Water Policy 17 (2015) 1143–1162

Application of intelligent optimization techniques and investigating the effect of reservoir size in calibrating the reservoir operating policy

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Abstract

In this study, we applied the most recently developed artificial bee colony (ABC) optimization technique in search of an optimal reservoir release policy. The effect of the optimization algorithms was also investigated in terms of reservoir size and operational complexities. Particle swarm optimization, genetic algorithm and neural network-based stochastic dynamic programming are used to compare the model performances. Two different reservoir data were used to achieve the detailed analysis and complete understanding of the application efficiency of these optimization techniques. Release curves were developed for every month as guidance for the decision-maker. Simulation was carried out for each method using actual inflow data, and reliability, resiliency and vulnerability are measured. The release policy provided by ABC optimization algorithms outperformed in terms of reliability, less waste of water and handling critical situations of low inflow. Also, the ABC showed better performance in the case of complex reservoirs.

Keywords: Artificial bee colony; Genetic algorithm; Particle swarm optimization; Reliability; Reservoir release policy; Risk analysis

1. Introduction

Like other optimization models, a reservoir system operation model consists of a single or multi-objective function to be minimized or maximized, based on the reservoir functionality. To get the maximum benefit from a dam/reservoir – one of the most expensive structures – researchers are still trying to improve the existing methods to operate it in an optimal way. The most popular and vastly used optimization tool is the genetic algorithm (GA), where both real valued and binary coded GAs have been successfully applied in search of reservoir release policies (Chang & Chen, 1998; Wardlaw & Sharif,

doi: 10.2166/wp.2015.023

1999; Ahmed & Sarma, 2005; Jothiprakash & Shanthi, 2006). In this field, another population-based optimization algorithm known as particle swarm optimization (PSO) gained popularity over the GA as it's free from the complexities of those basic operators of the GA. According to the study of Kumar & Reddy (2007), a modified version of PSO (elitist-mutated PSO) performed better than the GA and standard PSO in reservoir release policy. Even though PSO is very fast in searching for the optimal solution, it has some drawbacks and application difficulties too. Premature convergences, failure to find a better solution for complex functions and asking for fine tuning of the parameters are the common problems of PSO algorithms (Reddy, 2006).

In this paper, we have introduced the artificial bee colony (ABC) algorithm, the most recently developed swarm intelligence, to formulate the rule curve for reservoir operation. First, Tereshko (2000) observed the foraging techniques of the honey bee and developed a model, based on reaction–diffusion equations. His model brings the idea of adopting the natural honey bee's technique in searching for the global optimum solution by sharing the knowledge of local optima among the so-called particles or agents. Karaboga (2005) proposed the ABC algorithm to optimize numerical equations. In his study, he applied ABC in solving three classical benchmark functions – sphere function, Rosenbrock valley, and Rastrigin functions. Karaboga & Akay (2009) also compared the performance of ABC and found it to work well over the GA, PSO, differential evolution algorithm and evolution strategies in solving a set of different benchmark functions.

To develop a release policy for a reservoir system, the total natural inflow for the reservoir is categorized into three states (i.e. high, medium, and low) and for each state optimum releases are calibrated for different storage conditions. The decision-maker should realize the category of the inflow and finally can decide the release amount of water through the developed release curves on a monthly basis. The verification of each optimization model is achieved by observing the simulation results, which is done by using the actual historical inflow data as an input of each optimization process. Previously, many studies (such as Hashimoto *et al*., 1982; Moy *et al*., 1986; Serdjevic & Obradovic, 1998) have given the idea to check the performances of a reservoir optimization model by computing three major indices. In this study, we adopt all these indices including some extra measures to analyse the performances of these optimization procedures. On the other hand, reservoir size or operational criteria may affect the optimization process too. Previously, the effect of the dam size and operational complexity has not been investigated over the optimization process. So, this study also includes the effect of reservoir size and operational complexity on different optimization methods and concludes what is the most suitable optimization policy for all situations.

2. PSO, GA and neural network-based stochastic dynamic programming (NN-SDP) approaches in reservoir release policy

2.1. PSO

The optimal decision rules for monthly release are generated by using the PSO methodology. Both the GA and PSO begin by generating a random decision variable set. The random variables are called 'particles' and the variable set is called a 'swarm' (given in Equations (1) and (2)). So, in a random water release string consisting of 12 values of water volume to be released from January to December, the 12 releases are considered to be particles and the population set of these particles is considered to be a swarm.

$$particles = [R_{Jan}, R_{Feb}, \ldots\ldots, R_{Dec}]$$
$$\text{where, } R_{\min} \leq R_i \leq R_{\max} \text{ for } i = Jan,\ Feb,\ \ldots\ldots, Dec. \tag{1}$$

$$\text{swarm} = \begin{bmatrix} particles_1 \\ particles_2 \\ \ldots\ldots \\ \ldots\ldots \\ particles_{popsize} \end{bmatrix} \tag{2}$$

$$[\text{swarm}]_{(popsize \times n\,var)} = (R_{\max} - R_{\min}) \times [r]_{(popsize \times n\,var)} + R_{\min}. \tag{3}$$

where, R = water release volume; *popsize* = population or swarm size; *nvar* = total number of variables; r = random number between 0 and 1.

The candidate solutions (decision variables: water releases) of the particles calculate and remember their own fitness, the value of the objective function. The position of any particle is accelerated towards the global best position by using Equations (4) and (5). In any search step t, the ith particle is used to update its candidate solution's current position (x_{ij}^t) by using local best (p_{ij}^t) and global best (p_{gj}^t) position achieved yet.

$$v_{ij}^{t+1} = wv_{ij}^t + \phi_1 r_1^t (p_{ij}^t - R_{ij}^t) + \phi_2 r_2^t (p_{gj}^t - R_{ij}^t). \tag{4}$$

$$R_{ij}^{t+1} = v_{ij}^{t+1} + R_{ij}^t. \tag{5}$$

where, v_{ij}^t = velocity measures for the particles; w = inertial weight; controls the velocity direction; ϕ_1 and ϕ_2 = acceleration coefficient; should be >1 (mostly taken as 2); r_1^t and r_2^t = random numbers; uniformly distributed between 0 and 1; R_{ij}^t = position of any particle at t; p_{ij}^t = best release options (providing lowest Z) at t; p_{gj}^t = best release options (providing lowest Z) achieved yet.

