

The Use of Multi-objective Optimization for Reservoirs' System Operation with an Evolutionary Algorithm: The case of the Metropolitan Region of Fortaleza, Brazil

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ABSTRACT

The Metropolitan Region of Fortaleza, with its 2.5 million inhabitants, is located in the state of Ceara, a semi-arid region of Brazil, and obtains water for domestic and industrial purposes through the use of a complex system of reservoirs, which are linked by canals and water pump stations, bringing water from different basins within the state. The system consists of 5 reservoirs, 5 pumping stations, and a long canal (102 km) that diverts water from the Jaguaribe River basin, a large and agricultural basin in which the largest reservoirs of the State, with inter-annual storage capacity, are located. The system is operated to meet domestic and industrial demands of the Metropolitan Region of Fortaleza. Current operating policy employed by the water management agency of the state, responsible for the system operation, is based on a relatively simple set of rules based upon current water storage in each reservoir. This paper focuses on the optimization of the reservoir's system operation, based upon a multi-objective approach, to derive new operating policies for the system. The multi-objective optimization procedure employs goals that are often considered in the water management process, namely, minimizing both the pumping cost and the amount of water losses through evaporation. The latter is justified by the extremely large potential evaporation rate observed in the region and the relatively different area-volume curves of these reservoirs. The paper develops and employs a new multi-objective version, based on the Pareto dominance concept, of the single-objective evolutionary algorithm Honey-Bee Mating Optimization (HBMO) and the Multi-objective Particle Swarm Optimization (MOPSO). Results based on a 25 year-validation period show that the use of a new operation policy derived in this study, based on a possible solution of the Pareto front, provides an economy of up to 4% in pumping costs (minimum cost) and a reduction of water losses through evaporation of 16% at most (minimum evaporation loss). Moreover, the methodology provides an approximation of the Pareto front of both objectives, which permits water managers to think more deeply about the value of water that is evaporated and the costs of trying to avoid these losses.

1- INTRODUCTION

The definition of how to operate a system with several reservoirs is a complex task because it includes many technical, social and political aspects, and involves multiple inter-related decisions in time (Loucks and Van Beek, 2005; Oliveira and Loucks, 1997). One important aspect of this complexity is the existence of multiple objectives, usually

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conflicting ones, such as meeting water supply and irrigation demands, energy generation, maintenance of aquatic species, flood control, navigation, etc.

Defining reservoirs' operating rules usually means to specify the volume of water that should be released by each reservoir over time. These rules are often specified in order to maximize or minimize one or more objective function that translates the objectives of operating a reservoirs' system. This optimization study has to respect some constraints, such as reservoir storage capacity, maximum pumping rate, maximum flow rate, minimum flow in river, etc. As the system gets more complex, it becomes very hard to find an optimal operating policy for the system.

There is a vast literature in optimization of reservoir operation. In the last decade, there has been observed a great effort of the community to develop global search algorithms. Within this class of algorithms, there is a class of evolutionary algorithms that has been applied quite successfully in many engineering problems [Fonseca and Fleming, 1993; Horn et al., 1994; Srinivas and Deb, 1995; Zitzler and Thiele, 1998; and Deb, 2001]. These algorithms have some advantages over some classical optimization techniques, for example, the direct use of the objective function, which avoids the computation of complex derivatives. Besides, these algorithms allow a more comprehensive investigation of the parameter space at each iteration, reducing the chances of being trapped in a local minimum (maximum). Their intrinsic stochastic nature provides a more diverse population of possible solutions, allowing the construction of a Pareto front in a single run of the algorithm, which makes them a good option for multiobjective problems.

This paper develops a multiobjective version of the uniobjective evolutionary algorithm named Honey-Bee Mating Optimization (HBMO), first presented by Haddad *et al.* (2006). This multiobjective version of HBMO, called herein MOHBMO, is employed along with the Multiobjective Particle Swarm Optimization (MOPSO) algorithm, developed by Kennedy and Eberhart (1995), to derive new operating policies for the reservoir's system that supply water for the Metropolitan Region of Fortaleza (RMF) and other smaller local demands. The optimization study presented here employs two different objective functions, one related to the total pumping costs of the system, while the other is concerned with the total amount of water that is lost by evaporation. The trade-off between these two objectives obtained from this study is of great value for the water managers as they will be able to think more carefully about these issues.

