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Honey-bee mating optimization (HBMO) algorithm for optimal reservoir operation

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Abstract

In recent years, evolutionary and meta-heuristic algorithms have been extensively used as search and optimization tools in various problem domains, including science, commerce, and engineering. Ease of use, broad applicability, and global perspective may be considered as the primary reason for their success. The honey-bee mating process has been considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of real honey-bee mating. In this paper, the honey-bee mating optimization (HBMO) algorithm is presented and tested with a nonlinear, continuous constrained problem with continuous decision and state variables to demonstrate the efficiency of the algorithm in handling the single reservoir operation optimization problems. It is shown that the performance of the model is quite comparable with the results of the well-developed traditional linear programming (LP) solvers such as LINGO 8.0. Results obtained are quite promising and compare well with the final results of the other approach.

Keywords: Honey-bee mating optimization; Single reservoir; Optimal operation; Continuous domain

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1. Introduction

Nonlinearities and complex interactions among design and operation variables in engineering problems form a search space with multiple optimal solutions, in which most local optima have inferior objective function values. Thus, gradient-based methods may not be good candidates for efficient optimization algorithms when applied to a broad range of engineering design and operation problems. Over the last decade, evolutionary and meta-heuristic algorithms have been extensively used as search and optimization tools in various problem domains. The broad applicability, ease of use, and global perspective of meta-heuristic algorithms may be considered as the primary reason for their extensive application and success as search and optimization tools in various problem domains. Among them, genetic algorithms (GAs) have been extensively employed as search and optimization methods in various problem domains, including science, commerce, and engineering [1–3]. GAs are search and optimization procedures that are motivated by the principle of natural genetics and natural selection. Fundamental ideas of genetics are borrowed and used artificially to construct search algorithms that are robust and require minimal problem information. Codes are available for solving multimodal problems [4], multi-objective problems [5] and scheduling problems, as well as fuzzy-neuro-GA implementation [6].

Over the last decade, modeling the behavior of social insects, such as ants and bees, for the purpose of search and problem solving has been the context of the emerging area of swarm intelligence. Usinf ant colony is a typical successful swarm-based optimization approach, where the search algorithm is inspired by the behavior of real ants. Using ant colony (ACO) algorithms as evolutionary optimization algorithms were first proposed by Dorigo [7] and Dorigo et al. [8] as a multi-agent approach to different combinatorial optimization problems such as the traveling salesman problem and the quadratic assignment problem. More recently, successful applications of ACO algorithms to a number of engineering design and operation problems, in various fields, has been reported [9–12].

Honey-bee are among the most closely studied social insects. Honey-bee mating may also be considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of marriage in real honey-bee. Honey-bee have been used to model agent-based systems [13]. In a recent work, Abbass [14,15] developed an optimization algorithm based on the honey-bee marriage process.

Bozorg Haddad and Afshar [16] presented an optimization algorithm based on honey-bee mating that was successfully applied to a single reservoir optimization problem with discrete decision variables. Later, Bozorg Haddad et al. [17] applied the same algorithm to three benchmark mathematical problems. This paper presents an improved version of the honey-bee mating optimization (HBMO) algorithm for continuous optimization problems and its application to a single reservoir problem, considering reservoir releases as continuous variables.

2. Honey-bee modeling

A honeybee colony typically consists of a single egg-laying long-lived queen, anywhere from zero to several thousand drones (depending on the season) and usually 10,000 to 60,000 workers [18]. Queens are specialized in egg laying [19]. A colony may contain one queen or more during its life-cycle, which are named monogynous and/or polygynous colonies, respectively. Only the queen bee is fed "royal jelly," which is a milky-white colored, jelly-like substance. "Nurse bees" secrete this nourishing food from their glands, and feed it to their queen. The diet of royal jelly makes the queen bee bigger than any other bee in the hive. A queen bee may live up to 5 or 6 years, whereas worker bees and drones never live more than 6 months. There are usually several hundred drones that live with the queen and worker bees. Mother nature has given the drones just one task, which is to provide the queen with some sperm. After the mating process, the drones die.

