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Load Optimization Distribution Among Cascade Hydropower Stations Based on the A* Algorithm

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Abstract: Under high-intensity peak shaving and frequency regulation, the output of hydropower plants fluctuates frequently, significantly increasing the complexity of load distribution among cascade hydropower plants (LDCHP). Currently, commonly used solution methods include traditional dynamic programming and intelligent optimization algorithms. The former suffers from the "curse of dimensionality" during computation, whereas the latter typically relies on population-based evolutionary mechanisms, often resulting in low convergence efficiency and suboptimal computational performance. To address the LDCHP challenge, this study develops a model for LDCHP and applies the A* algorithm to solve the related dispatching problem. Using cascade hydropower plants in the middle reaches of the Dadu River Basin, China, as a case study, the proposed approach is empirically validated. The results indicate that, compared with the DP algorithm, the A* algorithm achieves an average computational efficiency improvement of 5,372.9 times, alongside a 1.56% decrease in energy storage utilization efficiency. Furthermore, the total energy storage loss calculated by the A* algorithm is 22.41% lower than actual operational data, demonstrating its capacity to significantly enhance solution efficiency without compromising scheduling benefits. Overall, this approach provides valuable technical support for solving complex cascade hydropower dispatching models.

Keywords: Cascade hydropower plants, Optimal scheduling, Load distribution among cascade hydropower plants, A* algorithm; Heuristic algorithm

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1. Introduction

The extensive use of traditional fossil fuels has accelerated global industrialization; however, it has also resulted in a range of environmental and climatic challenges, including pollution and global warming. Consequently, the shift toward clean, low-carbon energy sources has gained widespread support worldwide (Liu, 2022). Hydropower, with its renewable, clean, and flexible resource, contributes approximately 15% to global electricity generation and plays a crucial role in ensuring the stability and reliability of power systems (Avesani et al., 2022). China possesses hydropower resources with a technical exploitation potential of 6.87×10^{8} kW, the largest in the world (Zhou et al., 2022). Following the completion of 14 major hydropower bases, a coordinated dispatch framework for large-scale, cross-basin hydropower plant clusters has been established (Cheng et al., 2019), and the focus of China's hydropower industry has gradually shifted from infrastructure construction to operation and management. Efficiently allocating dispatch instructions across various hydropower plants has become a critical factor influencing the overall power generation efficiency of cascade hydropower systems, and is essential for maximizing the engineering benefits of water conservancy facilities.

Load distribution among cascade hydropower plants (LDCHP) refers to the optimized operational process that aims to maximize the objective function based on the known initial state of the cascade, the total load distribution during the dispatch period, and the natural water inflow. The optimization results are directly applied to real-world production. In recent years, the acceleration of China's energy transition has led to a rapid increase in the share of renewable energy sources, such as wind and photovoltaic power. It is projected that the installed capacity of renewable energy will reach 12 TW by 2030 (Administration, 2022). However, the inherent uncertainty of wind and photovoltaic power generation has significantly impacted the economic benefits and stable operation of the power system (Huang et al., 2023; Ju et al., 2023), leading to more frequent load instructions (Cheng et al., 2023). As a result, higher requirements have been placed on the LDCHP response speed. Additionally, the problem of LDCHP is often subject to a complex and cumbersome set of constraints and requires a comprehensive consideration of multiple benefits (Jiang et al., 2022; Liu et al., 2024; Wu et al., 2020). This makes the LDCHP a multi-dimensional, multi-variable,

nonlinear, and highly constrained optimization problem (Ahmadianfar et al., 2019), which complicates model-solving. Furthermore, with the continuous development of China's hydropower industry, the scale of cascade hydropower plants has expanded annually, and the number of plants in each river basin has also increased. The interconnection between upstream and downstream water and electricity systems has become more intricate, and the characteristics of individual power plant units are increasingly complex and different from each other (Su et al., 2020; Wu et al., 2020). This has led to issues such as significant fluctuations in hydropower plant water levels and deterioration of unit operating conditions, further exacerbating the challenges of solving the optimization model.

In response to the challenges associated with LDCHP, scholars have proposed various optimization techniques. Traditional solution approaches include linear programming algorithms (Yoo, 2009), nonlinear programming algorithms (Ma et al., 2022), and dynamic programming (DP) algorithms (Ji et al., 2016). For instance, Ge et al. (Ge et al., 2014) developed a mixed-integer programming model that accounts for flow lag, which was subsequently transformed into a mixed-integer linear programming problem using integer algebraic methods. This model significantly reduces computational complexity and enhances the overall benefits of basin-wide operations. Zhang et al. (Zhang et al., 2015) integrated DP with parallel processing technology and proposed three parallel multi-dimensional DP algorithms, which substantially reduced computation time and improved the efficiency of solving optimal dispatch models for cascade hydropower systems. Chen et al. (Chen et al., 2022) applied the discrete differential DP method to effectively solve the multi-objective water and sediment regulation problem in cascade reservoirs, achieving scheduling solutions that balance multiple objectives, such as hydropower generation, sediment discharge, flood control, water supply, and ecological preservation.

However, among the traditional solution algorithms, linear programming has a relatively high solution efficiency, but the linearization processing of the model results in significant errors. Dynamic programming algorithms may be limited by problems such as dimensionality disasters and low solution efficiency. Under the backdrop of the gradual integration of water and electricity regulation in China and the continuous improvement of the requirements for refined dispatching, river basins are confronted with higher intensity and frequency requirements of peak shaving and frequency regulation. Traditional algorithms are no longer sufficient to meet the scientific and timely

demands of dispatching operations in river basins. With the establishment of bionics, scholars have developed heuristic algorithms based on biological evolution mechanisms. These algorithms possess excellent global search capabilities and have been widely applied in the optimal scheduling problem of cascade hydropower plants. Some scholars have made improvements to the problems existing in the algorithm itself. For instance, Li et al. (Li et al., 2009) addressed the issues of insufficient global optimization ability and convergence speed of the particle swarm optimization algorithm by introducing the immune information processing mechanism into the particle swarm optimization algorithm. By leveraging its unique concentration selection mechanism and immunization, the improved algorithm achieved higher convergence accuracy and efficiency. Jiang et al. (Jiang et al., 2018) integrated the mutation and selection operations in the differential evolution algorithm with the bat algorithm, which, to a certain extent, alleviated the problems of the algorithm being prone to falling into a local optimum and having low convergence accuracy. Zhang et al. (Zhang et al., 2024) studied the problem of short-term optimal dispatching of hydropower, they improved the genetic algorithm by introducing adaptive strategies and elite selection strategies and proposed a selection strategy combined with parallel computing technology, which significantly improved the solution efficiency of the model while ensuring the dispatching benefits. Meanwhile, some scholars have attempted to apply various algorithms proposed in recent years to dispatching problems. For instance, Liu et al. (Liu et al., 2025) applied the Harris hawks optimization algorithm to solve the economic dispatching strategy model for cascade hydropower plants considering the electricity market, demonstrating the effectiveness and economy of the strategy. Liu et al. (Liu et al., 2020) applied the lion swarm algorithm to the solution of the cascade hydropower plants dispatching problem, whose results were highly competitive compared with the genetic algorithm, particle swarm algorithm, and the improved cuckoo search algorithm.

The aforementioned algorithm partially addresses the limitations of traditional algorithms in solution efficiency; however, the results remain unstable (Zeng et al., 2023), with issues such as poor reproducibility, high dependence on parameter settings, and a tendency to fall into local optima. Additionally, in the context of high-intensity peak shaving and frequency regulation, it fails to fully meet the timeliness requirements for solutions. The A* algorithm, a type of heuristic algorithm, was first introduced by Hart et al (Hart et al., 1968). It combines the characteristics of breadth-first search

and heuristic search, reducing search space while efficiently identifying near-optimal solutions (Wang et al., 2024). This algorithm has been widely applied to path planning problems (Zhang et al., 2023). In fact, the path planning problem bears significant similarities to the LDCHP problem. Path planning involves searching for the shortest path from a starting point to a target point within a given space, aiming to achieve goals such as minimizing travel time, avoiding hazardous areas, or maintaining a safe distance. The path points are determined by spatial coordinates, and at each point, the next reachable point is determined by obstacles and the state of the moving entity. Similarly, the LDCHP problem involves regulating reservoir water storage and release strategies to determine the dispatching and operation process of reservoirs from the current period to the target period, whose goal is to optimize water resource utilization and enhance power generation efficiency. The state of a reservoir is influenced by the water levels of all hydropower plants involved in the dispatching process and the state of power generation and flood discharge facilities. For a given state of a cascade hydropower system, the next state is determined by constraints such as power plant capacities, water inflow conditions, and power generation plans. It is evident that both the path planning problem and the LDCHP problem involve searching for the optimal transition from an initial state to a target state within a constrained space, based on a defined objective. Therefore, the solution algorithms for both problems share certain commonalities, indicating that the A* algorithm is applicable to LDCHP, though adjustments are necessary to address its unique requirements.

