

Chapter 2

The Overview of Harmony Search

Abstract When musicians compose the harmony, they usually try various possible combinations of the music pitches stored in their memory, which can be considered as a optimization process of adjusting the input (pitches) to obtain the optimal output (perfect harmony). Harmony search draws the inspiration from harmony improvisation, and has gained considerable results in the field of optimization, although it is a relatively NIC algorithm. With mimicking the rules of various combining pitches, harmony search has two distinguishing operators different from other NIC algorithms: harmony memory considering rate (HMCR) and pitch adjusting rate (PAR) that are used to generate and further mutate a solution, respectively. This candidate generation mechanism and single search memory involved decide its excellence in structure simplicity and small initial population. This chapter presents the discussions of the inspiration of harmony search, the basic harmony search optimization algorithm, and an overview of different application areas of the harmony search.

Keywords Harmony search method • Optimization • Hybrid harmony search methods • Benchmarks

2.1 The Inspiration of Harmony Search

The HS was initially proposed by Geem [1] and applied to solve the optimization problem of water distribution networks in 2000. As a novel population-based meta-heuristic algorithm, during the recent years, it has gained great research success in the areas of mechanical engineering, control, signal processing, etc. However, different from most emerging NIC algorithms, the inspiration of the HS is not from the natural phenomena, for example, the CSA is inspired by artificial immune system, and the collective behavior among the unsophisticated individuals of some living creatures has promoted the swarm intelligence, but is conceptualized from the musical process of searching for a perfect state of harmony determined by aesthetic standards.

As we know, when musicians compose the harmony, they usually try various possible combinations of the music pitches stored in their memory. This kind of

Table 2.1 Comparison of harmony improvisation and optimization

Comparison factors	Harmony improvisation	Optimization
Targets	Aesthetic standard	Objective function
Best states	Fantastic harmony	Global optimum
Components	Pitches of instruments	Values of variables
Process units	Each practice	Each iteration

efficient search for a perfect harmony is analogous to the procedure of finding the optimal solutions to engineering problems. The HS method is inspired by the explicit principles of the harmony improvisation [2]. Table 2.1 presents the comparison of harmony improvisation and optimization [3].

2.2 The Basic Harmony Search Algorithm

The music improvisation is a process of searching for the better harmony by trying various combinations of pitches that should follow any of the following three rules [2]:

1. playing any one pitch from the memory;
2. playing an adjacent pitch of one pitch from the memory;
3. playing a random pitch from the possible range.

This process is mimicked in each variable selection of the HS algorithm. Similarly, it should follow any of the three rules below:

1. choosing any value from the HS memory;
2. choosing an adjacent value from the HS memory;
3. choosing a random value from the possible value range.

The three rules in the HS algorithm are effectively directed using two essential parameters: harmony memory considering rate (HMCR) and pitch adjusting rate (PAR). Figure 2.1 shows the flowchart of the basic HS method, in which there are four principal steps involved.

Step 1. Initialize the HS memory (HM). The initial HM consists of a given number of randomly generated solutions to the optimization problems under consideration. For an n -dimension problem, an HM with the size of HMS can be represented as follows:

$$\text{HM} = \begin{bmatrix} x_1^1, x_2^1, \dots, x_n^1 \\ x_1^2, x_2^2, \dots, x_n^2 \\ \vdots \\ x_1^{\text{HMS}}, x_2^{\text{HMS}}, \dots, x_n^{\text{HMS}} \end{bmatrix}, \quad (2.1)$$

where $[x_1^i, x_2^i, \dots, x_n^i]$ ($i = 1, 2, \dots, \text{HMS}$) is a solution candidate. HMS is typically set to be between 50 and 100.