Drones are the fathers of the colony. They are haploid and act to amplify their mothers' genome without altering their genetic composition, except through mutation. Therefore, drones are considered as agents that propagate one of their mother's gametes and function to enable females to act genetically as males. Workers are specialized in brood care and sometimes lay eggs. Broods arise either from fertilized or unfertilized eggs. The former represent potential queens or workers, whereas the latter represent prospective drones.

In the marriage process, the queen(s) mate during their mating flights far from the nest. A mating flight starts with a dance performed by the queen who then starts a mating flight during which the drones follow the queen and mate with her in the air. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony. Each time a queen lays fertilized eggs, she randomly retrieves a mixture of the sperm accumulated in the spermatheca to fertilize the egg [20].

The queen is pursued by a large swarm of drones (drone comets), when copulation occurs. Insemination ends with the eventual death of the drone, and the queen receiving the "mating sign." The queen mates multiple times but the drone, inevitably, only once. These features make bee mating the most spectacular mating among insects.

The mating flight may be considered as a set of transitions in a state-space (the environment) where the queen moves between the different states in some speed and mates with the drone encountered at each state probabilistically. At the start of the flight, the queen is initialized with some energy content and returns to her nest when the energy is within some threshold from zero to full spermatheca.

In developing the algorithm, the functionality of workers is restricted to brood care and therefore, each worker may be represented as a heuristic which acts to improve and/or take care of a set of broods (i.e., as feeding the future queen with royal jelly). A drone mates with a queen probabilistically using an annealing function as follows [14]:

$$\mathrm{Prob}(Q,\ D) = \exp[-\Delta(f)/S(t)], \tag{1}$$

where Prob (Q, D) is the probability of adding the sperm of drone D to the spermatheca of queen Q (that is, the probability of a successful mating); $\Delta(f)$ is the absolute difference between the fitness of D (i.e., $f(D)$) and the fitness of Q (i.e., $f(Q)$); and $S(t)$ is the speed of the queen at time t. It is apparent that this function acts as an annealing function, where the probability of mating is high when either the queen is still at the beginning of her mating flight, therefore her speed is high, or when the fitness of the drone is as good as the queen's. After each transition in space, the queen's speed and energy decays according to the following equations:

$$S(t+1) = \alpha(t) \times S(t), \tag{2}$$

$$E(t+1) = E(t) - \gamma, \tag{3}$$

where α is a factor $\in$ [0,1] and γ is the amount of energy ($E(t)$) reduction after each transition.

3. Working principle and mathematical presentation

The queens play the most important role in the mating process in nature as well as in the HBMO algorithm. Each queen is characterized with a genotype, speed, energy, and a spermatheca with defined capacity. The spermatheca is the repository for the drone's sperm after the mating process with the queen. Thus, for a queen's defined spermatheca size, speed and energy are initialized before each mating flight, with random realization in the range of (0.5, 1).

In the algorithm, a drone is represented by a genotype and a genotype marker. Because all drones are naturally haploid, a genotype marker may be employed to randomly mark half of the genes, leaving the other half unmarked. In this case, only the unmarked genes are those that form a sperm to be randomly used in the mating process [14].

Workers that are used to improve the brood's genotype may represent a set of different heuristics. The rate of improvement in the brood's genotype, as a result of a heuristic application to that brood, defines the heuristic fitness value.

Since the drones are assumed to be haploid, after a successful mating, the drone's sperm is stored in queen's spermatheca. Later in breeding process, a brood is constructed by copying some of the drone's genes into the brood genotype and completing the rest of the genes from the queen's genome. The fitness of the resulting genotype is determined by evaluating the value of the objective function of the brood genotype and/or its normalized value. It is important to note that a brood has only one genotype.