The paper starts with a description of the reservoirs' system, including a discussion of how the system works, followed by a discussion of the structure of the current operating policy employed by the water management company of the State of Ceará, responsible for the operation of the system. The paper continues with a description of both evolutionary algorithms employed in the study, including a brief discussion about the concept of Pareto optimum and Pareto front, the basis used in this study for dealing with multiobjective problems. Finally, a section with main results are presented and discussed, followed by the conclusions of the paper.

2- THE RESERVOIR SYSTEM

This section presents a description of the reservoirs' system used to provide water to the Metropolitan Region of Fortaleza (RMF), Brazil. The current system, with its five reservoirs, is linked to a much larger basin through *Canal do Trabalhador*, a canal that was built in 1993, during a severe drought period, to alleviate the water scarcity in the RMF and to reduce the risk of a collapse of the water supply system. *Canal do Trabalhador* diverts water from the Jaguaribe River basin at the city of Itaiçaba, near the estuary of Jaguaribe, downstream all the reservoirs located in this basin.

The operation of the current system assumes that the diverted flow from the Jaguaribe basin will always be enough to meet RMF's demands, respected the capacity of both the pumping station and the Canal do Trabalhador. In this study there was no concern on how to operate the reservoirs in the Jaguaribe River basin in order to be possible to deliver the necessary amount of water to the RMF. There is a study in progress that is trying to perform a much larger optimization study that considers not only the system of RMF, but also those reservoirs located in the Jaguaribe River basin. This study is important for planning purposes given the RMF's water demand is supposed to increase by almost 100% in the next 20 years.

The current reservoirs' system, presented in Figure 1, consists of five reservoirs: (1) Aracoiaba, with 170 hm³ of storage capacity and drainage area of 584 km²; located upstream of (2) Pacajus, whose drainage area is about 4,490 km², with storage capacity of 240 hm³; (3) Pacoti, which drains an area of nearly 1,080 km², and is linked through a canal to (4) Riachão, a small reservoir, whose drainage area is of just 34 km². Both Pacoti and Riachão, which have jointly a storage capacity of 380 hm³, are linked to (5) Gavião with 32.9 hm³ of storage capacity and nearly 95 km² of drainage area.

The system has also five pumping stations. The first one, named Itaiçaba Pumping Station, is used to bring water from the Jaguaribe River basin to the Pacajus reservoir. The Itaiçaba Pumping Station is able to divert up to 6 m³/s to *Canal do Trabalhador*, which has at the moment a maximum flow rate of 5 m³/s. Three other pumping stations, named PS0, PS1 and PS2, are used to bring water from the Pacajus reservoir to the Pacoti reservoir. PS1 operates only when the Pacajus water level is below 29.5 m. Between Pacoti and Riachão there is also a pumping station that operates only when the water level at Pacoti reservoir is below 36 m. The table below presents a summary of the pumping stations.

Table 1: Maximum pumping flow rate

Pumping Station	Maximum flow (m ³ /s)
Itaiçaba	6.0
PS0	5.0
PS1	5.0
PS2	5.0
Pacoti	5.0



Figure 1: Current reservoirs' system used for water supply of the metropolitan region of Fortaleza. The system consists of 5 reservoirs and 3 pumping stations. The *Canal do Trabalhador* diverts water from the Jaguaribe River Basin, near the city of Itaipaba into the Pacajus reservoir.

The system operates basically to supply the demands of the Metropolitan Region of Fortaleza, although small local demands, in the vicinity of the reservoirs, should also be met.

The Gavião reservoir is responsible for supplying water to the RMF's water treatment plant. Therefore, the system is operated in such a way that Gavião is always able to deliver $8 \text{ m}^3/\text{s}$ to the plant. Besides, both Pacajus and Aracoiaba need to meet local demands of 0.3 and $0.2 \text{ m}^3/\text{s}$, respectively.

3- CURRENT OPERATING POLICY

The reservoirs' system is operated to meet domestic and industrial demands of the Metropolitan Region of Fortaleza. The current operating policy employed by the water management agency of the state, responsible for the system operation, is based on a relatively simple set of rules that relates the amount of water that should be released from each reservoir based upon current water storage in each reservoir. When a reservoir is located downstream another reservoir, its release rule depends also on the current water storage at the reservoir located upstream.

