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Comprehensive Review of the Development of the Harmony Search Algorithm and Its Applications

ALA'A A. AL-OMOUSH, ABDULRAHMAN A. ALSEWARI, (Senior Member, IEEE), HAMMOUDEH S. ALAMRI, AND KAMAL Z. ZAMLI, (Member, IEEE)

Faculty of Computer Systems and Software Engineering, Universiti Malaysia Pahang, Kuantan 26300, Malaysia

Corresponding author: Abdulrahman A. Alsewari (alsewari@ump.edu.my)

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ABSTRACT This paper presents a comprehensive overview of the development of the harmony search (HS) algorithm and its applications. HS is a well-known human-based meta-heuristic algorithm that mimics the process of creating a new harmony in music. This algorithm can be applied to different fields of research, owing to its ability to balance between exploitation (i.e., searching around the known best) and exploration (i.e., roaming the entire search space). Thus, numerous studies have been conducted to utilize HS in real-world optimization problems, and many variants and hybrid algorithms of HS have been developed to cope with different problems. In this paper, HS and its variants are reviewed from various aspects. First, we describe the HS algorithm and present how its parameters affect algorithm performance. Second, we describe HS classifications based on the well-known HS variants and hybrid algorithms, along with their applications. Finally, a discussion conducted on the strengths and weaknesses of the HS algorithm and the possibilities for its improvement. Focusing on related work from diverse fields (such as optimization, engineering, computer science, biology, and medicine), this paper can foster interests on the application of HS for multidisciplinary audiences.

INDEX TERMS Harmony search, evolutionary algorithms, meta-heuristics, Optimization, computational intelligence.

I. INTRODUCTION

Optimization algorithms aim to find the fittest element from groups of choices subjected to specific constraints [1], [2]. The use of the optimization algorithm to solve real-world problems started in the early 1940s. The optimization algorithms have two main categories. The first category includes exact algorithms, which prove their ability to find optimal solution values in direct and typical models. However, real world optimization problems are complicated, and thus, are impossible to solve using exact algorithms [3]. The second category includes heuristic algorithms, which are developed to solve problems faster than classic methods by scarifying optimally or completeness to find a near optimal value.

Heuristic optimization technique contains a general design that does not require specific conditions or mathematical attributes of objective functions, such as gradient information and differentiable attributes; thus, researchers rely more on heuristic algorithms to find the most optimal solutions within a limited time [4]. The disadvantage of this method is the need to create a specific solution for a specified problem. Hence, one algorithm cannot be used for all types of problems.

Meta-heuristic algorithms are higher-level heuristic algorithms that can cover a wider range of problems [5]. The main functionality of meta-heuristic algorithms is obtained by merging rules and randomness to simulate natural phenomena, such as physical annealing in a simulated annealing (SA) algorithm [6], human intelligence in the harmony search (HS) algorithm [7], the biological evolutionary process in differential evolutionary algorithm (DE) [8], and animal behavior in Tabu search [9].

The effectiveness of meta-heuristic algorithms relies on the utilization of explorative (diversification) and exploitative (intensification) ranges through a search [10]. The exploitative process is achieved by utilizing the information gained to guide the search toward its goal. The explorative process is defined as the ability of an algorithm to investigate uncovered areas rapidly within large search sizes. Implementation performance will improve if the balance between these two features is achieved [11].

Some researchers categorize meta-heuristic algorithms based on their method of searching, such as trajectory-based or population-based algorithms [12]. The method used in searching has a special effect on optimization algorithms. For example, SA works through functional search nodes or agents that shape the Brownian motion path through its movement across certain targets. Meanwhile, population-based algorithms are implemented through the parallel use of various operators. Although both techniques have achieved successful results in different works, some studies suggest that population-based algorithm is more suitable for multi-objective optimization problems [13]. However, combining these two techniques can produce good results [4].

Geem *et al*. [7] proposed a well-known population-based meta-heuristic algorithm, known as harmony search algorithm(HS). This algorithm mimics the process of creating a new harmony in music to solve an optimization problem. HS has been proven to produce exceptional results over a vast scope of optimization problems because of its ability to handle different optimization problems in various fields, such as university timetable [2], [14], [15], structural design [3], [10], [16]–[18], water distribution [19]–[21], and other fields of research. The main advantage of the HS algorithm is that it is easy to code and apply to diverse problems [22].

The ability of the HS algorithm to achieve a balance between exploitative and explorative ranges is the reason for its strength and success. In the HS process, the exploitative range is mainly dominated by pitch adjustment rate *(PAR)* and bandwidth *(BW)*, whereas the explorative range is essentially controlled by the HS memory-accepting rate *(HMCR)* [2].

This review aims to present an overall summary of related studies on the HS algorithm, including its characteristics, variants, hybridizations, applications to different optimization fields, and future challenges and potentials. In this work, we classified HS algorithm research topics into four categories: HS general structure, classifications, hybridizations, and applications.

In this article, we determined the number of HS publications from various publishers: ACM, Hindawi, Taylor & Francis, Elsevier, IEEE, SpringerLink, and others. Fig 1 shows the number of published papers based on each database when the HS algorithm is applied to various optimization fields. Meanwhile, Fig 2 shows the growing interest in the utilization of the HS algorithm and its applicability to different fields of research compared to other recent metaheuristics based on the Google Scholar database for the period from 1999 until 2018.

The rest of this paper is organized as follows. Section 2 presents the general structure of HS. Section 3 discusses the effects of HS parameters and identifies well-known HS classifications and several HS-based variants. Section 4 describes hybrid HS and provides examples. Section 5 presents HS applications. Finally, Section 6 includes discussions and concludes the paper.

