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A Comprehensive Survey of the Harmony Search Algorithm in Clustering Applications

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Abstract: The Harmony Search Algorithm (HSA) is a swarm intelligence optimization algorithm which has been successfully applied to a broad range of clustering applications, including data clustering, text clustering, fuzzy clustering, image processing, and wireless sensor networks. We provide a comprehensive survey of the literature on HSA and its variants, analyze its strengths and weaknesses, and suggest future research directions.

Keywords: harmony search algorithm; meta-heuristic optimization algorithms; optimization problems; clustering applications

1. Introduction

Optimization is a universal technique, whether it is engaged in engineering drawing or industrial applications, scientific, mathematic operation, etc. [1]. Usually, optimization techniques are utilized and employed to solve various optimization problems intelligently by determining the best of an extensive number of possible solutions [2,3]. Meta-heuristic Algorithms (MAs), especially the Harmony Search Algorithm (HSA), have gained a reputation of being better than other search methods in addressing optimization problems because of their robustness and the simplicity of the outcomes they generate. These algorithms have been used in widely different fields, including ad-hoc and sensor networks [4], linear dynamic domains [5], autonomous smart microgrids [6], feature selection [7], benchmark functions [8], text clustering [9], parallel machine scheduling [10], and data clustering [11]. The meta-heuristic community has established many research projects, which include the launching of new optimization methods, applications, and performance examination.

Recently, real-world optimization problems have become more complex and challenging to explain, because they are determined in high-dimensional search areas where there are insufficient mathematical notations to express and present the problem. Because of these difficulties, traditional search techniques cannot find complicated solutions. The current trend is toward the use of MAs, which can provide adequately optimal solutions by an iterative development search process [12].

There are two classes of search algorithms: (1) single-solution algorithms and (2) population-based algorithms. A single-solution algorithm typically runs using a set of candidate solutions (randomly generated); then, a new solution is created using the available candidate solutions, and this improvement process is iterated. Some examples are hill climbing, simulated annealing, β hill climbing, and Tabu search [13].

A population-based algorithm also starts with a set of random candidate solutions. The algorithm works iteratively to identify a subset of high-performing solutions among them. During the improvement processes, the solutions iteratively concentrate near (at least locally, and often globally) optimal solutions utilizing optimization operators. Some examples are the Ant Colony Optimization (ACO) algorithm [14], Spherical Search Optimizer (SSO) [15], Particle Swarm Optimization (PSO) algorithm [16], Group Search Optimizer (GSO) [17], Multi-verse Optimizer Algorithm (MOA) [18], Cuckoo Search Algorithm (CSA) [19], Gravitational Search Algorithm (GSA) [20], Krill Herd Algorithm (KHA) [21], Grasshopper Optimization Algorithm (GOA) [22], and HSA [23].

The two most critical issues in optimization algorithms are exploration/diversification and exploitation/intensification [24]. Exploration search strategy is the strength to explore the research area that encourages the algorithm to examine the different sections of the search area while evading getting stuck in local optima diversely. On the other hand, exploitation search strategy is the convergent technique that maintains a specific exploration along with the process or state of converging. To obtain useful outcomes in a reasonable time, the search algorithm should make suitable trade-offs between these two strategies.

Geem et al. in [23] proposed the HSA, a population-based meta-heuristic optimization algorithm, in 2001. The HSA imitates the design of a unique harmony in music to address an optimization problem. It has provided excellent results across an enormous range of sophisticated problems, such as flow for power systems [25], university timetables [26], congestion management [27], job shop scheduling [28], clustering [29], structural design, renewable energy [30], neural networks [31], water distribution [32], and data mining [33]. The main advantages of the HSA are its clarity of execution, its record of success, and its ability to tackle several complex problems. The HSA can make trade-offs between convergent and divergent regions, and this is the main cause for its energy, success, and reputation. In the HSA rule, exploitation is chiefly controlled by pitch adjustment rate (PAR) and bandwidth (BW) [32,34], and exploration is controlled by the harmony memory considering rate (HMCR) [35,36].

Optimization algorithms can be tested by searching for minima or maxima; authors will note their approach. Figure 1 shows the quantity of issued papers (i.e., conferences, book chapters, and journal articles) concerning the HSA as of February 2020, sorted by publisher (IEEE, Wiley, Elsevier, Springer, Taylor & Francis, and others). Figure 2 shows the number of published papers on each of the main variants of the HSA, and Figure 3 shows the number of publications on applications of the HSA to clustering.

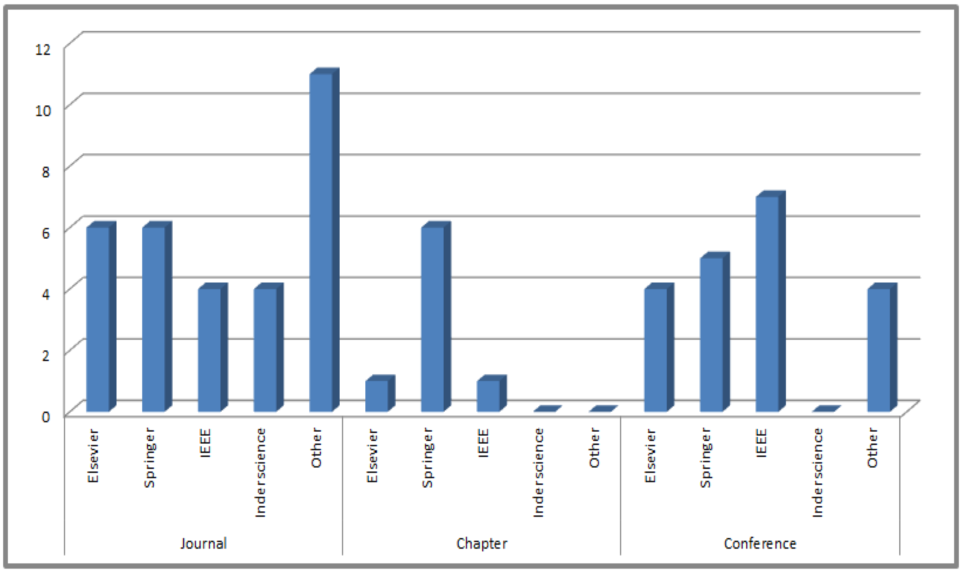

Figure 1. Number of publications on the Harmony Search Algorithm (HSA) since it was proposed until the first half of 2020, sorted by publisher and type.

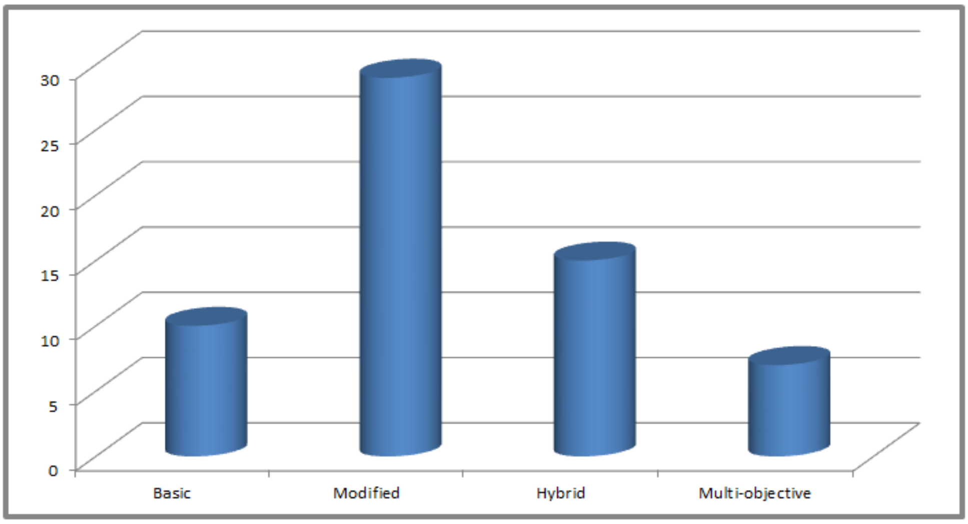

Figure 2. Number of publications on variants of the Harmony Search Algorithm since it was proposed until the first half of 2020.