Thus, an HBMO algorithm may be constructed with the following five main stages:

1. The algorithm starts with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). A drone is then selected from the list randomly for the creation of broods.
2. Creation of new broods (trial solutions) by crossovering the drone's genotypes with the queens.
3. Use of workers (heuristics) to conduct local search on broods (trial solutions).
4. Adaptation of worker's fitness, based on the amount of improvement achieved on broods.
5. Replacement of weaker queens by fitter broods.

The algorithm starts with three user-defined parameters and one predefined parameter. The predefined parameter is the number of workers (W), representing the number of heuristics encoded in the program. However, the predefined parameter may be used as a parameter to alter the number of active heuristics if required; that is, the user may choose the first heuristic, where W is less than or equal to the total number of heuristics encoded in the program. The three user-defined parameters are the number of queens, the queen's spermatheca size representing the maximum number of mating per queen in a single mating flight, and the number of broods that will be born by all queens. The energy and speed of each queen at the start of each mating flight is initialized at random. A set of queens is then initialized at random. A randomly selected heuristic is then used to improve the genotype of each queen, assuming that a queen is usually a good bee. A number of mating flights are then undertaken. In each mating flight, all queens fly based on the energy and speed of each, where both energy and speed are generated at random for each queen before each mating flight commences. At the start of a mating flight, a drone is generated randomly and the queen is positioned over that drone. The transition made by the queen in space is based on her speed which represents the probability of flipping each gene in the drone's genome. At the start of a mating flight, the speed may be higher and the queen may make very large steps in space. While the energy of the queen decreases, her speed decreases, and as a result, the neighborhood covered by the queen, decreases. At each step in the space, the queen mates with the drone encountered at that step using the probabilistic rule in Eq. (1). If the mating is successful (i.e., the drone passes the probabilistic decision rule), the drone's sperm is stored in the queen's spermatheca. To sum up, the algorithm starts with a mating flight where a queen selects a drone with a predefined probabilistic rule. By cross-overing the drone's genotypes with the queen's, a new brood (trial solution) is formed which later can be improved, employing workers to conduct local search.

When all queens complete their mating flight, they start breeding. For a required number of broods, a queen is selected in proportion to her fitness and mated with a randomly selected sperm from her spermatheca. A worker is chosen in proportion to its fitness to improve the resultant brood. After all broods have been generated, they are sorted according to their fitness. The best brood replaces the worst queen until there is no brood that is better than any of the queens. Remaining broods are then killed and a new mating flight begins until all assigned mating flights are completed or convergence criteria are met. The main steps in the HBMO algorithm are presented in Fig. 1. Also a full scale computational flowchart in Fig. 2 clarifies the algorithm documentation as well as

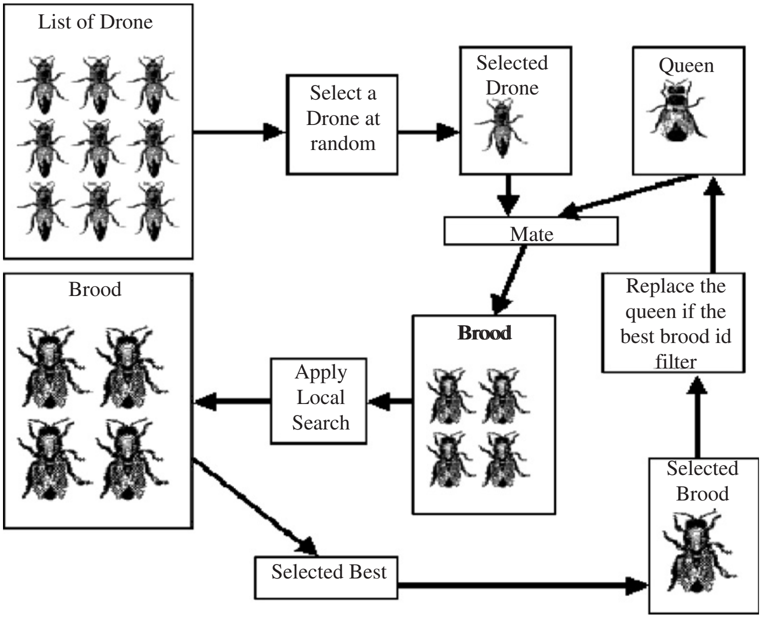

Fig. 1. The HBMO algorithm [14].