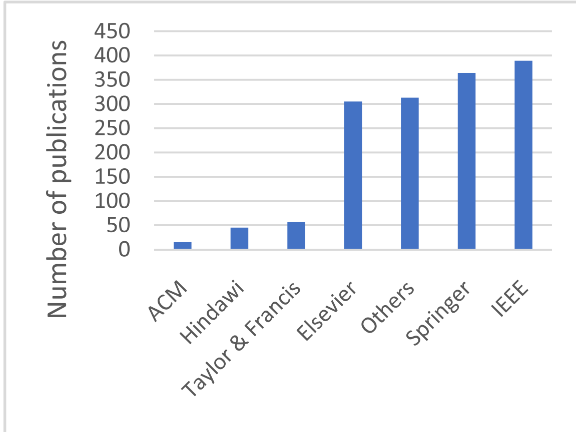

FIGURE 1. The number of HS publications per database for several journals: ACM, Elsevier, Hindawi, IEE, Springer, Taylor & Francis, and other journals as one group.

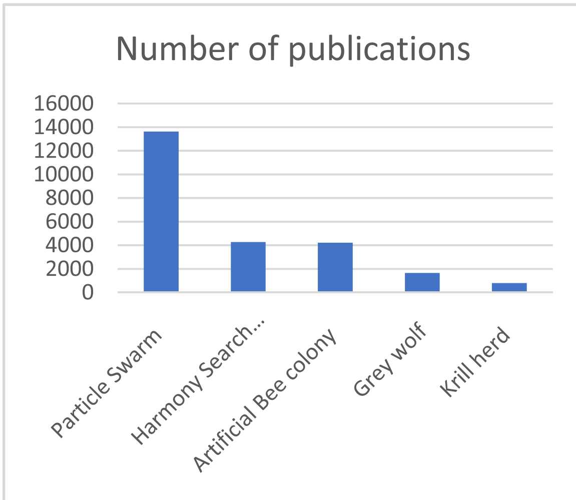

FIGURE 2. The number of publications between (1999 – 2018).

II. THE GENERAL STRUCTURE OF THE HS ALGORITHM

HS is a well-known (EA). EA basically begins by creating random values that are possible solutions to a specific problem. The fitness of each value is evaluated based on the evaluation function. A nomination process must be used in every rotation within EA to create a better population. The main objective of the nomination process is to deviate the search toward fitter values, capture these values, and include them in the next population [23].

The HS algorithm is applied in different areas due to the following special advantages: HS requires lower mathematical operations than traditional heuristic algorithms, does not use premier amount or gradient search for decision variables, and does not consider the derived values because stochastic inspections are used [3].

The main similarities between the HS algorithm and music harmony improvisation processes are as follows. First, a musician searches for the most beautiful music harmony (ideal condition) as specified by the standard for tunes, while the HS algorithm searches for the global solution (ideal condition) as specified by an objective function. Second, every pitch of a musical instrument contributes to the level of music harmony and beauty, which is similar to the objective function value specified by the combination of values assigned to each decision variable [3], [10].

HS involves processes that are analogous to those of other meta-heuristic algorithms. For example, it saves the history of visited vectors in harmony memory *(HM)*, which is comparable with the memory of the Tabu search algorithm. HS is capable of mutating the *(HMCR)* through the entire calculation process, similar to SA. HS considers all vectors, which is similar to a genetic algorithm (GA). The main difference between HS and GA is that the latter creates a new vector based on two previous vectors (called parents). By contrast, HS considers all previous vectors before creating a new harmony vector [10].

The HS algorithm process contains five main steps, as illustrated in Fig 3.

Step 1: Initialize values of the HS parameters, such as *HMCR, BW, PAR*, number of iterations *(NI)*, and *HM* size (*HMS*).

The optimization problem goal will be determined in this step, either by using maximum or minimum objective function $f\ (x_i)$, where x_i will be the possible solution from N ($N \in$ *all the decision variables of* x_i).

Step 2: *HM* values will be initialized, as x_i within the upper and lower boundary ranges, using the following equation:

$$x_i = lowerbound + R1 \times (upperbound - lowerbound) \\ .\{R1\ is\ random\ number\ (0-1)\} \quad (1)$$

Step 3: Improvisation of the new harmony is performed using a combination of three major parameters: *HMCR, PAR*, and BW. The improvisation has two main steps, as shown in Algorithm 1. First, two random values (a & b) will be created between ($0 \sim 1$), and if ($a > HMCR$), then a new value x_j will be created using Eq. (1), as a new generated vector ($x_j^{'}$).

Second If the value of ($a < HMCR$), then a random value from $HM\ (x_i)$ will be selected, and if the value of ($b < PAR$), then x_i will be modified using Eq. (2).

$$x_j^{'} = x_{new,j} \pm bw * rand \quad (2)$$

Step 4: Memory is updated if the new generated vector of the last step ($x_j^{'}$) is better than the worst vector in *HM*, based on the objective function.

Step 5: After each improvisation, the algorithm will check the stopping criteria, such as the maximum number of improvisations, to end the search process. The next pseudocode describes the improvisation process of HS algorithm:

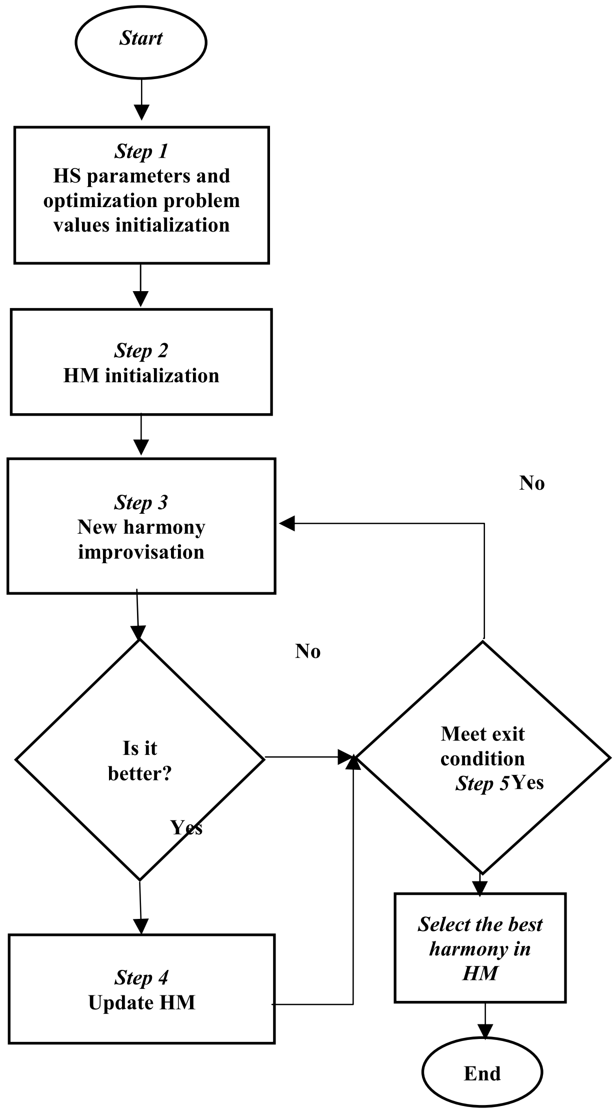

FIGURE 3. HS flow chart.

III. HS CLASSIFICATIONS

The following parameters affect the performance of HS: *HMS, HMCR, BW*, and *PAR*. Many researchers have tried to enhance the performance of HS algorithm by selecting the ideal combination of these variables [24]. In this section, we will show the descriptions of these parameters from previous studies, some suggested values, and how they affect HS.

HMCR enables selecting one of the existing values in *HM* ($x_{i,j}$) or creating a new value x_j^{new} through the improvisation process; that is, the larger the value of *HMCR*, the larger the convergence rate of HS. Hence, a small *HMCR* value will increase the diversity of the algorithm. *PAR* enables modifying the selected value $x_{i,j}$. Large *PAR* values will improve the intensification ability of HS, whereas small *PAR* values will improve the diversity or exploration of *HM*. Large *PAR* and *HMCR* values are better for unimodal problems, whereas small values are better for multimodal problems.

Algorithm 1 Harmony Search Algorithm Improvisation

$while\ (t < Max\ number\ of\ iterations)$
$for\ (j = 1\ toD) = \{D : number\ of\ dimensions\}$
$If\ (R2) \leq HMCR\ \{Memory\ consideration\ \}$
$x_i^{'} = x_{i,j}\ \{i\ is\ a\ random\ integer\ \ (1, \ldots\ HMS\ )\}$
$if\ (R3 \leq PAR)\ \{Pitch\ adjustment\ \}$
$x_j^{'} = x_j^{'} \pm R4 \times bw$
$end\ if$
$else$
$x_j^{'} = LB + R5 \times (UB - LB))$
$end\ if$
$end\ for$
$Update\ HM\ :$
$if\ \left(x_j^{'}\ better\ than\ worst\ x_j \left\{x_j \in HM\right\}\right)$
$x_j = x_j^{'}$
$t = t + 1$
$End\ while$
$return\ best\ harmony$

Selecting fixed *HMCR* and *PAR* values is difficult because characteristics differ for each optimization problem [25].

Different variants of the HS algorithm have been developed to cope with various types of parameters, such as binary, discrete, and continuous. Selecting the appropriate values for HS parameters is one of the difficulties in using the HS algorithm and other meta-heuristic algorithms; numerous variants have been created to address this problem by replacing these values with new dynamic values or by adding another component to solve this issue [26]. In the next sections, the classifications of some variants and their enhancement of the original HS algorithm are described.

A. CONTINUOUS-BASED HS ALGORITHMS

Different variants of HS have been created to deal with continuous variable problems. We present some well-known HS continuous variants and how they differ from the original HS algorithm.

1) AN IMPROVED HARMONY SEARCH ALGORITHM FOR SOLVING OPTIMIZATION PROBLEMS (IHS; 2007)

Mahdavi *et al.* [1] developed a dynamic method to generate *PAR* and *BW* values. Eq. (3) describes dynamic *PAR* as follows:

$$\mathrm{PAR}\ (\mathrm{t}) = \mathrm{PAR}_{\min} + \frac{(\mathrm{PAR}_{\max} - \mathrm{PAR}_{\min})}{NI} \times t. \tag{3}$$

PAR(t) is the value of *PAR* for each iteration (t), and its value is increased in every iteration based on *PARmin* and *PARmax*, which are the minimum and maximum values of *PAR*, respectively. *NI* denotes the number of iterations.

Meanwhile, *BW* also has a dynamic value for each iteration based on the minimum and maximum values of bandwidth (BW_{min}, BW_{max}), as shown in Eqs. (4) and (5):

$$C = \left(ln\left(\frac{BW_{min}}{BW_{max}}\right) \div NI\right) \tag{4}$$

$$BW\ (t) = BW_{max} \times e^{(c\times t)}. \tag{5}$$

Mahdavi applied the new algorithm on benchmark functions and other engineering optimization problems (e.g., minimization of the weight of a spring and pressure vessel design) to compare the results with the original HS and other optimization algorithms. The new variant provided better results. This variant of HS inspired many researchers to develop modified versions of the original HS and improve its performance. The problem with IHS is that it requires selecting the upper and lower values of the variable BW within a large range ($0 \sim \infty$).

2) GLOBAL-BEST HARMONY SEARCH (GHS; 2008)

Omran *et al.* [23] proposed a new variant of HS, called GHS. GHS can handle discrete and continuous cases. It utilizes the concept of swarm intelligence in particle swarm optimization (PSO) [27] to replace the *BW* value. Replacement is accomplished by using the best *HM* value for pitch adjustment instead of *BW*. The effects of *HMS* and *HMCR* were tested on the GHS algorithm. A higher value of *HMCR* was suggested to obtain a better result for high-dimensionality problems, whereas a lower result is better for low-dimensionality problems. The results show that GHS outperforms HS and IHS except at low dimensions. GHS has the same steps as IHS except for the pitch-adjusting step. Eq. (6) describes how GHS uses the best result in *HM* to replace *BW* values.

$$if\ (rand \leq PAR)\, x_j = x_{best,n}, \quad n \in \{1, 2, 3, \ldots ND\} \tag{6}$$

Although GHS eliminates the use of the BW value, lower and upper PAR values should still be specified.