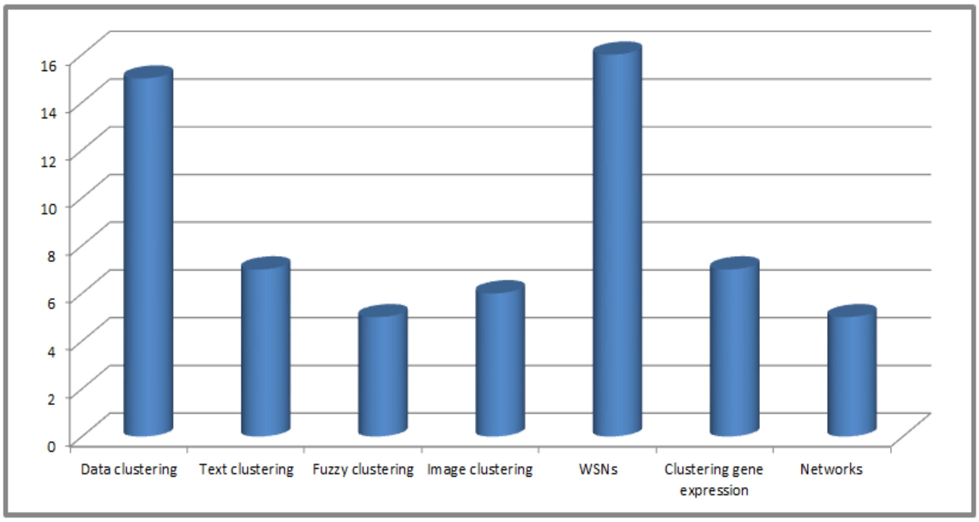

Figure 3. Number of publications on clustering applications of the HSA since it was proposed until the first half of 2020. WSN = Wireless Sensor Networks.

Many different variants of HSA have been developed since the basic algorithm was introduced: enhanced, hybrid, modified, and multi-objective HSAs [37–41]. These algorithms were proposed to deal with different problems having a complex dependence on variables and associated fitness functions [42,43]. Moreover, researchers have elaborated on the basic HSA by producing novel procedures, including specific operators, chaotic maps, hybridization, and exploratory search [44]. Some of these proposed enhancements lead to more efficient HSAs in terms of computational values and solutions. The existence of these different variants and improvements encourages researchers to address difficulties in real-world problems.

The sections of this survey paper are organized as follows. In Section 2, the main procedures of the HSA are presented. Section 3 shows the variants of the HSA that have been used in solving clustering problems. Such applications to clustering are discussed further in Section 4. Discussion and theoretical analyses are given in Section 5. Finally, the outcomes of the survey and prospects for further investigation are presented in Section 6.

2. Main Procedures of the HSA

The HSA, which was designed in 2001, is launched by the way that on-screen musicians extemporaneously change the pitches of their instruments to create new harmonies, for example during jazz improvisation [23]. The most important steps of the HSA are displayed as pseudo-code in Figure 4. Let X denote the entire space of possible solutions. Each of the individual solutions $x \in X$ depends on N decision variables. The optimization problem requires finding the maximum or minimum value of the fitness function esteem f_{X_i} for all the $i = 1...N$ variables.

```
Algorithm 1 Harmony search algorithm
Input: Generate the initial harmonics randomly.
Output: Optimal solution with its fitness value.
Algorithm
Initialize the parameters of the HS HMCR, PAR and etc.
Initialize harmony memory (HM)
Evaluate all solutions using the fitness function.
while Termination criteria do
  new solution=φ.
  if rand < HMCR then
    Memory consideration.
    if rand < PAR then
      Pitch adjustment
    end if
  else
    Random consideration.
  end if
  Evaluate the fitness function of the new solution.
  Replaces the worst solution in HM by the new solution.
end while
```

Figure 4. Pseudo-code of the basic Harmony Search (HS) Algorithm.

(1) Initialize the HS parameters: The control parameters of the HSA are given their values in this step: the Harmony-Memory Considering Rate $HMCR$ and the Pitch-Adjusting Rate (PAR), both lying between 0 and 1, will be utilized during the period of improvement (step 3 below), while the maximum number of generations (I_{max}) is compared to the max course of emphases [45]. HMS is the number of candidate solutions, discussed in the next step; it is obviously constrained to be less than or equal to the number of solutions in X.

(2) Initialize the harmony memory: From the possible solution space X we choose (i.e., stochastically generate) some number HMS of candidate solutions, analogous to the population solutions in genetic algorithms or PSO. Let $x_{i,j}$ be the value of the j-th decision variable of the i-th solution. The Harmony Memory (HM) is the matrix having these values as elements:

$$HM = \begin{bmatrix} x_1^1 & \dots & x_j^1 & \dots & x_{N-1}^1 & x_N^1 \\ x_1^2 & \dots & x_j^2 & \dots & x_{N-1}^2 & x_N^2 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{HMS-1} & \dots & \dots & \dots & \dots & x_N^{HMS-1} \\ x_1^{HMS} & \dots & \dots & \dots & \dots & x_N^{HMS} \end{bmatrix} \quad (1)$$

(3) Improvisation of a new solution: In this step, a new candidate solution is produced utilizing three operators, specifically harmony-memory consideration, pitch adjustment, and random selection, as shown in Equation (2).

$$Xi = (x_{i,1}, x_{i,2}, ..., x_{i,j}, ..., x_{i,t}) \tag{2}$$

The HS calculation produces a new, previously unused solution, as shown in Equation (3), improving the optimal solution in the HM by improvisation. (The pseudo-code of the processes generating the new solution is presented in Figure 5.)

$$x_{new,j} \leftarrow \begin{cases} x_{new,j} \in \{x_{1,j}, x_{2,j}, ..., x_{S,j}\}; & \text{if } rand < HMCR \\ x_{new,j} \in \{0,1\}; & \text{otherwise} \end{cases} \tag{3}$$

where $x_{new,j}$ is the value of the j-th decision variable of the new harmony (solution), and each variable is selected concurring with Equation (3). The probability that the candidate value of each variable is selected from the current candidate values within the current HM is HMCR.

(4) Updating the HM solutions: The produced solution is assessed by its fitness function. In the event that the fitness function esteem of the new solution is superior to that of the worst solution within the HM, the worst solution will be replaced in the HM by the new solution [46].

(5) Check the stopping criterion: When the maximum number of iterations is reached, the HSA stops its procedure for improvements. Until then, steps (3) and (4) are executed to improvise new candidate solutions.

Algorithm 2 :Improvise a new solution

```
Input: Harmony memory HM solutions
Output: A new solution.
for each j ∈ [1, t] do
  if rand[0, 1] ⩽ HMCR then
    x_ij = HM[i][j] where j ∈ U(1, 2, ...., t)
    if rand(0, 1) ⩽ PAR then
      x_ij = x_ij ± rand× bw(i), where rand ∈ [0, 1]
    end if
    else x_ij = LBi + rand × (UBi − LBi)
  end if
end for
```

Figure 5. Improvisation of a new solution. Here, UBi and LBi are upper and lower bounds, and bw denotes bandwidth.

3. Variants of the HSA

In this section, modified versions of the HSA that have been used to solve the clustering problems are presented [47]. Table 1 shows an overview of the variants of the HSA for clustering applications.