In order to understand the operating policy, one needs to know how the system works. As described earlier, the Gavião reservoir is responsible for providing water to the RMF's water treatment plant. The Gavião reservoir receives water only from Pacoti-Riachão

reservoirs, which are considered in the optimization procedure as a single reservoir given they are connected through a canal. Pacoti-Riachão reservoirs, in turn, receive water only from the Pacajus reservoir, which can be supplied either from Aracoiaba reservoir or Canal do Trabalhador, which brings water from the Jaguaribe River basin.

Table 2 summarizes the current operating policy. Columns Q+ and Q- indicate the amount of water that should flow into and be released from each reservoir, respectively. As can be seen, these releases depend on the current water storage. One can notice that the operating policy presented in Table 2 doesn't define rules for operating the Aracoiaba reservoir nor Canal do Trabalhador. This is the case because the operating policy considers both the Aracoiaba reservoir and Canal do Trabalhador as one system that releases water to Pacajus reservoir. Therefore, it doesn't specify for any given situation how much water should be brought by Canal do Trabalhador. The rule applied in practice, and also employed in this study, is the following. In case the Aracoiaba reservoir is operating above 50% of its storage capacity, the water needed to be released to Pacajus reservoir is fulfilled by the Aracoiaba reservoir and nothing comes from the Canal do Trabalhador. In case the Aracoiaba is operating below 25% of its storage capacity, the Pacajus reservoir receives water only from Canal do Trabalhador. Finally, in case the Aracoiaba water storage is within 25-50% of its storage capacity, 50% of the water released to Pacajus comes from Aracoiaba and the other 50% comes from Canal do Trabalhador.

Having said that, let us understand the operating policy provided in Table 2. For instance, if Pacoti-Riachão water storage is within 25-50% of its storage capacity and the Pacajus reservoir is also within 25-50% of its storage capacity, Pacoti-Riachão should release 8 m³/s to Gavião so as to meet the RMF's demand. Besides, it should also receive 4.53 m³/s from the Pacajus reservoir, which, in turn, should receive 2.27 m³/s from either Aracoiaba reservoir or Canal do Trabalhador, or a combination of both. If Pacoti-Riachão water storage is larger than 50% of its storage capacity, it releases 8 m³/s to Gavião but it does not receive water from Pacajus reservoir, which means the Pacajus reservoir doesn't need water from neither Aracoiaba reservoir nor Canal do Trabalhador. On the other hand, if Pacoti-Riachão is operating below 25% of its storage capacity, it still should release 8 m³/s to Gavião reservoir, but it needs to receive 6 m³/s from Pacajus. In this situation, the amount of water that the Pacajus reservoir should receive depends on its storage capacity. If it is operating above 50% of its storage capacity, it does not receive water from any source. However, if it is operating within 25-50% or below 25% of its storage capacity, it should receive 3 m³/s or 6 m³/s, respectively, which must come from either from Aracoiaba reservoir or Canal do Trabalhador.

Table 2: Current Operating Policy

		Pacajus Reservoir					
		>50%		25-50%		<25%	
Pacoti/Riachão Reservoirs		Q+	Q-	Q+	Q-	Q+	Q-
	> 50%	0,00	GAV	0,00	0,00	0,00	0,00
	25-50%	4,53	GAV	0,00	4,53	2,27	4,53
	< 25%	6,00	GAV	0,00	6,00	3,00	6,00

3- OPTIMIZATION WITH EVOLUTIONARY ALGORITHMS

The study presented here employed multiobjective versions of two evolutionary algorithms to improve the current operating policies of the reservoirs' system, namely, the Honey-Bee Mating Optimization (HBMO) and the Particle Swarm Optimization (PSO). This section starts with a brief description of the approach used to deal with multiobjective problems, and it continues with an introduction of both HBMO and MOPSO, and their multiobjective versions.

3.1 – Multiobjective Approach

Unlike in the uniojective case, in a multiobjective analysis, the choice of the best solution is no longer possible. The literature presents many different methods to deal with multiobjective decisions. This study applies the concept of Pareto dominance.

Suppose one wants to minimize several objective functions,

$$\min f(\mathbf{x}) = [f_1(\mathbf{x}) \ f_2(\mathbf{x}) \ \dots \ f_M(\mathbf{x})] \quad (1)$$

where $f_i(\mathbf{x})$ is the i^{th} objective function and \mathbf{x} is the vector that contains a possible solution to the problem. In the reservoir operation, \mathbf{x} may contain the releases of all reservoirs over time.