To implement the PSO algorithm in this study, a population was generated with random values of possible water releases for every month and the fitness of each particle was computed. By using Equations (4) and (5), the updating of particle members was carried out and again the fitness was calculated to search for the particles that posed better fitness values. For every update, we carefully tuned the particles to remain in the reservoir release bounds. The procedures followed in this study to adopt PSO methodology in constructing release curves are given as:

1. Define objective function.
2. Set the PSO parameters.
3. Generate an initial population with random values within the allowable water release ranges.
4. Calculate the fitness of the particles.
5. Store the local best and global best among the population.
6. Generate random initial velocity with the same dimensions as population in step 3.

7. Update the particles to create new population by using Equations (4) and (5).
8. Crop to upper and lower range to maintain the allowable water release bounds.
9. Return to step 4, if the iteration criteria are not fulfilled.

2.2. GA

To date the GA has been very popular in the field of reservoir optimization. The literature and application procedure of the GA in this research field are nicely described in many studies (Oliveira & Loucks, 1997; Chang & Chen, 1998; Wardlaw & Sharif, 1999; Kim & Heo, 2004; Ahmed & Sarma, 2005). Like PSO, the GA also begins with random variables. In a reservoir operation problem, normally releases are taken as the decision variables. A set of encoded variables is called the population (which is similar to the swarm in PSO). Each random value of the variables represents a gene and different combinations of these genes make up different strings/chromosomes. So, the population size of the algorithm actually refers to the number of strings of any iteration. In this case, a set of 12 consecutive months' (January–December) release options are considered as a string.

The algorithm begins with an initial population consisting of randomly generated possible answers of water releases. Three main operators of GA – selection, crossover, and mutation – work with this population and update it by eliminating the weaker solution. For selection purposes different selecting rules can be applied (Goldberg & Deb, 1991). Here, we sort the strings according to their objective function values. As the problem is minimization of water deficit, the sorting is done in the manner of lower to greater fitness values. After selecting the strings that contain better solutions, crossover and mutation take place in the algorithm. Here, we use a modified crossover technique described in the study of Haupt & Haupt (2004). The priority of being selected as a good solution solely depends on the fitness values (objective function values) of the corresponding solutions. After a certain iteration, the algorithm reaches the optimal solution. The application procedure followed in this study to implement the GA in finding the optimum releases with maintaining storage bounds and continuity constraints is given as:

1. Build up the objective function.
2. Generate an initial population with random values within the allowable water release ranges.
3. Compute the fitness values of the strings of the population.
4. Search the minimum fitness values and the responsible strings causing the lower fitness.
5. Replace the weaker string by the string stored in step 4 (for minimization problem, strings posing greater fitness values are considered as weaker solutions).
6. Create new population members by using the basic operators of the GA, i.e. selection, crossover, and mutation.
7. Update the old population with new member of step 6.
8. Return to step 3, until the iteration condition is fulfilled.

2.3. NN-SDP

El-Shafie & El-Manadely (2011) proposed a stochastic dynamic programming that is incorporated with a neural network in searching for an optimum reservoir release policy for Aswan High Dam

(AHD) located in Egypt. Similar data as in AHD were used (provided by El-Shafie and El-Manadely) in this research. According to their study, NN-SDP provided an impressive optimum release policy for AHD. To compare the model performances the results are also compared with the NN-SDP simulation results. The basic description of the NN-SDP method is briefly given here and for detailed information about this method we referred to the study of El-Shafie & El-Manadely (2011). In their study, the formulation of general SDP slightly changed. Normally SDP uses the objective function values for each possible decision to identify the optimum solutions, but NN-SDP compares the risk associated with each release option. The risk curves provide the risk for a possible solution and are the input to the NN. The modified recursive function for NN-SDP is given in Equation (6).

$$f_n(s, i) = \underset{k}{NN}\,(g_n(s, i, k)) \tag{6}$$

Here, the reservoir inflow $i = 1, 2, \ldots, i$; storage level $s = 1, 2, \ldots, s$ and $\underset{k}{NN}$ is the NN operator that can make the pair-wise comparison of k risk curves. The term $g_n\,(s,i,k)$ is represented as Equation (7).

$$g_n(s, i, k) = \{(R_1, P_1), (R_2, P_2), \ \ldots, (R_\alpha, P_\alpha), \ \ldots, (R_G, P_G)\} \tag{7}$$

where R is possible loss for a decision and P is the cumulative probability for corresponding loss. G is the total number of pairs used to define the risk curve. The simulation model results, by using the historical inflow of AHD, were taken from the study of El-Shafie & El-Manadely (2011) and compared with the ABC results.

3. ABC optimization in reservoir release policy

Karaboga developed the algorithm first in 2005 and applied it in solving a number of numerical benchmark equations. After that, Karaboga and his colleagues performed several studies on solving mathematical classical optimization problems where they showed that the ABC performed comparatively better than the evolutionary algorithms (mainly the GA) and other swarm intelligence techniques (Karaboga, 2005; Karaboga & Basturk, 2007, 2008; Karaboga & Akay, 2009).

In this algorithm, the position of a food source is considered as the solution (here release option) of the optimization problem, and the fitness values of the corresponding solutions represent the quality or choosing criteria of that food source. So for a typical monthly water supply problem of a reservoir, a set of release options (consisting of 12 values, one for each month) can be taken as a food source. That means a single source contains 12 consecutive monthly release options, R. The quality of each source is the fitness value of the objective function considered as minimized or maximized according to the service criteria of the reservoir. The following expressions (Equations (8) and (9)) represented the food source for the bee as the searching space for optimum releases.

$$\begin{aligned} &source = [R_{Jan}, R_{Feb}, \ \ldots\ldots\ldots, R_{Dec}] \\ &\text{where, } R_{\min} \le R_i \le R_{\max} \text{ for } i = Jan,\ Feb,\ \ldots\ldots\ldots,\ Dec. \end{aligned} \tag{8}$$

$$foods = \begin{bmatrix} source_1 \\ source_2 \\ \ldots\ldots \\ \ldots\ldots \\ source_{popsize} \end{bmatrix}. \tag{9}$$

3.1. Initialization and algorithm set-up

The ABC algorithm begins by choosing a definite number of food sources. Similar to the GA and PSO methodology, the initial population (in the ABC 'foods') is generated randomly from the allowable release range ($R_{\min}$ to $R_{\max}$) for the reservoir. The ABC algorithm has the advantages of having fewer handling parameters than PSO and being free from the evolutionary operators of the GA. The fitness values are computed and the best food source among the population is recorded. After that, the food sources are processed by the employed bees. The generation of *foods* and the fitness calculation process are given below.

$$[foods]_{(popsize\times n\mathrm{var})} = (R_{\max} - R_{\min}) \times [r]_{(popsize\times nvar)} + R_{\min} \tag{10}$$

where, $popsize$ = total number of *sources* considered (population size); $nvar$ = total number of variables and r = random number between 0 and 1.

