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Stimulate hydropower output of mega cascade reservoirs using an improved Kidney Algorithm

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A B S T R A C T

The evolutionary algorithms can solve reservoir operation with a fast convergence rate whereas the major impediments in handling the joint operation of mega cascade reservoirs easily trigger the technical bottlenecks, i.e. trapping into a local optimum, instability and loss of good solutions. This study proposes a methodology that fuses three auxiliary strategies into the Kidney Algorithm (KA) to optimize the hydropower output for conquering the bottlenecks in the KA concerning the joint operation of six mega cascade reservoirs located in the Jin-Sha River basin in China. The proposed theme would contribute to the application of the state-of-the-art evolutionary algorithms in boosting the cleaner hydropower production of mega cascade reservoirs. The three auxiliary strategies are that: firstly, the exploration and exploitation strategy is employed to stimulate the movement of solutions to surmount technical drawback of trapping into a local optimum; secondly, the adaptive strategy is used to automatically adjust algorithm parameter values to overcome the instability problem; lastly, the elitism strategy is introduced to preserve the best solution at every epoch to avoid the loss of good solutions. Our methodology, without expanding or upgrading hydraulic infrastructures, can increase the hydropower production of the six mega cascade reservoirs by 7.8%, as compared with the standard operation policy. The hydropower production can reach 4.8 billion kW·h/year, which can decrease 3.77 billion kg/year in CO_2 emission, and bring 217.44 million USD/year in hydropower benefits. The improved KA can considerably increase the reliability and resilience of hydropower output as well as largely decrease the vulnerability of hydropower output. The results suggest that our methodology can stimulate hydropower output to yield more benefits regarding cleaner production, carbon emission reduction and sustainability.

1. Introduction

Renewable energy spreads to a growing number of developing and emerging economies. In some areas, renewable energy has become a pivotal electricity source due to the rapid growth in the population under urbanization. The ongoing growth in magnitude and geographical expansion of renewable power capacity are driven by the continuing decline in price for renewable energy technologies, by raising power demand in some countries and by targeting renewable energy support mechanisms. Nowadays, most new renewable energy power plants are installed in developing countries, especially in China, which is the largest developer over the past eight years. By the end of 2016, the top regions or countries for total installed renewable energy capacity are China, Europe, USA, India and Japan (Fig. 1 (a)). In 2016, the renewable energy production estimated to reach 30% (2016.8 GW) of the world's generation capacity. This amount is enough to provide 24.5% of global actual energy consumption. Among the renewable energy sources, hydropower has a low mean power generation cost and high generation stability (Global Status Report of renewable energy, 2017). Globally, hydropower provides 16.6% global energy consumption (Fig. 1 (b)), and this number exceeds 20% in China (REN21,

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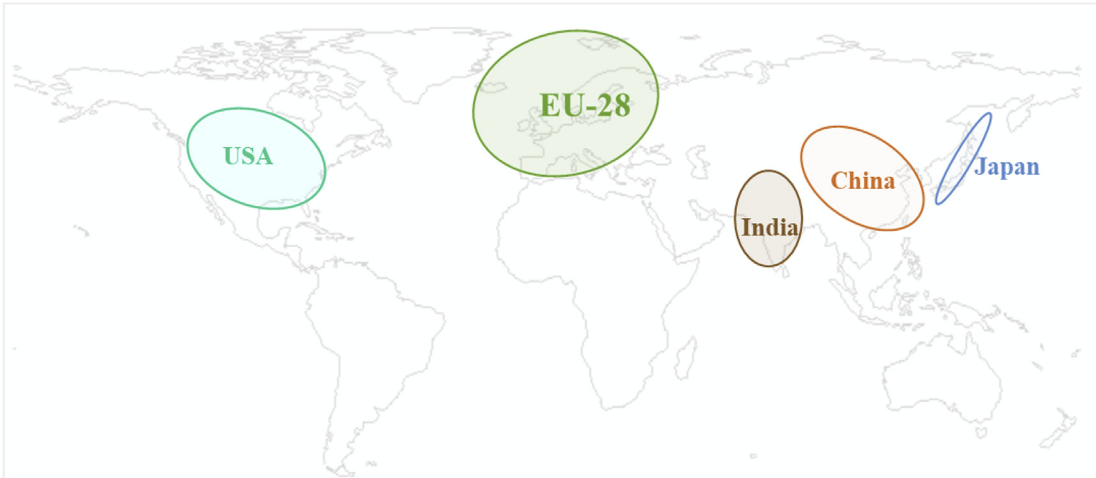
a.



Renewable energy technology	Global	EU-28	China	USA	India	Japan
	GW					
Hydropower	1096	127	332	80	47	23
Wind power	487	154	169	82	29	3.2
Solar PV	303	106	77	41	9.1	43
Bio-power	112	37	12	16.8	8.3	4.1
Others	18.8	3.5	0.4	5.3	0.2	0.5

b.

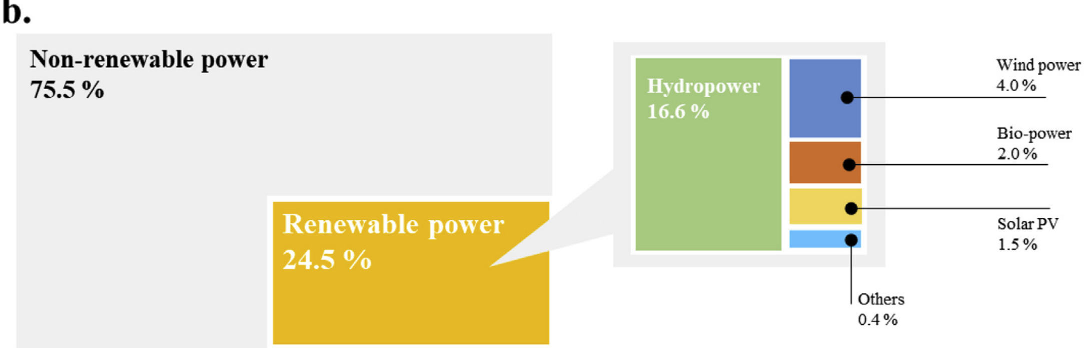


Fig. 1. Global renewable energy capacity and production in 2016. **a.** Global renewable energy capacity of top regions/countries. **b.** Renewable energy share of global energy production.
Notes: EU-28 consists of 28 European Countries. The data tracked 155 countries including Africa, Asia, Central America, the Caribbean, Eurasia, Europe, Middle East, North America, Oceania, South America, China, India and the United States, covering 96% of global GDP and representing 96% of global population. (Extracted from the REN21 Renewables Global Status Report, 2017).

2017). The hydropower will continue to grow (from 13% in 2000 to 19% in 2016) to compensate for the decline in thermal power production (from 85% in 2000 to 73% in 2016). Compared with other renewable energy sources, hydropower is flexible in electricity generation and supply, and hence hydropower yields more social benefits for energy economy (He et al., 2018), energy safety (Cheng et al., 2018), carbon emission reduction (Hu et al., 2011; Dou, 2013) and non-fossil energy expansion (Feng et al., 2018a, b). Besides, many countries and regions are working to improve hydropower infrastructure, operation and market design to facilitate hydropower output (Ehteram et al., 2017; Singh and Singal, 2017). To raise cleaner production, our study is concentrated on probing into a joint operation of mega cascade reservoirs to lift synergy of water-energy nexus and significantly mitigate CO_2 emission with the use of Artificial Intelligence (AI)-based heuristic techniques.

Modernization and retrofitting of existing facilities continue to be a vital part of hydropower operations, including the implementation of advanced AI technologies and data analytics for digitally enhanced hydropower generation (Singh and Singal, 2017; Jha et al., 2017). In recent years, researchers are seeking to imitate nature by evolutionary algorithms because the designs and abilities of nature are tremendous (Fister et al., 2013; Molina et al., 2018), and therefore nature is the best trainer for technology. Since the two domains and fields (nature & technology) have a much stronger connection and similarity, easy mapping is possible from nature to technology in the real world. Evolutionary algorithms inspired by nature mechanisms and used as a branch of AI techniques for solving various optimization problems have evolved rapidly over the last few decades (Maarouf et al., 2015; Allawi et al., 2019). The evolutionary algorithms are derived from the activities of physical or biological systems in the natural world. Some examples of evolutionary algorithms in the literature are listed in Table 1. The Genetic Algorithm (GA) (Goldberg, 1989), Simulated Annealing (SA) (Johnson et al., 1989), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Harmony Search (HS) (Geem et al., 2001), Ant Colony Optimization (ACO) (Bianchi et al., 2002), Honey Bee Optimization (HBO) (Pham et al., 2005), Intelligent Water Drops (IWD) (Hosseini, 2007), Cuckoo Search (CS) (Yang and Deb, 2009), Bat Algorithm (BA) (Yang, 2010a), Firefly Algorithm (FA) (Yang, 2010b), Black Hole (BH) (Hatamlou, 2013) and Kidney Algorithm (KA) (Jaddi et al., 2017) have been widely applied to optimizing hydropower stations (or cascade reservoirs) long term operation and short term operation as well as to renewable energy hybrid operation. For instance, Wang et al. (2018) proposed an effective procedure to strengthen the hydropower scheme by minimizing spillages in the cascade reservoirs short-term operation. Uen et al. (2018) developed a holistic scheme that integrated the long-term and short-term reservoir operation for improving the synergistic benefits of water-energy nexus. Ming et al. (2018a, b) fused the CS algorithm into dynamic programming to optimize the joint operation of large hydro–photovoltaic hybrid power plants. Shen et al. (2019) combined evolutionary algorithm and decision-making analysis to optimize the operation of interprovincial hydropower System. In comparison to the above mentioned evolutionary algorithms, the KA is introduced to optimize joint operation of mega cascade reservoirs on the grounds that: firstly, the KA was introduced by Jaddi et al. (2017) as a successful state-of-the-art optimization algorithm suitable for different engineering applications versus the other algorithms (Ekinci et al., 2018; Jaddi and Abdullah, 2018) in term of its computation speed, convergence, stability, and secondly, a review of the available literature indicates the KA has not been applied in mega cascade reservoirs operation. KA's application for the first time to a reservoir operation made by Ehteram et al. (2018a, b). To the best of our knowledge, although the KA can be used to solve the optimization of low dimensional reservoir operation (e.g. one reservoir, 12 (months) decision variables and 48 (= 12 months * 4 constraints) physical constraints at monthly time scale in a year), but its reliability and practicality of solving the high dimensional cascade reservoirs operation has not been explored. The major difficulties in handling a large number of decision variables and constraints closely associated with the optimization of cascade reservoirs operation and non-convex objective function (Cheng et al., 2012). They easily trigger the technical drawbacks, i.e. trapping into a local optimum, loss of good solutions as well as the instability problem (or lack of robustness) in evolutionary algorithms. Consequently, it is imperative to conduct in-depth research on the KA for enhancing its robustness of exploration and exploitation in solving the nonlinear non-convex objective function and high dimensional optimization operation of mega cascade reservoirs.