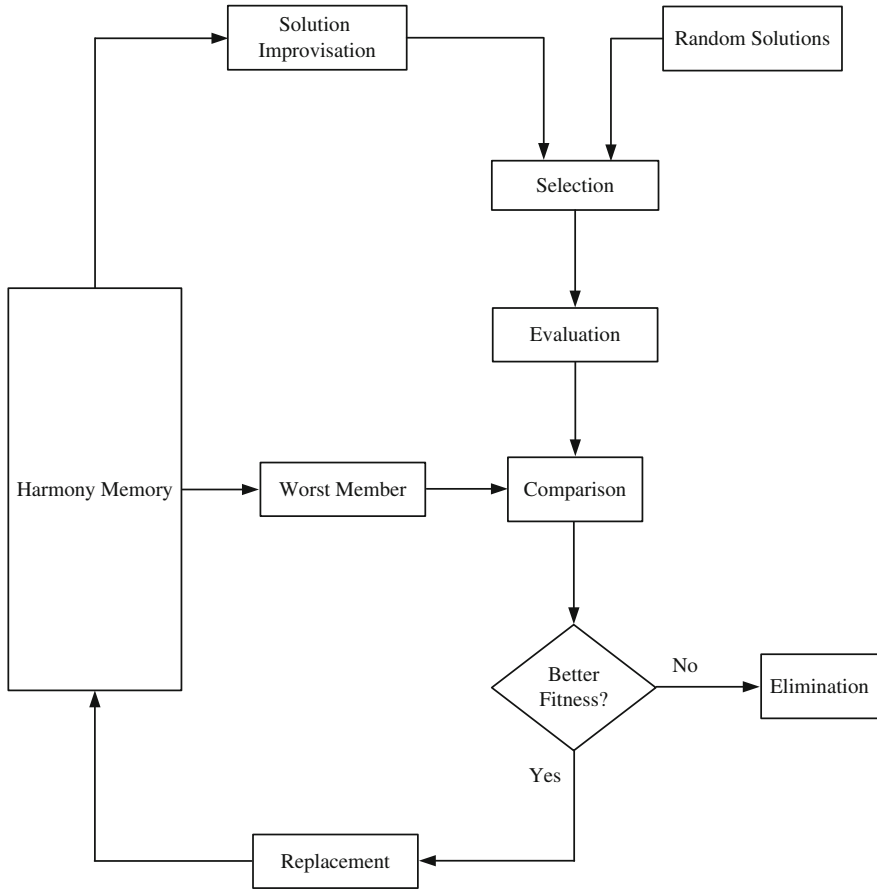


Fig. 2.1 Harmony Search (HS) method

Step 2. Improvise a new solution $[x'_1, x'_2, \dots, x'_n]$ from the HM. Each component of this solution, x'_j , is obtained based on the HMCR. The HMCR is defined as the probability of selecting a component from the present HM members, and 1-HMCR is, therefore, the probability of generating it randomly. If x'_j comes from the HM, it is chosen from the j th dimension of a random HM member, and it can be further mutated according to the PAR. The PAR determines the probability of a candidate from the HM to be mutated. Obviously, the improvisation of $[x'_1, x'_2, \dots, x'_n]$ is rather similar to the production of the offspring in the genetic algorithm (GA) [4, 5] with the mutation and crossover operations. However, the GA creates fresh chromosomes using only one (mutation) or two (simple crossover) existing ones, while the

generation of new solutions in the HS method makes full use of all the HM members.

- Step 3. Update the HM. The new solution from Step 2 is evaluated. If it yields a better fitness than that of the worst member in the HM, it will replace that one. Otherwise, it is eliminated.
- Step 4. Repeat Step 2 to Step 3 until a preset termination criterion, e.g., the maximal number of iterations, is met.

Apparently, the HMCR and PAR are two basic parameters in the HS algorithm, which control the component of solutions and even affect convergence speed. The former is used to set the probability of utilizing the historic information stored in the HM. For example, 0.9 indicates that each component of a new solution will be chosen from the HM with 90 % probability, and 10 % probability from the entire feasible range. Each component of the solution is subject to whether it should be pitch-adjusted, which is determined by PAR. 1-PAR means the rate of doing nothing. For example, a PAR of 0.3 indicates that the neighboring value will be chosen with 30 % probability.

