HBMO IN OPTIMAL RESERVOIR OPERATION

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ABSTRACT

The broad of applicability, ease of use, and global perspective of so-called 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. Honey bees are among the most well-studied social insects. Their mating process may also be considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of real honey bees mating. This paper presents a honey bee mating optimization algorithm (HBMO) to solve a real world continuous optimization problem. To do so, a single reservoir with 60 operation period is considered. A fitness function is defined as the total square deviation from target demand. Releases from the reservoir are considered as decision variables, resulting in reservoir storage as continuous state variable. Employing one queen with 130 drones and 1000 mating flights, the model converged to a near global optimum. Results obtained from 10 different runs are quite promising emphasizing the capability of the developed algorithm in handling constrained-continuous engineering optimization problems.

Key Words: Honey Bee Mating Optimization; continuous variables; Single-Reservoir Optimum Operation.

INTRODUCTION

Traditional optimization methods may be classified into direct and gradient-based methods. Most of the direct and/or gradient based methods suffer from (1) dependency on chosen initial solution, (2) limited capabilities in handling problems with discrete variables, (3) pre-mature convergence and trapping in suboptimal solutions, and (4) inability to handle a broad range of optimization problems.

Therefore, for one reason or another, traditional methods may not be good candidates as efficient optimization algorithms for a broad range of engineering design and operation problems. Over the last decade, evolutionary and meta-heuristic algorithms (EAs) have been extensively used 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, biology and engineering.

Modeling the behavior of social insects, such as ants and bees, and using these models for search and problem solving are the context of the emerging area of swarm intelligence. Ant Colony Optimization (ACO) is a typical successful swarm-based approach to optimization, where the search algorithm is inspired by the behavior of real ants.

Ant colony algorithms, as a form of evolutionary optimization were first proposed by Dorigo (1992) and Dorigo et al. (1996) as a multi-agent approach to different combinatorial optimization problems such as the traveling salesman problem and the quadratic assignment problem.

The successful application of ACO to engineering design and operation problems in various fields has been reported (Abbaspour et al. 2001; Simpson et al. 2001; and Jalali et al. 2003, 2004).

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 real honey bee mating.

Honey bees are also used to model agent-based systems (Perez-Uribe and Hirsbrunner 2000). In a recent work, Abbass (2001a, b) developed an optimization algorithm based on the honey bee mating process.

Haddad and Afshar (2004) presented an optimization algorithm based on honey bee mating that was successfully applied to single reservoir optimization. Later, Haddad et al. (2005) applied the same algorithm to 3 benchmark mathematical problems. The present paper benefits from an improved version of the developed HBMO algorithm for continuous optimization problems in its application to the same single reservoir problem considering the reservoir release as continuous variable.

HONEY BEE COLONY STRUCTURE

A honey bee colony can be founded in two different methods (Dietz, 1986). In "independent founding", the colony starts with one or more reproductive females that construct the nest, lay the eggs, and feed the larvas. The first group of broods is reared alone until they take over the work of the colony. Subsequently, division of labor takes place and the queen specializes in egg laying and the workers in brood care (Dietz, 1986). Another founding method is called "swarming", in which the colony is founded by one or more queens along with a group of workers from the original colony. Haplometrosis and Pleometrosis refer to the case in which the colony is founded by a single or more than one queen, respectively. In this method, labor division starts as the queens specialize in egg laying and brood care is left to the workers. A colony may contain one queen or more during its life-cycle, which are termed Monogynous and/or Polygynous colonies, respectively.

Only the queen bee is fed “Royal Jelly”. Royal jelly 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 larger than any other bees 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.

Generally, a normal honey bee colony consists of the queen(s), drones, workers, and broods. Queens represent the main reproductive individuals in some types of honey bees, such as the European Apis Mellifera and specialize in egg laying (Laidlaw and Page 1986). 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, where as the latter represent prospective drones.

The mating process represents one type of action that has proved to be difficult to study because the queens mate during their mating-flights far from the nest. A mating flight begins 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 a typical mating flight, each queen mates with seven to twenty drones. 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 retrieves at random a mixture of the sperm accumulated in the spermatheca to fertilize the egg (Page 1980).

MODELING HONEY BEE MATING

In a mating flight, the queen moves between different states at some speed and mates with the drone encountered at each state probabilistically. In fact, a mating flight may be considered as a set of state-space transitions. 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 above zero or when her spermatheca is full.

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).

