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Research Article

Sustainable Optimization for China's Hydropower Project Investment Portfolio Using Multiobjective Decision Analysis

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The development of renewable energy becomes increasingly important because of exhaustion of fossil energy. Hydropower is one of the most important ways to generate electricity from renewable energy because of its relatively stable output among them. However, hydropower project development with some inherent characteristics is highly susceptible to social and natural environments, which complicates the investment process. For this purpose, this paper proposes a feasible comprehensive optimization model of portfolio investment from the perspective of sustainable development, describing the tradeoff relationship between economic, social, and ecological factors. As a hybrid uncertain NP-hard optimization problem, there are three critical challenges: (1) achieving comprehensive balance between economy, society, and ecology; (2) identifying available multiple conflicting objectives and reasonable constraints; (3) analysing the hybrid uncertain environment. Therefore, a practical problem-oriented multiobjective decision analysis model is established. Then, a multiobjective adaptive particle swarm optimization algorithm is designed to solve the model. Finally, a case study is carried out to verify the practicality of the model and the effectiveness of the improved algorithm. The result demonstrates that the model can be applied as a useful decision-making tool for decision-makers in sustainable hydropower project development.

1. Introduction

Energy is the key strategic resource and basic industry of the national economy [1]. With environmental and climate issues being taken seriously in most countries, the development of clean and renewable energy (RE) has become a major energy strategy. Many scholars point out that the energy of flowing water is becoming an alternative to fossil fuels [2, 3]. From the 21st century renewable energy policy organization in Paris, hydropower generation accounts for 16.4% of the global power generation share that is more than the sum of all other REs. Figure 1 shows large and medium-sized hydropowers' approximate location on five continents. Referred to IHA [4], East Asia and the Pacific region possessed the highest annual increase rate in hydropower installed capacity in 2017, with over 90% of capacity derived from China. Those abundant hydropower resources give unprecedented advantages and opportunities for the rapid development of hydropower generation in China [5].

Unfortunately, hydropower investment, especially in China, has already been caught in a dilemma [6]. Hydropower development is characterized by the irreversible investment and long payback period. And such investment process has been greatly influenced by the social and natural environment. Therefore, various problems have already been come up, such as imperfect electricity market, lack of flexibility in short-term demand, and incomplete market rules. Furthermore, China is a country with even more complex energy market. Enterprises investing in energy, government subsidies, and state-owned companies sell energy uniformly. These factors make it much difficult for hydropower investors to make energy investment decisions in China. In addition, there are many conflicts of interest in the process of hydropower development [7] such as the contradiction between the development and application of hydropower resources and river ecological protection. As there are higher demands for hydropower sustainability

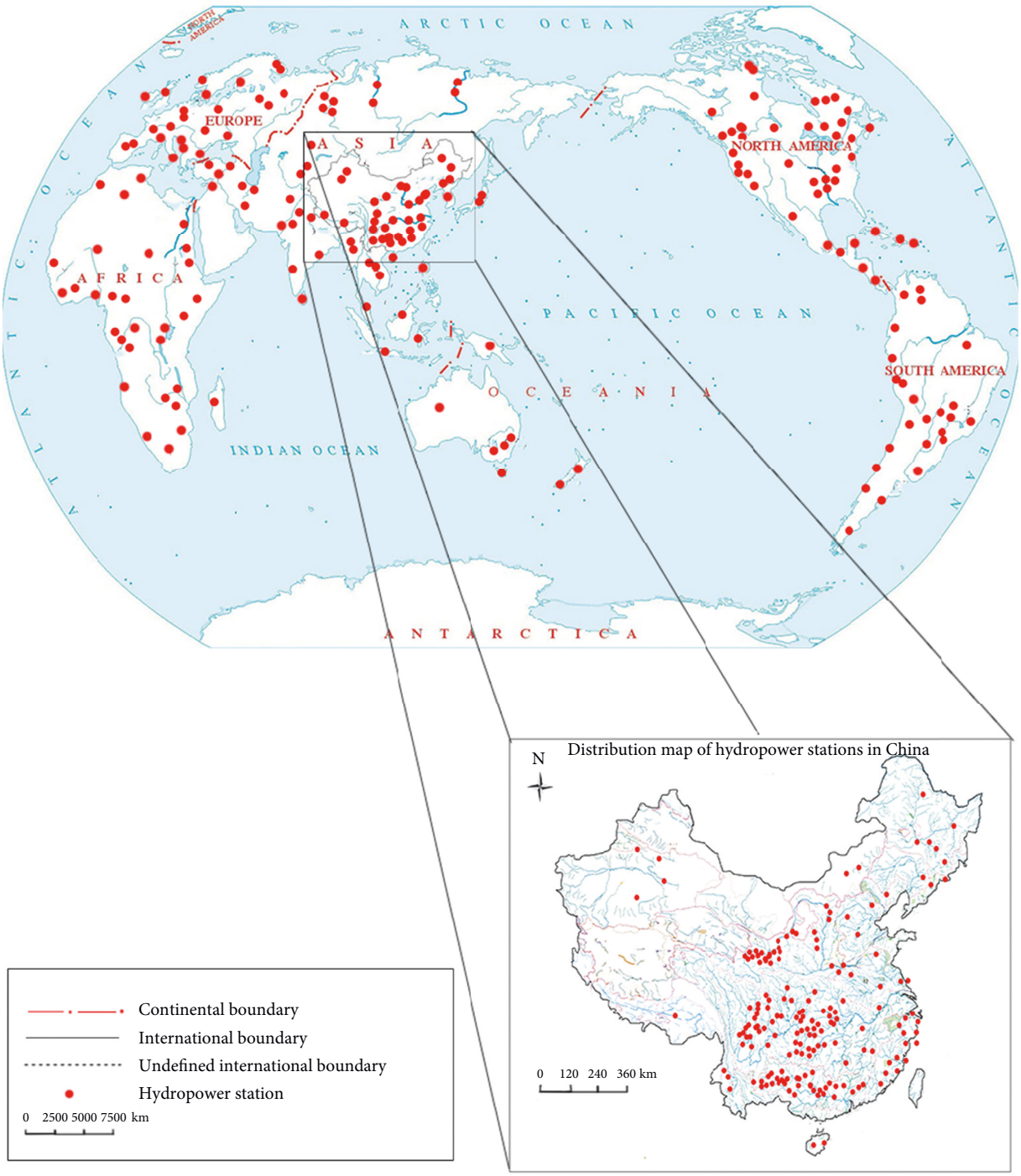

Figure 1: Current status of hydropower development in the world.

development, Huang and Yan [8] point out that the focus should be shifted to the comprehensive goal rather than single economic benefit. Some researchers have shown that environmental, economic, and social factors must be taken into account in the decision-making analysis of hydropower investment [9–11]. Consequently, under the complicated environment and limited conditions, it is of great significance to obtain the optimal combination scheme while improving economic, social, and ecological benefits.

Till now, a lot of research has been done on the hydropower investment problem (HIP) [12–17]. The domain of research on HIP involves orientation, theory, and methodology. Research subjects such as energy strategy and policy [9–11], energy planning [18, 19], environment [13], benefit evaluation [14], climate, and the conflicts of interest in various members have often been the study focus on HIP [7, 15, 17, 20–22]. However, there are few academic works specifically for portfolio optimization of multiple development projects. Under such challenges,

the optimization of portfolio based on multiobjective decision analysis has become the key problem for the development of hydropower.

At the same time, due to the influences of market, social, natural environmental variation, policy changes, and other factors, the uncertainty in the decision-making of hydropower project has been widely recognized [23–27]. However, when the decision-making environment contains both the objective randomness but also the ambiguity of the subjective judgment, there will be a gap with the reality if there is only a single uncertainty to describe its decision-making environment. It can be known that the study of the development decisions of existing hydropower projects is not enough for such complex uncertainties, especially for the hybrid uncertainty environment. Thus, further research on related issues would have more research space.

Starting from the research of Zhang et al. [28], this study preliminarily explored the multidimensional objectives of project participants in the whole hydropower project cycle. Multiple objective decision-making (MODM) is used to solve the decision problem with some incomparable competitive objectives in practical applications [29]. And it has been found that MODM is a very effective method in optimizing the tradeoff between different targets [30–32]. For example, Niu et al. [31] built a multiobjective model for hydropower projects to balance the relationship between power generation efficiency of cascade hydropower stations and enterprise output. Carlos et al. [33] established a model for the complementary operation of a photovoltaic-wind-pumped storage system to discuss the effect of pumped storage station on economic objective. Inspired by these successful researches, this paper proposed and investigated a comprehensive multiple objective decision-making (MODM) approach, to overcome these challenges and optimize portfolio investment of hydropower projects through a comprehensive multiple objective decision-making (MODM) approach.

Especially, the integrated MODM approach in this paper consists of a multiple objective programming model, a hybrid uncertain parameter transformation process based on chance-constrained programming (CCP), and a multiobjective adaptive particle swarm optimization (MOAPSO). In detail, the multiobjective programming model is based on the decision-making objectives of the decision-makers and is transformed into an exact mathematical model on account of the actual situation. The uncertain parameter transformation process involves identifying uncertain parameters and converting them into random variables and fuzzy variables and then processing the two uncertain variables with the CCP model. Finally, the transformed mathematical model calculated by MOAPSO, and the Pareto-optimization solution for hydropower investment optimization is obtained. This model is proposed for hydropower enterprise to achieve comprehensive targets. Overall, the framework of the study can be shown as in Figure 2.

