CONSTRAINED BIG BANG-BIG CRUNCH ALGORITHM FOR OPTIMAL SOLUTION OF LARGE SCALE RESERVOIR OPERATION PROBLEM

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ABSTRACT

A constrained version of the Big Bang-Big Crunch algorithm for the efficient solution of the optimal reservoir operation problems is proposed in this paper. Big Bang-Big Crunch (BB-BC) algorithm is a new meta-heuristic population-based algorithm that relies on one of the theories of the evolution of universe; namely, the Big Bang and Big Crunch theory. An improved formulation of the algorithm named Constrained Big Bang-Big Crunch (CBB-BC) is proposed here and used to solve the problems of reservoir operation. In the CBB-BC algorithm, all the problems constraints are explicitly satisfied during the solution construction leading to an algorithm exploring only the feasible region of the original search space. The proposed algorithm is used to optimally solve the water supply and hydro-power operation of "Dez" reservoir in Iran over three different operation periods and the results are presented and compared with those obtained by the basic algorithm referred to here as Unconstrained Big Bang–Big Crunch (UBB–BC) algorithm and other optimization algorithms including Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) and those obtained by Non-Linear Programming (NLP) technique. The results demonstrate the efficiency and robustness of the proposed method to solve reservoir operation problems compared to alternative algorithms.

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1. INTRODUCTION

Various methods with different level of complexity and success have been proposed and used to solve reservoir operation problems. These methods can be divided into two general categories: 1- Traditional or mathematical methods such as linear programming (LP), non-linear programming (NLP), and dynamic programming (DP); 2- Metaheuristic algorithms such as Genetic algorithms (GA), Particle swarm optimization (PSO), Ant Colony Optimization (ACO), Simulating Annealing (SA) and Honey Bee Mating Optimization (HMBO) algorithm. Amongst mathematical methods, LP is well known as the most simple optimization technique because it is easy to understand and does not need any initial solution. The first use of LP in reservoir operation optimization problem has been reported by Dorfman [1] illustrating the use of LP to maximize an economic objective function. ReVelle et al. [2] proposed the chance-constrained LP method for the optimal operation of a reservoir system under probabilistic constraint. Windsor [3] developed a LP model for flood control operation of a multi-reservoir system. Marino and Mahammadi [4] developed a model based on chance‐constrained LP (CCLP) and dynamic programming (DP) to determine the optimum monthly releases from a multipurpose reservoir. Martin [5] used a Successive LP (SLP) to iteratively change the daily reservoir releases to improve system performance. Mohan and Raipure [6] developed a linear multi-objective programming model to derive the optimal releases for various purposes from a large‐scale multireservoir system in India. Dahe and Srivastava [7] extended the basic yield model and presented a multiple-yield model for a multiple-reservoir system consisting of single-purpose and multipurpose reservoirs. Tu et al. [8] developed a mixed integer LP (MILP) model considering both the traditional reservoir rule curves and the hedging rules to manage and operate a multi-purpose, multi-reservoir system.

   NLP methods is not widely used in water resource problems mainly due to the fact that the optimization process is very slow and require large amounts of computer storage and time compared to alternative methods. Nevertheless, some researchers have used NLP to solve some of the problems raised in water resource management. Tejada-Guibert et al. [9] developed a NLP model for the monthly optimal operation of a hydro-power system. Ostfeld and Shamir [10] develop a model for the optimal operation of a multi-quality water supply system under steady-state conditions. Pezeshk et al. [11] used a NLP model to minimize pumping costs of a well field and a water supply distribution system. Teegavarapu and Simonovic [12] developed a mixed integer NLP model for the short term operation of hydropower reservoirs in Manotba, Canada. Ghahraman and Sepaskhah [13] developed a NLP optimization model with an integrated soil water balance for allocation of a limited water supply. Mouatasim [14] formulated the pump operations optimization problem as a Boolean Integer Nonlinear Programming (BINLP) problem to minimize the cost of electrical energy pump operation of a multi-reservoir system..

   DP, originally developed by Bellman [15] decomposes a complex problem into a series of simpler sub-problems which are solved sequentially, while transmitting information from one stage of the computations to the next stage. Young [16] used a deterministic DP to determine Operating rule of a single reservoir. Hall et al. [17] used DP to maximize revenues from the sale of water and energy of a single reservoir. Dudley and Burt [18] used Stochastic DP (SDP)

to maximize net benefits from irrigation water for a single crop situation. Arunkumar and Yeh [19] used the stochastic DP to maximize firm power output of hydropower system. Becker and Yeh [20] used a form of DP for the selection of an optimal reservoir storage policy and a LP for period by period optimization. Collins [21] developed a DP model to optimal operation of a 4-reservoir water supply system. Allen and Bridgeman [22] applied DP to three case studies involving hydropower operation objective. Margeta and Fontane [23] combined DP optimization and hydraulic simulation model for the operation of hydroelectric reservoir facilities during periods of flood flows. Feiring and Sastri [24] addressed an application of SDP to a water resource system with a dual-purpose of generating electricity and supplying water for agricultural irrigation. Tilmanta et al. [25] presented a Fuzzy Stochastic Dynamic Programming (FSDP) approach to derive steady-state multipurpose reservoir operating policies. Liu et al. [26] proposed Dynamic Programming Neural-network Simplex (DPNS) model to derive refill operating rules in reservoir operation and applied to the case study of Three Gorges Reservoirs. Ganji et al. [27] used the game theory fundamentals to develop a Stochastic Dynamic Nash Game with perfect information (PSDNG) model to resolve the associated conflicts among different consumers due to limited water. Nandalaln and Bogardi [28] discussed applicability and limitations of DP models, specifically in reservoir operation problems. Kumar et al. [29] adopted Folded Dynamic Programming (FDP) for developing optimal reservoir operation policies for flood control. Goor et al. [30] illustrated the difference between the two SDDP formulations on the energy generation and the allocation decisions using a network of hydropower plants and irrigated areas in the Nile Basin. While DP has proved to be an effective method, it lacks efficiency in particular when solving large scale reservoir operation problems.