Table 1. Variants of the HSA

Proposed	Application	Description	Results and Conclusion	Year	Authors/(Ref)
HSA	Data clustering	A new method is proposed for clustering application and feature selection together using an improved HSA	The obtained results showed that the proposed HSA is a robust clustering technique, and it got better results in terms of precision compared to similar algorithms.	2010	Sarvari et al. in [48]
IGBHSK	Text clustering	A new description algorithm, called IGBHSK, is proposed for solving the web document clustering using the hybridization of the Global-Best HSA with the K-means	The proposed IGBHSK algorithm was evaluated on Reuters-21578 and DMOZ datasets. The obtained results showed that the proposed algorithm got promising results in terms of precision compared with other similar methods.	2010	Cobos et al. in [49]
HSA	Data clustering	A new hybrid optimization algorithm is proposed based on using the HSA to solve the data clustering problems	Standard datasets were used to evaluate the proposed method. The obtained results reported that the proposed HSA minimizes the challenge of determining the initial cluster centroids.	2011	Moh'd Alia et al. in [50]
HSA	Data clustering	A new hybrid method is proposed based on using improved HSA with K-means	The obtained results showed that the proposed HSA is a robust clustering technique, and it got better results in terms of precision compared to other similar algorithms.	2011	Chandran and Nazeer in [51]
HSA	Data clustering	The influence of adjusting parameters such as HMCR and PAR (Pitch-Adjusting Rate) is studied, and a method for parameter tuning is proposed	The obtained results showed that the proposed algorithm gives better results compared to other similar methods in regards to precision, recall, inter-cluster, G-Measure, and intra-cluster distance.	2012	Kumar et al. in [52]
HSA	Data clustering	A new clustering method is proposed based on using HSA with features of K-means and ABC	The proposed hybrid algorithm got better results compared with other similar methods such as HS, PSO (Particle Swarm Optimization), and K-means in regards to precision and convergence velocity.	2012	Krishnaveni and Arumugam in [53]
HSA	Data clustering	An automatic clustering method is proposed based on using the basic HSA	The proposed algorithm was tested on well-known datasets, and the obtained results proved that the proposal obtained the optimal proper number of clusters and areas of initial centers.	2013	Beesetti et al. in [54]
HSA-K	Data clustering	A hybrid clustering method is introduced based on using the Term Frequency and Inverse Document Frequency (TF-IDF) of each feature to measure its importance, and HSA with K-means to cluster the documents	Comparisons were conducted among all of these and other methods, and the obtained results proved that the proposed concept factorization produces better results.	2014	Devi and Shanmugam in [55]
HSA	Data clustering	Introduced a new modified version of the HSA to solve the clustering problems	The obtained results were promising and confirmed that the proposed clustering method gave much better results in regards to precision, recall, inter-cluster, G-measure, and intra-cluster distances.	2014	Kumar et al. in [56]
HSA	Data clustering	A novel hybrid clustering algorithm is introduced based on the parameter of the HSA	The obtained results reported that the proposed method produced better results in regards to the weighted average, precision, recall, G-Measure, and F-Measure.	2015	Vijay et al. in [57]
HS-GA	Clustering problems	A hybrid algorithm is proposed based on HSA and GA named HS-GA to solve clustering optimization problems	The obtained results showed the superior performance of the proposed HS-GA method.	2016	Abedini et al. in [58]
HSAK	Wireless Sensor Networks (WSNs)	Two methods, HSA and K-means, are proven to produce satisfactory results separately when used for the clustering method	The proposed method got better results compared to the basic versions of HSA and K-means.	2016	Raval et al. in [59]

Table 1. *Cont.*

Proposed	Application	Description	Results and Conclusion	Year	Authors/(Ref)
H-KHA	Data clustering	Introduced a new data clustering method based on a hybrid strategy of the KHA and HSA, called Harmony-KHA	The obtained results revealed that the proposed hybrid method (Harmony-KHA) provided accurate clusters, especially for the large dataset.	2016	Abualigah et al. in [29]
HSA	Wireless Sensor Networks	A new clustering method, based on using improved HSA, is proposed to address the energy hole problem.	The obtained results showed that the proposed HSA is a robust clustering technique, and it got better clustering results.	2017	Saha and Gupta in [60]
P-HSA	Wireless Sensor Networks	An approach for developing network lifetime is proposed by utilizing PSO algorithm-based clustering and HSA-based routing in WSNs	The obtained results showed that the proposed P-HSA is a robust clustering technique, and it got better clustering results.	2017	Anand and Pandey in [61]
HMS-CD	Clustering application in networks	A Protein–Protein Interaction (PPI) network systems exposure algorithm is proposed based on the HSA (HMS-CD)	The obtained results on a real benchmark dataset like a yeast PPI network confirmed that the proposed method using the HSA obtained better detection precision rate than the basic HSA and typical MCODE algorithm.	2017	Chen et al. in [62]
HSA	Wireless sensor networks	A new grouping protocol for WSNs is proposed, which can reduce entire network power and increase the network lifetime	The results showed that the proposed protocol obtained an optimal number of clusters.	2018	Moh'd Alia in [63]
HSA	Wireless sensor networks	A novel HSA is proposed based on energy-efficient load-balanced clustering method	The obtained results confirmed that the proposed method has faster convergence and provides secure and efficient load-balanced clustering compared to the basic HSA and other several similar methods in the literature.	2018	Singh and Sharma in [64]
CS-HSA	Clustering protocols	A hybrid CS with HSA-based energy equivalent node clustering protocol is proposed, which utilizes a new objective function for the uniform pattern of cluster leaders	The proposed routing clustering protocol using CS-HSA exhibited significant enhancement matched to the other similar clustering protocols.	2018	Gupta and Jha in [65]
HSA	Wireless sensor networks	Multiple solutions based on using HSA are proposed and compared in terms of their effectiveness for solving the clustering protocols in WSNs	The proposed method decreased the computational time demands and enhanced network performance in regard to power mode and data transfer from the sensor joints to the base location.	2018	Raval et al. in [66]
CDHS	Text clustering	CDHS, a new text-clustering method, is proposed based on using the DE crossover with the Differential HSA for more search space exploitation	The proposed CDHS obtains highly competitive results. At the same time, the proposed method (CDHS) obtains superior results compared to other similar methods.	2018	Al-Jadir et al. in [67]
MH-CACA	Wireless sensor networks	A multi-objective tournament HSA coverage aware load-balanced (MH-CACA) is proposed to solve the clustering problems in WSNs	The proposed method obtained better results in terms of coverage charge, lifeless gateways, lifeless sensors, power consumption, and network lifetime compared to other similar methods.	2019	Singh and Kumar in [68]

3.1. Basic Versions of the HSA

Kumar et al. in [52] presented a new method to improve the basic HSA by analyzing the influence of its adjusting parameters, such as HMCR and PAR. The proposed method offers changes in the basic HSA by taking precise rates of these adjusting parameters and enabling them to grow exponentially through the development processes. The proposed version of the HSA has been assessed on standard data clustering datasets. The clustering production of the method is compared with K-means, HA, and an enhanced variant of the HSA. The proposed algorithm gives better results than other similar methods in regard to precision, recall, inter-cluster, G-measure, and intra-cluster distance.

Beesetti et al. in [54], proposed a clustering method based on the basic HSA. In the proposed method, the power of the HSA is employed to develop the best variety of clusters automatically and to find the areas of cluster centers. By straightforwardly incorporating the concept factorization for each harmony solution, the proposed method converts the variables of cluster centers at every iteration. The cluster validity criterion is employed as an objective function to verify the clustering result obtained from every solution. The proposed method is tested on well-known datasets, and the results show that the proposed method obtains the correct variety of clusters and areas of centers.

Singh and Sharma proposed in [64] a novel method based on using the HSA to solve the clustering problem in energy load balancing. The proposed method is examined in an extensive sample network. The results show that the proposed method reached the optimal solution more quickly and produces secure and green balanced clustering matched to the basic HSA and other various comparable approaches in the literature. Furthermore, the robustness and influencing parameters of the proposed HSA are also examined for numerous instances of Wireless Sensor Networks (WSNs).

3.2. Modified Versions of the HSA

Sarvari et al. in [48] introduced a new integrated method for clustering and feature selection applications using an improved HSA. The method performs the feature selection task as a fundamental component of the global clustering search process. It aims to overcome the problem of clustering by encouraging locally optimal solutions in the feature selection and clustering process without any previous assumptions regarding the number of cluster centroids. A shifting composite design is proposed to convert both given applications. Moreover, local search procedures are employed to enhance feature selection and cluster centers. The results show that the proposed HSA is a robust clustering technique and obtains better results in regard to precision measures than other similar algorithms.

Krishnaveni and Arumugam in [53] proposed a new clustering approach based on using HSA with the capabilities of K-means and ABC. Because HSA fails to converge to the critical area in the given search space, the exploitation feature of the ABC algorithm is utilized to enhance the solutions of the HSA based on their fitness values, and thus to increase the convergence velocity. The proposed method achieves more powerful outcomes than comparable techniques, such as HS and PSO, in regard to precision and convergence speed.