According to Alvarez et al. (2005), two different solutions, \mathbf{u} and \mathbf{v} , may be related in the following ways,

- If $f_i(\mathbf{u}) \leq f_i(\mathbf{v}) \mid \forall i = 1 \dots M$ and $f_i(\mathbf{u}) < f_i(\mathbf{v})$ or at least one i , then \mathbf{v} is strictly dominated by \mathbf{u} , represented by $\mathbf{u} \prec \mathbf{v}$;
- Or if $f_i(\mathbf{u}) \leq f_i(\mathbf{v}) \mid \forall i = 1 \dots M$, then \mathbf{v} is said to be weakly dominated by \mathbf{u} , represented by $\mathbf{u} \preceq \mathbf{v}$.

In case \mathbf{u} is not dominated by \mathbf{v} and \mathbf{v} is not dominated by \mathbf{u} , it is said that \mathbf{u} and \mathbf{v} are non-dominated solutions. It is clear that multiobjective problems don't have one single optimum solution, but a set of solutions that are non-dominated. This set of non-dominated solutions is called Pareto front.

Figure 2 illustrates the concept of Pareto optimum. On the left one can see the two-dimensional parameter space with the contour plots of two objective functions and associated minimum points A and B. On the right, one see the same problem represented in the objective function space. The black line that links both minimum values represents the non-dominated solutions of the problem. Any solution on that line is a Pareto solution.

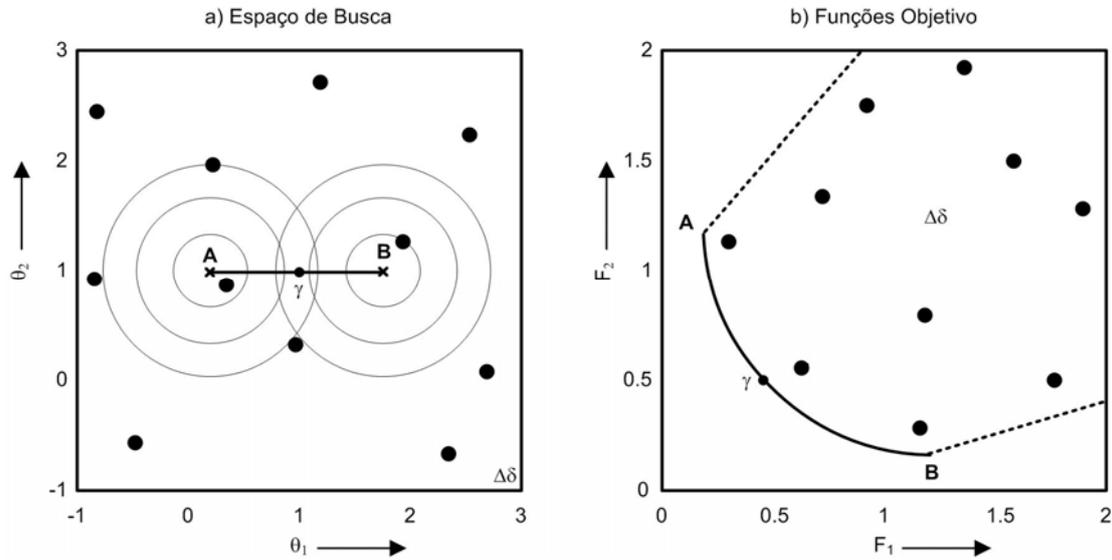


Figure 2: Illustration of the concept of Pareto solutions for a minimization problem with two objectives (F_1, F_2) in a two-dimensional parameter space ($\Delta\delta$). Adapted from Vrugt *et al.* (2003).

3.3 – Multiobjective Honey-Bee Mating Optimization Algorithm - MOHBMO

This study employs a multiobjective version of the uniojective Honey-Bee Mating Optimization algorithm introduced by Haddad *et al.* (2006), whose inspiration comes from the behavior of domestic bees. This section starts with the description of the uniojective case followed by a discussion about the modifications employed to turn the algorithm into a multiobjective one.

The HBMO algorithm starts with the generation of an initial population, which represents the hive. This initial population is generated randomly from a uniform distribution. Each solution of the initial population is assigned a fitness value given by the objective function.