Despite some benefits of the traditional methods, these methods suffer from some disadvantages. LP methods can only be used for linear problems while most of the real world operation problems are nonlinear. NLP methods are only reliable when used for the solution of convex problems while most of hydropower operation problems are non-convex problems. DP and its variants are theoretically capable of globally solving any reservoir operation problems but these methods are known to be computationally very demanding. For large scale operation problems, DP based method are faced with the so-called curse of dimensionality making them impractical to use.

Metaheuristic algorithms has been introduced and used in water resource problems to overcome some of the complexities such as nonlinearity, non-convexity, discontinuity and discreteness which limit the applications of mathematical optimization methods in reservoir systems optimization [31].

GA, as the first meta-heuristic algorithm used to solve water resources problems, is a robust method for searching the optimum solution to a complex problem although it may not necessarily lead to the best possible solution. The method was originally introduced by Goldberg [32] and is now developed into a powerful optimization approach. East and Hall [33] applied a GA to the four–reservoir problem. Oliveira and Loucks [34] used a GA model to derive operating rules for multi reservoir systems. Sharif and Wardlaw [35] applied GA for the optimization of multi-reservoir system in Indonesia. Kerachian and Karamouz [36] developed a modified version of the simple GA for application to a reservoir operation problem. Chang et al, [37] proposed a constrained GA (CGA) for multi-use water resources

management incorporating human needs and ecological sustainability requirements. A critical review and state-of-the-art applications of GAs in water resources planning and management field can be found in Nicklow et al. [38].

Particle swarm optimization (PSO) originally proposed by Eberhart and Kennedy [39] as a population-based heuristic search technique inspired by the social behavior of bird flocking has also been used in reservoir operation field. Reddy and Kumar [40] proposed a multi-objective PSO approach for generating Pareto-optimal solutions for reservoir operation problems. Afshar [41] introduced two mutation mechanisms to balance the explorative and exploitative characteristics of the PSO algorithm and applied them to single reservoir operation problems. Baltar and Fontane [42] presented a multi-objective PSO (MOPSO) solver and used it to generate Pareto optimal solutions for two water resources problems with up to four objectives.

Ant Colony Optimization Algorithm (ACOA) is another meta-heuristic optimization algorithm proposed by Dorigo [43] which has been extensively used to solve different optimization problems including reservoir operation problems. Jalali et al. [44] used a multi-colony ACOA to solve a multi-reservoir operation problem with ten-reservoir. Kumar and Reddy [45] used ACOA for solving multi-purpose reservoir operation. Afshar and Moeini [46] presented a constrained formulation of the ACOA for the optimization of large scale reservoir operation problems.

Some researchers have used Simulated Annealing (SA) introduced by Kirkpatrick et al. [47] as a stochastic search technique inspired by the process of metals annealing in physics for reservoir operation. Teegavarapu and Simonovic [48] were the first to use this technique in reservoir systems operation problems. Chiu et al. [49] proposed a hybrid GA-SA algorithm for fuzzy programming of reservoir operation.

Haddad et al. [50] used Honey Bees Mating Optimization (HBMO) algorithm inspired by the process of mating in real honey bees for single reservoir operation and compared the results with those obtained by GA.

In this paper, the newly proposed method of Big-Bang Big Crunch algorithm is used for the optimal solution of reservoir operation problems for the first time. Application of this method to other engineering problems has revealed its potential as a powerful optimization technique. A constrained formulation of this algorithm named Constrained Big Bang-Big Crunch (CBB-BC) is also proposed to improve accuracy and convergence characteristics of the method. In the constrained version, all the explicit constraints of the problem are enforced during the solution construction so that the BB-BC search is only carried out in the feasible region of the problem search space. Efficiency and accuracy of the original BB-BC referred to here as Unconstrained Big Bang-Big Crunch (UBB-BC) and the proposed CBB-BC for the optimal operation of reservoirs systems are compared for the water supply and hydropower operation of "Dez" reservoir in Iran for three operation periods and the results are presented and compared to those obtained by other meta-heuristic approaches.