The probability of adding the sperm of drone D to the spermatheca of queen Q, that is, the probability of a successful mating may be defined as:

$$Prob(Q,D) = e-\Delta(f)/S(t) \qquad (1)$$

In which $\Delta(f)$ 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 at the beginning of her mating flight and therefore her speed is high, or when the fitness of the drone is as good as the queen's. After each transition in the space, the queen's speed and energy decay as in the following equations:

$$S(t+1) = a*S(t) \qquad (2)$$

$$E(t+1) = E(t) - \gamma \qquad (3)$$

where α is a factor $\in [0.1]$ and γ is the amount of energy reduction after each transition.

SINGLE RESERVOIR OPERATION OPTIMIZATION; CONTINOUS DOMAIN

To illustrate the performance of the developed algorithm in a continuous real world engineering problem, the operation of the Dez reservoir with effective storage volume of 2510 MCM is selected as a case study. Monthly inflows to the reservoir along with the monthly demand are presented in Figure (1).

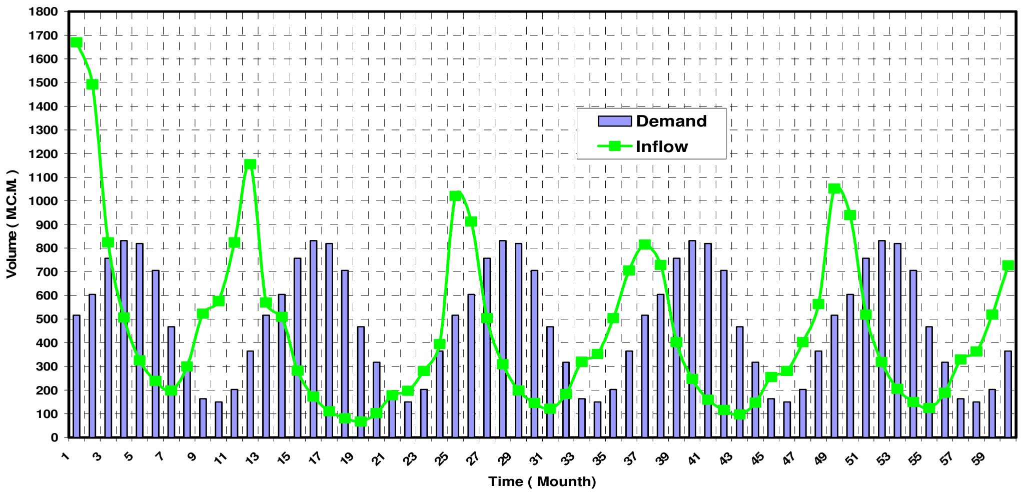

Figure 1. Monthly inflow to the reservoir and monthly demand

Average annual inflow to the reservoir and annual demand are estimated as 5900 and 5303 MCM, respectively. The objective of the study is defined as the minimization of the total squared deviation (TSD) of releases from target demands as follows:

$$\text{Minimize TSD} = \sum_{t-1}^{nt} (R_{(t)} - D_{(t)})^2 \qquad (4)$$

This problem was first attacked by Haddad and Afshar (2004) discritizing the storage volume into 14 discrete levels. In the present case, however, the reservoir storage volume, as well as releases from the reservoir, is considered as continuous decision and state variables, respectively.

In this problem, one queen with 130 drones were 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 of the model in terms of storage volume at the end of each period are presented in Figure (2).