3) A SELF-ADAPTIVE GLOBAL BEST HARMONY SEARCH ALGORITHM (SGHS; 2010)

Pan *et al.* [25] created a new variant of HS based on GHS [23] for continuous optimization problems. The new variant has a new improvisation technique and dynamic *HMCR* and *PAR* based on a learning procedure. The *BW* value is reduced dynamically with an increasing number of iterations based on Eq. (7 & 8).

$$BW\ (t) = BW_{max} - \frac{BW_{max} - BW_{min} \times 2t}{NI} \quad if\ t < \frac{NI}{2} \tag{7}$$

$$BW\ (t) = BW_{min} if t \geq \frac{NI}{2}\ (8) \tag{8}$$

To update *HMCR* and *PAR* values, the initial values of HMCRm (e.g., 0.98) and PARm (e.g., 0.9) are provided, and *HMCRm* and *PARm* values are generated using a normal distribution (Gaussian) in every iteration. After a specific number of iterations, such as 100 iterations in this work, the mean values of *HMCR* and *PAR* are calculated to obtain a successful result, and then used in the next iteration. This step is repeated until the stopping criteria are achieved.

For *HMS*, the author suggested that the use of small fixed values ($5 \sim 10$) is best based on their experiments.

4) NOVEL GLOBAL HARMONY SEARCH ALGORITHM FOR UNCONSTRAINED PROBLEMS (NGHS; 2010)

Zou *et al.* [28]. developed another variant that excludes *HMCR* and *PAR* variables and replaces them with position updating and genetic mutation, respectively. The concept of position updating was borrowed from PSO to prevent the NGHS algorithm from getting trapped in the local optimum. The next pseudocode shows the manner of improvisation of NGHS:

Algorithm 2 NGHS Improvisation (Zou 2010)

$for\ (j = 1\ to\ D)\ \{D : number\ of\ dimensions\}$
    $X_R = 2 \times X_j^{Best} - X_j^{worst}$
    $if\,(X_R > x_U)$
        $X_R = x_U$
    $else\ if\,(X_R < x_L)$
        $X_R = x_L$
    $end\ if$
    $\acute{x}_i = x_j^{worst} \pm rand\ (0 \sim 1) \times X_R - X_j^{Worst}$
    $if\,(rand\ (0 \sim 1) \leq \mathrm{Pm})$
        $\acute{x}_i = x_L + rand\ (0 \sim 1) \times (x_U - x_L)$
    $end\ if$
    $Update\ The\ Memory$
$end\ for$

where X_j^{Best} and X_j^{worst} are the best and worst X_i in HM, respectively, based on the objective function $f(x)$; x_U and x_L are the upper and lower bounds of the objective function, respectively; and $rand\ (0 \sim 1)$ is a random value between 0 and 1. Another modification on the original HS is when the worst value is updated with the new X_j even if the new value is not better than the worst one.

5) AN IMPROVED GLOBAL-BEST HARMONY SEARCH ALGORITHM (IGHS; 2013)

El-Abd [29] developed an improved variant of GHS by focusing on the explorative range at the beginning, and then on the exploitative range at the end of a search. To accomplish this, the author used Gaussian distribution to select the random pitch adjustment, as described in Equation (9):

$$X_j^{'} = HM_d^r + Gauss\,(0, 1) \times BW \tag{9}$$

where HM_d^r is a randomly selected value from HM, and Gauss is a random number with a mean of 0 and a standard deviation of 1. For pitch adjustment, Equation (10) is used as follows:

$$X_j^{'} = HM_d^{best} + \emptyset \times BW \tag{10}$$

where HM_d^{best} is the best value in HM based on the objective function evaluation $f(x)$. The value $\emptyset$ is a random number that is uniformly distributed within the range $\{-1, 1\}$. *PAR* value is decreased within the iterations to achieve great exploitation, as described by Wang and Huang [30]. For *BW*, the author borrowed its formula from the IHS [1] variant. The algorithm was compared with seven previous HS variants using the benchmark function from CEC05.

6) A DIFFERENTIAL-BASED HARMONY SEARCH ALGORITHM FOR THE OPTIMIZATION of CONTINUOUS PROBLEMS (DH/BEST; 2016)

Abedinpourshotorban *et al.* [31] introduced a new HS variant by modifying two aspects of the original HS. The first modification is applied to the initialization of HS by using a new method to initiate feasible solutions with less randomness. The second modification involves replacing pitch adjustment with the updated version inspired by the differential evolution (DE) mutation strategy and excluding the *BW* parameter.

The following algorithm describes the new initialization processes, which is implemented by replacing the random value with a new calculation based on HMS:

Algorithm 3 *DH/Best Initialization* (Hosein *2016*)

$for\ (j = 1\ toD)\ \{D = dimensions$
    $for\ (i = 1\ toHMS)$
    $temp_i = LB + ((i - \frac{0.5}{HMS})) \times (\text{UB-LB})$
        $end\ for$
    $Shuffle\ the\ temporary\ array$
    $for\ (i = 1\ toHMS)$
        $HM = temp_i$
    $end\ for$
$end\ for$

where *UB* and *LB* are the upper and lower bounds of the decision variables. The new variant eliminates the requirement of setting *BW*, and pitches are adjusted based on the distances between the pitches in *HM* by using DE/best/1 mutation, as described in the following pseudocode:

Algorithm 4 *DH/Best Improvisation* (Hosein *2016)*

$for\ (i = 1\ to\ D)$
    $if\ (r(0 \sim 1) \leq HMCR)$
        $X_i^{'} = X_{ij}\ (i\ is\ random\ integer\ from 1..HMS)$
        $if\,(r(0 \sim 1) \leq PAR)$
            $X_i^{'} = X_{best} + r\ (0 \sim 1) \times (X_{r1,J} - X_{r2,J})$
            $if\,(X_j^{'} < LBorX_j^{'} > UB)$
                $X_j^{'} = r\ (0 \sim 1) \times (\text{UB-LB}) + LB$
            $end\ if$
        $end\ if$
    $else$
        $X_j^{'} = r\ (0 \sim 1) \times (\text{UB-LB}) + LB$
    $end\ if$
$end\ for$

where *UB* and *LB* are the upper and lower bounds of the decision variables, $r(01)$ is the random value between 0 and 1,

X_{best} is the best X_i in HM based on the objective function, and $X_{r1,J}$ and $X_{r2,J}$ are two random values in the jth dimension.

