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Utilizing the Sobol′ Sensitivity Analysis Method to Address the Multi-Objective Operation Model of Reservoirs

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Abstract: The operation of reservoirs has significantly influenced the river ecological system. Upholding the ecological integrity of rivers during reservoir operations has been the focus of research over the years. When the Dahuofang reservoir project started, focus moved to ecological goals to address the Biliuhe reservoir's environmental issues. The water strategy limits usage for various purposes and outlines the diversion route, complicating Biliuhe operations. In this study, to comprehend the effects of individual water level guidelines and their combined influence on these goals, the Sobol′ sensitivity analysis was introduced as an initial measure to tackle the optimization challenge. The results show that removing the insensitive water levels during specific periods of reservoir scheduling lines and beginning with sensitive water levels for local optimization to identify viable solutions, and then moving to wider optimization, significantly enhances the search efficiency, solution quality, and operational speed compared with an exhaustive search without any preceding steps. This sensitivity analysis technique is crucial for fine-tuning multi-objective reservoir operations.

Keywords: sensitivity analysis; multi-objective operation; preceding step; Sobol′ method

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1. Introduction

Water is essential to life and underpins production [1]. As urbanization and industrialization expand, water scarcity becomes a pressing issue. This scarcity is magnified by the inconsistent spatial and temporal distribution of water resources, leading to significant imbalances between supply and demand in various regions [2]. Such water-related challenges pose a grave risk to the sustainable growth of regional economies. To mitigate the economic impact of water shortages, humans have implemented inter-basin water diversion projects [3]. While these projects have successfully addressed discrepancies in water distribution, providing numerous benefits [4], reservoir operations have historically prioritized maximizing economic gains [5]. However, this focus has inadvertently harmed river ecosystems [6,7]. It underscores the increasing importance of developing ecological scheduling methods for water diversion projects that ensure water supply for industrial, domestic, and agricultural needs and maintain our rivers' ecological health [8].

Numerous scholars have extensively studied how to uphold the ecological integrity of rivers during reservoir operations. For instance, the authors of [9] introduced a constraint to ensure a minimum environmental flow from reservoirs to protect downstream ecosystems. Meanwhile, Higgins et al. [10] designed a model focusing on restoring natural flow elements crucial for river ecosystems in the South Australian River Murray. Similarly, Mao et al. [11] prioritized environmental water demands in multi-reservoir systems, while Adams et al. [12] introduced an "environmental hedging" approach to balance environmental and human water needs. Additionally, Feng et al. [13] presented an optimization algorithm targeting the hydro-power reservoir's optimal dispatch for both power generation and ecological needs, a concept further explored by Niu et al. [14]. Li et al. [15] tackled challenges in sustainable water management for ecosystems and agriculture in China's Heihe River Basin. Dong et al. [16] developed a model that optimally reconciled power generation with ecological conservation along the lower stretches of the Jinsha River. Lastly, Bai et al. [3] proposed various ecological flow strategies and made recommendations for the Hanjiang to Weihe River transition, factoring in seasonal variations.

Managing the ecology of reservoirs is seen as a complex, nonlinear, multistage optimization challenge [17]. Over the years, numerous renowned optimization techniques have been introduced to tackle such challenges [18]. Some of these include linear programming [19], dynamic programming [20], network-based programming [21], the genetic algorithm (GA) [22], and particle swarm optimization (PSO) [23], among others. Despite their success across various domains, the broad adoption of these methods for intricate reservoir operations is hindered by issues like the "curse of dimensionality" [24], extensive computational demands [25], and the problem of premature convergence [26]. Current methods for modeling solutions lack efficiency in delivering top-notch ecological operation results. Thus, there is an ongoing and pressing need to devise more potent optimization techniques for sophisticated ecological scheduling models.

As the complexity of scheduling objects, periods, and constraints in the ecological scheduling for inter-basin diversion projects increases, the problem becomes more challenging to address [27]. While certain water levels during specific periods of reservoir scheduling may not significantly impact the overall optimization, their presence complicates achieving optimal solutions. Yet, starting with higher-quality initial solutions can enhance optimization search efficiency [28]. Sensitivity analysis (SA) serves as a tool to understand the effects of uncertain parameters on mathematical models, helping simplify them [29]. The Sobol' method, a prominent variance-based global sensitivity analysis technique [30], offers substantial benefits. Among its key advantages is its ability to furnish an intricate overview of the way individual variables, along with their interactions, influence the performance of a model [31,32]. Its exemplary effectiveness in pinpointing parameters has led to its widespread application in tasks such as model identification, calibration, and system optimization [33,34]. By applying this method, one can pinpoint sensitive water levels for various optimization aims. The next step is optimizing a simplified problem based on these sensitivity parameters to produce viable solutions. These are then used as starting points for global optimization, leading to better efficiency and more desirable final outcomes.

To improve the ecological health of the lower sections of the Biliuhe reservoir, previous studies have combined environmental goals with water diversion, industrial, domestic, and agricultural goals within our comprehensive dispatching model. This has caused the operation model for the Biliuhe reservoir to be more complex. When dealing with these intricate optimization problems, we encounter the significant hurdle known as the "curse of dimensionality", which affects the efficiency of solving the model. By employing the Sobol' sensitivity analysis approach to the sensitive water levels for localized optimization to obtain the feasible solutions, and then progressing to a broader optimization, the search efficiency, quality of solutions, and processing speed are markedly improved compared with a full search approach without any prior processing. This research aims to find effective solutions for our dispatching model.

2. Materials and Methods

2.1. Study Area

The Biliuhe reservoir, constructed in 1958, is located in the main stream of Biliuhe in Dalian, Liaoning Province, China. It is "the source of life" of Dalian City, undertaking about 70~80% of the water supply task of Dalian City. The climate type of Dalian City is temperate continental monsoon climate, and the annual precipitation is 550–1000 mm. The Biliuhe reservoir has a 934 million m^3 capacity and a drainage area of 2085 km^2. It is a large-scale hydro project with multiple purposes, including a primary objective of water supply, and a number of secondary objectives, such as flood control, hydro power generation, irrigation, and fish farming. Water supply mainly consists of I&D and agricultural users—the amount is 430 million and 40 million m^3 with a required reliability of 95% and 75%, respectively. The dead water level for the reservoir is 47 m and the normal water level is 69 m. After the water diversion project from the Dahuofang reservoir, the ecological objective will be considered to improve the ecological environment of the reservoir lower reaches, with an amount of 160 million m^3. Moreover, the water supply for I&D, agriculture, and ecosystem can be reduced to 90%, 70%, and 50%, respectively, of their normal requirements during droughts. The geographic location of the Biliuhe reservoir is shown in Figure 1.