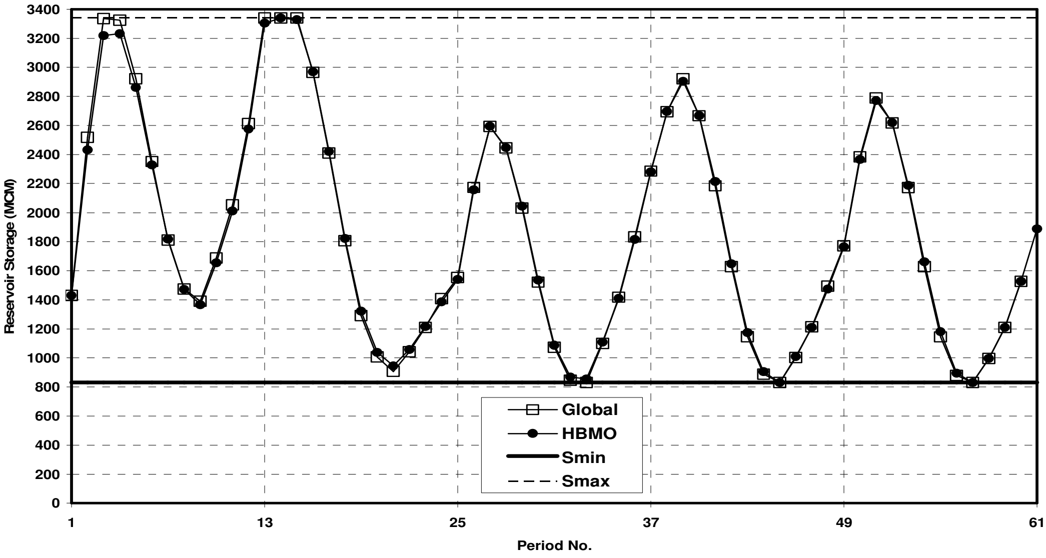

Figure 2. Storage volume at the end of each period

For the same problem, along with the global optimum, the monthly releases resulting from the HBMO model with 1000 mating flights (or iterations) are presented in Figure (3). Monthly demands and the global optimum results are presented in the same figure.

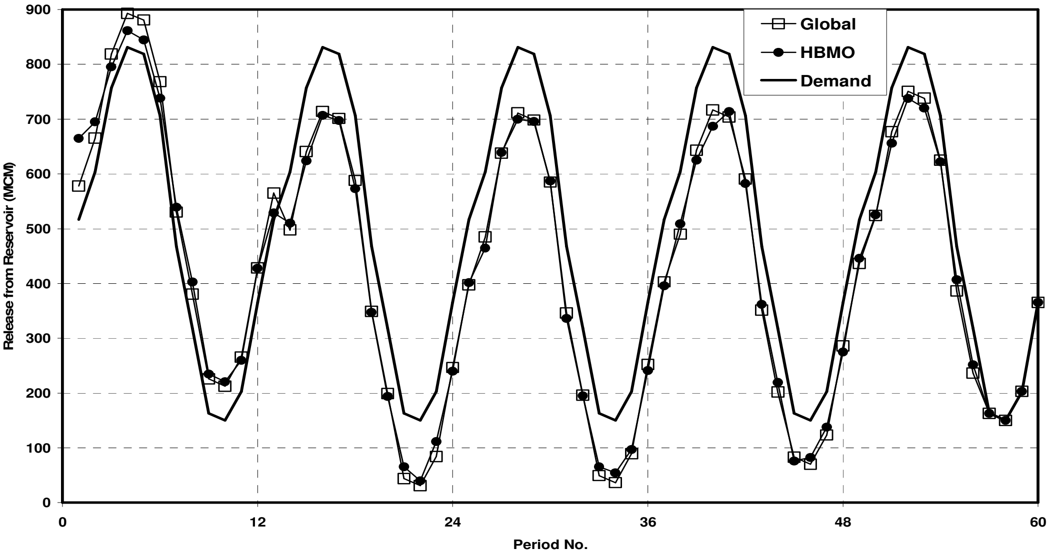

Figure 3. Monthly releases resulting from the HBMO model and global optimum

Figures (4) and (5) present an illustration of the rate of convergence of the model, Very rapid convergence, as well as comparable total squared deviation from the target demands, suggests that the approach and algorithm are quite promising for further development and application in the field of water resources planning and management.