3.2. Adopting employed bee's behaviour

In the employed-bee phase, a single parameter (release for a single month) of a food source is selected at random for improvement. The updating process is carried out for each source one by one with the involvement of another neighbour source, as given in Equation (13). For instance, if the algorithm chooses a source m from the population set to update its single release parameter (R_{change}), the *neighbour* source will be the other sources of the population. The neighbour source must be different from the currently updating food source (if not, then both parameters will be the same). Two equations control the selection process of choosing a single release and other neighbour sources to perform the updating process.

$$R^{o}_{change} = \mathrm{round}(r \times nvar)\,\mathrm{for}\, m = 1, 2, \,\ldots\ldots\ldots popsize. \tag{11}$$

$$source^{neighbour} = \mathrm{round}(r \times popsize). \tag{12}$$

$$R^{o}_{new} = R^{o}_{change} + r(R^{o}_{change} - R^{neighbour}_{change}). \tag{13}$$

where, o = location of a source within the population set; $change$ = location of release for a single month within o^{th} source; round{.} = round to nearest integer; $nvar$ = total number of variables;

neighbour = denoting other sources rather than o; R^o_{new} = updated value of release for *change*th location of o^{th} source; $R^{neighbour}_{change}$ = release for *change*th of the *neighbour*th source; r = random number between 0 and 1.

In case of any violation of release's maximum and minimum bounds (after using Equation (13)), the updated food sources need to be cropped to the allowable ranges of the reservoir release. The qualities (fitness values) of the new food sources are checked again with the previously stored optimum solution. The decision for survival of a particular source solely depends on the fitness of the solutions.

3.3. Adopting onlooker bee's behaviour

The onlookers begin to work with the information about the food sources provided by the employed bees. Onlookers select the sources according to their probability of being selected. The probability of each source depends on the fitness value (Z) and, for the total *popsize* number of sources, it can be expressed as Equation (14).

$$P_o = \frac{f(source_o)}{\sum_{n=1}^{popsize} f(source_n)} \tag{14}$$

In Equation (14), the probability (P_o) of any o^{th} source is the ratio of its individual fitness to the sum of the fitness of all sources. After selection, onlookers also act as employed bees and use Equations (11)–(13) to maintain the diversion of the sources. According to the probability of each source, the onlooker selects the source and updates its release options one by one. After the updating process, the fitness (Z) of all sources (release policies) will have been computed and compared. The best fitness source is marked as the local best for that particular iteration process.

3.4. Adopting scout bee's behaviour

After treatment by the employed and onlooker bees, some release policies (sources) might still pose weaker fitness. For those food sources, the scout-bee phase is adopted. In this phase, these weaker solution strings are replaced by randomly generated other food sources. After updating one source by using Equation (13), the fitness of that solution is compared with the current best solution. If the solution string still poses a weaker solution than the current best, the source is discarded from the population. The position of these discarded sources is filled by other randomly generated solution strings. The foraging process of the bees is given in Figure 1.

4. System performance indices

The performance checking of a hydrological model usually depends on using sequential historical data (such as rainfall, inflow, reservoir level). After getting the results from a simulation, the system failure/success is measured by different indices. The common three indices for measuring the level of performances are: reliability, resilience, and vulnerability (Hashimoto *et al.*, 1982). In this study,

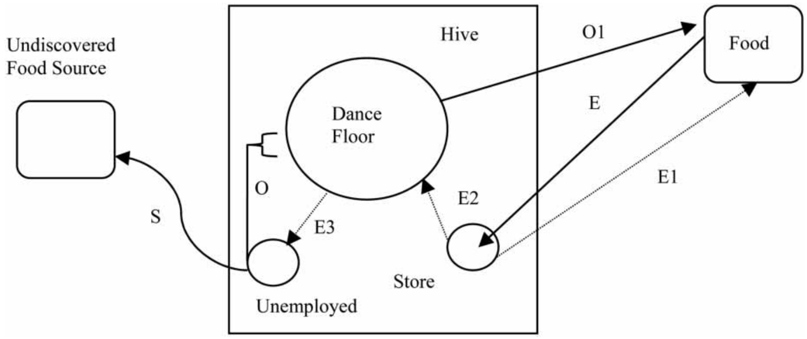

Fig. 1. Foraging behaviour of honey bees.

we adopted all these measures and also added some extra observations (such as model performance on critical low flow) to provide a complete reservoir optimization study.

4.1. Reliability

For a reservoir optimization model, reliability is the most important index in checking the model performance in terms of fulfilling the objectives. Wurbs (1996) provides the concept of volumetric (R_v) and periodical (R_p) reliability as shown in Equations (15) and (16).

$$R_v = (\frac{v}{v}) \times 100\% \tag{15}$$

$$R_p = (\frac{N}{n}) \times 100\% \tag{16}$$

In Equation (15), v is the volume of water supplied or released and V is the volume of targeted demand. In Equation (16), we need to count how many times (n) a model output succeeded in meeting the demand for the simulation of total N time period. Another approach that can describe reliability for a model is the shortage index (SI). The SI value can provide both volumetric and periodical information together for an optimization–simulation model and is expressed as

$$\mathrm{SI} = \left(\frac{100}{T}\right)\sum\left(\frac{\text{water deficit}}{\text{target}}\right)^2 \tag{17}$$

In this study, we considered water deficit values rather than only water shortages, which represent shortage as well as surplus release of water. So the squared deficit provides a magnitude of model failure in both conditions – water shortage and excess releases. Also, for periodical reliability measures, we provided the results from the simulation in three different manners – exact period (releases meeting demand), surplus period (releases more than demand), and shortage period (releases less than demand).

4.2. Resilience

By the resilience of any model, we can measure the capability of the model to recover the failure (here in terms of meeting demands). Resilience is the probability for a shortage period to be immediately followed by a period in which the release meets the demand. Loucks & Beek (2005) took the ratio of number of satisfied releases that follow an unsatisfied value and the total number of unsatisfactory occurrences as the resilience of a model.

$$\text{Resilience} = \frac{\text{no. of periods where a satisfactory value follows a shortage}}{\text{total no. of shortage periods}} \tag{18}$$

The maximum number of consecutive failures can also be taken to measure the ability of a model to get back on track after one failure. But in this way, the lower number of consecutive failures is better for measuring the resilience of a model.

4.3. Vulnerability

Vulnerability measures the magnitude of the failure criteria of a reservoir system model. According to Loucks & Beek (2005), vulnerability can be measured from any simulation results as

$$\text{Vulnerability} = \frac{\text{sum of positive values of (Demand} - \text{Release)}}{\text{no. of unsatisfactory periods}} \tag{19}$$

In this study, Equation (19) was used to calculate the vulnerability, and also the maximum shortage was recorded to explain the vulnerability of the model. Another useful measure can be helpful to prove model efficiency in system performance analysis. The mean inflow was computed for every year and pointed out the critical inflow situation (lowest/highest average inflow) of a particular year. For that critical period, the water deficit was computed and observed to measure the performance of each model.

