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Effect of the quality of streamflow forecasts on the operation of cascade hydropower stations using stochastic optimization models

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ABSTRACT

Determining the economic value of streamflow forecasts is essential to judging the operation of cascade hydropower systems and investing in improved forecasting systems. Previous analyses of the streamflow forecast value are mainly based on deterministic optimization strategies. This paper investigates the impact of long-term (10-day-ahead) streamflow forecasts on the operation of a cascade hydropower system using stochastic dynamic programming (SDP) and Bayesian stochastic dynamic programming (BSDP). Synthetic streamflow forecasts with different bias, variance, and precision are generated by the generalized maintenance of variance extension approach. A case study is performed to evaluate the performance of these strategies in terms of cumulative annual power revenue (CAPR) and system reliability (SR). The results show that, even when using the forecast with the largest uncertainty and bias, the stochastic optimization strategies increase at least 6.63 × 108 CNY in CAPR and 33.89% in SR compared with a reference strategy that uses no forecast information. The SDP performs best with forecast systems that have a negative bias and high accuracy. Compared with the SDP, BSDP increases at least 1.80 CNY in CAPR and 0.28% in SR and is better able to handle forecast uncertainty, and is insensitive to forecast bias.

1. Introduction

The joint operation of cascade hydropower stations, which exploits the hydrological, hydraulic, and electric connections between cascade reservoirs, is a critical means of satisfying the rising demand for energy and ensuring the stable operation of the power system [1–3]. Using precipitation and hydrological information, meteorological–hydrological forecast models are widely used in the operation of hydropower systems [4–6]. However, although deterministic streamflow forecasts are generally superior to historical streamflow data, the forecast uncertainty has a negative effect on the efficient use of hydropower energy [7–9]. Compared with single hydropower stations, the joint operation of cascade hydropower stations can significantly improve the hydropower energy utilization rate with a relatively small increase in investment cost [10–12]. Generally, the leading reservoir in the cascade has the best regulation performance, with the regulation performance of downstream hydropower stations being relatively poor [12,13]. Hence, when streamflow forecast errors occur, the available reservoir storage water volume and available storage capacity within the operation horizon are sufficient for the current plan [14]. Analyzing the effect of the quality of streamflow forecasts on the joint operation of cascade hydropower stations is important as it provides decision-makers with the means to increase operational benefits and improve system reliability.

Streamflow forecasts are produced at different lead times, corresponding to different degrees of forecast uncertainty [15,16]. Compared with short-term forecasts, which have a limited forecast horizon, long-term forecasts with long horizons are less accurate but play a more important role in decision-making [17,18]. As a result, more investment has gone into improving the reliability of long-term streamflow forecasts. This raises two important questions: how does the quality of the streamflow forecast affect the operation of cascade hydropower systems? and will improved streamflow forecast quality leads to an increase in the streamflow forecast "value"? To respond to these questions, numerous studies have evaluated the forecast value, which is defined as

Abbreviations: SDP, Stochastic dynamic programming; BSDP, Bayesian stochastic dynamic programming; GMOVE, Generalized maintenance of variance extension; CAOS, Cumulative annual output shortage; CAPR, Cmulative annual power revenue; SR, System reliability.

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the economic gain obtained by optimizing the operation of a cascade hydropower system through improved streamflow forecasts [19–21].

To understand the relationship between the quality of the streamflow forecast and its economic value, a synthetic streamflow can be generated with certain key attributes (e.g., bias, variance, and accuracy), and then the optimal operation of the cascade hydropower system can be simulated [22–24]. There are usually two approaches to generating synthetic streamflow forecasts. The first approach is to use a conceptual hydrological forecast model with historical climatological forcing data [25]. However, a major concern with this approach is that it can be data-intensive. Moreover, such hydrological forcing data do not always exist over much of the historical simulation period, leading to forecasts generated by statistical methods that do not serve the intended purpose [26]. The second approach is to use a statistical method and hydrological data to generate synthetic forecast series with the desired statistical characteristics and relationship to the observed flows. Several studies have used a seemingly intuitive solution: simply add some random error to the observed flows [27–29]. However, the results from this approach omit the correlation between forecast error and observed streamflow, and create unrealistic forecasts, which may result in an unreasonable evaluation of the forecast value.

In addition to the quality of streamflow forecasts, operation strategies also impact the use of forecast data for the management of cascade hydropower systems [30,31]. Traditionally, reservoir operation curves are determined by historical streamflow records and depend on the day of the year and reservoir storage level [32,33]. Thus, even a perfect streamflow forecast would not improve reservoir operation efficiency when operation curves are used. Recently, various optimal models informed by streamflow forecast products have been introduced to increase hydropower generation with almost no additional investment [34–36]. The optimization models that have been used to manage cascade hydroelectric reservoirs can be classified into two categories: (1) Deterministic optimal models, which use a specific sequence of streamflow data (historical, forecasted, or synthetically generated) to determine the operating policies; correspondingly, techniques such as linear and nonlinear programming, dynamic programming and its variants, and heuristic programming have been widely used to solve the optimal model [37–39]. (2) Stochastic optimal models, which use statistical descriptions of the streamflow and a forecast process instead of a specific streamflow sequence to obtain the operating policies. Compared with deterministic optimal models, stochastic models can effectively capture the natural uncertainty and forecast uncertainty in the streamflow data [40–43]. Stochastic dynamic programming (SDP) and Bayesian stochastic dynamic programming (BSDP) are widely used to solve stochastic optimal models [44–46].

Presently, while the analysis of forecast quality is receiving considerable attention, with numerous scores developed to quantify the gains from a forecasting system, there have been few evaluations of streamflow forecast value for cascade hydropower systems. Additionally, most studies adopt deterministic optimization to derive operation strategies, and the performance of stochastic optimization techniques in handling the impact of streamflow quality attributes is relatively poor. Considering the above issues, this study aims to investigate the impact of different attributes of long-term (10-day-ahead) streamflow forecasts on the management of cascade hydroelectric reservoirs under two classic explicit stochastic optimization models, namely SDP and BSDP. Compared with previous studies, the main contributions of this study are as follows (1) The different statistical attributes (e.g., bias, variance, and accuracy): of the streamflow forecast are accurately captured, and the generalized maintenance of variance extension (GMOVE) approach, using historical streamflow series as the input, is adapted to generate synthetic streamflow forecasts with different forecast qualities. (2) The natural uncertainty and forecast uncertainty in streamflow data are captured through two stochastic optimal models informed by synthetic streamflow forecasts, which supports the cascade hydropower generation. Different attributes of the forecast streamflow are analyzed in terms of their influence on the economic value and system reliability of cascade hydropower stations. A flowchart of the framework of this study is presented in Fig. 1.

Compared to the current research of the impact of forecast uncertainty on hydropower stations operation, the highlights and advantages of our study are as follows: (1) Establish a framework for quantifying the quality of the streamflow forecast that affects the operation of cascade hydropower systems using stochastic optimization models. (2) Analyze how the improvement in streamflow forecast quality affects the streamflow forecast value and the operation of hydropower systems. (3)•Disclose the behavior of the stochastic optimization model in handling the streamflow forecast with different qualities.

The remainder of this paper is organized as follows. Section 2 describes the synthetic forecast streamflow data, the formulation model, and the implementation of a 10-day-ahead hydropower production plan. Section 3 introduces a case study of the Jinguan cascade hydropower station in the Yalung River Basin, China. Section 4 presents the main results and analysis. Finally, the conclusions to this study are drawn in Section 5.

2. Methodology

To investigate the impact of the forecast quality on the management of hydroelectric reservoirs, the first step is to generate a synthetic streamflow forecast with different qualities in terms of bias, variance, and accuracy. In this study, a GMOVE approach with three explanatory variables is constructed to simulate the streamflow forecasts. Second, to derive the optimal output policies of cascade hydropower stations, two stochastic optimal models with different hydrological state variables are developed. An optimal load allocation model is then established to handle the contradiction between the immediate and carryover utilities for long-term hydropower reservoir operation.

2.1. Generation of synthetic streamflow forecasts

Given a series of observed streamflow data, an appropriate conceptual model for generating a synthetic streamflow forecast can be represented as an intuitive and simple regression model [26].

$$q_t = f_t + e_t \tag{1}$$

where f_t and q_t are the forecast and observed streamflow data in period t, respectively; e_t is the additive random forecast error in period t.