Kumar et al. in [56] introduced a new modified version of the HSA to solve the clustering problem. The two parameters HMCR and PAR play an essential role in improvising a new solution. This research examined the influence on the outcomes when K-means are initialized with the solution delivered by the proposed HSA. The influence of HM size was also examined. The experiments were conducted on data clustering problems using nine benchmark datasets. The performance of the proposed clustering method is on par with K-means, FCM, genetic algorithm (GA), and four similar variants of the HSA. The results obtained are promising and confirm that the proposed clustering method gives much better results in regard to precision, recall, inter-cluster, G-measure, and intra-cluster distances.

Saha and Gupta in [60] proposed a new clustering method, based on using an improved HSA, to address the energy problem. The improved version of the HSA was used for protocol clustering in mobile-based WSNs. A new objective function is employed for arranging the cluster sources. In addition, mobile sink re-localization methods are also used to decrease and adjust power damage.

The performance of the proposed method was assessed by changing various network scenarios and comparing it with other similar methods. The results showed that the proposed HSA is a robust clustering technique and obtains better clustering results.

Anand and Pandey in [61] presented P-HSA, a new approach for developing network lifetime by utilizing PSO algorithm-based clustering and HSA-based routing in WSNs. Global optimal group energy is chosen, and gateway nodes are included to reduce energy loss while transferring aggregated data to a base station (BS). Alongside this, the HSA-based local search strategy is used to determine the best routing path for gateway nodes to the BS. The results show that the proposed P-HSA is a robust clustering technique and produces good clustering results in terms of accuracy measure.

Moh'd Alia in [63] proposed a new strength-green grouping tool for WSNs that can decrease total network strength dissipation and increase the network lifetime. The proposed method is divided into two sections. The first component deals with building infrastructure for the assigned WSN. An improved algorithm is used based on the HSA to outline the most popular variety of clusters and allocate sensors into precise clusters. The second component is involved with transmitting sensed facts from nodes to their cluster source. The results show that the proposed grouping protocol receives the most positive variety of clusters, increases the network lifetime, and improves the records transfer at the BS when matched to different similar clustering routing protocols.

3.3. Hybrid Versions of the HSA

Numerous methods for tackling clustering problems may be found in the literature. Of these, meta-heuristic optimization strategies show particular promise. When a hybrid of two algorithms is established to take advantage of the most useful features of each, more dependable results may be expected.

HSA and K-means, the methods discussed in [59], provide the best results for clustering; when combined in a hybrid, they give even higher outcomes. Cobos et al. in [49] proposed a new improved algorithm to address internet document clustering using a hybridization of the basic HSA and the K-means approach called IGBHSK. The proposed method determines the optimal area of clusters. The hybrid HSA produces an extensive search for exploration within the available search space. The K-means approach is applied to determine the optimal solution in a neighborhood. The proposed IGBHSK algorithm was evaluated on the Reuters-21578 and DMOZ datasets. The algorithm obtains promising results in terms of precision compared with other similar methods.

Moh'd Alia et al. in [50] proposed a new hybrid optimization method based on using the HSA to address the clustering problem. The proposed method works in two steps. In the first step, the HSA examines the search place of the supplied dataset to locate the nearest vital clusters. The centers are selected through the HSA and then assessed by means of the adapted C-means technique. In the second step, the excellent centers from the first step are utilized as preliminary centers for the C-means technique. Standard datasets were used to assess the performance of the hybrid method. The proposed HSA solved the problem of finding the initial centroids efficiently.

Chandran and Nazeer in [51] proposed a new hybrid technique based on using a stepped-forward HSA with K-means. The proposed method is meant to solve the weaknesses of the initial centroids. The results showed that the proposed HSA is a reliable clustering technique, obtaining higher outcomes in terms of precision than other similar algorithms. Devi and Shanmugam in [55] adopted a hybrid clustering approach using Time Frequency and Inverse Document Frequency (TF-IDF) to measure significance, and HSA with K-means to cluster the documents. In the proposed method, an attempt is made to apply the concept factorization approach for record clustering and to get better clusters in a significant amount of time. A comparison was performed with many other methods, and the assessment proved that the proposed concept factorization produces better clustering results. In [69], another approach based on the use of the HSA with the concept factorization method for document clustering is proposed. The obtained results show that concept factorization can enhance the performance of the HSA.

Kumar et al. in [57] introduced a novel hybrid clustering algorithm based on adjusting the parameters of the HSA. The new parameter adaptive HSA (PAHS) is used to improve the cluster centers, which are themselves utilized in initializing the HSA clustering method. The proper number of clusters is defined through four similar cluster validation criteria. The proposed algorithm was assessed on three real-life data clustering datasets and its performance was contrasted with that of K-means, FCM, and HS. The proposed method produced better clustering results in regard to the weighted average, precision, recall, G-measure, and F-measure.

Abualigah et al. in [29] introduced a new data clustering method based on a the KHA-HSA hybrid strategy called Harmony-KHA for enhancing the data clustering procedure. This hybrid approach attempts to improve the global search capability of the basic KHA by adding a global search from the HSA for exploration near the optimal solution in the KHA. Thus, krill positions proceed to the global best solution. The proposed method is used to find the best solution through position calculation. Experiments were carried out using four datasets from the UCI Machine Learning Repository Repository. Harmony-KHA provided accurate clusters, especially for large datasets.

Gupta and Jha in [65] proposed a hybrid CS with a primarily HSA-based strength equivalent node clustering protocol, utilizing a new function called CS-HSA for the uniform pattern of cluster leaders. The proposed CS-HSA is mainly based on a protocol for routing the data package deal among cluster heads. The performance of the proposed hybrid CS-HSA was assessed using the average power loss, path of active nodes, route of dull nodes, and network lifetime. The proposed routing clustering protocol using CS-HSA exhibited excellent enhancement over similar clustering protocols.

3.4. Multi-Objective Versions of the HSA

Abedini et al. in [58] introduced a new approach for solving the security and industrial problems of microgrids (MGs) by creating several self-adequate self-governing sub-MGs via a clustering method. Hence, a multi-objective optimization algorithm was produced, where power waste minimization, energy profile development, and reliability improvement are recognized as objective functions. A hybrid algorithm based on HSA and GA, named HS-GA, is presented to solve the mentioned optimization problems. Furthermore, a load waft manner was provided to different model representations of MGs. The overall performance of the proposed HS-GA approach was assessed using several case studies. The obtained results confirmed the superior performance of the proposed HS-GA method.

Raval et al. in [66] proposed multiple solutions based on using HSA. An effectiveness comparison of the proposed methods was made in solving the clustering protocols of WSNs. Pareto optimality theory is incorporated for the multi-objective clustering problem in WSNs. Multiple objectives-based strategies with customized stopping measures in the proposed method give optimal solutions with decreased computational time demands and enhanced network performance in regard to power mode and data transfer from the sensor joints to the base location.

Singh and Kumar in [68] proposed a multi-objective tournament HSA coverage-aware load-balanced clustering algorithm (MH-CACA) to solve clustering problems in WSNs. To confirm the performance of the proposed MH-CACA, a comprehensive network was analyzed, and the obtained results confirmed that the proposed method has better results in terms of coverage charge, lifeless gateways, lifeless sensors, power consumption, and network lifetime compared to other similar methods.

4. Clustering Applications of the HSA

In this section, clustering applications based on the use of HSA are presented [70]. Table 2 shows an overview for the clustering applications of the HSA. As evident in the literature of the HSA, most of the researches have been conducted in order to solve clustering problems, which means that these applications of the clustering are essential in the literature of the HSA to be studied further and analyzed.

Table 2. Clustering applications of the HSA.