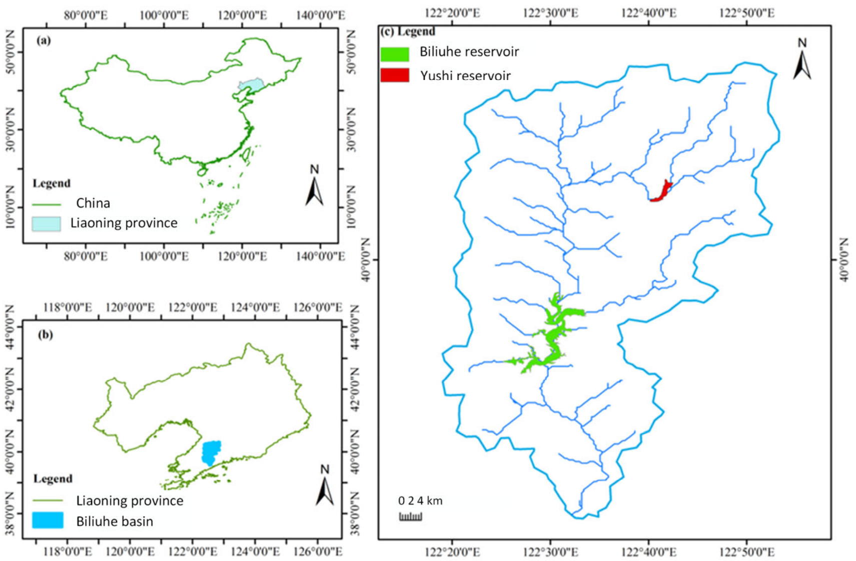

Figure 1. The geographic location of the Biliuhe reservoir. (**a**) Location of Liaoning Province in China, (**b**) Location of Biliuhe Reservoir in Liaoning Province, (**c**) Drainage map for Biliuhe basin.

The Dahuofang reservoir water diversion project uses the surplus capacity of the Dahuofang reservoir to supply water to Dalian. The designed water supply capacity of this project is 300 million m^3/year, the pipeline transmission scale is 900,000 t/d, and the water leakage loss is 4%. Considering the characteristics of the inflow and water consumption of the Biliuhe reservoir, the amount of water diverted from the Dahuofang reservoir should be at full capacity of the pipeline during the year but for four periods, including mid-July, late July, early August, and mid-August, during which the reservoir has adequate inflow. The annual inflow (1958–2021) for each 10 days of the Biliuhe reservoir is shown in Figure 2.

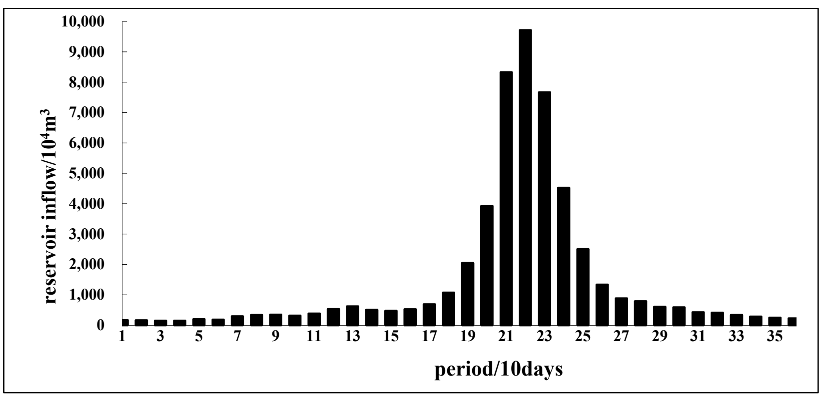

Figure 2. The annual inflow (1958–2021) for each 10 days for the Biliuhe reservoir.

2.2. Sobol′ Method

The Sobol′ method disintegrates the output variance into the sum of the fractional model input variances, i.e., variances of the respective parameters and their interactive effects. The first-order index is used to measure the main effect of each parameter, while the high-order index measures the contribution of multiple parameters, and the total-order index measures the main effect of each parameter and its interactions with all of the other parameters. When the studied parameters are a k-dimensional hypercube, the function $f(x)$ can be decomposed into the contribution of inputs and their interaction as follows:

$$f(x) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{1 \le i \le j \le k} f_{i,j}(x_i, x_j) + \ldots + f_{1,2,\ldots,k}(x_1, x_2, \ldots, x_k) \quad (1)$$

where f_0 is a constant; $f_{\mathrm{i}}(x_i)$ is first order function; $f_{\mathrm{i,j}}(x_i, x_j)$ is second order function (interaction between parameter x_i and x_j), and so on.

Equation (1) can also be written in terms of the partial variances as follows:

$$D = \sum_{i=1}^{k} D_{x_i} + \sum_{1 \le i < j \le k} D_{x_i,x_j} + \ldots + D_{x_1,x_2,\ldots,x_k} \quad (2)$$

where D_{x_i} is the fraction of total variance D, contributed by the parameter x_i; D_{x_i,x_j} is the fraction contributed by interaction between parameter x_i and x_j. The Sobol' indices can be defined as the ratio of the partial variances to the total variance, as follows:

$$\begin{aligned} S_{x_i} &= \frac{D_{x_\mathrm{i}}}{D} \\ S_{x_i,x_j} &= \frac{D_{x_i,x_\mathrm{j}}}{D} \\ S_{x_i,x_j,\ldots,x_l} &= \frac{D_{x_i,x_j,\ldots,x_l}}{D} \qquad (1 \le i \le \ldots < l \le k) \end{aligned} \quad (3)$$

where S_{x_i} is the first-order sensitivity index, which accounts for the main contribution of each input parameter in the output variance, excluding any interaction terms; S_{x_i,x_j} is the second order sensitivity index. which is also called interaction between the input parameters; $S_{x_i,x_j,\ldots,x_l}$ is the l-order sensitivity index, which denotes the higher order of interactions up to k (total input parameters of the model).

The total sensitivity index is the mean output variance for keeping parameter x_i fixed. In other words, it implies the main effect of parameter x_i and its interactions with other parameters. The corresponding index is defined below:

$$ST(x_i) = 1 - S_{\sim x_i} = 1 - \frac{D_{\sim x_i}}{D} \quad (4)$$

where ~x_i means all input parameters except for the parameter x_i. $D_{\sim xi}$ is the variance contribution on account of all parameters, except for parameter x_i. The difference between $ST(x_i)$ and S_{x_i} is the impact of interactions with other parameters for parameter x_i.