This study addresses the inefficiencies and limited dispatching benefits in the LDCHP problem, particularly in the context of high-intensity peak shaving and frequency regulation. It proposes a solution method for the LDCHP problem based on the A* algorithm. The main contributions of this work are as follows: (1) A cost function, which incorporates power generation benefits, is constructed based on the heuristic search principle of the A* algorithm. Additionally, a water-energy conversion rate prediction method is introduced into the heuristic function to guide the algorithm in prioritizing high-benefit paths. (2) To address the complexities of continuous state variables, intricate hydraulic connections, and path search challenges in reservoir dispatching, a nearby node expansion method suitable for the LDCHP problem and the solution process of the A* algorithm are proposed to improve the solution efficiency of the algorithm and the benefits of the results.

The remainder of this paper is organized as follows: Section 2 outlines the objective function

and constraints of the LDCHP model. Section 3 introduces the load distribution method based on the A* algorithm. Section 4 discusses the research results. Section 5 presents the conclusions of the study.

2 Optimization model for LDCHP

The LDCHP requires dynamic regulation of the water level process at each plant in response to environmental changes, aiming to maximize overall water resource utilization within the basin. This constitutes a multi-dimensional, nonlinear optimization problem with strong constraints (Ahmadianfar et al., 2019). On the one hand, load distribution must satisfy grid demand to ensure the safe and stable operation of the power system. On the other hand, it is necessary to maintain sufficient energy storage within the constraints of ecological flow and water level requirements, thereby preserving the basin's power generation capacity and enhancing its resilience to unforeseen circumstances. For a given dispatching period, different load distribution strategies adjust the output sequence and outflow of each plant, altering the spatial distribution and consumption rate of water, and thus affecting the efficiency of subsequent water–energy utilization. Variations in operational strategies lead to different levels of water consumption across plants, ultimately producing discrepancies in reservoir levels at the end of the dispatching period and, consequently, differences in total energy storage.

In practice, the power dispatching department typically assigns 96 load tasks per day (at 15-minute intervals) to the generation department. Based on the initial operating state of each hydropower plant, the aggregate load, and corresponding hydrological inflow data, these tasks are systematically allocated to individual hydropower plants.

For a single hydropower plant, the variation in energy storage over a given time period can be equivalently expressed as a change in water volume. Accordingly, minimizing water consumption can be adopted as the dispatching objective, and the corresponding objective function is expressed as follows:

$$EW = \min \sum_{t=1}^{T} Q_{outflow,t} \Delta t \tag{1}$$

where, EW is the water consumption during the dispatching period; T is the number of

scheduling periods; $Q_{outflow,t}$ is the average outflow of the hydropower plant in period t; Δt is the time interval.

However, in cascade hydropower systems, water consumption alone does not adequately reflect the variations in hydraulic head across different plants. If the objective is limited to minimizing water consumption, the upstream plant may prioritize power generation until its water level approaches the dead storage level, while downstream plants maintain relatively high water levels. Such an imbalance can compromise the safe and stable operation of the entire cascade system. To better account for hydraulic head differences among plants, some scholars have proposed maximizing final energy storage as the optimization objective. The corresponding objective function is expressed as follows:

$$EN = \max \sum_{i=1}^{n} E_i \left(Z_{i,final} \right) \tag{2}$$

where, EN is the energy storage at the end of the dispatching period; n is the total number of cascade hydropower plants; $E_i(*)$ is the energy storage function, which describes the functional relationship between the water level and energy storage of the hydropower plant i; $Z_{i,final}$ is the final water level of the hydropower plant i.

This objective function clearly represents the energy storage consumption associated with different scheduling strategies. However, in practical applications, the final energy storage of cascade hydropower plants depends solely on the final water levels at each plant. Consequently, it is difficult to apply phased optimization methods during the solution process, which significantly limits their applicability. If the initial stepwise energy storage is predetermined, the final energy storage can be expressed as follows:

$$EN = E + \sum_{t=1}^{T} ES_t \tag{3}$$

where, E is the initial energy storage of the cascade hydropower plant; ES_t is the energy storage increment of the cascade hydropower plant during period t.

When the initial cascade energy storage is fixed, maximizing the terminal energy storage at the end of the scheduling period is equivalent to maximizing the total incremental energy storage of the cascade hydropower plants across all dispatch periods. Based on this equivalence, the original

problem can be reformulated as a multi-stage optimization problem. This transformation overcomes the limitation whereby the computational characteristics of maximizing final energy storage restricted its applicability. However, compared with the traditional water consumption minimization model, this approach significantly increases computational complexity. In this study, scheduling is optimized with the objective of maximizing incremental energy storage, and the corresponding objective function is expressed as follows:

$$ES = \max \sum_{i=1}^{n} \sum_{t=1}^{T} 9.81\left(Q_{inflow,i,t} - Q_{flood,i,t} - Q\left(N_{i,t}, H_{i,t}\right)\right) \sum_{j=i}^{n} H_{j,i} \Delta t \tag{4}$$

where, ES is the energy storage increment of the cascade hydropower plant during the dispatching period; $Q_{inflow,i,t}$ refers to the average inflow of hydropower plant i during period t. $Q_{flood,i,t}$ indicates the average flood discharge flow from hydropower plant i during period t. $Q(*)$ is the power generation flow consumption function, which describes the functional relationship between power generation flow consumption, hydraulic head, and unit output. $N_{i,t}$ stands for the output of hydropower plant i during period t. $H_{i,t}$ is the average hydraulic head of hydropower plant i during period t.

The constraints include:

(1) Water balance constraint

$$V_{i,t+1} = V_{i,t} + \left(Q_{inflow,i,t} - Q_{outflow,i,t}\right) \Delta t \tag{5}$$

where, $V_{i,t}$ is the water storage capacity of the reservoir at hydropower plant i during period t. $Q_{outflow,i,t}$ is the average outflow of hydropower plant i during period t.

(2) Power balance constraint

$$E_{order,t} = \sum_{i=1}^{N} N_{i,t} \Delta t \tag{6}$$

where, $E_{order,t}$ is the instruction for the total power generation of the cascade hydropower plants issued by the power dispatching authority during the initial period. $N_{i,t}$ is the output of hydropower plant i during period t.

(3) Output constraint

$$N_{i,t}^{\min} \le N_{i,t} \le N_{i,t}^{\max} \tag{7}$$

where, $N_{i,t}^{\min}$ and $N_{i,t}^{\max}$ represent the upper and lower bounds of hydropower plant i during period t, respectively.

(4) Power generation flow constraint

$$Q_{i,t}^{e,\min} \le Q_{i,t}^{e} \le Q_{i,t}^{e,\max} \tag{8}$$

where, $Q_{i,t}^{e}$ is the average power generation flow of hydropower plant i during period t. $Q_{i,t}^{e,\max}$ and $Q_{i,t}^{e,\min}$ represent the upper and lower bounds of the power generation flow of hydropower plant i during period t, respectively.

(5) Reservoir outflow constraint

$$Q_{outflow,i,t}^{\min} \le Q_{outflow,i,t} \le Q_{outflow,i,t}^{\max} \tag{9}$$

where, $Q_{outflow,i,t}$ is the average outflow of hydropower plant i during period t. $Q_{outflow,i,t}^{\max}$ and $Q_{outflow,i,t}^{\min}$ represent the upper and lower bounds of the outflow of hydropower plant i during period t, respectively.