The main objective of this study is to promote the application of the state-of-the-art evolutionary algorithms for improving the cleaner hydropower production of mega cascade reservoirs. The innovative nature of this study lies in fusing three auxiliary strategies into the KA to overcome its technical bottlenecks. The improved KA is applied for optimizing the hydropower production of six mega cascade reservoirs. This is the first time that the KA is modified by using three auxiliary strategies and used to solve a complex joint operation of mega cascade reservoirs. The exploration is placed on two focuses. Firstly, the cascade reservoirs operation objective is defined as to maximize the hydropower generation, which a penalty function is added to the objective function to avoid violations of the guaranteed (or firm) power output. Secondly, an improved KA with three auxiliary strategies is employed to solve the optimization problem in a hierarchical structure. The auxiliary strategies consist of: for the movement operator and filtration operator, the exploration and exploitation strategy is introduced to stimulate the movement of solutions, and the adaptive strategy is used to adjust algorithm parameter values respectively. Before reaching the maximum epoch or stopping criterion, the elitism strategy is adopted for preserving the best solution in every epoch. The six mega cascade reservoirs located at the middle reach of Jin-Sha River in China are selected as a case study to assess the applicability as well as reliability of the proposed method.

This paper is organized into five sections. Section 2 introduces the study area and data. Section 3 describes the framework of the proposed method consisting of the joint operation model of mega cascade reservoirs, the standard KA and the improved KA. Section 4 presents results and discussion on the methods in the study case. Section 5 summarizes the results.

2. Study area and data

Effective management of hydropower stations is the key to the sustainability of our energy sources of tomorrow. China has greatly

Table 1
Examples of evolutionary algorithms in the literature.

Evolutionary algorithms	Imitation	References
Genetic Algorithm (GA)	Natural selection operator and genetic variation	Goldberg (1989).
Simulated Annealing (SA)	Steel annealing process	Johnson et al. (1989).
Particle Swarm Optimization (PSO)	Swarm behavior	Kennedy and Eberhart (1995).
Harmony Search (HS)	Finding the harmony in music	Geem et al. (2001).
Ant Colony Optimization (ACO)	Finding shortest path to the food sources of ants	Bianchi et al. (2002).
Honey Bee Optimization (HBO)	Food-foraging behavior of honey bee colonies	Pham et al. (2005).
Intelligent Water Drops (IWD)	Destination finding behavior of natural rivers	Hosseini (2007).
Cuckoo Search (CS)	Reproduction behavior of the cuckoo	Yang and Deb (2009).
Bat Algorithm (BA)	Echolocation behavior of bat	Yang (2010a).
Firefly Algorithm (FA)	Flashing light emitted by fireflies in the natural world	Yang (2010b).
Black Hole (BH)	Black hole phenomenon	Hatamlou (2013).
Kidney Algorithm (KA)	Kidney process in the human body	Jaddi et al. (2017).

endeavoured to make transit-oriented development of renewable energy systems for fulfilling the pledge of carbon emission reduction and non-fossil energy expansion to 20% by 2030 or earlier. The installed hydropower capacity of China reached 332 GW by the end of 2016, which was attributed to the fast development of hydropower resources and the intensive construction of power grids during the past three decades. Hydropower resources are concentrated mainly in south-western China while electricity loads occur mainly around the Yangtze River Delta and the Pearl River Delta. Being credited to the merits in nature, the Yangtze River basin possesses the largest water and hydropower resources in China. A total of 267 large reservoirs (more than 100 million m^3 storage) and 1525 medium-scale reservoirs (more than 10 million m^3 storage) with hydropower plants have been built in the end of 2016, and their total installed hydropower capacity is 200 GW, which accounts for over 60% of the installed hydropower capacity (332 GW) in China.

Jina-Sha River located at the upstream of Yangtze River possesses the largest hydropower potential in the 13 large hydropower bases of China. The six mega cascade reservoirs have been constructed in the middle reach of Jin-Sha River (Fig. 2 (a)) and are the pivotal hydropower bases for the China Southern Power Grid (http://eng.csg.cn/home/index.html). The mega reservoir is defined herein the reservoir with the total storage capacity greater than 100 million m^3, the height of the dam more than 100 m, and the installed power capacity larger than 1000 MW. The climate in Jin-Sha River basin is the humid subtropical climate with the average annual rainfall of 736 mm, and the average annual runoff is 53 billion m^3. The topography is high mountains with a large relief. Thanks to the humid climate and mountainous topography, this area has a high hydropower potential. The interannual variability of rainfall is high, with 65% falls during flood season. The flood season generally lasts from June to September. The mega cascade reservoirs which served as multiple purposes not only can generate approximately 13.76 GW of hydropower (i.e. installed capacity) but also can protect millions of downstream residents from flood hazards. These mega cascade reservoirs have been managed to meet electricity demands of domestic and industrial sectors, enable hydropower generation, and carry out flood control operation. The six cascade reservoirs have total reservoir storage of 7.14 billion m^3 and total watershed area of 250 thousand km^2 respectively. The characteristic parameters of cascade reservoirs are listed in Table 2.

According to the Chinese Flood Control Act, reservoir water levels generally are not allowed to exceed the top of the buffer pool (see in Table 2) during flood season to provide adequate storage for flood prevention. During the impoundment operation period in the Jin-Sha River basin, the reservoir water level would be raised from the top of buffer pool on August 1st to the top of conservation pool (see in Table 2) by the end of October. If the reservoir water level is below the top of the conservation pool by the end of October, the water level rising would continue into November. From November to the end of May in the following year, the reservoir water level would generally be operated at the Zone I or II and it would be lowered gradually through control of the reservoir water release, which depends on the reservoir inflow (Zhou et al., 2014, 2015). As shown in Fig. 2 (b), every reservoir authority has implemented the current operation rule curves (i.e. the standard operation policy (SOP)) to give guidance in hydropower generation (He et al., 2019). The guidance is described as follows.

In Zone I (Power output < Guaranteed power output): the reservoir water release is equal to the reservoir inflow if the reservoir water level locates in the Zone I and the reservoir inflow is less than or equal to the water consumption corresponding to generating the guaranteed power output, otherwise the reservoir water release is equal to the water consumption corresponding to generating the guaranteed power output if the reservoir inflow is larger than the water consumption corresponding to generating the guaranteed power output.

In Zone II (Guaranteed power output ≤ Power output < Maximum power output): the reservoir water release is equal to the water consumption corresponding to generating the guaranteed power output if the reservoir water level locates in the Zone II.

In Zone III (Power output = Maximum power output): the reservoir would increase the water release to decrease the reservoir water level into Zone II in the next time step if the reservoir water level locates in the Zone III at the current time step.

Data used in this study consist of a total 65 742 (= 365 days (or 366 days) * 30 years * 6 reservoirs) reservoir inflow datasets collected in 30 hydrological years (June 1st-the next May 31st, 1988–2018) at a temporal scale of day. The cascade reservoirs characteristics and inflow data are extracted from the Changjiang Water Resources Commission in China (http://www.cjw.gov.cn/, in Chinese). Three hydrological scenarios (dry, normal, wet) are designed to assess the impacts of different reservoir inflows on the hydropower output of cascade reservoirs.

3. Methods

This paper proposes an improved KA to optimize the hydropower generation of the cascade reservoirs by introducing three auxiliary strategies. The improved KA can overcome the shortcomings of the standard KA encountered in the nonlinear and nonconvex objective function as well as the high dimensional optimization operation of the cascade reservoirs. Fig. 3 illustrates the architectures of the hydropower generation model (Fig. 3 (a)), the standard KA (Fig. 3 (b)) and the improved KA (Fig. 3 (c)). The standard KA and GA served as the benchmark in this study. The methods used in this study are briefly introduced as follows.

3.1. Problems formulation of mega cascade reservoirs operation

The optimization operation of the cascade reservoirs is modelled for maximizing total hydropower generation equipped with the penalty function to avoid violations of the guaranteed (or firm) power output. The objective is to specify the optimal solution to maximize energy generation during the operation period in consideration of different operational and physical constraints. A sketch of the variables used to define the objective function and constraints is presented in Fig. 3 (a). The objective function is defined to maximize hydropower generation:where HG is the average annual hydropower generation of the cascade reservoirs. T is the number of time-steps in a year. N is the number of years. M is the number of reservoirs. Δt is the time-step. P_g is the guaranteed (or firm) power output of the cascade reservoirs. θ is the penalty factor, in which the value of θ is 1 on condition that the hydropower output of the cascade reservoirs is less than the guaranteed power output. $P_j(t)$ is the output power of the jth reservoir at the tth time. $RT_j(t)$ is the water release through the turbine of the jth reservoir at the tth time. $H_j(t)$ is the hydraulic head difference between the turbine intake and the last tank of the jth reservoir at the tth time. $\eta_j(t)$ is the dimensionless efficiency coefficient of the jth reservoir at the tth time and is a function $\phi(\cdot,\cdot)$ of the water release and water head, in which the relation curve of efficiency coefficient ($\eta_j(t)$), water release ($RT_j(t)$) and hydraulic head ($H_j(t)$) can be found in the technical manual of the turbine developed by the manufacturers. ρ is the density of water. g is the gravity acceleration.

