Optimization of Hydropower Storage Projects Using Harmony Search Algorithm

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Abstract. This paper proposes a harmony search algorithm-based optimization of design and operation of hydropower storage systems. The optimization formulation of the problem is a nonconvex nonlinear program difficult to solve by gradient-based nonlinear programming techniques. The search space of the problem is large due to number of operational variables. Harmony search optimization algorithm is applied in the problem of design and operation optimization of Bakhtiari Dam and its powerplant project in Iran. The problem is solved in two cases of optimizing only design variables and optimizing design and operational variables, simultaneously, and the promising results obtained are presented.

Keywords: Optimization · Harmony search algorithm · Reservoir operation · Hydropower

1 Hydropower Reservoir Operation Optimization

Optimization is widely used in engineering design and operation problems. Gradient-based optimization approaches, including successive linear programming, quadratic programming, dynamic programming, dual dynamic programming, etc., have been widely used in hydropower systems operation optimization (Kim and Palmer 1997; Barros et al. 2003; Yeh et al. 1979; Grygier and Stedinger 1985; Diaz and Fontane 1989; Mousavi et al. 2004). To estimate design parameters of a hydropower reservoir system, i.e. reservoir capacities, powerplant production capacity and the reservoir's minimum option level, for any combinations of these design parameters, the reservoir system operation needs to be simulated over a representative hydrologic period using sequential the streamflow routing (SSR) method (Afzali et al. 2007). To do so, the release volume from the reservoir must be determined in each time step of the simulation model through either an operating policy (design optimization problem) or an optimization scheme (design-operation, DO, optimization problem). The end-of-month storage is then calculated using mass balance equation, and the process

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continues until the last time step of the simulation. This paper shows how to solve design and DO optimization of hydropower storage systems by using harmony search algorithm as a metaheuristic optimization scheme.

2 Harmony Search Algorithm

Harmony search algorithm (HSA), developed by Geem et al. (2001), is derived from the concepts of musical improvisations and harmony knowledge, and is a widely used metaheuristic algorithm. The HSA and its improved variants have proved its advantages over other optimizers (Kim et al. 2001; Vasebi et al. 2007; Mahdavi et al. 2007; Chakraborty et al. 2009; Gao et al. 2009; Geem and Sim 2010). Recently, HS has been applied to various research areas and obtained considerable attention in different disciplines (Yoo et al. 2014). The HS intellectualizes the musical process of searching for a perfect state of harmony (Geem et al. 2001). Musicians seek a fantastic harmony determined by aesthetic estimation. Similarly, optimization techniques seek a best state (global optimum) determined by an objective function 47 value. Aesthetic estimation depends on the set of the sounds played by a musical ensemble, whereas the objective function is evaluated by a set of adjustable variables. More aesthetic sounds can be produced by constant practice, and the optimization of the objective function can generally be improved by repeated iterations. Further details of HS can be found in the work of Geem et al. (2001) and Kim et al. (2001). We use HSA in the real-world problem of optimal operation of Bakhtiari Dam hydropower project in Iran, and show the promising results obtained are presented.

3 Optimizing Hydropower Systems Design and Operation

Optimal selection of design variables such as normal and minimum reservoir operating levels as well as the powerplant production capacity is important in hydropower storage projects. The energy potential of the project for any possible combinations of the design variables is under hydrologic variability of inflows to the reservoir. This requires the analysis of the system performance over a long representative hydrologic period in order to assess the expected costs and benefits resulted from the project's construction and operations for those combinations as the candidate solutions. Since there are many alternatives for the values of the design variables to choose from, their best values resulting in the highest expected net benefit, can be determined by using an optimization model. On the other hand, as the model solution is under hydrologic uncertainty, the energy yield of the system may be assumed as a random variable with a certain probability to be realized. In this case, designer may like to have the model's solution at different levels of reliability of meeting the system's energy yield In other words, they like to formulate an optimization model in which the reliability of the meeting the energy yield can be specified by the designer. The general formulation of the optimization model for this purpose may be written as follows (Mousavi and Shourian 2010):

$$Min\ \mathrm{Cost}_{total}^{1} = CRF \times (DC + PC + PeC) - fvalue \times nyear \times \sum_{t=1}^{12} FE - svalue \times \sum_{t=1}^{T} SE(t) + \sum_{t=1}^{T} Spill(t) \quad (1)$$

