Harmony Search Algorithm

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Chapter 1
Harmony Search Algorithm:
Basic Concepts and Engineering Applications

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ABSTRACT

Harmony search (HS) is a meta-heuristic search algorithm which tries to mimic the improvisation process of musicians in finding a pleasing harmony. In recent years, due to some advantages, HS has received a significant attention. HS is easy to implement, converges quickly to the optimal solution and finds a good enough solution in a reasonable amount of computational time. The merits of HS algorithm have led to its application to optimization problems of different engineering areas. In this chapter, the concepts and performance of HS algorithm are shown and some engineering applications are reviewed. It is observed that HS has shown promising performance in solving difficult optimization problems and different versions of this algorithm have been developed. In the next years, it is expected that HS is applied to more real optimization problems.

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INTRODUCTION

Most often, engineering optimization problems have non-linear and non-convex objective functions with intense equality and inequality constraints along with various types of decision variables. As a result, solving such optimization problems using traditional methods faces with increasing difficulties. Meta-heuristic optimization algorithms can be efficient alternatives to conquer the difficulty of complex optimization problems. Originally invented in (Geem et al. 2001), HS is a meta-heuristic optimizer inspired by the music improvisation process. In music improvisation process, a predefined number of musicians attempt to tune the pitch of their instruments to achieve a pleasing harmony (best state). In nature, a harmony is defined by a special relation between several sound waves that have different frequencies. The quality of the improvised harmony is determined by aesthetic estimation. In order to improve the aesthetic estimation and find the best harmony, the musicians make practice after practice.

There are similarities between musicians improvisation and optimization processes. In an optimization problem, the ultimate aim is to find the global optimum of the objective function under consideration by tuning a predefined number of decision variables. Indeed, in an optimization problem the decision variables make a solution vector. Then, the values of the decision variables are put into the objective function and the quality of the solution vector is calculated. The solution vector is updated during the iterations until the global optimum is obtained.

Comparison of musical and optimization processes reveals the following similarities:

- In musical process, the quality of a harmony is determined by aesthetic estimation. In an optimization process, the quality of a solution vector is determined by the objective function value.
- In musical process, the ultimate goal is to obtain the best (fantastic) harmony. In an optimization process, the ultimate goal is to obtain the global optimum.
- In musical process, musicians change the pitch of their instruments. An optimization algorithm changes the values of the decision variables.
- In musical process, any attempt to play a harmony is called practice. In an optimization, each attempt to update a solution vector is called iteration.

In general, when a musician wants to tune the pitch of his/her instrument (for example fiddle, saxophone, etc) and sound a note, he/she utilizes one of the three possible ways. Theses rules are the main body of HS algorithm.

1. He/she can sound a note from the possible range randomly.
2. He/she can sound a note from his/her memory.
3. He/she can sound a note near-by one note from his/her memory.

In the following next sections, HS implementation for optimization, HS variants and HS applications have been explained in detail.

HS IMPLEMENTATION FOR OPTIMIZATION

In HS algorithm, a feasible solution is called harmony and each decision variable of the solution is corresponding to a note. HS includes a harmony memory (HM) in which a predetermined number of harmonies (*N*) have been stored. Suppose the goal is to minimize/maximize a fitness function (*f*) subject to *d* decision variables. This optimization problem is defined as follows:

$$Min.\left(or\ \ Max.\right) \quad f\left(x_1, x_2, \ldots, x_d\right) \tag{1}$$

where f is the fitness function, x_i ($i = 1,2,\ldots,d$) is decision variable i and d denotes the problem dimension.

In order to implement HS algorithm for optimization, the following steps should be used:

Step 1. A harmony memory is initialized.
Step 2. A new harmony is improvised.
Step 3. The new harmony is included in the HM or excluded.
Step 4. Steps 2 and 3 are repeated until the stopping criterion is met. When the stopping criterion is met, go to
Step 5. The best harmony stored in HM is returned as the found optimum solution.

The details of each step are as follows:

Step 1. Initialization of HM

In HS, at first, *N* harmonies are produced in the search space and stored in HM. Table 1 shows the structure of the HM.

As Table 1 shows, harmony i can be specified by a vector, harmony $i = [x_{i,1} x_{i,2} \ldots x_{i,d}]$. In order to initialize the HM, Eq. (2) can be used. The last column of HM is the fitness function values corresponding to each harmony. For example, f_1 means

Table 1. The structure of harmony memory

	x_1	x_2	…	x_d	f
Harmony 1	$x_{1,1}$	$x_{1,2}$	…	$x_{1,d}$	f_1
Harmony 2	$x_{2,1}$	$x_{2,2}$	…	$x_{2,d}$	f_2
⋮	⋮	⋮		⋮	⋮
Harmony ***N***	$x_{N,1}$	$x_{N,2}$	…	$x_{N,d}$	f_N

the value of the fitness function for harmony 1. This value is calculated by putting the decision variables of harmony 1 into the fitness function.

$$x_{i,j} = l_j + rand \times \left(u_i - l_j\right) \qquad i = 1,2,\ldots,N; \quad j = 1,2,\ldots,d \tag{2}$$

where l_j and u_j are the lower and upper bounds of decision variable j, respectively, and *rand* is a random number with uniform distribution from [0 1]. Mathematically, the HM is shown by the following expression:

$$HM = \begin{bmatrix} Harmony\ 1 \\ Harmony\ 2 \\ \vdots \\ Harmony\ N \end{bmatrix} = \left[\begin{array}{cccc|c} x_{1,1} & x_{1,2} & \cdots & x_{1,d} & f_1 \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} & f_2 \\ \vdots & \vdots & & \vdots & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,d} & f_N \end{array}\right] \tag{3}$$

Step 2. Improvisation of a New Harmony

The next step is to improvise a new harmony, $x_{new} = [x_{new,1} x_{new,2} \ldots x_{new,d}]$. The main feature of HS algorithm in comparison with other metaheuristics such as genetic algorithm (GA) is that in HS, a new harmony is generated by use of all the existing harmonies. For generation of decision variable j, the following procedure is conducted. This procedure in done for all the decision variables until a new harmony is obtained.

Stage 1

A random number with uniform distribution from [0 1] is generated (*rand*). If *rand* > *HMCR*, the decision variable of the new harmony ($x_{new,j}$) is randomly generated by Eq. (4). *HMCR* which is the abbreviation of harmony memory considering rate varies between 0 and 1.

$$x_{new,j} = l_j + rand \times \left(u_i - l_j\right) \tag{4}$$

Otherwise, if $rand \leq HMCR$, one of the harmonies stored in HM is randomly selected, for example *k* where $1 \leq k \leq N$. Then, $x_{new,j}$ is selected by the corresponding value of harmony *k* from HM as Equation 5.

$$x_{new,j} = x_{k,j} \tag{5}$$

Stage 2

In order to escape from local optima, HS makes use of pitch adjustment mechanism by which the improvised note may be shifted to a neighbour value with respect to the possible range. In HS, there is a parameter named pitch adjusting rate (*PAR*) which varies between 0 and 1. Small values of *PAR* leads to having a weak pitch adjustment mechanism and large values of *PAR* result in having a rich pitch adjustment mechanism. In order to perform pitch adjustment mechanism, after stage 1, a random number from [0 1] with uniform distribution is generated (*rand*). If $rand \leq PAR$, the improvised note should be shifted to a neighbour value by using Equation 6. Otherwise, if *rand* > *PAR*, the improvised note does not change.

$$x_{new,j} = x_{new,j} + bw \times \left(rand - 0.5\right) \times \left|u_j - l_j\right| \tag{6}$$

where *bw* is called the bandwidth of generation and *rand* is a random number between 0 and 1 with uniform distribution. The term of $\left(rand - 0.5\right)$ generates a random number from [-0.5 0.5]. Since the users donot know that it is better to increase the value of the decision variable or decrease its value, the term of $\left(rand - 0.5\right)$ is used to randomly select the direction of movement. In Eq. (6), the term of $\left|u_j - l_j\right|$ is used to control the scale of the decision variables since in an optimization problem, the scale of the decision variables may vary significantly such as -10^4 to 10^4 in one dimension and -10^{-5} to 10^{-5} in another one.