Similar to the GA, particle swarm optimization (PSO) [6–8], and differential evolution (DE) [9, 10], the HS method is a random search technique. It does not require any prior domain information, such as the gradient of the objective functions. However, different from those population-based evolutionary approaches, it only utilizes a single search memory to evolve. Therefore, the HS method has the characteristics of algorithm simplicity. On the other hand, it occupies some inherent drawbacks, e.g., weak local search ability. In the following two chapters, the comparisons between the HS and other NIC optimization algorithms and the variations of the HS will be discussed individually.

2.3 Survey of the Harmony Search Applications

In the real world, modern science and industry are indeed rich in the problems of optimization. Since the HS was originally proposed by Geem [11] and applied to solve the optimization problem of water distribution networks in 2000, the applications of the HS have covered many areas including industry, optimization benchmarks, power systems, medical science, control systems, construction design, and information technology [12].

2.3.1 Optimization Benchmarks

Optimization benchmarks for the hybridization of the HS method with other approaches are one principal application area. Different variants based on the HS have been demonstrated their improvement and efficiency through various

benchmark functions. Combined with semantic genetic operators, Castelli et al. [13] propose a geometric selective harmony search (GSHS) method with three main differences from the original HS: (1) the memory consideration process involves the presence of a selection procedure, (2) the algorithm integrates a particular recombination operator that combines the information of two harmonies, and (3) the algorithm utilizes a mutation operation that uses the PAR parameter. Therefore, geometric semantic crossover produces offspring that is not worse than the worst of its parents, and geometric semantic mutation causes a perturbation on the semantics of solutions, whose magnitude is controlled by a parameter. Five different HS algorithms have been compared using 20 benchmark problems, and the GSHS outperforms the others with statistically significant enhancement in almost all the cases.

2.3.2 Industry

Industry is a prominent area full of various practical optimization issues subject to multi-modal, constrained, nonlinear, and dynamical. The HS algorithm proposed by Saka [14] determines the optimal steel section designations from the available British steel section table, and implements the design constraints from BS5950. Recently, an enhanced harmony search (EHS) in [15] is developed enabling the HS algorithm to quickly escape from local optima. The proposed EHS algorithm is utilized to solve four classical weight minimization problems of steel frames including two-bay, three-storey planar frame subject to a single-load case, one-bay, ten-storey planar frame consisting of 30 members, three-bay, twenty four-storey planar frame, and Spatial 744 member steel frame. In [16], the HS is used to select the optimal parameters in the tuned mass dampers [16]. Fesanghary et al. [17] propose a hybrid optimization method based on the global sensitivity analysis and HS for the optimal design of shell and tube heat exchangers.

2.3.3 Power Systems

There is a lot of work focused on the optimization issues concerning power systems, such as cost minimization. A modified HS algorithm is proposed to handle non-convex economic load dispatch of real-world power systems. The economic load dispatch and combined economic and emission load dispatch problems can be converted into the minimization of the cost function [18]. Sinsuphan et al. [19] combine the HS with sequential quadratic programming and GA to solve the optimal power flow problems. The objective function to be optimized is the total generator fuel costs in the entire system. The chaotic self-adaptive differential HS algorithm, proposed by Arul et al. [20], is employed to deal with the dynamic economic dispatch problem.

2.3.4 Signal and Image Processing

Li and Duan [21] modify the HS by adding a Gaussian factor to adjust the bandwidth (bw). With this modified HS, they develop a pre-training process to select the weights used in the combining of feature maps to make the target more conspicuity in the saliency map. In their method based on the HS, Fourie et al. [22] design a harmony filter using the improved HS algorithm for a robust visual tracking system.

2.3.5 Others

In addition to the aforementioned applications, the HS has also been widely employed in a large variety of fields, including transportation, manufacturing, robotics, control, and medical science [11]. Many traffic modeling software are capable of finding the optimal or near-optimal signal timings using different optimization algorithms. For example, Ceylan [23] proposes a modified HS with embedded hill climbing algorithm for further tuning the solutions in the stochastic equilibrium network design. The modified HS algorithm is also used in parameter identification of the solar cell mathematical models [24]. Miguel et al. [25] employ the HS in damage detection under the ambient vibration.

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