It also should be noted that Sobol' indices are non-negative indices and all sensitivity indices add up to 1, and have the following property:

$$\sum_{i=1}^{k} S_{x_i} + \sum_{i=1}^{k} \sum_{\substack{j=1 \\ i \ne j}}^{k} S_{x_i,x_j} + \ldots + S_{x_1,x_2,\ldots,x_k} = 1 \quad (5)$$

In this paper, the Latin hypercube sampling (LHS) technique is used to compute the Sobol' sensitivity indices, which is different from the normal pure Monte Carlo method based on a pseudo-random sequence. The LHS method takes full advantage of the abundant computing resources to produce some representative samples that can cover the entire search space [35,36]. It can provide a better convergence in the input space and lead to a better predictive quality because its ability to uniformly sample the unit hypercube by minimizing sample discrepancy and maximizing the distance between sampling points [37]. In the LHS method, there is an obvious improvement in the calculation efficiency due to the reduced number of samples. The process to generate N points for the k-dimension problem is given below:

- Each dimension in the uncertainty space is split into N intervals with an equal length, and equally spaced levels corresponding to [0, $1/N$), [$1/N$, $2/N$), . . ., [1–$1/N$, 1] for each variable;
- A random point in the range is generated in any one interval of each variable. Then, they are combined into multivariate samples that preserve the space-filling property of the marginal distribution [38].
- All of the samples produced by *LHS* form a $N \times k$ matrix ($x_{i,j}$), where N represents the number of samples and k denotes the number of variables, and $x_{i,j}$ is the value of the jth variable in the ith sample.

2.3. Ecological Scheduling Method

The indicators of hydrologic alteration (IHA) [39] method has been widely used in river management because it can comprehensively describe the overall status of ecosystems. It contains 33 hydrologic parameters, which are categorized into five groups of hydrologic features, ranging from magnitude to frequency. For river aquatic ecosystems, the closer to its natural (or pre-dam) state, the healthier the ecosystem is [40]. To calculate the membership degree of each hydrological indicator to the natural state value and explore the method with the least river hydrological changes affected by reservoir operation, in this paper, a Gaussian shaped membership function is adopted and the ecological indicator is fuzzified as a fuzzy number. The equation is expressed as follows:

$$\mu(x_\mathrm{i}) = e^{\frac{(x_i - m_i)^2}{2{\sigma_i}^2}} \tag{6}$$

where $\mu(x_\mathrm{i})$ denotes the membership value of the ith ecological indicator; xi is the present (or post-dam) value of the ith ecological indicator; m_i and ${\sigma_i}^2$ denote the original mean value and variance of the ith indicator, respectively.

According to the formula above, we can see that the closer the discharge from reservoir is to the natural runoff, the better the aquatic ecosystem can be maintained. However, if the discharge exceeds the suitable ecological runoff, it will have a negative impact on the river ecosystem. For an environment system composed by n ecological indicators, the ecological objective function can be expressed as follows:

$$maxP_{eco} = max\sum_{i=1}^{n} \omega_i \times \mu_i \tag{7}$$

where P_{eco} denotes the overall value of the ecological objective and ω_i is the weighting coefficient of the ith ecological indicator.

Although the ecological flow plays a fundamental role in determining the ecological characteristics and functions of the river, the socioeconomic benefits still are the most important purposes for the construction of reservoirs [41]. In this paper, a restrained water supply strategy for the ecosystem was proposed to reduce water supply stress on industrial and domestic (I&D) and agricultural water users caused by the consideration of ecological environment water supply during water shortage periods. Based on the conventional dispatching diagram, an ecological water supply limit line was designed for the reservoir. By optimizing the water levels on the ecological dispatching line, the ecological water supply strategies under different reservoir storage conditions would be made to obtain the optimal water supply rule for each water supply target.

To determine the priority of water supply for ecosystems and other water users, the positions of different lines in the dispatching diagram must to be confirmed. According to the actual dispatching and water supply task for the Biliuhe reservoir, the ecological water supply should be satisfied on the premise of the I&D and agricultural water supply guarantee. Thus, in this paper, the ecological dispatching line should be located above other dispatching lines and at the top of the dispatching diagram. In addition, the ecological water demand is flexible, and the water shortage within a short time and an acceptable range will not result in serious damage to the river ecosystem. Conversely, deep damage to I&D and agricultural water supply will be caused if the reservoir still supplies adequate water to the ecosystem in a consecutive water shortage year. According to the water shortage range that a river ecosystem can bear, we set the limiting factor value as 0.5, that is, the ecological water supply will be restricted to 50% of its normal water demand when the current storage or the incoming water in the future is not sufficient for the reservoir. For the inter-basin water diversion reservoir, considering the ecological environmental water supply, the water diversion and water supply dispatching diagrams and rules are shown in Figure 3 and Table 1.

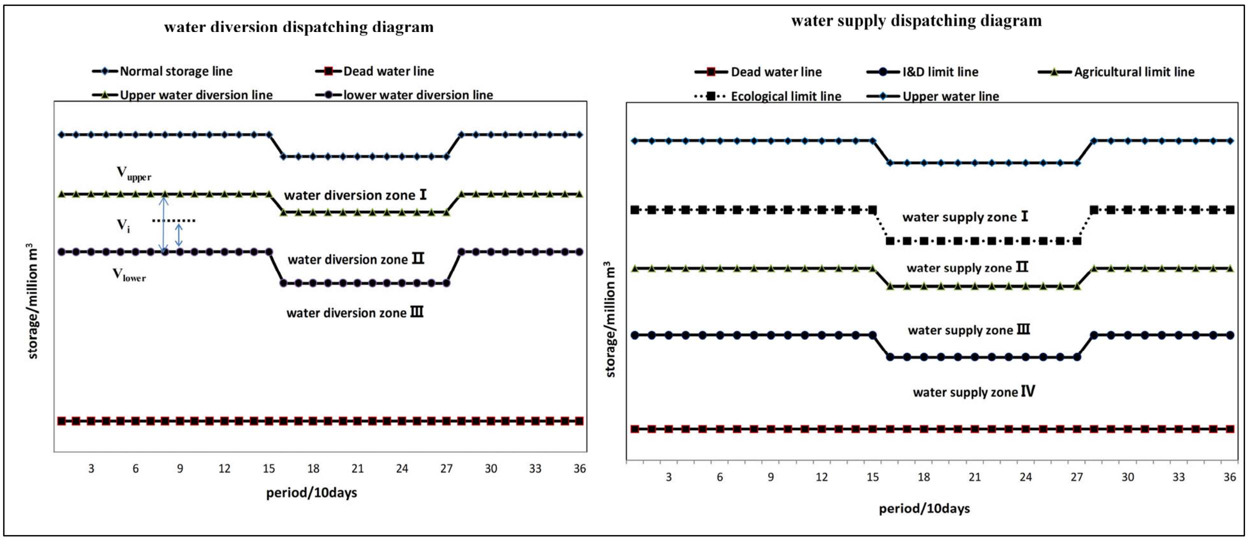

Figure 3. The water diversion and water supply dispatching diagrams for the inter-basin water diversion reservoir.