2. INTRODUCTION TO BB–BC METHOD

Two of the famous theories about of the evolution of the universe are Big bang and Big

crunch theories. According to Big bang theory, the universe, originally in an extremely hot and dense state that expanded rapidly, has since cooled by expanding to the present diluted state and continues to expand today. This theory explains beginning of the creation of the universe very well but does not explain the end of the universe. One of the scenarios about the end of the universe that considered by astronomers is Big Crunch theory. It tells us that the Universe's expansion, which is due to the Big Bang, will not continue forever. Instead, at a certain point in time, it will stop expanding and collapse into itself, pulling everything with it until it eventually turns into the biggest black hole ever. Erol and Eksin [51], inspired by these theories, introduced a new optimization algorithm named Big Bang-Big Crunch (BB-BC) algorithm. This algorithm has two phases; Big Bang phase similar to Big Bang Theory and Big Crunch phase similar to Big Crunch Theory. In the Big Bang phase, the randomly generated population of candidates is uniformly distributed over the search space. Then, in the Big Crunch phase these candidates are concentrated to a point using a convergence operator namely center of mass. Using of center of mass, the new position of each candidate is calculated. This process is repeated until convergence is achieved.

In the original version of the algorithm, center of mass is calculated as follows:

$$x_j^c = \frac{\sum_{j=1}^{N} \frac{1}{f^i} x_j^i}{\sum_{i=1}^{N} \frac{1}{f^i}} \qquad\qquad i = 1,2,...,N \qquad\qquad (1)$$

where x_j^c is the jth component of center of mass, x_j^i is the jth component of ith candidate, f^i is fitness of the ith candidate, and N is the number of candidates in the population. The algorithm updates the new population of solutions by using of the center of mass as follows:

$$x_j^{i,new} = x_j^c + r \times c_1 \times \frac{(x_j^{max} - x_j^{min})}{1 + k / c_2} \qquad\qquad (2)$$

where $x_j^{i,new}$ is the new value of the jth component from ith candidate, r is a random number with a standard normal distribution, c_1 and c_2 are tow constants and k is the iteration index. x_j^{max} and x_j^{min} are maximum and minimum value of the j th component of the variable x.

Other forms of the center of mass can also be used. Here, the best solution of each iteration is used as the center of mass.

Most of the applications of BB-BC algorithm in engineering field have been reported for the optimal design of structures. Camp [52] used BB-BC algorithm to minimize the total weight of structures subjected to material and performance constraints. Kaveh and Talatahari [53] used a Hybrid BB-BC (HBB-BC) for the optimal sizing of space truss structures which was later extended for optimal design of schwedler and ribbed domes [54]. Tang et al. [55] used BB-BC algorithm for parameter estimation of structural systems.

3. SINGLE RESERVOIR OPERATION PROBLEMS

Reservoir operation is a large scale multi-objective optimization problem involving hydrology, reliability, hydropower, agriculture, and environment. No algorithm is shown to be practically capable of handling all the aforementioned requirements. Due to the complexity of the problem, most of the existing algorithms are therefore restricted to considering some simplified form the problem depending on the characteristics of the search algorithm used. Reservoir operation is a complex problem due to the nonlinearity of the objective functions and the number of constraints presenting a challenge to optimization techniques. Here the water supply and hydropower operation of a single reservoir is considered in such a way that complexity of real-world reservoir operation problems namely the nonlinearity of the objective function and the number of constraints are reflected in the apparently simple problem considered. Extension of the method to multi-reservoir problems will pose no problem once the basics of the method are understood.

The water supply operation of a single reservoir can be expressed as:

$$Minimize \quad F = \sum_{t=1}^{NT} \left(\frac{D(t) - r(t)}{D_{max}} \right)^2 \tag{3}$$

subject to

$$s(t+1) = s(t) + I(t) - r(t) \tag{4}$$

$$s_{min} \leq s(t) \leq s_{max} \tag{5}$$

$$r_{min} \leq r(t) \leq r_{max} \tag{6}$$

where $D(t)$ is water demand in period t in Million Cubic Meters (MCM), $r(t)$ is release from the reservoir in period t (MCM), D_{max} is maximum demand in the whole operation period (MCM), NT is the number of operation periods, $s(t)$ is storage at the start of period t (MCM), $I(t)$ is inflow in period t (MCM), s_{min} and s_{max} are minimum and maximum available storage in reservoir (MCM), respectively and r_{min} and r_{max} are minimum and maximum allowed release from reservoir (MCM), respectively.

The hydropower operation of a single reservoir, on the other hand, is defined as:

$$Minimize \quad F = \sum_{t=1}^{NT} \left(1 - \frac{p(t)}{power} \right)^2 \tag{7}$$

subject to the constraints of (4) to (6) defined above. Here $p(t)$ is power generated in Mega Watt (MW) by the hydro-electric plant in period t, *Power* is total capacity of hydro-electric plant (MW). The power generated at operation period t can be stated as follow:

$$p(t) = min\left[\left(\frac{g \times \eta \times r(t)}{PF} \right) \times \left(\frac{h(t)}{1000} \right), power \right] \tag{8}$$

With

$$h(t) = \left(\frac{H(t) + H(t+1)}{2} \right) - TWL \tag{9}$$

And

$$H(t) = a + b \times s(t) + c \times s(t)^2 + d \times s(t)^3 \tag{10}$$

Where g is the gravity acceleration equal to 9.81 m^2/s, η is the efficiency of the hydroelectric plant, $r\ (t)$ is release from reservoir (m^3/s), PF is the plant factor, $h\ (t)$ is the effective head of the hydroelectric plant (m), $H\ (t)$ is the elevation of water in reservoir at period t (m), TWL is the downstream elevation of the hydroelectric plant (m), $a,\ b,\ c$ and d are four constant which can be obtained by fitting equation (10) to the existing data.