Step 3. Replacement

After Step 2, we have a new feasible harmony. The fitness function of the new harmony (f_{new}) is calculated. In this Step, we compare the new harmony and the worst harmony stored in HM. Suppose harmony *h* ($1 \leq h \leq N$) is the worst harmony stored in HM in terms of the fitness function value. In this case, if f_{new} is better than fit_h, harmony h is removed from the HM and the new harmony is replaced. Otherwise, if f_{new} is worse than fit_h, the new harmony is abandoned.

Step 4. Stopping Criterion

Most often, the stopping criterion of optimization algorithms is to reach to a predefined number of iterations (t_{max}). When this criterion is met, the algorithm is terminated and we go to Step 5. Otherwise, Steps 2 and 3 are repeated until the stopping criterion is satisfied.

Step 5. Final result

In this Step, the best harmony stored in HM is returned as the optimum solution of the problem under consideration. Figure 1 shows the flow chart of HS implementation for optimization.

HS has three parameters, namely, *HMCR*, *PAR* and *bw*. The role of these parameters on HS performance is as follows:

- ***HMCR*:** The value of *HMCR* which belongs to [0 1], denotes the probability of using historical values stored in HM for playing a note. Small values of *HMCR* result in random search (with the probability of 1-*HMCR*) and vice versa. For example, *HMCR* of 0.9 means that the note will be sound from the HM by the probability of 0.9 and will be sound randomly by the probability of 0.1 from the possible range.
- ***PAR*:** By this value which belongs to [0 1], each value improvised from the HM, has a change to be replaced by a value located at the vicinity of the selected value from HM. In HS, this chance is provided and controlled by the probability of *PAR*. As a result, large values of *PAR* increase the probability of pitch adjustment and vice versa.
- ***bw*:** If the pitch adjustment mechanism is selected, the value of *bw* controls the step size of movement. By using large values of *bw*, the distance between the new value and the HM value increases. Indeed, we can tune the global and local search by *bw* value.

As the first investigation, the Rosenbrock's banana test function, defined by Equation 7, is used to illustrate the performance of HS algorithm. Figure 3 indicates the schematic of the test function. The global minimum of this function is 0 which is located at $x_1 = 1$ and $x_2 = 1$. HS algorithm is used to find the solution of the Rosenbrock's banana test function. The parameter setting of HS is as follows: $N = 20$, $HMCR = 0.95$, $PAR = 0.8$, $bw = 0.2$ and $t_{max} = 10000$.

$$\begin{aligned}&Min. \quad f\left(x_1, x_2\right) = Ln\left(1 + (1 - x_1)^2 + 100(x_2 - {x_1}^2)^2\right)\\&-10 \leq x_1, x_2 \leq 10\end{aligned} \tag{7}$$

HS algorithm can successfully find the global solution of the Rosenbrock's banana test function. Figure 4 shows the position of the initial solutions stored in HM. Figures 5 to 8 shows the position of the produced solutions after 100, 1000, 5000 and 10000 iterations, respectively. As can be seen, HS algorithm can provide a good balance between diversification and intensification during its search process.

In order to evaluate the search power of the classical HS algorithm, Griewank test function in 30 dimensions is used as a multimodal high-dimensional test function where there are many local optima over the search range. The expression of this function is shown by Equation 8. The global minimum of this function is 0 which is located at (0,0,….,0).

$$\begin{aligned}&Min.\ f(x) = \frac{1}{4000}\sum\nolimits_{i=1}^{n}(x_i)^2 - \prod\nolimits_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1\\&-600 \leq x_i \leq 600 \qquad i = 1, 2, ..., 30\end{aligned} \tag{8}$$

In order to solve the Griewank test function, the parameter setting of HS is as follows: $N = 50$, $HMCR = 0.9$, $bw = 0.1$ and $t_{max} = 50000$. Table 1 shows the impact of different PAR values on the performance of HS over the Griewank test function. The statistical results reported in this table have been obtained over 30 independent runs. As can be seen, the best performance is achieved when the value of PAR is set to 0.1. In Table 1, $PAR = rand$ means that the value of PAR is adjusted by a random number between 0 and 1 drawn from a uniform distribution.

Figure 8 and Figure 9 show the convergence rate of HS algorithm during the first 5000 iterations. These figures show the fitness function value of the best harmony stored in HM at each iteration. It is clear that HS finds a good region of the search space at the first iterations and tries to converge to the solution.

Table 2 represents the impact of different bw values on the performance of HS over the Griewank test function. In this case, the parameter setting of HS is as follows: $N = 50$, $HMCR = 0.9$, $PAR = 0.1$ and $t_{max} = 50000$. It is observed that by use of $bw = 0.01$, HS can find better results than the other values for the studied test function.

