

Optimum design and operation of a hydropower reservoir considering uncertainty of inflow

Toktam Hoseinzadeh, Mojtaba Shourian and Jafar Yazdi

ABSTRACT

Due to the large number of variables and nonlinear relations, hydropower plant design and operation optimization problems belong to the Non-polynomial hard class of problems. In this study, optimum design and operation of a hydropower reservoir is compared in two cases using deterministic and stochastic inflows by two meta-heuristic algorithms. Particle swarm optimization (PSO) and cuckoo optimization algorithm (COA) are applied under two conditions of using the historical inflow time series as a deterministic approach and the eigenvector-based synthetic generations as a stochastic approach for optimum design and operation of the Bakhtiari hydropower plant in Iran. The problem is solved in two states of finding the optimum values for the reservoir and power plant capacities (as the design decision variables) with known standard operation policy (SOP) and optimum values for the capacities and the reservoir releases variables (as the design and operating variables). Results obtained by the models indicate that the role of operation optimization is negligible as the SOP used in the design models led to near optimum solutions. Considering uncertainty in the reservoir inflows resulted in an increase of the installation capacity and consequently the energy production. In addition, PSO demonstrated more efficiency compared to COA in dealing with the proposed optimization problem that has a complex feasible search space.

Key words | COA, design and operation, eigenvector, hydropower plant, inflow uncertainty, PSO

HIGHLIGHTS

- Optimum design and operation of a hydropower reservoir plant is compared in two cases using deterministic and stochastic inflows.
- Particle Swarm Optimization (PSO) and Cuckoo Optimization Algorithm (COA) are applied.
- Two conditions of using the historical time series of the reservoir inflow as a deterministic approach and the eigenvector-based synthetic generations as a stochastic approach are compared.
- The problem is solved in two states of finding the optimum values for the reservoir and power plant capacities (as the design decision variables) with known Standard Operation Policy (SOP) and the optimum values for the capacities and the reservoir releases variables (as the design and operating variables).
- The results obtained from the models indicate that the role of operation optimization is negligible as the SOP applied in the design models led to good solutions for the problem.

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INTRODUCTION

Given the increase in population and the limitation and non-uniform distribution of water resources, as well as the overuse of these limited resources, the need for optimal management and utilization of the existing resources has become more evident. In addition to significantly reducing the costs, renewable hydroelectric energy helps with the environmental sustainability. Considering the limitation of fossil resources as well as the adverse environmental effects of fuel consumption, and due to the growth of population and the ever-increasing need for energy, the tendency to using clean energies has increased significantly. Today, hydropower is the most important source of renewable energy in the world (Hatamkhani *et al.* 2020).

Optimization of the design and operation of hydroelectric reservoirs through classic optimization methods is associated with difficulties such as nonlinearity and non-convexity of the problem, as well as the procedure of determining the stochastic constraints related to the reliability of energy demands. In this regard, the simulation-based meta-heuristic search algorithms are suitable alternatives (Mousavi & Shourian 2010). In addition, attention to the issue of uncertainty in hydrological variables is a common problem in planning water resource systems. The main objective of this study is to optimize the design and operation of a hydropower reservoir considering the uncertainty of the inflow to the reservoir as the one of the most important factors affecting the rate of energy generation.

In this field, Afzali *et al.* (2008) developed a reliability-based simulation model with one-period optimization sub-models for a multi-reservoir hydropower system operation. Mousavi & Shourian (2010) optimized the design and operation of a hydropower reservoir using a particle swarm optimization algorithm in combination with the sequential streamflow routing (SSR) simulation model. Rahi *et al.* (2012) employed particle swarm optimization (PSO) for the maximization of the benefit to cost ratio in a hydropower plant system. The results indicated that the benefit-cost ratio obtained was well above unity, which proved the feasibility of power plants construction. Jothiprakash & Arunkumar (2013) optimized a hydropower reservoir operation using an evolutionary algorithm coupled with chaos.

Bozorg-Haddad *et al.* (2014) focused on simultaneous design–operation optimization in the design phase of pumping systems (pump–storage) in reservoir power plants. The optimization model maximized the net benefit of installations in reservoir systems while determining design decision variables, including volume of reservoir, installed capacity of power plants, diameter of water transmission installations and operation decision variables including output volume of the reservoir at each time step and number of hours the power plant works in a day. Li & Qiu (2015) proposed an optimization model based on PSO in order to determine the optimal distribution of the electrical load in the hydropower plants. They developed a multi-objective reservoir optimization model for balancing energy generation and firm power. Hosseini-Moghari *et al.* (2015) optimized operation of a reservoir using two evolutionary algorithms of imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA). Jahandideh-Tehrani *et al.* (2015) assessed the performance of hydropower production by reservoirs with and without climate change impacts on river discharge. Reservoir simulation and optimization models were implemented to calculate hydropower production in the base and future periods. The hydropower production obtained with the optimization model was found to be larger than that obtained with the simulation model. Their results demonstrated the benefit of applying optimization modeling for hydropower production in the multi-reservoir systems to mitigate and adapt to climate-change impacts on river discharge.

Soleimani *et al.* (2016) investigated the reservoir operation rules with uncertainties in inflow and agricultural demand derived with stochastic dynamic programming and showed the advantage of considering the uncertainty. Hatamkhani & Alizadeh (2018) dealt with optimal design of a hydropower project's capacity when an analyst may take into account different economic analysis approaches and considerations. They formulated the problem using mixed-integer nonlinear programming including an economic objective function and governing hydropower constraints. They employed an effective simulation–optimization approach coupling PSO and Water Evaluation and Planning

(WEAP) software that they customized for hydropower simulation using scripting capabilities of the software. Their results showed how inclusion of externality and a clean development mechanism could affect the project's design and measures. Yazdi & Moridi (2018) proposed a multi-objective optimization model for determination of design parameters in cascade hydropower multi-purpose reservoir systems. A multi-objective evolutionary algorithm known as non-dominated sorting differential evolution was developed to solve the problem and reduce the computational costs. Based on the results, it is possible to supply various demands such as environmental demands of the aquatic ecosystems with high reliability as well as generating firm hydropower energy through optimal design of cascade hydropower reservoirs. Hatamkhani & Moridi (2019) used a simulation-optimization approach to solve the problem of optimal planning at the watershed scale. The WEAP simulation model was linked with the multi-objective particle swarm optimization (MOPSO) model for optimal long-term planning at the basin scale. Their results demonstrated the proper performance of the simulation-optimization model in the optimal allocation and planning of water resources at the basin scale. Hatamkhani et al. (2020) developed a simulation-optimization model for optimal design of hydropower systems with a systematic view of the basin. They employed WEAP to develop the simulation model of water allocation in the basin. For simulating the hydropower energy production, a hydropower energy simulation module was developed within the software and linked to the optimization algorithm. This model was used to find the optimal value of design parameters of normal water level, minimum operation level and installation capacity of a hydropower project in the Karkheh basin in Iran.

