algorithm.

In the context of environmental quality, [S22] proposed algorithm is known as HHO-MLP which hybridizes HHO algorithm and MLP method to examine the bearing capacity in the position of a classification issue in the geotechnical engineering problem. Seven settlement key factors were used to validate the algorithm. Moreover, the improved HHO-MLP was compared to DA-MLP algorithm. To validate the comparison results, MSE and MAE measurements are assessed. Results have shown that DA-MLP outperforms HHO-MLP in terms of consistency and obtains desired classification values.

In [S23], to landslide susceptibility analysis, proposed hybrid algorithm called HHO–ANN that is comprised of HHO and ANN is implemented. The experiment study involved 14 landslide conditioning factors that were used to evaluate the effectiveness of the proposed algorithm. Three statistical measurement metrics (e.g., AUROC, MSE, and MAE) were used to validate the comparison results of the HHO-ANN algorithm in relation to the ANN algorithm. The statistical analysis results prove that HHO effectively improved the performance of the ANN algorithm.

4.1.4 Solar photovoltaic

In the domain of engineering problems, [S26] proposed hybrid HHO algorithm with the ANN algorithm, named as HHO_ANN, to optimize productivity prediction accuracy of active solar still. Its performance was assessed using the dataset of 72 experiments with five variables performed for 3 solar cell cases, and it was compared to the other two algorithms; ANN and SVM. The comparison between these algorithms is carried out using seven measurement criteria such as RMSE, MAE, MRE, EC, R2, CRM, OI. The statistical results show that HHO_ANN has optimal prediction accuracy over ANN and SVM.

To measure the parameters of the single-diode photovoltaic model, [S27] presented a modified version of the HHO algorithm. The modified algorithm BHHO aims to control the balance between exploration and exploitation phases, enhance the performance of HHO in terms of increasing the population diversity and improving the convergence rate. To validate the performance of BHHO algorithm, experimental data of a Kyocera KC120-1 multicrystalline PV module form for seven weather conditions were used. Also, to measure the performance of BHHO, it was compared to many algorithms involved HHO, WOA, FPA, FA, ER-WCA, MVO, MFO, SSA, BOA, ABC, CS, EM, Rcr-IJADE, IADE, PDE, and PSO. The comparison results were validated based on multiple measurement values of RMSE, R2, STD, AE, TS, and MSE. Statistical results revealed that BHHO provides high consistent convergence comparing to other algorithms.

In the microgrid, HHO was applied to design an optimum controller for load frequency control [S28]. Five transfer functions were used to validate the algorithm. The conventional HHO was compared to three various algorithms, namely GOA, CSA, and GA. Results have shown that conventional HHO effectively outperforms other algorithms in terms of less overshoot and minimum settling time.

The work in [S29] used HHO algorithm to select the unknown parameters of the three-diode photovoltaic model. Experimental dataset of nine electrical parameters of TDPV model of KC200GT and CS6K280 M-PV modules was used to validate the conventional HHO. Also, to evaluate algorithm performance, it was compared with five state-of-the-art algorithms which are MLE, WOA, SFO, GA, and SA. The analytical results revealed that HHO has a smaller error, and HHO can be used to find the electrical parameters of any PV panels.

To measure the parameters of solar cells models of the three-diode photovoltaic model, the research in [S30] introduced the chaotic HHO algorithm by combining it with OBL mechanism and CLS strategy. The suggested algorithm is known as EHHO concerned with real-world engineering problems. EHHO aims to control the balance between exploration and exploitation phases and enhance the performance of HHO in terms of increasing the population diversity and improving the convergence rate. The effectiveness of the proposed algorithm was measured using the experimental dataset of three manufacturer's datasets. Moreover, EHHO was compared to four algorithms (e.g., BLPSO, CLPSO, IJAYA, and GOTLBO). Wilcoxon test of five measurement metrics, namely BEST, WORST, STD, and mean of RMSE result, was adopted to validate the result of performance comparison. Results show that EHHO improves search space and decrease stagnation, enhance the population intensification, and outperform other algorithms.

4.1.5 Power systems

In [S31], conventional HHO algorithm was used to address the directional overcurrent relays coordination problem. Four test systems: three-bus, four-bus, eight-bus, and nine-bus, and one measurement metric (e.g., STD) were used to evaluate the performance of conventional HHO. Moreover, it was compared with many state-of-the-art algorithms which are Seeker, GA, GA-LP, BBO, BBO-LP, and Jaya. The analysis result found that the conventional HHO outperforms other algorithms.

In real-world engineering problem, [S32] proposed hybridized HHO algorithm by combining the mutation-based GWO algorithm. The suggested algorithm MHHOGWO aims to enhance multistep short-term wind speed forecasting. The effectiveness of the proposed algorithm was measured using nine benchmark functions. Moreover, MHHOGWO was compared to seven algorithms (e.g., PSO, ALO, SCA, MFO, WOA, GWO, and HHO). Three statistical values: RMSE, MAE, and MAPE, are used to measure the performance of the compared algorithms. Results show that HHO can effectively achieve the simultaneous realization of parameters optimization and FS.

The work in [S33] implemented conventional HHO algorithm that aims to enhance the performance of ANFIS for online voltage stability assessment in the context of real-world engineering problems. Three test systems: IEEE standard 39-bus, 118-bus and 300-bus, were employed to validate the conventional HHO algorithm. Moreover, it was compared to different algorithms (e.g., LS + BP, GS + MLPNN, RWT + PCA + RBFNN) to evaluate its performance using RMSE, and STD measurement metrics tests. The statistical results demonstrate that HHO algorithm effectively improved the performance of ANFIS.

Conventional HHO algorithm, which aims to enhance power system performance by extracting the optimal parameters of load frequency control in the domain of power systems, was introduced by work in [S34]. Four different controller parameters were used to validate the performance of conventional HHO algorithm. The analytical results prove that HHO algorithm effectively improved the performance of the power system.

In the context of power systems, the work in [S35] proposed algorithm known as MHHOS, which is a modification of the HHO algorithm. It aims to optimize the damping oscillations controller design and to increase the population diversity. Five control parameters of PSS STATCOM were used to validate the algorithm. Moreover, the improved MHHOS was compared to ALO, WOA, and HHO algorithms to assess its performance. Results exposed that MHHOS outperforms other algorithms in terms of maximizing the minimum damping ration.

To enhance the power quality indicators, optimizing the design and control of MMC STATCOM is done using hybrid of HHO and ASO (e.g., HHO-ASO) [S36]. To achieve the validity of proposed HHO-ASO, authors used the objective function of THD. The improved algorithm was compared to three algorithms (e.g., ASO, HHO, and PSO). The experimental result revealed that HHO obtained the optimal solution in less time comparing to other algorithms.

Conventional HHO algorithm, which aims to optimize harmonic overloading of the frequency-dependent component, was presented by [S37]. Three different objective functions of C-type harmonic filter were used to validate the conventional HHO algorithm. The performance of HHO was obtained using BEST, WORST, mean, and STD measurement metrics and compared to three algorithms (e.g., SSA, CSA, and PSOGSA). The analytical results demonstrate that HHO outperforms other algorithms in terms of finding: (1) the minimum power loss and harmonic overloading level, and (2) the frequency-dependent components.

