ENHANCING CASCADE RESERVOIR DISPATCHING WITH IMPROVED KIDNEY ALGORITHM

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ABSTRACT

Addressing the intricate optimization challenge of cascade reservoir dispatching, this paper introduces a novel Improved Kidney Algorithm (IKA) to overcome the limitations of traditional and heuristic methods. Traditional optimization approaches often exhibit slow convergence and high computational costs, while natural heuristic algorithms can suffer from premature convergence and suboptimal solutions. To improve the optimization effectiveness, the IKA combines a migration strategy with an initial solution of the scaling factor and an adaptive parameter adjustment mechanism. Its application to the long-term power generation scheduling of a cascade reservoir demonstrates significant improvements in multi-year average power generation and reduction of discarded water, substantiating its potential for addressing complex optimization problems.

1. INTRODUCTION

Cascade reservoir systems play a vital role in water resource management and power generation, particularly in regions with significant hydroelectric potential (Fan et al., 2015). The optimal scheduling of cascade reservoirs is a complex and challenging problem (He et al., 2019) due to the nonlinearity of the system, multiple operational constraints, and the need to balance water release for power generation, irrigation, flood control, and environmental preservation (Bai et al., 2017). Traditional optimization methods such as linear, non-linear, network flow, and dynamic programming often encounter difficulties in efficiently solving the large-scale, multi-objective optimization problem (Dao et al., 2022) associated with cascade reservoir dispatching (T. Wang et al., 2023).

In recent years, heuristic optimization algorithms have gained attention for their ability to address complex optimization problems (Sun et al., 2018). However, existing algorithms, including the standard Kidney Algorithm (KA)(Jaddi et al., 2017), have limitations such as low population vitality, slow convergence speed, and premature convergence, which hinder their effectiveness in solving the cascade reservoir dispatching problem. The KA is a heuristic optimization algorithm inspired by the physiological function of kidneys in the human body. It simulates the process of blood filtration and reabsorption in the kidneys to develop an efficient and effective optimization algorithm for solving complex optimization problems (Ehteram et al., 2018). The algorithm is designed to maintain population diversity, adaptability, and vitality, drawing analogies from the biological processes of filtration, reabsorption, and excretion in the human kidneys (Ekinci & Hekimoğlu, 2019).

Due to the drawbacks of the standard KA algorithm such as slow convergence speed, low population vitality, and premature convergence, this research suggests an Improved Kidney Algorithm (IKA) that incorporates a migration strategy with a scaling factor and an adaptive parameter adjustment strategy (Ehteram et al., 2018). The IKA is then employed to solve the optimal scheduling of a cascade reservoir (Y. Wang et al., 2020) for long-term power generation to showcase its viability and efficiency.

The main goals of this study are outlined as follows: This paper offers a comprehensive explanation of the optimization principle of the standard KA algorithm. It presents an IKA that tackles the deficiencies of the standard algorithm, improving population diversity and convergence speed. The IKA is utilized to address the optimal scheduling of long-term power generation in a cascade reservoir, demonstrating its effectiveness in enhancing multi-year average power generation and decreasing discarded water. By addressing these objectives, this research aims to contribute to the optimization of cascade reservoir dispatching and highlight the potential of the IKA in addressing complex optimization problems in water resource management and power generation. The subsequent sections of this paper will delve into the background and related work, the optimization principle of the standard KA algorithm, the strategies of the IKA, its application in cascade reservoir dispatching, and conclude with potential future research directions.

2. BACKGROUND AND RELATED WORK

Cascade Reservoir Dispatching

Cascade reservoir systems are essential for managing water resources and generating hydropower in regions with abundant water sources (Thaeer Hammid et al., 2020). These systems consist of multiple interconnected reservoirs, each serving various purposes such as flood control, irrigation, and power generation (Dao, Nguyen, Do, et al., 2023). The optimal scheduling of cascade reservoirs involves determining the release policies for each reservoir over an extended time horizon to meet multiple objectives while adhering to operational constraints (Suwal et al., 2020). The illustration in Figure 1 depicts a cascade reservoir system that is connected to the management of water resources and the production of hydropower, and it has ample water sources.

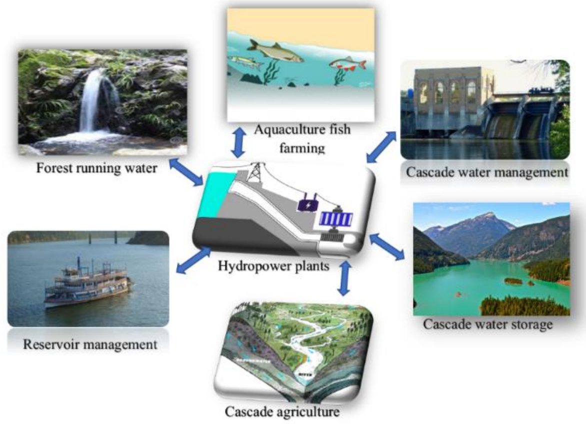

Figure 1. An example of a cascade reservoir system with abundant water sources is related to managing water resources and generating hydropower.

The complexity of cascade reservoir dispatching arises from the need to balance conflicting objectives, such as maximizing power generation (Asfaw & Saiedi, 2011), ensuring water supply for irrigation (Chen et al., 2021), and maintaining ecological flow, while considering uncertainties in inflow, energy prices, and environmental regulations

(Lai et al., 2022). Traditional optimization methods, including linear programming and dynamic programming, face challenges in efficiently solving the large-scale, multi-objective, and non-linear optimization problem associated with cascade reservoir dispatching.