4. PROPOSED CONSTRAINED BIG BANG-BIG CRUNCH (CBB-BC) ALGORITHM

Formulation of the optimal operation of a single reservoir as an optimization problem requires that the decision variables of the problem are defined. Basically, two different set of decision variables can be selected in reservoir operation problems, namely storage volumes or releases at each period. Different methods have used different set of decision variables for the reservoir operation problems. Here, the storage volumes are taken as the decision variables of the problem while the method can be used with release volumes taken as decision variables. Assuming a known value for the storage volume at the beginning of the operation period, the total number of decision variables would be equal to the number of operation period NT.

For the problem so defined, application of the UBB-BC is straightforward and does not require detailed description. Each candidate solution, $x_j^i;\ j = 1,..., NT$ is created randomly at the start of the computation within the bounds defined in Eq. (5). The centre of gravity is computed using Eq. (1) for the current population and each candidate solution is then updated using Eq. (2) to form the new population. The process is continued until some convergence criterion is fulfilled or the maximum number of populations is exhausted. A note, however, has to be made regarding release constraint satisfaction in UBB-BC algorithms. The solutions created by the UBB-BC might violate the release constraint of Eq. (6). To force the algorithm to produce feasible solutions, the solutions that have violated the release constraints are penalized depending on the magnitude of the constraint violation. For any trial solutiondefined by the known values of the storage volumes at the beginning and the end of each period and using the continuity equation, release volumes can be calculated at each period. The releases values are then used to calculate the constraint violation of the solution using the following non-dimensional form of Eq. (6):

$$CV(t) = \begin{cases} \left(\dfrac{r(t) - r_{max}}{r_{max} - r_{min}} \right) & if \quad r(t) > r_{max} \\[3ex] \left(\dfrac{r_{min} - r(t)}{r_{max} - r_{min}} \right) & if \quad r(t) < r_{min} \\[3ex] 0 & if \quad r_{min} < r(t) < r_{max} \end{cases} \qquad (11)$$

Where $CV(t)$ is the constraint violation at period t.

The original objective function of (3) or (7) is now rewritten in a penalized form as follows:

$$Minimize \quad F_p = F + pen \times \sum_{t=1}^{NT} CV(t) \qquad (12)$$

Where F is the original objective function, F_p is the penalized objective function, and *pen* is the penalty parameter with large enough value so that any infeasible solution has a penalized objective function greater than any feasible solution.

An interesting feature of BB-BC algorithm which can be found in some of the heuristic search methods such as ACOA and PSO is the incremental solution building capability which is very useful in solving optimization problems of sequential nature such as reservoir operation problems. This feature allows for the explicit satisfaction of the problem constraints which leading to reduction of the search space size depending on the characteristics of the problem and its constraints. This can, in turn, improve the efficiency and effectiveness of the algorithm. This concept is used here to develop constraint a version of BB-BC algorithm referred to as Constrained Big Bang-Big Crunch (CBB-BC) algorithm in which all constraints of the problem are satisfied during the solution construction.

The proposed concept is introduced into the BB-BC method in two stages. In the first stage, infeasible regions of the problem is partially determined and excluded from the search space prior to the main calculation to prevent candidates to select options located in infeasible area. For this, the periods of operations are swept in reverse order and a set of new bounds are calculated for the storage volumes such that the CBB-BC algorithm defined above is not given any chance of producing infeasible solutions. To clarify this, consider the continuity equation at a period t along with the release and storage volume constraints:

$$s(t+1) = s(t) + I(t) - r(t) \qquad (13)$$

$$s_{min}(t+1) \le s(t+1) \le s_{max}(t+1) \qquad (14)$$

$$s_{min} \le s(t) \le s_{max} \qquad (15)$$

$$r_{min} \le r(t) \le r_{max} \qquad (16)$$

Substituting *s(t+1)* from Equation (13) into Equation (14), leads to the following constraints for the storage volume *s(t)* at the beginning of the period ensuring that the end of the period storage volume *s(t+1)* is feasible.

$$s_{min}(t+1)-I(t)+r(t)\leq s(t)\leq s_{max}(t+1)-I(t)+r(t) \qquad (17)$$

For this constraint to be valid for any value of release in the range $[r_{min},r_{max}]$, the following equation should hold.

$$s_{min}(t+1)-I(t)+r_{min}\leq s(t)\leq s_{max}(t+1)-I(t)+r_{max} \qquad (18)$$

Combining Equation (18) with the original constraints of Equation (15) leads to the following constraints for the storage volume at the beginning of the period.