The work in [S38] used conventional HHO algorithm that aims to enhance power system performance by determining the gains of the PID in automatic generation control problem. Two power systems-based nine parameters and three transfer functions were used to evaluate the effectiveness of HHO algorithm. Moreover, ISE test was conducted to evaluate the performance of HHO. The performance result was compared to two algorithms SOS and ABC. Hence, the analytical results have shown that HHO outperforms other algorithms in terms of tuning parameters of PSS and STATCOM.

To address optimal power flow problems, the work in [S39] hybridized HHO algorithm with the DE algorithm. The introduced algorithm known as HHODE aims to optimize the solution for solving the optimal power flow problem. DE algorithm was used to maintain the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate. To assess the effectiveness of the HHODE, 13 benchmark functions of IEEE CEC2005 and IEEE CEC2017 were used. Also, to measure the HHODE performance, it was compared to various algorithms involved, HHO, GA, BBO, DE, PSO, CS, TLBO, BA, BAT, FPA, FA, GWO, and MFO. Results have shown that HHODE algorithm virtually outperforms other algorithms and maintained trade-off balance between exploration and exploitation phases.

In the context of the power system, the work in [S40] suggested an improved version of HHO to optimize high dimensionality of power flow problems in order to minimize fuel cost, emission, and power loss. The suggested algorithm (e.g., LMHHO) consists of a combination of HHO and long-term memory concept. LM aims to enhance the balance between exploration and exploitation phases and enhance the performance of HHO in terms of increasing the population diversity and improving the convergence rate. In the experiment study, 29 benchmark functions of CEC'17 are used to validate the effectiveness of LMHHO algorithm. Next, the performance of LMHHO is compared with nine algorithms involved, PSO, FPA, MFO, FA, WOA, SOS, Jaya, GWO, and BSA. *P* value, STD, mean measurement metrics are used to validate the comparison results. Results of this study revealed that LMHHO: (1) did not lose exploration ability throughout iterations; (2) maintained trade-off balance between exploration and exploitation; and (3) generated superior results than the competitive methods.

The work in [S41] introduced hybrid HHO, which is known as HHO-MLP. It aims to improve the heating ventilation and air-conditioning system. Dataset of heating load and the cooling load was used to validate the HHO-MLP algorithm. Moreover, the hybrid algorithm was compared with EHO-MLP and ACO-MLP. Next, the accuracy assessment results are validated using RMSE, MAE measurement metrics. The analysis results found that the proposed HHO-MLP has mostly underestimated the cooling load values and performed more accurately between the cooling load and input factors.

The paper in [S42] proposed algorithm known as LogHHO, which used logarithmic function to modify the HHO algorithm. The proposed algorithm aims to select the best allocation of DG units in the radial distribution system. Dataset of power system with VSC-based STATCOM device was used to validate the algorithm. Moreover, the improved LogHHO was compared to three various algorithms, which are HHO, GWO, and MFO. Results have shown that logHHO effectively finds optimal control parameters.

To address the distribution generation allocation problem, the work in [S43] proposed multiobjective of HHO based on grey relation decision making, which is called IHHO. The proposed algorithm aims to enhance the random location and find the best compromise solution among the nondominated solutions. The experiment study involved three objective functions (e.g., power loss, VD, and VSI), IEEE 33-bus, and IEEE 69-bus standard to validate the effectiveness of the proposed algorithm. The performance of IHHO is compared with PSO, MOPSO, LSF, fuzzy-IAS, BSOA, BFOA, TLBO, QOTLBO, SIMBO-Q, QOSIMBO-Q HHO, GA, GA /PSO, TM, MOTA, and MOHHO. Furthermore, in order to validate the efficiency of IHHO algorithm, statistical analysis of BEST, AVERAGE, and WORST is calculated and compared with the conventional HHO. The analysis result indicates that the proposed IHHO algorithm proves it is sufficient for: (1) selecting optimal allocation of DG in the radial distribution system, (2) reducing the total power and voltage deviation; and (3) the overall voltage profile.

To optimize sitting and sizing of the renewable energy source of distributed generator units, hybrid HHO and POS were introduced as HHO-PSO algorithm by [S44]. PSO aims to improve the exploration of the available search space of HHO. Three radial distribution systems (e.g., standard IEEE 33-bus, standard IEEE 69-bus, and practical Portuguese 94-bus) are used to validate the effectiveness of HHO-PSO. The result of HHO-PSO is compared with five traditional algorithms such as POS, HHO, BSOA, KHA, and SKHA. Statistical analysis of BEST, WORST, mean and STD functions is conducted to ensure the validity of proposed comparison results. However, the experimental results ensure the superiority of HHO-PSO over other algorithms by maximizing the techno-economic benefits of the distribution systems. However, this method still is prone to slow lazy convergence and sometimes it cannot maintain a very stable balance among exploration and exploitation.

In [S45], modification of HHO was introduced as MHHO. The proposed algorithm aims to maintain a balance between exploration and exploitation phases of HHO through increasing convergence rate of HHO with the minimum number of iterations. In the context of the power system, MHHO aims to define the best interconnection for the modules in the considered photovoltaic modules array during partial shading condition. The experiment study involved 23 CEC2005 benchmark functions and used two measurement metrics (e.g., STD, Mean) to validate the performance of the proposed algorithm. The proposed algorithm was compared with four state-of-the-art algorithms which are TCT, CS, GA, and HHO. The analysis result shows that the proposed MHHO reduced the total power and voltage deviation, improved the overall voltage profile, and solved the multipeak issue in the characteristics of the photovoltaic module.

To address photovoltaic modules reconfiguration optimization problem, the work in [S46] developed a chaotic HHO algorithm by combining OL, GOBL, and HHO algorithms. The introduced algorithm known as EHHO aims to extract the optimal parameters of solar cells and photovoltaic modules effectively and accurately and maintain the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate. Authors used two datasets of France photovoltaic cell (RTC) and Photowatt-PWP 201 photovoltaic module to evaluate and validate the proposed algorithm. The chaotic algorithm was compared to eight different algorithms involved, HHO, CPSO, PS, LMSA, ABC, ABSO, GOTLBO, and GOFPANM. Results ensure the superiority of EHHO algorithm to estimate unknown parameters in different solar cells and photovoltaic modules. However, still, some weaknesses such as convergence to local optima or slow convergence can happen in this version. Also, the designed improvements increased the time of run and the complexity of the HHO considerably.

The work in [S47] applied conventional HHO algorithm to solve load frequency control problems. This target is done by measuring the best parameters of the proportional–integral (PI) controller—two interconnected systems connected to the photovoltaic module employed to validate the conventional HHO algorithm. Also, the Wilcoxon signed-rank test is conducted to validate the comparison results of four algorithms (e.g., ALO, GWO, SCA, and MVO). The test results ensure that HHO was more effective in designing load frequency control.