From the above discussion, this study mainly makes an effort to achieve the main contributions as follows:

(1) Establishing a multiobjective optimization model that better reflects the actual situation, which can dig into the optimal scheme of the portfolio scheme in hydropower projects with Chinese characteristics.

(2) Achieving an overall balance of economic, immigration, and ecology (EIE) aspects under the hybrid uncertain environment. Then, the random variable and fuzzy variable are used to describe the electricity demand and variable costs in the model.

(3) Taking the installed capacity and quantity of the power station as a decision variable, it can better reflect the actual situation of the investment decision of the hydropower station.

(4) Developing a searching algorithm for sustainable optimization scheme of hydropower project based on MODM.

This study explores HIP in sustainable energy through overall consideration of the EIE objective of portfolio scheme. This paper might enrich the orientation of traditional HIP, and the current methods might be enriched by the proposed model. In order to guarantee the convenience of the model in practical applications, the use of contrastive case and the intelligent algorithm can assist decision-makers to acquire an accurate and effective conclusion.

The rest of the article is structured as follows. Section 2 establishes a multiobjective programming model. Section 3 gives process of the hybrid uncertain parameter transformation and development of the proposed model. Section 4 introduces the study area of empirical analysis and displays the relevant data that the model needed. The calculated result of model and a further discussion are given in Section 5, which are used to prove the theoretical model. Finally, Section 6 summarizes the advantages and limitations of this work and describes the possible future extensions.

2. Integrate MODM Optimization Model

2.1. Objective Function. This study aims to coordinate these mutually conflicting but closely related objectives, i.e., try to seek balance among economy, social, and ecology. The mathematical model of this paper is established on the basis of the development company's acquisition rights. Therefore, the acquisition cost of the development right of the basin is not considered in this paper.

2.1.1. Investment Cost. The hydropower station encompasses a series of aggregated costs such as fixed operating cost, initial investment cost, and variable operating cost including the salary of employees and reservoir maintenance fees, as well as environmental cost and immigration cost. In this paper, the initial cost of the hydropower station construction is considered. Once the hydropower station is completed, the fixed and variable costs will be required for operation, which is the same as the environmental costs that is generated by the electricity production. According to the classification and design standard of water conservancy and

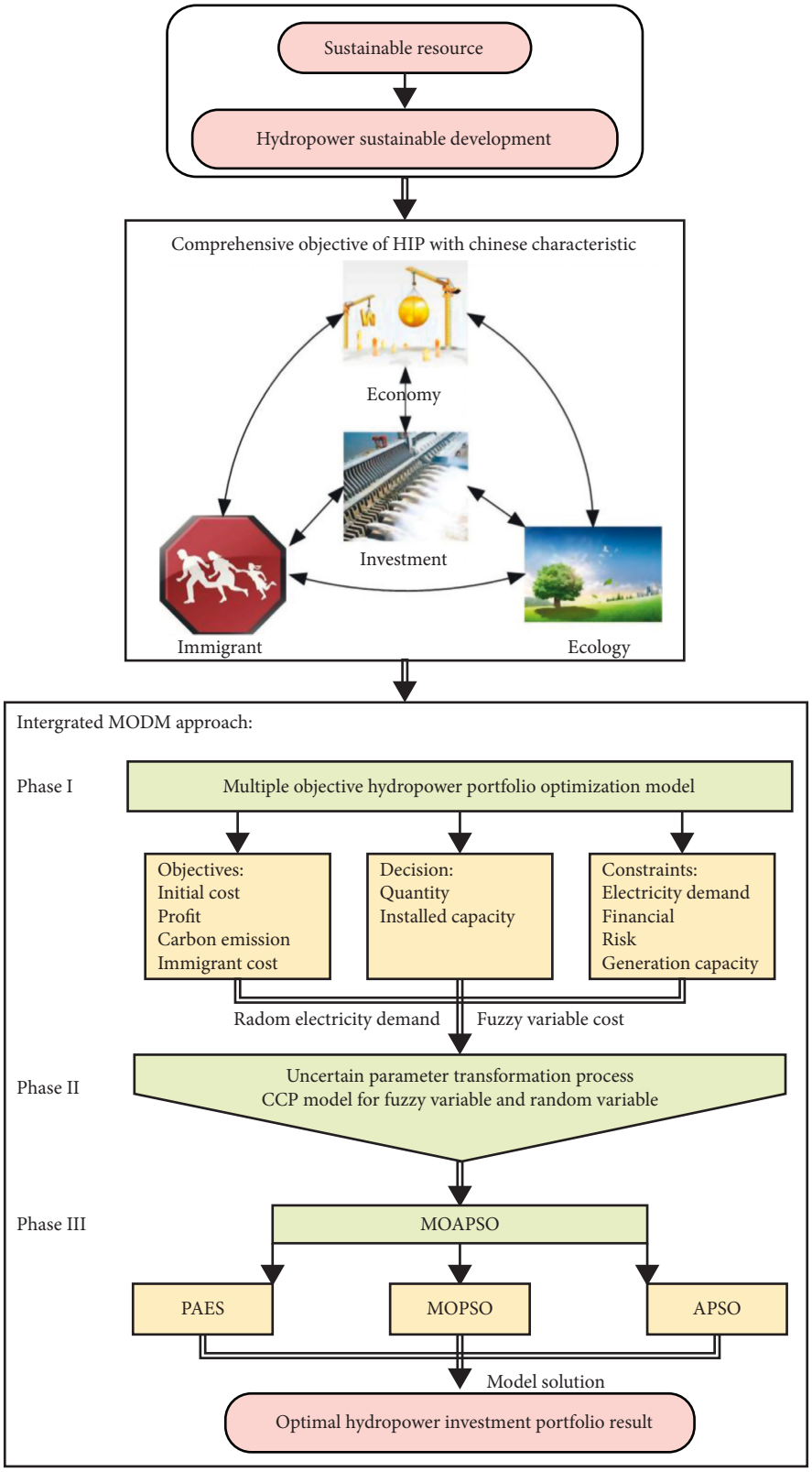

Figure 2: Framework of hydropower investment portfolio optimization.

hydropower hub project in China, the hydropower station can be divided into five categories according to installed capacity (i.e., Type I, Type II, Type III, Type IV, and Type V). The classification criteria are shown in Table 1. It can be seen that the installed capacity of different types of hydropower stations varies greatly, and it is well known that the initial

Table 1: Hydropower station installed scale division standard.

Type	I	II	III	IV	V
Installed capacity range (MW)	[1200, ∞)	[300, 1200)	[50, 300)	[10, 50)	(0, 10)

investment of hydropower stations (the construction investment in the previous construction phase) is great and irreversible.

In addition, through the investigation of the investment cost of hydropower stations, as shown in Figure 3, the cost per unit installed capacity corresponding to different scale power stations is quite different. For instance, when the installed capacity is 140 MW, the unit installation cost is $1.84 * 10^7$ Yuan and when the installed capacity is 300 MW, the unit installation cost is $2.65 * 10^7$ Yuan, and they all belong to the third type of hydropower station. Further, when the installed capacity reaches 600 MW, the unit cost is $8.7 * 10^6$ Yuan. It is usually not difficult to detect that the initial investment cost of different installed scales is quite different.

After consulting the investment cost data of the similar basins, such as Jinsha River, Yalong River, Nanya River, and Donggu River, the costs required for different types of hydropower stations can be calculated. In summary, costs for different capacities of hydropower stations are shown in the Table 2.

From the above table, it can be found that the development costs of hydropower stations with different installed capacities are quite different. Furthermore, the funds that hydropower developers can use to construct hydropower plants are limited. And due to the irreversibility of investment, developers prefer to use the funds in the construction and development stage as much as possible. Therefore, the primary goal of developers is to pay attention to the development costs of hydropower station in the early stage of construction, that is to say, to minimize the initial investment quota of hydropower station, which can be described as follows:

$$\min C = \sum_{i\in I}\sum_{j\in J}\left(\mathrm{CB}_{ij}x_{ij}y_{ij}\right) + f(x, y), \tag{1}$$

where i is a company's investment basin ($i = 1, 2, \ldots, h, \ldots, I$), j represents the hydropower station scales, x_{ij} is the number of type j hydropower stations in i basin, y_{ij} is the installed capacity of type j hydropower stations in i basin, CB_{ij} represents the investment cost, and $f(x, y)$ is the financing cost.