Proposed	Application	Description	Results and Conclusion	Year	Authors/(Ref)
HS	Zone structure	A new fuzzy method is proposed based on using the HSA to find the optimal parameters for the zone structure problem	The obtained results showed that the proposed HSA is a powerful method in the simultaneous clustering and their identical zone constructions.	2007	Ayvaz in [71]
HSA	Text clustering	New clustering methods are proposed based on using HSA for web document clustering purposes	The obtained results reported that the hybrid HSA got better clusters using several text datasets when compared to related methods. Moreover, it converged faster to the best-recognized optimum area.	2008	Forsati et al. in [72]
FHSClust	Fuzzy clustering	A new incorporated method is proposed based on incorporating a fuzzy approach into the enhanced HSA called Fuzzy Harmony Search Clustering (FHSClust)	The obtained results showed that the proposed FHSClust got almost the optimal solution. Moreover, it converged faster to the best-recognized optimum area.	2008	Malaki et al. in [73]
DCHS	Image segmentation	A novel effective clustering method is introduced based on using the HSA, called DCHS	The proposed DCHS method was employed on standard real images, and the obtained results reported that the proposed DCHS found a suitable number of clusters and found places of cluster centers. Additionally, it obtained promising results compared to other similar clustering algorithms.	2009	Moh'd Alia et al. in [74]
IHSK	Data clustering	A new clustering method is introduced based on using the HSA, called IHSK, with feature selection application in a linear system	The proposed IHSK algorithm was examined with collections of synthetic and real datasets. The obtained results were promising compared to other similar clustering methods published in the literature.	2010	Cobos et al. in [75]
HSA	Data clustering	A new method is proposed using HSA to overcome the weaknesses of the K-means technique	The obtained results showed that the proposed HSA is a robust clustering technique, and it got better results in terms of precision compared to similar algorithms.	2010	Amiri et al. in [76]
DCHS	Image segmentation	A new clustering method is proposed for the mechanical segmentation of Osteosarcoma in MRI images.	The obtained results were statistically assessed versus manually described data for four patients. The proposed algorithm obtained promising results with a score of 0.72 of the Dice measure.	2010	Mandava et al. in [77]
HSA	Wireless sensor networks	A new clustering method is proposed based on utilizing the HSA for reducing the intra-cluster range and finding the optimal energy expenditure of the network	The obtained results illustrated that the proposed method using HSA decreased power expenditure and increased the network's lifetime.	2010	Hoang et al. in [78]
HSKHM	Clustering gene expression	A hybrid clustering algorithm is proposed for solving the clustering gene expression, called HSKHM	The proposed HSKHM algorithm increased the convergence rate of the basic HSA and supported K-means in avoiding the neighborhood optima.	2012	Song et al. in [79]
SCAH-MOHSA	Clustering the network structure	A spectral clustering method is proposed based on hybridizing multi-objective HSA, called SCAH-MOHSA	The experiments were conducted using synthetic and real-world networks. The obtained results illustrated that the proposed method got partition results that fit real employment.	2012	Li et al. in [80]
HSA	Clustering the network structure	A nature-inspired method is proposed that can increase the Optimum-Path Forest (OPF) clustering method by finding the optimal parameters in a discrete framework	The proposed method was more agile than the regular algorithm; this is unusual for intrusion discovery systems in large-scale traffic networks.	2012	Costa et al. in [81]
HSA	Data clustering	The basic K-means and fuzzy C-means are hybridized with the meta-heuristic HSA	The overall accuracy from the simulation results revealed that the hybridized algorithms exceeded the basic K-means and fuzzy C-means clustering.	2013	Zainuddin et al. in [82]
HSA	Image clustering	A new unsupervised learning image clustering method is proposed based on using the HSA	The obtained results by the proposed algorithm revealed effectiveness in the constant clustering for the presented problem.	2013	Ibtissem and Hadria in [83]

Table 2. *Cont.*

Proposed	Application	Description	Results and Conclusion	Year	Authors/(Ref)
HSA	WSN	A new framework is proposed to facilitate the active development of localized cluster protocols established by the HSA for the WSNs	The obtained results showed that the WSNs' continuance increased using the proposed HSA in comparison with other similar methods.	2013	Hoang et al. in [84]
HSPSO	Clustering gene expression	A novel HSA is proposed, called HSPSO, which is used as a clustering algorithm and is employed for clustering purposes	The obtained results proved that the proposed HSPSO algorithm created clusters with better compactness and precision in comparison with K-means, PSO, and Fuzzy PSO clustering.	2014	Banu and Andrews in [85]
VHS	Data clustering	A novel variance-based HSA is introduced for addressing optimization problems, called VHS	The obtained results indicated that the proposed VHS clustering method got better results compared to the other similar clustering algorithms.	2014	Kumar et al. in [86]
HSA	Clustering gene expression	A Self Organizing Map (SOM)-Harmony Hybrid algorithm is introduced that calculated the optimal dimension of the SOM network	The obtained results illustrated that the proposed method got better clustering results.	2015	George et al. in [87]
HSA	Networks applications	A new method is proposed based on using HSA to distribute graphs using the modularity measure	The obtained results observed that HSA gave faster results in solving network clustering problems compared to other similar methods.	2015	Atay and Kodaz in [88]
HSM	Text clustering	A new hybrid text clustering method is proposed based on using the HSA and K-means	The obtained results reported that the proposed method produced better clustering results compared with other similar methods.	2016	Abedini et al. in [58]
EHS	Clustering gene expression	A new clustering method is introduced based on using HSA for clustering gene expression, called EHS	The obtained results revealed that the proposed EHS overwhelmed the basic HSA in both used benchmarks.	2016	Abedini et al. in [58]
IHS	Wireless sensor networks	A new clustering method is proposed based on an improved HSA (IHS) to increase the endurance of WSNs	The obtained results revealed that the proposed method got better clustering results.	2016	Dey et al. in [89]
PAHS	Image segmentation	A new automated clustering method is proposed, which uses a developed parameter HSA (PAHS) as an underlying algorithm	The obtained results showed that the proposed method is practical and useful.	2016	Kumar et al. in [90]
HSA	Image clustering	A new image clustering method is proposed to avoid the weakness with conventional clustering methods using HSA	The obtained results revealed that the proposed method produced better clustering solutions compared to other similar works.	2016	Bekkouche and Fizazi [91]
HSA	Data and image clustering	A new clustering method is introduced based on using HSA to get the cluster centers, and next group the data	The obtained results reported that the HSA efficiently addressed clustering problems.	2016	Senthilnath et al. in [92]
FLIHSBC	Wireless sensor networks	A double optimization method is proposed based on using a fuzzy logic strategy and HSA for solving the WSNs.	The obtained results demonstrated that the proposed FLIHSBC algorithm produces better lifetime for the WSNs.	2017	Agrawal and Pandey in [93]
HSA	Clustering for classification purposes	A fuzzy kernel clustering method with a new differential HSA is presented to adjust the distraction scheduling design classification	The obtained results revealed that the kernel clustering with the differential HSA gave a superior performance to address water diversion arrangement problems.	2017	Feng et al. in [94]
CRHS	Wireless Sensor Networks	HSA is proposed for routing purposes and utilizing the same adjusting parameters is suggested as a fitness function, called CRHS	The obtained results reported that the proposed CRHS gave superior achievements compared to other comparative techniques.	2018	Lalwan et al. in [95]
HSA	Clustering gene expression	A new meta-heuristic clustering method is proposed for solving the gene expression problems	The obtained results confirmed that the proposed method overwhelmed the other similar methods.	2019	Kumar and Kumar in [96]

4.1. Data Clustering Applications

K-means clustering is a commonly utilized technique for data and text clustering, used in the data-mining domain due to its homogeneity and high velocity in grouping massive datasets [97–99]. However, K-means has two main weaknesses, one involving the initial centroid and the other involving convergence to the exploration area.

Amiri et al. in [76] introduced a new method using HSA to overcome the weaknesses of the K-means technique. The HSA does not need an initial centroid and utilizes a stochastic search rather than a gradient search, so secondary data is unnecessary. The proposed HSA was compared with other heuristic algorithms by executing them all on different simulations and real datasets. The results obtained showed that the proposed HSA is a robust clustering technique, and obtains more precise clustering results than similar algorithms.

Cobos et al. in [75] presented a new clustering technique based on using the HSA, called IHSK, with natural selection utility. The proposed algorithm is combined with the basic HSA and K-means clustering. The selection method is used to train the low probability neighborhood of positions and move them toward the optimal solution. The proposed IHSK algorithm was tested on collections of synthetic and real datasets. The results were promising in comparison to those from similar clustering techniques published in the literature.

Clustering problems have become a common and vital task in modern computer science applications. Forsati et al. in [72] introduced new clustering methods using HSA for web document clustering purposes. The clustering task is presented as an optimization problem, and basic HSA-based clustering is employed initially to find near-optimal clusters within a reduced time. Then, a hybrid method using K-means and HSA is proposed to perform more reliable clustering. It was reported that the hybrid HSA can obtain better clusters using several text datasets when compared to related methods. Moreover, it converges more rapidly to the best-recognized optimum.