In the long-term power generation dispatch model of cascade reservoirs, the best way to use them is to use their hydrology and storage capacity to make up for differences between upstream and downstream reservoirs (Dao, Nguyen, Do, et al., 2023). This study's cascade reservoir power generation dispatching model aims to achieve the maximum multi-year average power generation with guaranteed output. According to the upstream water inflow and the water in each section during the dispatch period, various operation constraints and boundary conditions are considered, and the cascade reservoirs are optimized by optimizing each cascade reservoir. To maximize the power generation capacity of the cascade reservoirs to satisfy the guaranteed output of the cascade as much as possible (Yazdi & Moridi, 2018). The objective function is formulated for the generation dispatch model of cascade reservoirs. Let G represent the objective function for the optimal dispatch of cascade reservoirs. The maximum average outputs of G is computed as the objective function for the optimal dispatch problem of cascade reservoirs, expressed as follows.

$$max\overline{G} = \frac{1}{N}\sum_{t=1}^{T} \underline{\Delta} T(t) * \left(\sum_{m=1}^{M} P(m,t) - C\varphi\left(P_f - \sum_{m=1}^{M} P(m,t)\right)^{a}\right), \quad (1)$$

where $\bar{G}$ is is the average output amount of flowing (e.g., volume flowing water in or out of reservoirs); t and T are the time and total period time number (e.g., 12 month of period year cycle); $\Delta T\ (t)$ and N are calculated period (it is calculated, e.g., hours, day, or month) and year number during the dispatch period, respectively; m and M are reservoir numbers and the total number of reservoirs respectively; C, φ, and a are the penalty coefficients for the setting variables of guaranteed outputs, which are all non-negative variables. The objective function of the optimization is subject to constraints that need to be met, including both equality and inequality constraints. The constraints consist of both equality and inequality constraints, such as Eqs. 2 to 8, that must be satisfied as follows. A coefficient of φ is calculated as follows.

$$\varphi = \begin{cases} 0, & \sum_{i=1}^{M} P(m,t) \geq P_f \\ 1, & \sum_{i=1}^{M} P(m,t) < P_f \end{cases}, \quad (2)$$

where $P(m,t)$ is the average output of the m-th reservoir during t period; P_f is the guaranteed output of cascade reservoirs.

The equation constraints are the water balance equation, the hydraulic connection equation, and the boundary conditions; the inequality constraints are all non-negative constraints on power output, outgoing flow, water level (or storage capacity) and variables. The relevant mathematical expressions are as follows: water balance equation, hydraulic connection equation, boundary conditions, power output constraint, outbound flow restriction, and water level operation constraints. The water balance is calculated as follows:

$$V(m,t+1) = V(m,t) + [Q_{in}(m,t) - Q_{out}(m,t) - L(m,t)] * \Delta T(t), \quad (3)$$

where $V(m,t)$ and $V(m,t+1)$ are the average storage of the m-th reservoir during t and t+1 respectively; Q_{in} (m, t), Q_{out} (m, t) and L (m, t) are the average inflow, outflow, and loss flow including evaporation and seepage of the mth reservoir during t period, respectively. The hydraulic connection is computed as follows.

$$Q_{in}(m+1,t) = Q_{out}(m,t) + q(m,t), \quad (4)$$

where $q(m,t)$ is the average inflow between the m-th reservoir and the m+1th reservoir during t period. The initial water level is set by the boundary conditions as follows:

$$Z(m,1) = Z_b(m), \ \ Z(m,T+1) = Z_e(m), \quad (5)$$

where $Z(m, 1)$ and $Z(m, T + 1)$ are the initial water level $[Z_b(m)]$ and the end water level $[Z_e(m)]$ of the *m-th* reservoir operation. The inequality constraints are all non-negative constraints, as follows: Power output constraints:

$$P_{min}(m,t) \leq P(m,t) \leq P_{max}(m,t), \quad (6)$$

where $P_{min}(m,t)$ and $P_{max}(m,t)$ are the lower and upper limits of the average output of the m-th reservoir during *t* period. The outbound flow restriction is set as follows.

$$Q_{omin}(m,t) \leq Q_{out}(m,t) \leq Q_{omax}(m,t), \quad (7)$$

where $Q_{omin}(m,t)$ and $Q_{omax}(m,t)$ are the lower and upper limits of the *m*-th reservoir's discharge flow during *t* period. The water level operation constraint is set under the following equation:

$$Z_{min}(m,t) \leq Z(m,t) \leq Z_{max}(m,t), \quad (8)$$

where $Z_{min}(m,t)$ and $Z_{max}(m,t)$ are the lower limit and upper limit of the water level during t period of the mth reservoir, respectively.

3. IMPROVED KIDNEY ALGORITHM

Before going into more detail about proposing an Improved Kidney Algorithm (IKA) with strategies such as adaptive filtration threshold mechanisms and diversity maintenance, we will review the KA algorithm and its optimization principle.

3.1 The Kidney Algorithm and its Optimization Principle

The KA was introduced by Jaddi in 2017 (Jaddi et al., 2017) as a natural heuristic optimization algorithm inspired by the physiological mechanism of the human kidney, specifically its processes of filtration, reabsorption, secretion, and excretion of blood and urine. This algorithm is recognized for its robustness and strong optimization capabilities, achieved through minimal parameterization, including a single filter rate parameter, along with common heuristic algorithm parameters such as population size and maximum number of iterations. The KA's simplicity and ability to generate new individuals based on current and optimal solutions enable excellent global search capabilities. The optimization principle of the KA can be outlined as follows.