Table 1. The water diversion and water supply dispatching rules for the inter-basin water diversion reservoir.

Combined Dispatching Diagrams	Dispatching Zones	Dispatching Rules
water diversion dispatching diagram	water diversion zone I	no water diversion
	water diversion zone II	water diversion on a prorate
	water diversion zone III	water diversion based on the capacity of pipeline
water supply dispatching diagram	water supply zone I	normal water supply for I&D, agriculture, and ecosystem
	water supply zone II	normal water supply for I&D and agriculture, limited water supply for ecosystem
	water supply zone III	normal water supply for I&D, limited water supply for agriculture and ecosystem
	water supply zone IV	limited water supply for I&D, agriculture, and ecosystem
limiting factors	I&D is 0.9, agriculture is 0.7, ecosystem is 0.5	
dispatching time period	10-days	

2.4. Scenarios Design

2.4.1. The Objective Functions

In this paper, the ecological dispatching line is designed to provide ecological scheduling guidelines for reservoirs with different inflow and water use conditions. The water diversion and water supply dispatching rules are shown in Section 2.2, and the objective functions and constraints are as follows:

- I&D and agricultural objectives: To reflect the situations of I&D and agricultural water supply, the I&D water shortage index (ISI) and agricultural water shortage index (ASI) are used as objective functions. The shortage index (SI) is the indicator to measure the damage degree of water shortage to different users. Therefore, smaller SI values equate to better efficiency for I&D and agricultural water supply. The objective function is as follow:

$$minSI - min\frac{100}{NT}\sum_{j=1}^{NT}\left(\frac{D_{i,j} - W_{i,j}}{D_{i,j}}\right)^k \tag{8}$$

- where N is the total number of years; T denotes the time periods in a year; $D_{i,j}$ and $W_{i,j}$ are the water demand and water supply for the ith users (I&D or agriculture) during the jth time period, respectively; and k is an index to reflect the socio-economic impact of water shortage, which in this paper k is 2. Because I&D (or agricultural) the water supply is nonnegative, and it cannot be bigger than the water demand, the possible range of SI is from 0 to 100.
- Water diversion objective: In addition to the ecological objective, as mentioned in Section 2.2 (Formula (7)), the water diversion objective is also considered in this paper. To minimize the long-distance water division cost, the least amount of water should be diverted from the Dahuofang reservoir. The objective function is as follows:

$$minD = min\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n} d_{i,j} \tag{9}$$

- where D is the annual amount of diverted water; m and n are the number of years and the time periods in one year, respectively; and $d_{i,j}$ denotes the amount of diverted water in the ith year for the jth time period. The actual water supply capacity of this project is 288 million m^3/year after deducting the water leakage loss, so the value interval for water diversion objective D is (0, 288 million m^3/year).
- Constraints:

$$\text{Water balance constraint}:\ S_{t+1} = S_t + I_t - D_t - E_t - SU_t \tag{10}$$

$$\text{Water levels constraints}:\ \text{flood season}\ Z_{dead} \le Z_t \le Z_{\mathrm{lim}it} \tag{11}$$

$$\text{non} - \text{flood season}\ Z_{dead} \le Z_t \le Z_{normal} \tag{12}$$

$$\text{Duarantees constraints}:\ \text{for I\&D} \quad P_{ind} = \frac{f}{NT+1} \times 100\% \ge 95\% \tag{13}$$

$$\text{for agriculture}\ P_{agr} = \frac{y}{N+1} \times 100\% \ge 75\% \tag{14}$$

$$\text{Dispatch lines uncrossed constraint}:\ Z_t^1 \ge Z_t^2 \ge \ldots \ge Z_t^{num} \tag{15}$$

Limited water supply constraint: in this paper, the limited water supply strategies were implemented to prevent the disastrous impact on the reservoir caused by the alert operation below the dead water level in successive dry years, that is, a certain depth range of water supply damage is allowed for different water users when the storage is insufficient. In addition, considering the growth characteristics of crops, the limited water supply rule for agriculture is as follows: if the agricultural water supply is damaged in the current period, the water supply for all subsequent periods will be restricted in this year.

Where S_t and S_{t+1} are the reservoir storage for the beginning and the end of the tth time period; I_t is the reservoir inflow of the tth time period; D_t is the total amount of water supply for all users during the tth time period; E_t and SU_t are the evaporation water loss and the abandon water of the tth time period, respectively; Z_t is the reservoir water level of the tth time period; Z_{dead} is the dead water level of the reservoir, $Z_{\lim it}$ and Z_{normal} denote the flood limit and normal water level of the reservoir, respectively; P_{ind} and P_{agr} denote the water supply guarantee rate for I&D and agriculture, respectively; f and y are the number of time periods and years during which I&D and agricultural water supply are not damaged, respectively; Z_t^l is the limited water level for the lth water user during the tth time period; and $l = 1, 2, \ldots, num$, where num is the number of water users.

2.4.2. The Implementation of Sobol' Method

For the Biliuhe inter-basin water diversion project, considering the ecological environmental water supply, the water diversion and water supply dispatching diagram contains the upper water diversion line, lower water diversion line, I&D limit line, agricultural limit line, and ecological limit line. One calendar month is divided into three parts, each of which is used as one 10-day time step. Because the agricultural water supply is only from April to early September, the number of decision variables is 16. For the other lines, the water diversion and water supply are for the whole year, so the number of decision variables is 36. The target of the Sobol' method is to identify the sensitivity water levels on the dispatching lines for different scheduling objectives. Its concrete implementation is as follows:

- Parameters of the model: In the water diversion and water supply combined operation model, the parameters are the water levels on different dispatching lines during the operation time periods. In this paper, the total number of parameters is 160 (agricultural limit line 16, I&D limit line 36, ecological limit line 36, upper water diversion line 36, and lower water diversion line 36).
- Range of parameter values: For the parameters of each dispatching line at different periods, the water level values range from the normal water level (the flood-limit water level in the flood season) to the dead water level.
- Sampling method: The LHS technique is used to compute the Sobol' sensitivity indices. All of the parameters obey the uniform distribution. A set of 2000 LH samples is used per parameter and a total number of $2000 \times (160 + 2) = 324000$ model simulations are required to compute the Sobol' indices.
- Sensitivity calculation: The sampled parameters are placed into the reservoir multi-objective operation model to obtain the objective function values for different sampling sequences. Then, the variance-based analysis method is applied to analyze the influence of single and multiple water levels on other objectives at different time periods.