According to the literature, most hydropower planning and operation studies have solved the problem with deterministic historical inflows. Paying attention to uncertainty is important for designing and operation of hydropower plants to estimate the potential energy production and determining design parameters based on what may occur in future. Accordingly, in this research optimum design and operation of the Bakhtiari hydropower plant in Iran is studied considering the uncertainty of the reservoir inflow and the results are compared with the deterministic historical state. To do so, probable future inflows are generated

using the eigenvector method. In spite of the abilities of COA, it has been rarely used in hydropower plant design and operation optimization problems that belong to the Non-polynomial hard (Np-hard) class of problems. PSO is a well-known metaheuristic optimization algorithm which has shown its ability in various optimization applications and can be used as a reference for comparing the results. As the marginal contribution, performances of the COA and PSO algorithms are investigated and compared in this study, too. Four models of A1, A2, B1 and B2 are developed where models A1 and A2 optimize the design variables with a defined operation policy while the operational variables are also optimized in models B1 and B2. Results are compared and the impact of considering the uncertainty in reservoir's inflow is discussed.

METHODS

Cuckoo optimization algorithm

Cuckoo optimization algorithm is introduced by Rajabioun (2011), inspired from the lifestyle of a bird called a cuckoo. In nature, cuckoos choose the nests of other birds to lay their eggs. If the living area of a cuckoo is the decision space, each habitat is a solution for a problem. Therefore, the algorithm begins with an initial population of cuckoos that live in different places (Hosseini-Moghari et al. 2015):

$$\text{habitat} = [V_1, V_2, \dots, V_N] \quad (1)$$

$$\text{Cost} = F(\text{habitat}) \quad (2)$$

where V_1, V_2, \dots, V_N are decision variables, F is the objective function, and Cost is the value of F . The maximum distance for moving in the next iteration is called egg laying radius (ELR) where each cuckoo lays its eggs in this radius randomly. In an optimization problem for variables with upper and lower limit (Var_{max} and Var_{min}), ELR is calculated by the following equation:

$$\text{ELR} = \alpha \times \frac{\text{Number of the current cuckoo's eggs}}{\text{Total number of eggs}} \times (\text{Var}_{max} - \text{Var}_{min}) \quad (3)$$

α is an integer number which handles the maximum value of ELR. Because cuckoos are found in different parts of the decision space, it is difficult to determine which cuckoo is related to which group. K-means clustering method is used for grouping cuckoos. The destination of other groups in the next generation is the group which has the best relative optimality. Cuckoos go through only λ percent of the distance to destination and in this way have a deviation with φ value. λ is a random number between zero and one, with a uniform distribution, and φ also has uniform distribution in $[-w, w]$. Usually, w is equal to $\pi/6$ which has shown good convergence to the optimum solution. λ and φ cause a more global search in the decision space.

$$\lambda = U(0, 1) \quad (4)$$

$$\varphi = U(-w, w) \quad (5)$$

There is usually a balance between populations of birds in nature because of factors such as hunting, lack of food etc. Therefore, in COA, a number of N_{max} controls the maximum number of cuckoos. After several iterations, cuckoos

converge to the point with the best objective function. In Figure 1, a flowchart of COA is shown.

Particle swarm optimization

In PSO, each individual of the population has an adaptable velocity (position change), according to which it moves in the search space. Moreover, each individual has a memory, remembering the best position of the search space it has ever visited (Kennedy & Eberhart 1995). Equation (6) updates the velocity for each particle in the next iteration step, whereas Equation (7) updates each particle's position in the search space:

$$v_{id}^{n+1} = \chi(\omega v_{id}^n + c_1 r_1^n (p_{id}^n - x_{id}^n) + c_2 r_2^n (p_{gd}^n - x_{gd}^n)) \quad (6)$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \quad (7)$$

where d is the dimension, i is the number of the particle, χ is the constriction factor usually equal to 1, ω is the inertia weight linearly degrading from 1.2 to 0.1, c_1, c_2 are two positive constants that values of 2.5 and 1.5 for them

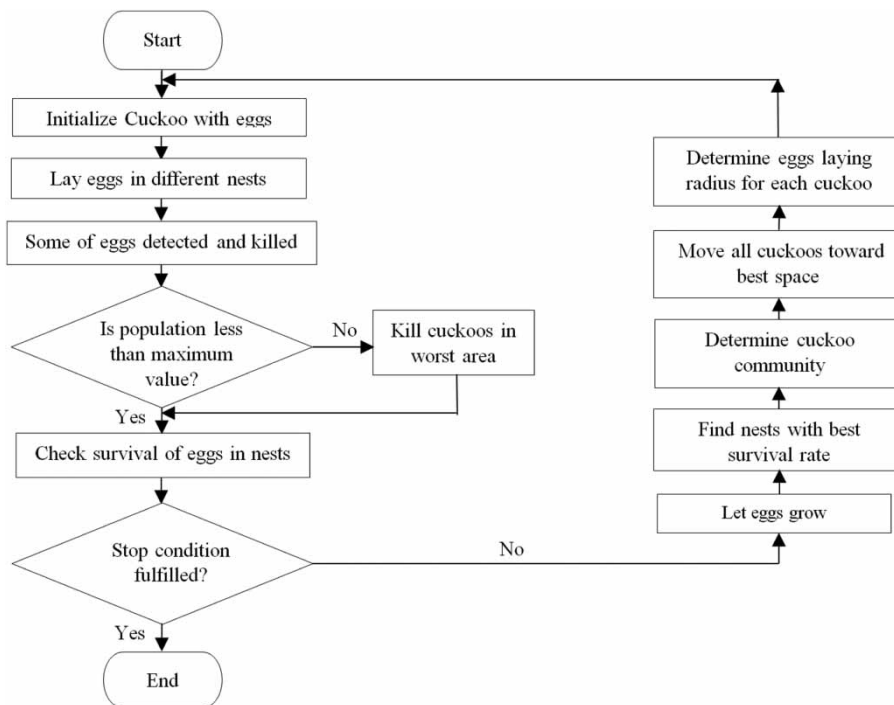


Figure 1 | Cuckoo optimization algorithm.

respectively have shown good performance, r_1 , r_2 are random numbers uniformly distributed in [0 1] and n represents the iteration number. For more details about PSO and the flowchart of the algorithm, please refer to Shourian et al. (2008).

Generating synthetic streamflow using eigenvectors

The eigenvector of a matrix is a vector whose direction remains unchanged when multiplied in that matrix and only its size changes:

$$Av = \lambda v \quad (8)$$

A is a $n \times n$ matrix (like the covariance matrix of the data), v is the eigenvector and λ is the eigenvalue of the matrix A . Eigenvectors can specify the directions in which the maximum and minimum variations occur (the eigenvector values specify the amount of these changes). This feature can be used to generate stochastic data where the data are dependent. The relationship between eigenvectors is written in the following form:

$$Cov(x)v = v\Lambda \Rightarrow Cov(x) = v\Lambda v' \quad (9)$$

In the above relations, $Cov(x)$ is the covariance matrix of the variable x , v is the matrix of eigenvectors and Λ is the diagonal matrix of eigenvalues. To find variables in the direction of eigenvectors, the following change of variables is used:

$$W = v'X \quad (10)$$

Thus, we can obtain the expected value and the covariance of the new variable W :

$$E(W) = v'E(X) \quad (11)$$

$$Cov(W) = v'Cov(X)v = v'(v\Lambda v')v = \Lambda \quad (12)$$

Therefore, the covariance matrix of W is a diagonal matrix which means that there is no linear relationship between variables in the new coordinate space. Therefore, it is possible to generate separate data for each variable as

needed and then transfer the generated data to the main coordinate space using the relation: $X = v \times W$. The steps of river flow stochastic data generation through eigenvectors method can be summarized as follows (Yazdi 2013):

1. After calculating the covariance matrix, eigenvalues and vectors (λ and v) are obtained from the following equations:

$$|Cov(X) - \lambda I| = 0 \quad (13)$$

$$Cov(X) \times v = v \times \Lambda \quad (14)$$

2. The following transformation of variables is done:

$$W = v'X \quad (15)$$

3. The expected value of the variables in the new space and the covariance matrix which is diagonal in the new coordinate space, are calculated:

$$E(W) = v'E(X) \quad (16)$$

$$Cov(W) = \Lambda \quad (17)$$

Then, in the new coordinate space, an adequate number of new data are generated.