Filtration: In this phase, a diverse population of candidate solutions, referred to as individuals or "nephrons," is generated and evaluated based on their fitness concerning the problem objectives and constraints.

Reabsorption: The algorithm selects the fittest individuals, akin to the reabsorption of essential kidney substances, to be retained in the population for further exploration and exploitation.

Excretion: Less fit individuals are eliminated from the population to maintain diversity and prevent premature convergence, mirroring the excretion process in the kidneys.

The optimization principle of the KA can be further summarized as follows:

Step 1 Initialization: The algorithm initializes a diverse population of candidate solutions, often represented as a set of chromosomes or vectors, to form the initial population of nephrons. The population initialization starts by randomly initializing a population of agents, known as population size *Np*, within the search space boundaries [Ub_i, Lb_i]. Each bat is assigned a position and a frequency. Let S be a vector representing the solution, with consideration as the decision variable starting at an initial position expressed as follows.

$$S_i = Lb_i + rand() \cdot (Ub_i - Lb_i), \quad (9)$$

where S_i denotes the solute of the individual *i* at the current iteration *t*, which is considered the candidate solution for the optimal algorithm.; Ub_i and Lb_i are the upper and lower boundaries of the solution space for a decision variable, where *i* is the index of the decision variable, and $rand()$ is a variable random with a value range ∈ [0,1] in the normal distribution.

Step 2- Fitness Evaluation: After the initial population generated, we calculate the objective function values of all individuals in the population, and use the individual with the largest objective function value as the currently discovered optimal solution S_{best}. Set KA parameter values, e.g., filter rate parameter α and maximum number of iterations *Imax*. Each individual in the population is evaluated based on its fitness with respect to the optimization objectives and constraints, typically involving assessing its performance in the context of the specific optimization problem.

Step 3-Filtration: The algorithm selects individuals from the population based on their fitness, aiming to maintain a diverse set of potential solutions for further exploration. For the *i-th* iteration (i⩾ 1), a new solute (individual) is generated by simulating the movement of the current solute individual to the optimal solution. The calculation formula for solute transport is as follows:

$$S_i = S_{i-1} + rand() \cdot (S_{best} - S_{i-1}), \quad (10)$$

where S_{i-1} and S_i are the solutes (solutions) in the i-1th and i-th iterations respectively; rand () is a uniformly distributed random number generator. The real number of the interval. Filtration operation is used to calculate the filtration rate value f_r filter the solute in the population, and the filtered solute will be divided into blood (FB) and urine liquid (W).

$$f_r = \alpha \cdot \frac{\sum_{j=1}^{N_p} f(S_j)}{N_p}, \quad (11)$$

where f_r is the filtering rate; $f(S_j)$ is the objective function value of the *j-th* solute S in the population; the filtering parameter α is a real number located in [0,1].

Step 4-Reabsorption: it is the process in which the fittest individuals are retained in the population for subsequent iterations, ensuring a focus on exploiting the most promising regions of the search space. The reabsorption operation calculates the objective function value of all solutes in the urine stock solution W. Solutes with larger objective function values will be reabsorbed by blood FB, and solutes with smaller objective function values or outsides of limitation boundaries (FB_{max} and FB_{min}) will be excreted and go out.

$$FB(t) = FB_{max} \times f_r \times \cos\left(\frac{\pi}{2} \times \frac{t-1}{T_{max}}\right) + FB_{min}, \quad (12)$$

where FB_{max} and FB_{min} are maximun and minimun of the flood flow; *Tmax* is a maximum number of iterations; *t* is current time; FB is the flood flow.

Step 5-Secretion operation: adjustment with the objective function value of the solute reabsorbed by FB and the solute in urine. A secreted solute is calculated as follows.

$$W(t) = W_{max} \times exp^{\left(\frac{\ln\left(\frac{W_{min}}{W_{max}}\right)}{T_{max}}\right) \times t}, \quad (13)$$

where $W_{\max}$ and $W_{\min}$ are the max and min adjusted ranges, respectively; t is the current iteration and $Tmax$ is the maximum iteration number.

Step 6-Excretion operation: For individuals in the original urine, if they cannot become individuals in the blood after re-collection and filtration operations, they will be excreted. Then, the individuals in the blood are sorted according to the objective function value, and the optimal individual Sbest is updated. Combine blood F solutes (solutions)B and original urine W, update the filtration rate value fr, and enter the next iteration: i=i+1. A generated new solute in the population as a solution set. The decision variables of the solution vector is expressed as follows.

$$S_{new}(i) = \begin{cases} S(i) + rand(0,1) \times W, if(rand(0,1) < FB) \\ S(i) \qquad\qquad otherwise \end{cases}, \quad (14)$$

where S_{new} is a new solute (solution) population, i-th index; $rand(0,1)$ is a random number arange of ∈[0,1].

Step 7-Iterative Refinement: The algorithm iteratively performs filtration, reabsorption, and excretion steps over multiple generations to improve the quality of solutions and converge towards optimal or near-optimal solutions. Determine whether the calculation meets the termination principle (the maximum number of iterations or the objective function value of the optimal solution for consecutive iterations remains unchanged); if yes, output the optimization result; otherwise, repeat steps (2) to (6).