Kumar et al. in [86] introduced a novel HSA for addressing optimization problems, called VHS. VHS combines principles taken from the optimization system to enhance the performance of the HSA. This reduces the problem of fixed-parameter context inside the HS rule-set. VHS utilizes a variety of candidate solutions to improve solution positions. The effects of scalability, turbulence, HM length, and HMCR have additionally been studied with the proposed HSA. VHS is then implemented for the documents clustering problem. Four real-life datasets were selected from the UCI. The proposed VHS clustering approach produced good results compared to the different clustering algorithms.

As evident in the literature of the HSA for solving the data clustering problems, most of the researches have been conducted using several versions of the HSA to solve clustering problems, especially the data clustering problems, which means that data clustering applications still have a wide space for further investigations and analysis.

4.2. Text Clustering Applications

Text clustering is one of the main well-known problems in the literature [100]. Ibtissem and Hadria in [83] proposed a new unsupervised clustering method based on use of the HSA, and assessed the performance of the proposed approach by analyzing its effects. The results showed the effectiveness and production inside the regular clustering for the problem considered. Abedini et al. in [58] produced a new hybrid text clustering technique based on the use of the HSA and K-means method. This hybrid method attempts to exploit the capacity of KSA and K-means together. It was reported that the proposed method produced higher results compared with similar methods.

In [67], Al-Jadir et al. proposed a new text clustering method, called CDHS, based on using the crossover with the HSA for enhanced search space exploitation. Furthermore, in this method, crossover (Cr) and mutation (F) are dynamically arranged through generations. Memetic optimization is applied to improve the local search ability of CDHS. Furthermore, CDHS was compared to other similar document clustering techniques, such as HS, DHS, and K-means. The results revealed that

CDHS obtained competitive results. Moreover, CDHS achieved superior results in comparison to various comparable methods.

Regarding text clustering, HSA has been used for solving text clustering problems in fewer ways. Most of the researches have been conducted using several versions of the HSA to solve text clustering problems, which means that text clustering applications still have a wide space for further investigations and analysis.

4.3. Fuzzy Clustering Applications

Ayvaz, in [71], proposed a new fuzzy method using the HSA to find the optimal parameter values for the zone structure problem. The problem was solved based on three guidelines, namely residual failure, parameter change, and structural distinction. A mathematical version supplied in the literature was determined to improve the overall performance of the proposed HSA. Moreover, a sensibility evaluation was performed to study the performance of the HSA for numerous businesses of solution parameters. The obtained results demonstrated that the proposed HSA is a powerful method for performing simultaneous clustering.

In [73], Malaki et al. introduced a new integrated method, called Fuzzy Harmony Search Clustering (FHSClust), by employing a fuzzy approach to enhance the HSA. The results of FHSClust were fed into a Fuzzy C-Means (FCM) algorithm, which then practiced its convergence speed, to improve the solution. This method merged the advantages of fuzzy HSA with the convergence acceleration of the fuzzy C-means technique. The obtained results showed that FHSClust obtained a nearly optimal solution. Furthermore, it converged quickly to the optimal-recognized optimum. Van Tinh, in [101], proposed a hybrid design method based on hybridizing K-means and HSA to overwhelm the K-means problems. The proposed hybrid method obtained better results and a suitable interval length.

Agrawal and Pandey, in [93], introduced a hybrid optimization approach based on the use of a fuzzy suitable judgment method and HSA for solving the clustering protocols in WSNs. The proposed method, which used a fuzzy strategy and improved HSA, is called FLIHSBC. The FLIHSBC algorithm exhibited reduced power consumption and assisted in increasing the lifetime of the network. The obtained results confirmed that FLIHSBC performs well with regard to increasing the lifespan of WSNs.

Feng et al., in [94], introduced a fuzzy kernel clustering technique with a new differential HSA to manage the classification process. First, a self-adaptive solution approach and differential evolution update procedures were proposed to improve the basic HSA. Second, differential HSA was employed to the kernel fuzzy clustering technique to help the clustering technique in reaching more leading results. Later, the fuzzy kernel, combined with differential HSA, was used for water entertainment arrangements. The proposed approach was then compared with other similar methods. The acquired results revealed that the proposed fuzzy kernel clustering combined with the differential HSA demonstrated a superior overall performance with regard to water diversion arrangements. Regarding the fuzzy clustering, several HSAs have been used for solving the different problems using fuzzy techniques, which means that fuzzy clustering applications still have space for further investigations and analysis.

4.4. Clustering Applications for Image Segmentation

Moh'd Alia et al., in [74], introduced a novel effective clustering method, called DCHS, based on the HSA. In the proposed algorithm, the basic HSA is improved to automatically develop the appropriate number of groups and areas of cluster centers. By combining the idea of position length in each solution, DCHS can convert the changeable number of nominee cluster centers at each iteration. DCHS was employed on standard real images, and the obtained results showed that DCHS finds a suitable number of clusters and locations of cluster centers. Further, it obtained promising results compared to other similar clustering algorithms.

Mandava et al., in [77], introduced a new clustering method for automatic segmentation in MRI images. The proposed method is based on using a new effective clustering technique in intelligent behavior, called DCHS, that hybridizes the basic HSA with FCM. The idea of changeable positions in each solution was employed to convert the number of nominee centers at each repetition. Moreover, a unique operator was included to assist the choice of negative choice variables in the solution. Furthermore, a subset of Haralick construction features and pixel depth values was adopted as a feature location in DCHS to describe tumor sizes. The obtained results were statistically assessed versus manually described data for four patients. The proposed algorithm obtained promising results, with a Dice coefficient of 0.72.

In [90], Kumar et al. introduced a novel automatic clustering technique that uses a developed Parameter HSA (PAHS) as the underlying algorithm. It utilizes the real-coded variable-period solution, which can understand the routes of clusters automatically. Recent ideas regarding threshold putting and cutoff were implemented to improve the optimization procedure. The distribution of information factors to various cluster centers was executed based on the produced weighted Euclidean distance, as opposed to the unique degree. The proposed approach found high-density clusters with a geometrical shape. Moreover, it was used for the automated segmentation of grayscale and coloration snapshots, and its overall performance was similar to that of various currently used algorithms. The acquired results showed that the proposed method is sensible and beneficial.

Furthermore, in [102], Wan et al. proposed a Self-Adaptive Multi-Objective HSA-based Fuzzy Clustering technique (SAMOHSFC) for solving the clustering problem in image segmentation. The proposed SAMOHSFC method develops different cluster centers in one solution and optimizes multiple objectives. In addition, the spatial data of the image are considered as a characteristic of the input attributes of the grey data of the input image. The superiority of the proposed method over three comprehensive segmentation strategies was confirmed using synthetic and picture datasets with regard to quantitative and visual functions. Furthermore, various instructions regarding spatial facts were analyzed based on the segmentation achievement of the proposed SAMOHSFC.

4.5. Image Clustering Applications

Ibtissem and Hadria, in [83], proposed a novel unsupervised image clustering technique using the HSA. Subsequently, they assessed the overall performance of the proposed approach by analyzing the acquired effects, which proved that the efficacy criterion automatically manages the proper route of training that describes an image. The proposed approach, which was executed with numerous productiveness rules, allowed the pleasant validity criterion to be obtained, which enabled the evaluation of the overall performance and robustness of the proposed technique. The results acquired using the proposed algorithm demonstrated its effectiveness.

Bekkouche and Fizazi [91] proposed a new picture clustering technique to overcome the limitations of conventional clustering methods, including premature convergence and sensibility to initialization centroids. HSA was used in this study to combine the critical additives of population methods and single solution methods in an optimization design. The proposed method employs hybridization fuzzy clustering and the HSA to develop its exploitation rule and to further improve the created solutions. Furthermore, Fourier transforms are employed to enhance the dimensions of the information in the images. The obtained results revealed that the proposed approach produced more optimal solutions in comparison to different methods.