4. By transforming the variable $X = v \times W$, the data are transferred to the main space.

Hydropower reservoir simulation

In order to calculate the energy potential of the system, a reliability-based simulation (RBS) model is used. It is first necessary to estimate the capacity of the plant installation. An initial production capacity may be estimated by the following equation:

$$IC = \frac{2.73 \times Q_{ave} \times H_{max}}{PF \times n \text{ hours}} \quad (18)$$

where IC is the power plant's initial production capacity (MW), Q_{ave} is monthly inflow to reservoir (mcm), H_{max} is initial maximum net head on turbines as the difference

between the normal and tail water levels (m), PF is the specified plant factor that defines the number of hours per day in which the power plant generates power with its production capacity (%) and $nhours$ is the number of hours per month (hr). It may be desirable to maximize the system's energy yield that can reliably be produced. Given the estimated production capacity and specified plant factor, the plant's monthly energy yield, EF (MWh) is estimated as follows:

$$EF(t) = IC \times nhours \times PF(t) \quad (19)$$

The reservoir operation is simulated over a representative hydrologic period using the sequential stream flow routing (SSR) method to determine the energy yield reliability. The power plant's capacity is then adjusted accordingly, if required. The energy generation in each time step is calculated as follows:

$$E(t) = 2.73 \times R(t) \times (0.5 \times (h_1(t) + h_2(t)) - h_{tail}(t) - h_f(t)) \times e_p(t) \quad (20)$$

where $E(t)$ is energy generated in month t (MWh) to be maximized by sum as the objective function in all models, $R(t)$ is the turbine release (mcm), $e_p(t)$ is power plant's efficiency (%), $h_1(t)$ and $h_2(t)$ are beginning and end-of-month reservoir levels (m), respectively, $h_{tail}(t)$ is average tail water level (m) and $h_f(t)$ is total minor and frictional losses in conveyance structures (m) all in month t . The monthly turbine release would then be obtained as follows:

$$R(t) = \frac{EF(t)}{2.73 \times (0.5 \times (h_1(t) + h_2(t)) - h_{tail}(t) - h_f(t)) \times e_p(t)} \quad (21)$$

$h_2(t)$, $h_{tail}(t)$ and $h_f(t)$ depend on the turbine release making the equation implicit with respect to $R(t)$. Therefore, it has to be solved iteratively. Assume an initial end-of-month reservoir storage that yields the initial $R(t)$ from Equation (21). The new end-of-month reservoir storage is then determined from the mass balance equation as follows:

$$S(t+1) = S(t) + Q(t) - R(t) - Evp(t) - Spill(t) \quad (22)$$

$Evp(t)$ and $Spill(t)$ are evaporation and spill (mcm) in month t , respectively. The new end-of-month storage is compared with the one initially assumed. If they are not the same, the next estimation of the turbine release in Equation (21) is determined from the new end-of-month storage. The procedure is repeated to get the end-of-month storages and releases converged to the same values in two successive iterations. It should be noted that the end-of-month storage determined by Equation (22) is checked if it is within its acceptable range of $[S_{min} S_{max}]$. If it is above S_{max} , the turbine release and the energy generated will be increased (as secondary energy) so that the ending storage equals S_{max} . Of course, the excess turbine release and the generated energy are limited, respectively, by the power plant's hydraulic capacity and the maximum energy that can be generated according to the installation capacity estimated. If any of those limits are touched, the excess release is spilled, not contributing in energy generation. On the other hand if reservoir storage falls below the S_{min} , the end-of-month storage is set to S_{min} , and consequently the turbine release and the energy generated will be decreased. In this situation, the energy generated will be less than the estimated monthly energy yield, resulting in a failure in that month. This operating policy implies that the release in each time period is determined so that the energy generated equals the estimated energy yield, if possible. By repeating the above-mentioned procedure over the simulation horizon, one can estimate the energy-yield reliability as:

$$REL = \frac{\sum_{t=1}^T z(t)}{T} \quad (23)$$

where $z(t)$ is a binary variable equal to zero if the energy generated is less than the target energy yield and to one, otherwise and T is the number of monthly time steps. If the estimated reliability is within the desired range specified for target reliability ($TarREL - \delta \leq REL \leq TarREL + \delta$), the estimated production installed capacity (IC) and energy yield will be acceptable; otherwise, they will be increased or decreased accordingly. Then all of the steps explained above are repeated until the production capacity and energy yield values are converged and the reliability of

generation of the energy yield reaches the specified target value (TarREL). The converged values are in fact the maximum production capacity and energy yield values that can be achieved at the specified level of reliability (Mousavi & Shourian 2010). The workflow of the proposed method is shown in Figure 2.

Hydropower plant optimum design models

Hydropower reservoir design optimization is formulated in two forms of A1 and A2 models. In Model A1, the independent decision variables are the normal and the minimum water levels optimized by the search algorithms. The power plant installation capacity is the third design

variable that is dependent on other characteristics of the system and is calculated using the RBS process (Equation (19)). In Model A2, the power plant capacity is considered as a decision variable searched by the meta-heuristic algorithms. This means that by search-based generation of the normal and minimum water levels and the power plant capacity, the reservoir storage volume, the energy production and other dependent variables are calculated using the sequential stream flow routing (SSR) method with the objective function of maximizing the total energy production (Equation (20)). In this model, the constraint of satisfaction of the reliability to be equal to TarREL is added as a penalty term to the objective function.