B. DISCRETE-BASED HS ALGORITHMS

Lee *et al.* [18], Geem [32], and Wang *et al.* [33] developed several versions of HS to address the discrete variable problem. In these previous works, HS was used to solve engineering design problems, which are discrete by nature. In another research, Al-Betar used HS to solve another discrete problem, which is a university course timetabling optimization problem [14]. Moreover, Gao *et al.* [34] utilized the HS algorithm in the no-wait flow shop scheduling problem with total flow time criterion.

The improvisation process of discrete HS for X_i is described in equation (11), and for continuous in equation (12):

$$x_i^{'} \leftarrow x_i\,(\mathrm{i}+\mathrm{c})\ \textit{For discrete design variables} \tag{11}$$

$$x_i^{'} \leftarrow x_i + a\ \textit{For}\ \text{continuous}\ \textit{design variables} \tag{12}$$

We select the neighbor value by adding $\mathrm{c} \in (-1 \sim 1)$ for the discrete problem and $a = BW \times u$ for the continuous problem, where BW is the bandwidth value and u is a random value between $(-1 \sim 1)$.

For the mixed problem between discrete and continuous problems, such as the work of Lee *et al.* [35], HS is used in a truss design problem that requires solving both types of optimization problems (discrete and continuous) in parallel. HS shows that it can effectively cope with all these types of problems.

C. BINARY-BASED HS ALGORITHMS

Many researchers have been using HS in discrete and continuous optimizations in different fields of science and engineering. Some researchers have utilized HS in binary problems. Although HS with binary coding can be used to address binary-coded problems, the pitch adjustment operator is inferior in binary space, which degrades the performance of the algorithm because PAR is typically eliminated. For example, Geem [36] utilized HS with binary coding to address water pump switching problems and the PAR parameter was eliminated in this work. Another utilization of binary HS was performed by Geem and Williams [37] to cope with an ecological optimization problem that achieved competitive results. The next variant demonstrates how HS binary variants handle binary problems.

AN IMPROVED BINARY hARMONY SEARCH ALGORITHM (ABHS; 2013)

Wang *et al.* [38] developed a new HS variant to cope with the binary optimization problem. In the beginning, HM is initialized by generating random binary numbers for each value within HM. Then, a new pitch adjustment is created to handle the binary problems and improve HS capabilities by replacing the adjacent value in the original HS with a global optimal adjacent value as follows:

$$X_{ij} = \begin{cases} hbj & r < PAR \\ X_i & else \end{cases} \tag{13}$$

where hbj corresponds to the best value within HM (i.e., global optimal harmony).

Two updating techniques: memory consideration strategies (serial and parallel update mechanisms) and (individual and bit selection mechanisms) were studied.

Individual selection strategy:

$$X_{ij} = \begin{cases} h_{pj} & if\ r1 < HMCR \\ R & else \end{cases} \tag{14}$$

$$R = \begin{cases} 0 & if\ r1 < 0.5 \\ 1 & else \end{cases} \tag{15}$$

where X_{ij} is the jth bit of X_j, the new improvised vector p is the random value of HMS, and $r1$ and $r2$ are two random values between the range of 0 and 1.

The algorithm achieves good results after being tested by benchmark functions and the knapsack problem.

D. CHAOTIC-BASED HS ALGORITHMS

Chaotic maps are similar to randomness in their functionality. However, these algorithms are less sensitive to the initial condition and parameters due to their deterministic nature. Chaotic-based HS algorithms are applied to many meta-heuristic algorithms to improve their performance. Some HS algorithm variants have been used in chaotic maps [22], [39]–[41]. The following variant describes how chaotic maps are applied to HS.

CHAOTIC HARMONY SEARCH ALGORITHMS (CHS; 2010)

Alatas developed a new HS variant by using chaotic maps for parameter adoption. the main objective was to avoid falling into the local optimum and to improve the convergence of HS.

Seven chaotic maps were used to generate random values instead of the original random generator in HS.

Maps were used in this work for different parameters of HS, such as in *HM, PAR*, and *BW* generation. Some of the maps enhanced solution quality and helped HS escape from the local optimum. In this work, Alatas used only two benchmark functions to demonstrate the capabilities of the new variant.

E. OPPOSITION-BASED HS ALGORITHMS

Gao *et al.* [42] and other researchers used the opposition-based intelligent computation approach to enhance HS performance, by creating opposite values from the new improvisation results and replacing the improvisation values if the new results are found to be better. Successful variants that use opposition-based methods are presented in the succeeding subsections.

1) AN IMPROVED GLOBAL BEST HARMONY SEARCH ALGORITHM FOR FASTER OPTIMIZATION (IGHS; 2014)

Xiang *et al* [43] recently developed a new HS variant based on the GHS [23] algorithm. The new variant exhibits four modifications from the original GHS. First, it uses the opposition technique (OBL) [44] during initialization to obtain more diverse initial values and avoid falling into the local optimum. Second, the DE concept is adopted to implement new improvisations. Third, HS exploration is improved and falling into the local minimum is avoided by using two concepts based on the artificial bee colony algorithm [45] and the OBL scheme. Fourth, the *HMCR* and *PAR* parameters are updated based on the sign and periodic functions.