In [S48], the authors introduced hybrid HHO, which is achieved by a robust integrated algorithm called FNN to HHO. The proposed algorithm, which is known as HHO-FNN, aims to reduce the prediction error by enhancing the performance of FNN. Collected datasets of weather data of the Queensland region were used to validate the HHO-FNN method. Moreover, the hybrid algorithm was compared with three state-of-the-art algorithms such as PSO-ANN, PSO-LSSVM, and BPNN. The statistical analysis result of MAPE, SMAPE, and D shows that the proposed HHO-FNN algorithm was effectively used for optimizing the weight and basis of neurons of the FNN algorithm.

The work in [S49] proposed hybridized HHO algorithm which is applied to improve the performance of the ANN algorithm in order to optimize solutions of getting the best of nonlinear Van der Pol dynamic heart model. It combines two main algorithms: HHO and IPA. IPA is aimed to improve the performance of HHO in determining the best solution. Different measurement methods (e.g., MAD, ENSE, RMSE, GbMAD, GbENSE, GbRMSE) were used to validate the improved HHO-IPA algorithm. Also, it was compared to the RNS algorithm. Results found that the proposed HHO-IPA outperforms RNS algorithm.

4.1.6 Other engineering areas

To synthetic aperture radar target recognition and predict the stock market, the research in [S10] proposed a new algorithm known as IHHO-SVM, which hybridizes four main algorithms, namely HHO, ATA, SVM, and ELM. The main goal of the proposed algorithm is to add velocity into the exploration phase. To accomplish the validity of the IHHO-SVM, authors used 23 benchmark functions. The improved algorithm was compared to eleven algorithms (e.g., ALO, DA, DE, GA, GWO, MFO, SCA, WOA, PSO, AT, HHO). Results of this study revealed that IHHO-SVM improved the position vectors of HHO, found the optimal solution faster, and increased the convergence rate.

In [S11], to predict the students' entrepreneurial intention on self-employment, hybridization algorithm of HHO, GB, and KELM was introduced. The new algorithm is called GBHHO-KELM. In this study, GB algorithm was combined with HHO to improve the exploration and exploitation ability of HHO. Next, the developed GBHHO is integrated into KELM to support the optimization performance for tuning parameters of KELM. The experiment study involved 30 IEEE CEC 2014 benchmark functions and used four measurement metrics (e.g., *p*-value, STD, mean, AVE) to validate the effectiveness and performance of the proposed algorithm. The proposed algorithm was compared with nine state-of-the-art algorithms which are MFO, FA, GWO, HHO, WOA, ACWOA, OBSCA, OBLGWO, and SCADE. The statistical analysis results prove that the proposed GBHHO-KELM achieved smaller fitness and variance and obtained better parameter combinations and feature subset. However, there are some weaknesses in this study; first, the cost of computation is considerably increased. Second, sometimes the results are not very near to global optima, and convergence to local optima or slow convergence can happen in this version. Also, the dataset of this paper was limited, and a more comprehensive test could show more positive and negative aspects of this version in training KELM.

In [S12], the authors introduced chaotic HHO by using chaos strategy. The proposed algorithm, which is known as CHHO, aims to obtain the proper operating parameters of PEMFC in the exploration phase. Ten chaotic functions and different measurement metrics (e.g., STD, BEST, WORST, MAE, RMSE, RE, median, mean) were used to validate the CHHO algorithm. Moreover, the CHHO was compared with four state-of-the-art algorithms which are: HHO, GWO, CS-EO, and SSO. The analysis result found that the proposed CHHO achieves high accuracy in extracting the optimal parameters of PEMFC, and it outperforms other algorithms. Though, this paper applied the chaos to enhance the performance, but, the studied chaotic signals are limited as they could apply some chaos-based operators for the method in the various phases with no extensive cost. Also, some flaws, such as convergence to local optima or slow convergence, can happen in this chaotic version because some main components of the HHO are still unchanged in this version. Also, this study did not include comparisons with other variants of HHO or enhanced versions of the PSO, or DE to confirm the efficacy more strongly.

To extract the global optimal solutions for high-dimensional problems, hybridization HHO called HHO-FORM was suggested in [S13]. To measure the effectiveness of the proposed algorithm, five explicit and implicit performance functions were used. Also, the performance of HHO-FORM was measured by comparing it with different algorithms (e.g., PSO-FORM, jHLRF, GWOFORM, iHLRF, SSA-FORM, DA-FORM, SQP, HLRF) based on multiple measurement metrics, which includes STD, BEST, average, and mean. Results have shown that HHO-FORM was able to increase the convergence rate.

The researchers in [S14] have employed conventional HHO algorithm to enhance the performance of microchannel heat sinks. Its performance was assessed using two dimensionless parameters, and it was compared to other algorithms; PSO, DA, WOA, and GOA. Results show that HHO can outperform other algorithms in a reduced amount of CPU time. However, this study did not include comprehensive comparisons with more methods and the other variants of HHO, DA, WOA, GOA, PSO, or DE to verify the performance more deeply. Also, from the components of this variant, the power of this variant is very delicate.

In [S24], to address the engineering problem, authors proposed hybridization HHO algorithm that is comprised of HHO and MSCA algorithms, known as MSCAHHO. Such integration aims to diagnose the faults in rolling bearings. To confirm the algorithm, nine benchmark functions were used. To evaluate the suggested algorithm effectiveness, the proposed MSCAHHO algorithm was compared to SCA, HHO, PSO, and BPNN algorithms using the STD and mean measurement metrics test. The analysis results show that MSCAHHO outperforms PSO and BPNN for improving the performance of SVM.

To optimize the prediction accuracy of slope stability conditioning factors, a hybridization HHO called HHO–ANN was suggested [S25]. To measure the effectiveness of proposed algorithm, 75 datasets of four slope stability conditioning factors were used. Also, the performance of HHO-ANN was measured by comparing it with the MLR algorithm based on multiple measurement metrics, which include RMSE, MAE, and R2. Results ensure that HHO is able to increase the prediction accuracy of the ANN and it outperforms MLR. However, this version is elementary, and still, it is prone to high chance of stagnation problems, especially if we add more datasets and if we give less iterations. Also, this study did not include comparisons with more cutting-edge variants of PSO, or DE to verify the performance more strongly.

4.2 Computer science

4.2.1 Data mining and processing

In the context of task scheduling in cloud computing, [S50] presented a modified version of HHO that aims to find an optimization of the solution of scheduling jobs. The improved algorithm named as HHOSA was introduced to enhance the performance of HHO by improving the convergence rate and improving local search. To validate the improved algorithm, two standard parallel workloads (NASA Ames iPSC/860 and HPC2N) were used. The improved algorithm was compared to five different algorithms involved, SSA, MFO, PSO, FA, and HHO. Results of this study revealed that HHOSA outperforms other scheduling algorithms in terms of achieving near-optimal performance. However, the convergence rate and intensification traits are improved to a limited extent, and if this version is applied to more variety of problems, maybe it quickly faces stagnation problems. Also, this study did not include comparisons with more advanced variants of PSO, or other advanced variants of SSA, MFO, GWO, or DE.