The algorithm chooses the best solution (Queen) based on the fitness value. Given the objective is to minimize the objective function, the best solution is the one that has the least fitness value. The remaining solutions are discarded and the iterative process starts.

In the beginning of each iteration, the algorithm generates different solutions (Drones, D) based on the best solution (Queen, Q) of the previous step. The degree of dependence with the characteristics of the best solution changes as the process evolves. In the beginning, the dependence is weak, but it gets stronger with the number of steps, being zero in the first iteration, and 100% in the last step.

Equations presented below show how the solutions are generated and how the dependency with the best solution is modeled. In the first case, the dependence is linearly related to the number of steps in the iterative process, while in the second case the dependency varies quadratically with the number of steps,

$$D = Q \times [(i-1)/N] + d \times [(N-(i-1))/N] \quad (2)$$

$$D = Q \times [1 - (\delta^2/N^2)] + d \times [\delta^2/N^2] \quad (3)$$

where i is the current iteration, N is the maximum number of iterations, d is a random solution in the feasible space. The parameter δ is given by

$$\delta = N - (i-1) \quad (4)$$

These equations show that as the iterative process approaches the final iteration, there is an increase in the dependency between the random solution (Drones) and the best solution (Queen), providing the right conditions for the convergence of the search. A strategy to preserve the diversity of the solutions is to set a minimum degree of randomness to generate new solutions (Drones).

At each iteration, a selective test (mating flight) is performed so as to decide probabilistically whether the best solution (Queen) will receive information (mating) from the selected randomly generated solutions (Drones). This is done by applying an annealing function, also known as Boltzman probability, suggested by Abbas (2001),

$$P(Q,D) = \exp[-\Delta(f)/Sp(t)] \quad (5)$$

where $P(Q,D)$ is the probability that the best solution Q receives information from the selected solution D (crossover between the Drone D and the Queen Q), $\Delta(f)$ is the absolute difference between fitness values of Q and D , and $Sp(t)$ is the temperature (flight velocity of the Queen) of the annealing function at time t (during the flight).

The annealing function clearly shows that the probability that the best solution will get information from the selected randomly generated solution (mating with a Drone) is larger when the temperature of the annealing is high (flight velocity of the Queen) or when the differences in fitness are small (the fitness of the Drone is as good as the fitness of the Queen). If $P(Q,D)$ is greater than one, the information from the specified solution will be selected, otherwise, the algorithm will select the information with probability $P(Q,D)$. In case the information (genetic information of the Drone) of solution is selected, it is storage in a repository, and the temperature (flight velocity of the Queen) of the annealing is reduced according to the following,

$$Sp(t+1) = \alpha(t) \times Sp(t) \quad (6)$$

$$\alpha(t) = [M - m(t)]/M \quad (7)$$

where $\alpha(t)$ varies form zero to one, M is the size of the repository, and $m(t)$ is the number of randomly generated solutions (Drones) selected for crossover. The algorithm assumes that there is a maximum number of selective tests for each flight, which are related to the energy of the Queen. The energy of the Queen at any given iteration is given by,

$$E(t+1) = E(t) - \gamma \quad (8)$$

where $E(t+1)$ and $E(t)$ are the energy of the Queen at times $(t+1)$ and t , respectively, and γ is the reduction of the energy at during the time step. In this study, γ is equal to one.

After the selection of the solutions, the algorithm generates new solutions by performing a crossover between the best solution (Queen) and the solutions contained in the repository (selected Drones). For the generation of each new solution, the algorithm randomly selects a single solution contained in the repository.

The generation of new solutions employs two different crossover operators, the Arithmetic Crossover and the Blend Cross Over. In the beginning of the iteration process, both operators are equally likely to be selected. As the process evolves, the probability of a given crossover operator is selected depends on its performance up to the current iteration. The performance in this case is measured by its contribution to the generation of best solutions.

After the generation of new solutions, the algorithm uses a mutation procedure in order to provide marginal improvements to the new solutions and to the best solution as well (Queen). The mutation is randomly applied to a given percentage of the new solutions. In this study, the mutation was applied to 5% of the new solutions. There is also a probability that mutation is applied to the best solution (Queen). Here, this probability was set equal to 5% as well.