The non-dominant sorting genetic algorithm with elite strategy (NSGA-II) is combined with the Sobol' method to obtain the sensitivity indices. The basic parameters of the NSGA-II method are set as follows: the population size is 100, the crossover probability is 0.1, the mutation probability is 1/m (m is the number of parameters), and the number of evolutionary iterations is 500,000. By using the NSGA-II method, two comparative optimization scenarios are as follows:

- All of the water level parameters will be optimized by 500,000 calculations, which is the full search scenario;
- Firstly, the sensitivity parameters are optimized by 5000 calculations to obtain the feasible solutions, then these solutions are subsequently taken as the initial solutions for the global optimization problem of all parameters, and (500,000–5000) calculations are run to search for the final feasible solutions, which is the pre-conditioned full search scenario.

2.5. The Evaluation Indicators

In order to compare the optimization efficiency of the global optimization method with the local−global optimization method, three evaluation indicators of the calculation, namely the generational distance, additive indicator, and hypervolume indicator, were selected in this paper. The definition and evaluation criteria of the three indicators are as follows:

- Generational distance: Generational distance was proposed by Van Veldhuizen and Lamont in 1998 [42]. This indicator is used to measure the gap between the solutions obtained by the algorithm and the real Pareto frontier solutions. It is defined as follows:

$$GD = \frac{1}{n}\sqrt{\sum_{i=1}^{n} d_i^2} \tag{16}$$

- where n is the number of the optimal solutions, d_i is the minimum Euclidean distance between the target space and theoretical Pareto front for the *ith* individual. The smaller the value for the generation distance, the closer the solutions obtained are to the real Pareto frontier solutions. When all of the solutions obtained by the algorithm are exactly the real Pareto frontier solutions, GD = 0.
- Additive indicator: The additive indicator [43] evaluates the minimum distance for which the current solutions can completely dominate the reference solutions. It is defined as follows:

$$I_{\varepsilon+}(\mathrm{Q}) = \inf_{\varepsilon \in R}\{\forall P_i \in R \mid \exists\, Q_i \in Q\ : P_i \leq Q_i + \varepsilon, \forall i\ \} \tag{17}$$

- where Q is the non-inferior solution sets, and $I_{\varepsilon+}(\mathrm{Q})$ is the approaching degree of the non-inferior solution sets and the Pareto front. The smaller the value of the additive indicator, the closer the current solutions are to the reference solutions.
- Hypervolume indicator: The hypervolume indicator [44] is used to evaluate the target space of the dominated solutions. It not only shows the distance between the current solutions and the optimal solutions, but also the distribution of the current solutions in the target space. It is defined as follows:

$$HV = volume\left(\cup_{i=1}^{|S|} v_i\right) \tag{18}$$

- where $|S|$ represents the number of non-dominant solution sets and v_i represents the hypervolume formed by the reference point and the ith solution. The bigger the value of the hypervolume indicator, the greater the improvement in the current solutions and the farther away they are from the worst solution.

3. Results and Discussion

3.1. The Sensitive Parameters

To address the complex, nonlinear, multistage optimization problem, previous studies have conducted a lot of work, mainly on algorithm improvement, over the years [18–23]. Little attention has been paid to the sensitivity of water levels on scheduling lines for different operation objectives. In this paper, the Sobol' method was used to analyze the sensitivity of water levels for the I&D, agricultural, ecological limit line, and the upper and lower water diversion line for different operation objectives. According to the results, an index value of 0.035 is defined as the sensitivity parameter. The sensitivity parameters for different operation objectives are shown in Figure 4.

Most water levels on the I&D limit line are sensitive to the ISI objective, and in the non-flood season it is more sensitive than in the flood season (from June to September). The reason is that the ISI is up to both I&D water demand and supply. The I&D water demand stays the same for different time periods in the year, so the I&D water supply is the predominant determinant factor for the ISI objective. Water levels on the I&D operation rule curve are not sensitive to the ISI objective in the flood season because there is abundant water. However, water levels are sensitive during the non-flood season because there is not enough rainfall to increase the reservoir water level during this time period, yet the reservoir water supply remains unchanged.