In [S51], to determine the best position vectors of centroids that represent the best representative of clusters, chaotic sequence-guided HHO was introduced as CHHO. This algorithm aims to avoid the problem of local entrapment at the exploration phase. The experiment study involved 12 benchmark datasets of the UCI machine learning repository and used two different tests: Friedman test and Iman–Davenport test, to validate the performance of the proposed algorithm. The CHHO was compared with six competitive algorithms which are HHO, GWO, BOA, MVO SCA, and SSA. The analysis result shows that the proposed CHHO outperforms other algorithms in terms of position vectors that are best representative of clusters. However, the convergence rate and intensification traits are improved to a limited extent, and if this version is applied to more variety of problems, maybe it quickly faces stagnation problems.

In [S52], a hybridization of HHO and SSA was introduced as IHHO and implemented to optimize feature selection tasks in the context of data mining. IHHO aims to increase the population diversity, improve the convergence rate, and control the balance between exploration and exploitation levels of the traditional HHO. The experiment study involved 23 benchmark functions in validating the effectiveness and applicability of the proposed algorithm. The IHHO was compared with 11 state-of-the-art algorithms which are HHO, DE, GWO, WOA, SSA, MFO, SCA, PSO, MVO, ALO, and GOA. The analysis results of mean and STD show that the proposed IHHO (1) provides better solution quality and faster convergence speed; (2) improves optimization search process; (3) has adequate global exploration ability; and (4) avoids falling into a local optimum. However, the convergence rate and intensification traits could be designed to reach better quality, and if this version is applied to more variety of problems, maybe it quickly faces stagnation problems due to the limited potential of the SSA algorithm, as the paired method. Also, this study did not include comparisons with more advanced variants of HHO, DE, GWO, WOA, SSA, MFO, SCA, PSO, MVO, ALO, and if they could consider, maybe the goodness of results could be questioned.

The work in [S53] presented hybridization HHO algorithm known as BHHO that aims to optimize feature selection tasks in the context of data mining. Nine datasets and Wilcoxon rank-sum test were used to validate the BHHO algorithm. The BHHO was compared to six algorithms (e.g., BGSA, BSSA, GA, BPSO, BBA, BALO). The analytical results have shown that HHO algorithm effectively handles the problem of dealing with high-dimensional real-world datasets that have a low number of samples. The proposed model has a good accuracy of the results. However, this research did not conduct extensive comparisons with more advanced variants of GOA like the GOAEPD, asynchronous SSA, and other well-established feature selection tasks, and if they could consider, maybe the goodness of results could be questioned. The comparison methods could be more to verify the convergence of the proposed BHHO more deeply. Also, they have not applied time-varying transfer functions to the proposed BHHO-based feature selection method, and if they could do, it could show more valuable results.

4.2.2 Image thresholding

In [S56], image segmentation problems were represented by determining the optimum thresholds of the color image, addressed by using an improved version of the HHO algorithm. The improved algorithm consists of the DE algorithm and HHO named as HHO-DE. It aims to enhance the basic global and local search capacities preserved in the exploration phase of standard HHO. To validate the performance of HHO-DE algorithm, ten benchmark images and multiple measurement functions (AFV, STD, PSNR, SSIM, and FSIM) were used. The improved algorithm was compared to seven different algorithms involved, HHO, DE, SCA, BA, HSO, PSO, and DA. Statistical analysis results revealed that HHO-DE outperforms other algorithms in terms of determining the optimum thresholds of the color image. However, this method still is prone to weak convergence, and sometimes it cannot uphold a very stable balance among exploration and exploitation. Also, this research has not performed comparisons with more advanced variants of HHO, DE, SCA, BA, HSO, PSO, and DA, and if they could study, maybe the claims of the paper were more strong.

To solve image segmentation problems, [S57] suggested a hybridization HHO and SSA algorithms that were introduced as HHOSSA.[1] The enhanced algorithm aims to optimize the solution for multilevel image segmentation and maintain the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate. Thirty-six IEEE CEC 2005 benchmark functions and 11 natural grayscales were used to evaluate the effectiveness of the proposed algorithm. Also, to measure the HHOSSA performance, HHOSSA was compared to 13 competitive algorithms involved, HHO, GWO, WOA, SCAOBL, SSA, LSHADE, SCA, MSADE, SHO, ABC, BSOMFO, MFO and MVO. Wilcoxon's rank-sum test is used to validate the comparison results. As per the analysis of results, they ensure the superiority of HHOSSA algorithm over other algorithms in terms of optimizing solution for multilevel image segmentation and reaching a more stable level of performance. However, the immature convergence trends can be still observed in dealing with some image datasets, and sometimes HHOSSA cannot uphold very stable stability among exploration and exploitation due to the limits of the integrated SSA.

To optimize the solution for multilevel image segmentation and to control parameter E (escaping energy) of HHO algorithm, a hybridization of HHO and DEA algorithms which are known as DEAHHO, was suggested by [S58]. The effectiveness of the proposed algorithm was measured using 23 benchmark test functions and 500 images. Moreover, DEAHHO was compared to seven algorithms (e.g., HHO, CS, PSO, FA, WDO, STOA, and DE) to evaluate its performance using PSNR, SSIM, and FSIM measurement metrics. The analysis results revealed that DEAHHO (1) outperforms other algorithms in terms of optimizing solution for multilevel image segmentation and (2) could be used in the segmentation of biomedical images.

The work in [S59] presented the modified version of the HHO algorithm. The modified algorithm named as MCET-HHO.[2] It aims to optimize the solution for multilevel image segmentation and enhance the performance of HHO in terms of improving the convergence rate and local search. To evaluate MECT-HHO effectiveness, three sets of benchmark images were used. Next, MCET-HHO was compared with nine algorithms, namely HHO, PSO, FFO, DE, HS, ABC, SCA, K-means, and Fuzzy IterAg. Statistical analysis result of multiple measurement metrics (e.g., STD, PSNR, RMSE, SSIM, FSIM, G, PC, PRI, VoI, and GCE) validates the performance of MCET-HHO algorithm. MCET-HHO algorithm proves its superiority over other algorithms in terms of optimizing solution for multilevel image segmentation. However, the immature convergence tendencies can be still observed in dealing with some image datasets. Also, they have not compared their method with other advanced variants of HHO, DE, PSO, or improved FFO, HS, ABC, and SCA versions.

To address multilevel color satellite images segmentation problems, [S60] presented a chaotic HHO algorithm by combining DCPS and DE/best/2 (mutation operator to enhance population diversity) strategies. The introduced algorithm known as DHHO/M aims to extract boundaries, locate objects, and separate regions in a high-resolution satellite in addition to maintaining the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate. To evaluate DHHO/M effectiveness, eight satellite images were used. Also, to measure the DHHO/M performance, it was compared to eight different algorithms involved, HHO, TLBO, IDSA, BDE, MGOA, MABC, MFPA, and GWO, using multiple measurement metrics (e.g., AFV, STD, PSNR, MSE, SSIM, FSIM, ACT). Results have shown that DHHO/M algorithm effectively improves the quality of the result for satellite images in terms of objective function value practicality and feasibility.