(6) Water level constraint

$$Z_{i,t}^{\min} \le Z_{i,t} \le Z_{i,t}^{\max} \tag{10}$$

where, $Z_{i,t}$ is the water level of hydropower plant i during period t. $Z_{i,t}^{\max}$ and $Z_{i,t}^{\min}$ represent the upper and lower bounds of the water level of hydropower plant i during period t, respectively.

3 Optimization model for LDCHP based on the A* Algorithm

3.1 Principle of the A* algorithm

The A* algorithm is a heuristic search technique widely applied to path planning problems. Its core cost function F_m is formulated as follows:

$$F_m = G_m + H_m \tag{11}$$

where, G_m is the cost from the initial node to the current node; H_m is the estimated cost from the current node to the target node; m is the node number. In path planning problems, the movement cost is generally proportional to the travel distance (Wang et al., 2024). Accordingly, G_m is calculated from the actual travel distance, whereas H_m is estimated using the expected

travel distance.

An illustrative example of a path planning problem in two-dimensional space is shown in Figure 1. In practical applications, such problems are typically abstracted into a graph structure, where the reachable positions during the search process are represented as nodes. For simplicity, movement is assumed to be restricted to four directions: up, down, left, and right. As noted earlier, if the movement cost is defined as the travel distance, then in this example, the actual path cost from the initial node to the current node is denoted as G_m, while the estimated cost from the current node to the target node is denoted as H_m. The sum of these two values defines the cost function F_m for the current node. Adjacent nodes are all nodes that can be reached from the current node in the next search step. The set of adjacent nodes is determined by the permitted movement directions and the presence of obstacles. Once the current node is identified, its adjacent nodes are generated accordingly. In this example, since only four directions are permitted—up, down, left, and right—the adjacent nodes of the current node correspond to these directions. The adjacent node with the lowest cost function value is selected as the next search target and becomes the current node in the subsequent step. At the same time, this node is marked as visited, and the remaining unvisited adjacent nodes are designated as recorded nodes.

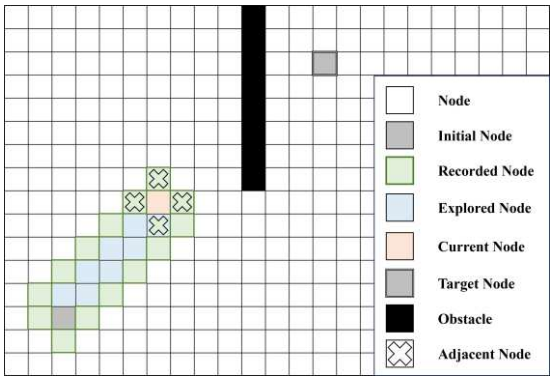


Fig. 1. Schematic of the path planning problem in a two-dimensional space

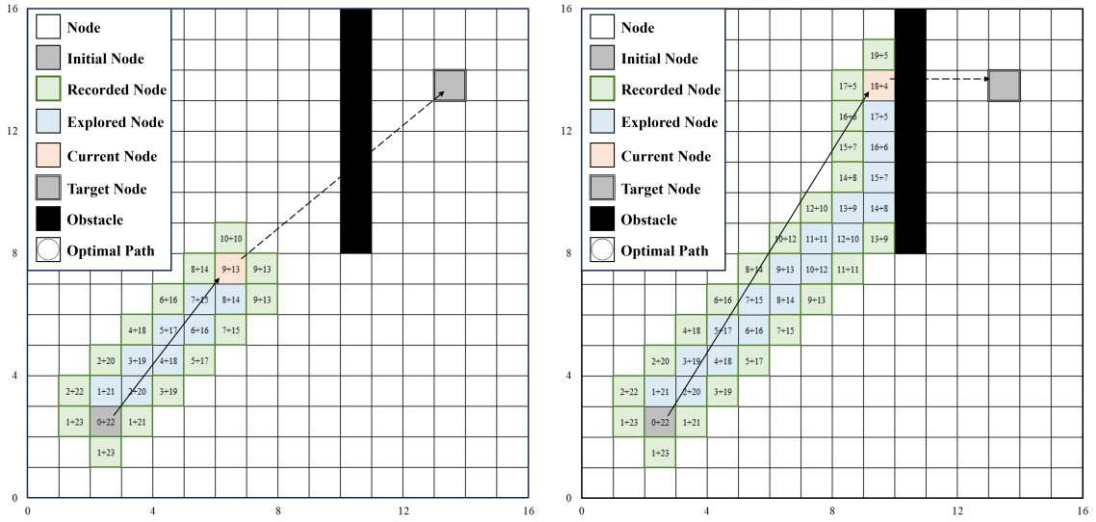
The search process for solving path planning problems using the A* algorithm is illustrated in Figure 2. In a two-dimensional grid map, distances between nodes are generally calculated using one of three methods: Manhattan distance, diagonal distance, and Euclidean distance. This study adopts the Manhattan distance, which is appropriately suitable when movement is restricted to the four cardinal directions—up, down, left, and right—consistent with the current assumption. The Manhattan distance is defined as the sum of the absolute differences between the coordinates of two

nodes along each axis. Accordingly, the distance between two points, (x_1, y_1) and (x_2, y_2), in a two-dimensional space can be expressed as follows:

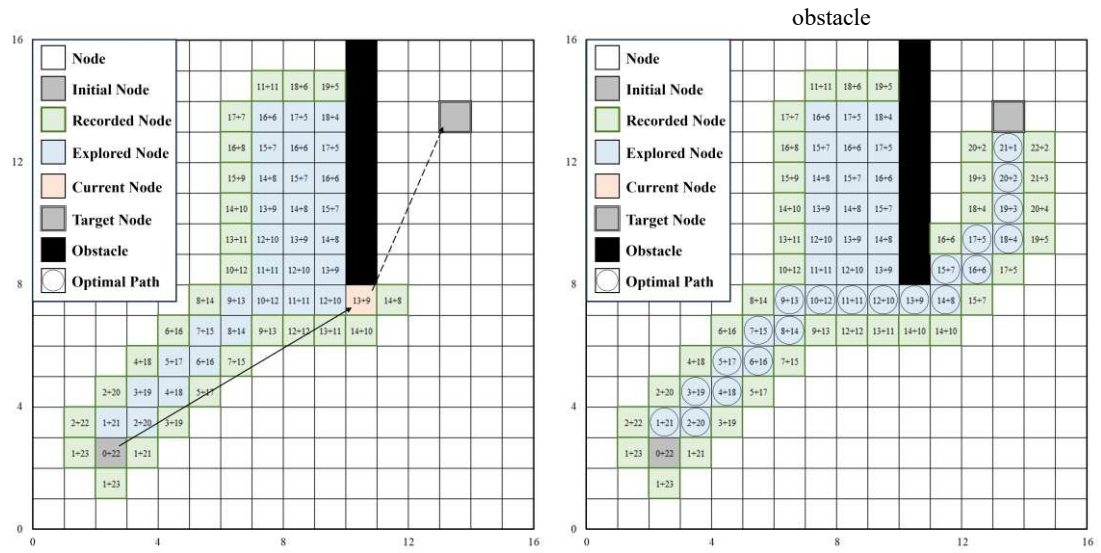
$$D = |x_1 - x_2| + |y_1 - y_2| \tag{12}$$

where, D is the Manhattan distance between points (x_1, y_1) and (x_2, y_2).

In the initial phase, the algorithm starts at the initial node and selects, from all recorded nodes, the one with the lowest cost function value as the current node for the next step. This process progressively guides the search toward the target node under the influence of the cost function, as illustrated in Figure 2(a). In the figure, the total movement cost at each node is represented as the sum of two components. The first is the actual movement cost, defined as the cumulative cost required to reach the node from the initial node along the actual path. The second is the estimated movement cost, which refers to the cost from the current node to the target node. Because obstacles cannot be fully accounted for when estimating the movement cost, the algorithm may temporarily deviate from the optimal path upon encountering obstacles, as shown in Figure 2(b). Nevertheless, guided by the cost function, the algorithm continues to select the recorded node with the lowest cost value as the current node and updates its parent node accordingly. As the search advances and the explored area expands, the optimal path through the obstacle can eventually be identified, as shown in Figure 2(c). Once the obstacle is successfully bypassed, the algorithm resumes selecting the node with the lowest cost function value among the recorded nodes as the current node for the next iteration. This process continues until the target node is reached, after which the optimal path is reconstructed through backward traversal, as illustrated in Figure 2(d).