Figure 1. Flow chart of harmony search algorithm for optimization

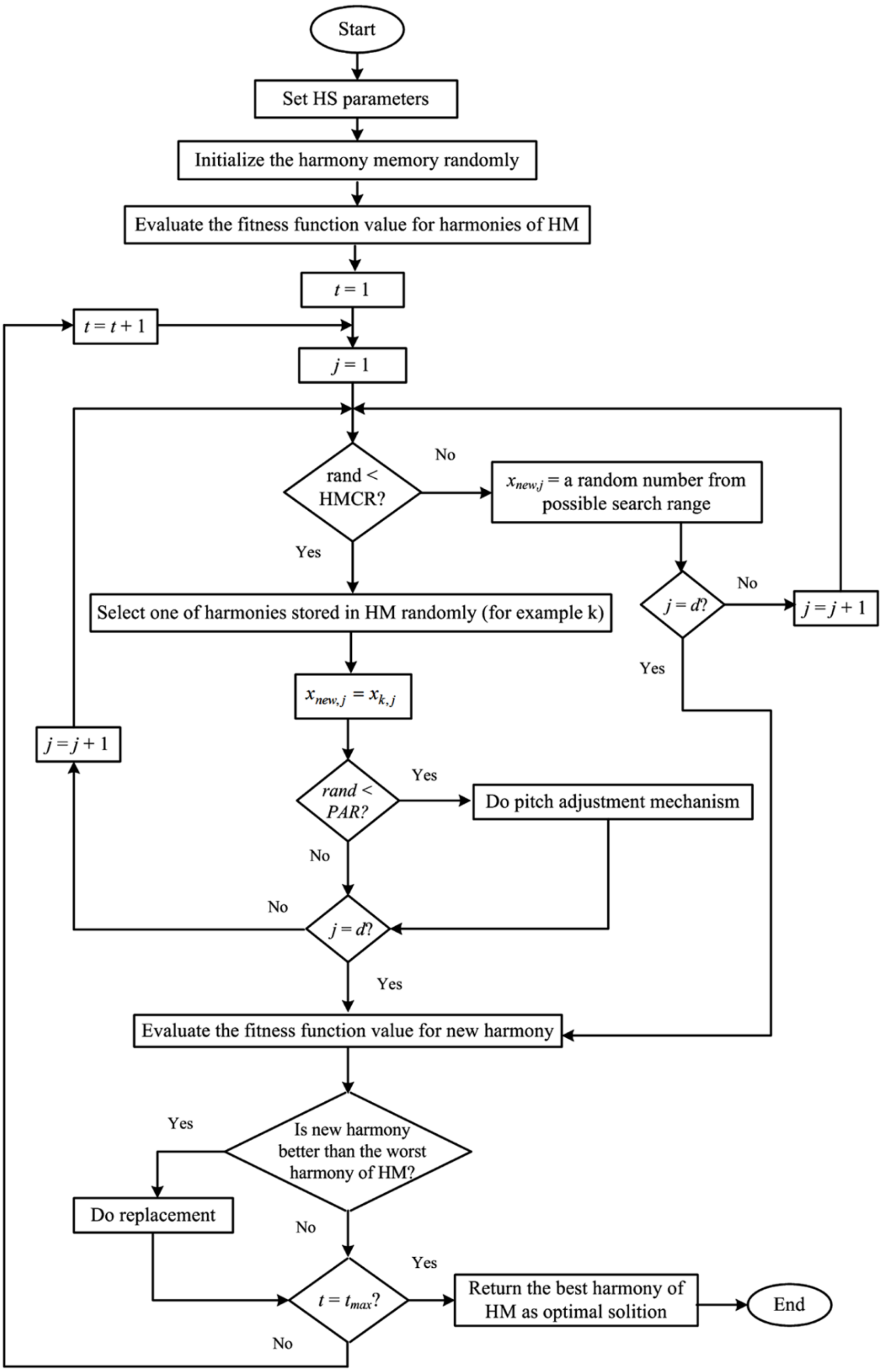


Figure 2. The graph of the Rosenbrock's banana test function

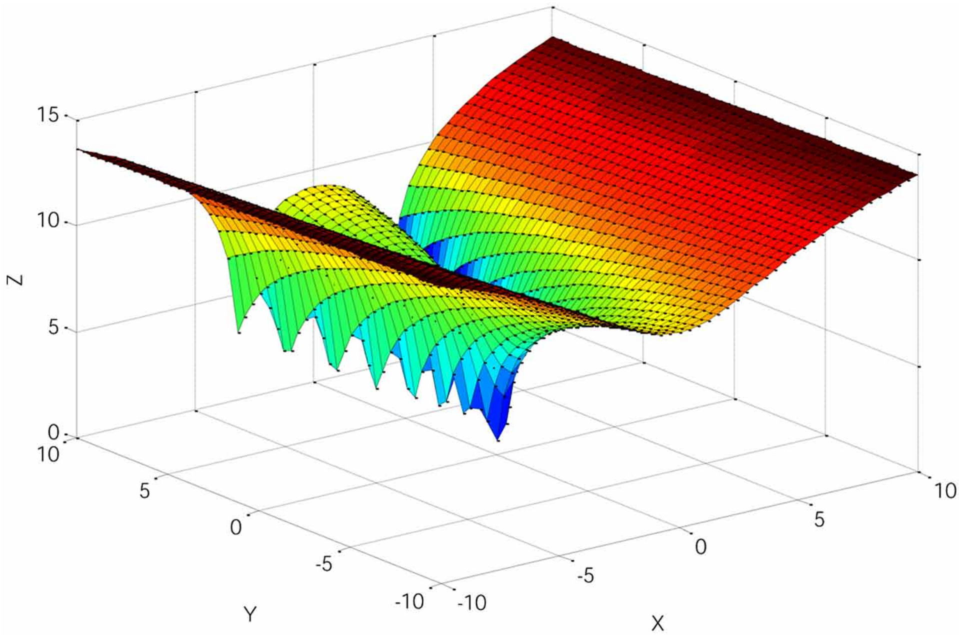


Figure 3. The initial positions memorized in HM

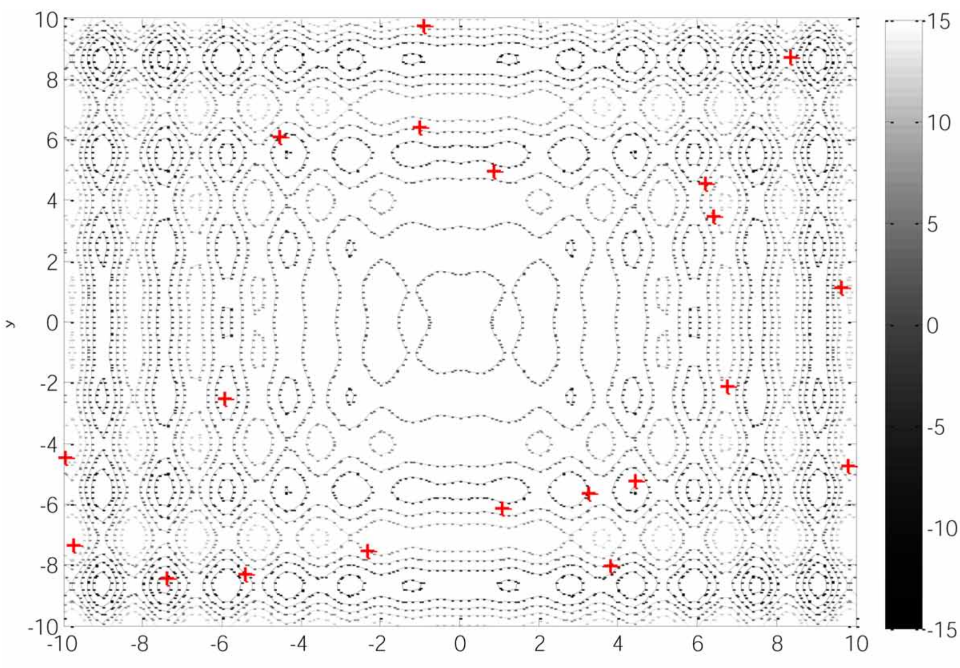


Figure 4. The positions generated by HS algorithm during the first 100 iterations

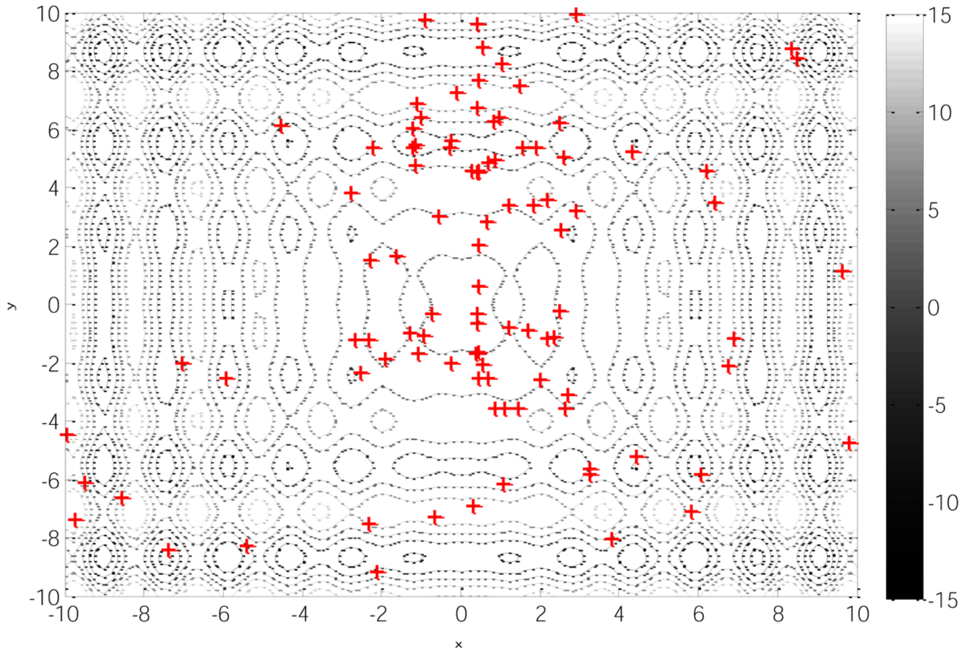


Figure 5. The positions generated by HS algorithm during the first 1000 iterations