2.1.2. Investment Returns. The long-term goal of a company's operations is profitability, which means investment efficiency. The annual investment returns of the hydropower station construction is constrained by annual fixed operating cost, annual pumping cost, annual carbon emission cost, and annual variable operating cost. Among those, the annual variable management cost in this paper includes the cost of payroll and employee benefits where the cost is closely related

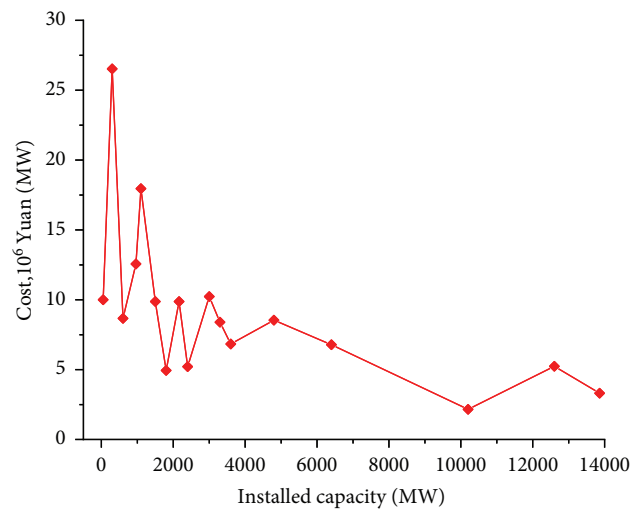

Figure 3: Costs for different capacities of hydropower stations.

Table 2: Costs for different capacities of hydropower stations.

Hydropower station scale	Type I	Type II	Type III	Type IV	Type V
Cost per kilowatt (yuan)	6996.22	14270.05	14270.71	10000.00	10000.00

to employee numbers. For the investment decision-making of hydropower combination optimization, decision-makers fail to give an exact number of employee numbers of the hydropower station before the power station operation begins. So it is difficult to illustrate these problem parameters as vague values, therefore becoming an uncertainty factor in the decision-making stage. There are some studies that have mentioned this uncertainty in power station optimization [34, 35]. In this paper, the variable management cost is defined as a fuzzy aspect that influences the investment decision-making of hydropower combination optimization. Therefore, the investment benefit of this paper can be expressed as the difference among power generation revenue and annual fixed operating cost, annual pumping cost, annual carbon emission cost, and annual variable operating cost. The maximum objective function is expressed as the following formula:

$$\max \mathrm{IE} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[p_t q_{ij,t}\Delta t - \left(\widetilde{\mathrm{CV}}_{ij} + \mathrm{CP}_{ij} + \lambda_c \mathrm{CE}\right)q_{ij}\Delta t - \mathrm{CF}_{ij}x_{ij}y_{ij}\right](1+k)^{-t}, \tag{2}$$

where t expresses the planning horizon in years, p_t is the annual average price of electricity on sale for year t, Δt is the number of generating hours, λ_c is the CO_2 emission coefficient, and k is the annual discount rate, $\widetilde{\mathrm{CV}}_{ij}$, CP_{ij}, CE, and CF_{ij} are the costs of variable operation and management, pumping cost, CO_2 emission subsidy cost, and fixed operation and management cost, respectively. $q_{ij,t}$ is the average generating capacity in t year. Due to natural conditions and system scheduling, the $q_{ij,t}$ of power station is

usually lower than the installed capacity. On this basis, we determine the average power generation capacity by conducting an investigation of experts working in hydropower stations all the year round. Through interviews with three experts who have worked in the Dadu River Basin for nearly ten years, the $q_{ij,t}$ in this case is 0.8 times the installed capacity.

2.1.3. Immigrant Cost. The construction of hydropower stations involves the relocation of residents around the original water areas. There are different policies for different regions, so the immigrant cost is related to the geographical conditions of the basin itself and the number of immigrants that cannot be generalized. Moreover, the migration costs of upstream and downstream power stations are quite different. In this paper, the relatively costs involved in similar watersheds during the survey are considered as follows to realize the minimum:

$$\min \mathrm{IC} = \sum_{i\in I}\sum_{j\in J}\left(x_{ij}y_{ij}\mathrm{CI}_{ij}\right), \tag{3}$$

where CI_{ij} expresses the migration cost of type j generating units in i basin.

2.1.4. Environment Efficient. Nowadays, environmental issues have drawn worldwide attention. The environmental factors must be considered in project construction. In this paper, the impact on the environment in hydropower projects mainly considers carbon dioxide emissions. Hydropower is a clean energy source that generates extremely low carbon emissions during power generation. If more hydropower can be introduced into the power system, environmental problems can be alleviated to some extent. Therefore, the environmental benefit in the sustainable optimization of hydropower investment decisions is to minimize carbon emissions. In this paper, the environmental benefits of hydropower are obtained by comparing the carbon emissions from hydropower with those from standard coal-fired power generation. λ_s indicates the carbon emission coefficient of standard coal thermal power generation; the carbon emission factors of hydropower is determined by interviews with engineers and experts, which is represented as λ_c:

$$\max \mathrm{EC} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}(\lambda_s - \lambda_c)q_{ij,t}\Delta t. \tag{4}$$

2.2. Constraints

2.2.1. Relationship between Hydropower and Electricity Demand. The demand for hydropower can be predicted by historical data that come from the Chinese Yearbook 2001–2017. As is shown in Figure 4, the electricity consumption has increased year by year.

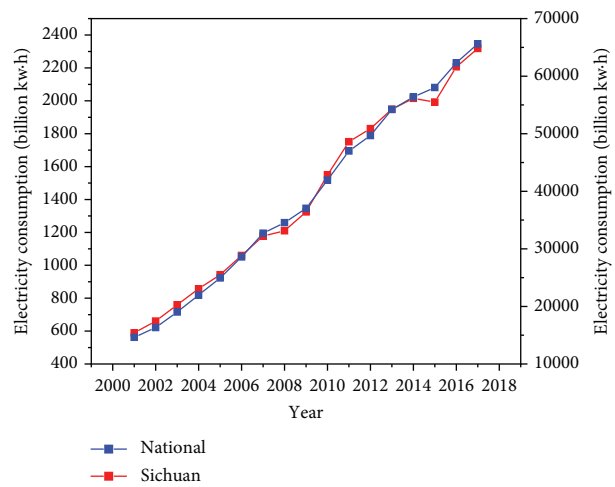

Figure 4: Electricity consumption of the whole society from 2001 to 2017.

Therefore, in the current power market, which has been vigorously developing RE power generation, the demand for hydropower should adjust accordingly. That is to say, the amount of hydropower must meet the demand for real-time electricity consumption to a certain extent. Furthermore, electricity demand is a common uncertain factor, which affects the operation of hydropower station. Due to the changes of natural and social environment, such as weather and economic development especially for long-term decision, it is difficult to accurately predict. Nevertheless, those factors significantly affect investment and operation of hydropower station. Unfortunately, it cannot be directly acquired for the annual electricity demand during the operation of hydropower station at the investment decision stage. Many researches have referred to the uncertainty of electricity demand [18, 36]. In this paper, the factors affecting the investment decision of hydropower portfolio optimization are regarded as random factors.

Thus, the total power generation of the hydropower station developed by the company should be greater than the load demand allocated by the power grid company during the planning period, as shown below:

$$\overline{D}_t \le \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} q_{ij,t}\Delta t, \tag{5}$$

where $\overline{D}_t$ represents the electricity demand for year t.

2.2.2. Relationship between Power Generation Capacity and the Design Value. Similarly, for the upper limit demand forecast, the power-generating capacity of the entire generator set during the planning period should be less than or equal to the designed installed capacity. Here, assume that the utilization of hydropower generating units is constant, the installed capacity constraints of the units are as follows:

$$q_{ij,t} \leq \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\alpha_t x_{ij} y_{ij}, \tag{6}$$

where α_t denotes the utilization ratio at time t.

2.2.3. Installed Capacity Constraint. Hydropower station scale is defined as follows: (1) Type I Hydropower Station, (2) Type II Hydropower Station, (3) Type III Hydropower Station, (4) Type IV Hydropower Station, and (5) Type V Hydropower Station ($j = 1, 2, 3, 4, 5$). The installed capacities of these different types of hydropower stations are as follows:

$$\begin{aligned}
&\text{For j = 1,} \quad y_{ij} \geq 1200 \times 10^3 \text{ kw},\\
&\text{For j = 2,} \quad y_{ij} \in \left[300 \times 10^3 \text{ kw}, 1200 \times 10^3 \text{ kw}\right),\\
&\text{For j = 3,} \quad y_{ij} \in \left[50 \times 10^3 \text{ kw}, 300 \times 10^3 \text{ kw}\right),\\
&\text{For j = 4,} \quad y_{ij} \in \left[10 \times 10^3 \text{ kw}, 50 \times 10^3 \text{ kw}\right),\\
&\text{For j = 5,} \quad y_{ij} < 10 \times 10^3 \text{ kw}.
\end{aligned} \tag{7}$$

2.2.4. Relationship between Hydroelectric Generation and Water Flow. The hydroelectric stations are interrelated and mutually constrained in a watershed. Especially for cascade hydropower stations, there is a hydraulic connection between them to form an overall coordination of hydraulic power. Considering the impact of water flow on power generation, the generation capacity should be less than or equal to the amount of hydropower available in the basin during the planning period. In this study, the water flow connection between the hydropower stations is assumed to meet the following conditions: (1) Water head connection: The cascade hydropower station is intermittently connected where the downstream water level of the upstream hydropower station is determined by the lower drain flow. Besides, the head changes of the adjacent two cascade hydropower stations are irrelevant. (2) Water flow relation: The distance between two adjacent cascade hydropower stations is moderate. To do so, the water flow changes of the two power stations can occur simultaneously. Further, the interval flow is increased in the drainage ditch of the upstream power station, which finally constitutes the inflow flow of the downstream hydropower station. (3) In this paper, the water flow time lag of the upstream drain flow and the water loss are not considered. The power generation limit of the hydroelectricity set is as follows:

$$\sum_{j\in J} q_{ij,t}\Delta t \leq W_i, \quad \forall i, t, \tag{8}$$

where W_i denotes the available capacity in the i basin.