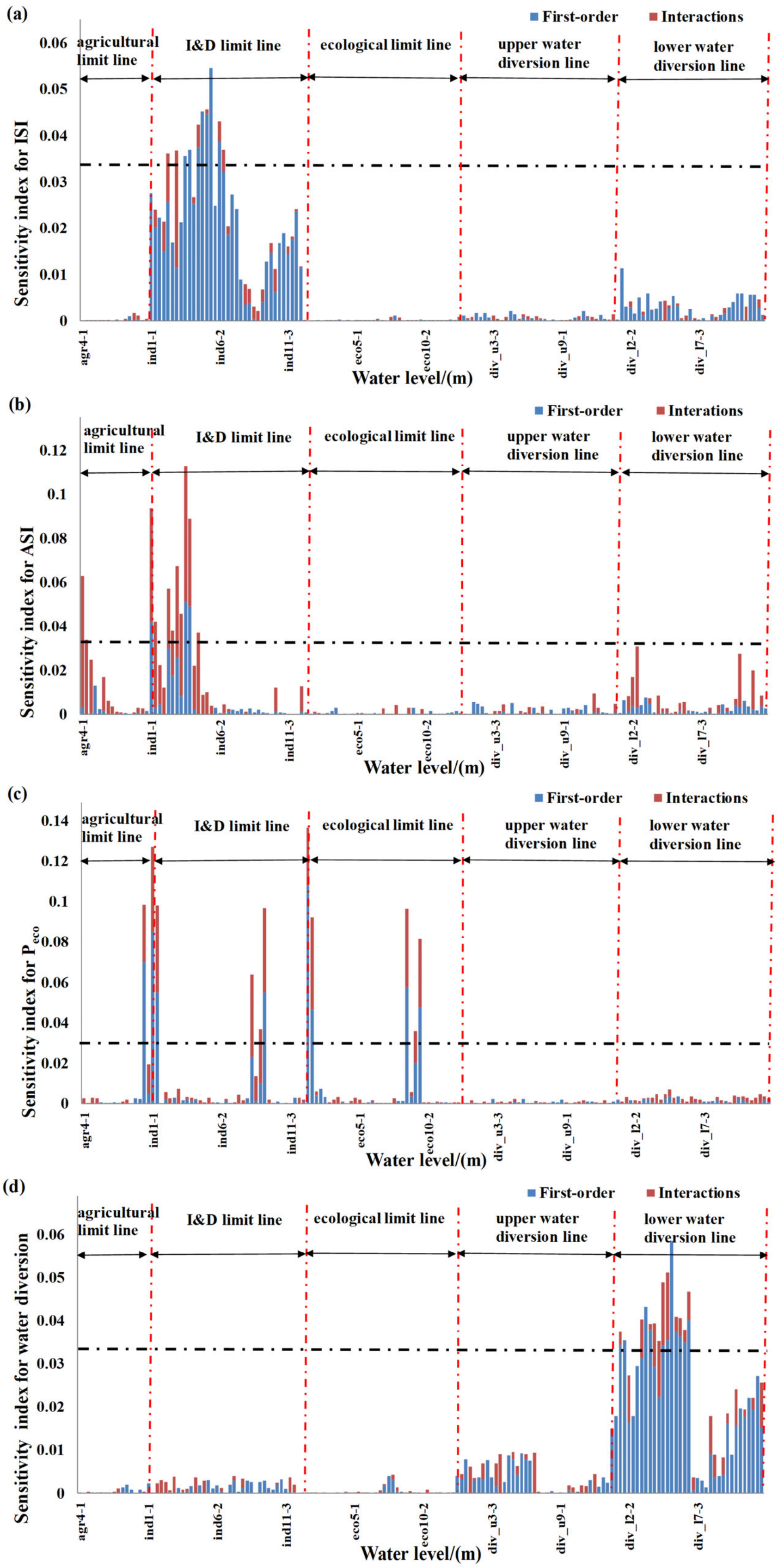

Figure 4. The sensitivity analysis results for different operation objectives. (**a**) for ISI (**b**) for ASI (**c**) for P_{eco} (**d**) for water diversion.

The water levels on both the I&D and agricultural limit lines in the first few time periods are sensitive to the ASI objective. Because the agricultural water supply rule is that once the water supply is restricted in current period, it will be reduced to 70% of its normal requirement during the following periods in the year, so water levels on the agricultural limit line in the first few time periods are sensitive. Interestingly, the water levels of the I&D operation rule curve before the flood season are also sensitive to ASI, and the interactions contribute to the total sensitivity. This is because the I&D water demand amount is more than agriculture water demand, when the reservoir is under water-stressed condition especially from January to May, competition exists between these two water users. Thus, I&D water supply makes reservoir water storage insufficient and influences the agricultural water supply. In April, agriculture water supply occurs which places pressure on I&D water supply. So water levels of the I&D limit line during these periods are sensitive to ASI objective.

The water levels on the I&D, agricultural, and ecological limit lines are sensitive to the ecological objective. After the construction of the reservoir, extreme discharge such as the maximum and minimum discharge changed a lot compared with the natural (or pre-dam) flow discharge, thus water levels of the ecological limit line during these time periods such as January, August, and September is sensitive. Water levels of the I&D and agricultural limit line are sensitive to the ecological objective because the ecological flow comprises by agricultural water supply and water spill. Water will be spilled only if the reservoir storage exceeds its capacity on the condition of satisfying the water supply. Thus, as the central part of the water supply for the Biliuhe reservoir, I&D water supply is the determining factor for water spill. In addition, the complex composition of the ecological flow results in these interactions, which are also the major components of sensitivity.

Only the water levels on the lower water diversion line are sensitive to the water diversion objective because the amount of water diversion is determined through the water diversion operation rule curves. And the lower water diversion line means there are not enough water storage while the Biliuhe reservoir must fetch water from the Dahuofang reservoir. Meanwhile, the upper water diversion line means there are enough water for Biliuhe reservoir so it is the time to terminate water diversion from the Dahuofang reservoir. Thus, water levels on the upper water diversion line are not as sensitive as those of the lower water diversion line to the water diversion objective.

By the Sobol′ sensitivity analysis results in this paper, some implications can be obtained for the management of reservoir operation. Firstly, for different reservoir operation objectives, the sensitivity parameters and extent of sensitivities vary considerably. The manager should consider the combined effects of water levels on different dispatching lines during different time periods when making water supply decisions. Secondly, the water levels at some specific time periods are sensitive to more than one reservoir operation objective. Reservoir managers should pay more attention to these time periods because they can simultaneously affect many operation objectives, and at the same time making the search process more complex. At the last, interactions between water levels significantly contribute to the variances in many objectives, such as ASI and ecological objectives. This indicates that these objectives are difficult to control by only adjusting some individual water levels. Otherwise, two or more water levels should be adjusted together [45].

3.2. The Evaluation Indicators

Based on the sensitivity analysis results, a total number of 38 parameters were selected to form a simplification multi-objective optimization problem. By using the NSGA-II method, the full search scenario and the pre-conditioned full search scenario were set to compare the algorithmic efficiency. The results for the three evaluation indicators, including the generational distance, additive indicator, and hypervolume indicator, are shown in Figure 5.