(a) Initial phase of the search process (b) Deviation from the optimal path after encountering an



(c) Return to the optimal path after expanding the search range

(d) Completion of the optimal path search

Fig. 2. Example of solving a path planning problem using the A* algorithm

During the execution of the A* algorithm, it is necessary to record the cost function values of each explored node, along with their corresponding predecessor nodes (hereafter referred to as parent nodes). To accomplish this, two data structures—*OpenList* and *CloseList*—are needed. The *OpenList* stores nodes that have been recorded but not yet explored, together with their cost function values, whereas the *CloseList* stores nodes that have already been explored, along with their associated cost function values.

3.2 Application of the A* Algorithm in LDCHP

When applying the A* algorithm to the LDCHP problem, the cost function can be expressed in terms of scheduling benefits. Figure 3 illustrates an example of a single-plant scheduling process. The scheduling benefit accumulated from the initial state to the current state corresponds to the actual cost of reaching that state, while the estimated scheduling benefit from the current state to the target state represents the heuristic estimate of the remaining cost. The sum of these two components constitutes the cost function value for the current state. An adjacent state refers to a state that can be reached in the subsequent time period, subject to specific dispatching constraints. For clarity, the figure presents only a subset of possible adjacent states as examples. Unlike path planning problems, where obstacles are physical entities, the “obstacles” in scheduling problems are constraints such as water level and flow rate. These constraints vary by time and state; therefore, their influences on water levels are not explicitly shown in the figure. Furthermore, when solving reservoir dispatching

problems using the A* algorithm, it is necessary to record the cost function values stored in the *OpenList* and *CloseList*, as well as the predecessor state of each state from the previous time period.

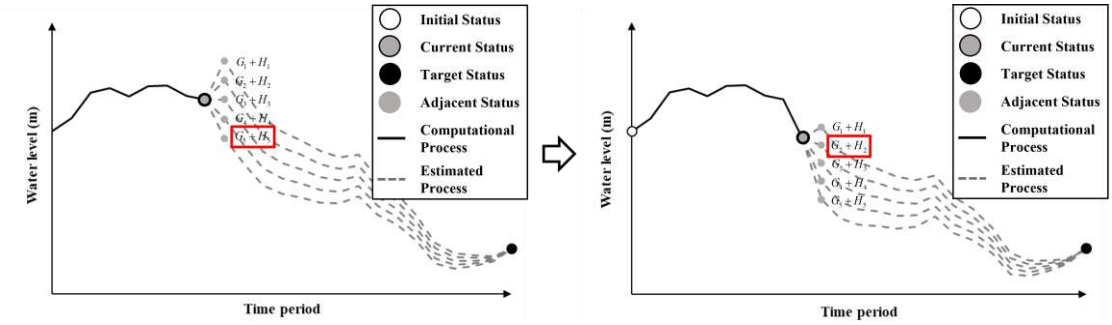


Fig. 3. Example of a hydropower plant dispatching problem

This study addresses the LDCHP problem, proposes methods for calculating both actual and estimated costs, and improves the algorithmic process accordingly.

(1) Current cost calculation

In path search problems within an N-dimensional space, the position of each node can be represented by a set of spatial coordinates. In reservoir dispatching, the state of a cascade hydropower system at a given time (hereinafter referred to as a "node") comprises both temporal information and the operating conditions of each hydropower plant:

$$P_m(t) = (t, S_1, S_2, S_3, \mathrm{L}\ , S_n) \tag{13}$$

where, $P_m(t)$ is the coordinates of the m node at time t; S_n is the operational state of the n hydropower plant, including parameters such as water level, load, inflow, and outflow.

This paper aims to maximize the incremental energy storage in a stepwise manner. Accordingly, the actual cost can be represented as the negative value of the stepwise energy storage increment. When the search process reaches period t_0, the corresponding actual cost can be expressed as:

$$G_m^{'} = -\sum_{i=1}^{n}\sum_{t=1}^{t_0} 9.81(Q_{inflow,i,t} - Q_{flood,i,t} - Q(N_{i,t}, H_{i,t}))\sum_{j=i}^{n} H_{j,t}\Delta t \tag{14}$$

(2) Estimated cost calculation

In path planning problems solved by the A* algorithm, the estimated cost from the current node to the target node is a critical component of the heuristic search, as it determines the search direction (Wang et al., 2024). When the heuristic function $H_m = 0$, the cost function reduces to $F_m = G_m$, transforming the A* algorithm into Dijkstra's algorithm. Conversely, when H_m is significantly

larger than G_m, the influence of G_m diminishes, and the algorithm approximates a breadth-first search.

The relationship between the heuristic estimate H_m and the actual cost from the current node to the target directly affects both the accuracy and efficiency of the algorithm. If H_m overestimates the actual cost, the search process accelerates but cannot guarantee an optimal solution. If H_m equals the actual cost, the algorithm achieves optimal performance by identifying the shortest path without exploring unnecessary nodes—an ideal but rarely achievable condition. If H_m underestimates the actual cost, the algorithm will still identify the optimal path; however, greater underestimation requires exploration of more nodes, thereby reducing computational efficiency.

To address the complexity of solving the LDCHP model, algorithmic efficiency must be prioritized. Therefore, the estimated cost should be greater than or equal to the actual optimal cost. Moreover, since this estimate is repeatedly calculated during the search process, it must be computationally efficient. As noted earlier, the estimated cost for each state guides the search direction of the A* algorithm. Consequently, the computation of estimated costs should incorporate the influence of the current state on future scheduling decisions.

The method for calculating the precise energy storage increment in cascade hydropower plants is presented in Equation (15):

$$ES = \sum_{i=1}^{n}\sum_{t=t_0}^{T} 9.81(Q_{inflow,i,t} - Q_{flood,i,t} - Q(N_{i,t}, H_{i,t}))\sum_{j=i}^{n} H_{j,t}\Delta t \tag{15}$$

However, this calculation method requires determining the water levels as well as the inflow and outflow of each power plant across multiple time periods. This substantially increases the computational complexity of the estimation process and fails to meet the requirement of simplifying the overall calculation. Therefore, a more streamlined approach is required.

To address this issue, this study adopts an aggregated hydropower plant model, in which multiple hydropower plants are consolidated into a single equivalent hydropower plant. Figure 4 shows a schematic of aggregated cascade hydropower plants.

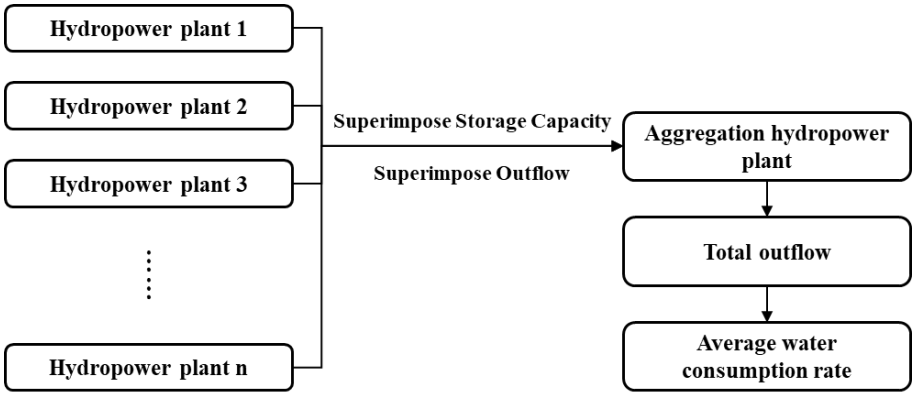


Fig. 4. Schematic of aggregated cascade hydropower plants

In this aggregated model, the total reservoir capacity and total inflow are obtained by summing the respective capacities and inflows of all individual plants, as expressed below:

$$V_t^{agg} = \sum_{i=1}^{n} V_{i,t} \tag{16}$$

$$Q_{inflow,t}^{agg} = \sum_{i=1}^{n} Q_{inflow,i,t} \tag{17}$$

$$Q_{flood,t}^{agg} = \sum_{i=1}^{n} Q_{flood,i,t} \tag{18}$$

where, V_t^{agg} is the water storage capacity of the aggregation reservoir during period t. $Q_{inflow,t}^{agg}$ is the average inflow to the aggregation reservoir during period t. $Q_{flood,t}^{agg}$ is the average flood flow to the aggregation reservoir during period t.