To address image denoising problems, the work in [S61] proposed hybridization algorithm called HHO-JADE that is

[1] The access to materials of this research is available at: https://aliasgharheidari.com/publications/HHOSSA.html

[2] The access to materials of this research is available at: https://aliasgharheidari.com/publications/MCETHHO.html

comprised of HHO and JADE. The proposed algorithm aims to process the denoised image data for finding the improved parameters of the thresholding functions. The experiment study involved six satellite images that were used to evaluate the effectiveness of the proposed algorithm, in addition to two measurement metrics (e.g., PSNR, MSSIM) which are used to validate the performance of the HHO-JADE algorithm in relation to three state-of-the-art algorithms which are JADE, BM3D, and WNNM. The analysis result shows that the algorithm performs much better than other algorithms visually and quantitatively.

The work in [S62] hybridized HHO algorithm by combining the SSBS algorithm. The improved algorithm is named as HHO-SSBS. It aims to process the denoised image data for finding the improved parameters of the thresholding functions. To evaluate HHO-SSBS effectiveness, three satellite images were used. Also, to measure its performance, the algorithm was compared to five state-of-the-art algorithms; JADE, Sahraeian's TNN, Noorbakhsh-TNN, Sahraeian-HHO, and Noorbakhsh-HHO. Results of the analysis revealed that HHO algorithm performs much better than other algorithms visually and quantitatively.

4.2.3 Networking

To solve a complex combinatorial optimization problem, the work in [S54] improved chaotic HHO algorithm by combining NCPS, ROBLS, and HHO algorithms. The suggested algorithm known as NOL-HHO aims to estimate the optimal constrained DNA-sequence lower bound and maintain the balance between exploration and exploitation phases in terms of increasing the population diversity and improving the convergence rate of conventional HHO. Authors used 23 benchmark functions to evaluate and validate the proposed algorithm. The chaotic algorithm was compared to ten competitive algorithms involved, HHO, GA, PSO, BBO, FPA, GWO, BAT, FA, MFO, and DE. Wilcoxon rank-sum test results had shown that NOL-HHO algorithm effectively provides better solution quality and faster convergence speed, improves the optimization search process, adequate the global exploration ability, and avoids falling into a local optimum.

In the context of visible light communications [S55], authors introduced hybridization HHO which is known as HHO-FNN and aims to optimize the sum rate of ground users subject to constraints on power allocation in the domain of distributed systems. GRPA, RandP, and Conventional OFDMA [1.46] procedures were used to validate the HHO-FNN algorithm. Moreover, the hybrid algorithm was compared with three state-of-the-art algorithms which are PSO, ES, and GA. The analysis result found that the proposed HHO-FNN outperforms other algorithms in terms of optimization problem—power allocation problem.

To solve the service composition problem, the research in [S63] presented the chaotic HHO algorithm by combining it with LCSDP strategy. The presented algorithm is known as CHHO. It aims to improve the local search of HHO in the exploration phase in order to address the QoS-aware web service composition problem. The effectiveness of the proposed algorithm was measured using QWS2.0 Datasets. Moreover, to evaluate the performance of CHHO, it was compared to three algorithms (e.g., HHO, ESWOA, and mABC). Friedman test and Wilcoxon signed-rank test results show that CHHO outperforms other algorithms in terms of performance, especially in large-scale scenarios.

[S64] implemented conventional HHO algorithm that aims to allocate distributed generations (DGs) along with DNR in the context of distribution network reconfiguration problems. Eighty-three-node practical distribution system was employed to validate the conventional HHO algorithm. The analytical results have shown that HHO improves loss minimization level and enhances voltage stability.

[S65] implemented conventional HHO algorithm that aims to optimize the network lifetime in the context of large-scale wireless sensor networks deployment problems. Twelve parameters of LSWSNs were employed to validate the effectiveness of conventional HHO algorithm. Moreover, it was compared to six algorithms (e.g., PSO, FPA, GWO, SCA, MVO, WOA) to evaluate its performance using measurement metrics (e.g., mean, STD, BEST, WORST). The analytical results have shown that HHO achieved the best solutions with the lowest energy consumption and localization error.

4.2.4 Software engineering

Conventional HHO algorithm was applied to select the best test cases in the context of minimizing regression testing expense problems [S66]. Five different objects of SIR were used to validate the conventional HHO algorithm. It was compared to the HS algorithm to measure its performance. In terms of the fault coverage, HHO outperforms HS algorithm.

The work in [S67] developed hybridization HHO which is comprised of HHO and EB algorithms which are known as EBHHO. EBHHO aims to optimize the solution for predicting the faulty components in a software project. The hybridization HHO aims to preserve the balance between exploration and exploitation phases, to increase the population diversity and to improve the convergence rate of HHO. Fifteen well-regarded SFP datasets were used to validate the EBHHO method. Also, to evaluate EBHHO performance, it was compared with eight state-of-the-art algorithms which are ESBHHO, EVBHHO, BGSA, BGOA, WOA, BBA, GA2, and bALO. The analysis result ensures the superiority of EBHHO algorithm over other algorithms when were used with LDA classifier.

4.3 Medicine and public health

The work in [S68] proposed an integrated SVM and KNN algorithm with hybridized HHO to select the best feature for achieving high classification accuracy of chemical descriptor selection and chemical compound activities, in terms of drug design chemical descriptor selection problems. Two chemical datasets (MonoAmine Oxidase and QSAR Biodegradation) were used to validate the proposed integrated model. To evaluate algorithm performance, it was compared with nine state-of-the-art algorithms which are GWO, DA, SCA, HHO, SSA, BOA, MFO, PSO, and SA, using various validation measurement metrics (e.g., mean, BEST, WORST, STD). The analytical results revealed that the optimization model outperforms other algorithms in terms of obtaining the optimal features.

To solve feature selection-breast mass classification problems, the research in [S69] proposed an improved chaotic HHO algorithm by combining opposition-based strategy. The suggested algorithm is known as OHHO concerned with feature selection in breast masses. The effectiveness of the proposed algorithm was measured using seven benchmark functions. Moreover, OHHO was compared to four algorithms (e.g., PSO, SCA, GWO, and HHO). The comparison result was validated using mean and STD measurement metrics. Statistical results show that OHHO outperforms other algorithms in terms of feature selection in breast masses classification.

5 Evaluation of the HHO

The HHO is one of the population-based metaheuristic algorithms proposed to address single-objective optimization problems. Naturally, it is inspired by the hunting behavior of Harris hawks. Methodically, HHO aims to find one single unsystematic solution that is improved by conducting several iterations. Mathematically, the HHO model consists of three phases: exploration phase, a transition from exploration to exploitation, and exploitation phase.