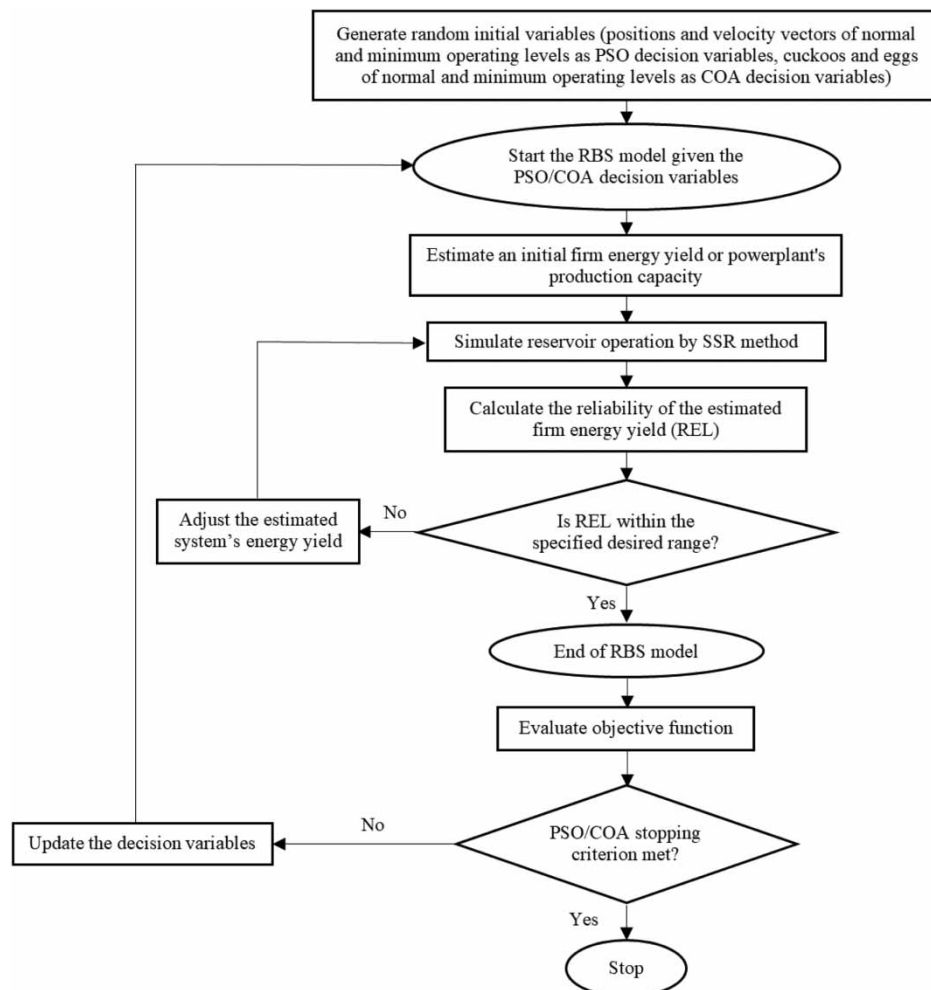


Figure 2 | Workflow of the simulation-optimization model used for hydropower plant design and operation.

Hydropower plant optimum design and operation models

In the design optimization models (Models A1 and A2), a standard operation policy is used in which the reservoir release is equal to the downstream demand at each time step and the energy is produced as the lateral purpose. In optimum design and operation models, instead of applying a standard operation policy, the monthly releases from the reservoir are also optimized by the search algorithms to maximize the energy production. Here also, two models of B1 and B2 are defined for optimum design and operation of the hydropower reservoir. In Model B1, a linear operation policy is used for the months of a year as follows:

$$R(t) = a_m \times I(t) + b_m \times S(t) + c_m$$

$$m = 1, \dots, 12; \quad t = 1 \dots, T \quad (24)$$

a_m , b_m , and c_m are the coefficients of the release rule in month m of a year to be optimized and T is the number of monthly time series of the operation period. Therefore, there are 39 decision variables in Model B1 searched by the optimization algorithm which are three design variables of the normal and minimum water levels and the power plant capacity, and 36 operation rule coefficients.

In Model B2, instead of applying a linear rule, the monthly releases over the 20-year reservoir simulation period are directly considered as the operational decision variables. Therefore, in this case, the optimization model searches for 243 decision variables (three design and 240 monthly releases operation variables) to be optimized by the applied metaheuristic algorithms.

In Table 1, the decision variables of the optimization models used in this study are briefly presented.

The objective function is to maximize the total energy production (Equation (20)) in all models. By trial-and-error, values of the parameters of COA and PSO algorithms are selected based on the best solutions obtained by the algorithms in the deterministic case. These values are given in Table 2. Due to the high time-consumption of execution of the models in the stochastic cases, these values are used by the algorithms in these cases too. Maximum iteration for both algorithms is 300 and they stop if

Table 1 | Decision variables of the hydropower plant optimization models

Model	Decision variable	Type
A1	Normal water level	Design
	Minimum operation level	Design
A2	Normal water level	Design
	Minimum operation level	Design
	Energy production capacity	Design
B1	Normal water level	Design
	Minimum operation level	Design
	Energy production capacity	Design
	36 parameters of a year linear release rules (Equation (24))	Operation
B2	Normal water level	Design
	Minimum operation level	Design
	Energy production capacity	Design
	240 reservoir monthly releases	Operation

Table 2 | Values of the parameters of COA and PSO algorithms

Algorithm	Parameter	Model			
		A1	A2	B1	B2
COA	Initial no. of cuckoos	5	10	20	30
	Min. no. of eggs	2	2	2	2
	Max. no. of eggs	4	4	6	4
	Max. no. of cuckoos	10	12	25	35
	Motion coefficient	9	9	12	10
	KNN cluster no.	1	1	2	1
PSO	No. of particles	10	15	50	100
	c_1	1.5	2	1.5	1.5
	c_2	1	1.5	1.5	1.2
	Constriction	0.9	0.9	0.9	0.9
	Max. inertia	0.8	0.8	0.8	0.8
	Min. inertia	0.3	0.3	0.3	0.3

there is no improvement in the best solution in 30 successive iterations.

Case study

The Bakhtiari Hydropower Reservoir is located on the Bakhtiari River in west of Iran which is one of the two main streams of the Dez River and originates from the Ghalikoo Mountains. Figure 3 shows the catchment area of the Bakhtiari River and location of the dam on the river. The main characteristics of the Bakhtiari hydropower plant are presented in Table 3.

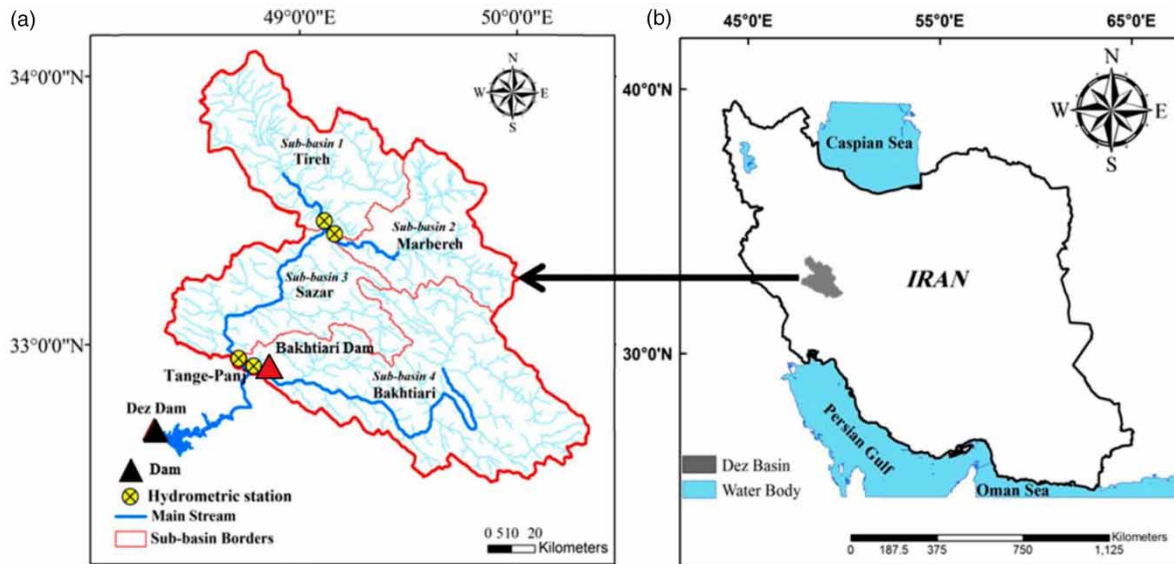


Figure 3 | Bakhtiari River basin and location of the Bakhtiari hydropower reservoir.

