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# Improved Memetic Algorithm for Economic Load Dispatch in a Large Hydropower Plant

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## Abstract

This paper is intended to study the method of solving the economic load dispatch problem (ELDP) of hydropower plants via using memetic algorithm. Based on characteristics of economical operation of the hydropower plant, this paper proposes an improvement method of mutation operator and selection operator of memetic algorithm. Taking Three Gorges hydropower station in China as an example, the performance of memetic algorithm before and after improvement is tested separately. The test result shows that the average water consumption for simulation of the improved memetic algorithm is less than that for simulation of the standard memetic algorithm by 1.35%–16.19%. When the total load of the hydropower station is low (8GW–10GW), the water consumption for the improved memetic algorithm is less than that for the standard memetic algorithm by more than 10%. When the total load of the hydropower station is high (11GW–16GW), the water consumption for the improved memetic algorithm is less than that for the standard memetic algorithm by more than 1%. This shows that improvement of mutation operator and selection operator can improve the global and local optimization capacity of memetic algorithm a lot indeed. In addition, by comparing the optimization result of memetic algorithm with that of DP algorithm, it finds that the optimization result of improved memetic algorithm can reach the same precision of optimization result of DP algorithm. Therefore, using the improved memetic algorithm to solve the ELDP problem of large hydropower stations is practical and feasible. Since “curse of dimensionality” may occur frequently while using DP algorithm to solve the ELDP problem of large hydropower plants, as a new heuristic algorithm, memetic algorithm has obvious advantages in solving large-scale, complex, highly-dimensional and dynamic problems.

**Keywords:** economic load dispatch problem, Three Gorges hydropower station, memetic algorithm

## 1. Introduction

All the time, humans are inspired from the nature and discover many natural laws by observing and thinking natural phenomena. People have obtained abundant inspirations for solving various problems based on these natural laws and their own

thoughts [1]. In 1975, Holland proposed a stochastic optimization algorithm by reference to the natural law of “survival of the fittest” in the biosphere and the algorithm was called genetic algorithm (GA) later [2]. Although the genetic algorithm has a strong global optimization capacity, it has many defects [3]. For example, the genetic algorithm searches the whole objective group but only converges to one optimal solution finally. To improve the addressing efficiency, the genetic algorithm does not search all populations and individuals, causing failure to explore the whole available space. Hence, diversity of populations is lost and finally GA cannot find out the real optimal solution correctly but can only find out the relatively optimal solution [4]. In 1989, Moscato proposed to combine global search based on population with local heuristic search based on individual, so as to prevent insufficient search scope of genetic algorithm and prematurity of the algorithm [5, 6]. This is the primary design concept of memetic algorithm (MA). At first, the memetic algorithm was regarded as improvement of genetic algorithm and therefore was called “hybrid genetic algorithm” [7, 8]. With continuous research, the memetic algorithm has been developed into a general evolutionary algorithm framework consisting of global search strategy and local search strategy [9, 10].

Within the framework, great improvement space exists in the memetic algorithm. For a specific problem, a memetic algorithm suitable for the problem can be constructed flexibly [11–13]. During construction of the memetic algorithm, on the basis that the global search strategy of genetic algorithm is reserved, the researcher generally proposes an improvement scheme of local zone search strategy based on the problem characteristics, so as to construct various memetic algorithms. For example, Yeh [14] developed a memetic algorithm by combining a genetic algorithm and the greedy heuristic using the pairwise exchange method and the insert method, to solve the flowshop scheduling problem. Boughaci et al. [15] proposed an improved memetic algorithm by using a stochastic local search (SLS) component combined with a specific crossover operator. The resulting algorithm is proved to be able to solve the optimal winner determination problem in combinatorial auctions. Zou [16] solved the traveling salesperson problem (TSP) by using an improved memetic algorithm. The algorithm applies multiple local search strategies and each search operator executes with a predefined probability to increase the diversity of the population, so as to ensure a higher search efficiency of the algorithm. Castro et al. [17] proposed a new memetic algorithm for solving the traveling salesperson problem (TSP) with hotel selection. Using tabu search algorithm and individual neighborhood information as the meta-heuristics search algorithm and genetic algorithm as the global search strategy may obtain several feasible schemes in one time. In fact, the memetic algorithm has achieved a very good application effect in solving the scheduling problem in material distributing and supply chain management [18–20].