For the simple regression model shown in Eq. (1), it is reasonable to assume that f_t and e_t are independent. Therefore, according to the analysis of variance for ordinary least-squares, the variance of the streamflow forecast q_t can be defined as

$$\sigma_{q_t}^2 = \sigma_{f_t}^2 + \sigma_{e_t}^2 \tag{2}$$

where $\sigma_{q_t}^2$, $\sigma_{f_t}^2$ and $\sigma_{e_t}^2$ denote the variance of q_t, f_t, and e_t, respectively. As shown in Eq. (1), the accuracy of the forecast f_t depends on the variance $\sigma_{e_t}^2$ of the forecast error e_t, and the accuracy of the forecast f_t increases as $\sigma_{e_t}^2$ decreases. For a perfect forecast, $\sigma_{e_t}^2 = 0$ and the forecast error is a constant value. The generation of forecasts is therefore as simple as generating random errors e_t, with the desired error variance describing the forecast accuracy. However, the problem with this approach is that the errors e_t are generally assumed to be independent of the flows q_t. This assumption may lead to undesirable results, in reality, forecast errors are autocorrelative and are related to the magnitude of flow [6,16,22,27]. To overcome the drawback of the simple regression model in Eq. (1), the GMOVE approach is introduced to generate synthetic streamflow forecasts. The GMOVE approach for generating f_t was developed by Grygier [47] and further extended by Lamontagne and Stedinger [26]:

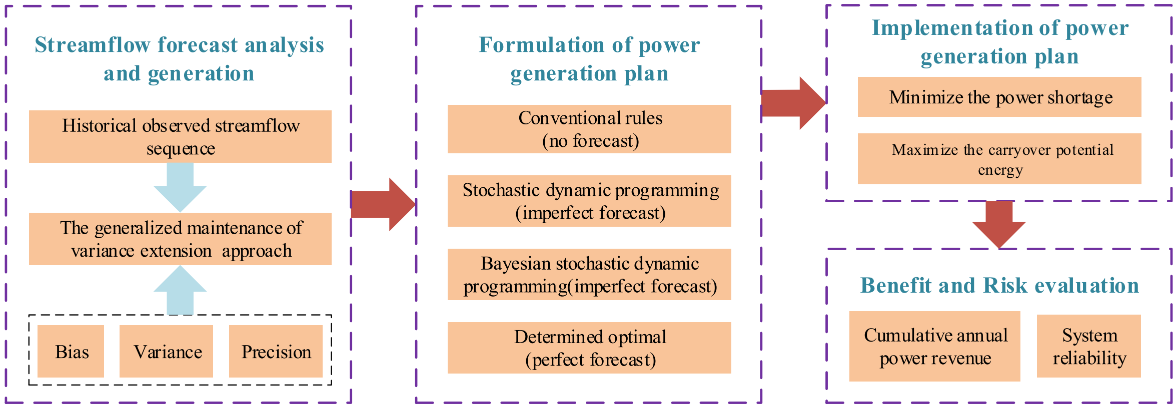


Fig. 1. Framework for evaluating the effects of forecast quality on the operation of cascade hydropower stations.

$$f_t = u_{q_t} + c(q_t - u_{q_t}) + d(q_{t-1} - u_{q_{t-1}}) \tag{3}$$

where u_{q_t} is the mean of q_t and c, d are model parameters.

Unlike the simple regression model shown in Eq. (1), the GMOVE model introduces the explanatory variables c and d to capture the variance of the forecast streamflow and the variance of the forecast error. Notably, the autocorrelation property of forecast error is introduced in this way. The values of c and d are given as follows [47].

$$c = \left(\sigma_{q_t f_t} - d s_{q_{t-1} q_t}\right) \Big/ s_{q_t}^2 \tag{4}$$

$$d = \sqrt{\left(\sigma_{f_t}^2 - \sigma_{q_t f_t}^2 \Big/ s_{q_t}^2\right) \Big/ \left(s_{q_{t-1}}^2 - s_{q_{t-1} q_t}^2 \Big/ s_{q_t}^2\right)} \tag{5}$$

where $\sigma_{q_t f_t}$ is the covariance of q_t and f_t; $s_{q_{t-1} q_t}$ is the sample covariance of q_t and q_{t-1}; and $s_{q_t}^2$ is the sample variance of q_t. For describing the precision and accuracy of a forecast, Lamontagne and Stedinger [26] introduce the coefficient of determination R^2 as a measure. For a given R^2, the variances of f_t and e_t are calculated and the value of c and d are determined.

$$\sigma_{e_t}^2 = (1 - R^2)\sigma_{q_t}^2 \tag{6}$$

$$\sigma_{f_t}^2 = R^2 \sigma_{q_t}^2 \tag{7}$$

Further, to introduce the bias, multiplying a spread factor b into equation (3) yields

$$f_t = b u_{q_t} + c(q_t - u_{q_t}) + d(q_{t-1} - u_{q_{t-1}}) \tag{8}$$

Based on these three explanatory variables (b, c, and d), the synthetic streamflow forecast has the desired bias $b u_{q_t}$, the correct variance $R^2 \sigma_{q_t}^2$, and the desired forecast precision $(1 - R^2)\sigma_{q_t}^2$ [26]. Additionally, the drawbacks encountered with Eq. (1) are removed. Depending on the value of b, the random sampling will be biased ($b \neq 1$) or unbiased ($b = 1$). We created synthetic streamflow forecasts with negative bias ($0 < b < 1$) and positive bias ($b > 1$), corresponding to forecasts that underestimate and overestimate the observations, respectively. The accuracy of the forecast depends on R^2, with $R^2 = 1$ indicating that the forecast explains all of the variability of the flows q_t, so that $\sigma_{e_t}^2 = 0$, and $R^2 = 0$ indicating that the forecast is unable to explain any of the variability in the flows q_t, so that $\sigma_{e_t}^2 = \sigma_{q_t}^2$. As R^2 increases from zero, the accuracy of the forecast increases.

2.2. *Decision formulation based on the stochastic optimization model*

By considering the forecast streamflow and the constraints of the hydropower station system, a rolling forecast–optimization–decision framework for each period can be obtained. In this section, two SDP strategies with different hydrological state variables are developed to formulate the optimal output decision. The natural streamflow uncertainty and streamflow forecast uncertainty are addressed differently by the two stochastic models. In addition, owing to the curse of dimensionality, the aggregation–disaggregation approach is used to improve computational efficiency, whereby a system of cascaded hydropower stations is simplified as a single virtual reservoir through the aggregation of the storage, and the aggregated storage is decomposed into values for each reservoir based on the storage–discharge relationships derived using historical data [15,46].

2.2.1. *Uncertainties of streamflow*

Based on the streamflow forecast, the decision-makers face two independent sources of streamflow uncertainty in deriving the optimal operation scheme. The first is the natural uncertainty of the streamflow q_t, which exists before generating the forecasts f_t and is normally represented by a prior streamflow transition probability p_{ij}^t. The second source of uncertainty concerns the accuracy of forecasts, which can be characterized by the likelihood probability p_{kj}^t.

$$p_{ij}^t = p_{q_t=j|q_{t-1}=i}^t \tag{9}$$

$$p_{kj}^t = p_{q_t=j|f_t=k}^t \tag{10}$$

where i, j, and k are the streamflow class intervals of q_{t-1}, q_t, and f_t, respectively. Based on p_{ij}^t and p_{kj}^t, the posterior probability p_{ikj}^t and predictive probability p_{jl}^t can be calculated using Bayes' theorem and the probability multiplication theorem as

$$p_{ikj}^t = p_{q_t=j|q_{t-1}=i, f_t=k}^t = \frac{p_{jk}^t p_{ij}^t}{\sum_j p_{jk}^t p_{ij}^t} \tag{11}$$

$$p_{jl}^t = p_{f_{t+1}=l|q_t=j}^t = \sum_j p_{jk}^{t+1} p_{ij}^{t+1} \tag{12}$$

2.2.2. *Objective function and constraints*

2.2.2.1. Objective function. In this study, the purpose of the long-term power generation operation model is to maximize the total power production while minimizing the deviation from the required system output so as to guarantee the stability of the power supply. Thus, the objective function consists of two components: power production and a penalty for deviating from the system requirements. These can be written as

$$F_t(s_{t-1}, q_t) = \max\left\{\sum_{t=1}^{T} E[B(s_{t-1}, q_t, s_t)]\right\} \tag{13}$$

$$B(s_{t-1}, q_t, s_t) = \left\{ b(s_{t-1}, q_t, s_t) - \alpha[\max(e - b(s_{t-1}, q_t, s_t), 0)]^\beta \right\} \cdot c_t \cdot \Delta t \tag{14}$$

$$b(s_{t-1}, q_t, s_t) = \sum_{i=1}^{N} \eta_i * q_i(t) * h_i(t) \tag{15}$$

where $F_t(s_{t-1}, q_t)$ is the maximum expected hydropower generation for the entire planning horizon T; s_{t-1} is the aggregate storage at the beginning of period t; $b(s_{t-1}, q_t, s_t)$ is the hydropower output in period t; N is the set of reservoirs; η_i is the hydroelectric coefficient of reservoir i; $q_i(t)$ is the generating water flow of reservoir i in period t; $h_i(t)$ is the net hydraulic head of reservoir i in period t; Δt is the time duration; c_t is the price of hydropower in period t; and α, β are penalty factors.

2.2.2.2. Constraints. The main constraints in the model are presented in Supplementary Material (S1).

2.2.3. Stochastic optimization model

2.2.3.1. SDP model. The choice of hydrological state variables in an SDP model depends on the system characteristics and the information available for decision-making. Computational considerations often influence how hydrological information is represented in the SDP. When the streamflow forecast is informed, the most common choice of the state variable is the current flow q_t. The current flow is then known at the beginning of the period, and a recursive equation can be established as

$$F_t(s_{t-1}, q_t) = \max_{s_t} \left\{ B(s_{t-1}, q_t, s_t) + \sum_j p_{ij}^{t+1} F_{t+1}(s_t, q_{t+1}) \right\} \tag{16}$$

For this benefit function, the forecast is considered to be accurate, and therefore $q_t = f_t$. The natural uncertainty of the streamflow data is addressed by the prior streamflow transition probability p_{ij}^{t+1}, and the optimal output decision is determined by optimizing the present benefit plus the expected future benefit in each period. In Eq. (16), the streamflow forecast f_t at period t and the aggregate storage of the equivalent reservoir at the beginning of time step t are taken as state variables, and the aggregate storage at the end of period t is taken as the decision variable.