Table 3 | Characteristics of the Bakhtiari hydropower plant

Item	Value
Max. normal water level (masl)	830
Dead volume level (masl)	660
Tail water elevation (masl)	533.5
Head loss (m)	3
Plant efficiency	92%
Plant factor	0.25
Energy production target reliability (TarREL)	90%

The range of the normal water level for the Bakhtiari dam could vary between 770 and 830 meters above sea level (masl) (Mahab-Ghods Consulting Engineers 2002). A monthly time series for 20 years (1990–2010) is used as the reservoir inflow for the operation simulation. The series is considered as it contains drought and wet periods to include various hydrologic conditions for the reservoir operation. In Figure 4, historical time series of the inflow to the Bakhtiari reservoir is plotted.

RESULTS AND DISCUSSION

For generation of the synthetic time series to see the effect of uncertainty in the reservoir inflow on the optimum design

and operation of the hydropower plant, a normal distribution function is fitted on the monthly historical data. The next step in the eigenvector method is to create random time series using the historical series. Since the available time series is dependent, the required random series are obtained using the eigenvector method. In Figure 5, the generated time series for the reservoir inflow using the historical data and the eigenvector method are plotted.

To evaluate the sufficiency of the number of generated time series, the hydropower reservoir RBS procedure is executed with a pre-determined set of decision variables while increasing number of generated inflow time series and the mean capacity of the power plant is obtained for each number of time series as shown in Figure 6.

As seen in Figure 6, the mean installed power plant capacity converges to an approximately constant level with 80 time-series meaning that this variable is not affected significantly by further increase in the number of generated time-series. Therefore, with regard to the use of a large number of samples leading to a high runtime, it is decided to utilize 100 generated time series samples for the stochastic models.

By preparation of 100-inflow time series, four developed models of A1, A2, B1, and B2 are executed with

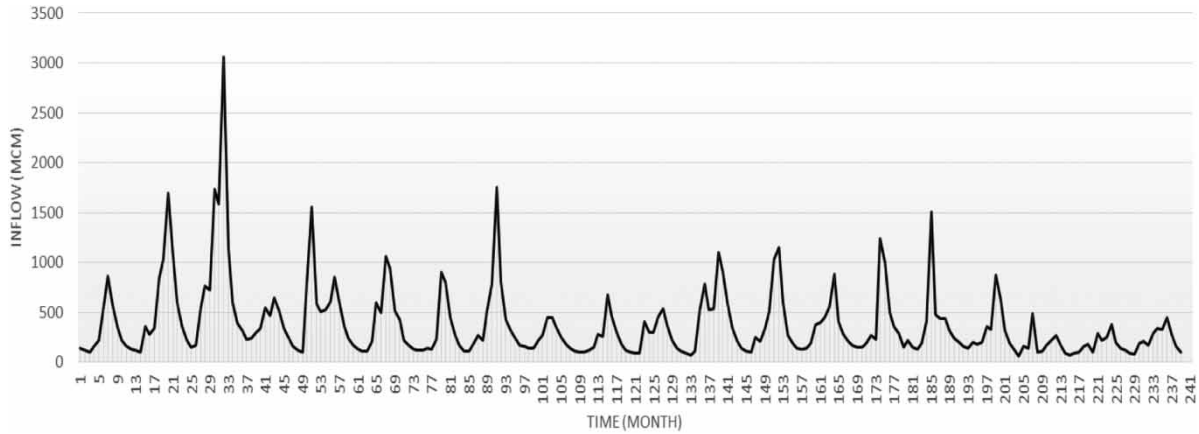


Figure 4 | Historical monthly time series of the inflow to the Bakhtiari reservoir.

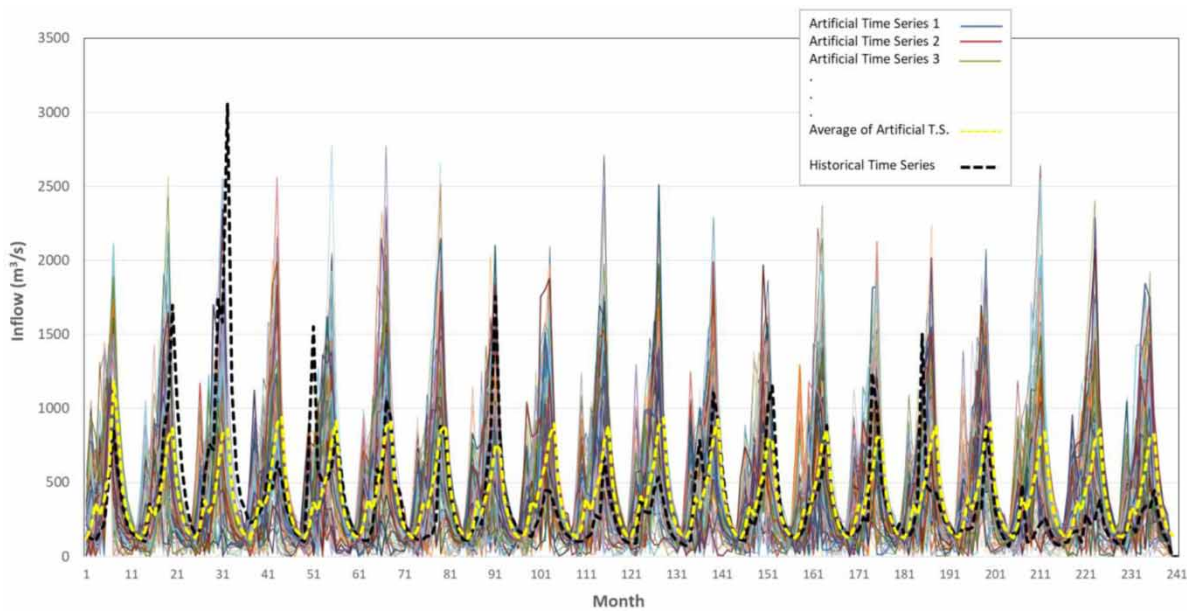


Figure 5 | Synthetic generated inflow time series using the eigenvector method.

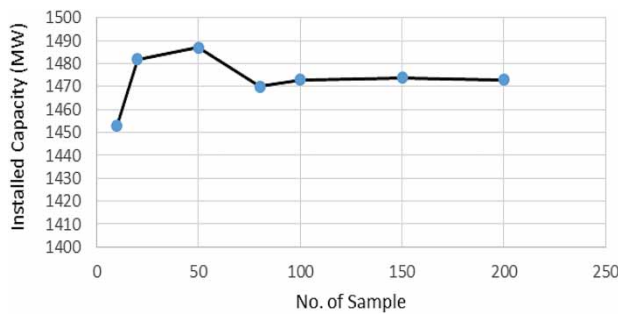


Figure 6 | Average power plant's maximum production capacity obtained versus number of generated inflow time series.

both deterministic and stochastic reservoir inflow time series. The execution procedure for the stochastic models is similar to the deterministic ones. However, in this case, for each individual or particle of the optimization algorithm, the reservoir simulation process is executed for each sample of the inflow time-series and eventually an average hydropower energy production over 100 simulation runs is calculated for the obtained decision variables to compute the individual's objective function value.

Deterministic approach results

The design and operation optimization models are executed with COA and PSO algorithms. Each model is executed ten times to assure the model's convergence and the best result is assessed. In the first stage, as the deterministic approach, the historical inflow time series is used as the input to the reservoir. To show the convergence ability of the COA and PSO algorithms, a box-plot of the optimum objective function values obtained in ten runs of the models is shown in Figure 7.