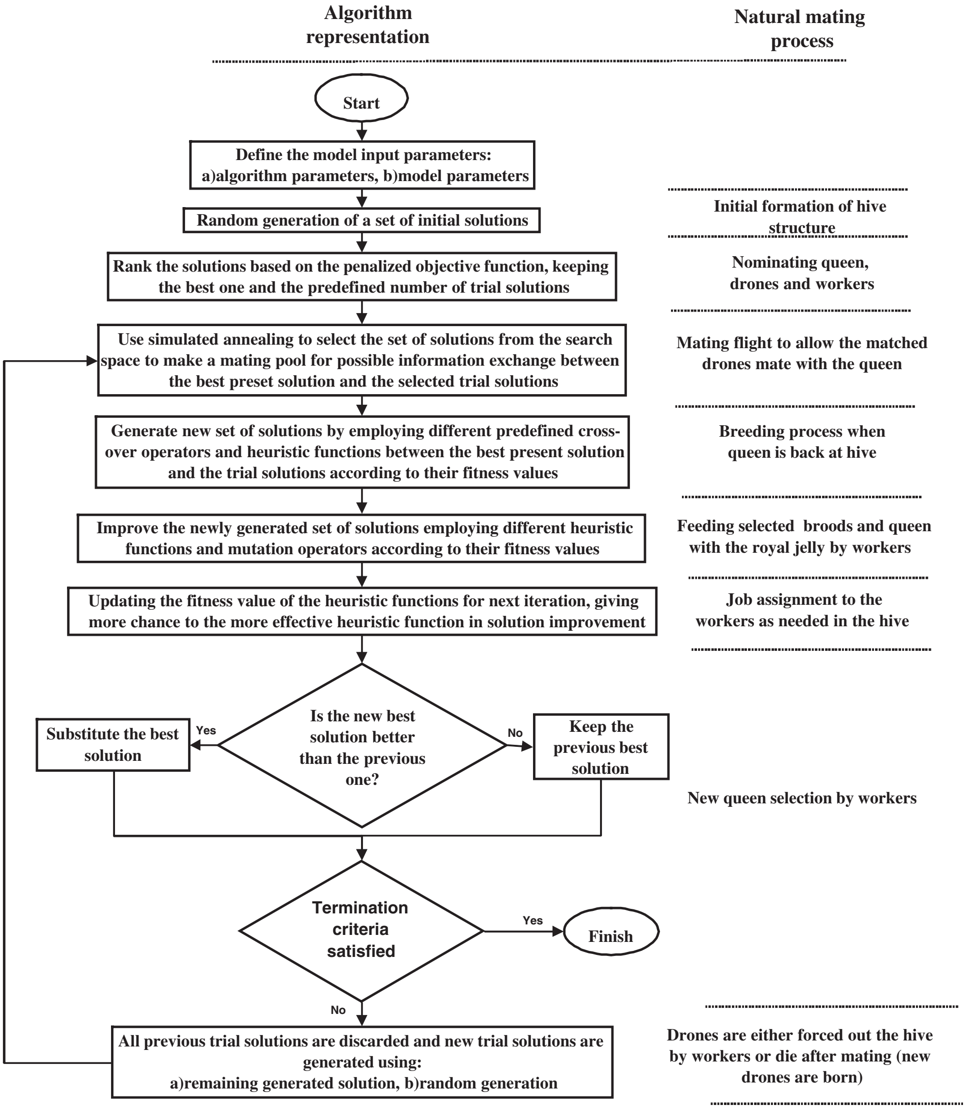

Fig. 2. Algorithm and computational flowchart and equivalent natural processes.

translating biological terms from the natural honey-bee mating process into technical terms.