The KA's optimization principle is guided by the principles of population diversity, adaptability, and vitality, drawing inspiration from the biological processes of kidney function. The algorithm's ability to maintain a diverse population and adapt to changing environmental conditions makes it suitable for addressing complex optimization problems, including cascade reservoir dispatching. In the subsequent section, the research paper will introduce the Improved KA (IKA), which builds upon the principles of the standard KA to address its limitations and enhance its effectiveness in solving complex optimization problems such as cascade reservoir dispatching.

3.2. Improved Kidney Algorithm (IKA)

The IKA is an enhanced version of the KA (Jaddi et al., 2017) that incorporates novel strategies to address the limitations of traditional heuristic optimization algorithms and improve its effectiveness in solving complex, non-linear, and multi-objective optimization problems. The IKA builds upon the principles of the standard KA while introducing innovative mechanisms to enhance population diversity, convergence speed, and solution quality.

Strategies: The IKA employs several key strategies to overcome the limitations of traditional heuristic optimization algorithms and enhance its performance in solving complex optimization problems. The following strategies are integral to the IKA's approach:

Adaptive Filtration Threshold: The IKA introduces an adaptive filtration threshold mechanism to dynamically adjust the selection criteria for individuals during the filtration phase. This adaptive threshold allows the algorithm to maintain population diversity while focusing on exploring promising regions of the search space.

Dynamic Excretion Mechanism: The IKA incorporates dynamic excretion mechanisms to intelligently eliminate less fit individuals from the population, thereby preventing stagnation and facilitating the exploration of new solution regions. The initial solution set is constructed using the uniform design method for the dynamic nature of the excretion process, which contributes to maintaining population vitality and adaptability. The population size increases the diversity of the early solutions by generating initial solution workable as follows.

$$S(i) = \begin{cases} S_r(i), & if\,(\,rand(0,1) < PR) \\ S_{min} + rand(0,1) \times (S_{max} - S_{min}), & otherwise \end{cases} \quad (15)$$

where $S(i)$ is the newly generated solute; $S_r(i)$ is any one in the initial solutes; PR is the variable of probability value referring to the individual body's immune system (in the experiment, it is a specific value set to 1/2); $rand()$ is the random number ∈[0,1]; S_{max} and S_{min} are the upper and lower limits of the body solutes bank, respectively. A selected $\mathrm{S}(i)$ from the current body memory that needs to be fine-tuned by adjusting the immune system.

Adaptive Parameter Control: The IKA employs adaptive parameter control mechanisms to dynamically adjust algorithmic parameters based on the evolving characteristics of the optimization landscape. This adaptability allows the algorithm to respond effectively to changes in the problem space and environmental conditions. The discrete decision variables of the solution vector converted from continuous decision variables are expressed as follows. The enhancement ensures the algorithm exploits the most promising solutions while adapting to changing environmental conditions.

$$S_{new}(i) = \begin{cases} S(i+k), & rand(0,1) < FB \\ S(i), & else \end{cases} \quad (16)$$

The objective function $Of(.)$ for each solute and updating the solute with the updated criterion is the greedy criterion. That is, if $Of_{new} > Of(S_i)$, the new harmony S_{new} replaces the solutes S_i; otherwise, it remains the unchanged solution.

Multi-objective optimization can be implemented in other multi-objective optimization problems, the IKA incorporates mechanisms to handle conflicting objectives and constraints. By integrating multi-objective optimization techniques, the algorithm can effectively balance trade-offs and generate Pareto-optimal solutions. The paper currently focuses on a single function.

The reservoir water level at the end of the period is calculated as follows:

$$S(i,n) = S_{min}(i,n) + \lambda * [S_{max}(i,n) - S_{min}(i,n)] \quad (17)$$

where $S(i,n)$ is the reservoir water level of the i-th solute in the interval number; $S_{min}(i,n)$ and $S_{max}(i,n)$ are the lowest and highest possible reservoir water levels of the i-th solute during the nth period, respectively *j-th* is the solute number, λ is a random number uniformly distributed between [0,1].

By integrating these strategies, the IKA aims to address the limitations of traditional heuristic optimization algorithms and provide a practical framework for solving complex optimization problems, including cascade reservoir dispatching. The subsequent sections of this research paper will present the application of the IKA in the context of cascade reservoir dispatching and demonstrate its effectiveness in optimizing reservoir operations under diverse and conflicting objectives and constraints.

4. APPLICATION OF IKA IN CASCADE RESERVOIR DISPATCHING

This section presents an application of the IKA for cascade reservoir dispatching, which represents a significant advancement in addressing the complex and multi-objective nature of optimizing the operation of interconnected reservoirs. Cascade reservoir systems involve a series of interconnected reservoirs where the release decisions from one reservoir impact the downstream reservoirs, posing challenges related to water allocation, hydropower generation, flood control, and environmental considerations.

The IKA offers a promising approach to optimizing the operation of cascade reservoirs effectively while balancing conflicting objectives and constraints.

4.1 The IKA for Cascade Reservoir Dispatching

The nature of cascade reservoir dispatching can be addressed by applying IKA, where conflicting objectives such as maximizing hydropower generation, ensuring water supply, and mitigating flood risk need to be balanced. Cascade reservoir dispatching involves intricate operational constraints related to reservoir storage capacities, minimum and maximum release limits, environmental flow requirements, and downstream water demands. The IKA's ability to handle complex constraints and trade-offs through adaptive parameter control and dynamic excretion mechanisms makes it well-suited for addressing the operational complexities of cascade reservoir systems.