$$s_{min}(t)\leq s(t)\leq s_{max}(t) \qquad (19)$$

with

$$s_{min}(t)=max(\ s_{min},s_{min}(t+1)-I(t)+r_{min}) \qquad (20)$$

$$s_{max}(t)=min(\ s_{max},s_{max}(t+1)-I(t)+r_{max}) \qquad (21)$$

Where $s_{min}(t)$ and $s_{max}(t)$ are maximum and minimum of storage volume bounds at period *t* which could be different from one period to another in contrast to the original bounds of the storage volume s_{min} and s_{max} assumed to be constant for all periods. Starting from the last period of operation *NT*, Eq. (19) is used to calculate the new bounds for the storage volume at the beginning of the period *s(NT)* using $s_{min}(NT+1)=s_{max}$ and $s_{max}(NT+1)=s_{max}$. Having calculated the bounds $s_{min}(NT)$ and $s_{max}(NT)$, the same process is used to calculate the new bounds for the storage volume at the beginning of period NT-1. The process of updating the storage volume bounds is continued until all operation periods are covered leading to new storage bounds $s_{min}(t)$ and $s_{max}(t)$ for all t=2…,NT. It is obvious that the new search space defined by the updated bounds of the storage volumes is now much smaller leading to efficiency of the search method. Furthermore, the trial solution created by the BB-BC algorithm will be mostly feasible since the infeasible region of the search space is now partially excluded. This, however, does not guarantee that the all the solutions constructed by the BB-BC algorithm will be feasible. One obvious reason is that the operation is to start from a known storage volume. To completely remove the possibility of creating infeasible solutions, the above mentioned process is augmented with a mechanism which ensures the release constraint satisfaction during solution construction.

For this, starting from the first period of the operation and with the storage volume being known at the beginning of the period, the continuity equation is used to obtain a new set of bounds for the storage volume at the end of period such that the release constraintof Eq. (6)

is fully satisfied by the resulting release of the period. For this, assuming a known value of s(t) for the storage volume at the beginning of the period t, continuity equation is used to replace the release in terms of the end of the period storage volume s(t+1) in Eq. 6 resulting in the following constraint for s(t+1) .

$$s(t)+I(t)-r_{max} \leq s(t+1) \leq s(t)+I(t)-r_{min} \tag{22}$$

Combining these equations with the updated box constraints of storage volume defined by Eq. (19) leads to the following constraint.

$$s'_{min}(t+1) \leq s(t+1) \leq s'_{max}(t+1) \tag{23}$$

with

$$s'_{min}(t+1)=max(\ s_{min}(t+1),s(t)+I(t)-r_{max}) \tag{24}$$

$$s'_{max}(t+1)=min(\ s_{max}(t+1),s(t)+I(t)-r_{min}) \tag{25}$$

where $s'_{min}(t+1)$ and $s'_{max}(t+1)$ are new bounds for the storage volumes at the end of period t. Starting from period one and using the known value of $s(1)$, the above equation can be used to obtain a new set of bounds for the storage volume $s(2)$. Eq. (2) is now used to find the value of $s(2)$ representing x_1^i within the bounds $[s'_{min}(2),s'_{max}(2)]$already calculated using Eq. (24) and (25). The calculated value of $s(2)$ is then used to find the new bounds for the storage volume $s(3)$ and to update its value. This process is continued until all operation periods are covered leading to the complete construction of a new trial solution. Any trial solution $x_j^i ; j=1,....,NT$, defined by the storage volumes at the end of operation periods, constructed in this mannerwill automatically satisfy not only the storage volume constraint of Eq. (5) but also the release constraint of Eq. (6) and, therefore, constitute a feasible solution. The CBB-BC algorithm so defined will obviously be expected to show superior performance regarding both efficiency and effectiveness compared to the original UBB-BC algorithm.

4. CASE STUDY

To evaluate the performance of proposed algorithms, simple and hydropower operation of "Dez"reservoir in southern Iran is considered as test examples. Total storage volume of "Dez"reservoir is equal to 2510 MCM, and average of water inflow is equal to 5900 MCM over 40 years and 5303 MCM over 5 years. The initial storage of the reservoir is taken equal to 1430 MCM .The maximum and minimum allowable storage volumes are considered to be 3340 and 830 MCM, respectively. The maximum and minimum monthly water release is taken to be 1000 MCM and 0, respectively. The coefficients of the volume-elevation curve

defined by Equation (10) are taken as:

$$a = 249.83364, b = 0.058720, c = -1.37 \times 10^{-5}, d = 1.526 \times 10^{-9}$$

The hydroelectric plant consists of eight units; the capacity of each is equal to 80.8 MW working 10 hours per day, leading to a plant factor of 0.417. The total capacity of the hydroelectric plant is 650 MW and its efficiency is 90% ($\eta = 0.9$). The downstream elevation of the hydroelectric plant above sea level is 172 m ($TWL = 172$).

The problems are solved here using conventional UBB-BC and proposed CBB-BC algorithm using c_1=7.0 and c_2=1.0. The value of c_2=1.0 is assumed a priori and the value of c_1=7.0 was obtained via a tuning procedure. All the results presented here are obtained using 50 populations and 8000 iterations amounting to 400000 function evaluations.

Table 1 shows the solution obtained using the UBB-BC algorithm for the simple and hydropower operation of "Dez"reservoir over 5, 20 and 40 years, i.e.; 60, 240 and 480 monthly periods, respectively.As can be seen from Table 1, all the solutions obtained using UBB-BC in ten runs for simple and hydropower operations are feasible. These results can be compared with those obtained by the conventional Ant Colony Optimization Algorithm, referred to as UACOA, reported by afshar and Moeini [46]. The results show that UACOA was capable of producing 10 feasible solutions for the simplest case of simple operation over 60 monthly periods and 8 feasible solutions for the hydropower operation over60 monthly periods. In longer operation periods i.e. 240 and 480 monthly periods, the number of runs with infeasible solution increases. For 240 monthly periods, only 8 and 7 feasible solutions were created for simple and hydropower operations, respectively while for 480 monthly periods, UACOA was only capable of producing one feasible solution for both simple and hydropower operation. These results indicate that UBB-BC has been successful to solve large scale reservoir operation problems.