4. Algorithm application (single reservoir operation optimization, continuous domain)

To illustrate the model application and performance, the operation of the Dez reservoir in southern district of Iran is selected as a case study. Monthly inflows to the reservoir, along with monthly demands, are presented in Fig. 3. The average annual inflow to the reservoir and annual demand, are estimated as $5900 \times 10^6\,m^3$ and $5303 \times 10^6\,m^3$,

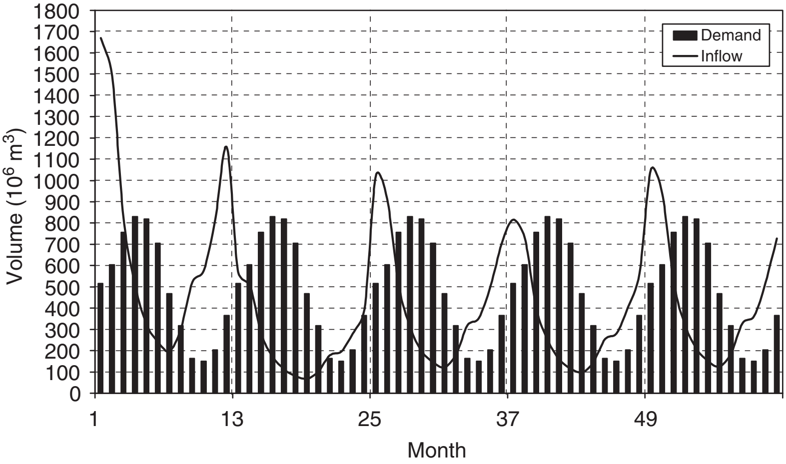

Fig. 3. Monthly inflow to the reservoir along with monthly demand.

respectively. The active storage volume of the reservoir is $2510 \times 10^6\,m^3$. The nonlinear objective function of the study is to minimize the total squared deviation (TSD) of releases (R_t) from the target demands (D_t):

$$Min\ TSD = \sum_{t=1}^{nt}((R_t - D_t)/D_{\max})^2$$

$$\text{or } Min\ RMSE = \sqrt{\frac{\sum_{t=1}^{nt}(R_t - D_t)^2}{nt}}, \tag{4}$$

where $D_{\max}$, is the maximum demand in all months which is equal to 831.1.

Releases from the reservoir are considered as decision variables, resulting in reservoir storage as a continuous state variable.

In this problem, one queen with 130 drones are employed in each mating flight (or iteration), with the total number of mating flights and the queen's spermatheca capacity limited to 1000 and 130, respectively. Results from the model in terms of storage volume at the end of each period are shown in Fig. 4. For the same problem, along with the global optimum, obtained from LINGO 8.0 NLP solver, the monthly releases, resulting from the HBMO model with 1000 mating flights (or iterations) are presented in Fig. 5. Monthly demands and the global optimum results are presented in the same figure. A systematic underestimation observed after period 13 in the amount of releases from the HBMO and even the global optimum may be warranted, reconsidering Fig. 5. As is clear, during the first 3 months, total inflow to the reservoir exceeds $4000 \times 10^6\,m^3$ which is approximately 1.6 times the reservoir's active storage. In other words, the first year is a highly wet year with total inflow exceeding $8500 \times 10^6\,m^3$, leaving much less annual inflow for the next 4 years.

Figs. 6 and 7 illustrate the rate of convergence of the model. Very rapid convergences as well as final TSDs are very near to those of the global optimum, suggesting that the approach and algorithm are quite promising for further development and application, in the field of water resources planning and management.