The IKA's emphasis on maintaining population diversity with local search techniques enables it to explore various operating strategies for cascade reservoirs. The exploration is essential for identifying non-dominated solutions representing the best trade-offs between conflicting objectives and providing decision-makers with valuable insights into the range of feasible operating policies.

Cascade reservoir systems are subject to variations in inflow patterns, energy market dynamics, and environmental regulations. The IKA's adaptability to changing conditions, facilitated by adaptive filtration thresholds and reabsorption mechanisms, ensures that the algorithm can continuously adjust its solutions to reflect evolving operational and environmental contexts. Figure 2 presents a simplified illustration of how a chain of chosen reservoirs are connected.

Assumedly, a cascade reservoir system includes three stations responding with three reservoirs (namely stations 01, 02, and 03) arranged in a series (01 -> 2 -> 3).

Let I_i be the water inflow, with each reservoir receiving water from the main river and supplementary sources (i = 1, 2, and 3).

Let R_i be the water outflow, with each reservoir discharging water with O_1, O_2 and O_3 into the main river downstream.

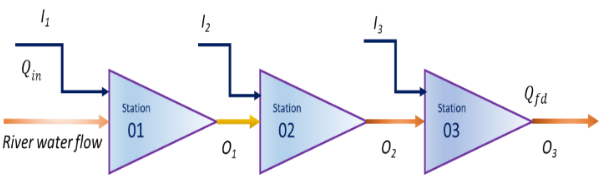

Figure 2. A simplified illustration of a chain of connected reservoirs as stations 01, 02, and 03.

The IKA's iterative refinement process allows for the generation of a diverse set of high-quality solutions, which can be evaluated using performance metrics such as hydropower generation, reservoir storage levels, and environmental impact. These solutions can then serve as a basis for decision support, enabling stakeholders to make informed decisions regarding reservoir operation. By applying the IKA to the domain of cascade reservoir dispatching, researchers and practitioners can benefit from a robust and adaptive optimization framework capable of addressing the complexities and trade-offs inherent in managing interconnected reservoir systems.

The multi-year average power generation of cascade reservoirs, the multi-year average water discarded and the multi-year average power generation guarantee rate are used to comprehensively evaluate the effect of the heuristic algorithm for optimizing power generation dispatching. Each reservoir has no water supply task and only has a single power generation function, and the evaporation and leakage losses of the reservoir are not included in the amount of discarded water. Referring to Eq. (1), a calculation formula for the average amount of water discarded annually is computed as follows.

$$\overline{S} = \frac{1}{N}\sum_{t=1}^{T}\sum_{m=1}^{M}[Q_{in}(m,t) - L(m,t) - Q_{fd}(m,t)], \quad (18)$$

where $\overline{S}$ the multi-year average water discarded; $Q_{in}(m,t)$, $Q_{fd}(m,t)$, and $L(m,t)$ are respectively the average inflow, outflow, and loss flow the power generation flow and power generation head of the *m-th* reservoir during the *t* period; including evaporation and seepage of the mth reservoir during *t* period, respectively. T and M are the total number of periods in the dispatch time, and cascade reservoirs composed of reservoirs, respectively.

$$Q_{fd}(m,t) = \frac{P(m,t)}{K*\overline{H}(m,t)}, \quad (19)$$

where $P(m,t)$ is the average output of the *m*-th reservoir during t period; $\overline{H}(m,t)$ is power generation head P_f is the guaranteed output of cascade reservoirs; K is the unit's comprehensive output coefficient. The year average power generation guarantee rate is expressed as follows.

$$\overline{R} = \frac{1}{N}\frac{\sum_{t=1}^{T} R_t}{T} \times 100\%, \quad (20)$$

where $\overline{R}$ is average power generation guarantee rate; R_t is the output statistical variable of the cascade reservoir is calculated as follows.

$$R_t = \begin{cases} 1 & \sum_{i=1}^{M} P(m,t) \geq P_f \\ 0 & \sum_{i=1}^{M} P(m,t) < P_f \end{cases}, \quad (21)$$

where R_t is the guaranteed output statistical variable of the cascade reservoir during the t period. The IKA algorithm is used to solve a long-term power generation optimization problem in the simulation that involves cascade reservoirs made up of M reservoirs. The optimization goal is to maximize power generation, with the optimization variable being the end of the period reservoir water level, Considering that the total number of periods in the dispatch period is T, each of the populations The total number of solutes possessing optimization variables and the population of each iteration contain optimization variables. The solution steps are described as follows:

Step1-Initialize the population: Taking the reservoir water level at the end of the period as the optimization variable, the reservoir water level sequence composed of M reservoirs is regarded as an individual solute (solution), using real number coding to optimize the variable (reservoir water at the end of the period *T*), and according to the equality and inequality constraints that the reservoir needs to meet Eqs (2)~(8), generate the initial population whose population size is N_p.

Step2-Evaluation of reservoir water level sequence: The objective function value is used to evaluate the reservoir water level sequence at the end of the period, and the best individual Sbest is selected based on this evaluation. In this study, the mathematical model represents a constrained maximum value optimization problem, and the IKA algorithm aims to evolve towards the maximum value. Therefore, the power generation of cascade reservoirs (where larger values are better) is used to assess the reservoir water level sequence at the end of the period in the IKA algorithm Eq.(18).

Step3: Divide the population. Randomly generate a filtering rate value between [0, 1], and calculate the filtering rate value fr, perform the filtering operation, and divide the initial population into blood FB as in Eq.(12) and urine W as in Eq.(13).