2.2.3.2. BSDP model. As shown in Eq. (16), for the classic SDP model, the natural uncertainty of the streamflow data is addressed as a simple Markov process, and the forecast uncertainty is not considered. The recursive equation for the BSDP model, which incorporates the posterior probability p_{ikj}^t, is defined as

$$F_t(s_{t-1}, q_{t-1}, f_t) = \max_{s_t} \left\{ \sum_{q_t} p_{ikj}^t \left[B(s_{t-1}, q_t, s_t) + \sum_l p_{jl}^t F_{t+1}(s_t, q_t, f_{t+1}) \right] \right\} \tag{17}$$

For this benefit function, the forecast is considered to be inaccurate, and the forecast uncertainty is captured by the conditional probability of the forecast given the actual streamflow. The optimal output decision is determined by optimizing the expected present benefit plus the expected future benefit in each period. In Eq. (17), the state variables are the streamflow data from two adjacent periods and the storage at the beginning of period t, while the decision variable is the storage at the end of period t. The impact of inflow forecast uncertainties on decision-making can be evaluated by comparing the performance of the SDP and BSDP models.

2.3. Decision implementation based on optimal load adjustment model

The uncertainty inherent in the runoff forecast means that the actual runoff may be higher or lower than the forecast value. However, the complex hydraulic and electrical connections among cascade reservoirs make it difficult to determine a load allocation scheme that alleviates the water abandonment or output shortages caused by forecast uncertainty. Therefore, an optimal load allocation model is developed to balance the contradiction between the immediate and carryover utilities for long-term hydropower reservoir operation.

2.3.1. Objective function

When the state variables are determined, the total output $N_p(t)$ of the cascade can be obtained. Furthermore, to satisfy the total hydropower demand of the current period while reserving enough water for future use, the following objective function is used to meet the load demand of the current period and increase the carryover potential energy:

$$\max \left\{ \sum_{i=1}^{N} \int_{V_i^{\min}}^{V_i(t+1)} \sum_{j=i}^{n} \eta_i h_j(t) dv - M\delta_t \left[\sum_{i=1}^{N} N_i(t) - N^p(t) \right] \right\} \tag{18}$$

$$\delta_t = \begin{cases} 1 & \left[\sum_{i=1}^{N} N_i(t) - N^p(t) \right] < \varepsilon \\ 0 & else \end{cases} \tag{19}$$

where δ_t is an index to show the happen of power shortage occurs; ε is an allowable error. The objective function in Eq. (18) includes two terms. The first term represents the carryover potential energy of cascade reservoirs, for which higher values are better. This ensures that there is sufficient hydro energy for future use. The second term represents the penalties in the case of a power loss, for which lower values are better. This meets the load demand which is given the highest priority.

2.3.2. Constraints

All constraints described in Section 2.2.2.2 are considered in the optimal real-time load adjustment model.

2.3.3. Model solution

When there is a deviation between the actual and forecast streamflow at period t, the optimal load allocation model is used to reallocate power generation in this period according to the actual streamflow. In this study, the proposed model is solved using a genetic algorithm, which is a powerful global optimization algorithm with the advantages of good convergence, conceptual simplicity, ease of use, and a small number of control parameters [48,49]. See Liu [6] and Wang [13] for more details.

3. Case study

3.1. Case study area

The Yalung River, located in the eastern part of the Qinghai–Tibet Plateau in China, is the largest tributary of the Jinsha River, which rises in the Bayankala Mountains. The Yalung River basin covers an area of 13.6×10^4 km^2. The Jinguan cascade hydropower system, including the Jinxi, Jindong, and Guandi hydropower stations, is downstream of the Yalung River basin and form the subject of this case study. These stations are a key component of China's Yalung River cascade hydropower system [6,9,41]. The main purpose of these cascade hydropower stations is to maximize the total hydropower generated and provide 2×10^8 m^3 reservoir capacity for flood control of the Three Gorges reservoir in the pre-flood season (June–July). The Jinxi hydropower station is the leading reservoir, and thus controls the annual regulation performance and plays an important role in maintaining the safe and stable operation of the cascade hydropower system while offering significant flood control capacity. The Jindong and Guandi hydropower stations can achieve daily regulation performance, having relatively large installed capacities. The three hydropower stations have different storage and regulation capacities, forming a typical large-scale cascade hydropower system with complex hydraulic connections. The main parameters of these stations are listed in Table 1 and the location of the cascade hydropower stations is shown in Fig. 2.

3.2. Data description

The observed streamflow data with a 10-day time scale over the 61 years from 1958 to 2018 were collected and used to generate synthetic streamflow forecasts. The mean and standard deviation of the streamflow are 574 m^3/s and 470 m^3/s, respectively. Fig. 3 shows a boxplot of the observed streamflow data from January to December and each month is approximately divided into three periods at a 10-day time step. The streamflow data exhibit large intra-annual variability across the whole year. According to the runoff magnitude and recharge sources, the data can be divided into three seasons: (1) the flood season from June to September (period 16–27), which is mainly supplied by rainfall; (2) the transition season from October to November (period 28–33) and from April to May (period 10–15), which is mainly supplied by river channels and snow melt; and (3) the dry season from January to March and December (period 1–9 and period 34–36), which is mainly supplied by groundwater. The streamflow data exhibit obvious changes in the flood and dry seasons, leading to a significant change in the operating water level of the Jinxi reservoir. Owing to the frequent rainfall that occurs during the flood season, the streamflow forecast error is higher in the flood season than in other seasons. The price of hydropower for the cascade system in 2019 was 0.2811 CNY/kW·h; this value is used in the present study.

3.3. Experimental setting

In this study, four strategies are proposed to determine the total output of the cascade in the current period. The streamflow forecast and its uncertainty are considered differently in each strategy.

Strategy A: At present, the reservoir operation curves are informed by historical streamflow records. The day of the year and the reservoir storage level are used to guide the long-term hydropower operation. Fig. 4 shows the reservoir operation curves for the Jinxi reservoir. the small regulation capacities of the Jindong and Guandi reservoirs mean that their water levels have been controlled at the average water level for many years (Jindong: 1644 m; Guandi: 1328 m). In this strategy, the streamflow forecast is not used in the decision-making process.

Strategy B: The SDP model with the recursive equation shown in Eq. (16) is used to determine the output of all hydropower stations. In this case, the decision-making is informed by the streamflow forecast and the natural uncertainty of the streamflow is considered.

Strategy C: The BSDP model is used to determine the output of all hydropower stations according to the recursive equation shown in Eq. (17). In this case, the decision-making is informed by the streamflow forecast, and both the natural uncertainty and forecast uncertainty of streamflow are addressed.

Strategy D: The observed streamflow is used as the input to the optimal model. The stochastic optimization model with the objective function given in Eq. (13) is converted to a deterministic optimization model with the following objective function:

Table 1
Main parameters for the Jinguan cascade reservoirs.

Items	Unit	Jinxi	Jindong	Guandi
Normal Level	m	1880	1640	1330
Dead Level	m	1800	1640	1321
Regulation volume	10^8 m^3	49.1	0.0496	1.232
Guaranteed output	MW	1086	1443	709.8
Installed capacity	MW	3600	4800	2400
Mean annual runoff	10^8 m^3	385	387.9	454
Mean annual flow	m^3/s	1220	1230	1440
Ecological flow	m^3/s	339	122	200

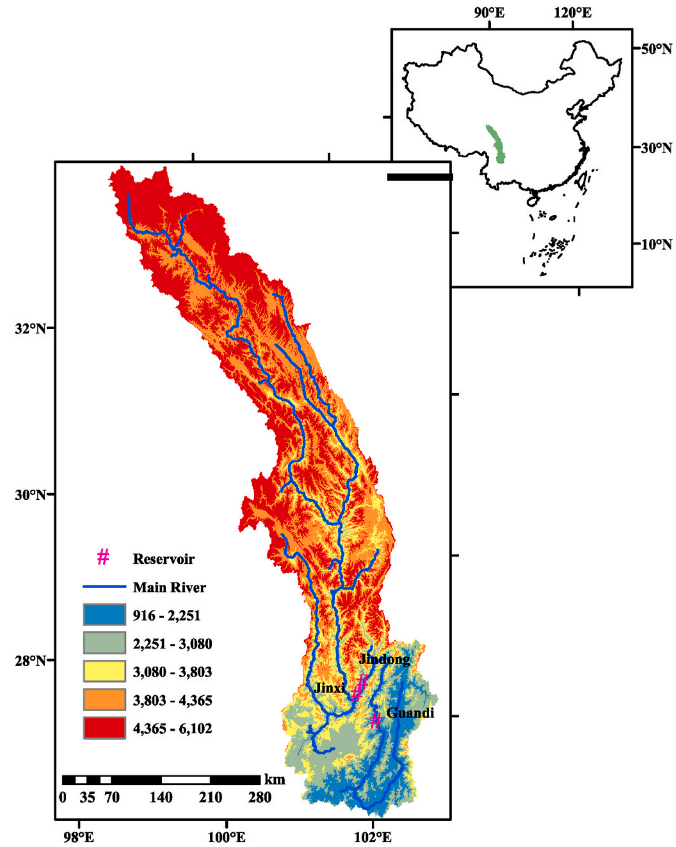


Fig. 2. Map and geographical location of the Jinguan cascade hydropower stations.

$$\max \sum_{t=1}^{T} B(s_{t-1}, q_t, s_t) \tag{20}$$

In this case, the forecasts are always identical to the observed inflows, which is equivalent to a "perfect forecasting system." Therefore, this strategy is equivalent to the maximum economic gain.