S.t:

$$DC = d_1 \times S_{\max}^2 + d_2 \times S_{\max} + d_3 \times z_1 \quad (2)$$

$$DC \le BigM \times z_1 \quad (3)$$

$$PC = p_1 \times Pcap^2 + p_2 \times Pcap + p_3 \times z_2 \quad (4)$$

$$PC \le BigM \times z_2 \quad (5)$$

$$S(t+1) = S(t) + Q(t) - R(t) - Spill(t) - L(t) \quad \forall t \quad (6)$$

$$E(t) = 2.73 \times R(t) \times (0.5 \times (h(t) + h(t+1)) - h_{tail}(t) - h_f(t)) \times e_p(t) \quad \forall t \quad (7)$$

$$h(t) = k_1 \times S(t)^3 + k_2 \times S(t)^2 + k_3 \times S(t) + k_4 \quad \forall t \quad (8)$$

$$h_{tail}(t) = k_5 \times (R(t) + Spill(t))^2 + k_6 \times (R(t) + Spill(t)) + k_7 \quad \forall t \quad (9)$$

$$FE = Pcap \times pf \times nhours \quad \forall t \quad (10)$$

$$E(t) \ge FE \times z(t) \quad \forall t \quad (11)$$

$$\frac{\sum_{t=1}^{T} z(t)}{T} \ge TarREL \quad \forall t \quad (12)$$

$$SE(t) = (E(t) - FE) \times z(t) \quad \forall t \quad (13)$$

$$E(t) \le E\max = Pcap \times nhours \quad \forall t \quad (14)$$

$$S_{\min} \le S(t) \le S_{\max} \quad \forall t \quad (15)$$

$$R_{\min} \le R(t) \le R_{\max} \quad \forall t \quad (16)$$

The objective function of the above program is minimizing the total cost, $Cost_{total}^{1}$, (or to maximize the total net benefit) which includes the capital and variable costs of dam, *DC*, powerplant, *PC*, and tunnel, *PeC,* constructions and operations deducted by the benefits resulting from firm and secondary energies sale. $CRF = \frac{(1+r)^{nyear}-1}{(1+r)^{nyear}-1}$ is the capital recovery factor converting the present value costs to their equivalent uniform annual costs and *r* is the annual discount rate of money. *FE is* the monthly firm energy yield of the system that can be produced in adverse hydrologic conditions at a certain level of reliability. Although the firm energy can be a seasonal variable depending on each calendar month m in general, we define it as an amount of monthly energy that is produced reliably at least $TarREL\%$ of total months $T = m \times nyear$ over a planning horizon with *nyear* years. $SE(t)$ is the secondary energy in period (month) t which is the energy produced in excess of the firm energy and *fvalue* and *svalue* are respectively the firm and secondary energy unit sales. *PeC* is the fixed cost of the penstock which does not affect the solution as it is assumed to be a constant value herein.

In above formulation, z_1 and z_2 are binary variables accounting for fixed cost of dam and powerplant constructions, respectively; $z(t)$ are binary variables which are equal to zero if the energy generated is less than the target energy yield and to one, otherwise. The constraint on meeting the energy yield at target reliability level (*TarREL*) is satisfied through defining these binary variables. d_1 to d_3 and p_1 to p_3 are constants determined by fitting the best quadratic curves to the cost functions of dam and powerplant constructions, respectively; k_1 to k_4 and k_5 to k_7 are respectively the constants of elevation-storage and tailwater-discharge equations; *BigM* is a positive big number; $S(t)$ is the beginning-of-month reservoir storage, $Q(t)$ is the inflow to reservoir, $R(t)$ is the turbine release, $Spill(t)$ is the spilled release, and $L(t)$ is the net evaporation and seepage losses all in period t; *Pcap* is the powerplant production capacity and *pf* is the specified plant factor that defines the number of hours per day in which the powerplant is operating at its production capacity; $nhours = 720$ is the number of hours per month; $E(t)$ is the energy generated, $e_p(t)$ is the powerplant efficiency, $h(t)$ is the beginning-of-month reservoir level, $h_{tail}(t)$ is the tailwater level and $h_f(t)$ is the total minor and frictional losses in conveyance structures all in month t; $S_{\min}$ and $S_{\max}$ are respectively the minimum and maximum storage volumes of the reservoir; and $R_{\min}$ and $R_{\max}$ are the minimum and maximum turbine release volumes, respectively. Note that the last term in the objective function is defined to ensure that spillage may occur only if necessary and when $S(t) = S_{max}$.