Step4: Update blood and urine stock Re-absorption, secretion and excretion operations are used to update blood and urine stock; then according to the selected optimal time-end reservoir water level sequence Sbest and the segmented population. The migration strategy of the scaling factor is updated for all individuals Eqs. (14).

Step5: Update the filtration rate value fr, and then combine the blood and the original urine. First, update the filter rate value fr according to the adaptive parameter adjustment strategy, and then merge the blood and the original urineto enter the next iteration, Eq.(11).

Step6: Determine whether the calculation meets the termination principle. If the calculation reaches the maximum number of iterations, e.g., *max_iter* or the objective function value of the optimal solution for 500 consecutive iterations does not change, output the scheduling result (power generation, end-of-period reservoir water level, outbound flow, average output of the period, etc.), otherwise repeat at step 2.

4.2 Case of Scenario and Its Results

The objective of optimal operation for the three reservoirs' total annual power generation is calculated using Eq. (18). The selected system, with three pools, operates monthly, spanning from January to December. The 12-month cycle is detailed in Table 1, outlining specific reservoir parameters. The optimization variable is the water level, with the total power generation of the three power stations serving as the objective function. Algorithm 1 illustrates the pseudocode of the IKA process for the optimal operation of depatching cascade stations. The operation of the three reservoirs is scheduled for intervals, such as a monthly schedule covering a full year. The optimization goal is to achieve the maximum value of the total power generation from the three reservoirs over one year. Various scenarios, including typical rainy years, specific average years, and typical dry years, are selected to test the proposed scheme for optimal operation using the applied IKA. Eq. (18), which sums the power generation of the hydropower stations as determined through the optimization of the suggested scheme, serves as the objective function for the optimization.

Algorithm 1. Improved Kidney Algorithm Pseudocode for Cascade Reservoir Dispatching

1. Initialization: population size N_p, maximum iterations *max_iter*, fitness function Of Initialize population with random solutions S as Eqs.(9), (15) with equality and inequality constraints Eqs (2)~(8) and (19)~(21)
2. Main loop:

- For each iteration (iter) from 1 to max_iter:
  - Fitness evaluation:
    - Calculate the fitness of each solution: $Of(S)$ as Eq. (18)
  - Filtration:
    - Calculate filtration rate based on average population fitness.
    - Select promising solutions based on fitness and filtration rate (forming filtered_population). Eq. (16)
  - Reabsorption:
    - Apply a small random perturbation to improve each solution in filtered_population Eqs.(12), (21)
  - Secretion:
    - Generate new solutions randomly to complete the population size. Eq.(18)
  - Combine populations:
    - Concatenate filtered_population with the newly generated solutions (forming combined_population) as Eq.(13)
  - Excretion:
    - Sort combined_population by decreasing fitness.
    - Remove the worst solutions to maintain the original population size (keeping the top N solutions).
  - Update best solution:
    - Keep track of the solution with the highest fitness throughout the iterations (best_solution). Eq.(14)
  - Save results:
    - Store information like iteration number, best solution, and best fitness for analysis.

3. Post-processing:

- Ooutput optimal results and perform maping additional tasks as needed in paramters of reservoirs.

When IKA with reservoir dispatching is used, the results are compared with those from other schemes, such as the Genetic algorithm (GA) (Asfaw & Saiedi, 2011), Firefly algorithm (FA) (Chen et al., 2021), Simulated annealing (SA) (Azizipour et al., 2020), Particle swarm optimization (PSO) (Bai et al., 2017), and KA (Ehteram et al., 2018) algorithms for the operation plant stations. As with the compared schemes, the experiment environment system parameters are set up with the same conditions as the IKA scheme. For example, the number of search solutes is set to 100, the total number of iterations is set to 500, and the number of runs for each algorithm is set to 25. The IKA obtained statistical data compared with the other schemes, e.g., the GA (Asfaw & Saiedi, 2011), FA (Chen et al., 2021), SA (Azizipour et al., 2020), PSO (Bai et al., 2017), and KA (Ehteram et al., 2018)(Jaddi et al., 2017), to manage operation problems at the cascade reservoir stations. The obtained statistical data consist of the best value, worst value, average value, and standard deviation of the run results in different typical years. The scenario of varying water levels depends on the specific years that comprise the rainy year, the average year, and the dry year.

Table 1: A fundamental cascade hydropower station parameter setting specifications

Parameters	Station-01	Station-02	Station-03
Operations: Annual regulations	Annuals	Unfinished-annuals	Annuals
Reservoir's storage capacity (Bm^2)	34.165	7.752	1.943
Water normally leveled	715	612.2	511.26
Water limited leveled	613.8	617.8	552.7
Outcome coefficients of outflow R_i	5.675	4.5925	4.675
Coefficients water inflow I_i	4.857	3.235	3.275
Storage limited capacity (Bm^2)	1.0105	0.352	0.024
Setting up capacity (MW)	340	412.55	290
Storage capacity regulations (Bm^2)	21.4055	4.7005	0.9612

A basic set of parameter settings for a cascade hydropower station is provided in Table 1. Figure 3 compares the bar chart results of the IKA with the KA algorithm for power generation capacity. The observed result shows that the IKA produces better performance at most planning monthly periods in an annual year.