Two experimental studies were conducted to compare IGHS with the original HS and GHS (2008) and other meta-heuristic algorithms. Competitive results were achieved by IGHS.

2) GLOBAL HARMONY SEARCH WITH GENERALIZED OPPOSITION-BASED LEARNING (GOGHS; 2015)

Gou *et al*. [46] created a new HS variant because of the poor exploitation of the original HS. The new variant adopts the concept of generalized opposition [47], which is a modified version of the original opposition [44], in addition to utilizing NGHS [28].

GOGHS first initializes its *HM* in the same manner as the original HS. After initialization, a new candidate (X_i) is created using the NGHS algorithm [28]. A modified version of (X_i) is created in the new candidate harmony (O_X_i) by using the generalized opposition-based solution. Finally, the worst result in *HM* will be replaced with the best value between the new candidate and its opposition (X_i and O_X_i).

3) IMPROVED HARMONY SEARCH ALGORITHM: LHS (LHS; 2017)

Ouyang *et al*. [48] recently developed an HS variant by implementing three modifications to the original HS to improve its effectiveness. First, they used the opposition concept [44], within the harmony consideration process to obtain better diversity in the result. Second, they used self-adaptation in pitch adjustment to improve the intensification of the HS algorithm by mimicking the swarm intelligence concept of PSO. Third, they found the worst vector in *HM* and updated it with the best value between the improvisation and opposition results. Finally, they compared the new variant with 10 previous HS variants using 48 mathematical benchmark functions. The new variant exhibited higher competitive performance than the previous variants.

F. MULTI-OBJECTIVE HS ALGORITHM

After the success of applying HS to single-objective optimization problems, many researchers have applied HS to multi-objective optimization problems [49]–[52].

IV. HYBRIDIZATION OF THE HS ALGORITHM

The development of new meta-heuristic algorithms can be accomplished in several ways, and the creation of new hybrid algorithms based on existing heuristic algorithms is considered one of the most successful techniques [53]. The best way to create a new successful meta-heuristic algorithm is by using an appropriate assembly of existing meta-heuristic algorithms, such as combining a multi-agent algorithm with a trajectory algorithm, to create algorithms with enhanced capabilities [54]. The need to create a multi-objective meta-heuristic algorithm to handle NP-hard optimization problems remains a productive research area [4].

The hybrid algorithms of HS have proven their effectiveness in improving the performance of HS to cope with different cases [55]. The concept of hybridizing the HS algorithm with other meta-heuristic algorithms has recently become prevalent, and many hybrid algorithms have been developed and used [38]. We present well-known hybrid HS categories and provide examples for each.

A. HYBRIDIZATION WITH A LOCAL SEARCH-BASED ALGORITHM

Global search algorithms, such as HS, are well-known for their good exploration, whereas local search algorithms are appropriate for exploitation. Combining the two types will probably produce a strong algorithm for exploration and exploitation. The following hybrid algorithms are examples of HS algorithms with a local search algorithm.

1) HYBRIDIZING HARMONY SEARCH ALGORITHM WITH SEQUENTIAL QUADRATIC PROGRAMMING FOR ENGINEERING OPTIMIZATION PROBLEMS (HHSA; 2008)

Fesanghary *et al*. [56] developed an example of a hybrid HS algorithm with a local-based search algorithm. This hybrid algorithm is incorporated with sequential quadratic programming (SQP) to improve the local search speed and accuracy of the HS algorithm. The hybrid algorithm achieves better result compared with the original HS and other heuristic algorithms.

The effects of HS parameters, such as HMCR, HMS, and PAR, were also tested in this work. A small HMCR value will reduce the algorithm's efficiency, whereas a large value will result in better exploration. However, this condition may cause the algorithm to fall into the local optimum. For HMS, the larger the size, the better the results obtained with numerous iterations. However, this process can be time-consuming. By contrast, a small HMS value can cause premature convergence. The authors suggest using an HMS value between 4 and 10. For PAR, a large value with a small BW will increase HS efficiency.

2) HHS, HGHS, HMGHS (2010)

Wang *et al*. [33] made another hybrid local/global search algorithm in 2010, and developed three hybrid HS algorithms to reduce the total time of flow shop scheduling in a blocking optimization problem. The first algorithm is based on the original HS by Geem *et al*. [7], the second is based on GHS [23], and the third is based on a modified GHS. The authors hybridized the HS variants with a local search algorithm based on the insert neighborhood to balance the exploration and exploitation of the new algorithm. They implemented HM initialization using another heuristic algorithm (NEH) [57]. Furthermore, they transformed the continuous vectors of harmonies to discrete job adjustments based on the largest position value. To test the efficiency and effectiveness of their hybrid algorithms, the authors used the blocking flow shop scheduling problem, which is considered an NP-hard problem when more than two machines are involved.

B. HYBRIDIZATION WITH POPULATION-BASED ALGORITHM

Another way to improve population search algorithms is by creating a hybrid algorithm with another population search algorithm (or some of its components) to combine the advantages of both algorithms. The next hybrid algorithm is an example of a hybrid population-based algorithm.

AN EFFECTIVE HYBRID HARMONY SEARCH-BASED ALGORITHM FOR SOLVING MULTIDIMENSIONAL KNAPSACK PROBLEMS (2015)

Zhang *et al*. [58] developed a new hybrid algorithm of HS with fruit fly optimization (FFO) [59]. The main objective of this algorithm is to overcome the weak exploitation process of HS. This hybrid algorithm is used to solve MKPs.

Binary string values are used in this work to apply the new hybrid algorithm to MKPs, with few modifications to the original HS algorithm. The hybrid algorithm starts by using the original HS initialization process. Then, the global HS scheme is used to improvise the values in HM that are similar to GHS [23]. The smell-based FFO search is used to create modified values of HM and update each value of HM to see if each value is better than the original. A repair operator is used to ensure that the new improvised values satisfy the weight constraints.

