**MODELING AND ANALYSIS**

**Multiobjective optimization for hydro-photovoltaic hybrid power system considering both energy generation and energy consumption**

Fang-Fang Li\(^1,2,3\), Jun Qiu\(^2\) & Jia-Hua Wei\(^2,3\)

\(^1\)College of Water Resources & Civil Engineering, China Agricultural University, 100083, Beijing, China
\(^2\)State Key Laboratory of Hydrosience & Engineering, Department of Hydraulic Engineering, Tsinghua University, 100084, Beijing, China
\(^3\)State Key Laboratory of Plateau Ecology and Agriculture, Qinghai University, 810016, Xining, China

**Keywords**
Energy consumption, energy generation, hydro-photovoltaic hybrid system, multiobjective optimization, NSGA-II

**Abstract**

Hydropower can be an ideal compensation for fluctuant photovoltaic (PV) power due to its flexibility. In this study, a multiobjective optimization model considering energy generation and consumption simultaneously for a hydro-PV hybrid power system is proposed. With the daily mean radiation intensity and temperature, the PV power output is calculated. Taking reservoir release as the decision variable, the total energy generation of the hydro-PV system is maximized. Meanwhile, the gap between the energy generation and the energy consumption is minimized to reduce the abandoned PV power or hydropower. The proposed multiobjective model is optimized by Non-dominated Sorting Genetic Algorithms-II (NSGA-II). The Longyangxia Project, the largest hydro-photovoltaic hybrid power system in the world is taken as the study case to estimate the optimal operational strategies for different objectives in wet year, normal year, and dry year, respectively. The optimal operation process of the reservoir is presented, which is instructive for the operation in the future.

**Introduction**

Solar energy is the most abundant and widely distributed renewable energy resource on the earth, having a prospect of wide development and utilization. With the technology progress and the cost reduction, solar energy has attracted more and more attention all over the world.

The annual solar radiation on 2/3 of China’s territory is over 5000 MJ/m\(^2\), and the annual solar energy absorbed by the surface is equivalent to 170 billion tons of standard coal energy \([1]\). The latest data from National Energy Administration of China shows that by the end of 2016, the cumulative installed Photovoltaic (PV) capacity had exceeded 77 GW, ranking the first in the world. Its annual power generation was 66.2 billion kWh, taking up 1% of the total amount of national electric energy production \([2]\).

PV output is affected by solar radiation and temperature with obvious diurnal and seasonal cycles. In addition, affected by weather variations, PV output has strong intermittency. With the increasing proportion of the PV power in the power grid, the impact of PV power generation on the planning, security, scheduling, and control of the power...
system becomes more and more notable [3]. The power supply system needs to have enough reserve capacity and adjustment measures to mitigate such impact. Therefore, it is necessary to seek effective means to reduce the impact of PV power fluctuations on the operation of power grid.

As another important energy sources, hydropower has fast regulation ability, and often plays a role of peak regulation, frequency modulation, and emergency standby in the power system. Such characteristics can be used to compensate the PV power output fluctuation to provide high-quality electric energy for power grid.

The first 10 MW-level hydro-PV complementary power station in the world was built in 2009 in Yushu of Qinghai province in China [4]. In 2015, the Longyangxia project, which is the world’s largest hydro-PV power plant was completed and put into operation in Qinghai project with the total PV installed capacity of 850 MW [5].

There have been some researches and attempts on hydro-PV hybrid power systems, including its plan, design, construction, and control. Wu et al. analyzed the operation characteristics of small hydro/photovoltaic power system, and proposed a novel control strategy [6]. Meshram et al. simulated and modeled standalone DC linked hydro/PV/battery hybrid energy system and power management strategy for identifying the active power sharing [7]. Kenfack et al. simulated and sized a microhydro-PV-hybrid system for rural electrification [8]. Bekele et al. and Nfah et al. studied feasibility of small-scale Hydro/PV/Wind based hybrid electric supply system for off-grid rural electrification in Ethiopia [9] and pico-hydro/PV hybrid power system for remote villages in Cameroon [10], respectively. Besides these researches concentrating on the control techniques of small-scale, off-grid hydro/PV hybrid systems, studies on optimizing or evaluating the operation of the hybrid Renewable Energy Systems (RES) were also carried on. Beluco et al. evaluated of the use of water reservoirs and battery banks as alternatives for energy storage within a hybrid hydro-PV system, and proposed the concept of a theoretical performance limit for the plants and propose a method for the determination of this performance limit using computer simulations with idealized energy availability functions [11]. Patsialis et al. demonstrated that hydropower can provide additional flexibility to the local system and through reservoir operation to allow the connection of additional solar photovoltaic capacities [12]. François et al. analyzed the complementarity of solar power and run-of-the-river hydropower across different temporal scales using two indicators: the standard deviation of the energy balance and the theoretical storage required for balancing generation and load, and demonstrated that at small temporal scale (hourly), a high share of run-of-the-river power allows minimizing the energy balance variability [13]. Schmidt et al. concluded that the existing reservoirs of hydropower in Brazil are sufficient to balance variations in renewable electricity supply at an optimal mix of around 37% of PV, 9% of wind, and 50% of hydropower generation [14]. Kougiou et al. optimized the installation characteristics of the solar PV system to improve the total energy production of a hybrid solar PV and small hydropower system [15].