Reservoir operation should obey physical constraints containing the water balance equation, the hydraulic connection equation, the

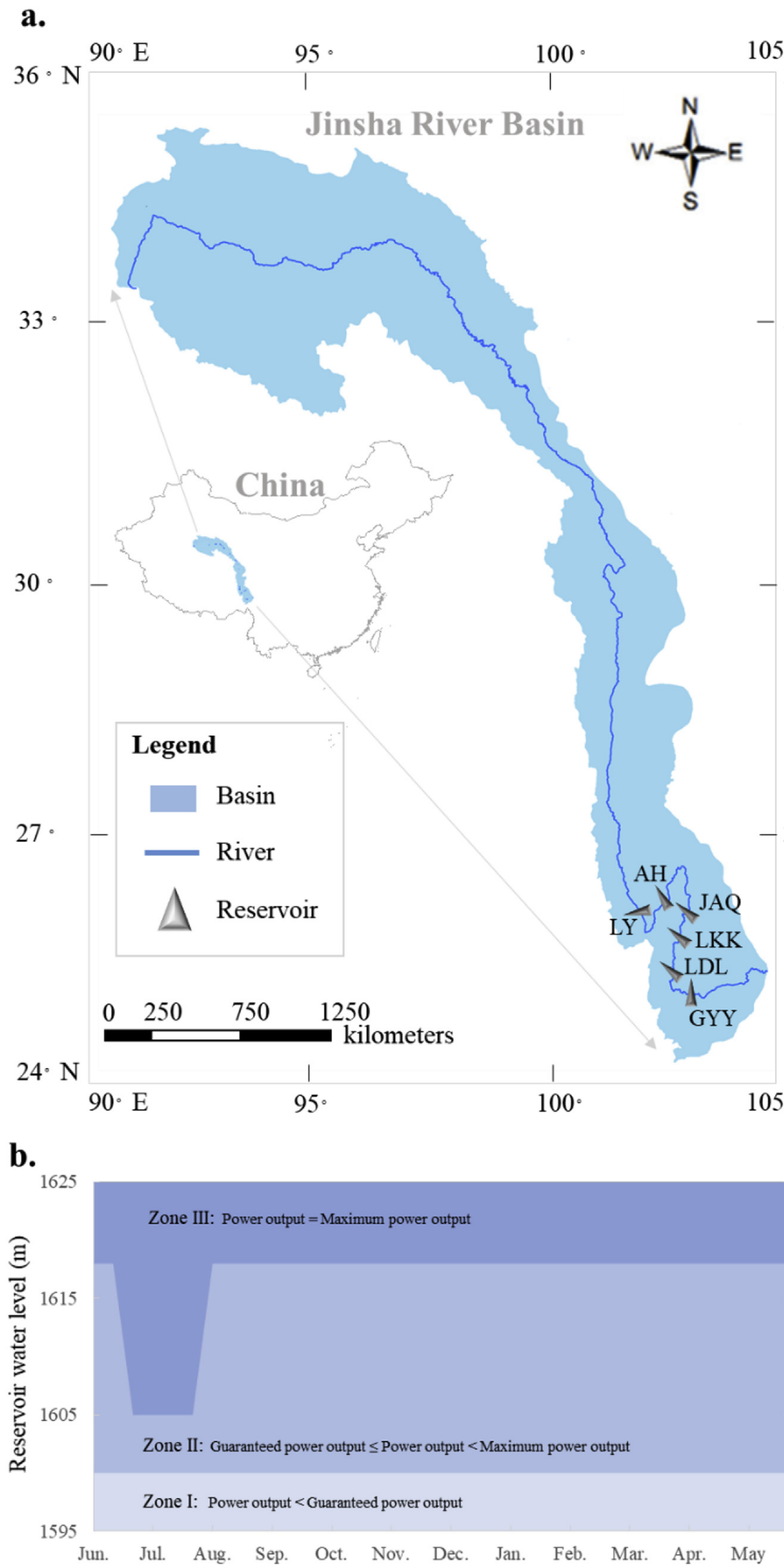


Fig. 2. Investigative area of this study and Standard Operating Policy (SOP) using operation rule curve. **a.** Investigative area. **b.** Operation rule curve. LY is the Li-Yuan reservoir. AH is the A-Hai reservoir. JAQ is the Jin-An-Qiao reservoir. LKK is the Long-Kai-Kou reservoir. LDL is the Lu-Di-La reservoir. GYY is the Guan-Yin-Yan reservoir.

Table 2
Characteristic parameters of cascade reservoirs in the middle Jin-Sha River reach.

Reservoir	Jin-Sha River Basin					
	LY	AH	JAQ	LKK	LDL	GYY
Total storage capacity (Billion m^3)	0.81	0.89	0.91	0.56	1.72	2.25
Top of buffer pool (m)	1605	1493.3	1410	1289	1212	1128.8
Top of conservation pool (m)	1618	1504	1418	1298	1223	1134
Installed power capacity (GW)	2.40	2.00	2.40	1.80	2.16	3.00
Minimum power capacity (GW)	0.41	0.29	0.50	0.33	0.43	0.57
Guaranteed power output (GW) of 6 cascade reservoirs	3.12					
Flood season	June 1st to September 30th					
Non-flood season	October 1st to the next May 31st					

feasible boundary of the water release, the hydropower output and the reservoir water level. The mathematical formulations of these constraints are given as follows:

$$V_j(t+1) = V_j(t) + \left[\frac{(I_j(t+1)+I_j(t))}{2} - \frac{(R_j(t+1)+R_j(t))}{2}\right]\cdot \Delta t \tag{2}$$

$$I_j(t+1) = R_{j-1}(t+1) + IF_j(t+1) \tag{3}$$

$$R_j(t) = RT_j(t) + RS_j(t) \tag{4a}$$

$$R_j^{min} \le R_j(t) \le R_j^{max} \tag{4b}$$

$$P_j^{min} \le P_j(t) \le P_j^{max} \tag{5}$$

$$W_j^{min} \le W_j(t) \le W_j^{max} \tag{6}$$

where $V_j(t)$, $I_j(t)$ and $R_j(t)$ are the water volume, inflow and water release of the *j*-th reservoir at the *t*-th time, respectively. $IF_j(t+1)$ is the streamflow of the intermediate catchment between the (*j*-1)-th reservoir and the *j*-th reservoir at the (*t*+1)-th time. $RS_j(t)$ is the water released through the spillway of the *j*-th reservoir at the *t*-th time. R_j^{min} and R_j^{max} are the minimum and maximum water releases of the *j*-th reservoir, respectively. P_j^{min} and P_j^{max} are the minimum and maximum power outputs of the *j*-th reservoir, respectively. $W_j(t)$ is the water level of the *j*-th reservoir at the *t*-th time. W_j^{min} and W_j^{max} are the minimum and maximum water levels of the *j*-th reservoir, respectively. The variables of the above equations are non-negative.

In this study, the W_j^{min} is equal to the top of the inactive pool in both the flood season and non-flood season whereas the W_j^{max} is equal to the top of the buffer pool in the flood season and the top of the conservation pool in the non-flood season respectively (Fig. 2 (b) and Table 2). Eqs. (2) and (3) are the water balance equation and hydraulic connection equation respectively. Eqs. (4)–(6) show the constraints of water release, hydropower output and reservoir water level respectively. Furthermore, the water releases of the cascade reservoirs are selected as the decision variables of the optimization model.

3.2. Kidney algorithm (KA)

The KA proposed by Jaddi et al. (2017) has been found a quite successful state-of-the-art optimization algorithm suitable for tacking a wide variety of engineering applications, (e.g., Ekinci et al., 2018; Jaddi and Abdullah, 2018). As known, the kidneys play a vital role in filtering blood in the body. They filter blood to repel additional materials and surplus water from the body and blood present.

There are parts in the structure of kidneys which are called nephrons. Each kidney contains millions of nephrons. Every nephron is considered as a filtration unit. Kidneys manipulate following the four processes, i.e., filtration, reabsorption, secretion, and excretion. According to the analogy between the KA and the kidney biological system, Fig. 3 (b) shows the flow diagram of the KA optimizing process. The implementation procedure is briefly described as follows:

Step 1: Initialization of feasible solutions and implementation of objective function evaluation. In a population of solutes, each solute within the blood present is taken as a candidate solution in the population of the algorithm. It is noted that each solute (or solution) is used to code the decision variables, i.e., the water release of the reservoir. For this study, real coded solutions are adopted, and then the objective function evaluation is implemented for each solution as well as ranking their values according to the descending sequence.

Step 2: Movement of Solutes (S). The movement operator is a process that the new solution (or solute) is produced through attempting to move a current solution toward the best solution based on the results of the objective function evaluation (Step 1), formulated as below:

$$S_{i+1} = S_i + \text{rand}(S_{best} - S_i) \tag{7}$$

where S_i is the solution in the population of the KA at the *i*-th epoch. S_{best} is the best solution at the current epoch. The value of *rand* is a random number between 0 and a given number (such as $(S_{best} - S_i)$).

Step 3: Filtration. The filtration operator is a process that the solutions in the population are filtered using a filtration rate through calculating a filtration function at each epoch. The filtrated solutes are moved to Filtrated Blood (FB) and the rest are transferred to Waste (W). In other words, if the objective function value of a solution is large than or equal to a filtration rate (*fr*), the solution will be transferred to a part of FB. Otherwise, it will be moved to a part of W. The filtration rate *fr* is formulated as below:

$$fr = \alpha \times \frac{\sum_{i=1}^{N_p} f(x_i)}{N_p} \tag{8}$$

where *fr* is the rate of filtration. α is the filtration coefficient (constant number) in the range of $(0, 1]$. $f(x_i)$ is the objective function of solution x at *i*th epoch. N_p is the population size.