In practical hydropower storage systems, a reliability-based reservoir simulation (RBS) model is commonly employed for a limited number of design variables combinations rather than using an optimization scheme. In the following, the single-reservoir RBS model is presented first and then it is explained how it will be linked with the HS algorithm for solving the problem of optimal design and operation of hydropower systems as defined by Eqs. (1)–(16).

3.1 Reservoir Operation Simulation Model

Assume a hydropower single-reservoir system with the given normal and minimum reservoir operating levels and a specified plant factor. Then, a reliability-based reservoir simulation model may be used to determine the maximum system's firm energy yield as follows (Afzali et al. 2007):

An initial production capacity may be estimated by the following equation:

$$Pcap = \frac{2.73 \times Q_{ave} \times h_{\max} \times \alpha}{pf \times nhours} \tag{17}$$

where $Pcap$ is the estimated production capacity, Q_{ave} is the mean monthly inflow to the reservoir, h_{max} is an initial estimation for maximum net head on turbines as the difference between the normal and tailwater levels, α is a decreasing factor considering the effect of dry periods ($0.5 < \alpha < 1$). *pf* and *nhours(t)* are defined previously.

Given the estimated production capacity (*Pcap*) and the specified plant factor (*pf*), the system's firm energy yield as $FE = Pcap \times nhours \times pf$ is estimated as defined in Eq. (10).

The reservoir system operation is simulated over a representative hydrologic period using sequential streamflow routing (SSR) method to estimate the energy-yield reliability. In each time period *t* of the simulation model, the energy generated, *E(t),* is set to be equal to the estimated firm energy yield, *FE:*

$$2.73 * R(t) \times (0.5 \times (ht) + h(t+1)) - h_{tail}(t) - h_f(t)) \times e_p(t) = FE \\ = Pcap \times nhours \times pf$$

Then, the turbine release in that period can be determined as:

$$R(t) = \frac{Pcap \times nhours \times pf}{2.73 * (0.5 * (h(t) + h(t+1)) - h_{tail}(t) - h_f(t)) * e_p(t)} \tag{18}$$

In Eq. (18), *h(t + 1)*, $h_{tail}(t)$ and $h_f(t)$ depend on the turbine release making the equation implicit with respect to *R(t)*. Therefore, Eq. (18) is solved in each time period *t* iteratively (see Afzali et al. (2007) for details). Taking on the final end-of-month storage as the beginning-of-month storage of the next time period, the procedure continues up to the final period of the planning horizon. Subsequently, the energy-yield reliability is determined by counting the number of failure months in which firm energy yield has not been met. Subsequently, the production capacity is adjusted according to the three following cases. If the determined reliability is within the desired range specified for target reliability ($TarREL - \delta \leq REL \leq TarREL + \delta$), the estimated production capacity and energy yield are acceptable; otherwise, they increase ($TarREL + \delta \leq REL$) or decrease ($REL \leq TarREL - \delta$). All of the steps explained are repeated until the production capacity and energy yield values converge, and the reliability of meeting the energy yield arrives at its specified target value.