5. Case studies and problem formulation

To find out the overall best-suited optimization technique in the reservoir operation, two different types of reservoir data were used in this study. Firstly, we created the release curves for a simple and comparatively small single reservoir – Klang Gates Dam (KGD) located in Malaysia. Secondly, AHM of Egypt was considered, which is complex in terms of operation and relatively larger than KGD in capacity. Descriptions and operating criteria for both dams are given in the following sections.

5.1. Case study 1: KGD

The KGD was opened in 1958 and is located in Taman Melawati, Malaysia. Main functions of the dam are water supply for the people of Klang area and their protection from flood. From the analysis of 22 years of historical inflow pattern, the monthly inflow to KGD was categorized, on the basis of

Table 1. Monthly inflow states and water demands.

	Case study 1: KGD (in MG)				Case study 2: AHD (in BCM)			
	High	Medium	Low	Demand	High	Medium	Low	Demand
January	1,506.89	760.85	123.12	1,298.64	4.8	3.15	1.9	3.5
February	1,901.08	1,024.49	259.34	1,083.09	3.7	1.95	0.8	3.8
March	2,831.7	1,646.31	923.24	1,152.45	3.5	1.7	0.55	4.4
April	2,919.74	1,959.92	764.88	1,173	2.7	1.15	0.3	4.1
May	2,974.2	1,786.87	938.31	1,198.73	2.5	1.35	0.65	5.1
June	2,825.69	1,355.22	447.97	1,271.73	2.8	1.65	0.9	6.3
July	2,717.32	1,618.95	645.61	1,258.14	7.7	4.75	2.8	6.8
August	2,948.26	1,644.53	816.78	1,206.41	27.5	20.4	15.05	5.9
September	3,368.12	1,859.86	631.15	1,160.05	31	24.05	18.55	4.5
October	3,545.83	2,316.13	654.35	1,204.14	21.2	15.6	11.3	3.9
November	3,838.47	2,342.89	1,021.79	1,213.09	10.9	7.3	4.75	3.8
December	2,699.3	1,455.7	340.69	1,290.59	6.5	4.3	2.7	3.7

monthly rainfall intensity, into three states – high, medium, and low – as shown in Table 1. The measuring unit of water volume was considered as million gallons (MG). Other constraints and reservoir bounds are given as follows:

- Storage constraint: the reservoir storage S in a month t should not be less than the dead storage and should not be more than the capacity of the reservoir, $16{,}48.67 \leq S_t \leq 6{,}194$.
- Release constraint: the release R_t of water from the reservoir to meet the water demand in any month t has a lower and upper bound, $868 \leq R_t \leq 1{,}379.50$.

5.2. *Case study 2: AHD*

AHD contributes as a major irrigation structure in Egypt (El-Shafie & El-Manadely, 2011). The river Nile annually supplies an average of 84×10^9 m^3 of water to the reservoir. The storage (S) – elevation (H) and the storage (S) – surface area (A) relationships that were used in the study of El-Shafie & El-Manadely (2011) were also used here to formulate the storage bounds and evaporation losses. For evaporation losses, the monthly evaporation rate is used and the volume of total evaporation losses are calculated from, the surface area of the catchment, which is given in the storage–surface area relationship as Equation (21). The measuring unit for water volume used here is billion (10^9) cubic metres (BCM).

$$H = 79.97 + 0.0369S + 18.87\ln(S) \tag{20}$$

$$A = -3164.28 + 25.49S + 1092.92\ln(S) \tag{21}$$

To calculate the total water loss in every month, the seepage (approximately 0.08 BCM/month) and rock absorption losses (approximately 0.125 BCM/month) are also added with the calculated evaporation volume (El-Shafie & El-Manadely, 2011). The constraints and the reservoir maintenance criteria considered in this study are given below.

- Storage constraints: the water level for any time should remain in the range of 147–183 m. So, in terms of storage, the bound for storage capacity is 32–162 BCM. We have considered it as $32 \leq S_t \leq 162$. According to the dam authority, there is another criterion that should be followed in the model that, at the end of the month of July, the water level should be below 175 m as most of the intensive rainfall occurs after July. So, mathematically in terms of volume, we can represent the constraint as $S_7 \leq 122$BCM.
- Release constraint: in AHD, the authority has the flexibility to release no flow to maintain the storage bounds and specifications. A value of 7.5 BCM is taken as the maximum release in a month. So, the release constraint is $0 \leq R_t \leq 7.5$.

Previously, El-Shafie & El-Manadely (2011) proposed an NN-SDP model for AHD. In this study, we adopt the simulation results of their study in order to compare all methods.

5.3. Release curves and model formulation

The primary objective of the study was to provide a release curve for every month, varying with different inflow conditions (for high, medium, and low). The release curves are constructed by means of various storage conditions as well as reservoir levels. So, with these curves, a decision-maker can make the decision on releasing water for a month after observing the inflow conditions and storage level. Here, we aimed to minimize water deficit for both case studies by maintaining all reservoir bounds and authority-provided criteria. So, the objective function was considered as

$$\min f(x) = \sum_{t=1}^{12} (D_t - x_t)^2 \tag{22}$$

Here, D_t and x_t, respectively, are the downstream water demands and release in any time period t.

5.3.1. Constraint handling. Generally in the reservoir operation, the authorities may face two types of constraint in deciding on the release amount: bounds on release volume; and keeping the water level within a safe operational zone. In order to maintain these aspects, the problem has been formulated in the following form:

- Objective function/Fitness function
  - Minimization of water deficit (Equation (22))
- Subjected to
  - The releases (R) for any time period (t) must be within the upper and lower bounds,

$$R_t - R_{\min} \geq 0 \text{ and } R_{\max} - R_t \geq 0 \tag{23}$$

- Storages (S) for any time period (t) must be within the upper and lower bounds,

$$S_t - S_{\min} \geq 0 \text{ and } S_{\max} - S_t \geq 0 \tag{24}$$

- Continuity equation should be satisfied for any time period, t

$$S_{(t+1)} = S_t + Inflow_t - R_t - Losses_t \tag{25}$$

Other operational criteria should be satisfied (if any).