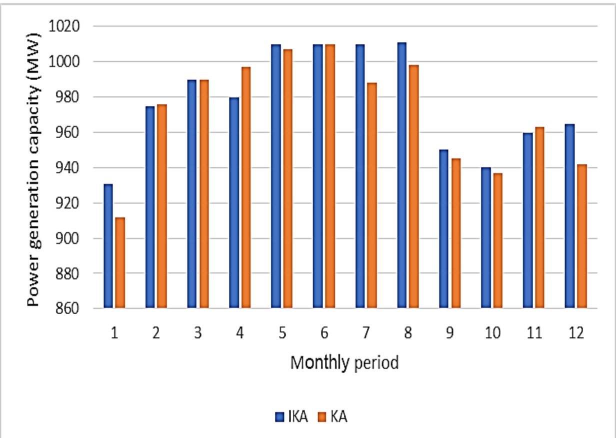

Figure 3. A comparison of performance results of the IKA with the KA algorithm for power generation capacity in planning monthly periods annually.

Specifically, the IKA algorithm consistently outperforms the KA algorithm in power generation capacity across all 12 months of the year. This suggests that the IKA algorithm is more effective in optimizing power generation capacity and can lead to greater efficiency and cost savings for power generation facilities. Further analysis of the data may provide insights into the specific factors that contribute to the superior performance of the IKA algorithm, which could be valuable for informing future planning and decision-making in the power generation industry.

Overall, these findings highlight the potential benefits of utilizing the IKA algorithm for power generation capacity planning. Table 2 provides a comprehensive analysis of the performance of the IKA, GA, SA, FA, PSO, and KA in the optimization of dispatching cascade hydropower station management. This table delves into a head-to-head comparison of IKA's performance against commonly used algorithms in comparing variables, e.g., best, standard deviation (Std.), and average (Mse.) values across 25 runs in different water years, e.g., rainy, normal, and dry year seasons, reveals the strengths and weaknesses of each approach.

The table presents the statistical results from 25 independent runs, each consisting of 500 iterations with 100 search agents (solutes) per algorithm. By comparing the best, worst, average, and standard deviation values across different water scenarios (rainy, normal, and dry year seasons).

Table 2 offers valuable insights into the effectiveness of each optimization strategy. This analysis serves to identify the most suitable approach for optimizing cascade hydropower station management under varying water conditions.

Figures 4 and 5 illustrate how the IKA algorithm optimizes dispatching reservoir station operation compared to other common methods like GA, SA, FA, PSO, and KA. The figure highlights the IKA's performance under different water levels in rainy and dry years.

Table 2. A comprehensive analysis of the performance of the IKA with the GA, SA, FA, PSO, and KA for the optimization of dispatching cascade reservoirs management

Years seasons	Methods	Best	Std.	Mse.
Rainy season	GA	57.77	51.28	49.67
	FA	56.95	49.96	48.68
	SA	56.02	49.61	48.31
	PSO	57.77	51.28	50.42
	KA	57.21	50.70	49.67
	IKA	**58.02**	**51.57**	**50.64**
Normal Season	GA	47.41	42.03	56.70
	FA	47.31	41.58	54.55
	SA	46.34	40.99	54.74
	PSO	47.97	42.60	56.70
	KA	47.4	42.03	55.95
	IKA	**48.09**	**42.75**	**57.10**
Dry Season	GA	39.85	36.28	41.90
	FA	39.95	36.95	41.95
	SA	39.65	36.96	41.39
	PSO	40.47	37.82	43.44
	KA	38.13	35.43	40.91
	IKA	**40.59**	**37.99**	**43.70**

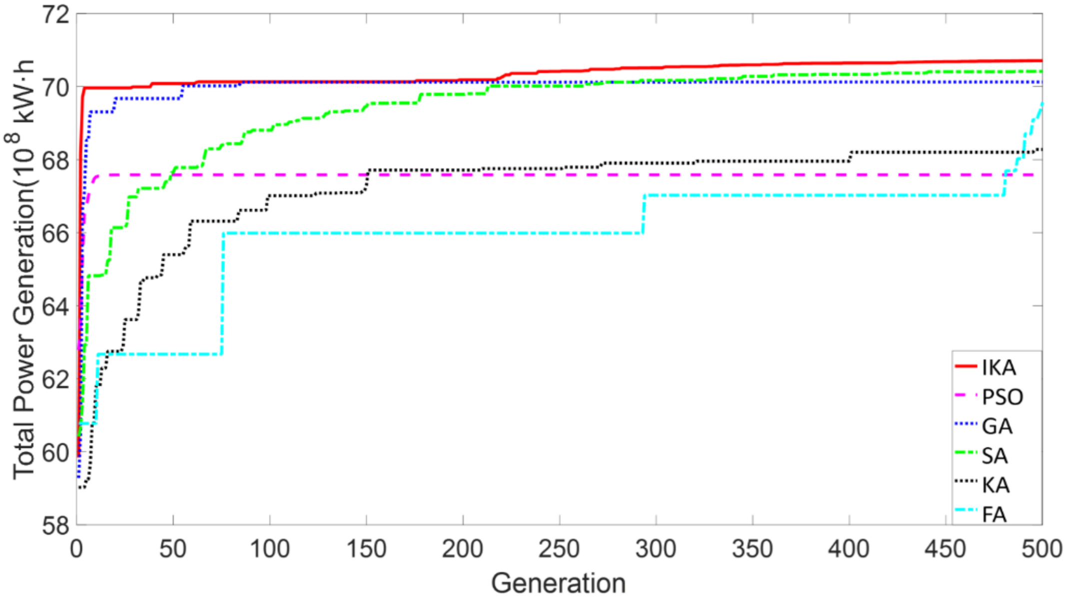

Figure 4. The comparison of graph curves of the obtained optimal result for power generation in a rainy season.