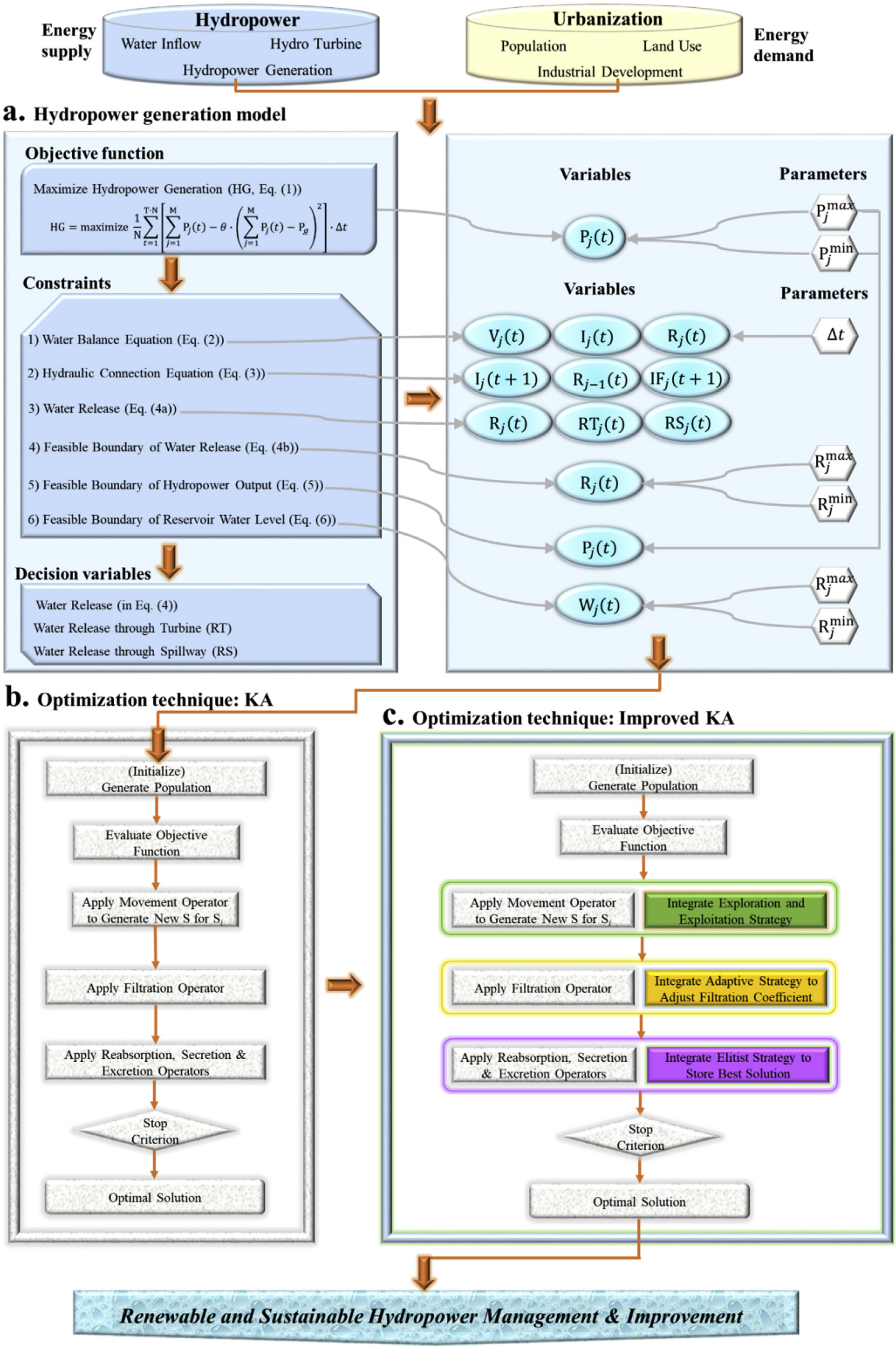


Fig. 3. Framework of optimization hydropower generation of mega cascade reservoirs. **a.** Hydropower generation model. **b.** Optimization technique: Kidney Algorithm (KA). **c.** Optimization technique: Improved KA.

Step 4: Reabsorption. The reabsorption operator is a process that the solutions of W would be given a chance to turn into part of FB, owing to executing the movement operator (Eq. (7)) again, on condition that it meets the requirement of the filtration rate and then would be transferred to a member of FB.
Step 5: Secretion. The process of secretion is for the solutions, which have been moved to a part of FB after reabsorption. If one of the mentioned solutions has a lower quality as compared with the worst solution in FB, it would be secreted from the blood current and is classified as a part of W. Otherwise, it would be reserved in FB as well as the worst solution in FB is secreted and is turned into a part of W.
Step 6: Excretion. The excretion operator is a process that the solutions in W excreted if they cannot meet the requirement of the filtration rate for becoming a part of FB after implementation of reabsorption for them. Meanwhile, these solutions would be excreted on condition that they do not have the capability for turning into a part of FB after conducting movement operator twice. Under this circumstance, such a solution in W would be substituted by a random solution. Before moving toward the next epoch, the excretion is used to update the S_{best}, merges W and FB solutions, while recalculating the filtration rate. Terminate the computation process subject to the stopping criteria (early stopping or the maximal epoch E_{max}). In the case of the maximization hydropower generation problem, if the value of the objective function does not increase over 100 consecutive epochs, hydropower generation can no longer be enhanced, which triggers the computation to stop. If the epoch number is less than the maximum epoch "E_{max}", then repeat Steps 2–6. Otherwise, stop and output the optimization results.

The parameters of the KA consist of the maximum epoch (E_{max}), the population size (N_p) and the filtration coefficient (α). The parameters of the KA could be obtained by using an intensive trial-and-error procedure for producing converged results.

3.3. Improved KA

Despite the KA has been demonstrated its success in coping with the reservoir optimization operation and other engineering applications, the KA, similar to other evolutionary intelligent algorithms, has the drawbacks of weak ability to identify the global optimal solution, especially in complex high-dimensional cascade reservoirs optimization operation with a non-convex function, a huge number of constraints and decision variables. In other words, the KA would demand auxiliary strategies to increase the performance and flexibility to cope with complex and real-world optimization problems. Therefore, to improve the ability to obtain the global optimal solution, three auxiliary strategies, i.e., the exploration and exploitation strategy for stimulating global optimization ability, the adaptive strategy for adjusting filtration coefficient and the elitist strategy for storing best solution, are fused into the standard KA in this study. The three strategies were briefly described as below.

3.3.1. Exploration and exploitation strategy for stimulating global optimization ability

It is worth noting that Eq. (7) could not offer a high diversity of solutions for promoting the global exploration capability and local exploitation ability, because the solutions only varied based on the current solution (S_i) and the best solution (S_{best}). Bearing this in mind as a motivation, the exploration and exploitation strategy is accordingly applied to stimulate the movement of solutions (or maneuver of solutions). One makes use of the current solution and a weighted difference between the best solution and random solutions to boost the global exploration ability. Another makes use of the best solution and a weighted difference between the current solution and random solutions to facilitate the local exploitation capability. The proposed exploration and exploitation strategy is formulated as below.

Global exploration strategy

$$S_{global} = S_{best} + \beta \cdot rand(|S_i - S_{FB}|) + (1-\beta)\cdot rand(|S_i - S_W|) \tag{9a}$$

Local exploitation strategy

$$S_{local} = S_i + \beta \cdot rand(S_{best} - S_{FB}) + (1-\beta)\cdot rand(S_{best} - S_W) \tag{9b}$$

Combination of exploration and exploitation strategy

$$S_{i+1} = \gamma \cdot \max\left(S_{global}, S_{local}\right) + (1-\gamma)\cdot \min\left(S_{global}, S_{local}\right) \tag{9c}$$

where S_{global} and S_{local} are the solutions raised by the exploration and exploitation strategy, respectively. β and γ are the random numbers in the range of $(0,1)$. S_{FB} and S_W are the random solutions in the part of FB and W, respectively, in which $S_{FB} \neq S_i \neq S_W$. In comparison to Eq. (7), Eq. (9) (a) can be useful for global exploration by taking full advantage of the information difference between the best solution and the random solutions of FB & W, whilst Eq. (9) (b) can be beneficial to local exploitation by making full use of the information difference between the current solution and the random solutions of FB & W. That is to say, the combination of exploration and exploitation strategy (Eq. (9) (c)) not only can be

$$HG = \text{maximize } \frac{1}{N}\sum_{t=1}^{T\cdot N}\left[\sum_{j=1}^{M} P_j(t) - \theta\cdot\left(\sum_{j=1}^{M} P_j(t) - P_g\right)^2\right]\cdot \Delta t \tag{1a}$$

$$\theta = \begin{cases} 1, & if\left(\sum_{j=1}^{M} P_j(t) < P_g\right) \\ 0, & else \end{cases} \tag{1b}$$

$$P_j(t) = \eta_j(t)\cdot\rho\cdot g\cdot RT_j(t)\cdot H_j(t) \tag{1c}$$

$$\eta_j(t) = \phi\left(RT_j(t), H_j(t)\right) \tag{1d}$$

applied to direct at the avoidance of low diversity and trapping into a local optimum but also can make a suitable tradeoff between the exploration and exploitation within the search domain for achieving the global optimum.

3.3.2. Adaptive strategy for adjusting filtration coefficient

It is also worth noting that the filtration coefficient (α) of the standard KA in Eq. (8) is a constant value in the range of (0, 1], which is given in advance. In general, the constant parameter values have a substantial impact on the quality of the solutions and the robustness of evolutionary algorithm (Srinivas and Patnaik, 1994; Molina et al., 2018). Additionally, the selection of appropriate parameter values is usually resolved by the trial-and-error procedure and demands the developers and users' prior knowledge, in which the process is time-consuming due to the sensitivity analysis of adjusting algorithm parameters. To conquer such technical bottleneck, the adaptive strategy for adjusting algorithm parameter values were adopted by a variety of researches and was widely used to enhance the quality of the solutions and the robustness of evolutionary algorithms (e.g., Zhang et al., 2007; Zhou et al., 2017). Owing to its reliability and wide practicality, the adaptive strategy for adjusting filtration coefficient is also integrated into the KA in this study and is formulated as below:

$$\alpha = \begin{cases} \varepsilon_1 \cdot \left[(f(\mathrm{S_{best}}) - f(\mathrm{S_{FB}})) \Big/ \left(f(\mathrm{S_{best}}) - f_{\mathrm{avg}} \right) \right], & \mathit{if}\left(f(\mathrm{S_{FB}}) \geq f_{\mathrm{avg}} \right) \\ \varepsilon_2, & \mathit{otherwise} \end{cases} \tag{10a}$$

$$f_{\mathrm{avg}} = \frac{\sum_{i=1}^{\mathrm{N_p}} f(x_i)}{\mathrm{N_p}} \tag{10b}$$

where ε_1 and ε_2 are the random numbers in the range of $(0, 1]$. f_{avg} is the average value of the objective function in the KA. $f(\mathrm{S_{FB}})$ and $f(\mathrm{S_{best}})$ are the objective function values of the random solution in the FB and the best solution, respectively.

3.3.3. Elitist strategy for storing best solution

The concept of elitism proposed by Goldberg (1989) intends to avoid the algorithm getting stuck in local optimal solutions, and the elitist strategy has been widely adopted for improving the performance of the evolutionary algorithms, for instance, GA (Goldberg, 1989; Wardlaw and Sharif, 1999), NSGA-II (Deb et al., 2002), PSO (Bai et al., 2017) and BA (Bora et al., 2012). Eq. (9) could provide the KA with a high diversity of solutions, whereas both Eqs. (7) and (9) could not guarantee that the good solutions would not be discarded even if they have been found before reaching the maximum epoch. Therefore, in this study, if the solution created in the previous epoch ($\mathrm{S}_{i\text{-}1}$) is not better than the current solution (S_i), the elitist strategy will be used with a certain probability. Inspired by the concept of elitism, the proposed strategy employs the best solution ($\mathrm{S_{best}}$) and a difference between the current and random solutions ($\mathrm{S_{global}}$, shown in Eq. (9) (a)) for lifting the performance of the KA to prevent the loss of good solutions once they are found, which is formulated as below:

In the case of maximization problem:

$$\mathrm{S}_i = \begin{cases} \mathrm{S}_i, & \mathit{if}\left(f(\mathrm{S}_i) \geq f(\mathrm{S}_{i-1}) \right) \\ \mathrm{S_{global}}, & \mathit{else\ if}\left(f(\mathrm{S}_i) < f(\mathrm{S}_{i-1}) \text{ and } \beta < 0.5 \right) \\ \mathrm{S}_{i-1}, & \mathit{otherwise} \end{cases} \tag{11a}$$

In the case of minimization problem:

$$\mathrm{S}_i = \begin{cases} \mathrm{S}_i, & \mathit{if}\left(f(\mathrm{S}_i) \leq f(\mathrm{S}_{i-1}) \right) \\ \mathrm{S_{global}}, & \mathit{else\ if}\left(f(\mathrm{S}_i) > f(\mathrm{S}_{i-1}) \text{ and } \beta < 0.5 \right) \\ \mathrm{S}_{i-1}, & \mathit{otherwise} \end{cases} \tag{11b}$$

where $f(\mathrm{S}_i)$ is the value of objective function of the solution at the ith epoch. Eq. (10) equipped with the elitist strategy can be used to avoid the loss of good solutions. That is to say, the good solutions would be stored when they have been found before meeting the requirement of the maximum epoch.