The concept of using a penalty function is based on adopting an extra parameter in addition to the objective function that controls the constraints and helps to eliminate the decision variables that cause violation of any constraints. As Equation (22) represents a minimization problem, the model always preferred to obtain the minimum value of Z. So, if any release policy causes the reservoir storage to violate the boundary condition (Equation (25)), then the penalty term will increase the value of Z based on the violation magnitude. The variables that increase the value of Z have been denoted as weaker solutions and have been eliminated to reach an optimum state. The penalty terms used in this study have been given as Equations (26) and (27) to discard the weaker solutions, where, C_1 and C_2 are big numerical values that increase the magnitude of the penalty.

$$penalty1 = \{^{0 \text{ if} S_t > S_{\min}}_{C_1 (S_{\min} - S_t)^2 \text{ if} S_t < S_{\min}} \tag{26}$$

$$penalty2 = \{^{0 \text{ if} S_t < S_{\max}}_{C_2 (S_t - S_{\max})^2 \text{ if} S_t > S_{\max}} \tag{27}$$

One of the objectives of this study was to analyse the sensitivity of any optimization process on the basis of reservoir size and operational complexity. For that reason, an extra penalty term has been applied only for the case of AHD reservoir (where extra operational conditions exist) as it consists of an end storage criterion. The extra penalty term for the complex reservoir has been considered as

$$penalty_{extra} = \begin{cases} 0 & \text{for KGD} \\ penalty_{complex} & \text{for AHD} \end{cases} \tag{28}$$

where,

$$penalty_{complex} = C_{extra} \times [\max(0, S_{end} - S_{allow})] \quad \text{for } S_{end} \leq S_{allow} \tag{29}$$

where, *penalty1* = penalty term to handle minimum storage bound; *penalty2* = penalty term to handle maximum storage bound; C_1, C_2 and C_{extra} = penalty coefficient (big numerical value); $penalty_{extra}$ = extra penalty term; $penalty_{complex}$ = extra penalty term for AHD; S_{end} = storage for ending of any time period; S_{allow} = allowable storage for that particular time period of S_{end}.

In the above penalty terms, the penalty coefficient C is generally given a high numerical value to control the magnitude of the penalty terms upon the constraint violation. Finally, the objective function has been converted from a constrained function to an unconstrained function and can be expressed as Equation (30).

$$\text{Min } Z = \sum_{t=1}^{12} (D_t - R_t)^2 + \sum_{t=1}^{12} (penalty1)_t + \sum_{t=1}^{12} (penalty2)_t + \sum_{t=1}^{12} (penalty_{extra})_t \tag{30}$$

6. Results and discussion

The convergence of all optimization techniques is given in Figure 2(a) and 2(b). For both cases we can see that the ABC algorithm reached optimum states comparatively very fast.

In this study, three inflow states represent the whole scenario of the monthly water gain to the reservoir. So, after observing the natural precipitation and other possible flow to the reservoir, an inflow state

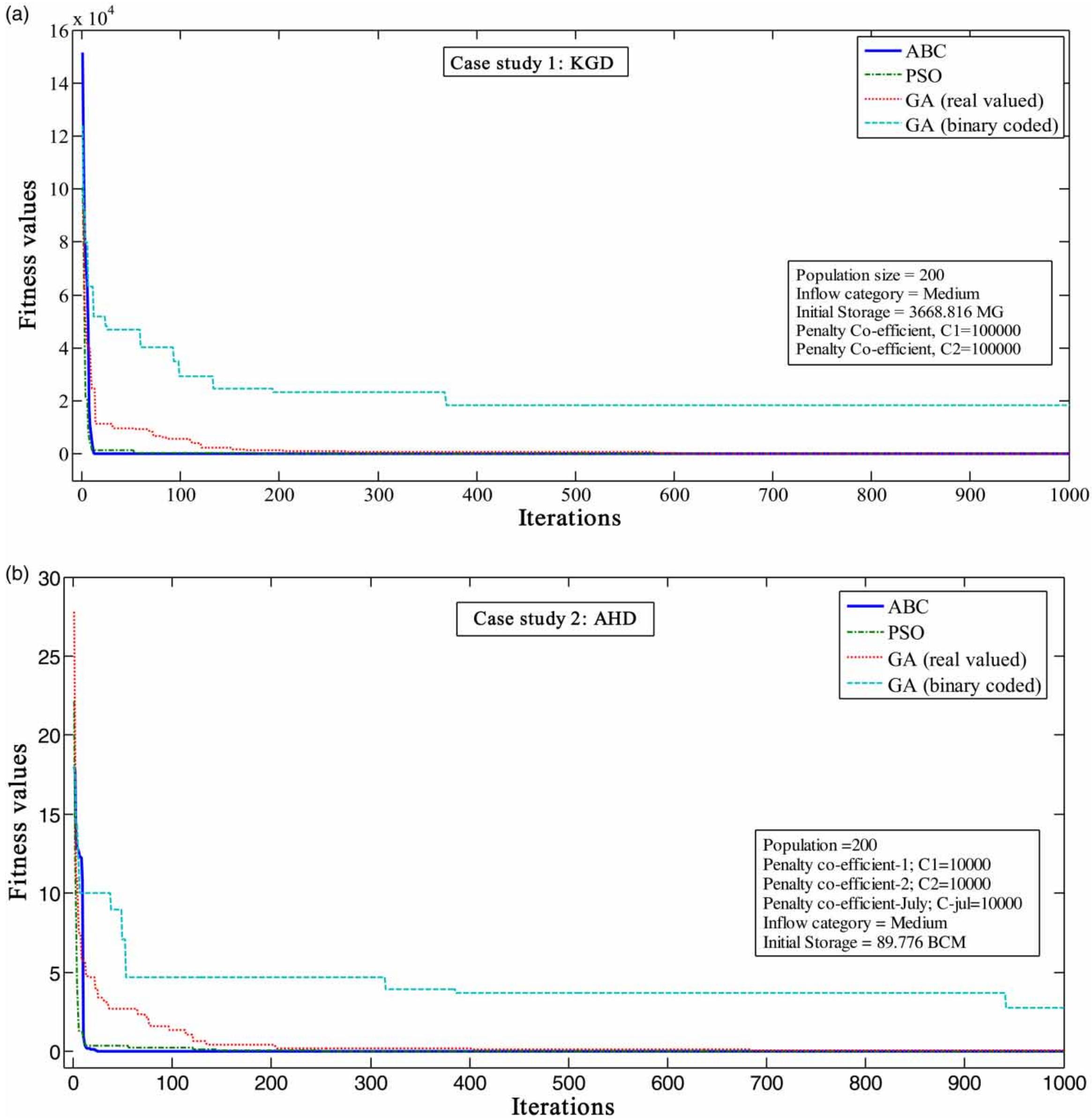

Fig. 2. Convergence of the algorithms for both case studies.

can be chosen in order to consider the right curves for decision-making. Each release curve provides the release amount under different storage conditions (can be obtained from current reservoir level). Such release curves are given in Figure 3(a) and 3(b) for KGD and AHD, respectively (only for the month of January).