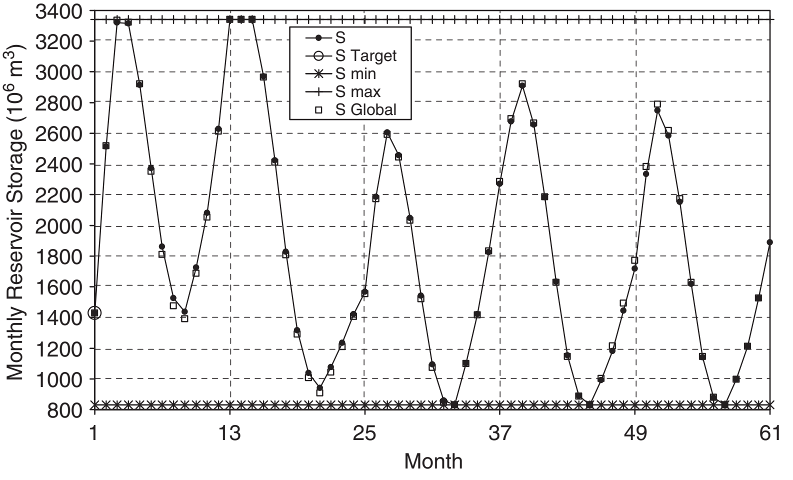

Fig. 4. Monthly optimum storage resulting from HBMO algorithm and global optimum in single reservoir problem.

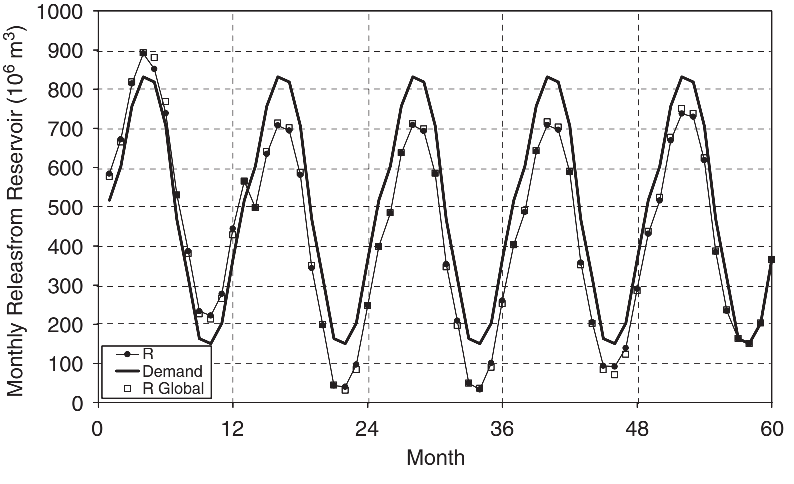

Fig. 5. Monthly optimum release resulting from HBMO algorithm and global optimum in single reservoir problem.

It is worth mentioning that the global optimum resulting for the same problem using LINGO 8.0 NLP solver with continuous variables has a fitness value of 0.796115. The proposed algorithm results in an average fitness value of 0.823595. The low value of the coefficient resulting from the variation of 10 different runs is also noted. The results of the 10 different runs with their statistics and execution times are presented in Table 1. It is noted that the coefficients of variation for the 10 different runs are as low as 0.015669, and the best and the worst fitness values are 0.810438–0.84931, respectively.