Accordingly, the outflow from the aggregated reservoir in the initial period can be calculated based on the initial storage capacity, final storage capacity, and inflow volume:

$$Q_{outflow,t}^{agg} = Q_{inflow,t}^{agg} + \frac{\left(V_{i-1}^{agg} - V_i^{agg}\right)}{\Delta t} \tag{19}$$

where, $Q_{outflow,t}^{agg}$ is the average inflow rate of the aggregation reservoir during period t.

In general, the storage capacity of a daily-regulating hydropower plant is relatively small. To meet daily power generation requirements, its water level often experiences substantial fluctuations, leading to significant variations in its operational state. However, when multiple daily-regulating or even annual-regulating hydropower plants are aggregated into a single equivalent plant, their combined regulation capacity increases due to the larger total storage volume. Consequently, the overall energy storage of the aggregated system remains relatively stable, with only minor fluctuations. In addition, the outflow from upstream hydropower plants becomes the inflow for

downstream plants, ensuring that the total discharge of the aggregated hydropower system remains stable and is not significantly affected due to the operational strategies of individual plants. For the estimation of future values, the cascade hydropower plants within a river basin are treated as a single aggregated plant, and the water consumption rate for power generation is determined accordingly. The formula for calculating the water consumption rate is as follows:

$$\lambda_t = \frac{\left(Q_{outflow,t}^{agg} - Q_{flood,t}^{agg}\right)}{E_{order,t}} \Delta t \tag{20}$$

where, λ_t is the average water consumption rate for power generation of the aggregated hydropower plant during period t.

Since the operational state of the aggregated hydropower plant remains relatively stable throughout the day, the future increase in energy storage of the cascade system can be estimated based on the current water consumption rate. Accordingly, the energy storage increase in the subsequent time period t is calculated as follows:

$$ES = \sum_{t=t_0}^{T} 9.81(Q_{inflow,t} - Q_{flood,t} - \frac{\lambda_{t_0} E_{order,t}}{\Delta t})\Delta t \tag{21}$$

where, $Q_{inflow,t}$ is the average inflow of the aggregation hydropower plant during period t. It is calculated by summing the natural water inflow from the leading hydropower plant and the interval inflow. $Q_{flood,t}$ is the average flood discharge flow of the aggregation hydropower plant during period t.

Compared with Equation (15), the calculated energy storage increase of the aggregated reservoir is lower than the actual value because the head effect of the water body is not considered. As previously noted, the cost value is expressed as the negative of the energy storage increase. Consequently, the estimated cost value tends to exceed the actual optimal cost. Moreover, when cascade hydropower plants are treated as an integrated system under fixed inflow and load conditions, the water consumption for power generation can be directly calculated, and the corresponding energy storage increase can then be derived. This approach enables rapid estimation of the generation value and avoids the loss of computational efficiency caused by repeated function calls during the search process. In addition, the current operating conditions of individual hydropower plants influence the overall water consumption rate of the cascade system, thereby

reflecting the effect of the current state on future scheduling decisions. Therefore, the estimated cost is expressed as follows:

$$H_m^{'} = -\sum_{t=t_0}^{T} 9.81(Q_{inflow,t} - Q_{flood,t} - \frac{\lambda_{t_0} E_{order,t}}{\Delta t})\Delta t \tag{22}$$

(3) Adjacent nodes expansion

The expansion of adjacent nodes is a core step in the A* algorithm, significantly affecting both search efficiency and solution quality. In reservoir dispatching problems, if state $P_m(t_1)$ is defined as an adjacent node of $P_m(t_2)$, it must satisfy not only the constraints of hydropower plant state transitions but also the temporal condition $t_1 = t_2 + 1$. During this process, the algorithm relies on two primary data structures: *OpenList* and *CloseList*. The *OpenList* stores nodes that have been recorded but not yet explored, together with their corresponding cost function values, while the *CloseList* contains nodes that have already been fully explored, along with their associated cost values. Figure 5 is the flowchart for extending adjacent nodes.

The procedure for expanding adjacent nodes is as follows:

Step 1: Construct $Nei(t)$ by collecting the adjacent states of the current cascade hydropower plant state P that are not included in the *CloseList*.

Step 2: Select any cascade hydropower plant state $P_m(t)$ from $Nei(t)$ and calculate its current cost, denoted as G_m.

Step 3: Determine whether $P_m(t)$ is in the *OpenList*. If $P_m(t)$ already exists in the *OpenList* and its newly calculated cost G_m is less than the previously stored cost $G_m(Open)$, update the scheduling information from the initial state to $P_m(t)$. Specifically, set the previous state of $P_m(t)$ to P, and update its cost function value. If G_m is greater than $G_m(Open)$, retain the existing scheduling information in the *OpenList*. If $P_m(t)$ is not in the *OpenList*, add it after computing G_m, and assign P as its previous state.

Step 4: Remove $P_m(t)$ from $Nei(t)$ and check whether $Nei(t)$ is empty. If it is, the expansion process ends; otherwise, return to **Step 3**.

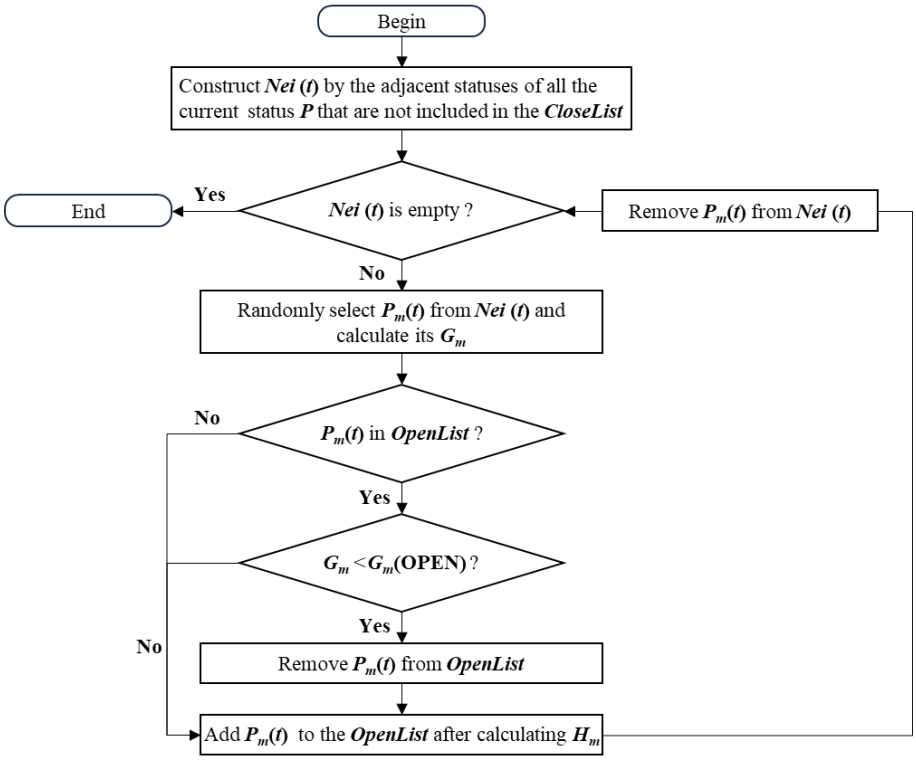


Fig. 5. Flowchart for expanding adjacent nodes

(4) Algorithmic process

In conventional path planning problems, the objective is typically defined by a specific spatial coordinate. However, in reservoir dispatching for cascade hydropower plants, the goal must incorporate both temporal factors and adaptability to varying operational requirements. In the LDCHP, two conditions are used to determine whether a plant group has reached the target state: (1) the current time coincides with the target time, and (2) the total power output of all plants in each period matches the target generation. This study applies the A* algorithm to the LDCHP problem. Figure 6 is the flowchart of A* algorithm used to solve the LDCHP problem.