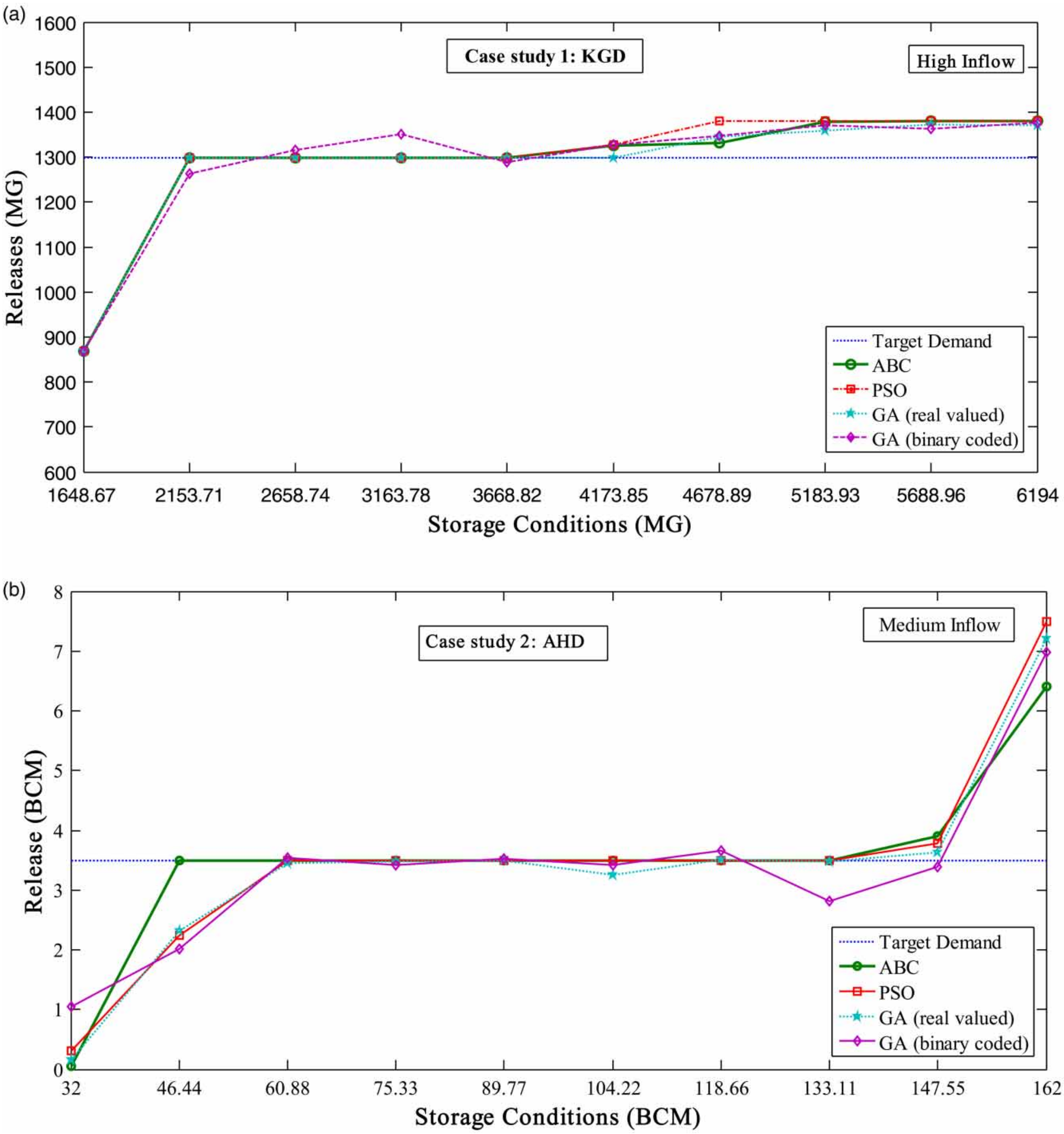

Fig. 3. Release curves for both case studies (for January month).

Each release curve provides the release amount under different storage conditions. The characteristics of the curves showed logical expressions with regard to the decision to release water. For the high and medium inflow categories, the release curves are able to meet the demand line for low storage amounts, as there is adequate water available to release from inflow. With increasing storage capacity, the suggested releases are more likely to meet the demand, and for extreme storage conditions it is suggested that more than demand is released to keep the storage levels in safe ranges. Also, for the lower inflow situation it is very difficult to supply adequate water for demand, and the water shortage (less than targeted demand) is very obvious in this situation.

To find out the closest curve to demand, a root mean square error (RMSE) approach was adopted here and given as in Equation (31), where, i is denoted as the indices of 10 known values of the release curve ($i = 1, 2 \ldots, 10$). The calculated value of RMSE for every month is given in Table 2. According to Table 3, ABC provides the minimum RMSE for both dams. Although RMSE is not sufficient to measure the efficiency of any hydrological optimization model, it can be used here for comparison purposes. For better analysis of the performance measuring process we have carried out the simulation by using actual historical inflow data.

$$\text{RMSE} = \sqrt{mean((x_i - Demand)^2)} \tag{31}$$

As discussed in Section 4, some system performance measuring indices need to be calculated to evaluate the application efficiency of the calibrated release curves. For this purpose, simulations were carried out for both case studies using the historical inflow data. For KGD, 264 monthly inflow data were used and the optimum release for those time periods was computed from the release curves. In the case of AHD, we used 18 years of historical natural inflow to the reservoir. The process of simulation using the actual historical data on the developed release curves is given as a flow chart in Figure 4.

Figure 5(a) presents the simulation results (last 14 years' results from the total 22 years of historical time period) for KGD using ABC release curves. The simulated release for AHD is shown in Figure 5(b). The

Table 2. Calculated RMSE for KGD and AHD: medium inflow category.