According to Figure 7, PSO shows more convergence ability compared to COA. In addition, the best value for the fitness function for each model obtained by PSO is a little higher than the COA's solution. Solutions obtained for Model B2 by both algorithms have a wider range of variation compared to Models A1, A2 and B1 because of a high number of decision variables, which makes it more difficult for the meta-heuristic algorithms to find the global optimum for the problem. The details of the best solution obtained by COA and PSO for the design and operation models of the Bakhtiari hydropower reservoir in the deterministic state are reported in Table 4.

By comparing the results obtained by COA, it is seen that the results of Models A1 and A2, which use the standard operation policy (SOP) for reservoir operation, are close in terms of the objective function and are among the good solutions for the problem, although in these models

the reservoir releases are not searched as the decision variables. Model A2 with three design decision variables has converged to the best net benefit while satisfying the desired reliability. In Model A2, the power plant capacity as well as the annual energy production is improved compared to Model A1. Model B1 with 39 decision variables has obtained the lowest net benefit among other models indicating that regression of a linear operation rule (Equation (24)) on the reservoir releases has not improved the reservoir efficiency and energy production. Model B2 with 243 decision variables also has found a solution worse than the optimum design models (A1 and A2) in terms of the objective function but it has found a better solution than Model B1. This is because of using a free policy for the reservoir operation in Model B2. For further investigation, the optimum result obtained by Model A2 was included as an initial solution in the first iteration of random generated solutions for Model B2 to see if it can progress the results or not and then Model B2 was executed. It was seen that Model B2-COA was not able to find a better solution obtained by Model A2-COA.

On the other hand, and as the results obtained by PSO, Model B2-PSO has converged to the best solution compared to the optimum design models and even this answer is the best of all. Also, it is seen that the results obtained by PSO are better than COA in terms of the net benefit. This indicates the higher capability of the PSO algorithm to deal with optimization problems with a high number of decision

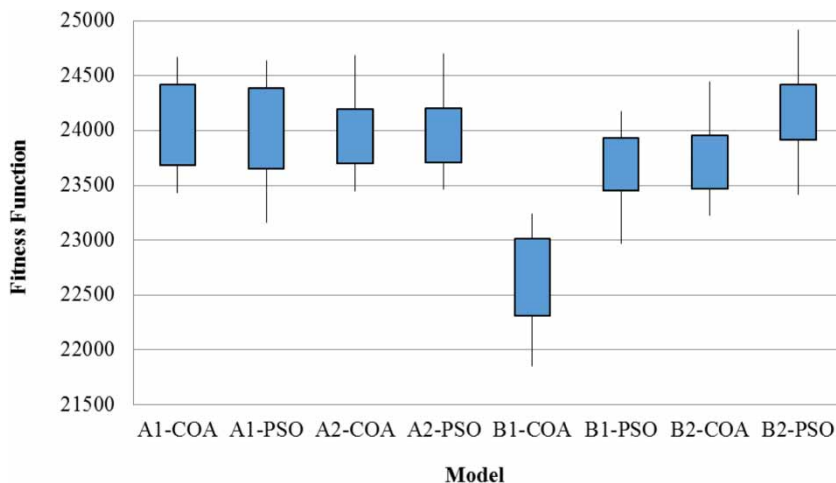
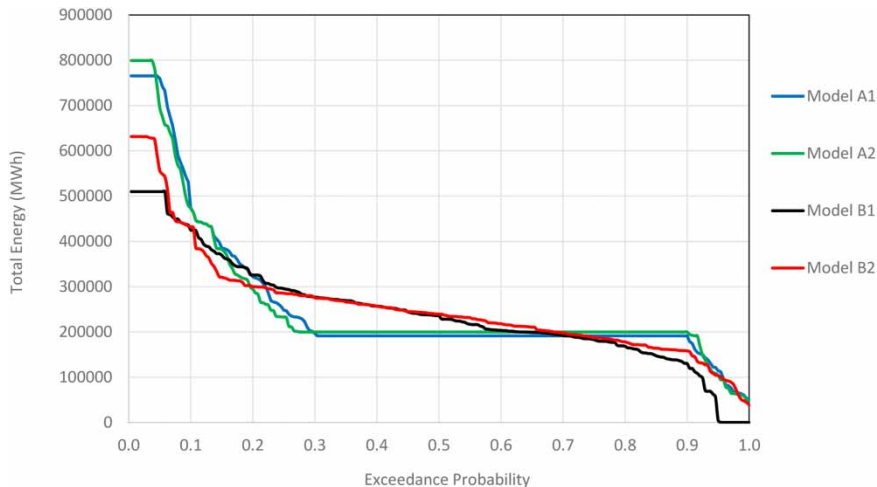


Figure 7 | Box-plot of the optimum objective function obtained in ten runs of models with deterministic inflow.

Table 4 | Details of the optimum solution obtained by models with deterministic historical inflow

Algorithm Model	COA				PSO			
	A1	A2	B1	B2	A1	A2	B1	B2
Net benefit (10^9 Rials)	24,669	24,685	23,243	24,446	24,635	24,699	24,177	24,915
Reliability of energy yield (%)	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Normal water level (masl)	830	830	828	830	830	830	830	830
Min. operating level (masl)	811	801	757	737	778	778	811	777
Power plant capacity (MW)	1,063	1,110	708	876	1,170	1,095	883	1,000
Annual total energy (10^6 MWh)	3.11	3.11	2.93	3.08	3.11	3.12	3.05	3.14
Annual firm energy (10^6 MWh)	2.16	2.34	1.45	1.88	2.49	2.33	1.79	2.13

**Figure 8** | Exceedance probability curve for energy production obtained by COA.

variables and complex search space. The reason for this issue could be the simpler and more efficient structure and computation in PSO compared to COA that enables this algorithm to explore more various regions in the search space of the problem resulting to find a better solution. Exceedance probability curves of energy production and reservoir releases obtained by four models using COA and PSO algorithms are presented in Figures 8–11.

According to the results obtained by COA in Figure 8, in 20% of the operation period, Models A1 and A2 have produced more energy than Models B1 and B2, which indicates fitness of the SOP used in these models as a proper policy for reservoir operation. In addition, in the range of 30–90% of the operation period, these models have produced a constant level of energy (200,000 MWh).

Model B1, with a yearly linear operation rule, has shown the worse performance among other models indicating that a linear rule does not fit a proper operation policy for the reservoir. Model A2-COA has generated more energy compared to the other models.

The results obtained by PSO for four models are closer to each other compared to the results obtained by COA, but the general scheme is the same as previous. Models A1 and A2 have found higher energy production here again. Model B2-PSO has resulted in the best objective function among other models, although Models A1 and A2 have generated more energy in some months of the operation period.

Optimum values obtained for the reservoir releases in Figures 10 and 11 follow the scheme of energy production.