In this study, we attempt to take the energy generation and consumption of the hybrid hydro-PV system into account simultaneously, and a multiobjective optimization model maximizing energy generation and minimizing the gap between the energy production and consumption energy for a hydro-PV hybrid power system is proposed. Taking reservoir release as the decision variable, and considering the multiannual means of daily radiation and temperature, the total amount of annual energy generation of the hydro-PV system is maximized; meanwhile, the gap between energy generation and consumption is minimized. The proposed multiobjective model is optimized by NSGA-II. The optimal operational strategies in different hydrologic years for the Longyangxia Project are estimated. Not only the trade-off relationships between the two objectives are presented, but also the corresponding operational strategies are analyzed, which is instructive for the operation in the future.

**Methodology**

**PV power output model**

Using the dual-axis tracking device and the Maximum Power Point Tracking (MPPT) technique, the output of the PV array is only affected by the solar radiation intensity and environmental temperature, where temperature is a parameter of the efficiency of the solar PV modules in equation (13). The output voltage at the maximum power point can be approximately considered to be constant. Hence, the basic output model of PV power generation system obtained by National Renewable Energy Laboratory (NREL) [16] is:

$$P_{PV} = P_{PV}^c \left( \frac{R_g}{R_{STC}} \right) \left[1 + \alpha_p(T_C - T_{STC})\right],$$  \hspace{1cm} (1)

where $P_{PV}$ and $P_{PV}^c$ are the actual and the rated power output, respectively; $R_g$ is the irradiation on the device surface; $R_{STC}$ represents the solar radiation intensity under the standard test conditions, equivalent to 1000 W/m²; $\alpha_p$ is the temperature coefficients of power output of the solar cell module, which is $-0.35%/^\circ C$ in this study; $T_C$ is the actual temperature of the module, and $T_{STC}$ is the
temperature under the standard test conditions, equivalent to 25°C.

**Hydropower output model**

**Calculation of hydropower output**

Hydropower station is a comprehensive engineering facility that converts water power into electrical energy. Hydropower station buildings concentrates water head of natural flow, and transports the water flow to the turbine. The water turbine and generator converts the concentrated hydro energy to electrical energy, which is then transmitted into power grid through transformer, switch station, and transmission lines. The basic calculation formula of hydropower is shown in equation (2).

\[
P_H = KQ_{out} \Delta H
\]

where \(P_H\) is the power output of the hydropower station; \(K\) is the synthetic output coefficient of the power station, whereas \(Q_{out}\) is the discharge flow of the reservoir, and \(\Delta H\) is the net water head of the power station, which is calculated by equation (3).

\[
\Delta H = L - T
\]

where \(L\) the reservoir water level, and \(T\) is the tailwater elevation.

The calculation of hydropower output in equation (2) involves multiple operational state equations representing the hydraulic and electric conditions and connections, mainly includes:

**Water balance equations**

Water balance equations shown in equation (4) imply the hydraulic relations between neighboring time steps:

\[
S^{t+1} = S^t + Q_{in}^t \times \Delta t - Q_{out}^t \times \Delta t,
\]

where \(t\) is time index; \(S\) is the storage volume in reservoir; \(Q_{in}\) is the inflow, and \(\Delta t\) is the length of the time period.