Table 1. The results obtained using UBB-BC algorithmover 10 runs

Operation method	Operation period	Minimum	Maximum	Average	No. of runs with feasible solution	Time
Water supply	60	0.76519	1.1937	0.89142	10	11.8
	240	5.2315	7.358	6.2119	10	28.5
	480	16.143	22.609	19.274	10	56.7
Hydropower	60	7.8215	11.576	8.7517	10	21.9
	240	25.839	30.506	27.695	10	67.3
	480	66.596	83.287	73.144	10	136.4

The problems are solved again by the proposed CBB-BC algorithm and the results are

presented in Table 2. As can be seen, the maximum, minimum, and average solution costs obtained using CBB-BC are all superior to those obtained by the UBB-BC for both types of operation and for all operation periods considered. To further evaluate the efficiency of the proposed algorithm, the results can be compared with the results obtained by genetic algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and those obtained by Lingo 9 using NLPpresented in Table 3 [56,46].

Table 2. The results obtainedusing CBB-BC algorithm over 10 runs

Operation method	Operation period	Minimum	Maximum	Average	Time
Water supply	60	0.734	0.73602	0.73507	12.7
	240	4.882	4.9266	4.902	33.3
	480	10.971	11.035	10.999	59.4
Hydropower	60	7.473	7.5987	7.5466	22.6
	240	25.086	27.555	25.928	77.7
	480	62.136	64.469	63.359	138.1

This table shows that while GA was unable to found a feasible solution for the longest operation period, the PSO algorithm could produce feasible solution only for the shortest operation period, andthe ACO algorithm, like GA, was unable to produce feasible solution for the longest operation period, the solutions obtained by the proposed CBB-BC algorithm are all feasible and superior to those of ACO, GA, and PSO by all measures. An improved version of ACOA referred to as Fully Constrained Ant Colony Optimization Algorithm (FCACO)was proposed by Afshar and Moeini [46] and used to solve these problems with the results shown in Table 3. Comparison of the results shows that while all the results produced by the FCACOA are feasible, they are inferior to the solutions obtained by the proposed CBB-BC algorithm.

Table 3. Results obtained using alternative methods for the operation of "Dez" reservoir

Model	Objective	Operation period	Minimum	Maximum	Average
GA	Water supply	60	7.75E−01	9.36E−01	8.70E−01
		240	4.17E+01	2.49E+02	1.12E+02
		480	7.41E+03	2.09E+04	1.34E+04
	Hydropower	60	8.08E+00	9.10E+00	8.48E+00
		240	5.51E+01	6.17E+02	1.59E+02
		480	2.73E+04	6.17E+04	4.00E+04
PSO	Water supply	60	1.07E+00	3.85E+00	2.06E+00
		240	1.26E+02	1.50E+03	5.94E+02
		480	8.47E+03	2.36E+04	1.45E+04

		60	9.26E+00	1.43E+01	1.13E+01
	Hydropower	240	2.21E+02	4.32E+03	1.60E+03
		480	2.51E+04	7.04E+04	4.18E+04
		60	7.85E−01	8.14E−01	8.00E−01
ACO	Water supply	240	1.03E+01	1.33E+01	1.20E+01
		480	6.56E+01	1.94E+02	1.13E+02
		60	7.91E+00	8.06E+00	8.00E+00
	Hydropower	240	3.53E+01	4.00E+01	3.76+01
		480	1.05E+02	2.75E+02	1.78E+02
		60	1.00E+00	1.12E+00	1.04E+00
	Water supply	240	7.98E+00	8.85E+00	8.43E+00
FCACOA		480	1.87E+01	1.99E+01	1.93E+01
		60	8.23E+00	9.01E+00	8.52E+00
	Hydropower	240	2.58E+01	2.83E+01	2.72E+01
		480	6.68E+01	7.00E+01	6.81E+01
		60	7.32E-01	-	-
	Water supply	240	4.77E+00	-	-
NLP		480	1.05E+01	-	-
(Lingo 9)		60	7.37E+00	-	-
	Hydropower	240	2.06E+01	-	-
		480	4.54E+01	-	-

The results of the proposed CBB-BC algorithm shown in Table 2 can be compared with the solutions obtained using global option of Lingo 9 which presumably yields global optimum even for non-convex problems[56]. Global solutions obtained by Lingo 9 are reported to be 0.732, 4.77, and 10.5for the simple operation over 60, 240 and 480 monthly periods, respectively, and 7.37, 20.6 and 45.4 for the hydropower operation over 60, 240 and 480 monthly operation periods, respectively. While the results obtained by the proposed CBB-BC are nearly the same as the global optimum for the shortest operation period, the results for the longest operation periods are sub-optimal only by 9 and 36 percent for the simple and hydropower operations, respectively.

This problem has also been solved by Jalali [57] for 5 and 40 years of water supply operation and 5 ofhydropoweroperation using ACO with Discrete Refining (DR) mechanism. The best solutions for the 5 and 40 years water supply operation were reported to be 0.803 and 36.46, respectively while the best solution obtained for the For 5 years hydropower operation was7.504.These can be compared with the solutions of 0.734 and 10.971 obtained by the proposed CBB-BC algorithm for the 5 and 40 years water supply operation and the solution of 7.473 obtained for the 5 years hydropower operation emphasizing on the superiority of the proposed methods to the existing methods for the problem considered in this paper.