The effect of the quality of the streamflow forecast on the operation of the cascade hydropower system is analyzed by comparing the results of these four strategies.

4. Results and discussion

4.1. Evaluation of the synthetic streamflow forecast quality

To validate the model used to generate synthetic forecasts of controlled quality, we evaluated the quality of each streamflow forecast system in terms of bias, variance, and accuracy. First, the quality of the different streamflow forecast systems is determined according to a combination of the coefficient of determination R^2 and the spread factor b. In this case study, the coefficient of determination ranges from 0 to 1 in steps of size 0.1, while the spread factor ranges from 0.8 to 1.2 in steps of size 0.05. Therefore, there are a total of $11 \times 9 = 99$ synthetic streamflow forecast systems. The quality of the synthetic streamflow forecast is evaluated at two different time scales, namely every 10 days and over the whole year. The analysis of forecast uncertainty is the basic research for the evaluation of different strategies and, therefore, the elaborate processes of results of the analysis of different quality of synthetic streamflow forecast generated by the GMOVE approach are given in Supplementary Material (S2). Results show that the GMOVE approach generates synthetic streamflow data with predetermined forecast quality attributes (bias, variance, and accuracy), which can prevent unrealistic operation strategies.

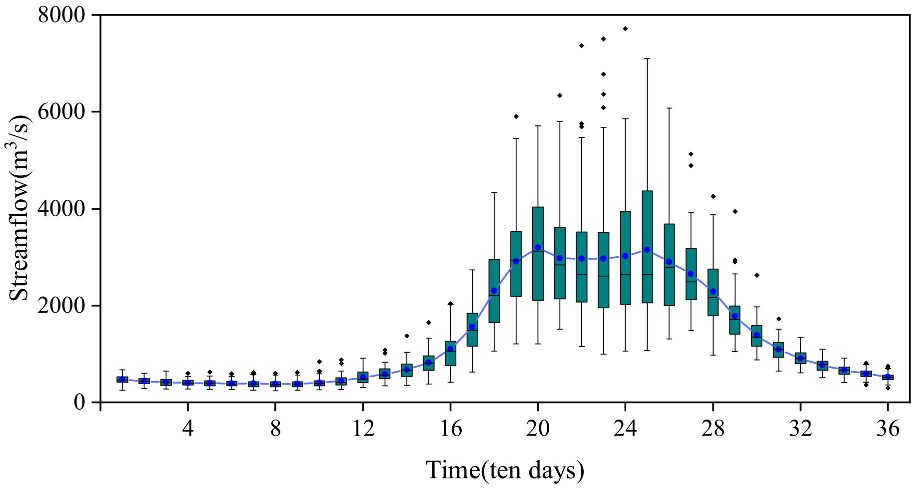


Fig. 3. Boxplot of observed streamflow over a time scale of 10 days.

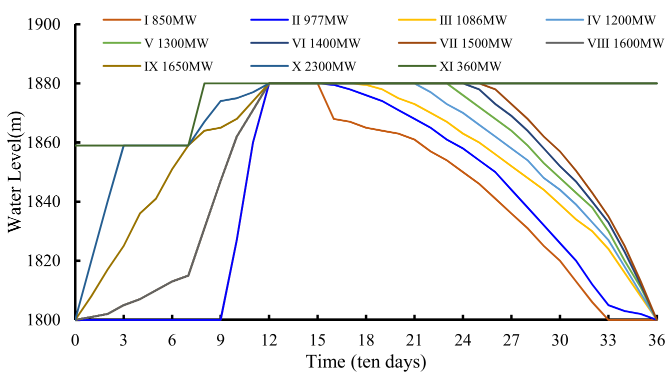


Fig. 4. Conventional rules for the operation of the Jinxi hydropower station.

4.2. Evaluation of the joint operation of cascade hydropower systems under synthetic streamflow forecasts with different variance and bias

The operation of cascade hydropower stations was simulated once using each strategy and the synthetic streamflow forecasts with different values of R^2 and b. The simulations used a time step of 10 days and a simulation period of 60 years. A total of 2160 periods (36×60) were simulated. For each period, the operating policy of all four strategies was applied. The results obtained with the two stochastic optimization models (Strategies B and C) under each synthetic streamflow forecast system were then evaluated against the results obtained using the two extreme reference strategies.

4.2.1. Performance evaluation of two reference strategies

Reference strategy A does not take forecast information into account and is based solely on historical observed streamflow scenarios, representing the worst operation strategy. Reference strategy D is informed by the perfect streamflow information, in which the forecasts are always equal to the observed streamflow, representing the ideal operation strategy. To illustrate the difference between the two reference strategies, the average water storage, total output, and water spill of the cascade reservoir are presented in Fig. 5. The average water storage represents the total water storage of three reservoirs at the end of every 10 days, noting that the regulation volume of the leading (Jinxi) reservoir is much larger than that of the downstream reservoirs in the cascade and plays a major role in water supply and storage. The water spill of the cascade is the outflow of the lowest reservoir in the cascade, and cannot be used for electricity production.

As shown in Fig. 5(a), Strategies A and D have the same tendency in terms of power generation, with more power generated during the flood season and less power generated in the dry and transition seasons. However, in terms of cumulative annual power revenue (CAPR), Strategy D (160.53×10^8 CNY) performs better than Strategy A (148.38×10^8 CNY). The reasons can be found in Fig. 5(b) and (c): because Strategy A depends on the day of the year and reservoir storage level and is limited by the flood control level in the pre-flood season, it results in conservative water consumption in the current period to ensure stable

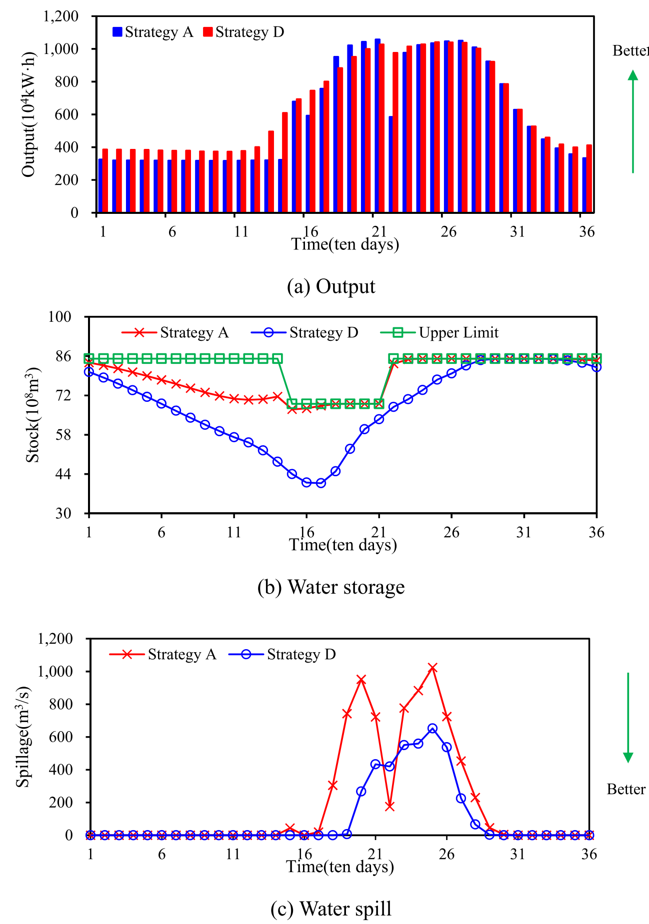


Fig. 5. Comparison of water spill, water storage, and output of cascade hydropower system for two reference strategies.

system operation in the future. Therefore, in each period, Strategy A stores more water than Strategy D, leading to a smaller total output in the non-flood seasons and higher levels of water spillage in the flood season (except for period 22) compared with Strategy D. The increase in power generation achieved by Strategy D comes from increased water use in the non-flood seasons and reduced water spillage in the flood season, reflecting the more efficient use of the reservoir regulation capacity.

The reliability (i.e., the probability that hydropower generation meets the guaranteed output demand) was also calculated using the two reference strategies, and the results are presented in Table 2. When the perfect forecast is used, the reliability of both the cascade system and each hydropower station can be effectively increased. As the cascade hydropower stations generally use the same electricity transmission lines, the system reliability (defined as the probability that the system output is not lower than the system guaranteed output) is more important than the reliability of a single hydropower station. Table 2 indicates that the system reliability of Strategy D can be up to 100%, which is the ideal operating policy for the cascade hydropower system. Note that reliability only measures the frequency of failures and provides no indication of the magnitude of failures. Thus, the cumulative annual output shortage (CAOS) is envisioned as the complement of system reliability in this study (see Table 2). We can see that Strategy D performs better than Strategy A in terms of CAOS.