**Water level-storage curves of the reservoir**

A nonlinear function \(f(x)\) is adopted to express the relationship between storage \(S\) and water level \(L\) according to the reservoir characteristic database:

\[
S = f(L) \cup L = f^{-1}(S)
\]

**Tailwater elevation curves at reservoirs**

Tailwater elevation \(T\) relates to the reservoir discharge, which can be calculated based on discharge-elevation curve \(g(x)\), as shown in equation (6):

\[
T = g(Q_{out})
\]

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Figure 1. Schematic diagram of a PV-hydro hybrid power system.
Optimization model for Hydro-PV hybrid power system

Objective function

Hydro-PV projects often rely on existing hydropower stations, and the new photovoltaic power plants is added into the system as the expansive capacity, as shown in Figure 1. Energy production and energy consumption are the key issues to be considered in power systems, which may be contradictory. In this study, maximizing the annual energy generation is set as the optimization objective $Z_1$, as in equation (7). Another objective $Z_2$ in equation (8) is related to energy consumption, which aims at minimizing the gap between the energy production and energy consumption for the given system. The energy generation is composed of hydropower and PV power, resulting from equations (1) and (2). The average daily solar radiation intensity and temperature is used to calculate the hydropower output scenarios in equation (1).

$$Z_1 = \text{Max } E(Q_{\text{out}} | R_t, T_c) = \text{Max } \sum_{t=1}^{N} [P_{Ht}(Q_{\text{out}} | Q_{\text{in}}) + P_{PV}(R_t, T_c)] \times \Delta t, \quad (7)$$

$$Z_2 = \text{Min } \sum_{t=1}^{N} [(P_{Ht}(Q_{\text{out}} | Q_{\text{in}}) + P_{PV}(R_t, T_c) - D)], \quad (8)$$

where $E$ is the total generated energy, $D$ is the energy consumption.

Decision variables

It can be seen from equations (7) and (8) that the only controllable variable in the hydro-PV power system is the reservoir release, which determines the power generation of the hydropower station and thus affects the benefits of the hybrid system. Hence, the reservoir release $Q_{\text{out}}'$ is selected as the decision variable $u$ in the optimization model, as shown in equation (9).

$$u = \{Q_{\text{out}}'\} \quad (9)$$

Taking 1 month as the time step, there are 12 decision variables for the annual optimization model. To improve the calculation efficiency, the reservoir release in the typical hydrological years deriving from frequency curve $Q_{\text{actual}}'$ is used as the reference to construct the initial solution space. A certain percentage of the actual discharge $\delta$ is added to the outflow trajectory to form a band of discharge, in which the candidate initial solutions are generated randomly, as shown in equation (10):

$$[Q_{\text{actual}} \times (1-\delta)] \leq Q_{\text{out}}' \leq [Q_{\text{actual}} \times (1+\delta)] \quad (10)$$

Constraints

Most scheduling requirements of a reservoir such as flood control, ice prevention, water supply, etc., can be realized by the control of water level and release, as shown in equations (11) and (12):

$$L_{\text{min}}' \leq L_t' \leq L_{\text{max}}' \quad (11)$$

$$Q_{\text{min}}' \leq Q_{\text{out}}' \leq Q_{\text{max}}' \quad (12)$$

where $L_{\text{min}}'$ and $L_{\text{max}}'$ are the minimum and maximum water levels of the reservoir permitted at the $t$-th time (day or month) period; $Q_{\text{min}}'$ and $Q_{\text{max}}'$ are the minimum and maximum water release of the reservoir permitted at the $t$-th time (day or month) period.

Optimization algorithm

Pareto-optimal solutions

Without loss of generality, a multiobjective optimization problem can be defined as a vector minimization problem:

$$\text{Minimize}_{\Omega} F(X) = (F_1(X), F_2(X), \ldots, F_m(X))^T, \quad (13)$$

Subject to $g_i(X) \geq 0 \quad i = 1, 2, \ldots, k, \quad (14)$

$h_j(X) = 0 \quad j = 1, 2, \ldots, l, \quad (15)$

where $X$ is a variable vector, $\Omega$ is a feasible solution space, and $F_1(X), F_2(X), \ldots, F_m(X)$ denote real valued objective functions.

Usually, the optimum for a multiobjective problem is a solution set instead of a single solution, known as Pareto-optimal solutions. For any two points $X_1$ and $X_2$ in $\Omega$, if the following conditions hold:

$$F_i(X_1) \leq F_i(X_2) \quad \forall i \in \{1, \ldots, m\}, \quad (16)$$

$$F_j(X_1) \leq F_j(X_2) \quad \forall j \in \{1, \ldots, m\}, \quad (17)$$
then $X_1$ is said to be superior to $X_2$, vector $X_1$ is at least as good as $X_2$ with respect to all $m$ objectives, and $X_1$ is strictly better than $X_2$ with respect to at least one objective. If no other solution is superior to $X_1$, then $X_1$ is called a Pareto-optimal solution. The boundary consisting of the set of Pareto-optimal solutions is called a trade-off surface, or a Pareto frontier.