The solution procedure is as follows:

Step 1: Define the initial cascade hydropower plant state and the target state B, then create and initialize the *OpenList* and *CloseList*.

Step 2: Add the initial state B to the *OpenList*.

Step 3: Check whether the *OpenList* is empty. If it is, the algorithm fails to find a solution. Otherwise, select the state with the lowest cost function value from the *OpenList*, designate it as the current state P, and add it to the *CloseList*.

Step 4: Determine whether the current state P corresponds to the target state E.

Step 5: If the current state corresponds to E, the path planning is successful. The algorithm then performs a backward traversal to generate the final path and outputs the result.

Step 6: If the current state does not match the target state E, the algorithm expands the adjacent cascade hydropower plant states. For detailed procedures, refer to **Section 3.2(3)**, and then the algorithm returns to **Step 3** for further execution.

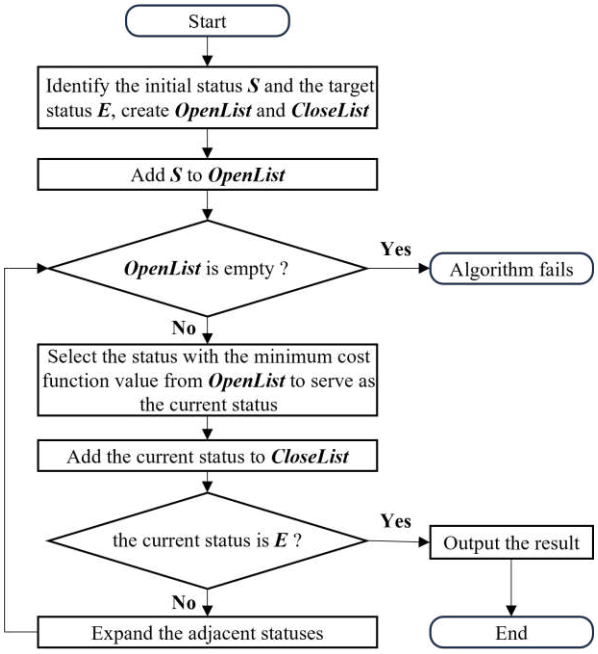


Fig. 6. Flowchart of A* algorithm used to solve the LDCHP problem.

4 Case Study

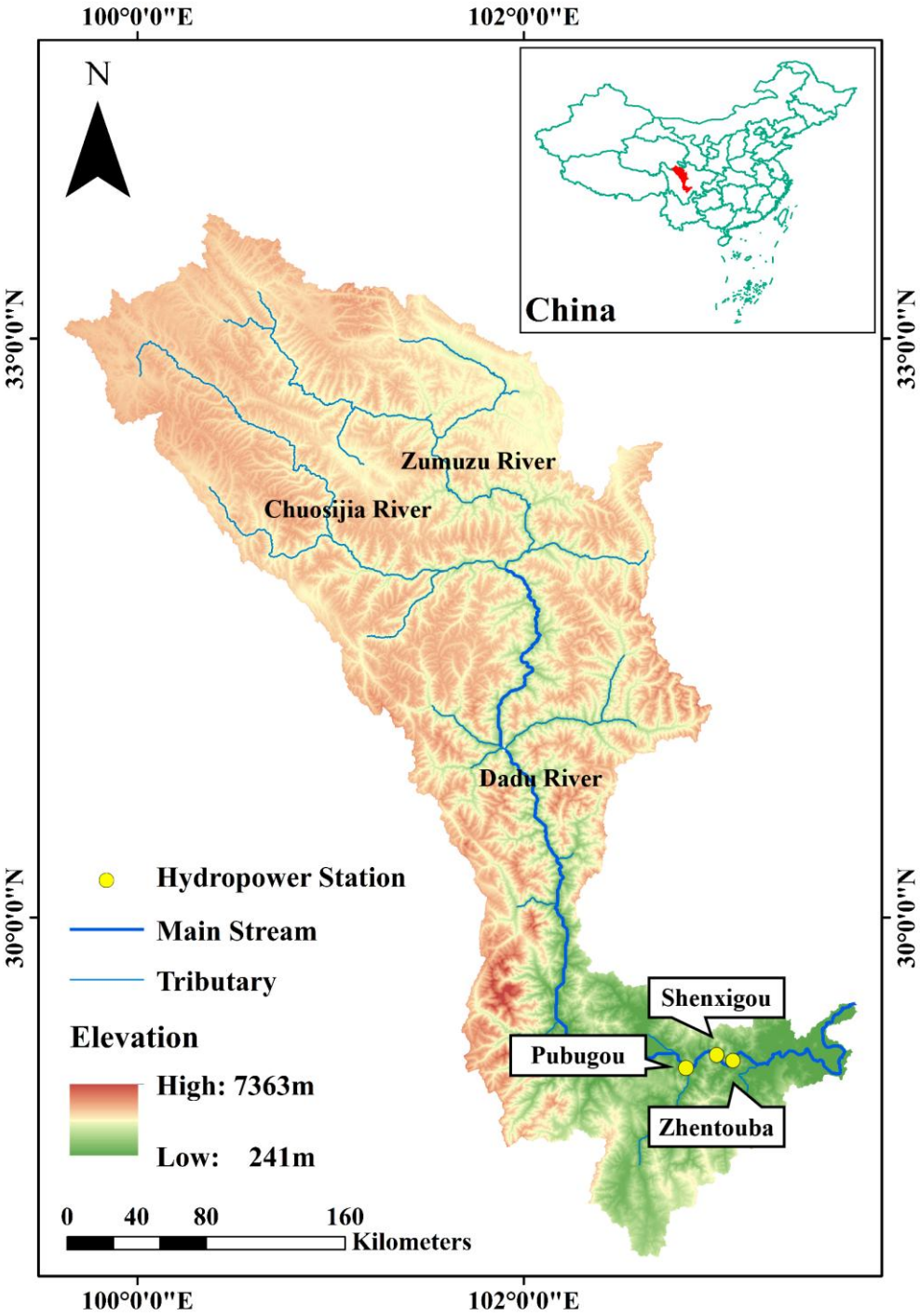
4.1 Study area and data

This study selects the Dadu River Basin in China as a case study, which constitutes the country's fifth-largest hydropower base. The spatial distribution of the river system is shown in Figure 7. Specifically, three hydropower plants in the middle reaches of the basin — Pubugou (PBG), Shenxigou (SXG), and Zhentouba (ZTB)—are chosen as the primary research subjects. Among them, PBG possesses an incomplete annual regulation capacity, whereas SXG and ZTB function as daily regulation plants. The main characteristics of each plant are summarized in Table 1.

These three plants share a common transmission line, and dispatch instructions from the power grid generally specify the total load for all of them combined. Therefore, the objective conditions

required for LDCHP are satisfied. Compared with PBG, SXG, and ZTB have smaller storage capacities and weaker regulation performance. Consequently, the dispatching mode of PBG strongly influences the downstream plants, leading to deteriorated unit operating conditions, reduced water-use efficiency, and increased complexity in joint optimization of cascade operations. Moreover, their close proximity causes short flow propagation times, which may lead to water spillage at downstream plants or sudden fluctuations in reservoir levels, thereby reducing the time available for dispatching decisions.

Meanwhile, with the large-scale integration of renewable energy sources such as wind and solar, the demand for flexible regulation in the power system has increased significantly (Zhang et al., 2021). Hydropower is increasingly required to serve as a regulating source to maintain grid stability, thereby imposing high-intensity peak-shaving and frequency-regulation tasks on the river basin. For instance, the cascade plants in the middle reaches of the Dadu River Basin may receive more than 9,000 load-regulation instructions within a week, placing even higher demands on the timeliness and efficiency of dispatching decisions.