Figures (1) to (6) compares variation of the minimum solution costs obtained by the UBB-BC and CBB-BC algorithm for different operation periods versus the number of function evaluation for the simple and hydropower operations. It is clearly seen that the cost of the solutions obtained by the proposed CBB-BC algorithm always stays lower than those of original UBB-BC algorithm with the difference increasing for the larger operation periods.
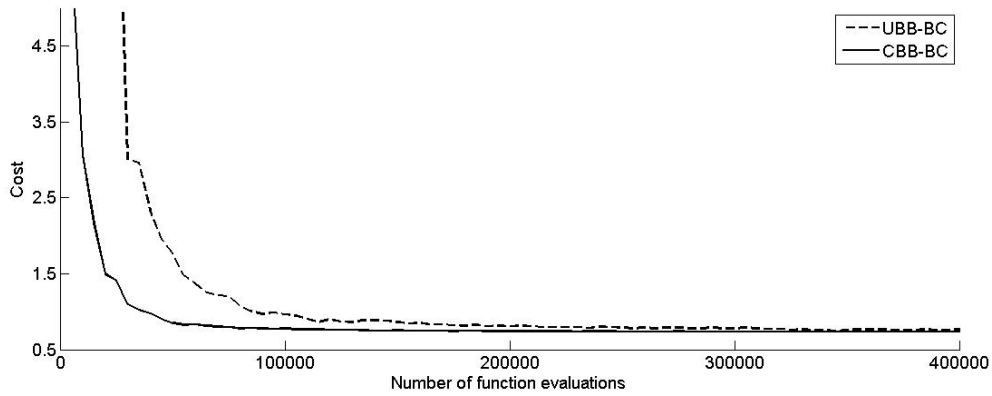
Figure 1. Convergence curve of minimum solution of water supply operation over 60 periods
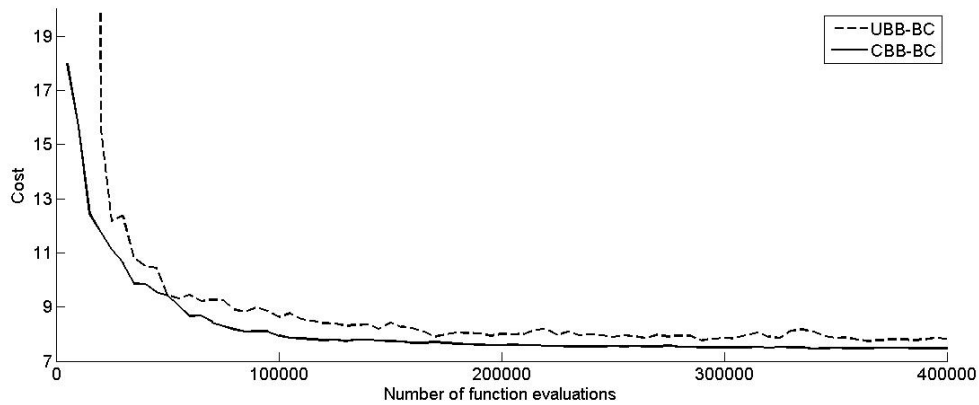
Figure 2. Convergence curve of minimum solution of hydropower operation over 60 periods
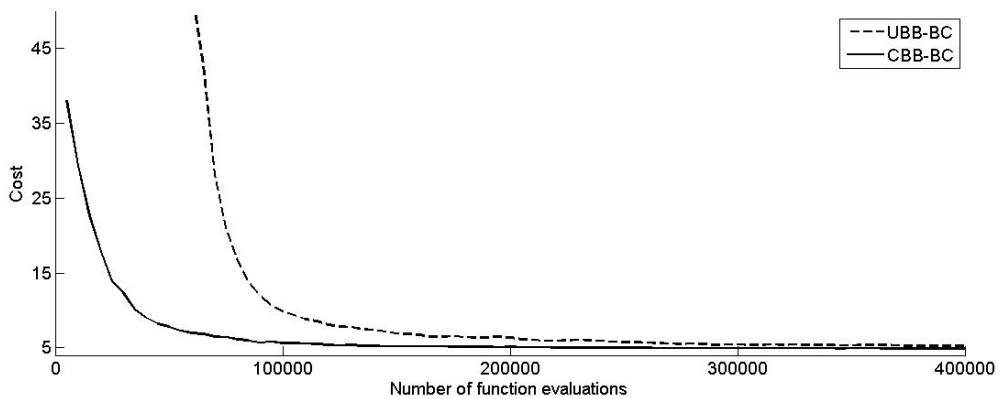
Figure 3. Convergence curve of minimum solution of water supply operation over 240 periods
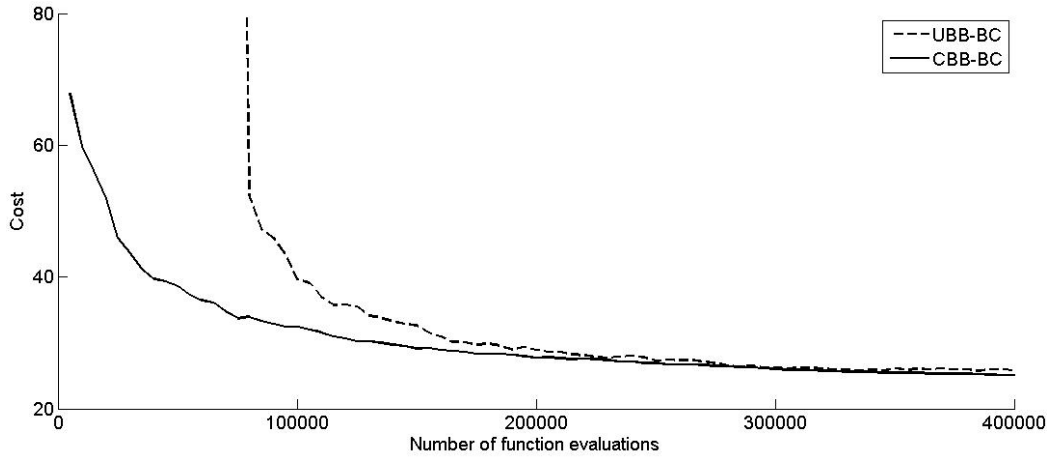
Figure 4. Convergence curve of minimum solution of hydropower operation over 240 periods
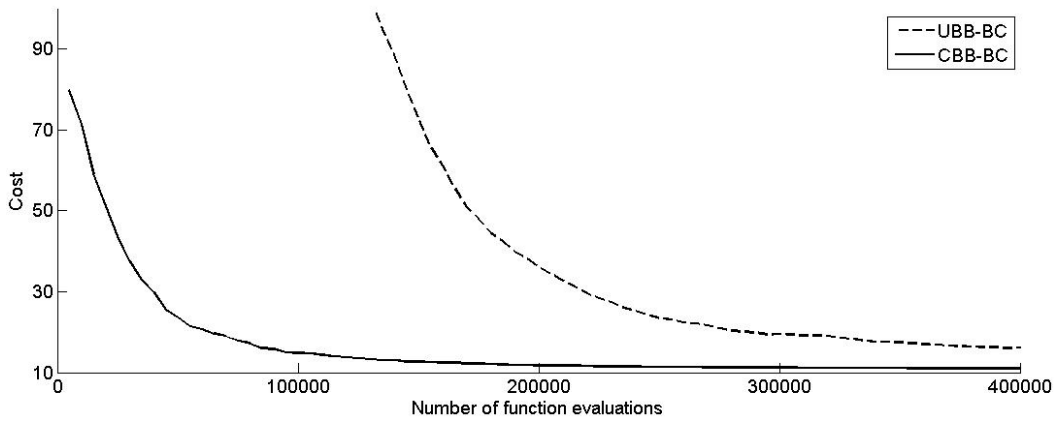