	Case study 1: KGD (in MG)				Case study 2: AHD (in BCM)			
	ABC	PSO	GA (real)	GA (binary)	ABC	PSO	GA (real)	GA (binary)
January	95.56296	97.33242	102.1057	118.6042	0.674934	0.872538	0.870275	0.857875
February	57.15567	61.46059	67.15825	63.49003	0.834693	0.721191	0.870397	1.111538
March	70.64764	62.91275	63.66787	75.55802	0.780319	0.778393	0.880802	0.950366
April	46.90427	56.11568	58.46889	80.2556	0.817354	0.711505	0.658767	1.069231
May	62.35557	56.7529	40.65074	101.9642	0.680464	0.716973	0.777302	1.005092
June	51.76583	57.15068	68.57881	41.41234	0.580933	0.594752	0.605499	1.041172
July	65.16919	56.19315	66.07014	96.61208	0.414547	0.393348	0.35347	0.615055
August	53.9695	54.98207	55.84364	68.20662	1.03E – 08	0.012532	0.059812	0.455971
September	0.001245	0.139859	8.186639	50.80872	9.38E – 09	0.001239	0.089109	0.686996
October	7.99E – 05	1.809941	20.48498	44.47532	2.39E – 08	0.008511	0.080879	0.482564
November	1.31E – 05	0.473721	17.7495	49.48262	5.03E – 09	0.007232	0.070218	0.651282
December	0.001268	1.878905	16.49303	56.6085	9.04E – 09	0.01244	0.065491	0.610952
Total	503.5332	507.2027	585.4582	847.4783	4.783244	4.830654	5.382023	9.538095

Table 3. Reliability and resilience measures for all methods[a].

Measures	ABC	PSO	GA (real)	GA (binary)
Case study 1: KGD				
Meeting exact demand (% of total time period)	61.36*	59.47	55.68	23.5
Oversupply (% of total time period)	12.12*	12.12*	14.4	28.4
Shortage/undersupply(% of total time period)	26.51*	28.41	29.92	48.10
Shortage index (Equation (17))	0.68	0.67*	0.67*	0.73
Resilience (Equation (18))	0.16*	0.15	0.14	0.90
Max. no. of consecutive shortage periods	10*	10*	11	12
Case study 2: AHD				
Meeting exact demand (% of total time period)	62.03*	58.8	51.85	18.1
Oversupply (% of total time period)	36.11*	38.89	39.81	52.7
Shortage/undersupply(% of total time period)	1.85*	2.31	8.33	29.2
Shortage index (Equation (17))	0.95*	1.02	0.97	1.4
Resilience (Equation (18))	14.5*	14	2.67	0.142
Max. no. of consecutive shortage periods	1*	1	2	4

[a](*) denotes the best results among all methods.

monthly release amount for this period was obtained from the release curves, optimized by the binary GA, real-coded GA, PSO and ABC algorithm. Both figures show the monthly releases and demands for this historical time period. For convenience, the last 14 years of the simulation results are given in these figures. The dotted line in the figures represents the monthly demand and the other line represents the

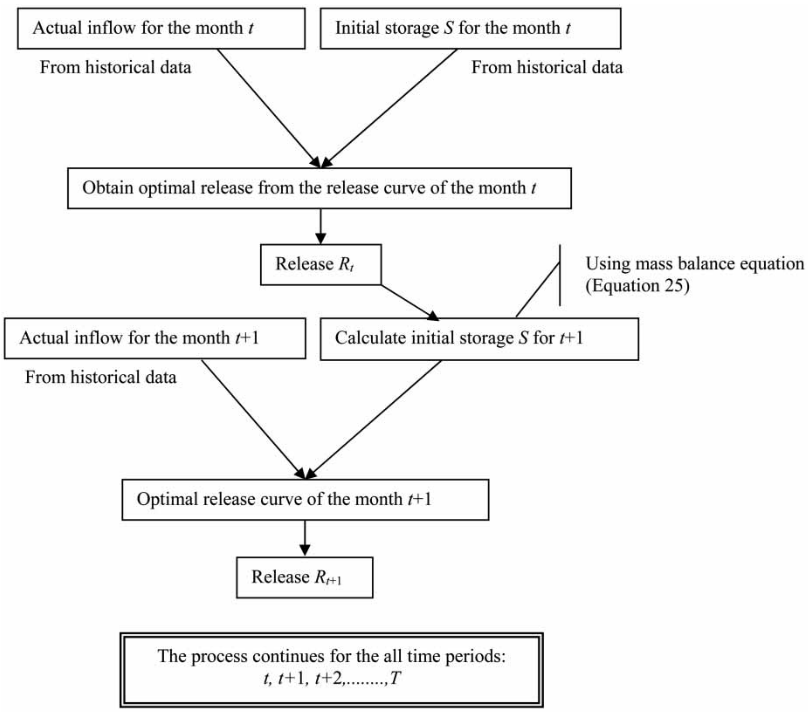

Fig. 4. Simulation process by using historical data.

output from the release curves. The risk analysis has been undertaken from these simulation results. The summary of the simulated release for all optimization techniques is given in Table 3. From the simulation we can see that the ABC release policy succeeded in meeting the demand for the maximum time period and also that it reduced the oversupply that may cause wastage of water.

The average annual inflows of historical data are shown in Figure 6. According to Figure 6, the lowest average inflow occurred in the hydrological year 1984–85 for AHD, and for KGD the lowest inflow occurred in 1992. We observed the model performances in this critical situation and compared them in Table 4. Also, the vulnerability of each model is given in Table 4.

The performance of the ABC was also compared with the NN-SDP given by El-Shafie & El-Manadely (2011) for AHD. In Table 5, the simulation results of their previous study are provided and compared with the ABC optimization results.