C. HYBRIDIZATION HS WITH OTHER COMPONENTS

The use of HS or its component to assist another meta-heuristic algorithm through hybridization has been realized in different studies [60]–[63]. The subsequent hybrid algorithm is an example of using HS as a component in the search process.

PSO, ANT COLONY OPTIMIZATION (ACO), AND HS SCHEME HYBRIDIZED TO OPTIMIZE TRUSS STRUCTURES

Kaveh *et al*. [64] proposed a new hybrid HS algorithm with PSO [27] and ACO [65]. HHS, HGHS, and HMGHS used the hybrid principle to solve the continuous and truss design optimization problems. In this work, the role of HS was to control the variable constraints through the design of the truss structure optimization problem.

V. APPLICATIONS OF HS ALGORITHM

Multiple mathematical techniques, such as dynamic, linear, and nonlinear programming, have been used to solve optimization problems before the existence of heuristic algorithms. All traditional techniques can find the global optimal solution, but special specifications or characteristics should be specified for each problem, and thus, covering NP-hard problems is impossible. Another disadvantage of these methods is that they consume considerable space and time in solving a problem, thereby increasing the complexity of the problem and making these methods impractical for real-world problems. Consequently, meta-heuristic algorithms have been developed by mimicking nature or human intelligence to solve these issues. These algorithms have proven their efficiency in handling real NP-hard problems [66].

HS was initially used to find the best design for water distribution networks by its original author Geem Thereafter, many researchers have utilized HS in different fields, such as engineering and information technology. Several categories of these works are described in the subsequent sections.

A. REAL-WORLD APPLICATIONS /INDUSTRIAL APPLICATIONS

Many researchers have used HS to solve real-world issues. Music composition, an example of a real-world application, has been conducted to support composers, such as Navarro *et al*. [67].

Al-Betar *et al*. [2], [15] and Chiarandini *et al*. [13] used HS and its hybrids to create a university course timetable, which is considered a real-world optimization problem. Many researchers have applied HS to solve real-world problems, such as tour planning, logistics, and project and flow shop scheduling, as shown in Table 1.

B. COMPUTER SCIENCE PROBLEMS

Different applications in computer science have been solved using the HS algorithm, such as web page and document clustering. Clustering refers to the automatic classification of a webpage or document content to reduce the amount of data and gain useful information. Forsati *et al*. [77], [78] used a hybrid HS with K-means to cluster web pages. Cobos *et al*. [79] used GHS [23] with K-means, frequent term sets, and the Bayesian information criterion to cluster webpage data. Text summarization is another computer application of text extraction that aims to summarize the text of web content, such that the end user can easily find what he/she is looking for in summarized form. Different studies have been conducted using HS and its variant GHS to accomplish text summarization [47], [80], [81].

Other computer applications of HS are used in the literature in other areas, such as Internet routing, visual tracking, robotics, and automatic software test case generation, as shown in Table 1.

TABLE 1. Applications of HS.

Field	Publications
Real-world applications /Industrial Applications	Music composition: [67] Timetabling: [2, 13-15] Tour planning: [68] Logistics: [69, 70] Project Scheduling[71] Decision support system:[72] Flow Shop Scheduling: [33, 34, 52, 73-75] Self-driving cars:[76]
Computer science	Web page & document clustering: [77-79] Text summarization: [80, 81] Internet routing: [82-84] Visual tracking: [85] Robotics: [86] Automatic software test case generation: [87-90] Word Sense Disambiguation: [91] Circle Detection: [92]
Electrical engineering problems	Energy system dispatch [93-96] Energy Management System[97] Heat Exchanger Design[98, 99] Power system design [49] Multi-level inverter optimization [100] Optimization for renewable energy charging [101] Photo-electronic detection [102] Cell Phone Network[103]
Civil engineering problems	Structural design[10, 104, 105] Water network design & Analysis [19, 106] Dam scheduling [107] Flood model calibration [83, 108, 109] Groundwater management [110] Soil stability analysis [111] Ecological conservation[37] Vehicle routing[112] Construction Site Layout [113] Risk Assessment of Tunnel [114] Anomalous Zone Prediction in Tunnel[115] Earthquake Motion [116] Transport Energy Modeling [117] Determination of Road Properties [118]
Mechanical engineering problems	Satellite heat pipe design[98] Offshore structure Fueling & Mooring [119, 120] Parameter Calibration: Face-Milling [121] Steel Making [122]
Biological and medical applications	RNA structure prediction[123, 124] Hearing aids[125] Forecasting Influenza Season [126] Protein Complex Prediction[127] Biological Motif[128] Disease-Associated SNP Detection [129] Noise Sound Level[130] Medical physics[131] Medical Image[132]

C. ELECTRICAL ENGINEERING PROBLEMS

Research on power dispatch and energy flow management systems has been utilizing HS in different works. Vasebi *et al.* [93] used HS to find the minimum cost of energy production while meeting power requirements. A new concept, namely, combined heat and power (CHP), was formed to achieve maximum efficiency because the primitive production of electricity with the use of fossil fuels can only achieve up to 60% efficiency, thereby causing wasted heat. However, balancing heat and power produced by the same units is required. Vasebi applied HS to solve the CHP economic dispatch problem by using two cases and compared the results with those of other meta-heuristic algorithms. Since then, other researchers have used HS to solve CHP problems [94], [95].

Table 1 shows that considerable research has utilized HS to optimize power streaming systems by achieving the minimum cost to transfer electricity in a power system. HS optimizes voltage nodes as a variable for a set of non-linear equations as an objective function. Sivasubramani and Swarup [49] developed multi-objective HS to minimize fuel consumption, which will reduce the cost and power transfer emission, which will then reduce energy loss. The results obtained were compared with those of GA. The HS results outperform those of GA.