4.2.2. Performance evaluation of two stochastic optimization strategies

Strategies B and C (SDP and BSDP, respectively) were simulated under the synthetic streamflow forecasts with different levels of variance and bias. The results are compared in terms of the CAPR, system reliability(SR), and CAOS. The CAPR is an important indicator of the hydropower system in terms of economic value. SR and CAOS are used to evaluate the probability and magnitude of reliability.

Fig. 6 shows the performance of the two stochastic optimization strategies (Strategies B and C) in terms of the three evaluation indices. Compared with the two reference strategies, Strategy B achieves higher (lower) CAPR and SR than Strategy A (Strategy D) under each synthetic forecasting system, with values ranging from 153.42 $\times$ 10^8 CNY to 156.50 $\times$ 10^8 CNY and 94.72%–99.03%, respectively. Similarly, Strategy C performs better than Strategy A but worse than Strategy D in terms of CAPR and SR, with values ranging from 157.25 $\times$ 10^8 CNY to 158.56 $\times$ 10^8 CNY and 99.35%–99.63%, respectively. Compared with Strategy A, even using random descriptions of the streamflow in future periods ($R^2 = 0$) allows strategy B to increase the CAPR by at least 6.63 $\times$ 10^8 CNY and the SR by 33.89%; under the same conditions, strategy C increases CAPR by at least 8.86 $\times$ 10^8 CNY and SR by 38.52%. The reason for this is that the hedging effect inherent to the two stochastic optimization strategies can balance the current water supply and future water shortages, which further stabilizes hydropower generation and improves the power quality. Thus, compared with Strategy A, the two stochastic optimization strategies informed by imperfect forecasts explicitly increase the economic gain and enhance the system reliability of the cascade hydropower system.

Although the hedging effect of the two stochastic optimization strategies is similar, there are differences between Strategies B and C in terms of CAPR improvement over Strategy A. For the same streamflow forecast system, Strategy C produces greater economic gains than Strategy B (see Fig. 6(a)). Fig. 6(b) and (c) show the probability and magnitude of reliability for the cascade hydropower system. Compared with Strategy B, Strategy C increase at least 1.80 CNY in CAPR and 0.28% in SR. For Strategy C, these two indices are better than those of Strategy A and worse than those of Strategy D; both indices are higher for Strategy C than for Strategy B under each synthetic forecast system. However, although the SR of Strategy B is better than that of Strategy A, the CAOS of Strategy B may be worse than that of Strategy An under streamflow forecasts with a larger positive bias and lower accuracy, meaning that the deficit situations for hydropower generation may become severe. Different from Strategy B, the CAOS of Strategy C is better than that of Strategy An under each synthetic streamflow forecast. Therefore, compared with Strategy B, which assumes the forecast is perfect, the ability of Strategy C to consider forecast uncertainty can produce economic gains and enhance system reliability in the cascade hydropower system.

Fig. 7 shows a 2D visualization of Fig. 6 to illustrate the performance of the two stochastic optimization strategies. From Fig. 7(a)–(c), we can see that Strategy B improves as R^2 increases and b decreases, indicating that the forecast with the highest positive bias and lowest accuracy generates the worst economic value and reliability in the cascade hydropower system. This result implies that more reliable streamflow forecasts are increasingly valuable in improving cascade hydropower system operation. From Fig. 7(d)–(f), we find that Strategy C produces an increase in CAPR with increasing R^2, but the trend is not obvious. Neither R^2 nor b has a significant effect on the system reliability or CAOS. To analyze the effects of forecast uncertainty and bias on the actual operation of cascade hydropower stations under the two stochastic optimization strategies, the differences in the increment of the average water storage, total output, and water spill relative to Strategy An under two types of synthetically generated forecasts are shown in Fig. 8.

Fig. 8(a) and (c) show results obtained from a synthetically generated forecast with $b = 1$, allowing us to analyze the effect of forecast uncertainty on the actual operation of cascade hydropower stations in each period of the year. We can see that the water spillage and water storage of the two stochastic optimization strategies in each period are less than 0, which means these two indices have decreased compared with Strategy A. The decrease in water spillage mainly occurs near the flood season (periods 15–28). The reason is that the two stochastic optimization strategies store less water in the flood season than Strategy A, and so the cascade reservoir has more capacity to store the streamflow during the flood season.

Fig. 8(a) and (c) indicate that, as R^2 increases, the water storage increases in the non-flood season and decreases in the flood season. Thus, with increasing R^2, water spillage can be decreased by the two stochastic optimization strategies. Moreover, the increment in the total output relative to Strategy A is greater than 0, which means the output has increased. The increase in output mainly occurs in periods 1–14 and periods 33–36, which is the non-flood season. The reason can be found in Fig. 8(a) and (c), in which the water storage decreases during the non-flood season and increases during the flood season. This behavior is close to that of Strategy D, which fully uses the reservoir regulation capacity. In summary, as R^2 increases, the total output increases in the non-flood season, which enhances both the *CAPR* and system reliability.

Fig. 8(b) and (d) illustrate the case in which R^2 is fixed to 0.5, allowing us to analyze the effect of the forecast bias on the actual operation of cascade hydropower stations in each period of the year. The water spillage and water storage of the two stochastic optimization strategies in each period are lower than with Strategy A. Additionally, compared with R^2, the spread factor b has the opposite effect on the water storage, water spillage, and the total output of Strategy B. Specifically, with increasing b, the amount of water storage and water spillage increase under Strategy B in all seasons. The reason is that owing to the same prior streamflow transition probability being used in different forecast scenarios, the decision result under SDP is only effect

Table 2
Reliability and output shortages under two reference strategies.

Schemes	Reliability (%)				CAOS (10^4kW)
	Jinxi	Jindong	Guandi	Cascade	Cascade
Strategy A	95.93	63.10	50.28	60.83	106.92
Strategy D	98.94	100.00	83.89	100.00	0.00

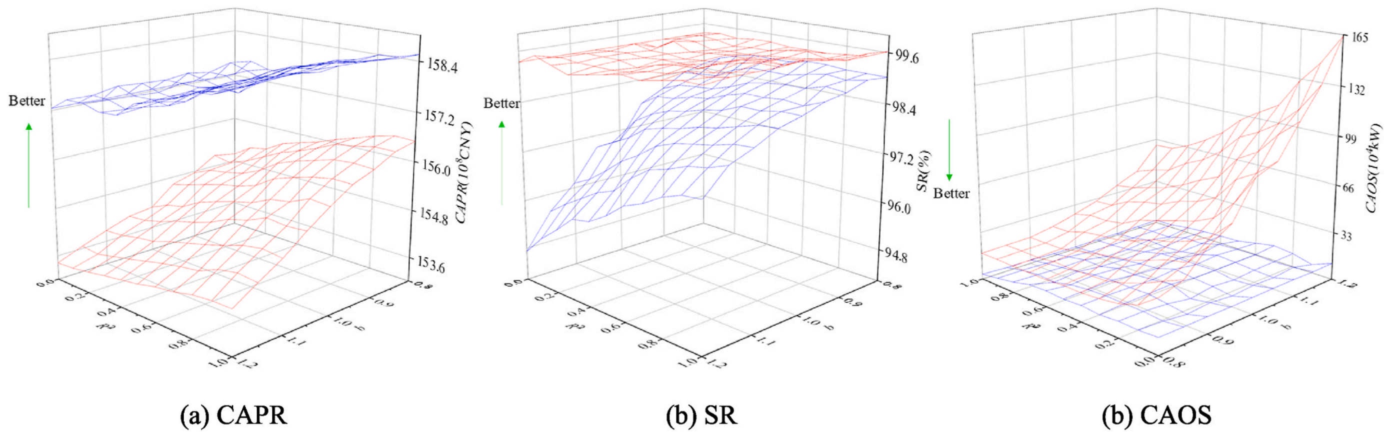


Fig. 6. System performance of two stochastic optimization strategies for 10-day-ahead synthetically generated forecasts under different values of R^2 and b(red: Strategy B; blue: Strategy C).