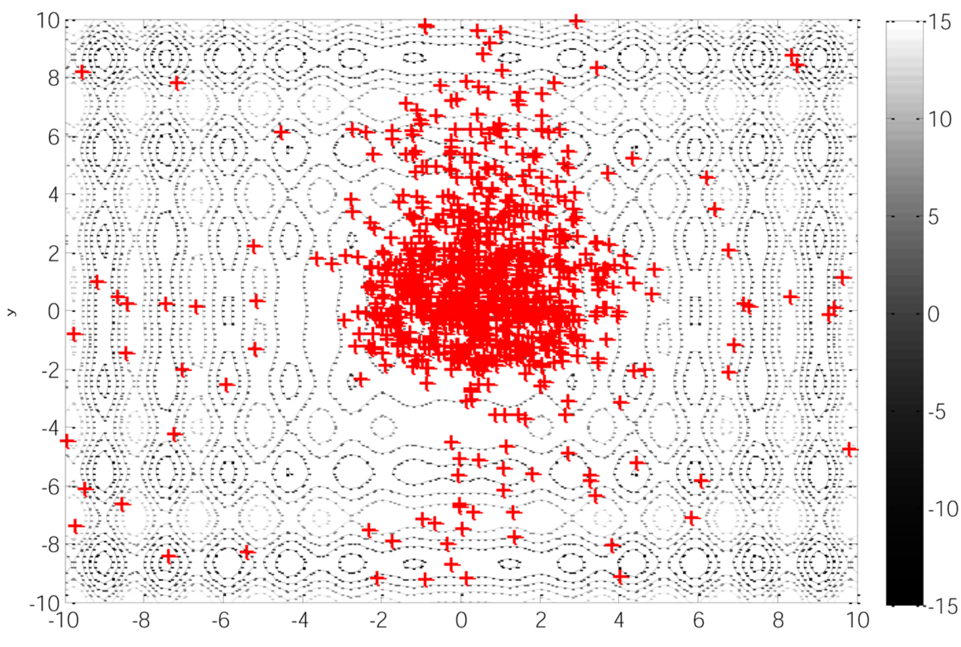


Figure 6. The positions generated by HS algorithm during the first 5000 iterations

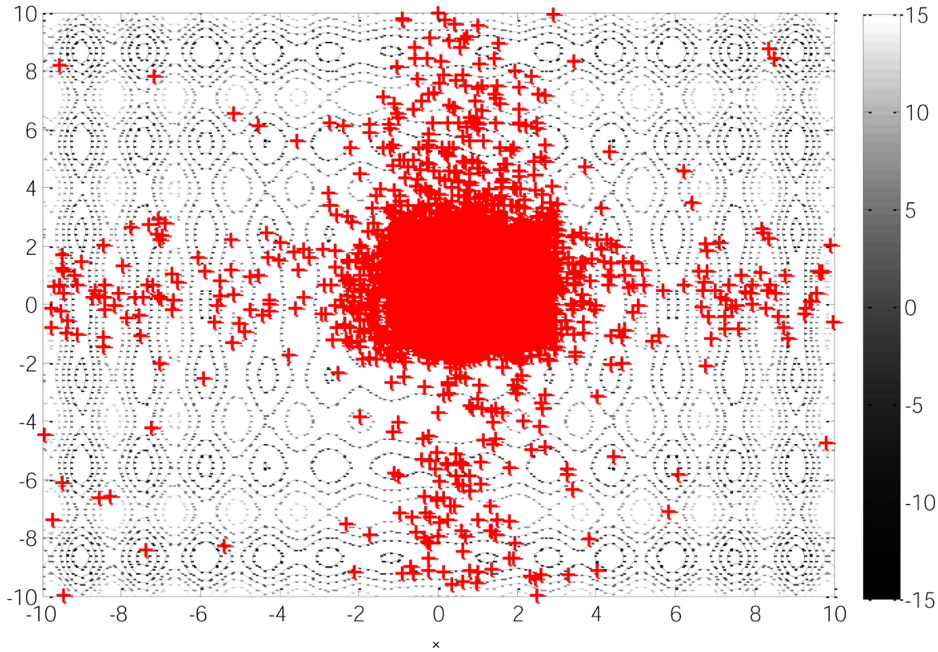


Figure 7. The positions generated by HS algorithm during the first 10000 iterations

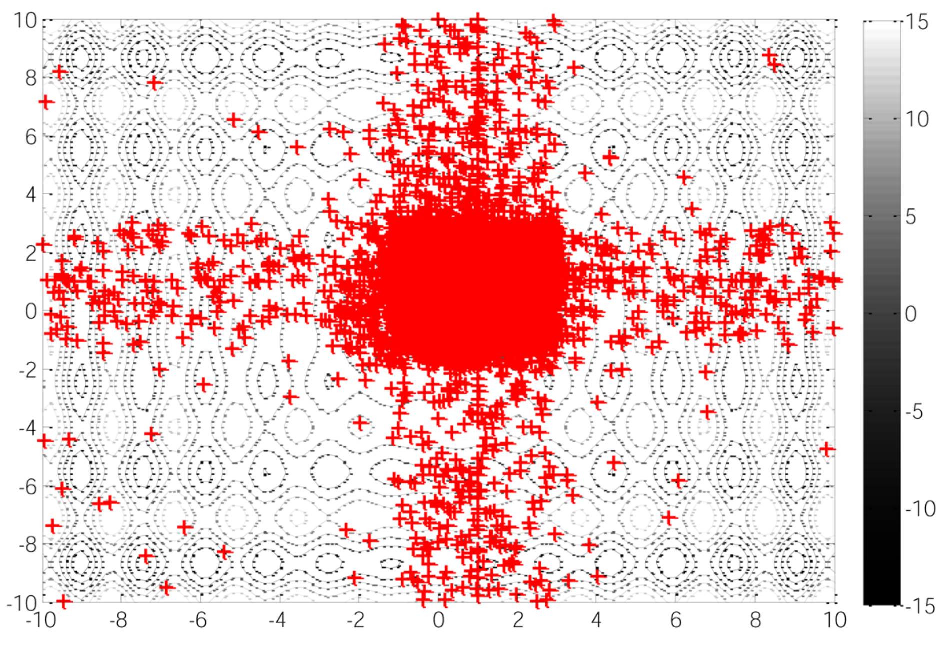


Table 2. Performance of HS algorithm on Griewank function considering different PAR values