**NSGA-II**

Evolutionary algorithms have been proved to be effective to deal with multiobjective problems (MOPs). The modified version of Non-dominated Sorting Genetic algorithm (NSGA), NSGA-II, proposed by Deb et al. [17] is one of the most efficient and commonly used evolutionary algorithms with are profit from its simplicity, effectiveness, and minimum user interaction [18].

First, the initial population composed of individuals represented in equation (9) is generated randomly within the feasible domain shown in equation (10). The fitness of each individual, that is, the objective function value described in equations (7) and (8) is then worked out by various relationships shown from equations (1) to (6). Then the population is layered and sorted to form multiple Pareto fronts with different ranks based on the domination level of each member determined by its own value of objective function. Such procedure is repeated until all solutions are set into fronts. The domination level is defined in equation (18):

$$X = \{x_1, x_2, \ldots, x_M\}$$
$$Y = \{y_1, y_2, \ldots, y_M\}$$

$$X \text{ Dom } Y \Leftrightarrow \forall i: x_i \leq y_i \text{ and } \exists j: x_j \leq y_j,$$

where $X$ and $Y$ are two individuals of population and $x_i$ and $y_i$ are objective functions that should be minimized and $M$ is number of objectives.

When the last front is under consideration, those configurations at a scarcely populated area which is far away from the other solutions are selected to fill up the rest of the positions. Such diversity is measured by crowding distance as defined in equation (19).

$$D(k) = \sum_{j=1}^{M} \frac{|f_{k+1}^j - f_{k-1}^j|}{f_{max}^j - f_{min}^j}$$

Selection operation is used to make better-performing members have large survival probability. The individual with higher front number is selected, and in the same Pareto front number, the individual with bigger crowding distance is selected. After selection procedure, simulated binary crossover and polynomial mutation operation are employed to form children population. Elite strategy is adopted to let superior members in parent population remain in children population. New parent population is formed by adding elite population members from the parents and children population based on the results of nondomination sorting and crowding distance calculation.

A scheme of the proposed optimization model is given in Figure 2.

![Figure 2. Proposed optimization model of hydro/PV hybrid system.](image-url)
Case Study

The Qinghai province is located in northwest of China with rich solar energy resources. The total annual radiation of the Qinghai province is between 5800 and 7400 MJ/m², more than 60% of which is the direct radiation [19]. The Longyangxia hydropower station on the Yellow River is located in the Gonghe County of the Qinghai province with the total installed capacity of 4×320 MW. The storage capacity of the Longyangxia reservoir is 14.700 billion m³, and it has good adjustment ability with the regulating storage capacity of 19.35 billion m³. The PV power station is located on the Talatan gobi desert in the Gonghe County with the total installed capacity of 850 MWp. Figure 3 shows the average daily solar radiation and temperature from the year 1984 to 2004, which is taken to calculate the daily PV power output of the PV power station in this study. The PV power is transmitted to the Longyangxia hydropower station with a circuit of 330 kV, and the compensatory power composed of hydropower and PV power is transmitted to the power grid by five circuits. When two of the four hydropower units in the Longyangxia hydropower station participate the complementary operation of hydro-PV hybrid power system, 75% of the 850 MWp of the PV power output can be compensated within the scope of 0–640 MW; while three or more sets of the hydropower units take part in the joint operation, the full capacity of 850 MWp of the PV power output can be compensated.

In this study, the long-time average annual value of the daily radiation and temperature at the Gonghe County is used to calculate the PV power output. Different hydrologic years from 2007 to 2014 are used to estimate the trade-off between the energy generation and the energy consumption, as well as the corresponding operational schemes for the dry years, normal years, and wet years, respectively. The NSGA-II code in Matlab developed by Kanpur Genetic Algorithms Laboratory (KanGAL) [20] is used for the optimization in this study.

Results and Discussions

The mean annual discharge into the Longyangxia reservoir is 650 m³/s. Table 1 shows the modulus ratio coefficients K_p defined in equation (20) of the inflow into the Longyangxia reservoir from the year 2007 to 2014.

\[ K_p = \frac{I}{\bar{I}} \]  

(20)

where I is the inflow into the reservoir, and \( \bar{I} \) is the mean annual inflow into the reservoir.