In [92], Senthilnath et al. proposed a new clustering approach, based on the HSA, to obtain cluster centers and consequently to design the statistics. Three commonly used datasets from the UCI repository and real images were applied to confirm the results obtained using the proposed approach. The overall performance of the proposed HSA was similar to that of preferred K-means clustering and to that of three similar optimization methods, namely the AG, PSO, and CS algorithms. The results were assessed using four evaluation measures, namely classification error, operating functions, computational time, and statistical significance evaluation. The acquired results illustrated that HSA can effectively address clustering issues. Image problems are some of the most studied applications by using HSA, and this means that HSA can reach better results in this domain.

4.6. Clustering Protocol for Wireless Sensor Network Applications

WSNs comprise small battery-powered machines with insufficient power supplies. Once used, the small sensor connections are generally unavailable to the user; therefore, the power supplier cannot be replaced [103–106]. Protocols for WSNs are being developed to reduce power damage [107]. The clustering method is one of the most used processes for increasing the lifetime of the network by data gathering and for trading off the energy expenditure between sensor connections of the network [108]. Hoang et al. [78] utilized the HSA for decreasing the intracluster variety and finding the optimal power expenditure of the network. HSA is a music-based optimization algorithm, which is similar to the track discovery approach, in which a participant continues to clean the pitches to achieve better consistency (harmony). Other similar cluster techniques were assessed for the clustering protocol in WSNs; the techniques were Low-Energy Adaptive Clustering Hierarchy (LEACH), PSO, GA, K-means, and FCM clustering algorithms. The results illustrated that the proposed approach using HSA decreased electricity expenditure and increased the network lifetime.

Hoang et al. in [84] proposed a new framework to facilitate the continuous improvement of localized cluster protocols using the HSA for WSNs. In the proposed framework, the clustering protocol applied the HSA in real-time. The experiments were performed with the same cluster protocols for WSNs using LEACH-centralized (LEACH-C) and a clustering protocol for the FCM algorithm. The results of the proposed approach with the HSA illustrated the security and monitoring applications for constructing ecosystems. The obtained results showed that the WSNs' lifespan had been increased with the proposed approach, compared with other similar methods.

Dey et al. [89] introduced a new clustering method based on an improved HSA (IHS) to increase the lifespan of WSNs. Its performance was evaluated via simulations on a less powerful WSN. The WSNs were partitioned into clusters by using the proposed IHS algorithm; the network lifetime and amount of information sent to the Base Station (BS) were assumed. The obtained results revealed that the proposed method provided better results.

Lalwan et al. in [95] introduced a clustering method based on HSA. They proposed a fitness function with the power, range, and node space as the parameters. Next, a possible function for the distribution of non-CH (cluster head) nodes to CHs was determined. Then, the HSA was used for routing purposes by adjusting the parameters of the fitness function; this method was called CRHS. Three standard tests were performed to evaluate the performance, and the proposed algorithm was compared with other similar existing techniques. The obtained results showed that the performance of the proposed CRHS was superior compared with other techniques.

4.7. Clustering Applications for Gene Expression

The clustering design is a diverse procedure for data mining. K-harmonic clustering is another version of the K-means technique; however, it falls into local optima. The HSA can address this issue, as it is a random optimization system. Song et al. [79] proposed a hybrid clustering algorithm known as HSKHM. The proposed set of rules is used along with the basic HSA and the K-means to maximize their advantages. The results on four gene expression datasets illustrated that the proposed HSKHM was superior to KHM and fundamental HSA in most cases. The HSKHM algorithm increased the convergence of the primary HSA and avoided the local optima.

The PSO algorithm is used for many applications; however, it fails to obtain the inputs for producing clusters and thus decreases the clustering precision. HSA is a conventional optimization algorithm that avoids divergence and can find the near-ideal solution by exploring the optimal solution region. Banu and Andrews [85] presented a novel HSA called HSPSO, which is used as a clustering algorithm for gene expression datasets for investigating brain tumors, Leukemia, colon cancer, lung cancer, etc. The obtained results showed that the proposed algorithm created clusters with better compactness and precision than the K-means, PSO, and fuzzy PSO clustering algorithms. George et al., in [87], claimed that the Self Organizing Map (SOM) dimension for the drawing schooling technique is not an appropriate technique, as it may not make specific a map with a shadow of quantization and topographic mistakes. They presented a SOM-concord Hybrid algorithm that calculated the maximum size of the SOM network with minimum topographic and quantization errors. The results indicated that the proposed method achieved better results.

Abedini et al., in [58], introduced a new clustering method based on HSA for clustering gene expressions called EHS. In this method, the local and global search processes are combined by decreasing the pitch rates and returning a part of devices with new tools. Experiments were performed with optimization test functions and gene expression datasets. The results revealed that the proposed EHS exhibits considerably better performance than the basic HSA for both benchmarks. Moreover, this study defined the biological validation of groups with gene ontology considering the function, process, and component.

Kumar and Kumar [96] proposed a new meta-heuristic clustering method for separating gene expression. A variance-based HSA was introduced as an underlying optimization technique. The performance of the proposed method was compared with twelve standard clustering methods on six benchmark datasets and matched. The results confirmed that the proposed method performed considerably better than other similar methods. The statistical significance tests also illustrated the superiority of the proposed method.

4.8. Clustering for Network Applications

Various studies have focused on place detection in complex networks in recent years [39,109]. Single-goal strategies that produce the handiest one-optimization function may additionally have defects, consisting of just a single solution that may be executed. Li et al. in [80] proposed a spectral clustering approach primarily based on hybridizing a multi-objective HSA, called SCAH-MOHSA. The proposed method was integrated with a new local search method to find the creation of clusters in complex networks. First, a more suitable spectral technique was used to transform the local search problem into an information clustering problem. Meanwhile, various representations of the HM were controlled. Then, an adaptive fusion multi-goal HSA was applied to decide the multi-objective problem to address community production. The experiments were conducted using synthetic and real international networks. The results illustrated that the proposed technique achieved better results than healthy employment.

Costa et al., in [81], introduced a nature-stimulated approach that can increase the Optimum-Path Forest (OPF) clustering method by finding the optimal parameters in a discrete framework. Experiments that were conducted with two comprehensive datasets have shown that the proposed approach can carry out comparable parameters' rates associated with the exhaustive exploration search. Although the proposed technique is more agile than the regular algorithm, it is less useful for intrusion discovery machines in large-scale visitor networks.

Atay and Kodaz [88] proposed a new method based on HSA to distribute graphs using the modularity measure. This method was examined with five different real-world network problems. In addition, the method achieved the best-known modularity measure, and the most advanced subsets were produced using this measure. The obtained results showed that the HSA provides faster results compared with other similar methods. However, the proposed algorithm required a larger HM size and more iterations to achieve the best modularity values.

Chen et al., in [62], presented a Protein–Protein Interaction (PPI) network systems exposure algorithm based on the HSA (HMS-CD). Compared with the simple HSA, the converting parameters of HMCR and BW are included to decorate the search method. The proposed approach is usually recommended to obtain a collection of nodes having a higher widespread series coefficient within the PPI network, which is the goal feature of the proposed methods. The obtained outcomes on a real benchmark dataset such as the PPI community showed that the proposed technique using the HSA achieved a better detection cost than the primary HSA and standard MCODE set of rules. Moreover, it can recognize complexes in the PPI network more accurately.

Network applications are one of the most studied applications by using HSA, especially wireless sensor networks. This means that HSA can reach better results in this domain. Most of the researches have been conducted using several versions of the HSA to solve wireless sensor networks applications, which means that wireless sensor networks applications still have space for further investigations and analysis.

4.9. Clustering for Neural Network Application

Artificial Neural Networks (ANNs) are critical computing systems that can be employed to handle complex actual global problems. Wavelet neural Networks (WANs), which are a modified form of ANNs, have been proposed based on the wavelet technique. For the preparation duration of WANs, various parameters must be initialized, inclusive of the wavelet activation purposes, interpretation vectors, and expansion parameters. Typical K-means and fuzzy C-means clustering were employed to select the translation vectors. However, the solution positions forces were caught in local minima. In this respect, the evolutionary HSA, which can search for the close-to-best solution both regionally and globally, was proposed to avoid this problem. In [82], the basic K-means and fuzzy C-means were hybridized with the meta-heuristic HSA. To obtain the evaluation of the global cautiously, those hybridized methods additionally endorse more than one technique for an essential issue, when one considers that many ability solution positions can be created and gathered within the HM. To confirm the robustness of the cautioned WNNs, the real international optimization problem of epileptic seizure publicity could be demonstrated. The general accuracy obtained from the simulation with the hybridized algorithms exceeded those of simple K-means and fuzzy c-mean clustering.