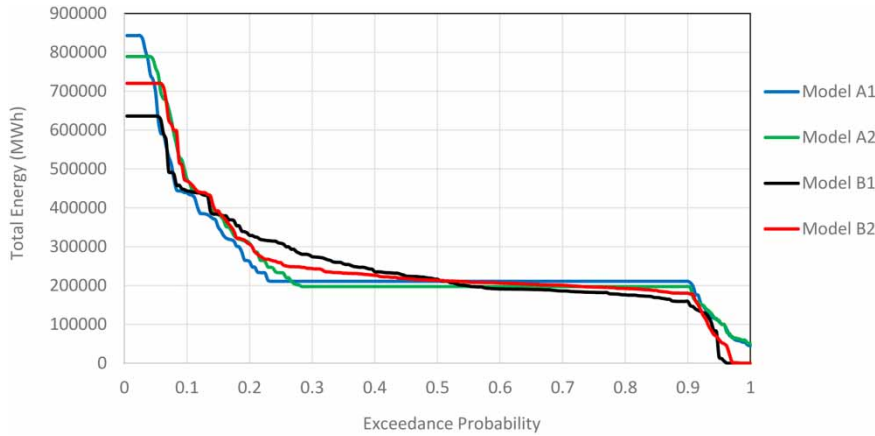


Figure 9 | Exceedance probability curve for energy production obtained by PSO.

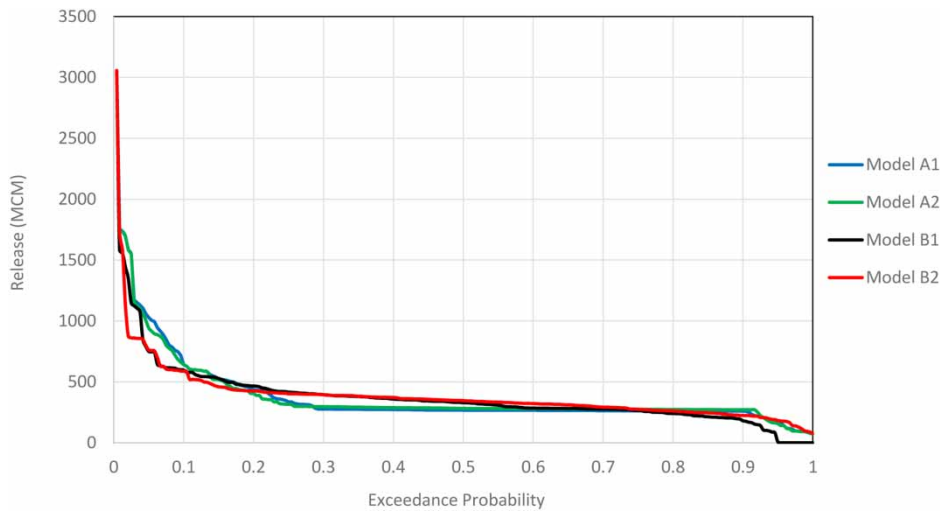


Figure 10 | Exceedance probability curve for reservoir release obtained by COA.

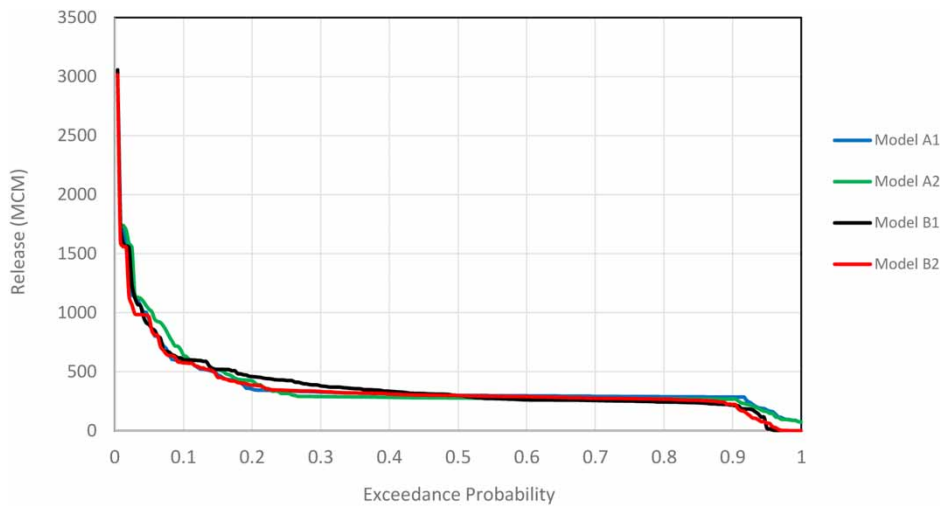


Figure 11 | Exceedance probability curve for reservoir release obtained by PSO.

Models A1 and A2 have resulted in higher releases than Models B1 and B2, while Model B2-PSO has found the best objective function among the other models.

Stochastic optimization approach results

To show the convergence ability of the COA and PSO algorithms in this state, a box-plot of the optimum objective function values obtained in ten runs of the models is shown in Figure 12.

Here again, PSO shows a little more convergence power compared to COA. Also, finding a same near optimal solution for Model B2 is much harder than the other cases. Details of the best solution obtained by COA and PSO for the Bakhtiari hydropower reservoir design and operation models in condition of stochastic inflows are presented in Table 5.

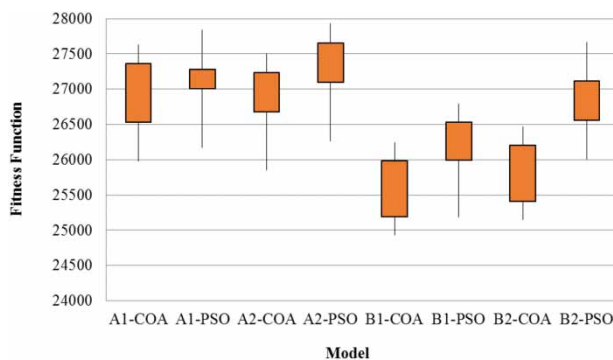


Figure 12 | Box-plot of the optimum objective function obtained in 10 runs of models with stochastic inflows.

According to Table 5, a higher value for the net benefit is obtained in conditions of using uncertain generated reservoir inflow time series instead of the historical data. In COA results, similar to the deterministic approach, the best objective function pertains to Model A2. Also this model using the PSO algorithm has found the best solution among all cases. The installation power plant capacity for four models has increased compared to the deterministic model results. The objective function value, the installed power plant capacity and consequently the produced energy are improved in the stochastic optimization approach.

Based on the results reported in Tables 4 and 5, in the deterministic approach, Model B2-PSO has converged to the best objective function. However, in the stochastic approach, this model has failed to reach the best result compared with the design models, which could be due to the narrow feasible solution domain and involvement of 240 operation variables in each execution of the model for each generated time series. For further investigation and to assess the improvement of the results of Model B2, by feeding the optimum solution obtained by Model A2 into Model B2 as an initial solution, it was observed that the model was not able to improve Model A2's results. Thus, it can be concluded that Model A2-PSO with three design decision variables and applying the standard operation policy for the reservoir releases has a good performance in dealing with the problem of optimum design and operation of a hydropower reservoir. For a general comparison, the optimum objective function values obtained by both

Table 5 | Details of the optimum plan obtained by models with stochastic generated inflows

Algorithm Model	COA				PSO			
	A1	A2	B1	B2	A1	A2	B1	B2
Net benefit (10^9 Rials)	27,636	27,506	26,244	26,473	27,840	27,936	26,796	27,671
Reliability of energy yield (%)	0.89	0.89	0.75	0.86	0.89	0.9	0.9	0.9
Normal water level (masl)	830	830	829	830	830	830	830	830
Min. operating level (masl)	802	799	777	806	814	807	803	800
Power plant capacity (MW)	1,459	1,472	1,173	982	1,278	1,395	955	837
Annual total energy (10^6 MWh)	3.47	3.46	3.46	3.39	3.50	3.49	3.47	3.35
Annual firm energy (10^6 MWh)	2.89	2.77	0.53	1.42	2.53	2.71	1.92	1.74