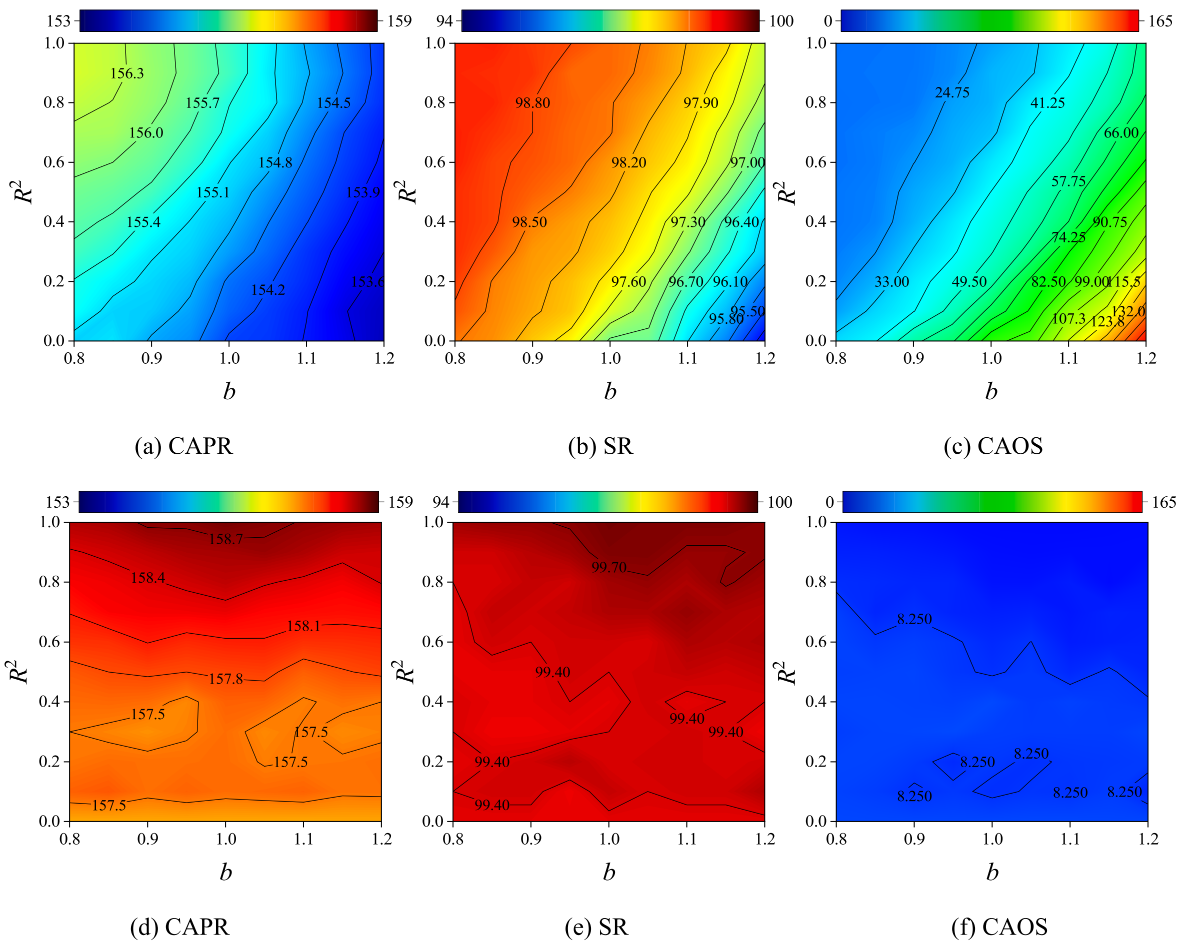
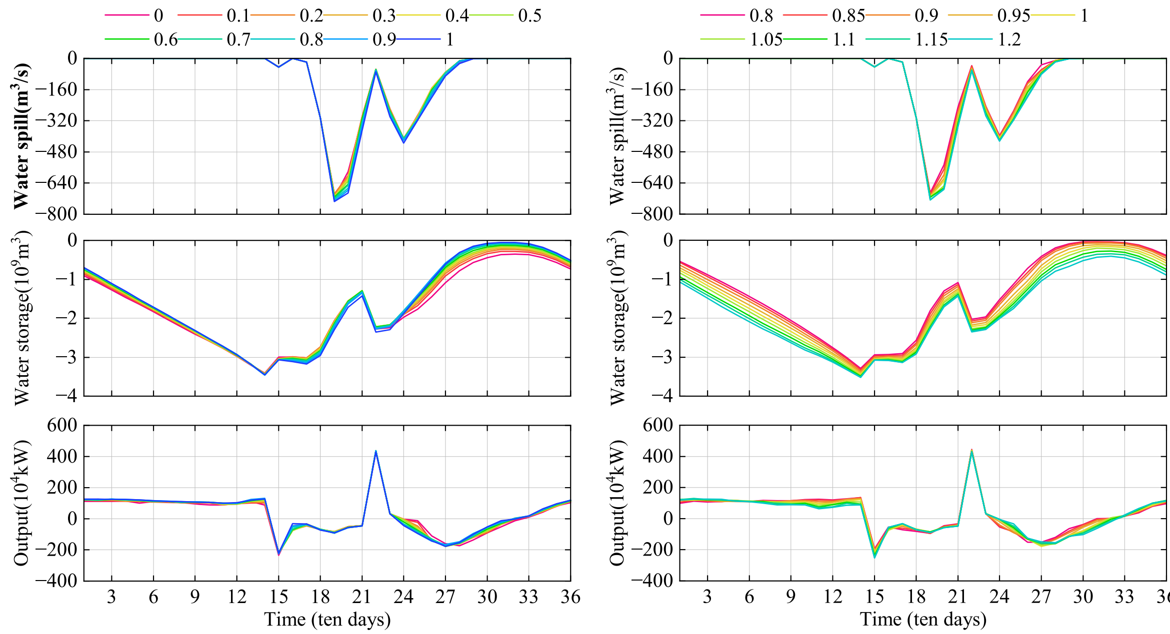


Fig. 7. System performance of two stochastic optimization strategies for 10-day-ahead synthetically generated forecasts with different values of R^2 and b. (a)–(c) Strategy B; (d)–(f) Strategy C.

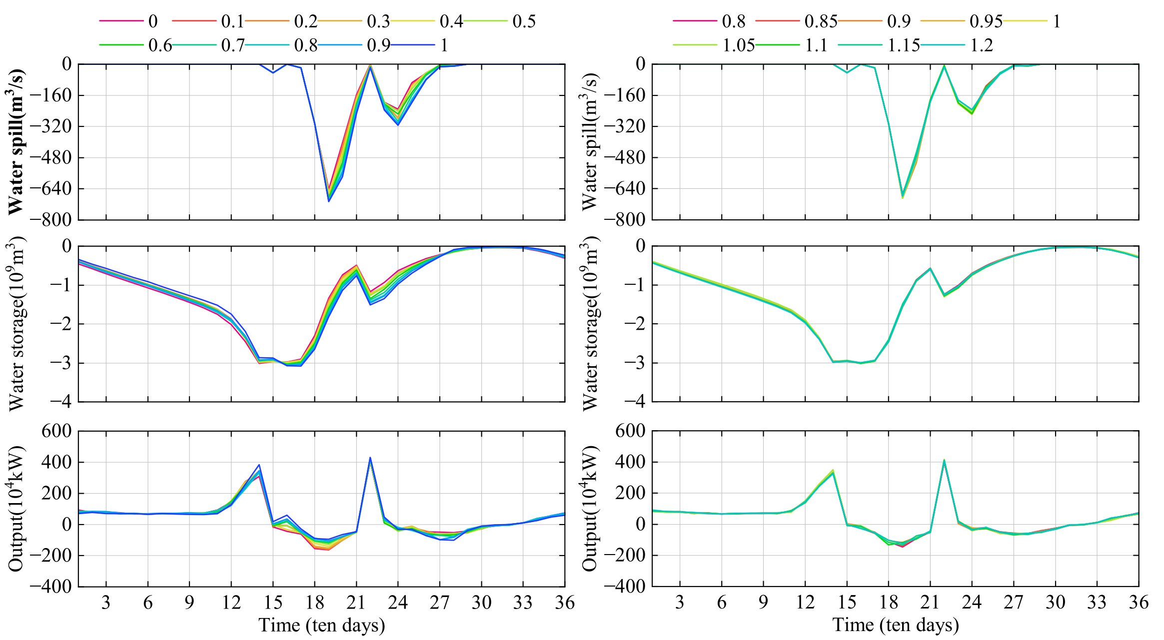
by the forecast inflow. Therefore, with the decrease of forecast bias, the reservoir will store more water and the net hydraulic head will increase in the dry season and transition season, leading to increases in CAPR and system reliability under Strategy B. However, different from Strategy B, the effect of an increase in b on water storage, water spillage, and total output is not obvious for Strategy C. The reason is the posterior probability change with the synthetic forecast, leading to the optimal operation police can adapt to different forecast scenarios.

As stated above, although the two stochastic optimization strategies informed by imperfect forecasts perform better than the strategy informed by no forecast, they produce differences in the actual operation of the cascade hydropower system. To analyze the differences induced by Strategies B and C, the average water storage, water spillage, and total output are compared with the actual operating results of the ideal operation strategy (Strategy D). Fig. 9 presents the differences in the water storage and the water spillage under these three strategies



(a) SDP under different R^2 with b = 1.