The RBS model may be repeated for different normal and minimum operating levels. Subsequently, an economic analysis can be used to choose the final normal and minimum operating levels of the reservoir, powerplant production capacity and other design and operational variables. However, such trial and error-based approach may not arrive at the best possible solution. It is, therefore, desired to employ the optimization model defined by Eqs. (1)–(16) to determine the optimal design configuration of the system. In order to solve this NP-hard optimization model, we will combine the HSA, as the optimizer module, and the reliability-based reservoir simulation (RBS) model as the simulator.

The problem is solved in two cases. In the first one, only the design variables are optimized, whereas the second case is about optimizing both design and operational variables.

3.2 Design Optimization Problem (Model A)

The aim in this problem is to find the best values of design parameters of the system maximizing the net benefit resulting from construction and operations of a hydropower system where the system operates based on a specified operating policy, which was explained in reservoir operation simulation module. The decision variables are the reservoir normal water level, corresponding to a specific height of the dam), the minimum reservoir operating level and the production capacity. The production capacity is found so that the maximum system's firm energy yield results at the specified level of reliability, *TarREL*. For any pairs of reservoir's normal and minimum water levels, the maximum achievable system's firm energy yield (powerplant production capacity) is determined as follow:

In this model the normal and minimum operating levels are searched for by HSA, and the reliability constraint on the energy yield is met using a penalty term in the objective function. In other words, the production capacity in model A is considered as a random-based search variable varying by HSA. The reservoir simulation model with a known operating policy, in which releases from the reservoir are determined by Eq. (18), is employed any candidate sets of design (decision) variables generated by HSA. The outputs of reservoir simulation model are the reliability level, annual firm and secondary energies associated with any candidate sets of these decision variables. A penalty term penalizing the deviation of the resulted reliability from the target one is added to the objective function as follows:

$$Cost^2_{total} = Cost^1_{total} + (|REL - TarREL|) * P \tag{19}$$

where $Cost^2_{total}$ is the total cost in model A, $Cost^1_{total}$ is as defined previously, *REL* is the level of reliability resulted from simulating the reservoir operation, *TarREL* is the target or desired reliability level, and *P* is a penalty factor that should be fine-tuned by a trial and error procedure. The penalty factor should not be very large to avoid premature convergence of the algorithm, and it should not be too small, resulting in a solution not satisfying the reliability constraint. In model A, the reservoir simulation model is the RBS model. However, adjusting (increasing or decreasing) the production capacity is not performed by the search procedure explained before; it is rather conducted by the HAS using the penalty approach.

3.3 Design-Operation Optimization Problem (Model B)

For the case of design-operation (DO) optimization, the operating policy is not specified a priori, but it is optimized by defining release rules whose parameters are considered as decision variables of the HS algorithm, in addition to the design variables considered before. In this model releases from the reservoir, *R(t)*, are also considered as the HSA decision variables. Therefore in our case study with a 41-years simulation horizon and 3 design variables, the optimization problem will include 495 decision variables, of which 492 variables are operational variables. This requires that special attention be given to generation of feasible solutions at early stages of the stochastic search algorithm.

4 Results

The case study of the paper is Bakhtiari Dam to be built on the Bakhtiari River in west of Iran. Tables 1 and 2 present input values to the models, i.e. basic characteristics of the system and the topographic data of Bakhtiari dam. Cost values for different dam and powerplant capacities are presented in Table 3. Firm and secondary energy unit sales, i.e. *fvalue* and *svalue*, are set to $160 * 10^{-4}$ monetary units per Mwh (Mousavi and Shourian 2010).

Table 1. Basic characteristics of Bakhtiari Dam and its powerplant

Maximum normal water level	830 Masl
Minimum water level	660 Masl
Tailwater elevation	533.5 Masl
Generator efficiency	92.12%
Head loss	3 M
Plant factor	0.25
Target reliability	90%

Table 2. Elevation-capacity relation at dam site

Elevation (Masl)	Capacity (MCM)
532	0
550	0.01
575	0.02
592	0.03
593	1.014
600	4.32
625	23.62
650	97
675	241.28
700	481.52
725	847.73
750	1371.57
775	2084.12
800	3031.3
825	4269
830	4582.37

Optimum values of objective function, design variables, average annual firm and secondary energies and the reliability levels obtained are presented in Table 4. Figure 1 shows the variation of the models' objective function against different iterations of the HSA. Model B outperforms model A in terms of objective function value. The difference, however, between the best objective function value of model B and that of model A is not significant. Although operational variables are optimized in model B, and its search space (495-dimensional) is much larger than that of model A (3-dimensional), model A has arrived at an objective value close to that of model B. Results presented are in good agreement with those obtained by particle swarm optimization (PSO) for the same problem reported in Mousavi and Shourian (2010).