After mutation, the algorithm evaluates the population of solutions based on the objective function. If the best generated solution is better than the best solution of the previous iteration (Queen), the best solution is updated (new Queen), otherwise, the algorithm keeps the old best solution. At each iteration, all generated solutions are discarded. The algorithm keeps only the best solution (Queen).

The process described above is repeated until a stop criterion is met. Here, the criterion used was the number of iterations. As an attempt to perform a more detailed search, Haddad et al. (2006) suggests the use of many Queens, selected based upon their fitness values. In this case, the process described earlier would be applied independently to each Queen. After each iteration, all descendants and Queens would be put together in order to select the new Queens. This approach of multiple Queens was used in the study.

The process presented so far applies to the uniobjective case. In order to be used in multiobjective cases, the HBMO was modified as follows. First, after the generation of the initial population (hive) and the evaluation of the objective functions, it is necessary to select the best solution. In the uniobjective case, this selection is straightforward. However, in a multiobjective approach, the selection of the best solution is no longer possible. Here, one needs to make use of the concepts of dominated and non-dominated solutions, which employs the idea of Pareto front, as described earlier. So, the selection

of “best solutions” in the initial population is, in fact, the selection of non-dominated solutions or solutions that form the Pareto front.

Having determined the non-dominated solutions (Queens), the iterative process starts, which includes the generation of new solutions (Drones) based on the non-dominated solutions (Queens), selection of the new solutions to be used in the crossover procedure, execution of crossover and mutation, and selection of new non-dominated solutions, as it was described for the uniojective case. Each non-dominated solution (Queen) generates a number of new solutions (descendants) at each iteration. The procedures to generate and improve the new solutions and the non-dominated solutions are the same used in the uniojective case.

Having the new solutions (new descendants) and the non-dominated solutions of the previous iteration, the algorithm updates the set of non-dominated solutions, which are called Pareto front. These new solutions will be the basis for the generation of new solutions in the next iteration. This process is repeated until the stop criterion is reached.

This approach, which uses every single solution of the Pareto front to generate new solutions, may lead to a situation in which there is a large and unnecessary number of solutions in the Pareto front causing a loss of efficiency in the algorithm. As an attempt to avoid this problem, a clustering technique [Seber, 1984; Spath, 1985] is used to select a limit number of non-dominated solutions of the Pareto front, providing a better distribution of solutions on the Pareto front.

3.4 – Multiobjective Particle Swarm Optimization - MOPSO

MOPSO is a multiobjective version of the uniojective Particle Swarm Optimization introduced by Kennedy and Eberhart (1995), inspired by the behavior of social groups, such as those of birds, fishes and insects. The version of MOPSO employed here is the one proposed by Alvarez *et al.* (2005). This section starts with a brief description of the PSO followed by the modifications that were made to allow the algorithm to deal with multiobjective cases.

Initially, the algorithm randomly generates a set of solutions (particles) within the feasible space. Each solution is assigned the value of the objective function, which is used as a metric of its fitness. Then, the algorithm selects the best solution among those contained in the initial set of solutions. In this case, the best solution (individual) is the one that has the least value of the objective function. The algorithm also considers the best solution as the best global solution (Swarm leader).

The algorithm uses the concept of best individual of each solution (particle), which is the best position up to the current iteration in the evolution of the search. In the beginning, the best individual of each solution is its initial value.

Each particle (solution) of the swarm of N particles has a current position, at the current iteration, and a given velocity, which is updated according to the particle's and group's

experiences. This way, a vector x that contains the positions of all particles of the population can be computed at each iteration as follows,

$$x^{(t+1)} = x^{(t)} + \chi v^{(t)} + \varepsilon^{(t)} \quad (9)$$

where $x^{(t+1)}$ and x^t are the vectors that contain the positions of the N particles (solutions) at iterations t and $t+1$, respectively, $v^{(t)}$ is the vector whose elements represent the velocity of the N particles, χ is a factor that controls the magnitude of the velocities (between 0 and 1), and $\varepsilon^{(t)}$ is a small stochastic perturbation known as “turbulence factor”, which helps the algorithm to avoid local optima and to increase the diversity of the search.