2.2.5. Finance Constraint. Since most of the funds needed for hydropower development rely on external financing, the investment decisions of renewable energy companies such as hydropower are significantly affected by external financing constraints [37]. Therefore, the constraints of financing quotas are considered in the investment scale of hydropower development. The finance constraints are given as follows:

$$f(x, y) = \begin{cases} 0, & \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[x_{ij}y_{ij}\left(\mathrm{CB}_{ij}\dfrac{k(1+k)^t}{(1+k)^t - 1}\right)(1+k)^{-t}\right] \leq F,\\ M, & \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[x_{ij}y_{ij}\left(\mathrm{CB}_{ij}\dfrac{k(1+k)^t}{(1+k)^t - 1}\right)(1+k)^{-t}\right] > F, \end{cases} \tag{9}$$

where M and F, respectively, represent an infinite value and the total amount of funds that the project can be integrated into.

2.2.6. Risk Constraint. The main focus of hydropower investment is expected return and investment risk. According to the mean-variance model proposed by Markowitz [38], the profit and risk are two factors that affect the investment decisions. Taking this in mind, the decision-making variables for investment income of hydropower stations need to be taken into account. That is to say, the investment risk cannot exceed the tolerance of investors. There are risk constraints as follows:

$$\begin{aligned}
&\sum_{i\in I} N_i = 1,\\
&\sigma^2 = \sum_{i\in I}\sum_{h\in H} N_i N_h \operatorname{cov}\left(R_i, R_h\right) \leq C,
\end{aligned} \tag{10}$$

where N_i is the proportion of investment in i basin, R_i is the rate of return on investment in i basin, $E(R_i)$ is the expected rate of return on investment in i basin by decision makers, and C is the constant of risk control.

2.3. Global Model. Based on the above description, a sustainable multiobjective optimization decision model is developed, which takes into account the economic, ecological, and immigrant hydropower portfolio system. And it is used to determine the balance among economic benefits, migration problems, and environmental impacts under electricity demand and capital constraints in order to achieve the sustainable development of hydropower. To achieve economic, immigrant, and environmental balance, the optimization decision model includes four objectives: minimizing initial investment costs, maximizing operational benefits, minimizing immigration costs, and maximizing the benefits of hydropower. In this model, the fuzzy theory is used to describe the change management cost of hydropower operation stage and the stochastic theory is used to describe the demand of electricity because these parameters are difficult to determine accurately. The model considers the optimal decision from the perspective of the developer. And the decision variables are composed of the installed quantity x_{ij} and the installed scale y_{ij} of the power station. Therefore, the sustainable optimization multiobjective decision model of the hydropower portfolio system is presented as follows:

$$
\begin{aligned}
&\min F_1 : C = \sum_{i\in I}\sum_{j\in J}\left(\mathrm{CB}_{ij}x_{ij}y_{ij}\right) + f(x,y),\\
&\max F_2 : \mathrm{IE} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[p_{ij}q_{ij}\Delta t - \left(\widetilde{\mathrm{CV}}_{ij} + \mathrm{CP}_{ij} + \lambda_{\mathrm{c}}\mathrm{CE}\right)q_{ij}\Delta t - \mathrm{CF}_{ij}x_{ij}y_{ij}\right](1+k)^{-t},\\
&\min F_3 : \mathrm{IC} = \sum_{i\in I}\sum_{j\in J}\left(x_{ij}y_{ij}\mathrm{CI}_{ij}\right),\\
&\max F_4 : \mathrm{EC} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}(\lambda_{\mathrm{s}} - \lambda_{\mathrm{c}})q_{ij,t}\Delta t,\\
&s.\mathrm{t.}\ \begin{cases}
\overline{D}_t \le \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} q_{ij,t}\Delta t,\\
q_{ij,t} \le \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} \alpha x_{ij}y_{ij},\\
\sum_{j\in J} q_{ij,t}\Delta t \le W_i, \quad \forall i,\\
\begin{cases}
0, & \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[x_{ij}y_{ij}\left(\mathrm{CB}_{ij}\frac{k(1+k)^t}{(1+k)^t-1}\right)(1+k)^{-t}\right] \le F,\\
M, & \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\left[x_{ij}y_{ij}\left(\mathrm{CB}_{ij}\frac{k(1+k)^t}{(1+k)^t-1}\right)(1+k)^{-t}\right] > F,
\end{cases}\\
\sum_{i\in I} N_i = 1,\\
\sigma^2 = \sum_{i\in I}\sum_{h\in H} N_iN_h\mathrm{cov}(R_i,R_h) \le C,\\
\text{For } j=1, \quad y_{ij} \ge 1200\times 10^3\ \mathrm{kw},\\
\text{For } j=2, \quad y_{ij} \in \left[300\times 10^3\ \mathrm{kw}, 1200\times 10^3\ \mathrm{kw}\right),\\
\text{For } j=3, \quad y_{ij} \in \left[50\times 10^3\ \mathrm{kw}, 300\times 10^3\ \mathrm{kw}\right),\\
\text{For } j=4, \quad y_{ij} \in \left[10\times 10^3\ \mathrm{kw}, 50\times 10^3\ \mathrm{kw}\right),\\
\text{For } j=5, \quad y_{ij} < 10\times 10^3\ \mathrm{kw}.
\end{cases}
\end{aligned}
\tag{11}
$$

3. Methodology

3.1. Uncertainty Treatment

3.1.1. Stochastic Electricity Demand. As described in Murto [39], uncertain electricity demand has been considered as a random variable in previous studies. Therefore, the random theory is used to deal with it. In order to take into the uncertainty that affects electricity demand account, a multivariate time series prediction model is utilized in this paper. The uncertainty description of electricity demand is obtained by the following procedure:

Step 1: collect historical data on electricity consumption D_a, GDP, and rate of three main industries, where $a = 1, 2, \ldots, m$.

Step 2: use multivariate time series prediction model to establish prediction equation (t), where $t = 1, 2, \ldots, m + T$.

Step 3: use prediction equation to forecast the electricity demand in the each of the previous m years $\widehat{D}_a$, where $a = 1, 2, \ldots, m$; then, the forecasting error is expressed as $\varepsilon_a = \widehat{D}_a - D_a$, $a = 1, 2, \ldots, m$.

Step 4: assume the annual forecasting error obeys the normal distribution $N(0, \sigma_V^2)$; then, the standard deviation σ_V can be calculated as follows:

$$\sigma_V = \sqrt{\frac{1}{m-1} \sum_{a \in m} (\varepsilon_a - 0)^2}, \quad a = 1, 2, \ldots, m. \tag{12}$$

Step 5: forecast the electricity demand $\widehat{D}_t$ for the t-th year; then, the electricity demand D_t is a random number which obeys the normal distribution $N(\widehat{D}_t, \sigma_V^2)$, $t = 1, 2, \ldots, m + T$.

3.1.2. Fuzzy Variable Management Cost. For the study, since there are not enough data to comprehensively analyse influencing factors, resulting in uncertainty, inaccuracy, or ambiguity [40]. Fuzzy factors are similar to those considered by Zhou et al. [41], and the fuzzy theory is used to deal with variable management cost, which is treated as fuzzy variables. In this article, the improved triangular fuzzy number is used to evaluate and the steps are detailed as follows:

Step 1: collect the variable management cost data of hydropower stations of Nanya River, Donggu River, and Jinsha River and divide the data into three groups

Step 2: Let the minimum value of each set become the lower bound of each group fuzzy number

Step 3: Let the maximum value of each set become the upper bound of each group fuzzy number

Step 4: Let the average value of each set become the intermediate coefficient of each group fuzzy number

3.2. Chance-Constrained Programming Model. The CCP method is a powerful competing tool proposed by Charnes and Cooper [42] and Miller and Wagner [43] to solve optimization problems under uncertainty. This method satisfies the use of known probability density or cumulatively distributed random variables at a confidence level of predetermined constraints, which can more accurately represent uncertainties in planning problems [44]. This method has been widely applied in various fields, such as investment [45] and power dispatching [46]. And it has achieved significant results. Since the uncertain parameters exist in the established model (i.e., random variables $\overline{D}_t$, fuzzy variables $\widetilde{\mathrm{CV}}_{ij}$), further processing is needed and it is converted into a resolvable model with mathematical implications. With this in mind, the CCP method is introduced to handle the uncertain programming.