According to the classification by [21], the year of 2012, 2014, and 2008 are selected to represent the wet year, normal year, and dry year, respectively.

Figure 3. Average daily solar radiation and temperature from the year 1984 to 2004 at the Longyangxia PV power station.

Table 1. Analysis of the runoff into the Longyangxia reservoir.

| Year   | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|--------|------|------|------|------|------|------|------|------|
| Annual runoff (m³/s) | 587  | 521  | 754  | 586  | 622  | 858  | 590  | 636  |
| Runoff modulus ratio | 0.90 | 0.80 | 1.16 | 0.90 | 0.96 | 1.32 | 0.91 | 0.98 |
| Classification | Dry  | Dry  | Wet  | Dry  | Normal | Wet  | Dry  | Normal |
In the NSGA-II implementation, the population is set to 200; the iteration stops after 500 times; the crossover probability of Simulated Binary (SBX) Crossover [22] is 0.90; and the mutation probability of polynomial mutation [23] is 0.10. Premature convergence appears prominent for genetic algorithms when decision variables have high dimension and the searching space is large. It is quite common to get inferior solutions with small fitness values or infeasible solutions during the early stage of the searching process [24]. In order to avoid the premature convergence, and take the power demand into account, the historical reservoir discharge scenario is used as a benchmark to construct solution space to generate candidate individuals for GA.

Figure 4 shows the Pareto Front of the selected years, which represents the trade-offs between energy generation and the variance of energy demand and energy generation, as well as the recommended optimal solutions. It can be shown from Figure 4A that with the increase in the energy generation, the variance between energy demand and generation rises. Thus, maximizing energy generation is contradictory with minimizing the gap between energy demand and generation. Interestingly, the two objectives almost keep a linear relationship with the same slope for different hydrologic years, although in the wet years, more energy could be generated. It implies that there exists a stable relationship between maximizing energy generation and minimizing the gap, which is determined by the characteristics of the power system instead of the environmental condition. In order to find out the optimal solution balancing the two objectives, the objectives are normalized into [0, 1], as shown in Figure 4B–D. Since the $Z_1$ needs to be as large as possible, whereas $Z_2$ should be as close to 0 as possible, the idealist solution should be at the point (0, 1) in the coordinate system. The point on the Pareto Front nearest to (0, 1) is labeled in Figure 4B–D, and taken as the recommend optimal solution considering energy generation and the variance.

![Figure 4. Optimized results (A) Pareto Front, representing trade-offs between energy generation and variance of energy demand and energy generation of different hydrologic years; (B) recommended optimal solution of the year 2008, representing dry years; (C) recommended optimal solution of the year 2014, representing normal years; (D) recommended optimal solution of the year 2012, representing wet years.](image-url)
Multi-objective optimization of hydro-PV

between energy generation and demand simultaneously. The corresponding operation schemes, the reservoir release scenarios, are presented in Figure 5, as well as those corresponding to the solutions with maximum energy generation and minimum variance, respectively. That is, Figure 5 shows the reservoir operation corresponding to the denoted point and the two endpoints on the curve in Figure 4.

The flood season lasts from June to September. Figure 5A shows that more water needs to be discharged to maximize energy generation in dry year. But if the water is sufficient in normal or wet years as in Figure 5B and C, a better way to increase energy production is to keep a high reservoir water level in nonflood season to improve power generation efficiency. Since the water level has to be lowered to the flood control level, increasing reservoir discharge is always the primary choice in flood season to maximize energy generation for both dry and wet years. To minimize the variance between energy generation and consumption, the reservoir release process needs to be gentler, as the energy demand does not fluctuate as violently as the reservoir inflow. The store and delay effect of the reservoir on flow plays a more important role when considering energy consumption. As to the recommended operation considering both of the two objectives, the release amount is basically in between. In nonflood season, the optimal operation is more inclined to maximize energy generation, while it concerns more about the energy consumption in flood season. Another knowledge implied by the results is that the regulation function of the reservoir needs to be paid more attention to in dry and normal years, when the operation schemes emphasizing different objectives discriminate greater.

The multiobjective model proposed in this study can be generalized to other hydro-PV hybrid power systems to derive the instruction for the reservoir operation, and better understand the characteristics of the power system.