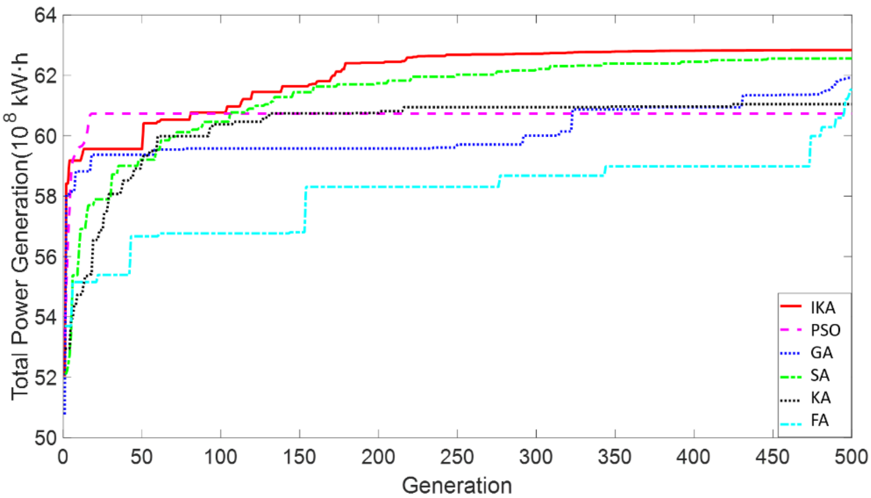

Figure 5. The comparison of graph curves of the obtained optimal result for power generation in a rainy season.

The IKA algorithm is particularly effective in managing the operation of reservoir stations across varying water levels and weather conditions. The comparison with other common optimization methods such as GA, SA, FA, PSO, and KA further emphasizes the superiority of the IKA algorithm in this specific application. The results presented in Figures 4 and 5 underscore the potential of the IKA algorithm to enhance the efficiency and effectiveness of reservoir station operations, particularly in the face of changing environmental conditions. These findings could have significant implications for the management and planning of water resource systems, particularly in regions prone to fluctuating water levels due to seasonal variations. Overall, the information in these figures supports the idea that the IKA algorithm is a useful scheme for improving the scheduling of operations at reservoir stations, which could lead to better use of resources and better operational performance.

5. CONCLUSION

This study presented the Improved Kidney Algorithm (IKA), a promising solution for addressing the intricate challenges associated with optimizing the operation of dispatching cascade reservoirs. By incorporating adaptive mechanisms such as reabsorption, constructing an initialized solution set, and adaptive parameter control with local search techniques, the IKA effectively manages conflicting objectives and constraints while exploring diverse operating strategies. Its adaptability to changing conditions and ability to handle complex operational constraints make it well-suited for real-world applications in water resources management. The simulations presented in the study demonstrate the effectiveness of the IKA in optimizing cascade reservoir operations under diverse and conflicting objectives and constraints. The algorithm's capacity to generate optimal solutions and offer decision support based on performance metrics such as hydropower generation and reservoir storage levels underscores its potential for real-world applications.

Future work in this area could further enhance the IKA's performance by integrating additional adaptive mechanisms and exploring its applicability to other domains such as flood control, water supply management, and environmental conservation (T. T. Nguyen et al., 2019)(T.-T. Nguyen et al., 2023).

Additionally, research could investigate the potential for integrating machine learning techniques with the IKA to improve its adaptability and decision-making capabilities (Dao, Nguyen, Ngo, et al., 2023).

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TĂNG CƯỜNG VIỆC ĐIỀU PHỐI MỨC NƯỚC HỒ CHỨA THỦY ĐIỆN SỬ DỤNG THUẬT TOÁN IKA CẢI THIỆN

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THÔNG TIN CHUNG

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TÓM TẮT

Giải quyết bái toán điều phối hồ chứa bậc thang cho trạm thủy điện là một nhiệm vụ tương đối phức tạp trên cơ sở tối ưu một loạt các tham số. Bài báo này, chúng tôi giới thiệu một thuật toán cải tiến(Improved Kidney Algorithm – IKA) để khắc phục những

TỪ KHOÁ

Quản lý hồ đập thủy điện;
Điều phối mức nước hồ chứa;
Thuật toán IKA;
Thuật toán tối ưu.

hạn chế của phương pháp tối ưu truyền thống và các thuật toán heuristic. Các phương pháp tối ưu hóa truyền thống thường hội tụ chậm và chi phí tính toán cao, các thuật toán heuristic tự nhiên có thể gặp phải tình trạng hội tụ sớm và có thể chỉ giải được dưới mức tối ưu cần thiết. Để cải thiện hiệu quả tối ưu hóa, chúng tôi đề xuất IKA kết hợp chiến lược di trú với giải pháp ban đầu về hệ số tỷ lệ và cơ chế điều chỉnh tham số thích ứng. Sau đó ứng dụng đề xuất vào việc lập lịch điều phối cho hồ phân cấp để điều tiết lượng xả nước cho đập thủy điện dài hạn của hồ chứa. Kết quả mô phỏng cho thấy sự cải thiện đáng kể trong việc sản xuất điện trung bình trong năm và giảm lượng nước xả tổn hao. Điều này cho thấy tiềm năng của việc áp dụng giải thuật tối ưu mới trong việc giải quyết các vấn đề tối ưu hóa của bài toán lập kế hoạch và điều phối phức tạp.