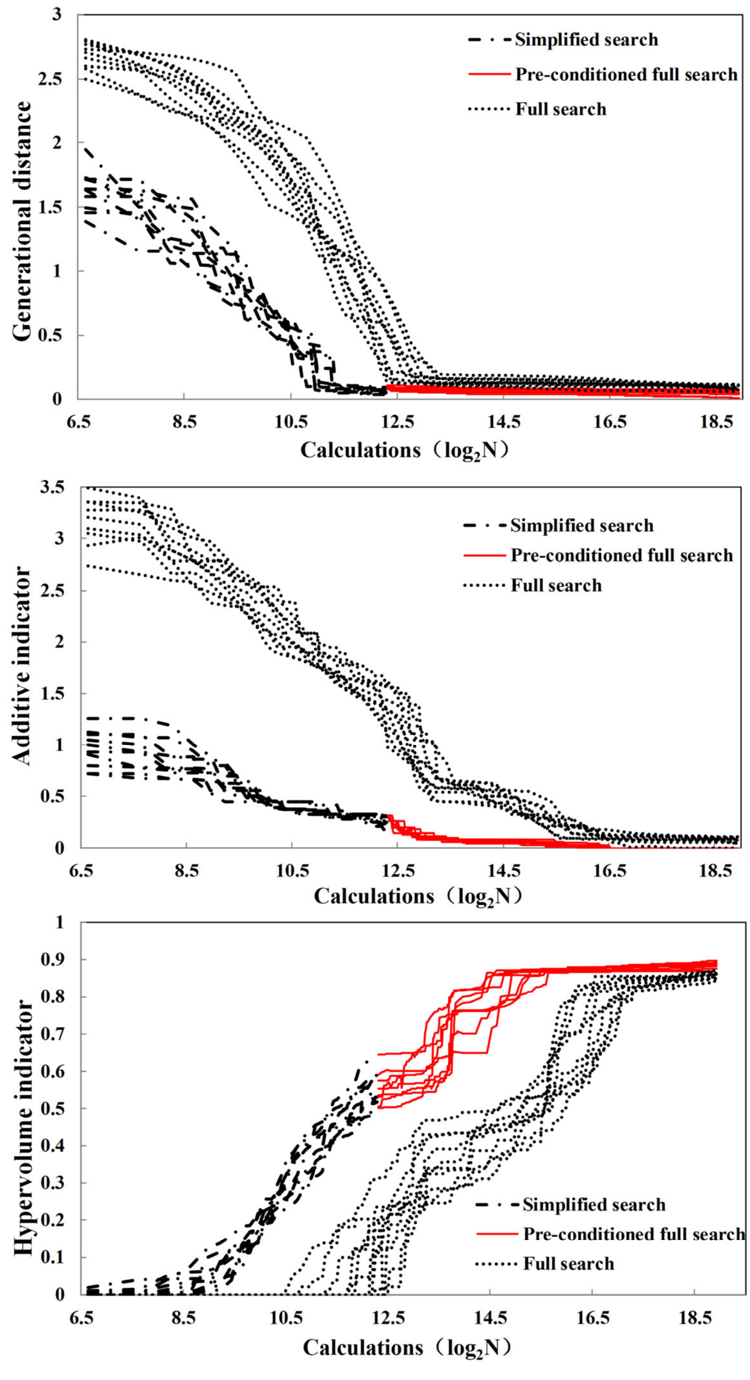

Figure 5. Comparison of three evaluation indicators for two different optimization scenarios.

As can be seen from Figure 5, the pre-conditioned full search method can obtain feasible solutions of a higher quality with less optimization calculations compared with the full search method. The tree evaluation indicators all show a significant improvement according to the sensitivity search with only 5000 evolutionary iterations. This indicates that the sensitivity parameter optimization method can allow the optimization problem to be converged quickly, which will greatly improve the search efficiency of the algorithm. However, because the search variables are incomplete at representing the whole optimization problem, it is difficult to obtain the final global optimal solution. So, better final feasible solutions will be gained if the sensitivity parameter search is combined with the full search.

From Figure 5, the importance of the initial solutions for the multi-objective optimization problems is clear. The better initial solutions can avoid the "curse of dimensionality" problem of the high-dimensional complex multi-objective operation model. In this paper, 30,000 evolutionary iterations almost obtained the globally optimized solution for the pre-conditioned full search; however, the full search needs 400,000 evolutionary iterations. This improvement in search efficiency is especially crucial for high-dimensional systems.

3.3. The Feasible Solutions Analysis

For further understanding the quality of feasible solutions obtained by the pre-processed sensitivity analysis, four groups of solutions containing at least one optimal objective were randomly selected from the pre-conditioned full search method and sensitivity analysis unprocessed search method, as shown in Figures 6 and 7.

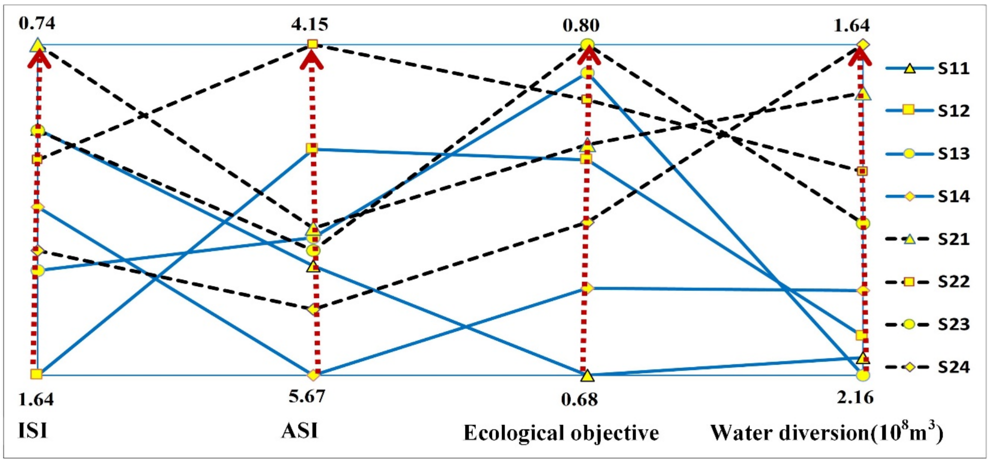

Figure 6. Comparison of the optimal solutions obtained using the sensitivity analysis pre-processed and unprocessed methods.

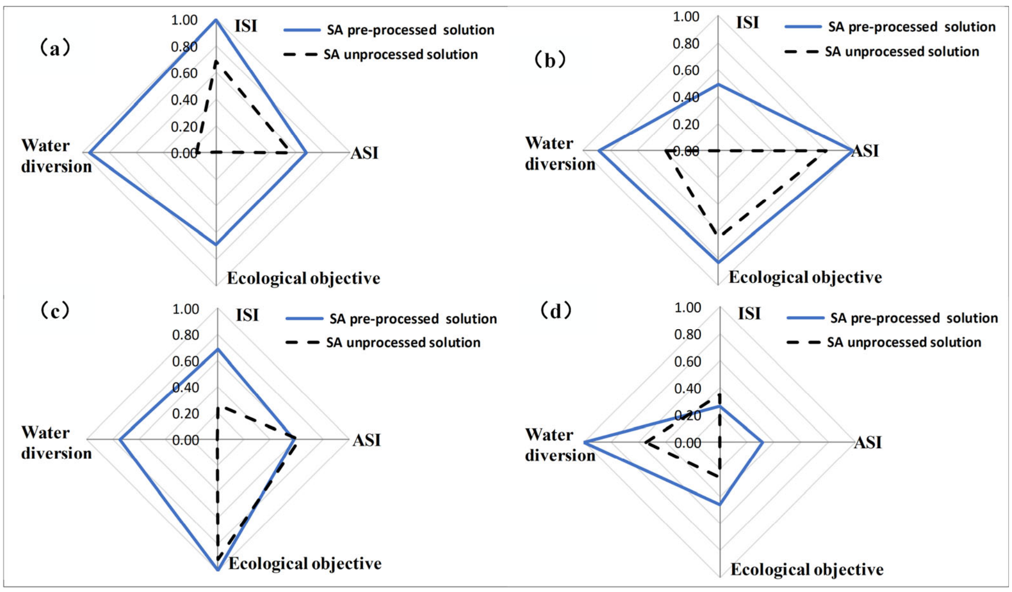

Figure 7. Comparison of the optimal solutions for each operation objective obtained using the sensitivity analysis pre-processed and unprocessed methods. (**a**) for ISI objective (**b**) for ASI objective (**c**) for ecological objective (**d**) for water diversion objective.