The velocity of each particle is updated at each iteration by the combination of two terms: the best position of the particle, contained in the vector P , which explores the best result experienced by the particle up to the current iteration, and the best global position, contained in the vector G , which is the best solution found up to this iteration by the whole population. The velocity vector of size $[N,1]$ is computed by the following expression,

$$v^{(t+1)} = w \times v^{(t)} + c_1 \times r_1 \times (P - x^{(t)}) + c_2 \times r_2 \times (G - x^{(t)}) \quad (10)$$

where w is the inertia of the particle, c_1 and c_2 are constants that control the influence of the individual and global velocities, and r_1 and r_2 are uniformly generated random numbers between $[0, 1]$. This study employed the following values of these parameters: $c_1 = c_2 = 1$, and w varying linearly between 0.95 and 0.4 in the first 70% of the maximum number of iterations, and equal to 0.4 for the remaining iterations.

The algorithm runs until the number of iterations reaches the maximum number of iterations specified by the user.

The PSO has provided good results for uniobjective problems. More recently, many authors have proposed modifications in the algorithm in order to be used in multiobjective frameworks [Coello and Lechuga, 2002; Hu and Eberhart, 2002; Parsopoulos and Vrahatis, 2002; Fieldsend and Singh, 2002; Alvarez *et al.*, 2005]. This study used the methodology proposed by Alvarez *et al.* (2005).

The main difficulty of using PSO in multiobjective problems is how to select the components that guide the particles. In PSO, at each iteration, particles are modified according to the best position that the particle experienced in the previous iterations and the best global position. If a new position of a particle is better than its best position up to this iteration, the best position of the particle is updated (Li, 2003). In this case, the best position of a particle has no relation with other particles of the same population. However, in the multiobjective framework, in which the objective is to obtain a set of non-dominated solutions (particles) that form the Pareto front, it is mandatory that all

particles share information with each other. Like in the MOHBMO described earlier, there is clear definition of best of the particle and global best solution.

The algorithm proposed by Alvarez *et al.* (2005) basically consists of building a Pareto front at each iteration. The Pareto front is then updated at each iteration with the inclusion of the new set of dominant particles (solutions) and removal of dominated particles (solutions). This process is repeated until the maximum number of generations is reached.

The algorithm starts with the random generation of a vector of positions of particles. At each iteration, one needs to evaluate if the new position of each particle, obtained by equations (9) and (10), is dominated by the best position of that particle up to the current iteration. In case the new position is not dominated, the best position of the particle is updated.

In MOPSO, each particle has a best global solution associated to it. The selection of this best global solution is based upon a random selection from the solutions contained in the Pareto front in case the particle is part of the front. If the particle is not contained in the Pareto front, the random selection is made among all particles that are dominant.

4- RESULTS

This section presents the main results of the optimization study to derive the new operating policy of the reservoirs' system of the Metropolitan Region of Fortaleza. Due to the lack of space, it was not possible to provide the details of the study. Those interested in a more deep analysis of this case are referred to Barros (2007).

The study used a record of 85 years of inflow data available for all reservoirs. The last 60 years of data were used to derive the new operating policy of the system, while the first 25 years were employed to evaluate and compare the performance of both evolutionary algorithms and both operating policies, the current one used by the water management company of the State and the one obtained in this study.

As it has been said before, the study employed two objective functions: (1) minimize the total pumping costs of the system, and (2) minimize the total amount of water evaporated during the simulation period.

The five pumping stations have different cost structures. Energy prices also vary seasonally. All these details were considered in the study. A more detailed description of the costs can be found in Barros (2007) and FUNCEME (2007).

Figure 3 presents the Pareto fronts obtained by both algorithms, MOHBMO and MOPSO, during the 60 year-optimization period. In fact, the figure shows 10 Pareto fronts for each algorithm given the study has been done with 10 different initial populations. One can see that MOHBMO, at least when 100,000 evaluations of the objective functions were allowed, provided better results than those obtained by MOPSO. MOHBMO was able to

provide solutions with the least pumping cost and the least amount of water lost by evaporation.

This result does not provide the final operating policy of the system given one still needs to pick a solution. Nonetheless, the Pareto front provides very interesting insights regarding both objectives. There is a strong feeling among water professionals that the water should be used in the most efficient way. Since the region presents a very large potential evaporation, water losses through evaporation is always a concern. This figure shows clearly that there is a cost for trying to avoid evaporation losses. This information is certainly valuable for those responsible for the operation of the system.