Table 3. Cost of dam and powerplant construction for various capacities

Capacity (MCM)	Cost (monetary unit)	Installed capacity (MW)	Cost (monetary unit)
1941.61	781.44	913	152.45
2652.43	897.52	1014	162.40
3526.38	1016.07	1110	173.25
4587.37	1139.20	1220	189.30
4590.00	5500.00	1500	225.00

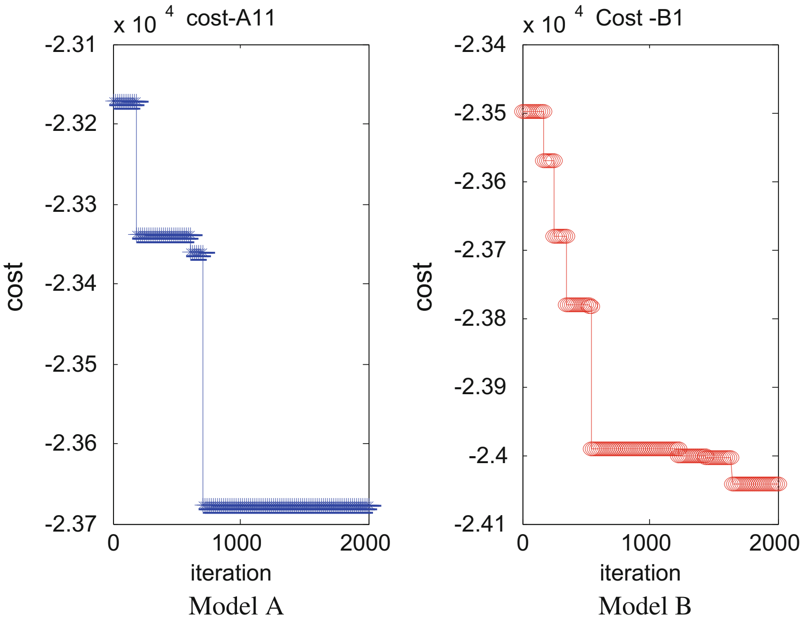

Fig. 1. Convergence curve of the objective function in HSA

Table 4. Optimal values of objective function, reliability and design variables resulted by the models

Item	Model A	Model B
Total cost	−23500.74	−24041.67
Reliability of meeting the energy demand (%)	90.85	91.26
Normal water level (Masl)	825.3	829.86
Min. operation level (Masl)	798.06	811.08
Powerplant production capacity (MW)	1194.3	1175.4
Annual firm energy generated (MWh)	2.5796×10^6	2.5389×10^6
Annual secondary energy generated (MWh)	3.112×10^6	3.183×10^6

5 Summary and Conclusions

The formulation of the problem of optimum design and operation of a hydropower reservoir system with a reliability constraint on meeting the energy yield is a non-convex MINLP. Therefore, we used harmony search algorithm (HSA) to solve this NP-hard problem. The objective function is to maximize the total net benefit resulted from design (constructing) and operation of the system over its life period. The problem was solved in two cases. In the first one, optimum design of Bakhtiyari hydropower system was considered, in which the decision variables were the normal and minimum operating levels of the reservoir as well as production capacity of the powerplant (model A). In the second case (model B), simultaneous optimization of design and operation variables of the system was carried out using HSA. In model B, the release decision variables were generated randomly in an incremental way at the first iteration of HSA so that a feasible solution can be obtained. HSA performed satisfactorily for both design and design-operation problems although model B was slightly better than model A.

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