The following section describes how to fuse the three auxiliary strategies into the standard KA for optimizing the cascade reservoirs operation. Fig. 3 (c) shows the flow diagram of the improved KA optimizing process. The implementation procedure is described as follows.

Step 1: Initialization of feasible solutions and implementation of objective function evaluation. Because none of the auxiliary strategies has been implemented for this step, this process could refer to the Step 1 in the standard KA.

Step 2: Movement of Solutions (or maneuver of Solutions) (S) using the exploration and exploitation strategy. According to the rankings of the objective function (Step 1), the improved movement operator (Eq. (9)) would be conducted to promote the movement of S.

Step 3: Filtration using adaptive strategy. The improved filtration operator (Eq. (10)) will be implemented for dividing the S into the two parts of the FB and W.

Step 4: Reabsorption. The reabsorption operator would be executed to render an opportunity for the solutions of W transferring into a part of FB if it satisfies the condition of the filtration rate. And then the improved movement operator (Eq. (9)) would be run once again in this procedure. That is to say, the course of the reabsorption can also be enhanced due to the improved movement of S.

Step 5: Secretion. This process can refer to the Step 5 in the standard KA.

Step 6: Excretion and implementation of the elitist strategy. The excretion operator would also be carried out if the solutions in W cannot meet the requirement of the filtration rate for becoming a part of FB. In addition, the elitist strategy (Eq. (11)) would be conducted to store the best solution. Terminate the computation process subject to the stopping criteria (early stopping or the maximal epoch $\mathrm{E_{max}}$). For the maximization hydropower generation problem, when the value of the objective function does not increase over 100 consecutive epochs, hydropower generation can no longer be improved, which induces the computation to stop. When the maximum epoch "$\mathrm{E_{max}}$" is reached, the computation process stops and outputs the optimization results. Otherwise, update the epoch and repeat Steps 2–6.

As compared with the standard KA, the merits of the improved KA consist of: firstly, in Step 2, the combination of exploration and exploitation strategy (Eq. (9) (c)) not only can conquer the bottlenecks of low diversity and trapping into a local optimum but also can make an adequate balance between the exploration and exploitation for searching the global optimum; secondly, in Step 3, the adaptive strategy is utilized for adjusting the filtration coefficient parameter to overcome the time-consuming encountered in the trial-and-error procedure (or sensitivity analysis) of selecting appropriate parameter values; lastly, in Step 6, the elitist strategy is used to avoid the loss of good solutions before reaching up to the maximum epoch.

4. Results and discussion

The results and findings are presented and discussed in details in the order of three parts: the sensitivity analysis of evolutionary algorithm parameters (GA served as the benchmark) as well as the comparison between the KA and the improved KA (KA served as the benchmark), and the summarization, shown as follows.

4.1. Sensitivity analysis of GA and KA parameters

In this section, special attention is paid to the extension of the KA to the optimization of mega cascade reservoirs at a time scale of day. The GA serves as a benchmark. And the parameters of the GA consist of the population size (N_p), the maximum epoch (E_{max}), the crossover probability (P_c) and the mutation probability (P_m). The sensitivity analysis of evolutionary algorithm parameters is conducted for the optimization operation of the six cascade reservoirs in the JinSha River basin (Fig. 2). Each evolutionary algorithm is driven by a total of 65742 (= 365 days (or 366 days) * 30 years * 6 reservoirs) datasets, which means we have 65742 decision variables and 262968 constraints (= 4 equations * 65742 decision variables). For the GA, various researches (e.g., Wardlaw and Sharif, 1999; Deb et al., 2002) have suggested that for complex cascade reservoirs system, a larger value of N_p is required to maintain the diversity in the population; a larger value of E_{max} is required to converge to a state at which there are no changes in the objective function value over 100 generation; good performance can be achieved using a high value of P_c and low value of P_m. For the KA, to obtain good performance, the parameter of the filtration coefficient (α) is additionally advised to use a medium-low value (Ehteram et al., 2018a, b). Therefore, on condition that both the KA and GA used the same population size ($N_p = 500$) and maximum epoch ($E_{max} = 1000$), we concentrate on the following sensitivity analysis: for the GA, the most appropriate P_c and P_m would appear to be in the range of 0.75 up to 0.95 and 0.05 up to 0.25 at an increasing step of 0.05, respectively; for the KA, the most appropriate α would appear to be in the range of 0.25 up to 0.55 at an increasing step of 0.05.

The results of the sensitivity analysis of the GA and KA parameters are shown in Fig. 4. Fig. 4 (a) indicates a distinct peak in performance at $P_c = 0.85$ as well as progressive deterioration in performance as the value of P_c increases beyond this, whilst there is a distinct peak in performance at $P_m = 0.10$ as well as progressive deterioration in performance as the value of P_m increased beyond this. That is to say, the most appropriate values of P_c and P_m are 0.85 and 0.10, respectively.

Fig. 4 (b) reveals that the best result (= 0.977) in the KA is achieved with the value of α (= 0.35) using the population size ($N_p = 500$) and maximum epoch ($E_{max} = 1000$) whereas there is a progressive deterioration in performance as the value of α increased beyond this. It needs to take about 2.1 h and 1.3 h computation time (mean of 10 runs of each evolutionary algorithm) for the implementation of the GA and KA to optimize the operation of the six cascade reservoirs, conducted by a DELL computer (Intel® CoreTM i5, 7th Generation CPU @ 2.50 GHz, RAM 8 GB and 1 TB Hard Disk). That is to say, in each trial-and-error computation process, it spends approximately 2.1 h for the GA to find the appropriate parameters of P_c (or P_m) whereas it spends 1.3 h for the KA to search the appropriate parameter of α. The most appropriate parameters of the GA are set as: $N_p = 500$; $E_{max} = 1000$; $P_c = 0.85$; and $P_m = 0.10$. The most appropriate parameters of the KA are set as: $N_p = 500$; $E_{max} = 1000$; and $\alpha = 0.35$. Table 3 summarizes the computation results of the evolutionary algorithms (GA & KA) in terms of 10 runs of the GA and KA using the most appropriate parameters. Firstly, from the standpoint of the final objective function value (normalization), the KA produces much higher final objective function values than the GA in terms of the best (0.981), average (0.977) and worst (0.974) final objective function values. At the same time, the standard deviation value of the final objective function in KA is equal to 0.0027, which is noticeably smaller than that (0.0042) of the GA. That means the robustness of the KA is stronger than that of the GA. Secondly, from the standpoint of the

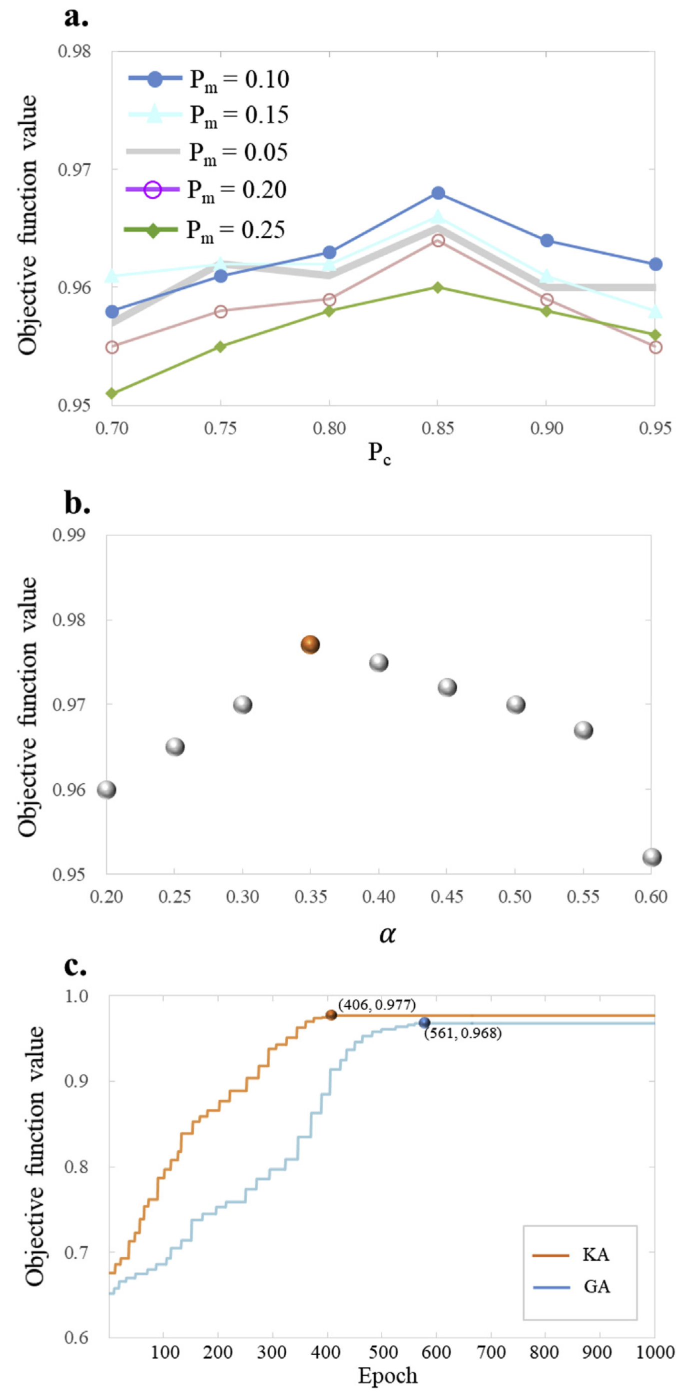


Fig. 4. Sensitive to optimization algorithm parameters and optimization progress using the population size ($N_p = 500$) and maximum epoch ($E_{max} = 1000$). **a.** Sensitive to the crossover (P_c) and mutation (P_m) probability of GA. **b.** Sensitive to the filtration coefficient (α) of KA. **c.** Optimization progress in GA using the most appropriate parameters ($P_c = 0.85$, $P_m = 0.10$, $N_p = 500$ & $E_{max} = 1000$) and KA using the most appropriate parameters ($\alpha = 0.35$, $N_p = 500$ & $E_{max} = 1000$). The computation result is the average result of 10 runs of each algorithm and the objective function value is normalized between 0 up to 1.