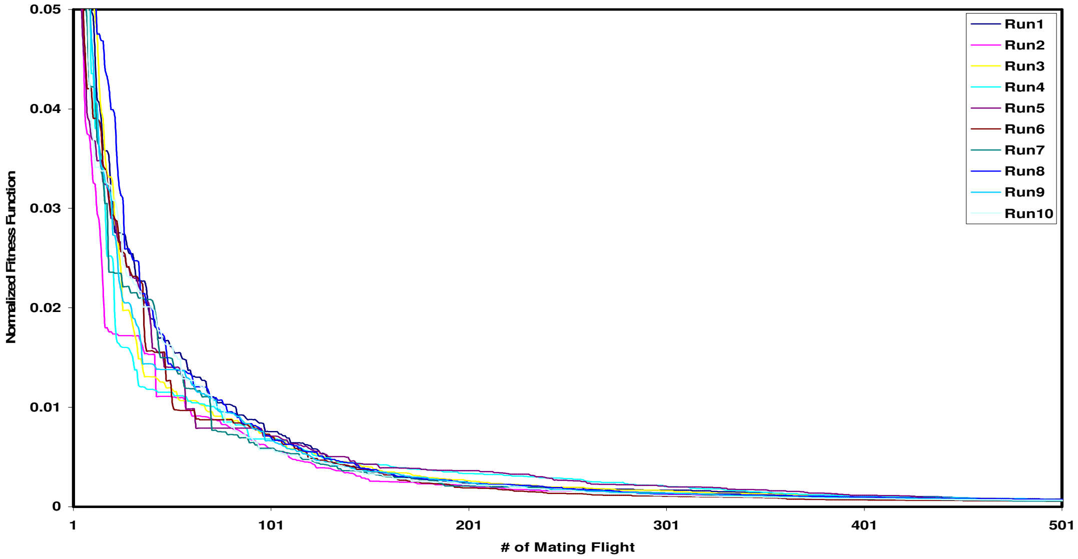

Figure 4. Rates of convergence of 10 runs of the model

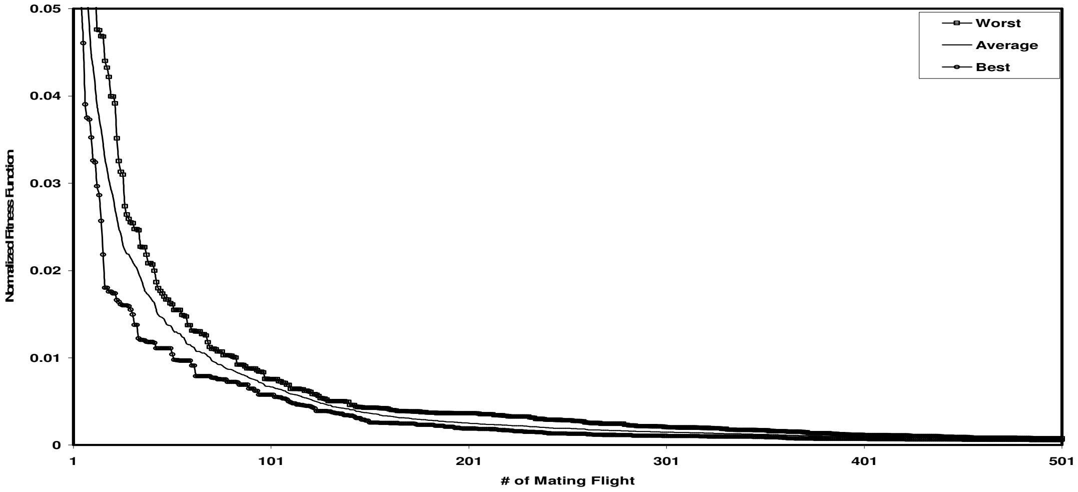

Figure 5. Best, worst and average rates of convergence of the model

It is worth mentioning that the global optimum result for the same problem with continuous variables has a fitness value of 0.796115. The proposed algorithm results in an average fitness value of 0.836743. The low value of the coefficients of variation of the 10 different runs is also noted.

Specifically, the results of the 10 different runs with their statistics and execution times are presented in Table (1). It is noted that the coefficient of variations for the 10 different runs as low as 0.005278, and the best and the worst fitness values range from 0.830763 to 0.842769.

Table 1. Results of 10 different runs with their statistics for the reservoir operation problem

Iteration number	HBMO	Global Optimum
1	0.842769	0.796115
2	0.830763	
3	0.832100	
4	0.842417	
5	0.832448	
6	0.837269	
7	0.833258	
8	0.836807	
9	0.840091	
10	0.839512	
Average	0.836743	
Best	0.830763	
Worst	0.842769	
Standard Deviation	0.004417	
Coefficient of Variation	0.005278	

CONCLUDING REMARKS

Few attempts have been made to employ the social behaviour of honey bees in real world optimization problems. Modeling the honey bee mating process as an optimization algorithm and its application to water resources management problems, such as reservoir operation, prove to be very promising. Its ability to consider discrete as well as continuous decision variables with little difficulty may be considered a particular strength of the algorithm. Preliminary results obtained from the model application compared very well with those from other heuristic methods as well as with global optimal results.

NOTATION

Prob(Q,D)	Probability of adding the sperm of drone D to spermatheca of queen Q
$\Delta(f)$	Absolute difference between the fitness of D (i.e. f(D)) and the fitness of Q (i.e. f(Q))
S(t)	Speed of the queen at time t
α	Factor of speed reduction after each transition $\in (0,1)$
E(t)	Energy of the queen at time t
γ	Amount of energy reduction after each transition
TSD	Total Square Deviation of release from demand in each operation time
R(t)	Release from dam in period t
D(t)	Demand in period t

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