Although the HHO was proposed two years ago, the increased interest has led to the growth of this algorithm significantly and broadly. Practically, as shown in Tables 1, 2, and 3 and discussed in Sect. 4, HHO demonstrates a clear superiority over the most advanced metaheuristic algorithms in solving several common and complex optimization problems in various fields. However, like all other optimization algorithms, the HHO has advantages and disadvantages (limitations). Generally, the main advantages of HHO are easy to be executed and flexibility, while the standard limitation of HHO is that HHO cannot be considered as optimal algorithm appropriate to all optimization problems. It is well known that there is no best optimizer for any possible computational task. Specifically, this study introduced four criteria to evaluate HHO algorithm. These criteria were described in greater detail as follows:

- *Usability:* It refers to the degree of how well users can use HHO to address optimization situations. This criterion was further divided into three subcriteria, which are:
- *Ease of use:* It refers to the simplicity of HHO implementation and execution. As shown in Algorithm 1, the logic of HHO is not complicated, which does not need significant computational effort for each iteration. Besides, the computational steps of HHO do not need much effort to learn it where it can be easily understood and implemented by most interested users in practice.
- *Usefulness:* It indicates that using HHO has a benefit to enhance optimization solutions. As presented in Tables 1, 2 and 3 and Fig. 5, HHO was applied to 12 domain areas (improved HHO, manufacturing industry, environmental quality, solar photovoltaic, power systems, other engineering areas, data mining and processing, image thresholding, networking and distributed system, software engineering, drug design and discovery, mammogram images classification) under three main domains (e.g., engineering, computer science, and medicine and public health) related to different optimization problems. As presented in the column "Result" in Tables 1, 2, and 3, there is a clear consensus from all studies on the usefulness and effectiveness of HHO algorithm in solving optimization problems.
- *Flexibility:* It indicates the ability of HHO to be improved (e.g., modification, hybridization, multiobjective, binarization, chaotic, etc.…). It is evident from Figs. 6, 7 and Tables 1, 2, and 3 the flexibility of HHO is improved and/or integrated with other algorithms in order to improve the quality of optimization solutions. This review identified and categorized 57 versions of HHO such as six modification versions and 36 hybridization versions to one multiobjective version 2 binarization version, and 12 chaotic version. This variant of HHO indicates the adaptability of HHO to develop solutions to various optimization problems.
- *Structure comprehensiveness:* It refers to the quality of exploration and exploitation phases to find a solution for the decision variables under different optimization situations (e.g., large-scale optimization problems, normal or complex optimization problems). According to [21, 22], the success of the search algorithm depends

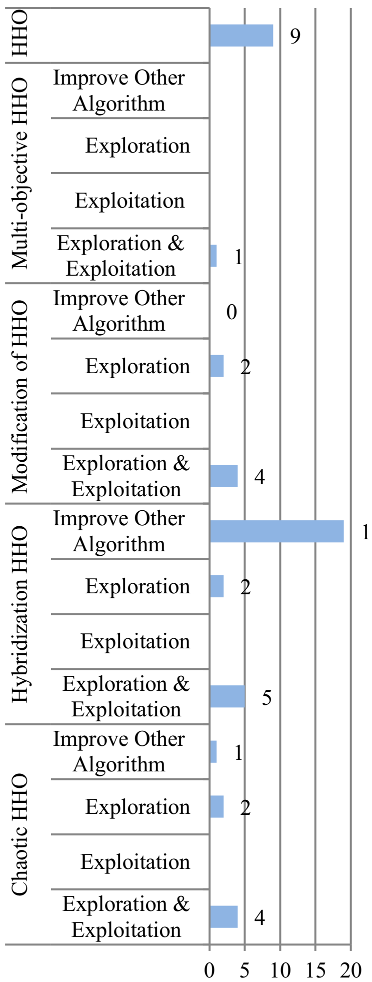


Fig. 6 HHO and HHO version in the engineering domain

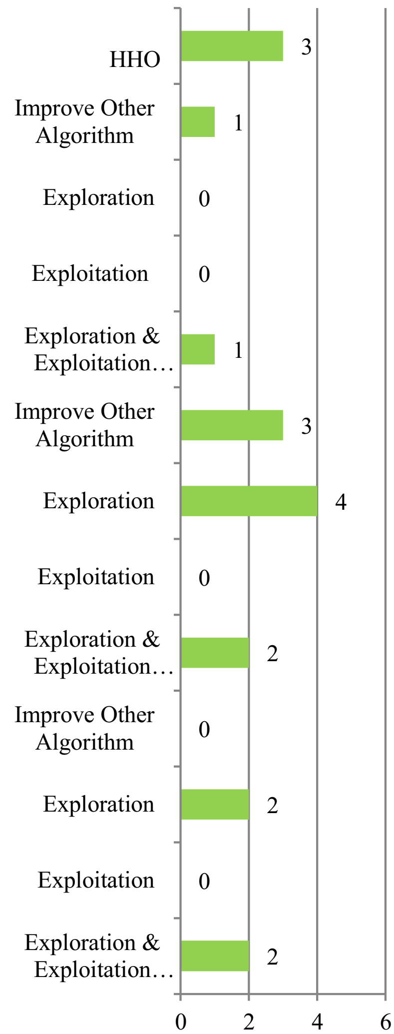


Fig. 7 HHO and HHO version in the computer science domain

on the ratio between exploration and exploitation. Therefore, guarantee not to be trapped in low diversity, local optima, and unbalanced exploitation ability are necessary to ensure the structure comprehensiveness of HHO. In Tables 1, 2, and 3, studies proposed by authors in [S14], [S28], [S29], [S31], [S33], [S34], [S37], [S38], [S47], [S64], [S65], [S66] ensure that HHO has high ability to exploit the local search space. However, this is true in the normal optimization situations. This is because (1) HHO applies sequences of searching strategies based on E and r parameters to select the best movement step, (2) applies quick team dives based on levy flight (LF) to improve the exploitation capacity. Besides, in exploratory and exploitative phases of HHO, the conducted progressive rapid dives improve the solution quality. Moreover, to avoid trapping into local minima, synchronization between exploration and exploitation is controlled using escaping energy. However, in dealing with large multimodal and composition optimization problems, HHO may still face some limitations. It is evident from Tables 1, 2, and 3, the column "area of improvement" that the overwhelming majority of the proposed studies attempt to improve either the Exploration phase or both the Exploration and Exploitation phases of HHO. This is consistent with the result of an experimental study conducted by Heidari et al. [1], which shows that HHO fails to give the best solutions in some cases of unimodal and multimodal problems. The majority of reviewed studies attribute this phenomenon to (1) lack global exploration ability to jump out of local optima, (2) lack of control the balance between exploration and exploitation (control parameter E may change convergence rapidly to the optimal solution that may fall among other solutions that already fallen into local optima), (3) unsatisfactory HHO performance in the case of higher multimodal dimensions problems.