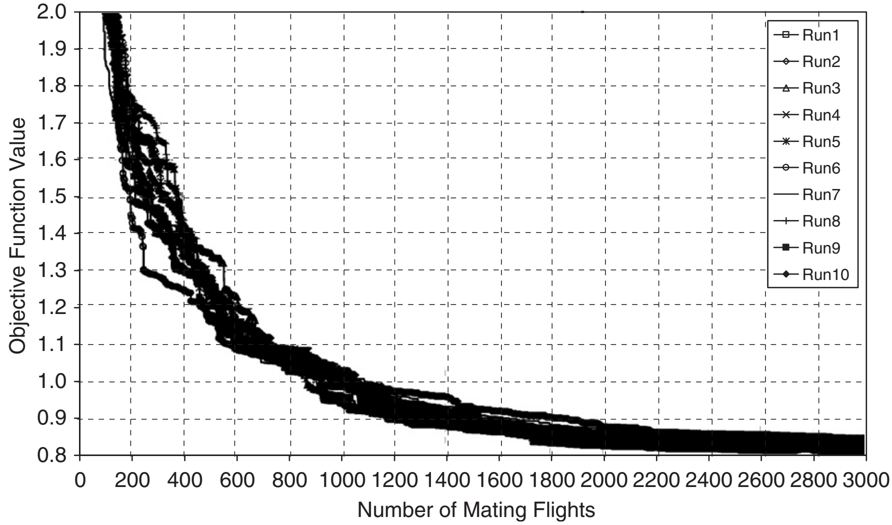

Fig. 6. Rate of convergence of 10 runs of the model in single reservoir problem.

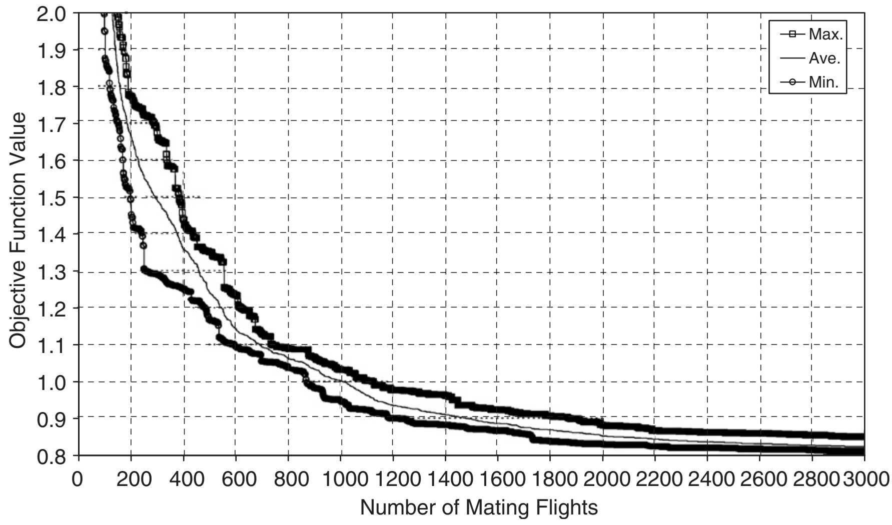

Fig. 7. Best, worst and average rates of convergence of the model over 10 runs in single reservoir problem.

5. Concluding remarks

A very limited attempt has been made to employ the social behavior of honey-bee in real-world optimization. The modeling of the honey-bee mating process as an optimization algorithm, and its application to several water resources management problems such as long-term single reservoir optimal operation with nonlinear constraints, in continuous domain, has partially revealed the high potential of the proposed algorithm to solve

Table 1
Statistical measures for 10 runs in single reservoir problem

Iteration number	*TSD*		*RMSE*	
	HBMO	Global optimum	HBMO	Global optimum
1	0.814573	0.796115	96.837273	95.733882
2	0.810438		96.591184	
3	0.810648		96.603731	
4	0.816722		96.964937	
5	0.837303		98.179108	
6	0.819344		97.120446	
7	0.834679		98.025116	
8	0.817582		97.015969	
9	0.825349		97.475733	
10	0.84931		98.880546	
Average	0.823595		97.369404	
Best	0.810438		96.591184	
Worst	0.84931		98.880546	
Standard deviation	0.012905		0.7605531	
Coefficient of variation	0.015669		0.007811	
Objective function after 65000 mating flight	0.803093		96.152483	

nonlinear water resources optimization problems. Results obtained for a single reservoir operation in a continuous domain from 10 different runs are quite promising, emphasizing the capability of the developed algorithm in handling constrained-continuous engineering optimization problems. Results obtained, compare well with those obtained using well-developed GAs, making the HBMO algorithm's application, quite promising. Its ability to consider discrete as well as continuous decision variables, with little difficulty may be considered a particular strength of the algorithm. The model performance in real-world water management problems, such as reservoir operation, proved to be very promising. Preliminary results obtained from the model application compared very well with those from similar heuristic methods as well as global optimum results.

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