Index	*PAR* = 0.1	*PAR* = 0.3	*PAR* = 0.5	*PAR* = 0.7	*PAR* = 0.9	*PAR* = *rand*
Average	1.39	2.86	4.59	6.38	7.89	4.70
Standard Deviation	0.07	0.20	0.47	0.44	0.97	0.32
Minimum	1.26	2.39	3.28	5.53	4.93	4.07
Maximum	1.54	3.35	5.32	7.12	9.90	5.45

Table 3. Performance of HS algorithm on Griewank function considering different bw values

Index	*bw* = 0.001	*bw* = 0.01	*bw* = 0.1	*bw* = 1	*bw* = *rand*
Average	1.20	1.03	1.39	9.33	3.74
Standard Deviation	0.06	0.03	0.07	2.02	0.46
Minimum	1.09	0.87	1.26	6.06	2.53
Maximum	1.31	1.07	1.54	13.47	4.39

COMPARATIVE STUDY OF VARIOUS VARIANTS

Investigations on HS performance show that this algorithm has a good ability in exploration and can discover the potential solution rapidly. However, the local search ability of HS is weak so that no better solution is expected at the latter iterations of HS algorithm. In the literature, various variants have been devised to improve the searching ability of HS.

Like other optimization algorithms, parameter setting of HS algorithm is a challenging task. Since *PAR* and *bw* have a great influence on the quality of the final solution, proper parameter setting of HS increases the probability of finding the global solution more and more. The absence of general rules for doing parameter setting of HS algorithm has guided the research towards developing new variants of HS which focus on parameter setting.

In this context, one of the most famous and popular variants of HS algorithms is the investigation made by (Mahdavi et al. 2007). They have proposed time-varying values for *PAR* and *bw*. Based on their suggestion, the value of *PAR* increases linearly during the iterations as follows:

Figure 8. Convergence rate of HS algorithm for solving the Griewank function considering different PAR values during the first 5000 iterations
For a more accurate representation of this figure, please see the electronic version.

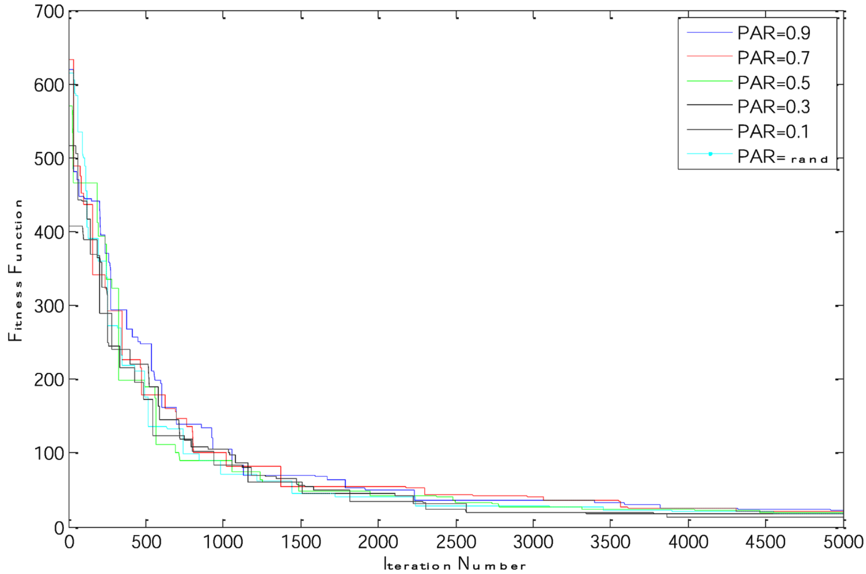
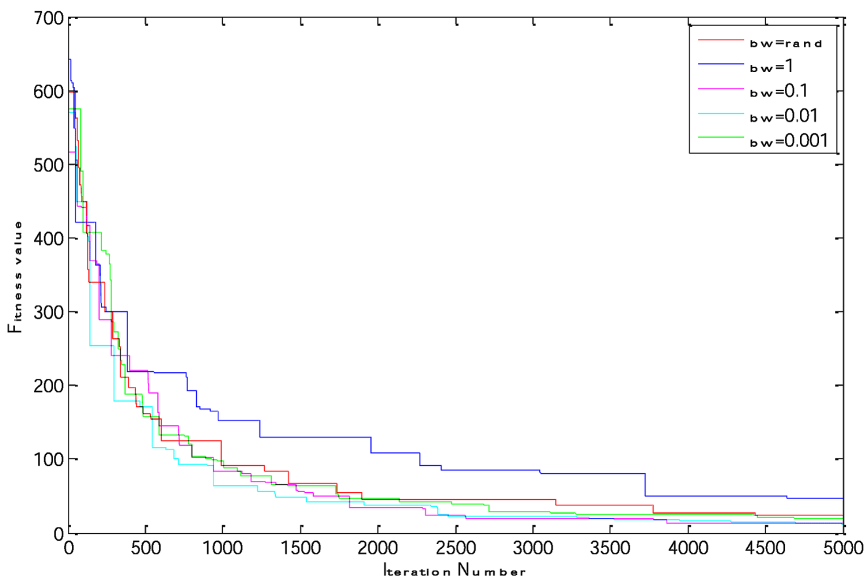


Figure 9. Convergence rate of HS algorithm for solving the Griewank function considering different bw values during the first 5000 iterations
For a more accurate representation of this figure, please see the electronic version.



$$PAR^t = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{t_{\max}} \times t \tag{9}$$

where PAR^t is the *PAR* value at iteration t, t_{max} is the maximum number of iterations, PAR_{min} is the minimum *PAR* value and PAR_{max} is the maximum *PAR* value.

The value of *bw* decreases nonlinearly during the iterations by the following exponential function:

$$bw^t = bw_{\max} \times \exp\left(Ln(\frac{bw_{\min}}{bw_{\max}}) \times \frac{t}{t_{\max}} \right) \tag{10}$$

where bw_{max} and bw_{min} are the maximum bandwidth and minimum bandwidth, respectively.

Based on this idea that a successful search should be proceeded progressively at the beginning of the algorithm and then gradually settled down, (Wang and Huang 2010) have developed a self-adaptive HS algorithm which utilizes a decreasing linear *PAR* during the iterations to prevent overshooting and oscillation. Indeed, this idea is the opposite of the idea used by (Mahdavi et al. 2007). Also, they have used the maximal and minimal values in the HM to conduct pitch adjustment mechanism instead of using the parameter of *bw*. For this aim, one of the following equations is used for doing the pitch adjustment:

$$x_{new,j} = x_{new,j} + \left[\max(HM^j) - x_{new,j}\right] \times rand \tag{11}$$

$$x_{new,j} = x_{new,j} - \left[x_{new,j} - \min(HM^j)\right] \times rand \tag{12}$$

where $\max(HM^j)$ and $\min(HM^j)$ are the highest and the lowest values of variable j in HM. By use of this pitch adjustment mechanism, the decision variables will not violate the boundary constraint.

There are other investigations which have developed HS variants with the aim of finding the best parameter setting. In (Geem 2006; Mukhopadhyay et al. 2008), optimum setting of *bw* has been discussed. In (Geem et al. 2005; Chakraborty et al. 2009), the parameter of *PAR* has been modified. In the first, it is proposed to replace the *PAR* parameter by a mutation operator borrowed from differential evolution (DE) algorithm and in the latter, a multi-pitch adjusting rate has been proposed. In (Hasancebi et al. 2009), the dynamic variation of *HMCR* and *PAR* values has been proposed.