Since the objective equation (2) has fuzzy variables and the random parameter in equation (5), it is difficult to exactly confirm the maximum investment benefit or accurate demand for electricity. Thus, the following is the processing of the objective function and constraint equation. Firstly, confidence levels of the decision-maker are predetermined as γ_1 and γ_2. Meanwhile, chance constraint that the objective function is better than ideal objective value IE is constructed. And what the decision-maker needs to optimize just is the ideal objective value, which is described as follows:

$$\begin{aligned} \max \mathrm{IE} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \Big[& p_{ij} q_{ij} \Delta t - \left(\widetilde{\mathrm{CV}}_{ij} + \mathrm{CP}_{ij} + \lambda_{\mathrm{c}} \mathrm{CE} \right) q_{ij} \Delta t \\ & - \mathrm{CF}_{ij} x_{ij} y_{ij} + (1 - \gamma_1) \alpha_{\mathrm{CV}_{ij}} q_{ij} \Delta t \Big] (1 + k)^{-t} \geq \mathrm{IE}. \end{aligned} \tag{13}$$

A similar method can be used to deal with equation (5) with a random variable. The situation that the demand of electricity $\overline{D}_t$ is no more than the hydroelectric power generation $\sum_{i \in I} \sum_{j \in J} q_{ij} \Delta t$ happens with a probability, and this probability is larger than γ_2. It can be described as the following equation:

$$\sum_{i \in I} \sum_{j \in J} q_{ij} \Delta t \geq \mu_{\mathrm{D}} + \Phi^{-1}_{(\gamma_2)} \sqrt{\sigma_{\mathrm{D}}^2}, \tag{14}$$

where $\Phi^{-1}_{(\gamma_2)}$ is the lower γ_2 quartile of standard normal distribution.

3.3. Solution Method

3.3.1. MODPSO. In multiobjective decision-making problem, there are conflicts and incomparable phenomena among multiple objectives. The main purpose of multiobjective optimization is to seek Pareto-optimal solutions (nondominated solutions) to optimize the tradeoff between multiple goals [47], where the Pareto-optimal solutions are expressed as the best compromise solution set among different objectives. In recent years, many intelligent algorithms have been used to solve multiobjective optimization problems. Among them, the particle swarm optimization (PSO) algorithm has been widely used to deal with the problems, and the application has achieved great success [48]. Compared with other biological algorithms, PSO algorithm has unique advantages [49, 50]: (1) the organizational structure and calculation formula are simple and easy to understand; (2) fewer parameters are required to be

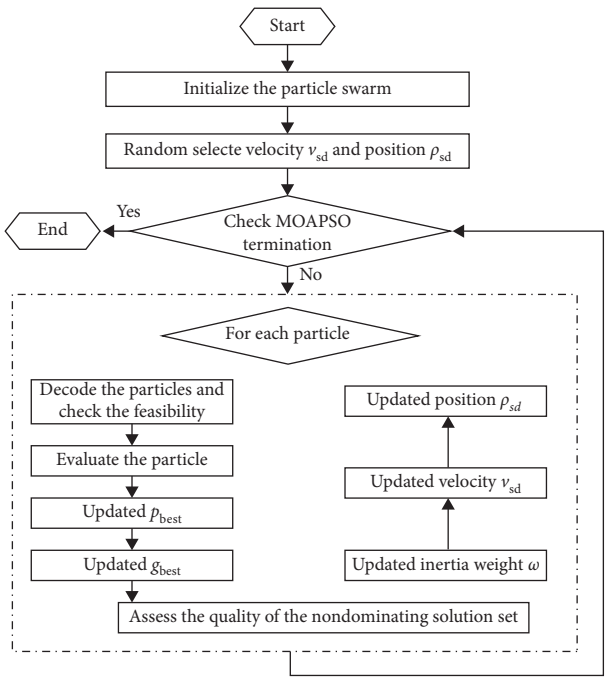

Figure 5: MOAPSO algorithm flow chart.

controlled by the operator; (3) less computational pressure. In this thought, an improved multiobjective PSO is adopted to solve the mathematical model to optimize the tradeoffs between the economy, the environment, and immigrants. We proposed the multiobjective adaptive particle swarm optimization (MOAPSO), which is made up of Pareto-archived evolutionary strategy (PAES), adaptive particle swarm optimization algorithm (APSO), and multiobjective particle swarm optimization algorithm (MOPSO). The proposed algorithm adjusts inertial weight ω to make up for the deficiency of traditional PSO, in which self-exploration ability in the initial stage and the group cognitive ability in the later stage are weak [51, 52]. At this point, an efficient solution can be acquired. The MOAPSO algorithm includes six steps, and the flow chart is shown in Figure 5.

Step 1. Particle swarm initialization and solution representation:s is described as the particle swarm size (particle index $s = 1, 2, \ldots, S$), and each particle has D_p dimension (particle dimension index $d = 1, 2, \ldots, D_p$). The maximum iteration of particle swarm is expressed as T_p (maximum iteration index $\tau = 1, 2, \ldots, T_p$). $c1$ and $c2$ are the acceleration constants of velocity; the inertia weight of particle $= \omega$. In this paper, $x_{p_{ij}}$ and $y_{p_{ij}}$(i.e., hydropower station investment scale) are represented by particle-represented solutions; they are composed of the type and quantity of hydropower stations.

Step 2. Feasibility checking and decoding method: as hydropower stations investment scale should meet the demand of electricity and logical constraints, it is necessary to inspect and discard the infeasible particle matter. Then, the particle-represented solution is decoded into a solution in a general way, called the hydropower stations investment scale.

Step 3. Particle evaluation: the random position of the sth particle is set in the sth solution set. Then, the hydropower stations investment scale (i.e., $x_{p_{ij}}$ and $y_{p_{ij}}$) can be obtained. Then, F1, F2, F3, and F4 are calculated, respectively.

Step 4. Multiobjective method: the PAES, test program, and selection consists of the multiobjective method, which is used to calculate p_{best} and g_{best}. At the first iteration, the initial solution of each particle is regarded as p_{best} and nondominant solution. The updated solution is considered as nondominant solution to calculate p_{best} when the iteration is updated. Since there is no global nondominated solution in the initial stage, the p_{best} of all particles can be used as the global optimal nondominated solution to calculate the g_{best}. Therefore, the final solution to the problem, the global optimal nondominated solution of the Tth iteration, can be obtained.

Step 5. Updating inertia weight: using the equation (15) to update the inertia weight in the τ iteration:

$$\overline{\omega} = \frac{\sum_{s\in S}\sum_{d\in D_p}\left|v_{sd}\right|}{S\cdot D_p}, \tag{15}$$

$$\omega^* = \begin{cases} \left(1-\dfrac{1.8\tau}{T}\right)\omega^{\max}, & 0\le\tau\le\dfrac{T_p}{2}, \\ \left(0.2-\dfrac{0.2\tau}{T}\right)\omega^{\max}, & \dfrac{T_p}{2}\le\tau\le T_p, \end{cases} \tag{16}$$

$$\Delta\omega = \frac{\omega^* - \overline{\omega}}{\omega^{\max}}\left(\omega^{\max}-\omega^{\min}\right), \tag{17}$$

$$\omega^{\tau+1} = \omega^{\tau} + \Delta\omega, \tag{18}$$

$$\omega = \omega^{\max}, \quad \text{if } \omega > \omega^{\max}, \tag{19}$$

$$\omega = \omega^{\min}, \quad \text{if } \omega < \omega^{\min}, \tag{20}$$

where v_{sd} describes the particle velocity of the sth particle in dth dimension, $\omega^{\max}$ is the maximum inertial weight value, and the minimum inertial weight value is expressed as $\omega^{\min}$.

Step 6. Updating velocity and position of each particle by using the following equations:

$$\begin{aligned} v_{sd}^{\tau+1} &= \omega v_{sd}^{\tau} + c1\left(p_{\text{best}}^{\tau}-\rho_{sd}^{\tau}\right) + c2\left(g_{\text{best}}^{\tau}-\rho_{sd}^{\tau}\right), \\ \rho_{sd}^{\tau+1} &= \rho_{sd}^{\tau} + v_{sd}^{\tau+1}, \\ \text{if } \rho_{sd}^{\tau+1} &> \rho_d^{\max}, \quad \text{then set } \rho_{sd}^{\tau+1} = \rho_d^{\max}, \\ \text{if } \rho_{sd}^{\tau+1} &< \rho_d^{\min}, \quad \text{then set } \rho_{sd}^{\tau+1} = \rho_d^{\min}, \end{aligned} \tag{21}$$

where ρ is expressed as the position of particles, $\rho_d^{\max}$ is used to describe the maximum value of ρ in the dth dimension, and $\rho_d^{\min}$ is used to describe the minimum value of ρ in the dth dimension.

Step 7. The algorithm termination checking:if the stopping criterion of the algorithm is satisfied (i.e., iteration-max), then the MOAPSO procedure is ended to acquire the optimal solution and the process is terminated. Otherwise, the algorithm will continue.

3.3.2. Nondominating Solution Evaluation. In this paper, four suitable indicators are used to assess the quality of the Pareto-optimal solution set based on the study of [53, 54].