In Figure 6, the horizontal direction denotes four scheduling objectives, the vertical direction represents the values of each objective for different feasible solutions, and the red doted arrows means the target value changed from the bad to the good. S11, S12, S13, and S14 are the feasible solutions obtained using the full search method, and S21, S22, S23, and S24 are the feasible solutions obtained using the pre-conditioned full search method. For the ISI, ASI, and the water diversion objective, the smaller the target value, the better; meanwhile, for the ecological objective, the bigger the target value, the better. From Figure 6, we can see that for each single objective, the optimal solutions obtained by the sensitivity analysis pre-processed were superior to those obtained by the unprocessed method. The solutions obtained by the pre-processed full search method show obvious advantages compared with the unprocessed method.

To compare the optimal solutions obtained using the two methods, the four targets are normalized in Figure 7. For the ISI, ASI, ecological objective, and the water diversion objective, the closer the target value is to 1, the better. From Figure 7, we can see that for each comparison solution, at least three target values are superior for the sensitivity analysis in the pre-processed method compared with the unprocessed method. Whether for a single target or the four overall goals, the solutions obtained by the pre-processed full search method have the absolute advantage.

With the help of the Sobol' sensitivity analysis, the sensitive water level parameters of scheduling lines for different objectives were selected and the insensitivity parameters were ignored; this made the optimization problem converged quickly in a good direction. In addition, the sensitivity parameter optimization can obtain high confidence feasible solutions, which can be used as the initial global optimization solution to obtain the final optimal solution with better quality. From our research in this paper, the Sobol' sensitivity analysis method can be used in the optimization of multi-objective scheduling model to obtain better feasible solutions.

3.4. The Processing Speed Analysis

For a high-dimensional complex multi-objective operation problem, the model's processing speed is also an essential indicator to judge the superiority of the algorithm. In this paper, the average processing time of 10 random seeds was 2117 s for the pre-processed sensitivity analysis scenario, while the unprocessed scenario was 2620 s. The optimization efficiency was improved to nearly 20%. The processing time for two different optimization scenarios was carried on statistics, as shown in Figure 8.

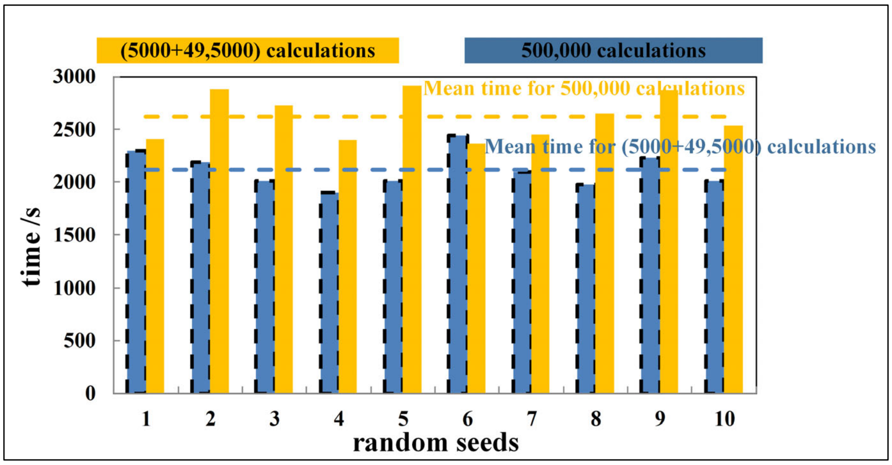

Figure 8. Comparison of the processing time for two different optimization scenarios.

The sensitivity analysis pre-processed scenario spent less processing time than the unprocessed scenario, although the time saved was only 503 s. However, in this paper, the operation problem considered only one reservoir, and the total number of parameters was 160. For most inter-basin water diversion projects or reservoir group regulation projects, the systems contain multiple cascade reservoirs with hundreds of parameters, and the processing time is the greatest challenge. In this case, the sensitivity analysis pre-processed method shows greater advantages.

In effect, the processing time is directly proportional to the evaluation indicator results in Figure 5. The sensitivity analysis reduced the global search time, resulting in a more optimal search. Three evaluation indicators, including the generational distance, additive indicator, and hypervolume indicator, reflect the degree of approximation between the current solution and the optimal solution; they all require less evolutionary iterations to approach the global optimized solution than the sensitivity analysis unprocessed method, so the processing time is naturally less.

3.5. The Implication for Reservoirs Management

In recent years, numerous scholars have extensively studied how to uphold the ecological integrity of rivers during reservoir operations. The increase in optimization parameters is related to the solution difficulty of the multi-objective scheduling model. The Sobol' sensitivity analysis method can generate initial solutions according to sensitivity parameters, which will significantly improve the efficiency and precision of the ecological scheduling model.

Traditionally, all water levels on the dispatching lines are thought to have the same degree of importance for different operation objectives in the reservoir ecological scheduling model. The optimization difficulty has greatly increased because of the simultaneous searching of all parameters. The Sobol' method can be used to obtain the sensitive water levels for the reservoir ecological objective, and by adjusting the scheduling rules of these time periods, the ecological requirements of the river ecosystem can be met during different periods.

For a cascade reservoir scheduling system with hundreds of parameters, simultaneously optimizing all of the parameters will take a lot of time and the algorithm will easily find the local optimal solution; meanwhile, the influence mechanism of the water levels on different dispatching lines for different scheduling targets is not clear. However, using the sensitivity analysis method mentioned in this paper, the sensitive water levels for different scheduling targets can be selected from the dispatching lines. Then, by adjusting dispatching rules of these time periods, the overall scheduling targets for the cascade reservoir system will be obtained. For example, the reservoir manager can achieve a better ecological environment effect by adjusting the sensitive water levels on the I&D, agricultural, and ecological water supply lines at different time periods of the year. The Sobol' sensitivity analysis method allows the reservoir ecological scheduling to be more targeted, and can improve the efficiency of the ecological scheduling models. Thus, this method should be widely applied in reservoir ecological operation.

4. Conclusions

This paper analyzes the sensitivities of objectives to water levels in operation rule curves using the Sobol' method. This method offers insights into how variables and their interactions affect different objectives. Such an understanding aids reservoir managers in addressing various operation goals, particularly ecological ones. Using the Sobol' method, we streamlined the optimization problem by focusing on the sensitive water levels, thus enhancing algorithm efficiency. Compared with conventional methods, our approach integrating the pre-processed full search with the Sobol' sensitivity analysis yielded better search efficiency and solution quality, as well as faster run times. After introducing ecological objectives into the Biliuhe reservoir operation, the model complexity increased. To combat challenges like the "curse of dimensionality", we employed the Sobol' sensitivity analysis. This will help managers understand variable impacts and improve optimization speed and solution quality. This research introduces a novel approach to solving multi-objective optimization issues.

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