- *Considering comprehensive classes of optimization:* It refers to the efficiency of HHO and/or HHO versions (chaotic HHO, hybridization HHO, modification of HHO, multiobjective HHO, binarization HHO) to handle various types of optimization problems such as unconstrained, constrained, variables (integer, continuous, discrete, binary), fitness function (linear, nonlinear, mixed-integer nonlinear), the search space (convex, nonconvex). Generally, as presented in Tables 1, 2, and 3 column "Problem type", HHO along with its versions has been successfully applied to several optimization problems such as global optimization problems, real-world optimization problems engineering design and optimization problems, classification and prediction problems, manufacturing optimization problem, geotechnical engineering problems, power quality problems, feature selection problem, image segmentation problems, drug design problem). Originally, the HHO was proposed to solve any continuous and unconstrained optimization problem [1]. Table 4 presents the most common classes of optimization problems which were addressed using HHO and/or HHO versions. Table 2 reveals that HHO and/or HHO versions were successfully applied and tested for solving very complex optimization problems. For example, the study proposed by [S2] implemented hybridization HHO that can handle constrained continuous, discrete, and nonlinear optimization problem. In [S63], chaotic HHO was proposed to solve the discrete and nonlinear optimization problem. However, modification of HHO proposed by [S5] is used to address constrained, discrete, nonlinear, and mixed-integer nonlinear problem. In addition, studies such as [S9], [S52], [S44], and [S43] addressed multiobjective optimization problem. Moreover, the work in [S31] tests HHO to solve unconstrained, constrained, continuous, discrete, linear, nonlinear, mixed-integer nonlinear optimization problem. Besides, as shown in Tables 1, 2, and 3, column "Benchmark functions/Performance metrics" HHO and HHO versions were validated and tested using a well-studied set of (various benchmark functions, datasets, test systems, and real-world problems) with diverse difficulty levels such as multimodal, unimodal, and fixed modal dimension. Hence, it can be safely said that HHO and HHO versions are provided comprehensive classes of optimization.
- *Performance (time, accuracy)*: It refers to the degree of how running fast (time) HHO takes to discover the best solution (accuracy) for a specific problem (functions) with diverse difficulty levels (problem dimensionality). Initially, the experimental and comparison results conducted by [1] ensure the superiority of HHO speed and accuracy over 11 other well-established metaheuristic techniques (e.g., GA, PSO, BBO, FPA, GWO, BAT, FA, CS, MFO, TLBO, and DE) applied on 29 benchmark problems selected form [23–25] and six real-world engineering problems (e.g., Three-bar truss design problem, tension/compression spring design, pressure vessel design problem, welded beam design problem, multiplate disk clutch brake, and rolling element bearing design problem). In this review, as presented in Tables 1, 2, and 3, column "variant/method" and column "compared algorithms" the speed and accuracy of HHO were compared with other competitive metaheuristic techniques on different real-world optimization problems. For example, HHO proves its superiority over PSO, BeA, DA, WOA, and GOA to solve an engineering microchannel heat sink optimization problem in less CPU time [S14]. In [S28], HHO outperforms other GOA, CSA, and GA for solving the problem of designing an optimum controller for load frequency control in the microgrid. Besides, HHO shows reasonably fast and low error over MLE, WOA, SFO, GA, and SA algorithms in finding the electrical parameters of any photovoltaic panels [S29]. In the context of improving the performance of ANFIS for online voltage stability assessment, HHO effectively improved the performance of ANFIS in the task of simultaneous realization of parameters optimization and feature selection [S33]. Moreover, [S47] ensures that HHO outperformed over ALO, GWO, SCA, and MVO to estimate the best parameters of the proportional–integral controller. However, in the computer since domain, HHO shows a competitive result comparing with PSO, FPA, GWO, SCA, MVO, and WOA for optimizing the network lifetime in wireless sensor networks by achieving the best solutions with the lowest energy consumption and localization error [S65].

Based on the above HHO evaluation criteria, it can be safely said that the HHO algorithm was well structured to be easy to use, useful, and flexible. Additionally, the structure of HHO plays a significant role in guaranteeing to converge close, improve the estimate of the solution of the different types of optimization problems and models rapidly and accurately comparing with other well-known nature-inspired techniques. However, the evaluation result reveals that even HHO is capable for solving various types of optimization problems, but in multiobjective, complex, and composite optimization problems population diversity, convergence rate, and balance between exploration and exploitation of HHO need to be improved.

Table 4 Most common classes of optimization problems addressed using HHO and/or HHO versions

Classes of optimization problems	Chaotic HHO	Hybridization HHO	Modification of HHO	Multi-objective HHO	Binarization HHO	HHO
Unconstrained optimization	N/A	[S13] [S24] [S57]	[S5]	N/A	N/A	[S31]
Constrained optimization	[S7] [S8] [S54]	[S2] [S13] [S24] [S44] [S57]	[S5] [S40] [S44]	N/A	N/A	[S31] [S37]
Continuous optimization	[S46]	[S2] [S17] [S18] [S52] [S61]	[S40]	N/A	N/A	[S31]
Discrete optimization	[S63]	[S2] [S20] [S44]	[S5]	N/A	N/A	[S31]
Binary optimization	[S69]	[S52] [S32]	N/A	N/A	[S67]	N/A
Linear optimization		[S15] [S24] [S26]	N/A	N/A	N/A	[S31] [S37]
Nonlinear optimization	[S7] [S30] [S46] [S51] [S54] [S63]	[S2] [S9] [S13] [S15] [S17] [S18] [S23] [S24] [S25] [S26] [S32] [S36] [S41] [S44] [S49] [S61] [S62] [S68]	[S40] [S5]	N/A	N/A	[S29] [S31] [S34] [S37] [S47]
Mixed-integer nonlinear programming	[S63]	N/A	[S5]	N/A	N/A	[S31] [S64]
Multi-objective optimization	N/A	[S9][S52][S44]	N/A	[S43]	N/A	N/A
Non-convex optimization	N/A	[S2][S55]	[S40]	N/A	N/A	N/A
Convex optimization	N/A	N/A	N/A	N/A	N/A	N/A

6 Results of HHO and discussion

In this section, we added the results of HHO in solving two engineering design problems (i.e., welded beam design problem and pressure vessel design problem).

The fundamental goal of the problem of the welded beam design is to identify the minimum cost of production by determining the optimum value of the given variables (four variables of optimization as shown in Fig. 8, particularly the length of the attached component of the bar (l), the weld thickness (h), the height of the bar (t), and the thickness of the bar (b).

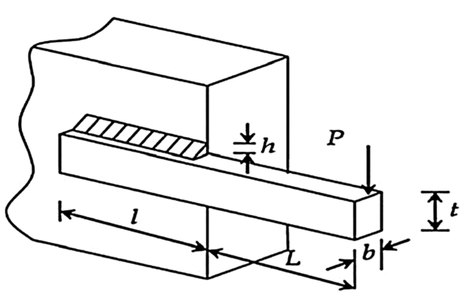


Fig. 8 Welded beam design problem: **a** schematic of the weld; **b** stress pattern evaluated at the optimum design; **c** displacement appearance at the optimum design

Table 5 shows the comparative methods' performance in including GSA, PHSSA, SIMPLEX, HS, OBSCA, DAVID, CSCA, MVO, APPROX, RO, GA, CPSO, WOA, and HHO for solving the welded beam design problem. It is clear that the HHO got promising results in solving the given problem compared to the published similar methods in the literature.