Table 3
Computation results of the evolutionary algorithms (GA & KA).

Number of runs	Normalization final objective function value	
	KA	GA
1	0.975	0.963
2	0.974	0.961
3	0.981	0.968
4	0.979	0.966
5	0.974	0.971
6	0.977	0.973
7	0.981	0.971
8	0.976	0.968
9	0.980	0.973
10	0.977	0.964
Mean	0.977	0.968
Best	0.981	0.973
Worst	0.974	0.961
Standard deviation	0.0027	0.0042
Mean of time cost (Hours)	1.3	2.1
Average annual hydropower generationa (Billion kW·h)	64.6	63.1
Average annual hydropower generation (Billion kW·h) using the SOP[b]	61.7	
Most appropriate parameters	$N_p = 500$ $E_{max} = 1000$ $\alpha = 0.35$	$N_p = 500$ $E_{max} = 1000$ $P_c = 0.85$ $P_m = 0.10$

Note: The daily data from June 1st 1988 up to May 31st 2018 (30 hydrological years) are used in this study.
[a] The hydropower generation is the average annual hydropower generation during 1988 and 2018 and is the average result of 10 runs of each algorithm.
[b] SOP is the Standard Operating Policy using operation rule curves.

convergence speed, the number (mean = 406) of epoch attained the convergence result is significantly less than that (mean = 561) of the GA. Such results demonstrate fewer epochs for the KA are required to search out the optimal solution (shown in Fig. 4 (c)). Thirdly, from the standpoint of the hydropower generation, the global optimal solution obtained from the KA can largely improve hydropower generation by 2.9 billion kW·h/year and 1.5 billion kW·h/year accordingly. In addition, the improved KA can achieve 64.6 kW·h/year hydropower generation (SOP, 61.7 billion kW·h/year and GA, 63.1 billion kW·h/year). The improvement rates reach 4.7% and 2.4%, respectively. The reasons for the KA's superior performance than that of the GA consist of: firstly, the filtration operator of the KA provides the algorithm with good exploitation and fast convergence in comparison to the selection operator of the GA; secondly, the movement and reabsorption operator of the KA gives the algorithm a good diversity of solution and thus superior exploration as compared with the crossover and mutation operators of the GA.

4.2. Comparison between KA and improved KA

In the case of six cascade reservoirs operation, the computation results (average results of ten runs) of the four schemes concerning the KA and improved KA are reported in Table 4. It is noted that: firstly, the difference between KA0 and KA1 (using one auxiliary strategy) is that the latter uses the exploration and exploitation strategy whereas the former does not; secondly, the difference between KA1 and KA2 (using two auxiliary strategies) is that the latter adopts the adaptive strategy for adjusting filtration coefficient whereas the former does not; and lastly, the difference between KA2 and KA3 (using three auxiliary strategies) is that the latter employs the elitist strategy for storing best solution whereas the former does not.

4.2.1. Hydropower generation

The results in Table 4 indicate that: firstly, in comparison to the SOP (61.7 billion kW·h/year), the improved KA1 can increase the hydropower generation 3.39 billion kW·h/year (5.5% improvement), owing to the exploration and exploitation strategy; secondly, the improved KA2 can lift the hydropower generation 3.89 billion kW·h/year (6.3% improvement), in the combination of the exploration and exploitation strategy as well as the adaptive strategy; lastly, the improved KA3 can enhance the hydropower generation 4.81 billion kW·h/year (7.8% improvement) due to integration of the three auxiliary strategies. As compared with the KA0, the improved KA3 can promote the hydropower generation of 1.91 billion kW·h/year (3.0% improvement). That is to say, the use of the three auxiliary strategies, the improved KA can dramatically enhance the hydropower generation in virtue of finding the global optimal solution. The average time cost (2.2 h) of the improved KA is higher than the KA (1.3 h), whereas the improved KA can save a lot of time searching appropriate algorithm parameter due to using the adaptive strategy for adjusting the filtration coefficient. That is to say, the improved KA not only can increase the hydropower generation but also can conquer the time-consuming encountered in the trial-and-error procedure (or sensitivity analysis) of selecting appropriate parameter values, in comparison to the standard KA.

To show the merits of the improved KA, an assessment is conducted on the results obtained from the convergence process of the four schemes (KA0-KA3) for optimization operation of the six cascade reservoirs (Fig. 5). The comparison between KA0 and KA1 (with one auxiliary strategy) shows that the final objective function value (0.985) of the improved KA1 is considerably larger than that (0.977) of the KA0. The combination of exploration and exploitation strategy (Eq. (9) (c)) not only can boost solution diversity and escape the trap of a local optimum but also can increase the objective function (i.e. hydropower generation). Moreover, the objective function values of the KA1 show more fluctuation than those of KA0, which implies the KA1 would easily trigger optimization process instability problem due to the utilization of the exploration and exploitation strategy.

The results indicate that the KA required more auxiliary strategies to handle its instability problem. The comparison between KA1 and KA2 (with two auxiliary strategies) shows that the

Table 4
Computation results of the four schemes concerning the standard KA and improved KA.

Scheme		KA0	KA1	KA2	KA3
Parameters	N_p	500	500	500	500
	E_{max}	1000	1000	1000	1000
	α	0.35	0.35	/	/
Auxiliary strategy	Exploration and exploitation strategy	/	Yes	Yes	Yes
	Adaptive strategy	/	/	Yes	Yes
	Elitist strategy	/	/	/	Yes
Number of objective function evaluations (Mean)		406	451	539	487
Mean of time cost (Hours)		1.3	1.5	1.8	1.6
Average annual hydropower generation[a] (Billion kW·h)		64.6	65.1	65.6	66.5
Average annual hydropower generation (Billion kW·h) using SOP[b]		61.7			

Note: The computation result is the average result of 10 runs of each algorithm and daily data from June 1st 1988 up to May 31st 2018 (30 hydrological years) are used in this study.
KA0: the optimization algorithm is the standard KA.
KA1: the optimization algorithm is the improved KA with one auxiliary strategy.
KA2: the optimization algorithm is the improved KA with two auxiliary strategies.
KA3: the optimization algorithm is the improved KA with three auxiliary strategies.
[a] Average annual hydropower generation is the mean of annual hydropower generated during 1988 and 2018.
[b] SOP is the Standard Operating Policy using operation rule curves.

objective function values of the KA2 fluctuated less and are moderately larger than those of the KA1, which demonstrates the KA2 can overcome the instability in virtue of the adaptive strategy for adjusting algorithm parameter values. The reason is that the adaptive strategy can dynamically adjust the parameter values in response to the higher solution diversity produced by the exploration and exploitation strategy. The comparison between KA2 and KA3 (with three auxiliary strategies) shows that the final objective function value (0.996) of the KA3 is considerably larger than that (0.987) of the KA2. The KA3 can converge faster and is more robust as shown in Fig. 5 and Table 3. The faster convergence and better robustness is the result of the good exploration and exploitation provided by the integration of the three auxiliary strategies.

The comparative results demonstrate that the improved KA not only best optimizes hydropower generation with fast convergence as well as the most stable objective function curve, but also can effectively conquer the shortcomings of trapping into local optimums, instability and loss of good solutions. This is due to the utilization of the exploration and exploitation strategy, the adaptive strategy as well as the elitist strategy.

4.2.2. Reliability, vulnerability and resilience of hydropower output

A coherent set of evaluation criteria is used to distil the merits of the improved KA to quantitatively assess the impacts and contributions of the KAs on the hydropower generation in different periods (year-round, flood season, non-flood season) and hydrological representative years (dry, normal, wet). The criteria are designed for assessing the reliability, vulnerability and resilience of hydropower output (Hashimoto et al., 1982; Zhou et al., 2017). Their formulations are given as follows.

Reliability of hydropower output: The reliability can be described by the probability that a hydropower energy system remains in a satisfactory state.

$$\text{Reliability} = \frac{n - \sum_{t=1}^{n} \text{NT}(t)}{n} \tag{12a}$$

$$\text{NT}(t) = \begin{cases} 1 & if\left(\sum_{i=1}^{M} \text{P}_i(t) < \text{P}_g\right) \\ 0 & else \end{cases} \tag{12b}$$

where NT(t) is the number of time that total hydropower output is less than the guaranteed power output of the cascade reservoirs at the t-th time. n (=N·T) is the total number of time steps in the operation period.

Vulnerability of hydropower output: The vulnerability represents the incompetence of a hydropower energy system to resist the effect of a hostile environment. It denotes the maximum ratio of hydropower output deficiency to installed power capacity if once occurs, shown as follows.

$$\text{Vulnerability} = \max_{1 \le t \le n} \text{VU}(t) \tag{13a}$$

$$\text{VU}(t) = \begin{cases} \dfrac{\text{P}_g - \sum_{i=1}^{M} \text{P}_i(t)}{\text{P}_g} & if\left(\sum_{i=1}^{M} \text{P}_i(t) < \text{P}_g\right) \\ 0 & else \end{cases} \tag{13b}$$

where VU(t) is the vulnerability of hydropower output at the t-th time.

Resilience of hydropower output: The resilience describes how quickly a hydropower system is likely to recover once hydropower output deficiency has occurred, shown as follows.

$$\text{Resilience} = \begin{cases} 1 & if(\text{Reliability} = 1) \\ \dfrac{\sum_{t=1}^{n-1} \text{RE}(t)}{\sum_{t=1}^{n} \text{NT}(t)} & else \end{cases} \tag{14a}$$

$$\text{RE}(t) = \begin{cases} 1 & if\left(\left(\sum_{i=1}^{M} \text{P}_i(t) < \text{P}_g\right) and \left(\sum_{i=1}^{M} \text{P}_i(t+1) \ge \text{P}_g\right)\right) \\ 0 & else \end{cases} \tag{14b}$$

where RE(t) is the number of times that the hydropower energy system is likely to recover from hydropower output deficiency at the t-th time. The higher index value of reliability and resilience, as well as the lower index value of vulnerability, indicate better model performance.