(i) The distance function $H_1(\Theta)$ is used to describe the average distance of the Pareto-optimal solution set:

$$H_1(\Theta) = \frac{1}{|\Theta|} \sum_{i_e \in I_e} \sqrt{\left(a_{i_e} - \overline{a}\right)^2}, \tag{22}$$

where $\overline{a} := (1/|\Theta|)\sum_{i_e \in I_e} a_{i_e}$, $a_{i_e} = \min\{\sum_{l \in L} \sqrt{(F_l(\rho_{i_e}) - F_l(\rho_{i_e}))^2}; \rho_{i_e}, \rho_{j_e} \in \Theta, i_e \neq j_e\}$, and $|\cdot|$ expresses the number of the set's elements.

(ii) The function $H_2(\Theta)$ combines the distribution with the Pareto-optimal solution set:

$$H_2(\Theta) = \frac{1}{|C_I^2|} \sum_{x \in \Theta} \left| \left\{ \left\| F_l(\rho_i) - F_l(\rho_j) \right\| < \sigma; \rho_i, \rho_j \in \Theta,\ i \neq j \right\} \right|, \tag{23}$$

where $\|\cdot\|$ expresses the element's distance, $\sigma = \kappa \max\|\cdot\|$, and, in this paper, $\kappa = 0.55$.

(iii) The range of the Pareto-optimal front is considered in the function $H_3(\Theta)$:

$$H_3(\Theta) := \sqrt{\sum_{l \in L} \left(F_l(\rho_i) - F_l(\rho_j)\right)^2}, \quad \rho_i, \rho_j \in \Theta,\ i \neq j. \tag{24}$$

(iv) The set convergence η is used to judge the steadiness of the Pareto-optimal solution:

$$\begin{aligned} m &\in M, \\ n &\in N, \\ \chi &= 0, \end{aligned} \tag{25}$$

where M is a set of solution in the present iteration and N is the solution set in the last iteration, if $n = m$, then $\chi = \chi + 1$.

$$\eta = \frac{\chi}{|M|}. \tag{26}$$

In other words, if $\eta \geq \upsilon$, the Pareto-optimal solution set is stable and the algorithm reaches approximately termination.

4. Case Study

4.1. Study Area. In this paper, the Nanya River tributary (NY) and Donggu River tributary (DG) of the Dadu River basin were studied and the computational experiments were carried out. As shown in Figure 6, the Ganzi region of Sichuan province is rich in water resources. Through the case study, the validity and practicability of the proposed model and developed algorithm can be verified.

4.2. Related Data. The data used in this paper were mainly obtained from Sichuan statistical yearbook and local field researches. The random electricity demand is obtained by the proposed method in the part of uncertainty treatment, which is based on historical data from Guodian Sichuan Power Generation Corporation and investigation of the basin of Nanya River and Donggu River. The electricity demand fitting function is obtained by the predictive model, and the coefficient of determination $R^2 = 0.984$. It can be seen that the prediction model has a good goodness of fit and higher prediction accuracy. In addition, the distribution of the fitted and historical values is given in Figure 7(a), and the prediction difference is small. In order to make the prediction more in line with the actual situation, the frequency distribution of the error value of the predicted value is given in Figure 7(b). The error value accords with a random normal distribution with a mean of −0.0768 and a standard deviation of 11.36282. Therefore, the electricity demand prediction equation $\overline{D}(t)$ can be expressed by the sum of the fitting function, and the error value and forecasting error random distribution function $g(\varepsilon)$ are as follows:

$$\begin{aligned} &\overline{D}(t) = [(3310.015t + 9340.584) * 0.006 + 40.499 + g(\varepsilon)] \times 10^8, \\ &g(\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_V} \exp\left(-\frac{(\varepsilon - \mu)^2}{2\sigma_V^2}\right), \quad \text{where } \mu = -0.0768, \sigma_V = 11.363. \end{aligned} \tag{27}$$

In this paper, two tributaries are used to make calculation experiment, where $i = 1$ for NY river tributary ands $i = 2$ for DG river tributary. In each tributary, there are five generation types $(j = 1, 2, 3, 4, 5)$.

It is assumed that fixed operation and management cost CF_{ij}, investment cost CB_{ij}, variable operation and management cost $\widetilde{\mathrm{CV}}_{ij}$, pumping cost CP_{ij}, and migration initial cost CI_{ij} are unchanged in the planning period $t = 1, 2, \ldots, 25$. Tables 3–5 displays the detail parameters.

5. Results and Discussion

5.1. Results. The improved algorithm is calculated by software MATLAB7.0, which runs on 3.50-GHz Intel Core with 4.00 GB memory. The algorithmic parameters that is adapted for the case problem are set as follows: iteration_max $T = 150$, swarm_size $S = 50$, inertia weight-max $\omega^{\max} = 0.8$, inertia weight-min $\omega^{\min} = 0.4$, and the accelerate constants of velocity $c1 = 0.79$ and $c2 = 0.48$. After the MOAPSO algorithm is iterated for 150 times, the iteration termination can achieve 8 runs in an average of 5 minutes; thus, the running time of the algorithm is reasonable.

The confidence level reflects the degree of acceptance of risk by decision-makers. Table 6 gives the optimization results of the decision model with confidence levels between

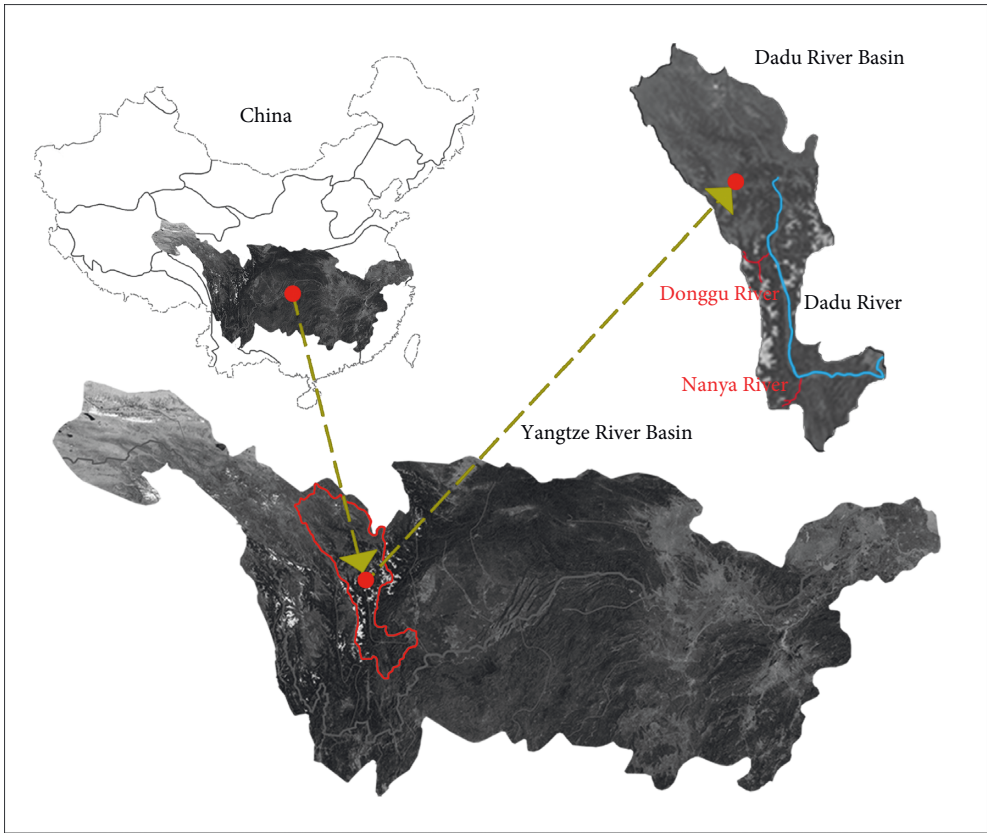

Figure 6: Location of Nanya River and Donggu River.

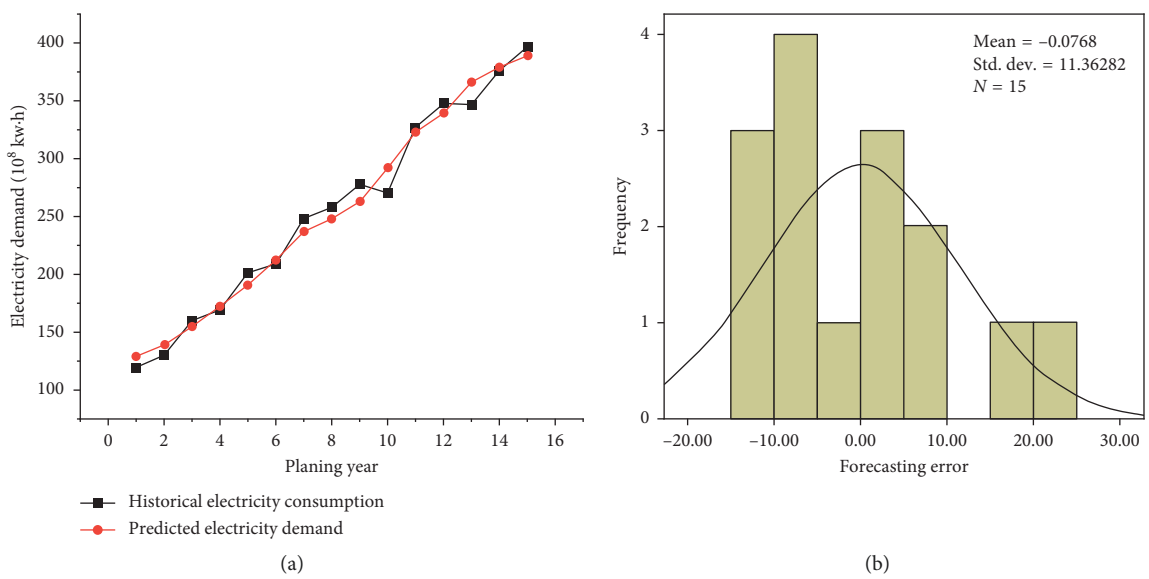

Figure 7: Comparison of predicted and historical values and distribution of error values.