5. Discussion

This section discusses the theoretical aspects, assessment, and evaluation of HSA.

Global mathematical optimization problems, such as benchmark test functions, yield near-optimal solutions of a mathematical representation by determining the desired minimum or maximum function value. Due to the increasing complexity of optimization problems, such as engineering and real-world problems, the development of powerful stochastic methods is becoming much more necessary, critical, and important than before. Over the past decade, several optimization methods have been used in different fields of biology or nature studies. The distribution of the addressing rule is classified into two stages, which is the prime advantage of multi-solution methods (i.e., stochastic search and exploration and exploitation). The above-mentioned exploration indicates a manner where the population (i.e., solutions) tends to be developed repeatedly and the encouraging areas of the search space are examined as wide as possible. By contrast, the search solutions are controlled by the exploitation or intensification to approach the optimal solution obtained in the global search stage.

Meta-heuristic algorithms are advantageous for many reasons. First, the random style encourages these algorithms to avoid falling into local optima and converge to the near-optimal solution. The objective is not to receive the optimum solution of the problem but to obtain the near-optimal solution (with a high fineness value within a reasonable running time). The main purpose of this is to ensure proper stability across search procedures. The purpose of exploration is to discover the more promising areas in a complex and wide search area. Consequently, the exploitation procedure is intensified by the local search procedure in these promising areas to yield better solutions. The optimal accomplishment and effectiveness of a special optimization technique is the trade-off of these techniques, and the better ability will be performed. The current meta-heuristic algorithms adjust the trade-off between these two approaches. They could be further optimized and adjusted for local or global search procedures. Two or more optimization techniques are mixed by combining their elements to obtain advantageous characteristics superior to those of each one alone while avoiding their disadvantages as much as possible. Second, the completion of optimization techniques depends on its origin, abilities, simplicity, and experimental balance.

Meta-heuristic optimization algorithms have been employed extensively to tackle complicated issues. However, for complicated issues, the largest portion of the optimization techniques still falls and is trapped in neighborhood search and fails to meet the close-to-global solution. The idea is that the week diversification search occurs inside the carried out method. Several different search procedures have been used to enhance the effectiveness of the optimization techniques and mitigate the disadvantages; these methods include hybridization and elitism (the survival of an elite as a dominating element in a gadget) [110,111].

The HSA algorithm has emerged rapidly and has become a strong tool for addressing complex problems, similar to other optimization methods. It is an artificial intelligence technique using stochastic computational mechanisms to determine the near-optimal solution for multi-dimensional and one-dimensional purposes according to its objective function. The HSA functions in a common manner, so it is easily implemented and can be efficiently used in a wide class of domains. The results summarized in this paper indicate the effectiveness and accuracy of the obtained results of the HSA. This is determined by comparing the obtained results of the HSA with those of other recently published optimization techniques.

Much like numerous optimization strategies, HSA has some advantages and some weaknesses. Even though there is no combined proof for this optimizer, the final capabilities are summarized in this assessment to confirm that the HSA is superior to different optimization algorithms regarding the convergence inspired rate. Table 3 lists the strengths and weaknesses of HSA.

Table 3. Advantages and disadvantages of HSA.

Advantages
- Combining HA with other algorithms is strongly satisfying [50]. - An excellent convergence acceleration [53]. - An elevated method of getting surprising answers [54]. - Appropriate for many forms of optimization problems [44]. - An efficient international scheme [54]. - Fitting for extensive space [34]. - Robust in dealing with a wide variety of determinations [79]. - Has higher feasibility and efficiency in generating global optima [58]. - Lower chance of getting stuck in nearby optima [68]. - HSA is straightforward in its concept and implementation associated with other heuristic optimization processes [23]. - Reasonable execution time [66]. - Some parameter tuning [111]. - Adaptability, robustness, and scalability are observed in critical characteristics.
Disadvantages
- The primary HSA has been proposed for discrete, single-objective, and multi-objective problems. - No theoretical converging body. - Suffers from premature convergence [91]. - Possibility distribution changes with the needs of generations [86].

The successful application of these algorithms, such as HSA, in industry and science indicates the advantages of using swarm techniques, due to the advantages of swarm algorithms. Firstly, swarm techniques retain information regarding the search space throughout iterations, whereas such data are rejected by evolutionary algorithms in each iteration. Secondly, there are fewer controlling parameters in swarm algorithms. Thirdly, the swarm algorithm is equipped with fewer operators than evolutionary algorithms. Finally, swarm techniques are adaptable, which make them easily applicable to problems in various fields.

The main difficulty of HSA is defining the probabilistic convergence properties of HSA, which are required to fully understand the given technique. The problem of early convergence (premature convergence) in the HSA normally causes the recovery procedure to become stuck during the exploitation search. This effect usually occurs when the solutions' divergence decreases and the solutions cannot avoid falling into the local optima. Furthermore, there is significant potential for researchers to employ and apply the advantages of HSA to approach complex industry and other real-world problems.

The theoretical analyses are essential inside the HSA, though it is easy in theory. To observe the effect of varied parameter settings on the exploration performance, the parameters of the HSA were tested in the same manner as in Gotmare et al. [111]. To analyze the answer clustering components in the HSA, the standard quantity of clusters varies in the course of the optimization technique were identified [54]. Further, the characterization of the population heterogeneity of the HSA has been proposed [86]. Many incomplete re-initializing answers procedures were tested to improve the population heterogeneity and to remove answers from nearby optima. The idea after the re-initialization is to create the possibility of solutions "jumping out" of neighborhood optima and to hold sufficient strength for the set of rules to yield "suitable enough" answers. The HSA is a typical example of a developmental swarm intelligence algorithm. The convergent and divergent traits in HSA correspond to the capacity developing and potential in higher answers, respectively.

The HSA has been particularly used in many different ways to solve clustering problems, such as data clustering, text clustering, feature selection, biological data clustering, protocol clustering in Wireless Sensor Networks (WSNs), microgrid clustering, and gene expression clustering [33]. The various versions of the algorithm and the multiple applications to clustering suggest the need for a comprehensive overview of the HSA, hybridization and other variants, and improvements in solving complex clustering problems. We attempted such a survey in this paper, discussed the algorithm's advantages and disadvantages, and suggested some future paths of investigation for researchers who are interested in the field.

Finally, HS has a simple structure; thus it can be easily hybridized with other algorithms for becoming a more efficient clustering solver. Additionally, we can further develop clustering-specific operators on top of the three existing ones (memory consideration, pitch adjustment, and random selection) in the future. These are promising research directions.

6. Conclusions

In this survey, over 100 research papers were analyzed to make a robust conclusion for the researchers interested in using the HSA. The papers were collected by using Google scholar by using four keywords (harmony, search, algorithm, and clustering). The survey exhaustively and comprehensively summarized the references published since it was proposed and until the first half of 2020. In the survey, we have analyzed articles in which HSA has been applied to various applications, many of these related to clustering, for example data clustering, fact clustering, text clustering, fuzzy clustering, image processing, and wireless sensor networks. Some of these applications used variants of the HSA to enhance its performance, including hybridization of HSA with other algorithms, as well as variants that allow for multi-objective optimization. The strengths of HSA include its efficiency and potential for modification and hybridization with other optimization algorithms, while its weaknesses include a tendency to getting trapping in local optima because of its emphasis on exploitation (i.e., local search and intensification) instead of exploration (i.e., global search). The performance of HSA is strongly dependent on parameter tuning. Future work can focus on methods for improving efficiency and for tuning the parameters to provide optimal performance. We recommend that the proposed techniques of HSA be included with any other method to flexibly tune the related parameters and enable them to be mutable or dynamic. The HSA set of guidelines can be carried out to engineer optimization issues and develop new meta hybrid strategies in order to treat extra-complicated optimization problems. Important directions of future research will include, on the one hand, using HSA in real-world industrial cases, and on the other hand, conducting comprehensive research on strategies to clear up multi-goal optimization problems.

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