458

459 **Fig. 7.** Distribution of hydropower plants in the middle reaches of the Dadu River Basin

460 **Table 1.** Basic characteristics of the hydropower plants

Plant	Regulation capacity	Installed capacity (MW)	Regulation storage capacity ($10^8 m^3$)	Z_{max} (m)	Z_{min} (m)
PBG	yearly	3600	38.26	850	790
SXG	daily	660	0.085	660	655
ZTB	daily	720	0.123	624	618

461 ## 4.2 Results and discussion

462 ### 4.2.1 Design of comparative test

DP algorithm is widely applied in optimization and decision-making problems in fields such as automatic control and engineering management. It is particularly effective for multi-stage decision-making processes, as it can derive globally optimal solutions, making it a crucial method for solving dispatch models in cascade hydropower plants. However, when applied to complex models, DP faces the intrinsic challenge of the "curse of dimensionality", which leads to excessive computational demands and significantly reduces efficiency. To evaluate the performance of the A* algorithm in solving LDCHP problems, a comparative analysis was conducted between the A* and DP algorithms. Actual inflow and power generation data from cascade hydropower plants in the middle reaches of the Dadu River Basin, covering January 1-14, 2019, were used. The load distribution model was solved separately using DP and the A* algorithm, with the scheduling horizon set to one day and divided into 96 intervals of 15 minutes each.

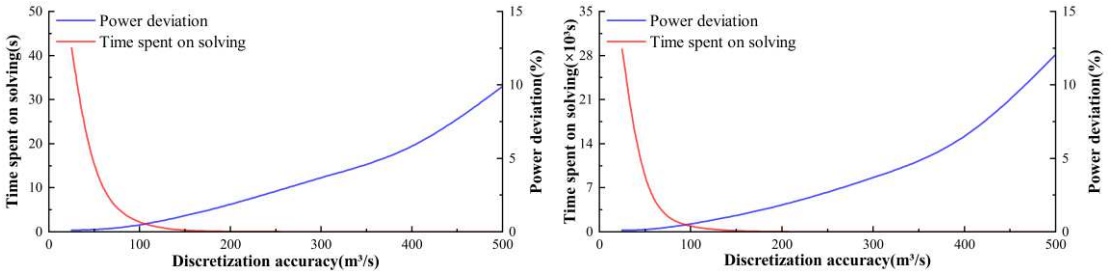
In addition, to assess the practical benefits of the A* algorithm in engineering applications, another comparative analysis was performed against the actual dispatch process of cascade hydropower plants in the same basin. Specifically, dispatch data on January 1, 2019, were selected. The A* algorithm was applied to solve the model, and the results were compared with the actual dispatch records. The scheduling period was again set to one day, divided into 96 intervals of 15 minutes. In real-world dispatch, recorded data such as water levels and flow rates may contain inaccuracies, and the characteristic curves used in the model may also involve errors. To address these issues, this study employed measured water level and inflow data, together with relevant characteristic curves, to calculate the power generation of each plant in each time interval. The calculated results were then compared with those obtained from the model to minimize the influence of measurement errors and curve deviations on simulation accuracy.

4.2.2 Results Analysis

(1) Comparison of the results between the DP and the A* algorithms

During the solution process, the choice of discretization accuracy directly influences both the computational efficiency of the model and the accuracy of the results. To ensure that the deviation between the total power generation of the cascade hydropower plants and the target power generation in each period remains within an acceptable range, a sufficiently high level of discretization accuracy must be maintained. However, excessively increasing the accuracy greatly

increases computational demands and reduces solution efficiency. Figure 8 illustrates the computational time required by the DP and A* algorithms under different levels of discretization accuracy, along with the deviations of their results from the target values.



(a) A* algorithm (b) DP algorithm

Fig. 8. Result deviations and computation time of DP and A* algorithms under different discrete accuracy

As shown in Figure 8, the deviation of the model results decreases with increasing discretization accuracy. When the discretization accuracy exceeds 50 m³/s, the deviations for both the DP and A* algorithms fall below 0.2%. However, further improvements in discretization accuracy do not significantly reduce deviations, while computational time increases correspondingly. When the discretization accuracy falls below 100 m³/s, the growth rate of computational time rises sharply. To balance accuracy and efficiency, a discretization accuracy of 50 m³/s was selected. Actual water inflow and power generation data from cascade hydropower plants in the middle reaches of the Dadu River Basin, collected between January 1 and 14, 2019, were used as model inputs. The model was then solved separately using the DP and A* algorithms.

The results are presented in Table 2. When addressing load distribution problems among plants, the A* algorithm demonstrates substantially higher computational efficiency than the DP algorithm, while both yield relatively similar scheduling benefits. Regarding computational performance, the DP algorithm required an average of 10,607.76 s over the 14-day period, with a maximum of 22,130.45 s and a minimum of 5,522.09 s. By contrast, the A* algorithm achieved an average computing time of only 1.97 s, with a maximum of 2.88 s and a minimum of 1.52 s. Solution efficiency varied considerably across dispatching processes, owing to differences in feasible domains under power deviation constraints, which in turn depend on inflow conditions and power generation targets. Consequently, the search ranges differed widely across processes, resulting in variations in efficiency. On average, the computational efficiency of the A* algorithm was approximately 5372.9 times higher than that of the DP algorithm.

With respect to solution benefits over the 14-day period, the DP algorithm produced a maximum power deviation of 0.189%, a minimum of 0.150%, and an average of 0.174%, with an average energy storage change of -0.482×10⁸ kW·h. In comparison, the A* algorithm yielded a maximum power deviation of 0.158%, a minimum of 0.110%, and an average of 0.139%, with an average energy storage change of -0.490×10⁸ kW·h. The reduction in energy storage improved by 1.56% when using the A* algorithm compared with the DP algorithm. The case study is based on actual inflow and power generation data from the Dadu River Basin in January. During this dry-season period, inflows were relatively low, and reservoir water levels had to be drawn down to meet power demand, resulting in a negative energy storage change.

Table 2. Comparison of results from the DP and A* algorithms

Time	Computing time (s)		Power deviation (%)		Energy storage variation (10^8kW·h)	
	DP	A*	DP	A*	DP	A*
January 1st	11499.08	1.84	0.178	0.131	-0.458	-0.464
January 2nd	16741.87	1.98	0.180	0.110	-0.890	-0.894
January 3rd	22130.45	1.79	0.178	0.136	-0.253	-0.263
January 4th	12689.43	1.52	0.189	0.144	-0.470	-0.478
January 5th	9809.57	1.71	0.150	0.124	-0.517	-0.526
January 6th	15482.07	2.74	0.175	0.141	-0.645	-0.656
January 7th	11589.32	1.92	0.168	0.143	-0.442	-0.450
January 8th	10557.43	2.88	0.168	0.156	-0.583	-0.591
January 9th	5814.37	2.56	0.177	0.152	-0.430	-0.439
January 10th	6919.88	1.84	0.170	0.135	-0.086	-0.088
January 11th	7830.04	1.66	0.171	0.142	-1.019	-1.026
January 12th	6142.93	1.54	0.178	0.136	-0.228	-0.235
January 13th	5522.09	1.67	0.175	0.134	-0.402	-0.410
January 14th	5780.09	1.99	0.175	0.158	-0.326	-0.334

Figure 9 illustrates the water-level search ranges for each cascade hydropower plant in the middle reaches of the Dadu River Basin during the solution processes of the DP and A* algorithms on January 3, 5, and 9. Across the cascade hydropower plants, the search range of the A* algorithm is significantly narrower than that of the DP algorithm. Unlike DP, the A* algorithm employs a heuristic function to guide the search direction, thereby effectively reducing the search space and improving computational efficiency. In model solving, the heuristic function estimates the change in basin energy storage when the power generation task is completed at the end of the scheduling period under the current state of the cascade hydropower plants. This mechanism directs the algorithm to prioritize dispatching processes that are more likely to approach the optimal solution,

thereby minimizing unnecessary computations.