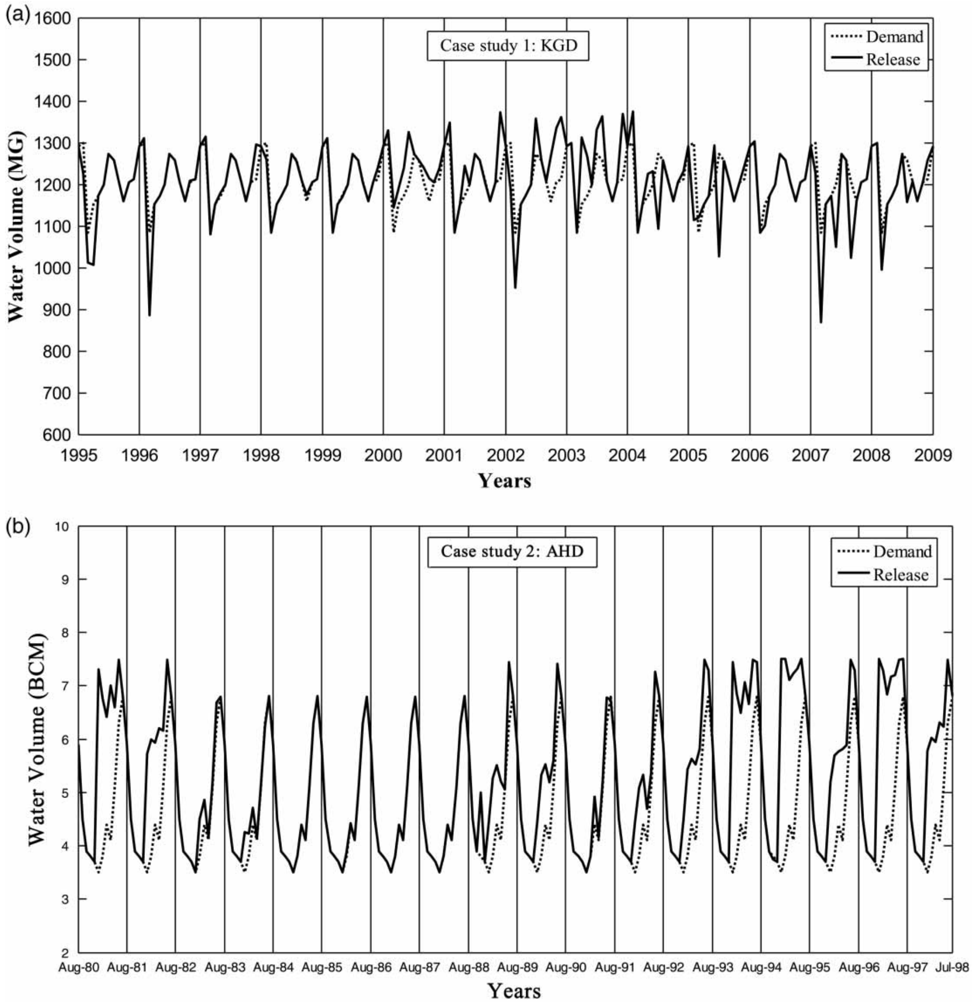

Fig. 5. Simulation results of ABC release curves.

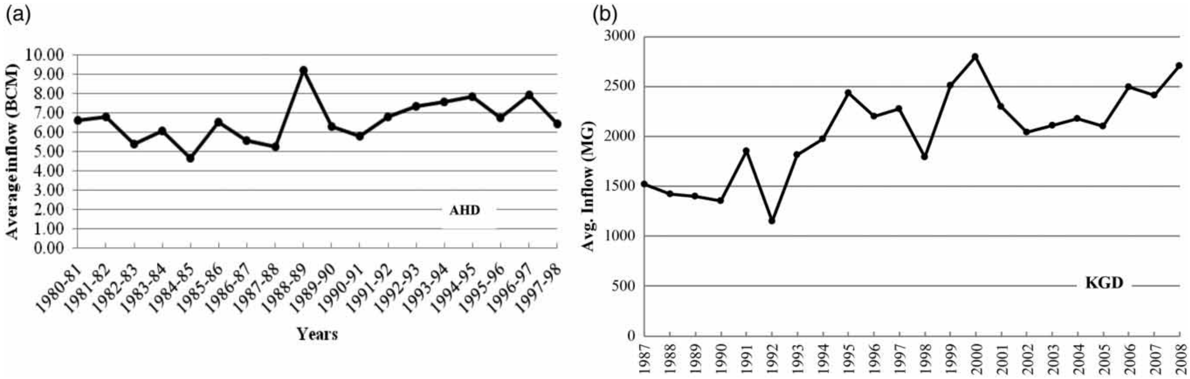

Fig. 6. Average inflow for historical period of KGD and AHD.

All performance-measuring indices indicated that the ABC optimization outperforms among PSO, GA and NN-SDP methods. ABC provides the maximum number of satisfactory periods in meeting demand, the minimum shortage periods, and also it reduces the oversupply that may cause wastage of water (according to reliability measures).

The simulation results and the system-performance indices are more effective tools for comparing the performances of the optimization models than the RMSE approach. Tables 3–5 report all the measures, including reliability, resilience, vulnerability and SI for both the simple and complex reservoirs in order to analyse the effect of reservoir size and operational complexity on the proposed optimization techniques. According to Tables 3–5, in most of the cases (such as reliability, resilience measures and handling low inflow) the ABC performed better than the evolutionary algorithms when applied to the KGD.

For the AHD, the model efficiencies can be clearly verified, as in all cases the ABC performed significantly better. Resilience and reliability are much higher for this swarm technique. The ABC release policy has also been compared with the previous study's results. So, in conclusion, the GA release policy may perform better in handling a few situations for small and simple reservoirs, but, when applied to a large reservoir system, it fails to achieve a higher degree of satisfaction. On the other

Table 4. Vulnerability and critical situation handling by all methods[a].

Performances	ABC	PSO	GA (real)	GA (binary)
Case study 1: KGD				
No. of shortage periods in 1992 (lowest inflow)	10*	10	11	12
Vulnerability (Equation (19))	220.94	203.27	199.15	136.91*
Worst shortage ever (% of demand)	53	53	51	44*
Case study 2: AHD				
No. of shortage periods in 1984–85 (lowest inflow)	0*	0*	1	3
Vulnerability (Equation (19))	0.06*	0.07	0.28	0.5
Worst shortage ever (% of demand)	1.11*	1.6	57.75	24.02

[a](*) denotes the best results among all methods.

Table 5. Comparing the simulation results between existing method and ABC for KGD.

Performance measuring indices	NN-SDP*	ABC optimization
Reliability	94%	98.14%
Max. no. of consecutive shortage periods (months)	2	1
Average deficit (BCM)	0.85	0.14

*Results obtained from the study by El-Shafie & El-Manadely (2011).

hand, the ABC-driven release policy acts very well in handling maximum performance measuring from the points of view of both small and large reservoir systems.

For a simple reservoir system like KGD, the performances of swarm intelligences (ABC and PSO) were better in terms of reliability, resilience and handling critical low-inflow situations, except that the GA release policy shows slightly better performance in terms of vulnerability.

7. Conclusion

The study presented in this paper is about developing an optimum reservoir release policy by using evolutionary methods and swarm intelligence-based optimization techniques. Regarding reservoir release policy, the most popular and well-developed techniques like PSO, GA and NN-SDP are compared with the newly developed ABC optimization algorithm. Also, the sensitivity of the reservoir size and characteristics has been analysed in this study. For a simple and small reservoir, the GA is adequate to produce good results, but the ABC algorithm is more reliable in handling both small and large reservoir systems. ABC is faster than PSO and GA in reaching the optimal state. Also, it has the advantage of fewer handling parameters. The inflow patterns are categorized into three different states from the available historical inflow records. According to the simulation results, the ABC optimization algorithm shows better performances than the GA and PSO. Less parameter handling, simplicity of the algorithm and – also very importantly – the practical application in a reservoir system suggest consideration should be given to using the ABC algorithm in this research field.

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Received 26 January 2014; accepted in revised form 26 March 2015. Available online 28 April 2015