There are investigations which have tried to eliminate the burden of manually finding the best parameter setting of HS algorithm. In (Geem, Sim 2010), an additional matrix is used for memorizing operation types (random selection, memory consideration, or pitch adjustment) in each variable. At each iteration, the parameters of *HMCR* and *PAR* are recalculated based on the matrix information. In (Askarzadeh, Zebarjadi 2014), the following equations have been proposed for tuning the HS parameters based on random numbers drawn from a uniform distribution between 0 and 1:

$$HMCR = 0.9 + 0.1 \times rand \tag{13}$$

$$PAR = \frac{1 - rand}{2} \tag{14}$$

$$bw = rand \tag{15}$$

In the pitch adjustment mechanism of original HS algorithm, the direction is selected randomly and the step size is determined by *bw*. Some researchers have tried to introduce new pitch adjustment mechanisms. In (Omran, Mahdavi 2008), a global-best HS (GHS) has been developed in which the pitch adjustment is only based on the best harmony of HM and there is no need to *bw*. In (Wang, Huang 2010), a variant, named self-adaptive HS (SAHS), has been proposed in which a new harmony is improvised based on the maximal and minimal values of HM. In some investigations, the hybridization of HS algorithm with concepts borrowed from the other meta-heuristic algorithms such as differential mutation (Wang, Li 2013) and particle swarm optimization (Pandi, Panigrahi 2011) has been investigated and satisfactory results have been reported.

APPLICATIONS

To date, HS is utilized to solve various engineering optimization problems. Some of the works have been reviewed below.

Electrical Engineering

The hybridization of HS and DE was developed in (De et al. 2015) for designing a CMOS inverter. The heuristic algorithm found the best design variables to optimize the system performance. The design variables were the ratio of the channel width to the channel length of the CMOS transistors and the output load capacitance.

Telecommunication

In telecommunication, HS was used for optimal designing of wireless sensor networks (WSN), antenna and radar. The pattern synthesis of linear antenna arrays was investigated in (Guney,Onay 2011). Pattern synthesis is the process of determining the parameters of an antenna array to achieve the target antenna radiation pattern. HS with a local search procedure utilized to solve the Spread-Spectrum Radar Polyphase (SSRP) codes design in (Gil-López et al. 2012). The variables are the magnitudes of the phase differences for the SSRP and the goal was the minimization of the module of the largest among the samples of the autocorrelation function. HS with a local search procedure was used for node localization in the wireless sensor networks with noisy distance-related measurements in (Manjarres et al. 2013). There were two objective functions of CF and CV. CF is the squared error between the estimated and the measured inter-node distances of the nodes that are in the connectivity range of each others and CV is the number of connectivity neighborhood constraints which are not satisfied by the candidate topology. The design of low complexity sharp Modified Discrete Fourier Transform (MDFT) filter bank using hybrid HS and Gravitational search algorithm were reported in (Sakthivel,Elias 2015). Filter coefficients are optimized to design a low complexity sharp MDFT filter bank with low power consumption, low chip area and high speed of operation.

Pattern Recognition and Image/Speech Processing

In the field of pattern recognition, there are two famous topics of classification and clustering. HS could be adopted to design a classifier or a clustering algorithm. The application of HS in recognizing patterns in image or speech data are reported in some researches.

Classification

Classification is the process of assigning category labels to any type of data. Two important parts of classification systems are classifiers and features. HS could help to improve the accuracy of the system by improving the classifier or selecting the best set of features. In (Kulluk et al. 2012), six benchmark classification problems were solved by an artificial neural network (ANN) which trained using self-adaptive global best version of HS. The process of training feed-forward NNs using HS was performed by optimizing the weights of links between the neurons to minimize the error. A hybrid harmony-based classifier was developed in (Karimi et al. 2012). HS produced if-then rules that determine the label of the data according to its attributes. Authors in (Wang et al. 2015b) used HS as a feature selection method for email classification. HS found the best discriminative features in regard to the document frequency and term frequency. Email classification could help for filtering spam. A self-adaptive HS utilized in (Huang et al. 2014) for local feature selection in the classification of music genre. Music features were five acoustic characteristics and the number of music genres was ten. The goal was the maximization of classification precision. In (Inbarani et al. 2015), the hybridization of HS and rough set theory was developed to select the best set of features to maximize the cassification accuracy. A hybrid HS combined with stochastic local search was produced in (Nekkaa,Boughaci 2015) to find the beneficial features for the classification outcome optimization. The support vector machine (SVM) was used as the classifier and its parameters (penalty parameter C and the gamma parameter for the RBF kernel) were tuned by an iterative search. A self-adjusting HS was produced in (Zheng et al. 2015a) to maximize the classification accuracy of C4.5 classifier by feature selection.

Clustering

Clustering is about discriminating data into some groups (called clusters), in such a way that data in a group are similar to each other and different from the other groups. Harmony K-means algorithm was produced in (Mahdavi,Abolhassani 2009) for document clustering. Documents were represented using term weights. HS found the center of the clusters and then the results were refined by K-means.

Image Processing

In the image processing algorithms, heuristic optimization algorithms like HS are useful for optimizing, tuning and enhancing the processing results. There are various works in this regard. In (Cuevas 2013), block matching for motion estimation was handeled by HS. The fitness function was the matching quality of each motion vector candidate. A window arround the current block was searched for the best matched block. The motion vector is the position difference between the current block and the best match block. In images, the saliency map is calculated by combining various information like color, intensity, orientation, and other feature maps. Saliency map is useful for target detection. To have more target conspicuity in the saliency map, a modified Gaussian HS was used in (Li,Duan 2014). Tuning the parameters of Deep Belief Networks was performed using HS in (Papa et al. 2015). Binary mage reconstruction was solved by this network to minimize the mean square error beween reconsrtucted and original image. Image restoration by projections onto convex sets was tackled in (Pires et al. 2015) where its parameters were optimized by HS. HS found the best parameters to maximize the improvement signal to noise ratio (ISNR).

Speech Processing

HS was used to solve part-of-speech (PoS) tagging problem in (Forsati,Shamsfard 2015) and find the best tagging quality. PoS is about syntactic tagging to every word in a sentence according to the context.

Water Management

To design and manage water distribution and water supply networks, there are some optimization problems that could be handled by HS. Water distribution network design problem was solved in (Geem 2012) by a diversity improved version of HS to minimize the construction cost. The problems have design constraints of nodal pressure and quantity and the decision variables are the diameter of the pipes. In (Baek et al. 2010), HS was employed to optimize the simulation of hydraulic under abnormal operating conditions in water distribution systems. HS built the model to minimize the error between the assumed and the calculated heads at the demand nodes. Pump scheduling problem in water distribution systems was tackled in (Kougias,Theodossiou 2013) using the polyphonic HS. The objectives were the minimization of quantity of pumped water and electricity and maintenance cost. The design of groundwater remediation systems was tackled by a probabilistic multi-objective fast HS in (Luo et al. 2014; Luo et al. 2012) to minimize the remediation cost and contaminant mass remaining in aquifer. Authors in (Atrabi et al. 2015) used HS for reservoir operation optimization to minimize the water supply deficit and flood damages of a reservoir. The subjected constraint was mass balance limitation.