The index values of reliability, vulnerability and resilience in different scenarios are depicted in Table 5. From the standpoint of different periods (year-round, flood season & non-flood season), the results indicate that the improved KA can rapidly increase the

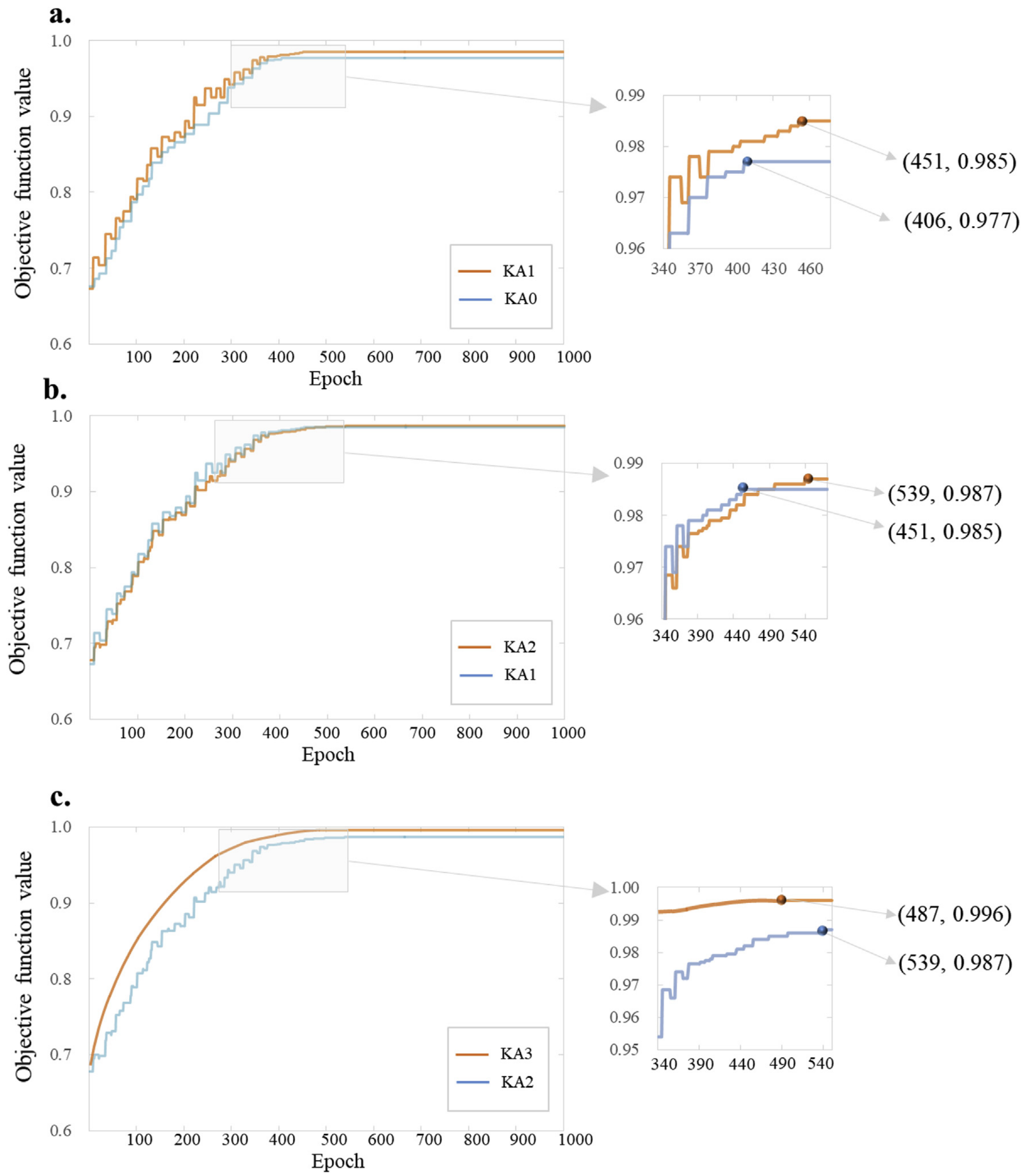


Fig. 5. Optimization progress in KA and improved KA. **a.** Comparison between KA0 and KA1. **b.** Comparison between KA1 and KA2. **c.** Comparison between KA2 and KA3.
KA0: the optimization algorithm is the standard KA.
KA1: the optimization algorithm is the improved KA with one auxiliary strategy.
KA2: the optimization algorithm is the improved KA with two auxiliary strategies.
KA3: the optimization algorithm is the improved KA with three auxiliary strategies.
The computation result is the average result of 10 runs of each algorithm and the objective function value is normalized between 0 up to 1.

index values of reliability (from 0.95 to 0.98) and resilience (from 0.87 to 0.93), and decrease the index value of vulnerability (from 0.11 to 0.07) in the case of year-round, as compared with the standard KA. Additionally, shown by the comparison with the SOP, the improved KA not only can raise the reliability and resilience with the improvement rates of 8.0% and 14.8% respectively but also can dramatically reduce the vulnerability by 46.7% in the case of the non-flood season. Such substantial improvement is mainly owing to the good performance of the improved KA whilst the objective function of maximization hydropower generation closely linked with the guaranteed power output (Eq. (1)) also contributed to such improvement. Some interesting characteristics in different periods can be found in Table 5. For example, in all cases (SOP, KA & improved KA), both the index values of reliability and resilience in flood season are equal to one, while the index value of vulnerability in flood season are equal to zero. In other words, in flood season, the hydropower output of the six cascade reservoirs is always larger than or equal to the guaranteed power output (3.12 GW, in Table 2). Both the index values of resilience and vulnerability in the non-flood season are equal to both the index values of resilience and

Table 5
Computation results of the KA and improved KA in the different scenarios.

Scheme	Indicators	Different periods		
		Year-round[a]	Flood season[b]	Non-flood season[c]
SOP	Reliability	0.92	1	0.88
	Vulnerability	0.21	0	0.21
	Resilience	0.81	1	0.81
KA	Reliability	0.95 (3.3 %[d])	1	0.92 (4.5%)
	Vulnerability	0.11 (26.7%)	0	0.11 (26.7%)
	Resilience	0.87 (7.4%)	1	0.87 (7.4%)
Improved KA (i.e. KA3)	Reliability	0.98 (6.5%)	1	0.95 (8.0%)
	Vulnerability	0.07 (46.7%)	0	0.07 (46.7%)
	Resilience	0.93 (14.8%)	1	0.93 (14.8%)
Scheme	Indicators	Hydrological representative years		
		Dry[e]	Normal[f]	Wet[g]
SOP	Reliability	0.92	0.95	1
	Vulnerability	0.34	0.22	0
	Resilience	0.72	0.80	1
KA	Reliability	0.95 (3.2%)	0.97 (2.1%)	1
	Vulnerability	0.20 (41.2%)	0.14 (36.4%)	0
	Resilience	0.79 (9.7%)	0.86 (7.5%)	1
Improved KA (i.e. KA3)	Reliability	0.97 (5.4%)	0.99 (4.2%)	1
	Vulnerability	0.15 (55.9%)	0.11 (50.0%)	0
	Resilience	0.85 (18.1%)	0.92 (15.0%)	1

Note: The computation result is the average result of 10 runs of each algorithm and the daily data from June 1st 1988 up to May 31st 2018 (30 hydrological years) are used in this study.
[a] Year-round is the hydrological year, starting from June 1st to the next May 31st in this study area.
[b] Flood season: starting from June 1st to September 30.
[c] Non-flood season: starting from October 1st to the next May 31st.
[d] Improvement rate $= \frac{|\text{Indicator(Evolutionary Algorithm)} - \text{Indicator(SOP)}|}{\text{Indicator(SOP)}} \times 100\%$
[e] Occurrence frequency of the dry year (2008) is 95% during 1988 and 2018.
[f] Occurrence frequency of the normal year (2003) is 50% during 1988 and 2018.
[g] Occurrence frequency of the wet year (2012) is 10% during 1988 and 2018.

vulnerability in year-round. The index value of reliability in year-round is always larger than the index value of reliability in non-flood season. The reason is the ratio of runoff in flood season to annual runoff ranges between 60% and 70% in this study area so that the hydropower output deficit always occurred in the non-flood season whereas both the reliability and resilience of hydropower output in flood season would reach up to 100%. In flood season, the potential of hydropower generation is driven by lessening the gap between hydropower output and installed (maximum) power capacity. However, in non-flood season, the potential of hydropower generation is driven by lessening the gap between hydropower output and guaranteed power output to improve the hydropower generation.

Table 5 also shows the sensitivity of reliability, vulnerability and resilience of hydropower output in response to the hydrological representative years (dry, normal, wet). The results indicate that: as compared with the SOP, the improved KA can noticeably increase the reliability and resilience as well as decrease the vulnerability in dry and normal years. The improvement rates of reliability (from 0.92 to 0.97, 5.4% improvement), vulnerability (from 0.34 to 0.15, 55.9% improvement) and resilience (from 0.72 to 0.85, 18.1% improvement) are higher especially in dry year. In all cases (SOP, KA & improved KA), both the index values of reliability and resilience in the wet year (2012, 10% occurrence frequency during 1988 and 2018) are equal to 1, while the index value of vulnerability in the wet year is equal to 0. In other words, in the wet year, the hydropower output of six cascade reservoirs is always larger than or equal to the guaranteed power output (3.12 GW, in Table 2).

4.2.3. Reservoir operation curves

Take the first reservoir (LY, Fig. 2) and the last reservoir (GYY, Fig. 2) of cascade reservoirs for example, Fig. 6 presents the differences in the reservoir water level, water release and hydropower output trajectories generated by the KA and improved KA in the scenario of the dry year (2008, 95% occurrence frequency during 1988 and 2018). It can be further seen from Fig. 6 (a) that: for flood season all the three trajectories are satisfied with the requirements of their constraints whilst for non-flood season sometimes dissatisfied the hydropower constraint in which the total hydropower output of two cascade reservoirs is less than the guaranteed (minimum) power output. Despite the violation of the constraint has occurred in both the KA and improved KA, the times (1 time in both two cascade reservoirs) generated by the improved KA is less than the times (2 times in both two cascade reservoirs) generated by the KA in the scenario of the dry year (marked in red circle).