0.75 and 0.9, respectively (i.e., $0.75 \leq \gamma_1, \gamma_2 \leq 0.9$). As shown in Table 6, with the continuous improvement of the confidence level, the accuracy requirements for the forecast of electricity demand and the description of variable cost are continuously improved and the investment income is reduced. And the risk of the decision model is gradually reduced. In actual operation, different decision levels can be selected for investment decisions based on the decision-maker's tradeoffs between risks and benefits. If investors are not willing to take too much risk (i.e., increasing the level of confidence), then investors will reduce the range of fluctuation in electricity demand and the range of variable costs, while reducing investment returns. Conversely, if investors pursue risk-returns (reducing confidence levels), then the

Table 3: Parameters for the investment cost of the hydropower station.

Index		Parameter				
		CF (yuan/kw)	CB (yuan/kw)	$\widetilde{CV}$ (10^7yuan/kw)	CP (yuan/kw)	CI (yuan/kw)
$j = 1$	$i = 1$	187.45	6996.22	(2.15, 2.41, 2.68)	0.013	610.2
	$i = 2$	205.82	6996.22	(2.15, 2.41, 2.68)	0.013	610.2
$j = 2$	$i = 1$	378.39	14270.05	(2.15, 2.41, 2.68)	0.013	610.2
	$i = 2$	415.85	14270.05	(2.15, 2.41, 2.68)	0.013	610.2
$j = 3$	$i = 1$	378.41	14270.71	(7.87, 8.27, 8.67)	0.013	610.2
	$i = 2$	415.87	14270.71	(7.87, 8.27, 8.67)	0.013	610.2
$j = 4$	$i = 1$	266.3	10000	(3.22, 3.31, 3.40)	0.013	610.2
	$i = 2$	292.57	10000	(3.22, 3.31, 3.40)	0.013	610.2
$j = 5$	$i = 1$	266.3	10000	(3.22, 3.31, 3.40)	0.013	610.2
	$i = 2$	292.57	10000	(3.22, 3.31, 3.40)	0.013	610.2

Table 4: Parameters of power generation and investment.

Parameters	Δt (h)	λ_s (t/kw·h)	λ_c (t/kw·h)	CE (yuan/t)	k (%)	p (yuan)	α	C
Value	5000	0.000997	0.00082	0.02	4.35	0.20847	0.8	0.008

Table 5: Parameters of river basin generation investment.

Index	Parameters		
	W (10^7 kw·h)	F (10^9 yuan)	$E(R)$ (%)
$i = 1$	2.335	6.535	8.529
$i = 2$	1.145	3.0	8.666

Table 6: Nondominating solution target value interval under different confidence levels.

Interval of target value	$\gamma_1 = \gamma_2 = 0.75$	$\gamma_1 = \gamma_2 = 0.80$	$\gamma_1 = \gamma_2 = 0.85$	$\gamma_1 = \gamma_2 = 0.90$
Investment cost (10^{11} yuan)	[2.117, 3.420]	[2.234, 3.093]	[2.185, 3.140]	[2.128, 2.936]
Investment benefit(10^{10} yuan)	[1.123, 1.882]	[1.177, 1.826]	[1.066, 1.717]	[1.192, 1.649]
Immigrant cost (10^9 yuan)	[0.909, 1.342]	[0.881, 1.292]	[0.901, 1.235]	[0.893, 1.215]
Environment efficient(10^7 kg)	[1.660, 2.451]	[1.741, 2.360]	[1.647, 2.255]	[1.631, 2.220]

demand for electricity will predict the range of fluctuations and variable costs will increase, while increasing investment returns and environmental benefits.

When the confidence level $\gamma_1 = \gamma_2 = 0.75$, the model nondominating solution set (i.e., hydropower investment scale combination) has 14 solutions. The details are shown in Tables 7 and 8. In addition, Figure 7 shows the nondominating values of 4 objective functions of investment decision-makers represented by hydropower developers. Among them, the No. 14 solution is the scheme of the lowest initial investment cost and the lowest resettlement cost. Compared with other schemes, No. 14 scheme has the minimal financial pressure for the company, but its corresponding income is lower among the 14 schemes. At the same time, the No. 5 solution is the best solution for investment income and environmental benefits. It is the solution that can bring the best benefits to the company in 14 schemes. Decision-makers can choose plans according to their decision-making preferences. If the decision-maker prefers the return on investment and can withstand the corresponding financial pressure, then Pareto-optimal solution 5 in Figure 8 can be selected, and vice versa. If the company's funding cost pressure for plan 5 is unacceptable, the corresponding plan can be selected among the remaining noninferior solutions according to the financial pressure that can be accepted by itself.

Although there are random and fuzzy variables in the established model, the theory of random and fuzzy is used to convert them into equivalent values in this paper; therefore, the decision results will not be affected.

5.2. Comparative Analysis and Discussion

5.2.1. Worthiness of Model and Solutions. In this paper, a comprehensive optimization model of hydropower investment portfolio is established, which combines objectives with constraints. Then, the multiobjective decision-making model is adopted to determine the optimal solution set for the proposed model and provides a more effective Pareto-solution set. For instance, if the decision-maker pursues the maximization of the return on investment, the nondominating solution 5 can be chosen. According to Figure 8, it can be seen that the nondominating solution 14 represents the scheme of the lowest investment costs and lower immigration costs and the Pareto solution 5 is expressed as the

Table 7: Nondominating hydropower stations investment number.

Hydropower	1		2		3		4		5		6		7		8		9		10		11		12		13		14		15	
Station type	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG	NY	NY
I	7	5	6	2	5	2	8	0	7	6	6	2	7	2	8	1	5	1	9	3	5	3	5	3	7	1	7	5	6	2
II	3	4	8	10	10	0	1	6	3	0	1	9	9	6	8	8	4	9	8	5	6	4	0	3	6	5	2	2	7	7
III	6	6	10	4	9	8	9	7	3	7	3	5	0	6	2	10	9	2	1	0	10	3	5	8	0	3	6	6	4	7
IV	2	3	7	8	8	1	7	7	2	8	6	1	6	9	6	9	2	9	9	2	6	6	9	2	1	1	5	6	8	1
V	6	2	9	6	7	3	6	10	7	3	1	0	2	1	8	4	3	8	7	9	2	4	6	7	5	8	2	3	9	10

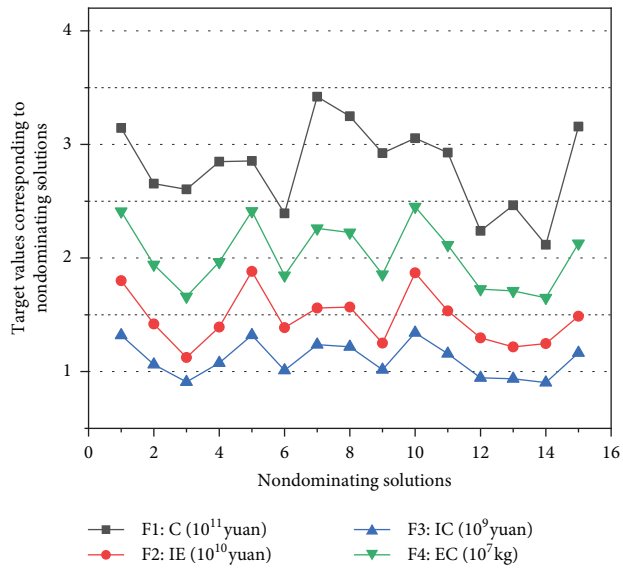

Figure 8: Nondominating values of four objective functions.

Table 8: Nondominating hydropower stations install capacity (MW).