(b) SDP under different b with R^2=0.5



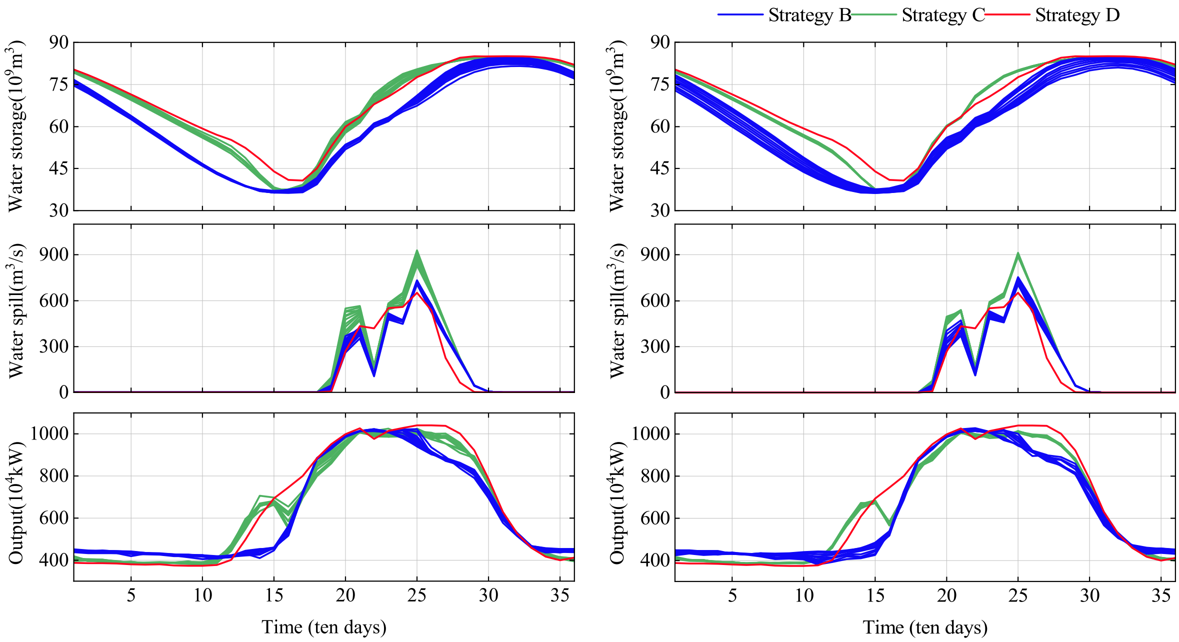
(c) BSDP under different R^2 with b = 1.

(d) BSDP under different b with R^2=0.5

Fig. 8. Comparison of water spillage, water storage, and output of the cascade for different strategies under different synthetic streamflow forecasts.

under two types of synthetically generated forecasts.

As can be seen in Fig. 9, under two synthetically generated forecasts, Strategies C and D tend to store water in the reservoir and reduce the amount of water used for power generation compared with Strategy B during the non-flood season (periods 1–14 and periods 33–36). As a result, Strategies C and D give a lower total output than Strategy B in these periods. However, as the water storage of the cascade decreases (periods 11–16), Strategies C and D achieve a larger total output than Strategy B because of the decrease in hydraulic head and available water resources. With the increase in rainfall during the flood season (periods 16–27), the available water resources increase and further cause water spills, leading to the total output of all three strategies being close to the installed capacity of the cascade (10800 MW). From periods 28–30, less water is used for power generation under Strategy B than under Strategies C and D, because more water is stored in the cascade reservoir for future use. In summary, compared with Strategies C and D, Strategy B uses more water before the flood season and stores water slowly during the flood season, leading to a decrease in the output of Strategy B. Overall, to fully utilize the water resource and increase hydropower generation, water spillage must be reduced and the production rate must be increased.



(a) Different R^2 with $b = 0$.

(b) Different b with R^2=0.5

Fig. 9. Comparison of water spillage, water storage, and output of the cascade for different strategies under different synthetic streamflow forecasts.

5. Conclusion

The purpose of this study was to identify the effect of forecast quality on the forecast economic value in the case of cascade hydropower systems based on stochastic optimization methods. Taking the Jinguan cascade hydropower system as a case study, we investigated the impact of different quality attributes of long-term (10-day-ahead) streamflow forecasts on several variables of four management strategies. Based on the observed streamflow over 61 years, the GMOVE approach was used to generate synthetic streamflow forecasting systems of varying quality in terms of bias, variance, and accuracy. The synthetic streamflow forecasts were then used to drive the cascade hydropower station strategies and the corresponding observed streamflow data were used to imply the output policies. The following findings have been obtained.

(1) Strategy A, which uses no forecast information, produced the lowest *CAPR* (148.38 × 10^8 CNY) and system reliability (60.83%). The other three optimization strategies performed better than Strategy A, increasing power generation through improved water use in the non-flood season and reduced water spillages in the flood season. Compared with Strategy A, the use of perfect forecast information by Strategy D increased *CAPR* by 12.15 × 10^8 CNY and improved system reliability by 39.17%. Strategy B (SDP) produced an increase of at least 6.63 × 10^8 CNY in *CAPR* and 33.89% in system reliability over Strategy A, while Strategy C (BSDP) enhanced *CAPR* by 8.86 × 10^8 CNY and system reliability by 38.52%. Under each synthetic streamflow forecast system, the consideration of forecast uncertainty and natural uncertainty by Strategy C resulted in better performance than Strategy B, which only considers natural uncertainty.

(2) For the two stochastic optimization strategies, improvements in forecast accuracy increase economic gain and enhance system reliability. However, the two stochastic optimization strategies have some significant differences. For Strategy B (SDP), forecast systems with a negative bias result in a tendency to keep more water for future use, so that the cascade reservoir can generate hydropower at a higher production rate. When the forecast system changes from negative bias to positive bias, the economic gain and system reliability of the cascade hydropower system derived from Strategy B become worse. Thus, the forecast with the highest positive bias and lowest accuracy generates the worst economic value and reliability under Strategy B. Strategy C (BSDP) can handle forecast bias better, such that the system reliability and economic revenue under Strategy C are not significantly affected by bias in the forecast.

While this study has analyzed the effect of forecast quality on the forecast economic value in the long-term operation of cascade hydropower systems, factors relating to climate change, the power market, and the complementary operation of wind–photovoltaic–hydropower systems have been neglected. The combination of long- and short-term streamflow forecasts on cascade reservoir operations is closer to the actual real-world scenario, and future work should focus on this aspect.

Author contribution

Yuan, Liu. and Changming, Ji. conceived and designed the experiments; Yuan, Liu, Xiaoning Huo performed the experiments; Yuan, Liu. and Yanke, Zhang. analyzed the data; Yi, Wang, and Yanke, Zhang. wrote the paper. Yi, Wang and Zhiqiang, jiang edited the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.127298.