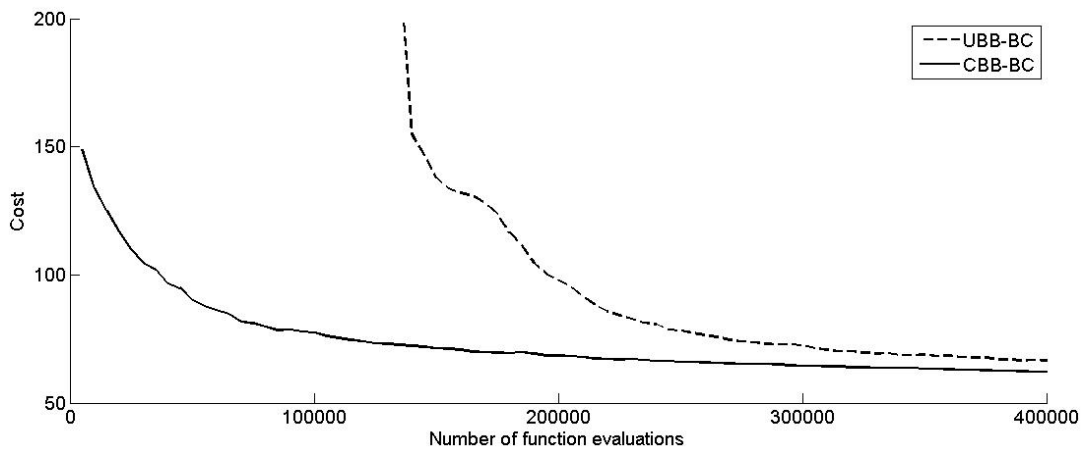Figure 5. Convergence curve of minimum solution of water supplyoperation over 480 periods

Figure 6. Convergence curve of minimum solution of hydropower operation over 480 periods

5. CONCLUDING REMARKS

In this paper, the newly proposed method of Big-Bang Big Crunch algorithm was used for the optimal solution of reservoir operation problems for the first time. A constrained formulation of this algorithm named Constrained Big Bang-Big Crunch (CBB-BC) wasalso proposed to improve accuracyand convergence characteristics of the method. In the constrained version, all the explicit constraints of the problem are enforced during the solution construction so that the BB-BC search is only carried out in the feasible region of the problem search space. Efficiency and accuracy of the original BB-BC referred to here as Unconstrained Big Bang-Big Crunch (UBB-BC) and the proposed CBB-BC for the optimal operation of reservoirs systems are tested against water supply and hydropower operation of "Dez" reservoir in Iran for three operation periods and the results are presented and compared to those obtained by other meta-heuristic approaches. The results indicated that the proposed methods and in particular the CBB-BC algorithm is very efficient and successful in obtaining near optimal solution for the problems considered.

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