Hydropower station type	1		2		3		4		5	
	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG
I	2431	1275	2261	1798	1308	1786	1936	1410	2490	1608
II	1076	810.2	377	392	910.3	831	967	1030.0	1180	664.1
III	285.1	143.4	99.6	102.3	112.8	236.2	233.2	180.3	281.7	130.7
IV	24.44	15.76	30.19	47.83	22.47	49.23	26.85	47.64	29.05	17.00
V	4.004	9.976	9.011	9.051	9.550	5.208	1.655	1.965	0.378	7.412
Hydropower station type	6		7		8		9		10	
	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG
I	2389	2141	1794	1481	1761	2394	1886	2367	2158	2018
II	837.7	462.6	867.1	798	1097.0	390	761.0	778.6	398.4	776.8
III	268.7	68.4	295.9	297.3	99.7	100.5	270.3	155.7	191.8	288.6
IV	26.45	21.44	32.95	47.56	26.89	25.04	19.64	45.80	35.10	16.90
V	1.029	2.533	9.968	2.504	7.671	7.476	0.926	2.546	3.578	0.907
Hydropower station type	11		12		13		14		15	
	NY	DG	NY	DG	NY	DG	NY	DG	NY	DG
I	2312	2166	2267	2064	1814	1420	1378	1441	1929	1965
II	802.3	468.5	923.7	595.8	460.7	1067.9	832.8	311.7	1071	624.5
III	296.0	162.9	255.9	290.7	243.0	259.3	216.8	231.3	165.3	54.84
IV	21.33	34.49	24.50	41.12	15.05	11.89	42.22	38.57	36.57	25.11
V	0.441	8.527	8.822	6.065	0.506	9.365	6.180	3.349	1.939	0.127

portfolio option with the highest environmental benefits. Compared with the traditional multiple target weighted sum method, the solution provided by this method can better reflect the preference of decision-makers, so the model proposed in this paper is more applied.

The fuzzy stochastic programming approach specifically takes the uncertainty environment into account, and the risk acceptance degree of decision-makers is considered by the model to make the model more realistic. For example, if the decision-making is risk averse, the values of γ_1 and γ_2 can be reduced. On the contrary, if the decision-maker is risk-biased, the value of preference coefficient can be adjusted to between 0.5 and 1, the specific values could depend on the degree of preference of the decision. Although the application of the method will increase the complexity of modelling to some extent, the model has been widely used in practical decision-making. Therefore, it is valuable to apply CCP to modelling and solve fuzzy stochastic problems.

5.2.2. Effectiveness of Algorithm. The quality of the multiobjective optimization solution is more complicated than single objective optimization. Four performance indexes and the number of solutions are discussed in order to describe the validity of Pareto-optimal solutions more deeply. Figure 9 displays the assessment result of Pareto-optimal solution performance indicators after operation.

The standard multiobjective PSO and improved algorithm are compared in this paper. In the proposed

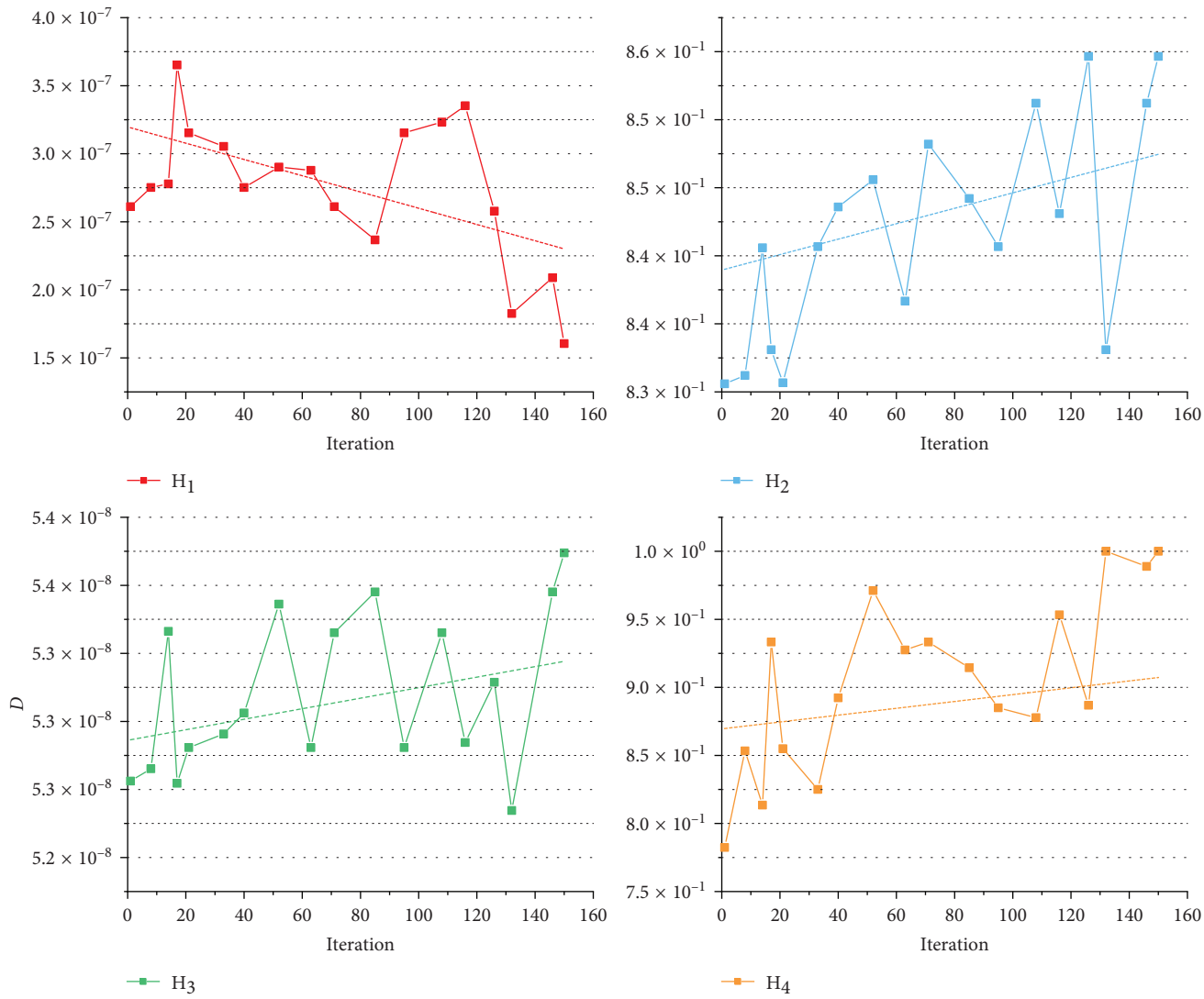

Figure 9: Assessment result of nondominating solution performance.

Table 9: Performance comparison of MOAPSO and basic PSO.

Algorithm type	Iteration	H_1	H_2	H_3	H_4	Solution amount
MOAPSO	150	1.54×10^{-7}	0.780	4.99×10^{-8}	1	15
PSO	150	1.90×10^{-7}	0.773	2.89×10^{-8}	1	12

MOAPSO, the solution represented by the particle associates the PSO particle with the solution of the problem and combines the hybrid update mechanism with the updation of inertia weight and velocity acceleration constants to successfully improve the particle search ability. As is shown is Table 9, the developed algorithm is an effective mean to solve the problem compared with the standard algorithm.

6. Conclusions

In order to improve hydropower investment efficiency and maximize comprehensive benefits, this paper studies the portfolio optimization problem in hydropower station construction and development under hybrid uncertain environment. Under the orientation of the goal of optimizing the comprehensive benefit of investment, a comprehensive model was proposed to obtain the optimal combination of hydropower investment scale. Furthermore, a MODM model for hydropower investment portfolio optimization was initially established. As random and fuzzy parameters exist in the established model, a CCP approach that considers the risk preference of decision-makers is introduced, which makes the model better applied to the actual uncertain decision-making process. Subsequently, based on random and fuzzy theory, it is equivalently converted into a crisp model. Furthermore, the MOAPSO algorithm is designed to solve the problem. At the same time, combined with the advanced Pareto-optimal solution judgment criteria, the quality of particle solutions is

further discussed. Finally, an example is given to illustrate the existence of the problem. The results of the example verify the value of the model and verify the solution and the efficiency of the algorithm and parameters. Based on this process, the following conclusions can be drawn:

(1) The proposed comprehensive optimization model is theoretically effective and reasonable and can be used to improve the comprehensive benefits of hydropower investment portfolios.

(2) Considering the uncertain environment in the model, a CCP model describing the acceptor's acceptance is established, which can make the hydropower combined optimization model closer to the actual situation.

(3) The result of the optimization model is calculated by MOAPSO. The MOAPOS algorithm and the standard PSO algorithm are evaluated and compared by using four evaluation indicators. The result shows that MOAPSO can be used to solve HIP problems effectively, which can provide nondominated solution sets with faster convergence and uniform distribution.

(4) Through the established model and the use of MOAPSO, the four objectives of minimum initial investment, maximum investment returns, minimum resettlement costs, and maximum environmental benefits are contradictory. That is to say, with the reduction of migration and initial investment costs, investment benefits and environmental benefits are reduced, and vice versa.

This paper is original. Nevertheless, there are still some fields that need further study. First, a more detailed and full description of the objective functions such as resettlement cost is necessary. Secondly, the proposed model in this paper only involves the construction and operation phases, so the costs and benefits of the demolition phase of the hydropower station planning period can be incorporated into the investment decision for a more comprehensive investment. Finally, in order to get a better and more efficient solution with shorter computation time and less memory, some alternative methods and algorithms can be explored, such as genetic algorithm, ant colony algorithm, and coevolution algorithm. These areas are fully significant and equally worthy of research.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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