References

[1] Tan Q, Fang G, Wen X, Lei X, Wang X, Wang C. Bayesian stochastic dynamic programming for hydropower generation operation based on copula functions. Water Resour Manag 2020;34:1589–607. https://doi.org/10.1007/s11269-019-02449-8.
[2] Zhang Z, Qin H, Li J, Liu Y, Wang Y, Wang C, et al. Short-term optimal operation of wind-solar-hydro hybrid system considering uncertainties. Energy Convers Manag 2020;205:112405. https://doi.org/10.1016/j.enconman.2019.112405.
[3] Zhu F, Zhong P, Xu B, Liu W, Wang W, Sun Y, et al. Short-term stochastic optimization of a hydro-wind-photovoltaic hybrid. Energy Convers Manag 2020;214:112902. https://doi.org/10.1016/j.enconman.2020.112902.
[4] Zhu F, Zhong P, Sun Y, Yeh WWG. Real-Time optimal flood control decision making and risk propagation under multiple uncertainties. Water Resour Res 2017;53:10635–54. https://doi.org/10.1002/2017WR021480.
[5] Gong Y, Liu P, Ming B, Li D. Identifying the effect of forecast uncertainties on hybrid power system operation: a case study of Longyangxia hydro-photovoltaic plant in China. Renew Energy 2021;178:1303–21. https://doi.org/10.1016/j.renene.2021.06.104.
[6] Liu Y, Ji C, Wang Y, Zhang Y, Hou X, Xie Y. Quantifying streamflow predictive uncertainty for the optimization of short-term cascade hydropower stations operations. J Hydrol 2021;605:127376. https://doi.org/10.1016/j.jhydrol.2021.127376.
[7] Zhao T, Zhao J. Joint and respective effects of long- and short-term forecast uncertainties on reservoir operations. J Hydrol 2014;517:83–94. https://doi.org/10.1016/j.jhydrol.2014.04.063.
[8] Yuan L, Zhou J. Self-optimization system dynamics simulation of real-time short term cascade hydropower system considering uncertainties. Water Resour Manag 2016;31:2127–40. https://doi.org/10.1007/S11269-017-1628-3.
[9] Jiang Z, Wu W, Qin H, Zhou J. Credibility theory based panoramic fuzzy risk analysis of hydropower station operation near the boundary. J Hydrol 2018;565:474–88. https://doi.org/10.1016/j.jhydrol.2018.08.048.
[10] Yuan L, Zhou J. Self-optimization system dynamics simulation of real-time short term cascade hydropower system considering uncertainties. Water Resour Manag 2016;31:2127–40. https://doi.org/10.1007/S11269-017-1628-3.
[11] Jiang Z, Ji C, Qin H, Feng Z. Multi-stage Progressive Optimality Algorithm and its application in energy storage operation chart optimization of cascade reservoirs. Energy 2018;148:309–23. https://doi.org/10.1016/j.energy.2018.01.176.
[12] Su C, Yuan W, Cheng C, Wang P, Sun L, Zhang T. Short-term generation scheduling of cascade hydropower plants with strong hydraulic coupling and head-dependent prohibited operating zones. J Hydrol 2020;591:125556. https://doi.org/10.1016/j.jhydrol.2020.125556.
[13] Wang L, Wang B, Zhang P, Liu M, Li C. Study on optimization of the short-term operation of cascade hydropower stations by considering output error. J Hydrol 2017;549:326–39. https://doi.org/10.1016/j.jhydrol.2017.03.074.
[14] Zmijewski N, Wörman A. Hydrograph variances over different timescales in hydropower production networks. Water Resour Res 2016;52:5829–46. https://doi.org/10.1002/2015WR017775.
[15] Xu W, Zhang C, Peng Y, Fu G, Zhou H. A two stage Bayesian stochastic optimization model for cascaded hydropower systems considering varying uncertainty of flow forecasts. Water Resour Res 2014;50:9267–86. https://doi.org/10.1002/2013WR015181.
[16] Zhao T, Wang Q, Bennett JC, Robertson DE, Shao Q, Zhao J. Quantifying predictive uncertainty of streamflow forecasts based on a Bayesian joint probability model. J Hydrol 2015;528:329–40. https://doi.org/10.1016/j.jhydrol.2015.06.043.
[17] Maurer E, Lettenmaier D. Potential effects of long-lead hydrologic predictability on Missouri river main-stem reser voirs. J Clim 2004;17:174–86. https://doi.org/10.1175/1520-0442(2004)017<0174:PEOLHP>2.0.CO;2.
[18] Zhao T, Zhao J. Joint and respective effects of long- and short-term forecast uncertainties on reservoir operations. J Hydrol 2014;517:83–94. https://doi.org/10.1016/j.jhydrol.2014.04.063.
[19] Turner S, Bennett J, Robertson D, Galelli S. Complex relationship between seasonal streamflow forecast skill and value in reservoir operations. Hydrol Earth Syst Sci 2017;21:4841–59. https://doi.org/10.5194/hess-21-4841-2017.
[20] Arsenault R, Côté P. Analysis of the effects of biases in ensemble streamflow prediction (ESP) forecasts on electricity production in hydropower reservoir management. Hydrol Earth Syst Sci 2019;23:2735–50. https://doi.org/10.5194/hess-23-2735-2019.
[21] Cassagnole M, Ramos M, Zalachori I, Thirel G, Garçon R, Gailhard J, Ouillon T. Impact of the quality of hydrological forecasts on the management and revenue of hydroelectric reservoirs – a conceptual approach. Hydrol Earth Syst Sci 2021;25:1033–52. https://doi.org/10.5194/hess-25-1033-2021.
[22] Zhao T, Zhao J, Yang D, Wang H. Generalized martingale model of the uncertainty evolution of streamflow forecasts. Adv Water Resour 2013;57:41–51. https://doi.org/10.1016/j.advwatres.2013.03.008.
[23] Anghileri D, Voisin N, Castelletti A, Pianosi F, Nijssen B, Lettenmaier D. Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments. Water Resour Res 2016;52:4209–25. https://doi.org/10.1002/2015WR017864.
[24] Liu H, Sun Y, Yin X, Zhao Y, Cai Y, YangW. A reservoir operation method that accounts for different inflow forecast uncertainties in different hydrological periods. J Clean Prod 2020;256:120471. https://doi.org/10.1016/j.jclepro.2020.120471.
[25] Alemu E, Palmer R, Polebitski A, Meaker B. Decision support system for optimizing reservoir operations using ensemble streamflow predictions. J Water Resour Plann Manag 2011;137:72–82. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000088.
[26] Lamontagne J, Stedinger J. Generating synthetic streamflow forecasts with specified precision. J Water Resour Plann Manag 2018;144:04018007. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000915.
[27] Chen L, Singh VP, Lu W, Zhang J, Zhou J, Guo S. Streamflow forecast uncertainty evolution and its effect on real-time reservoir operation. J Hydrol 2016;540:12–726. https://doi.org/10.1016/j.jhydrol.2016.06.015.
[28] Jiang Z, Li R, Li A, Ji C. Runoff forecast uncertainty considered load adjustment model of cascade hydropower stations and its application. Energy 2018;158:693–708. https://doi.org/10.1016/j.energy.2018.06.083.
[29] Yang Z, Yang K, Wang Y, Su L, Hu H. Multi-objective short-term hydropower generation operation for cascade reservoirs and stochastic decision making under multiple uncertainties. J Clean Prod 2020;276:122995. https://doi.org/10.1016/j.jclepro.2020.122995.
[30] Zhao T, Cai X, Yang D. Effect of streamflow forecast uncertainty on real-time reservoir operation. Adv Water Resour 2011;34:495–504. https://doi.org/10.1016/j.advwatres.2011.01.004.
[31] Côté P, Leconte R. Comparison of stochastic optimization algorithms for hydropower reservoir operation with ensemble streamflow prediction. J Water Resour Plann Manag 2015;142:04015046. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000575.
[32] Labadie J. Optimal operation of multireservoir systems: state-of-the-art review. J Water Resour Plann Manag 2004;130:93–111. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93.
[33] Turgeon A. Stochastic optimization of multireservoir operation: the optimal reservoir trajectory approach. Water Resour Res 2005;43:W05420. https://doi.org/10.1029/2005WR004619.
[34] Yao H, Georgakakos A. Assessment of Folsom Lake response to historical and potential future climate scenarios. 2. Reservoir management. J Hydrol 2001;249:176–96. https://doi.org/10.1016/S0022-1694(01)00418-8.
[35] Li X, Guo S, Liu P, Chen G. Dynamic control of flood limited water level for reservoir operation by considering inflow uncertainty. J Hydrol 2010;391:126–34. https://doi.org/10.1016/j.jhydrol.2010.07.011.
[36] Huang K, Ye L, Chen L, Wang Q, Dai L, Zhou J, Singh V, Huang M, Zhang J. Risk analysis of flood control reservoir operation considering multiple uncertainties. J Hydrol 2018;565:672–84. https://doi.org/10.1016/j.jhydrol.2018.08.040.
[37] Feng Z, Niu W, Chen C. Multi-objective quantum-behaved particle swarm optimization for economic environmental hydrothermal energy system scheduling. Energy 2017;131:165–78. https://doi.org/10.1016/j.energy.2017.05.013.
[38] Cheng C, Su C, Wang P, Shen J, Lu J, Wu X. An MILP-based model for short-term peak shaving operation of pumped-storage hydropower plants serving multiple power grids. Energy 2018;163:722–33. https://doi.org/10.1016/j.energy.2018.08.077.
[39] He Z, Zhou J, Qin H, Jia B, He F, Liu G, Feng K. A fast water level optimal control method based on two stage analysis for long term power generation scheduling of hydropower station. Energy 2020;210:118531. https://doi.org/10.1016/j.energy.2020.118531.
[40] Tejada J, Johnson S, Stedinger J. The value of hydrologic information in stochastic dynamic programming models of a multireservoir system. Water Resour Res 1995;31:2571–9. https://doi.org/10.1029/95WR02172.
[41] Tan Q, Wen X, Fang G, Wang Y, Qin G, Li H. Long-term optimal operation of cascade hydropower stations based on the utility function of the carryover potential energy. J Hydrol 2020;580:124359. https://doi.org/10.1016/j.jhydrol.2019.124359.
[42] Wan W, Wang H, Zhao J. Hydraulic potential energy model for hydropower operation in mixed reservoir systems. Water Resour Res 2020;56:6. https://doi.org/10.1029/2019WR026062. e2019WR026062.
[43] Xu B, Sun Y, Huang X, Zhong PA, Zhu F, Zhang J, Wang X, Wang G, Ma Y, Lu Q, Wang H, Guo L. Scenario-based multiobjective robust optimization and decision-making framework for optimal operation of a cascade hydropower system under multiple uncertainties. Water Resour Res 2022;58:e2021WR030965. https://doi.org/10.1029/2021WR03096.
[44] Stedinger J, Sule B, Loucks D. Stochastic dynamic programming models for reservoir operation optimization. Water Resour Res 1984;20:1499–505. https://doi.org/10.1029/WR020i011p01499.
[45] Karamouz M, Vasiliadis H. Bayesian stochastic optimization of reservoir operation using uncertain forecasts. Water Resour Res 1992;28:1221–32. https://doi.org/10.1029/92WR00103.

[46] Mujumdar P, Nirmala B. A Bayesian stochastic optimization model for a multi-reservoir hydropower system. Water Resour Manag 2007;21:1465–85. https://doi.org/10.1007/s11269-006-9094-3.
[47] Grygier JC, Stedinger JR, Yin H. A generalized maintenance of variance extension procedure for extending correlated series. Water Resour Res 1989;25P:345–9.
[48] Ene S, Küçükoğlu I, Aksoy A, Öztürk N. A genetic algorithm for minimizing energy consumption in warehouses. Energy 2016;114:973–80. https://doi.org/10.1016/j.energy.2016.08.045.
[49] Tsoulos IG, Tzallas A, Tsalikakis D. PDoublePop: an implementation of parallel genetic algorithm for function optimization. Comput Phys Commun 2016;209:183–9. https://doi.org/10.1016/j.cpc.2016.09.006.