Figure 5. Optimal operational scheme of (A) the year 2008, representing dry years; (B) the year 2014, representing normal years; (C) the year 2012, representing wet years.
Acknowledgments

This research was supported by National Key R&D Program of China (2017YFC0403600, 2017YFC0403602), the Open Research Fund Program of State key Laboratory of Hydroscience and Engineering, Tsinghua University (Grant No. sklhe-2016-B-03), and the Open Project of State Key Laboratory of Plateau Ecology and Agriculture, Qinghai University.(Grant No. 2016-KF-03).

Conflict of Interest

None declared.

References

1. Ruhang, X. 2016. Characteristics and prospective of China’s PV development route: based on data of world PV industry 2000–2010. Renew. Sustain. Energy Rev. 56:1032–1043.
2. http://www.cgdc.com.cn/zhzx/1019892.jhtml.
3. Tang, Y. H., J. Yang. 2005. Status and expectation of photovoltaic technology. Renew. Energy 3:68–69.
4. http://www.solarzoom.com/article-3847-1.html.
5. Zhang, P., T. Yang. 2015. Research on Longyangxia Hydro-photovoltaic complementary operation mechanism. J. N. China Univ. Water Resour. Electric Power 36:76–81.
6. Wu, C. S., H. Liao, Z. L. Yang, Y. B. Wang, Y. C. Peng, and H. H. Xu. 2009. Research on control strategies of small-hydro/PV hybrid power system. In Sustainable Power Generation and Supply, 2009. SUPERGEN’09. International Conference on. IEEE.
7. Meshram, S., G. Agnihotri, and S. Gupta. 2013. Power management strategy for active power sharing in hydro/PV/battery hybrid energy system. Chin. J. Eng. 2013: 1–7.
8. Kenfack, J., F. P. Neirac, T. T. Tatietsé, D. Mayer, M. Fogue, and A. Lejeune. 2009. Microhydro-PV-hybrid system: sizing a small hydro-PV-hybrid system for rural electrification in developing countries. Renew. Energy 34:2259–2263.
9. Bekele, G., and G. Tadesse. 2012. Feasibility study of small Hydro/PV/Wind hybrid system for off-grid rural electrification in Ethiopia. Appl. Energy 97:5–15.
10. Nfah, E., and J. Ngundam. 2009. Feasibility of pico-hydro and photovoltaic hybrid power systems for remote villages in Cameroon. Renew. Energy 34:1445–1450.
11. Beluco, A., P. K. de Souza, and A. Krenzinger. 2012. A method to evaluate the effect of complementarity in time between hydro and solar energy on the performance of hybrid hydro PV generating plants. Renew. Energy 45:24–30.
12. Patsialis, T., I. Kougiás, N. Kazakis, N. Theodossiou, and P. Droege. 2016. Supporting renewables’ penetration in remote areas through the transformation of non-powered dams. Energies 9:1054.
13. Francois, B., M. Borgia, J. D. Creutin, B. Hingray, D. Raynaud, and J. F. Sauterleute. 2016. Complementarity between solar and hydro power: sensitivity study to climate characteristics in Northern-Italy. Renew. Energy 86:543–553.
14. Schmidt, J., R. Cancelli, and A. O. Jr Pereira. 2016. An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil. Renew. Energy 85:137–147.
15. Kougiás, I., S. Szabó, F. Monforti-Ferrario, T. Huld, and K. Bódis. 2016. A methodology for optimization of the complementarity between small-hydropower plants and solar PV systems. Renew. Energy 87:1023–1030.
16. http://www.nrel.gov/homer.
17. Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6:182–197.
18. Niu, X., K. Liu, Y. Zhang, G. Xiao, and Y. Gong. 2017. Multiobjective optimization of multistage synchronous induction coilgun based on NSGA-II. IEEE Trans. Plasma Sci. 45:1622–1628.
19. http://www.gov.cn/guoqing/2013-03/26/content_5046173.htm.
20. http://www.iitk.ac.in/kangal/codes.shtml.
21. Ba Cunsheng, Z. J. 2003. Analysis of Longyangxia reservoir’s entering radial flow character and period. Qinghai Electric Power 4:4–6.
22. Deb, K., and R. B. Agrawal. 1995. Simulated binary crossover for continuous search space. Complex Syst. 9:115–148.
23. Deb, K., and M. Goyal. 1996. A combined genetic adaptive search (GeneAS) for engineering design. Comput. Sci. Inform. 26:30–45.
24. Chang, L.-C., F.-J. Chang, K.-W. Wang, and S.-Y. Dai. 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrol. 390:66–74.