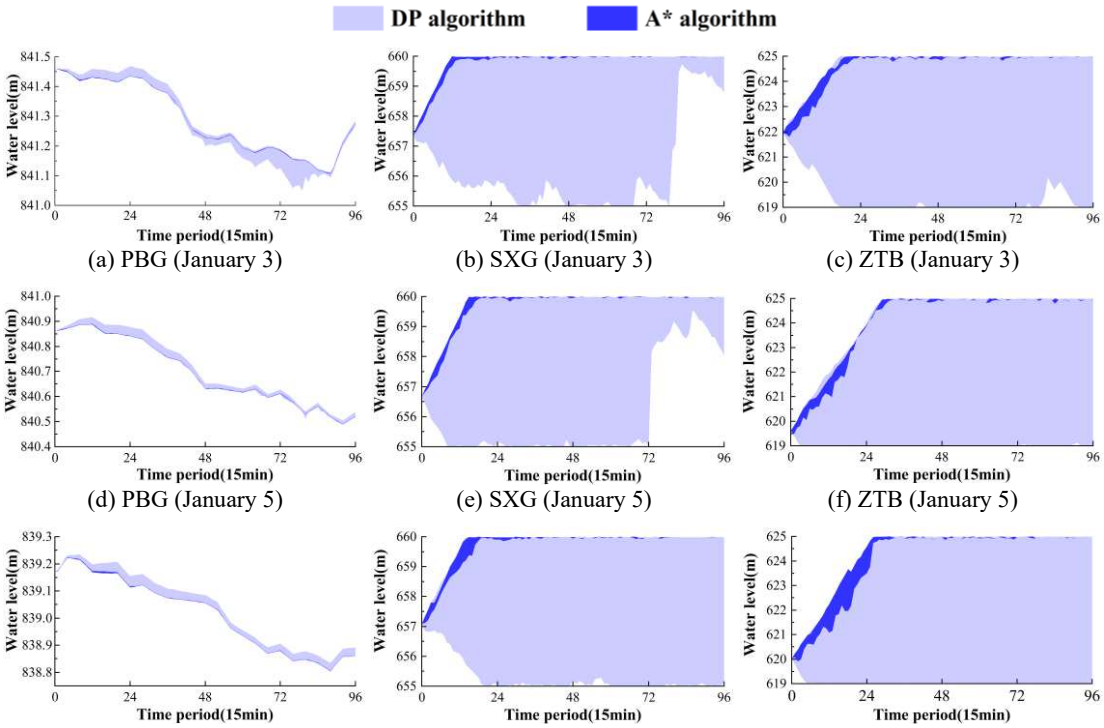


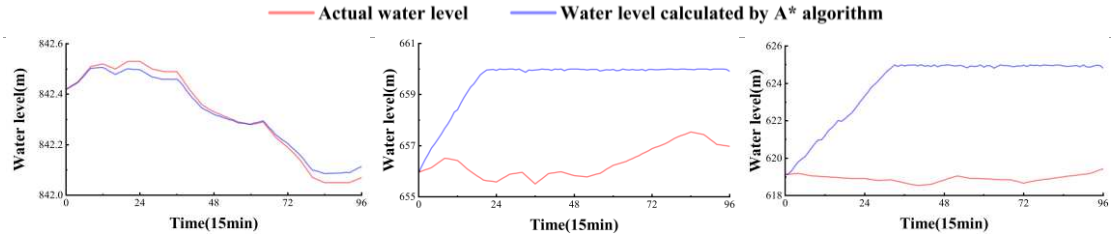
Fig. 9. Comparison of search ranges for different power plants and inflow process using the DP and A* algorithms

The case study shows that the DP algorithm's search scope is much larger than the A* algorithm, enabling it to obtain the global optimal solution. However, in practical dispatching operations, forecast inaccuracies necessitate rolling calculations based on real-time monitoring data. DP algorithm's average computational time during the solution process is 10,607.76 s (nearly 3 h), which far exceeds the required interval and fails to meet timeliness requirements, thereby limiting its applicability in actual production.

(2) Comparison of the results of the A* algorithm and the actual simulation process

The dispatching process used for simulation and optimization at each hydropower plant is shown in Figure 10. Under the condition of maintaining the same total power generation target across each dispatching period, the actual total energy storage reduction of the cascade hydropower plants was 0.568×10^8 kW·h, whereas the reduction calculated using the A* algorithm was 0.464×10^8 kW·h. This represents a 22.41% decrease compared with the actual dispatching process, indicating a significant improvement in water resource utilization efficiency for the cascade hydropower plants in the middle reaches of the Dadu River Basin. In current operations, load distribution for these cascade hydropower plants primarily relies on the Economic Dispatch Control (EDC) system, which

optimizes only for the current period without considering overall benefits across the entire dispatching horizon. Consequently, the result of A* algorithm has a much lower total energy storage reduction.



(a) PBG (b) SXG (c) ZTB

Fig. 10. Comparison of the actual scheduling process and the A* algorithm results

During the actual dispatching process, the hydropower generation flow at PBG was reduced before 3:00 p.m. to raise its reservoir level. To meet the generation requirements, the flows at SXG and ZTB were correspondingly increased, keeping their reservoir levels stable. After 3:00 p.m., however, the limited generation capacity of SXG and ZTB necessitated an increase in PBG's generation flow, which caused a subsequent decline in its water level. As a result, SXG and ZTB operated at low water levels throughout the dispatching period. Because PBG has a much larger reservoir capacity than the downstream plants, its water level increased only slightly during the early stage and then declined, leading to relatively low overall efficiency of water resource utilization. In contrast, the optimization results obtained using the A* algorithm suggested increasing generation flow at PBG before noon. This not only satisfied power generation requirements but also raised the reservoir levels at SXG and ZTB. Consequently, SXG and ZTB maintained higher water levels after 3:00 p.m., thereby improving the overall efficiency of water resource utilization in the cascade hydropower system.

5 Conclusions

This study proposes a method for LDCHP based on the A* algorithm. While ensuring operational reliability, the approach substantially improves computational efficiency, addressing the challenges of low solution efficiency and suboptimal dispatching performance in cascade hydropower plants under high-intensity peak shaving and frequency regulation. Using cascade hydropower stations in the middle reaches of the Dadu River Basin, China, as a case study, the effectiveness of the A* algorithm in solving LDCHP was evaluated, yielding the following

conclusions:

(1) The A* algorithm significantly reduces the computation time required for model solutions, thereby satisfying the timeliness requirements of scheduling decisions. In the case of LDCHP in the middle reaches of the Dadu River Basin, the A* algorithm achieved an average solution time of 1.97 s. Under the same discretization accuracy, its computational efficiency was, on average, 5,372.9 times higher than that of the DP algorithm.

(2) The A* algorithm improves the economic efficiency of dispatching and operation in cascade hydropower plants. When applied to LDCHP, it produced only a 1.56% difference in energy storage reduction compared with the DP algorithm under the same discretization accuracy. Furthermore, compared with actual dispatching practices, the energy storage reduction calculated using the A* algorithm decreased by 22.41%, significantly enhancing the overall efficiency of water resource utilization across the cascade system.

(3) The proposed A*-based method for LDCHP effectively addresses the complexity of load distribution models. Using an engineering example from the cascade hydropower plants in the middle reaches of the Dadu River Basin, the results demonstrated that this method markedly improved computational efficiency and generated dispatching outcomes that were considerably superior to those of the actual process.

Although the method effectively addresses LDCHP, this study focuses primarily on this specific dispatching scenario. Future research should further refine the calculation of cost functions under varying dispatching scenarios, which is essential for extending the A* algorithm to joint optimal dispatching of cascade hydropower plants.

Author contributions Data curation: Yuxi Lv; Methodology: Yuxi Lv and Jingjie Ma; Software: Yuxi Lv; Supervision: Jingjie Ma and Qiaofeng Tan; Validation: Yuxi Lv and Xin Wen; Visualization: Yuxi Lv and Wanjiao Luo; Writing-original draft: Yuxi Lv; Writing-review and editing: Yuxi Lv, Qiaofeng Tan and Xin Wen.

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Data Availability The data that has been used is confidential.

Declarations

Ethical Approval The manuscript has not been submitted to any other journal. The proposed work is original and has not been published anywhere else.

Consent to Publish All authors have consented to publish this manuscript.

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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