HS is utilized in different fields of electric engineering research, such as optimization for renewable energy charging [101], wind power generation [133], and multilevel inverter optimization [100].

D. CIVIL ENGINEERING PROBLEMS

Considerable research has been conducted on structural design optimization because it is considered a sensitive and difficult activity, particularly when time and cost are considered. Lee and Geem [10] used HS to cope with this optimization problem, and the result outperformed those of traditional techniques, such as linear and nonlinear equations, because unlike traditional techniques, HS does not require a high volume of gradient calculation. References [104] and [134] also used HS to cope with this problem.

E. MECHANICAL ENGINEERING PROBLEMS

Several works have utilized HS to cope with mechanical engineering problems. Zarei *et al.* [121] used the HS algorithm to find the ideal cutting parameters of a multi-pass face-milling machine, thereby improving production quality and minimizing the cost and time consumption. Different parameters have been optimized using HS to improve machine tool capabilities, such as the number of passes, the depth of cut for each pass, speed, and feed. The result showed better performance of HS compared with that of GA.

Another mechanical problem solved by HS is the scheduling of diesel generators in oil rig platforms, as reported by Yadav *et al.* [119]. The author attempted to reduce the fuel consumption of a diesel generator that supports the oil rig, while meeting load demand and operational constraints to achieve the optimum performance of the rig. The improved variant of HS obtained competitive results and convergence with the original HS and other meta-heuristic algorithms.

F. BIOLOGICAL AND MEDICAL APPLICATIONS

Forecasting infectious diseases is an interesting idea, and we can formulate strategies to minimize them by predicting their effects. A study was conducted by Hickmann *et al.* [126] on infectious disease forecasting using HS. Data were obtained from the Centers for Disease Control and Prevention and Wikipedia article access logs, and then analyzed using epidemiological models to predict the effect of infectious diseases in the United States. The HS algorithm was used in the prediction process to solve a nonlinear equation.

The HS algorithm was also used to optimize radioisotope placement and intensities by Panchal [131]. Radiation is used to diagnose and treat cancer as part of medical physics. GA and SA were applied to optimize the radioisotope, but the results were obtained faster by using HS compared with GA, thereby improving the patient treatment process.

Table 1 shows the full categories of HS applications with related research works.

VI. DISCUSSION AND CONCLUSION

This article describes the HS optimization algorithm, some of its variants, applications, and hybrid versions. The algorithm has maintained considerable interest since its inception until now because of its ability to balance between exploration and exploitation, and its ability to be used in different research areas because of its simplicity. The author of HS exerted considerable effort to utilize the algorithm in different research areas, and a webpage that contains the full information of HS is available for the benefit of other researchers.

We noticed considerable utilization of HS and improvement on HS. However, the utilization and improvement of HS continues, particularly in terms of its hybridization with other meta-heuristic algorithms. A standard framework or criterion to compare meta-heuristic algorithms or its variants in the meta-heuristic field is necessary.

Finally, the following are the advantages of HS over previous optimization algorithms:

- HS has proven its ability to be applied to different fields of real applications [66].
- HS can cover discrete or continuous optimization problems, and decimal and binary alphabets [66].
- HS can distinguish the high-performance zone in the solution range within a short time.
- HS requires less mathematical operations.
- HS does not exhibit divergence.
- Constructive information of the optimization problem is not important in HS because it uses random search.
- HS produces a new solution in accordance with all previous solutions and simultaneously covers all vectors.
- HS is easy to program, and its simplicity makes it easy to combine with other meta-heuristic algorithms.

The weaknesses of the HS algorithm are as follows:

- HS is highly sensitive to its parameter values, such as *HMCR*, *PAR*, and *BW* [30].
- HS gets stuck in a local search when applied to numerical applications.

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ALA'A A. AL-OMOUSH received the B.Sc. degree in computer science from Al Albayt University, in 2010, and the M.Sc. degree from University Putra Malaysia, in 2013. He is currently pursuing the Ph.D. degree in computer science with the Faculty of Computer Systems and Software Engineering, Universiti Malaysia Pahang. His main research interests include artificial intelligence and computational intelligence.

ABDULRAHMAN A. ALSEWARI was born in Sana'a, Yemen, in 1980. He received the B.Eng. degree in computer engineering from the Military College of Engineering, Baghdad, Iraq, in 2002, and the M.Sc. degree in electronic system design engineering and the Ph.D. degree in software engineering from Universiti Sains Malaysia, in 2008 and 2012, respectively. From 2012 to 2013, he was an Assistant Professor and the Head of the Information Technology Department, Engineering College, Darussalam International University for Science and Technology, Yemen. Since 2013, he has been a Senior Lecturer (Assistant Professor) and a Researcher with the Software Engineering Department, Faculty of Computer Systems and Software Engineering, Universiti Malaysia Pahang. He has authored or co-authored one book, more than 30 articles, and more than 10 inventions. His research interests include software engineering, software testing, optimization algorithms, artificial intelligence, soft computing, embedded systems, and image processing. He is a Senior Member of the IEEE.

HAMMOUDEH S. ALAMRI received the B.Sc. degree in computer engineering from Yarmouk University, in 2008, and the M.Sc. degree from University Malaysia Pahang, in 2016, where he is currently pursuing the Ph.D. degree in computer science with the Faculty of Computer Systems and Software Engineering. His main research interests include optimization algorithms, the IoT, and computational intelligence.

KAMAL Z. ZAMLI received the degree in electrical engineering from Worcester Polytechnic Institute, USA, in 1992, the M.Sc. degree in real-time software engineering from Universiti Teknologi Malaysia, in 2000, and the Ph.D. degree in software engineering from the University of Newcastle upon Tyne, U.K., in 2003. He is currently a Professor and the Dean of the Faculty of Computer Systems and Software Engineering, Universiti Malaysia Pahang. He has authored or co-authored one book, more than 30 articles, and more than 350 papers in journals and conferences worldwide mainly in the areas of (combinatorial t-way) software testing and search-based software engineering.