For flood season, the differences in the three trajectories generated by the standard KA and improved KA are small. The reservoir water level and hydropower output generated by the improved KA are slightly higher than that of the KA, whilst the water releases generated by the improved KA are briefly smaller than those of the KA in both two cascade reservoirs. For non-flood season the differences in the three trajectories generated by the KA and improved KA are considerable, in which the reservoir water levels and hydropower outputs generated by the improved KA are sharply higher than that of the KA whilst the water releases generated by the improved KA are sharply smaller than that of the KA in both 2 cascade reservoirs. In other words, for flood season the differences in the three trajectories generated by the KA and improved KA are small whereas for the non-flood season the differences in the three trajectories generated by the KA and improved KA are noticeable.

More interesting characteristic of the optimal hydropower output can be found in this study, for example, most of hydropower

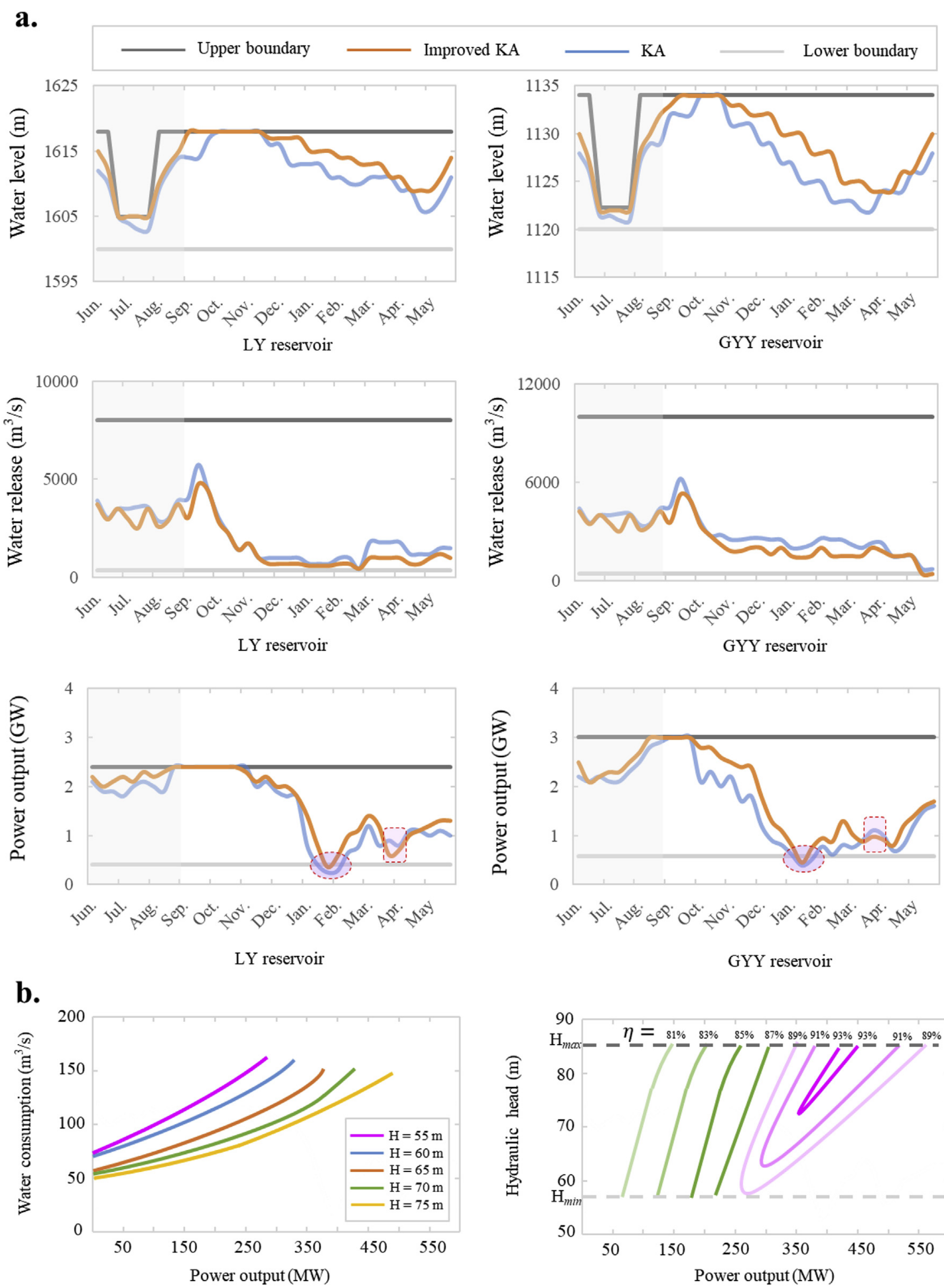


Fig. 6. Comparison of optimal trajectories generated by the KA and improved KA with respective to the LY and GYY reservoirs in a dry year (2008) as well as theoretical relationship curves between power output, hydraulic head, and water consumption of a hydro unit (i.e., unit performance curves). **a.** Comparison of optimal trajectories. **b.** Hydro unit performance curves.

output trajectories generated by the improved KA are larger than or equal to those of the KA whereas small minority of hydropower output generated by the improved KA is less than that of the KA in both 2 cascade reservoirs (marked in red rectangle). Therefore, the improved KA can rapidly increase the reliability of hydropower output in comparison to the KA. The difference in the hydropower output trajectories can demonstrate the performance of the improved KA is noticeably superior to the performance of the KA in the interests of hydropower generation maximization, whereas the differences in the reservoir water level or water release trajectories generated by the KA and improved KA does not necessarily indicate the superiority of one approach over the other. The reason is that: according to Eq. (1(c)), the value of hydropower output not only is not only dependent on the values of the water release ($RT_j(t)$) and hydraulic head ($H_j(t)$), but is also dependent on the value of efficiency coefficient ($\eta_i(t)$). The function $\phi(RT_j(t), H_j(t))$ (Eq. (1d)) is not monotonically increasing with the values of the water release (or water consumption) ($RT_j(t)$) and hydraulic head ($H_j(t)$) (Fig. 6 (b)).

In summary, these comparative results demonstrate that the improved KA with three auxiliary strategies not only can produce the largest objective function values and the most stable objective function curve but also can effectively increase hydropower generation of mega cascade reservoirs. Such achievement made by the KA3 could be owing to that the exploration and exploitation strategy improved the hydropower generation from the perspective of tacking the technical bottleneck of trapping into local optimums, the adaptive strategy improved the hydropower generation from the perspective of conquering the instability of optimization process, while the elitist strategy improved the hydropower generation from the perspective of overcoming the loss of good solutions. Additionally, the indexes of reliability, vulnerability and resilience are used to assess the KAs for different periods (year-round, flood season, non-flood season) and different hydrological representative years (dry, normal, wet) comprehensively. Compared with the SOP, the improved KA can increase the index values of reliability and resilience, and decrease the index value of vulnerability in different periods (year-round & non-flood season) and different hydrological representative years (dry year & normal year). The improvement rates of reliability, resilience and vulnerability are higher especially in non-flood season and dry year. The reason is that the probability of hydropower output deficit occurrence in the non-flood season and the dry year is higher than the probability of deficit occurrence in the flood season, and the normal & wet years. From the standpoint of hydropower benefits and CO_2 emission reduction, according to the hydropower price in China (45.3 USD/MW·h) and CO_2 emission reduction for hydropower production (0.785 kg CO_2 equivalent/kW·h) (Zhou et al., 2018a,b), in comparison to the SOP, the improved KA can dramatically stimulate the hydropower benefits 217.44 million USD/year (= 4.8 billion kW·h * 45.3 USD/MW·h) as well as reduce the CO_2 emission 3.77 billion kg/year (= 4.8 billion kW·h * 0.785 kg CO_2 equivalent/kW·h), respectively. To support the official mission – to fulfil the pledge of carbon emission reduction and non-fossil energy expansion to 20% in China by 2030 or earlier, this study indicates the niche and potential of the hydroelectricity as a guideline for the cleaner production.

In comparison to the dynamic programming methods, for instance, discrete differential dynamic programming, progressive optimality algorithm and dynamic programming successive approximation, the major advantage of the KA approach is that it does not demand the initial trial water release policy (Ehteram et al., 2018a, b), which can motivate the robustness of the algorithm and the stochasticity of solutions. As compared with the GA and KA, the main merit of the improved KA is the capability to find the global optimum with faster convergence speed. The reasons are as follows: firstly, the filtration operator provides the required exploitation while the reabsorption operator gives the necessary exploration for the evolutionary algorithm; the combination of exploration and exploitation strategy not only can conquer the bottlenecks of low diversity and trapping into a local optimum, but also can make an adequate balance between the exploration and exploitation for searching the global optimum; secondly, the adaptive strategy can automatically adjust the filtration coefficient parameter to overcome the time-consuming encountered in the trial-and-error procedure of selecting appropriate parameter values; lastly, the elitist strategy can avoid the loss of good solutions before reaching up to the maximum epoch.

5. Conclusion

In China, the developing hydroelectricity can provide a reliable and practical pathway in the transition to the low carbon and cleaner production for sustainable development. The optimization operation of mega cascade reservoirs can better produce hydropower outputs. However, the difficulty encountered in this process raises quickly since the number of cascade reservoirs, decision variables and constraints grow, in which the optimization process is easy to give rise to time-consuming and loss of good solutions as well as a trap into local optimum. In this study, we explored the KA with three auxiliary strategies for stimulating the hydropower output of cascade reservoirs. The standard KA, GA and SOP were selected as the benchmark for the comparison analysis. The improved KA was introduced to optimize the hydropower generation of six mega cascade reservoirs located at middle reach of Jin-Sha River in China. The mathematical model is driven by a huge number of inputs (i.e., 65742 inflow measurements and decision variables) and constraints (i.e., 262968 conditions).

Here we show that there is a great potential for application of the KAs to complex mega cascade reservoir operation. As compared with the SOP, the KA and improved KA can increase the hydropower generation 2.9 billion kW·h/year (4.7% improvement) and 4.8 billion kW·h/year (7.8% improvement) while boost the hydropower benefits 131.37 million USD/year and 217.44 million USD/year as well as decrease the CO_2 emission 2.28 billion kg/year and 3.77 billion kg/year, respectively. Additionally, the improved KA can increase the index values of reliability and resilience as well as decrease the index value of vulnerability. The limitation of the KAs is that if a multipurpose reservoir operation is taken into consideration, it demands to reconstruct the optimization mechanism from a single objective into multi-objective optimization to find the Pareto-optimal solutions. Consequently, follow-up studies will fuse the non-dominated sorting strategy and/or dynamically dimensioned search into a Multi-objective Kidney Algorithm for optimizing the multi-objective operation of cascade reservoirs.

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