The tension/compression spring design issue's primary objective is to find the minimum weight of the tension/compression spring to meet its design limitations: shear stress, surge duration, and defection, as seen in Fig. 9. It is vital to take into account three design variables: wire diameter (d), mean coil diameter (D), and the number of active coils (N).

Table 6 shows the comparative methods' performance in including CC, GA, ES, MVO, PHSSA, HS, WOA, CSCA, GSA, PSO, RO, and HHO for solving the tension/compression spring design problem. It is obvious that the HHO got encouraging results in solving the presented problem matched to the published similar methods in the literature.

Table 5 Results of the comparative algorithms for the welded beam design problem

Algorithm	Reference	*h*	*l*	*t*	*b*	Optimal Cost
GSA	[S70]	0.182129	3.856979	10	0.202376	1.87995
PHSSA	[S71]	0.202369	3.544214	9.04821	0.205723	1.72802
SIMPLEX	[S72]	0.2792	5.6256	7.7512	0.2796	2.5307
HS	[S73]	0.2442	6.2231	8.2915	0.24	2.3807
OBSCA	[S74]	0.230824	3.069152	8.988479	0.208795	1.722315
DAVID	[S72]	0.2434	6.2552	8.2915	0.2444	2.3841
CSCA	[S75]	0.203137	3.542998	9.033498	0.206179	1.733461
MVO	[S70]	0.205463	3.473193	9.044502	0.205695	1.72645
APPROX	[S72]	0.2444	6.2189	8.2915	0.2444	2.3815
RO	[S76]	0.203687	3.528467	9.004233	0.207241	1.735344
GA	[S77]	0.2489	6.173	8.1789	0.2533	2.43
CPSO	[S77]	0.202369	3.544214	9.04821	0.205723	1.72802
WOA	[S78]	0.205396	3.484293	9.037426	0.206276	1.730499
HHO		0.204039	3.531061	9.027463	0.206147	1.731991

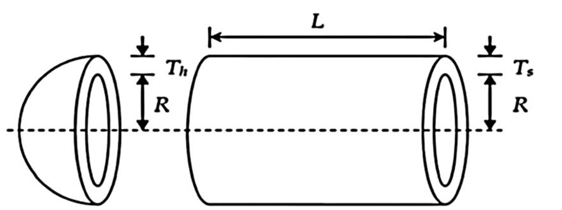


Fig. 9 Pressure vessel design problem: **a** schematic of the vessel; **b** stress pattern assessed at the optimum design; and **c** displacement pattern assessed at the optimum design

7 Conclusion and future directions

The HHO is a very recent algorithm that has received the special attention of many researchers to solve different types of optimization problems, for example, modification, hybridization, multiobjective, binarization, chaotic. It can be easily recognized as the most popular metaheuristic method in 2020. This increased interest is evident in this review, as 69 papers were selected from six sources published during one year and a half ago (March 2019 to May 2020). Also, the diversity of algorithm applications in three different research areas (e.g., engineering, computer science, and medicine and public health) to solve various optimization problems (e.g., power engineering problems, feature selections problems, image segmentation problem, manufacturing engineering problems, and drug design problem) under diverse difficulty levels shows how efficient, promising, and interesting this algorithm is. Several improved versions of HHO have been compiled, reviewed, and analyzed, where the proposed versions of HHO support to improve the performance of the original HHO. In this review, the most common improved areas of HHO were identified and discussed. Also, the approaches applied to validate the effectiveness and performances of HHO (benchmark functions/performance metrics and compared algorithms) were identified. Finally, to evaluate HHO, four evaluation criteria were identified and defined in this study, for instance, usability, structure comprehensiveness,

Table 6 Results of the comparative algorithms for the tension/compression spring design problem

Algorithm	Reference	*d*	*D*	*N*	Optimal cost
CC	[S79]	70.05	0.3159	14.25	0.012833
GA	[S80]	0.05148	0.351661	11.6322	0.012705
ES	[S81]	0.051643	0.35536	11.39793	0.012698
MVO	[S70]	0.05251	0.37602	10.33513	0.01279
PHSSA	[S71]	0.33168	12.83427	0.050191	0.012395
HS	[S82]	0.051154	0.349871	12.07643	0.012671
WOA	[S78]	0.051207	0.345215	12.00403	0.012676
CSCA	[S75]	0.051609	0.354714	11.41083	0.01267
GSA	[s70]	0.050276	0.32368	13.52541	0.012702
PSO	[S77]	0.051728	0.357644	11.24454	0.012675
RO	[S76]	0.05137	0.349096	11.76279	0.012679
HHO		0.051796	0.359305	11.13886	0.012665

considering comprehensive classes of optimization, performance. The evaluation results show that HHO is strongly viable for continued employment in the community due to several features offered by this algorithm, such as (1) ease of use, usefulness, and flexibility of HHO, (2) offering high quality of exploration and exploitation result to find a solution for the decision variables under different optimization situations, (3) efficiency of HHO and/or HHO versions to handle various types of optimization problems, variables, fitness function and search space, (4) offering competitive performance.

For possible future research directions, this review suggested the following recommendations:

- As presented in Sect. 3.3, there are wide varieties of available HHO versions that could confuse amateur users and students. Several HHO versions may appear to be suitable for the particular optimization problem. Thus, selecting the most appropriate optimizer from among several versions of HHO is a challenging task. Therefore, experimental study to evaluate and compare different HHO versions across a variety of optimization problems is a recommended future research direction. Such study may probably try to (1) explain which version of HHO is more appropriate for what type of undertaken optimization problem, (2) explain the advantages and disadvantages of applying one version over another, (3) explain whether the optimization solution changes when applying different versions, and (4) identify the factors that affect the performance of HHO versions.
- As shown in Table 4, most common classes of optimization problems addressed using HHO and/or HHO versions are unconstrained optimization, constrained optimization, continuous optimization, and nonlinear optimization. Furthermore, optimization problems were addressed using hybridization-based HHO algorithms. Therefore, this study recommends that future research should give more attention to address other classes of optimization problems such as discrete optimization, binary optimization, mixed-integer nonlinear programming, many-objective, robust optimization, fuzzy optimization, and multiobjective optimization. Accordingly, new proposed versions of chaotic HHO, modification of HHO, multiobjective HHO, and binarization HHO algorithms can be worthy future research topic.
- Development of a general framework for expressing tentative guidelines for selecting appropriate HHO versions to a specific optimization case is a challenging problem. Such study may probably try to propose a typology of the differences among HHO versions in terms of categorizing application domains, limitations, conditions of application, and theoretical, axiomatic, and pragmatic comparisons.
- Theoretical analysis of HHO is necessary. Therefore, more research needs to be done to explore the matters such as global convergence, local convergence, and number of populations, the communication between populations, the search area of populations, and the search strategy of populations of HHO and/or HHO versions. Such theoretical analysis is essential to develop a stable version of HHO to address a variety of optimization problems more effectively.

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Appendix: selected studies

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