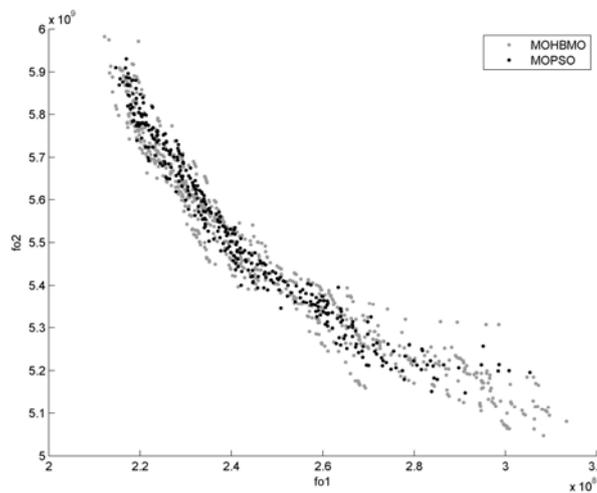


Figure 3: Pareto front obtained by MOHBMO and MOPSO with 10 initial populations and 100,000 evaluations (fo1 = pumping costs; fo2 = water evaporated).

In order to be able to compare the results obtained by this study with the results of the current operating policy, a minimum pumping cost solution was chosen. This solution indicates the operating policy presented in Table 3.

Table 3: Operating policy obtained by MOHBMO with minimum pumping cost. When Aracoiaba is above 24% of its storage capacity, only Aracoiaba supplies water to Pacajus, otherwise Canal do Trabalhador supplies water to Pacajus up to 5 m³/s. If necessary, the remaining amount of water comes from Aracoiaba.

		Pacajus Reservoir							
		> 49%		27 – 49%		≤ 27%			
		Q+	Q-	Q+	Q-	Q+	Q-		
Pacoti/Riachão	> 42%	0,01	GAV	0,45	0,01	0,74	0,01	3,34	0,01
	≤ 42%	5,60	GAV	1,30	5,60	5,06	5,60	5,18	5,60

Results based on simulation of the system for the 25 year-validation period shows that the optimized operating policy presented in Table 3 is better than the current policy presented in Table 2. The new operating policy obtained by MOHBMO provides a reduction of about 4% in total pumping costs during the validation period and 5% in the optimization period. Besides, the use of the current operating policy resulted in failures to meet the

demand in four months during the validation period and 8 months during the optimization period, while the use of the optimized policy resulted in only one failure during the validation period and none during the optimization one.

5- CONCLUSIONS

This paper develops and employs a multiobjective version, based on the Pareto dominance concept, of the uniobjective evolutionary algorithm Honey-Bee Mating Optimization (HBMO) and also uses the Multiobjective Particle Swarm Optimization (MOPSO) algorithm to derive new operating policies for the reservoirs' system of the Metropolitan Region of Fortaleza, Brazil.

This optimization study was based on the same decision structure of the current operating policy employed by the water management company of State. Current operations are based on a relatively simple set of rules that define the releases of each reservoir based upon the current water storage in one or more reservoirs, depending on its specific location within the system.

The goal of the optimization study presented here was to redefine the values of the current operating policy in order to minimize both the total pumping costs and the amount of water lost by evaporation, while meeting the water demands from the Metropolitan Region of Fortaleza.

Results based on a 25 year-validation period show that the total pumping costs can be reduced by 4% when the minimum cost objective function is used to define the best operating policy. This is an important reduction if one takes into account that the structure of the current operating policy has been preserved, and only the values of the releases and the ranges of water storages for each reservoir have been optimized. It is likely that a new structure of the operating policy can provide a more drastic reduction in costs and evaporation losses.

A different solution in the Pareto front, in the opposite direction of the minimization of pumping costs, is able to reduce the amount of water from evaporation by 16%, certainly not a negligible amount. However, the Pareto front indicates a clear trade-off between reducing pumping costs and reducing the amount of water evaporated from the reservoirs. No decision has been made to define the best strategy. The main result is the Pareto front that provides the necessary elements for the managers of the water management company to think more deeply about these issues.

Finally, some discussions were made regarding the capabilities of both algorithms in constructing the Pareto front. In case where 100,000 evaluations of the objective function were used, MOHBMO was able to identify better solutions in the extremes of the Pareto front than MOPSO. It means that MOHBMO generated solutions that provide the least pumping cost and the least amount of water lost by evaporation. When 10,000 evaluations were used, this conclusion is no longer valid.

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