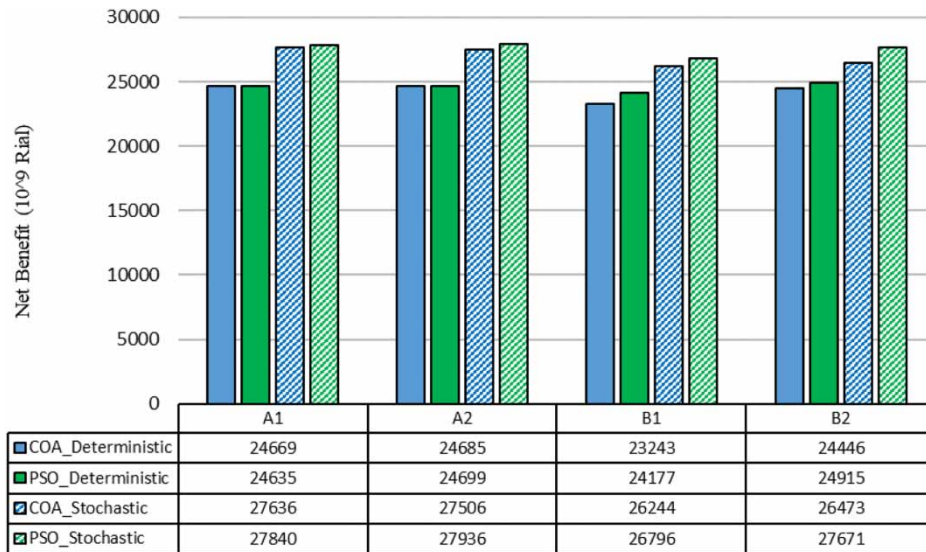


Figure 13 | Optimum objective function value obtained by COA and PSO algorithms in deterministic and stochastic models.

algorithms in deterministic and stochastic models are presented in Figure 13.

CONCLUSION

In this research, the cuckoo optimization algorithm and the particle swarm optimization are used to optimize the design and operation of hydropower reservoir in two approaches of using the historical inflow data and generated stochastic time series. The eigenvector sample generation method is used to produce probable reservoir inflows. A reliability-based simulation (RBS) is used for computation of the hydropower energy production. Four models are developed which, in the first two, the design variables are searched by the optimization algorithms and in the next two the operation variables are also added to the set of decision variables. Considering the uncertainty of the inflow to the reservoir, as an important factor, has been rarely seen in the optimum design and operation of the hydropower plants which is dealt with in the present research.

From the results, it can be concluded that the role of optimization of the operation variables is negligible and the standard operation policy used in Models A1 and A2 for determining the reservoir releases can lead to acceptable

good solutions compared to the results obtained by Models B1 and B2. The linear operation rule used by Model B1 could not be fitted effectively on the optimum reservoir releases. Also, the PSO algorithm showed a better efficiency compared to COA in dealing with problems with a narrow feasible solution domain and a complexity dependent search space. This could be due to the simpler and more efficient structure of PSO rather than COA. In the stochastic approach, the results were improved in terms of the objective function and the installed power plant capacity that directly affects the reliable energy production.

The main challenge of taking into account the uncertain inflow time series is the enormous increase in the computational time and cost, especially in the optimum design models that are based on iterative time-consuming RBS process. The COA algorithm consumes a longer runtime than the PSO algorithm due to its more complex structure where combination of this algorithm with the eigenvector-based generated time series increased the runtime of the models to several days. For future direction, applications of modified PSO and COA algorithms are suggested. In addition, using surrogate modeling (meta-models such as ANN) instead of the RBS process, which in turn decreases the computational cost and running time of the models, is recommended.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

- Afzali, R., Mousavi, S. J. & Ghaheri, A. 2008 Reliability-based simulation-optimization model for multireservoir hydropower systems operations: Khersan experience. *Water Resour. Plann. Manage.* **134** (1), 24–33.
- Bozorg-Haddad, O., Ashofteh, P. S., Rasoulzadeh-Gharibdousti, S. & Mariño, M. A. 2014 Optimization model for design-operation of pumped-storage and hydropower systems. *J. Energy Eng.* **140** (2), 04013016.
- Hatamkhani, A. & Alizadeh, H. 2018 Clean-development-mechanism-based optimal hydropower capacity design. *J. Hydroinf.* **20** (6), 1401–1418.
- Hatamkhani, A. & Moridi, A. 2019 Multi-objective optimization of hydropower and agricultural development at river basin scale. *Water Resour. Manage.* **33** (13), 4431–4450.
- Hatamkhani, A., Moridi, A. & Yazdi, J. 2020 A simulation-optimization models for multi-reservoir hydropower systems design at watershed scale. *Renew. Energy* **149**, 253–263.
- Hosseini-Moghari, M., Moravati, R., Moghadas, M. & Araghinejad, S. 2015 Optimum operation of reservoir using two evolutionary algorithms: imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA). *Water Resour. Manage.* **29**, 3749–3769.
- Jahandideh-Tehrani, M., Bozorg-Haddad, O. & Loáiciga, H. A. 2015 Hydropower reservoir management under climate change: the Karoon reservoir system. *Water Resour. Manage.* **29** (5), 749–770.
- Jothiprakash, V. & Arunkumar, R. 2013 Optimization of hydropower reservoir using evolutionary algorithm coupled with chaos. *Water Resour. Manage.* **27**, 1963–1979.
- Kennedy, J. & Eberhart, R. C. 1995 Particle swarm optimization. In *Joint Conference on Neural Networks*. IEEE Service Center, Piscataway, NJ, pp. 1942–1948.
- Li, F. & Qiu, J. 2015 Multi-objective reservoir optimization balancing energy generation and firm power. *Energies* **8** (7), 6962–6976.
- Mahab-Ghods Consulting Engineers 2002 *Economic Evaluation of the Bakhtiari Dam Project Report*. Mahab-Ghods, Tehran, Iran (in Persian).
- Mousavi, S. J. & Shourian, M. 2010 Capacity optimization of hydropower storage projects using particle swarm optimization algorithm. *J. Hydroinf.* **12** (3), 275–291.
- Rahi, O. P., Chandel, A. K. & Sharma, M. G. 2012 Optimization of hydro power plant design by particle swarm optimization (PSO). *Procedia Eng.* **30**, 418–425.
- Rajabioun, R. 2011 Cuckoo optimization algorithm. *Appl. Soft Comput.* **11**, 5508–5518.
- Shourian, M., Mousavi, S. J. & Tahershamsi, A. 2008 Basin-wide water resources planning by integrating PSO algorithm and MODSIM. *Water Resour. Manage.* **22**, 1347–1366.
- Soleimani, S. H., Bozorg-Haddad, O. & Hugo, A. 2016 Reservoir operation rules with uncertainties in reservoir inflow and agricultural demand derived with stochastic dynamic programming. *Irrig. Drain. Eng.* **142** (11), 04016046.
- Yazdi, J. 2013 *Optimization of Watershed-Scale Flood Control Systems Under Conditions of Flood Uncertainties*. PhD thesis, Tarbiat Modares University, Tehran, Iran (in Persian).
- Yazdi, J. & Moridi, A. 2018 Multi-objective differential evolution for design of cascade hydropower reservoir systems. *Water Resour. Manage.* **13** (14), 4779–4791.

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