Mechanical Engineering

In mechanical engineering, HS was utilized for optimizing mechanical process and mechanical design problems. Authors in (Abhishek et al. 2016) used a fuzzy embedded HS for tuning the machining process parameters of the carbon fiber reinforced polymer (CFRP) composites. These composites are used for manufacturing engineering components especially in aerospace and automobile industries. A fuzzy inference system was used to model the multiple performance characteristics into a single objective function. Some well-known constraint mechanical design optimization problems namely the pressure vessel design problem, the tension/compression spring design problem, and the welded beam design problem were solved in (Mun,Cho 2012) by a modified HS. Authors in (Razfar et al. 2011) found optimal cutting parameters in face milling process by HS to minimize the surface roughness. The surface roughness was modeled by feed forward artificial neural networks. Surface roughness formation and cutting force mechanisms modeling were also developed in (Zinati,Razfar 2012) by HS and artificial neural networks.

Chemical Engineering

Thermodynamic models in chemical engineering are useful for synthesis, design, optimization, and control of process systems (Merzougui et al. 2012). The parameter estimation of these models could be solved by heuristic optimization. HS was applied in (Merzougui et al. 2012) for estimation of binary interaction parameters in the liquid–liquid phase equilibrium model. The objective function was the data fitting between observed and calculated data. The support vector regression (SVR) estimated the relationship function between amount of asphaltene precipitation and titration data in (Fattahi et al. 2015). HS was tuned the SVR learning parameters and the data fit accuracy was defined as the objective function. This method is useful in petroleum industry.

Power Engineering

In the field of power engineering, there are many optimization problems like economic dispatch (ED), optimal power flow (OPF), unit commitment (UC), modeling problems, designing, and power system planning problems. HS was examined to solve these problems in various reported works.

Economic Dispatch

ED is defined by optimal determination of the generator power outputs while supporting the load demand. It has two types of static or dynamic dispatch and it has some equality and inequality constraints. Authors in (Arul et al. 2013a) utilized HS with chaotic self-adaptive differential mutation operator for optimal solving of dynamic ED with some constraints. The constraints were about real power balance, real power generation limits, and generating unit ramp-rate limits. The objective function was the total fuel cost. Combined heat and power economic dispatch optimized by HS in (Javadi et al. 2012). Three types of thermal units including co-generation, electrical only, and heat-only units were considered and the energy production cost was minimized. Authors in (Jeddi,Vahidinasab 2014) employed modified HS for economic load dispatch to minimize the generation cost while satisfying unit operating limits, power balance constraints, ramp-rate limits, and spinning reserve constraints. The modified HS was produced using wavelet mutation and a memory consideration scheme based on the roulette wheel. Authors in (Khazali,Kalantar 2011) used HS to find the settings of control variables to optimize the power transmission loss, voltage stability, and voltage profile in economic power dispatch problem. Control variables were generator voltages, tap positions of tap changing transformers and the amount of reactive compensation devices. Authors in (Niu et al. 2014) proposed HS with arithmetic crossover operation for solving five different types of ED problems, including static dispatch with valve point effects, ED with prohibited operating zones, ED with multiple fuel cells, combined heat and power ED, and dynamic ED. A differential HS was employed in (Wang,Li 2013) for solving the non-convex ED to minimize the total fuel cost. Constraints of generating capacity, power balance, ramp rate limit, and prohibited operating zones were handled by a repair procedure and three simple selection rules. Authors in (Arul et al. 2013a) solved non-convex ED using HS for generation cost minimization. The constraints of real power balance, generation limit, prohibited operating zones, ramp-rate, and system spinning reserve, were tackled by penalization. Non-convex ED was also solved in (Arul et al. 2014) by an improved version of HS.

Optimal Power Flow

OPF is defined by the minimization of generation costs and loss in power system variables under some equality and inequality constraints. OPF problem was solved using improved HS in (Sinsuphan et al. 2013) to minimize the total production cost under constraints for real and reactive power flow and variable limits. OPF was also solved by HS in (Sivasubramani,Swarup 2011) with the objectives of the total fuel cost, real power loss, and voltage stability index minimization. The authors in (Arul et al., 2013b) proposed a chaotic self-adaptive differential HS to solve OPF problems with non-smooth and non-convex cost functions.

Unit Commitment

UC is the problem of determining schedules of generating units including on/off states of the units and how much they generate hourly. The objective of UC is to minimize the total operating cost. UC is a large-scale, non-convex, and constraint problem. Security constrained unit commitment problem was handled in (Samiee et al. 2013) to minimize the fuel cost and startup and shut down costs of thermal units while satisfying constraints for: AC power flow constraints, up/down time duration, ramp rate, operating zones, system spinning, AC security, and reactive power generation. To handle these constraints, a hybrid method composed of tri-state algorithm and infeasible solution rejection technique was produced. The unit commitment problem was solved by an improved version of HS in (Morsali et al. 2014) to minimize the operation, start-up and shut-down costs. This objective function was subjected to the load demand constraints and ramp rate limits. To solve this problem, HS control parameters of memory size, *HMCR*, *PAR* and *bw* was adapted. In (Paqaleh et al. 2010), to solve UC by HS, the considered objectives were the fuel costs of generating units, the start-up costs of the committed units and shut-down costs of the decommitted units and the constraints were the power balance, spinning reserve capacity of generating units, unit ramp-up and ramp-down rates, minimum up/down time limit, and spinning reserve requirement.

Modeling

Grouping-based global HS was proposed in (Askarzadeh,Rezazadeh 2011) for modeling the voltage as a function of the current in proton exchange membrane fuel cell (PEMFC). HS found the parameters of the modele to fit the simulated data and minimize the error. Authors in (Askarzadeh,Zebarjadi 2014) used HS for wind power modeling by finding the optimum parameters of the model. Optimum parameters minimize the error between the model and actual wind powers. Authors in (Askarzadeh,Rezazadeh 2012) utilized HS for modeling the current as a function of the voltage in solar cells. HS identified the model parameters to minimize the difference between experimental data and the model results.

Designing and Planning

Optimum design of a PV/wind hybrid system was experimented in (Askarzadeh 2013b). A hybridization of HS with chaotic search and simulated annealing was used to find the number of PV panels, wind turbines and batteries which minimize the total annual cost of the system in the presence of some constraints. A discrete HS was proposed in (Askarzadeh 2013a) for determining the optimum size of wind–photovoltaic hybrid energy systems which minimize the total annual cost. Power network partitioning was solved by HS in (Ezhilarasi,Swarup 2012b) to minimize the number of nodes in a cluster and the interconnections between the clusters. Optimally partitioning the network into clusters enhances the computational complexity by parallel processing. This problem was also solved in (Ezhilarasi,Swarup 2012a) by HS and a graph bi-partitioning method called Kernighan–Lin strategy. Authors in (Javaheri,Goldoost-Soloot 2012) employed HS for optimal locating and sizing of FACTS devices in power systems to minimize the total generation cost. The optimal placement and sizing of capacitors in power distribution networks was handled in (Sirjani,Bade 2015) by an improved global HS, to minimize the power loss and total cost. The problem constraints were load unbalancing, mutual coupling and harmonics. Power transmission expansion planning was solved in (Rastgou,Moshtagh 2014) by improved HS to minimize the construction costs, congestion cost, and security cost. A hybrid self- adaptive global HA was utilized in (Shivaie et al. 2015) for reliability-based Distribution Expansion Planning (DEP). There were four objectives of the investment, maintenance, operation, and expected customer interruption costs with the problem constraints of operational restrictions, Kirchhoff's laws, radial structure limitation, voltage limits, and capital expenditure budget restriction.

Civil Engineering

In civil engineering, there are many complicated optimization problems that was solved by HS such as optimizing building structures, road construction, and solving structural design problems.

Optimizing Structural Designs

Special seismic moment reinforced concrete frames are used in buildings to resist earthquakes. Ref (Akin,Saka 2015) utilized HS for optimal design of these frames under earthquake loads to minimize the frame cost. The frame design variables are consisted of two groups of column design variables and beam design variables. Authors in (Amini,Ghaderi 2013) used the hybridization of HS with ant colony search algorithm for optimal locating of dampers in structural systems. The objective function was defined by the dynamic response of the system and the configuration and forces of the dampers which was minimized. Two improved HS algorithms were proposed in (Degertekin 2012) for optimally designing of truss structures. Size and shape of truss structures was also optimized in (Kaveh,Javadi 2014) with a hybrid method of PSO and HS to minimize the truss weight. A social HS model was employed for design of the composite floor with minimum cost in (Kaveh,Ahangaran 2012). Design variables were related to the concrete slab, steel beams, and the shear studs. Four classical weight minimization problems of steel frames were designed using an enhanced HS in (Maheri,Narimani 2014). Damage under ambient vibration in structural systems was detected by HS in (Miguel et al. 2012). HS produced numerical model for structural damage and minimized its difference with the experimental model. The structural damage was estimated from a model update process using damage-induced changes in the modal features. Steel frame optimization was solved in (Murren,Khandelwal 2014) to obtain least-weight designs subjected to design and drift constraints. A hybrid HS was proposed in (Segura et al. 2015) for optimizing the sustainability of post-tensioned concrete box-girder pedestrian bridges. HS found the structural design variables and the geometry for minimizing the costs while satisfying the constraints for structural safety and durability. Authors in (Bekdas 2015) designed post-tensioned axially symmetric cylindrical reinforced concrete walls and minimized the total material cost using

HS. These walls are used in storage tanks for liquids and solids. In (Carbas,Saka 2012), topological design of domes was performed by improved HS to minimize the weight of each dome. Optimal design of steel frames was developed in (Degertekin 2008) by HS to determine the design variables of steel and minimize the weight of the frame. Optimal sensor placement on gantry crane structures was solved by HS in (Jin et al. 2015). These sensors are used to evaluate the safety and reliability of structures. The number and the location of the sensors were determined by HS to improve the performance. Optimal design of geosynthetic-reinforced retaining walls was performed in (Manahiloh et al. 2015) by HS to minimize the construction cost in the presence of design constraints.

Road Transportation

The optimum signal settings in a road transportation with a hybridization of HS and hill climbing was performed in (Ceylan,Ceylan 2012) for minimizing the travel time and the fuel consumption. In (Salcedo-Sanz et al. 2013), the reconfiguration of one-way roads in a city by providing alternative routes was solved by a two-objective HS. The proposed method guaranteed the mobility of citizens. The value of this function was estimated by a Monte Carlo simulation. A modified HS was produced in (Lee,Mun 2014) to establish a dynamic model for describing the resistance for rutting and fatigue cracking of asphalt concrete mixture. HS found the parameters of the model to fit to the laboratory tests.

Financial Tasks

A self adaptive differential HS was used in (Dash et al. 2014) for designing a single hidden layer feed forward neural network. The optimized neural network was used for prediction of a financial time series data that was the closing price and volatility of five different stock indices. Forecasting of financial data was performed in (Dash et al. 2015) by an integrating model of a interval type2 fuzzy logic system and an artificial neural network. A proposed differential HS was used for optimizing the parameters of the fuzzy time series models for stock market volatility prediction. A stochastic replenishment intervals multiproduct inventory model with dynamic demand was solved by HS in (Taleizadeh et al. 2012) to minimize costs of holding, purchasing and shortage. Multi-site order planning problem was handled by HS in (Guo et al. 2015). This problem was defined in a make-to-order manufacturing environment considering multiple production uncertainties. The goal is to attain production objectives by effectively determining the allocation of customer orders to several self-owned or collaborative production plants placed in different regions.

Product Transportation

Multi-server location–allocation problem was tackled by multi-objective HS in (Hajipour et al. 2014). This problem is about placing a number of facilities in between a number of customers located at fixed points to minimize the transportation cost. Shipping cost in a transportation problem was minimized by hybridization of HS and simulated annealing in (Hosseini et al. 2014). In this problem, some vehicles transport goods from suppliers to the customers via three transportation systems. The problem of emergency air transportation was solved in (Zheng et al. 2015b) by a hybridization of biogeography-based optimization and HS, to maximize delivery efficiency. This problem is about the transportation of amounts of n different types of relief supplies from a set of m air freight hubs to the closest airport to the target disaster area.

Job Scheduling

Multi-objective flexible job shop scheduling problem solved by a Pareto version of HS with multiple harmony generation strategies in (Gao et al. 2014). HS with one-point crossover and iterative local search was employed in (Li et al. 2015) to solve the flow line manufacturing cell scheduling problem and minimize the total tardiness and mean total flow time. Cellular manufacturing system is a production system which needs cell scheduling before starting the production process. Two-sided assembly lines are kind of assembly lines in which tasks operations can be performed in them. Non dominated HS was proposed in (Purnomo,Wee 2014) to solve the task assignment problem in a two-sided assembly line with zone constraints. The objective was the maximization of the production rate and the distribution of the workload in the assembly line. Flexible job-shop scheduling problem was solved in (Gao et al. 2015) by discrete HS. The objectives were the weighted combination of the maximum of the completion time and the mean of earliness and tardiness.

Function Optimization

There are some enhanced versions of HS for numerical optimization examined by some standard function optimization: improved HS (Ashrafi,Dariane 2013), HS with a novel selection schemes (Al-Betar et al. 2012; Al-Betar et al. 2013), island-based HS (Al-Betar et al. 2015), Geometric Selective HS (Castelli et al. 2014), HS with dynamic control parameters (Chen et al. 2012), a learning automata-based HS (Enayatifar et al. 2013), HS with mutation operators (Hasan et al. 2014), global dynamic HS (Khalili et al. 2014), improved HS (Contreras et al. 2014), parameter adaptive HS (Kumar et al. 2014), intelligent global HS (Valian et al. 2014), HS with Gaussian mutation (Dai et al. 2015), HS with the population based incremental learning (Gao et al. 2012), hybridization of HS and cuckoo search (Wang et al. 2015a). High-dimensional multimodal optimization problems was solved by HS in (Tuo et al. 2015). 0–1 knapsack problems was solved in (Kong et al. 2015a, b) by new versions of binary HS. Furthermore, it was solved in (Layeb 2013) by a hybrid quantum HS.

CONCLUSION

As one of the powerful optimization algorithms, HS has attracted significant attention for solving different types of optimization problems during the recent years. The advantages of HS algorithm are easy implementation, simple concept, fast convergence speed and few parameters to adjust. Owing to these merits, HS has been considerably used to solve various problems in different fields like power system, communication, software, civil, water engineering, and pattern recognition. Study of the literature indicates that HS can effectively and efficiently solve different types of engineering optimization problems. In the literature, various variants of HS algorithm can be found which focus on improving improvisation process, harmony memory consideration and parameter setting. There are other variants which try to enhance the performance of HS by borrowing some ideas from the other metaheuristic such as GA, PSO, DE and chaotic search. By comparing the results obtained by HS and other algorithms it can be drawn that HS could be a good candidate to solve complex optimization problems.

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