In recent years, the memetic algorithm attracts more and more attention from researchers of other industries and the algorithm achieves considerable development with continuous efforts of many researchers [21–24]. Ammaruekarat and Meesad [25] proposed an improved multi-objective memetic algorithms (MOMAs) for solving the multi-objective decision problem. This paper proposes a new iterative search strategy—Chaos Search and uses it as the local search strategy of the memetic algorithm. Combining with Chaos theorem, the efficiency of solving the multi-objective decision problem will be improved a lot and good results are achieved. Özcan et al. [26] developed an Interleaved Constructive Memetic Algorithm (ICMA), and successfully applied ICMA for Timetabling problems with complicated and challenging structures. In addition, the memetic algorithm is also frequently applied to the neural network training algorithm. O’Hara and Bull [27] and Abbass [28] use the memetic algorithm to train the neural network separately and believe that the effect of neuron network training with the memetic algorithm

is better than that with the traditional method. Bonfim and Yamakami [29] not only use the memetic algorithm to train the neural network system, but also use it for Parallel Machine Scheduling, both which have achieved good effects.

Economical operation of hydropower plants is a very complex multi-objective optimization difficulty [30, 31]. Using traditional methods such as equal increment and dynamic programming for solving the problem cannot achieve perfect results [32, 33]. Especially for large hydropower stations, “curse of dimensionality” may occur frequently while using the dynamic programming algorithm for unit load dispatch, causing that load dispatch cannot meet the requirement of real-time control or the load cannot be dispatched at some times [34]. Three Gorges hydropower station in China is the hydropower plant with the largest installed capacity in the world at present; 32 units of seven types are installed; the capacity of single unit is 700,000 kW; and the total installed capacity is up to 22,400,000 kW. Although the generating capacity per unit is the same, the output character of unit is quite different due to different manufacturer of the unit [35]. Thus, using the simplified generating efficiency function to describe the generating character of all units is improper. Similarly, expressing the generating efficiency as the linear function of head will cause a big difference between the calculation result and actual operation condition [36].

Taking Three Gorges hydropower station in China (the largest hydropower station in the world) as an example, this paper studies the modeling method of economical operation model of Three Gorges hydropower station and proposes a method of using memetic algorithm to solve load dispatch and real-time scheduling of generating unit of Three Gorges hydropower station. On this basis, this paper refers to the optimization idea of differential evolution algorithm, further optimizes the solving process of ELDP problem and improves the memetic algorithm. The structure of residual parts of this paper is as follows: introduce the economical operation model of hydropower plant at first, introduce dynamic programming suitable for solving of the model, describe the standard memetic algorithm and its improvement method, use the memetic algorithm for solving of economical operation model of hydropower plant, compare the performance of memetic algorithm with that of dynamic programming, and discuss the possibility of application of memetic algorithm to the ELDP problem of hydropower plant. At last, this paper gives conclusions and looks forward to the application prospect of memetic algorithm.

## 2. Methodology

### 2.1 Formation of ELDP problem of hydropower plant

The ELDP problem of hydropower plant means that when the required load of system (the daily load chart is given generally in short-term economical operation) is determined, the consumed power discharge of the whole hydropower plant shall be the minimum, so as to obtain the maximum economic benefit of the hydropower plant [37]. For the economical operation model of hydropower plant, the minimum power discharge is the objective. The objective function and constraint conditions of the ELDP problem of hydropower plant are as follows:

Objective function:

$$\min Q = \sum_{i=1}^n q_i(N_i, H) \quad (1)$$

Load balancing constraint:

$$\min Q = \sum_{i=1}^n q_i(N_i, H) \quad (2)$$

Constraint of operation condition zone of unit:

$$0 \leq N_i \leq NH_i, \text{ and } N_i \notin [\underline{N}_{i,j}, \overline{N}_{i,j}], j \in \Omega_i(H) \quad (3)$$

Where,  $Q$  is the total power discharge;  $n$  is the number of units;  $q_i(\bullet)$  is the power discharge of unit  $i$  ( $\text{m}^3/\text{s}$ );  $N_i$  is the output of unit  $i$  (MW);  $H$  is the average head of time periods (m);  $Nd$  is the required load of power grid (MW);  $NH_i$  is the expected output of unit  $i$  (MW);  $\Omega_i(H)$  is the set of vibration zones of unit  $i$ ;  $\overline{N}_{i,j}$  and  $\underline{N}_{i,j}$  are the upper and lower limits of vibration zone  $j$  of unit  $i$  at the given head  $H$  respectively (MW).

It should be noted that the unit of hydropower plant will break through the constraint of unit operation condition inevitably during operation and operate in the restricted operation zone or even in the forbidden operation zone. If the unit operates in the restricted operation zone for a long time, the flow passage components will be damaged; the output and efficiency will be reduced; and noise and strong vibration of unit will be caused. In severe cases, longitudinal cracks will occur on the dam, endangering safety of the hydropower station and surrounding areas. To meet actual demands, not only the restriction of expected output of unit but also the requirements of avoiding unit cavitation zone/vibration zone are considered in the constraint of unit operation condition zone in the above model. In the optimization algorithm design later in this paper, the study will apply the penalty function method to handle the output-flow relation curve of unit cavitation zone/vibration zone, so as to make the unit avoid the unsafe operation zone as far as possible during load dispatch.

## 2.2 Solution approaches

### 2.2.1 Dynamic programming (DP): A review

Dynamic programming method is a classic and mature optimization algorithm. It regards the ELDP problem of hydropower plant as a multi-stage decision problem and has no restrictions on that whether the unit model is the same. In addition, the number of operating units, combination of units, load and corresponding water consumption of each unit can be obtained as well as the globally optimal solution [38]. The dynamic programming algorithm is used to solve the ELDP problem of hydropower plant. Details of the variable definition, constraint handling and solving process are as follows:

#### 2.2.1.1 Stage variable and state variable

The serial number  $i$  of generator unit is the stage variable while the cumulative output of  $i$  units ( $\sum_{t=1}^i N_t$ ) is the state variable.

The step size of state discretization is  $dN$  and the cumulative output is subject to state discretization as per the following formula:

$$Ns_{i,j} = \begin{cases} \min \left\{ j \cdot dN, \sum_{t=1}^i NY_t, Nd \right\}, & \text{when } i \neq n \\ Nd, & \text{when } i = n \end{cases} \quad (4)$$



Where,

$$j = 0 \sim \text{int} \left[ \min \left\{ \sum_{t=1}^i NY_t, ND \right\} / dN \right] + 1$$

$NS_{ij}$  is the state variable value at stage  $i$  and state  $j$ ;  $NY_t$  is the installed capacity of unit  $t$ ; and  $\text{int}[\cdot]$  is the Gauss rounding function.

### 2.2.1.2 Constraint handling

While using the penalty function to handle the output condition constraint of unit, consider that the objective function of penalty quantity at stage  $I$  ( $f_i(N_i, H)$ ) is as follows:

$$f_i(N_i, H) = q_i(N_i, H) + \Delta q_i + \Delta qp_i \quad (5)$$

$$\Delta q_i = \alpha_1 \cdot INF, \Delta qp_i = \alpha_2 \cdot INF \quad (6)$$

Where,

$$\alpha_1 = \begin{cases} 1 & N_i \in [N_{ij}, \overline{N_{ij}}], \exists j \\ 0 & N_i \notin [N_{ij}, \overline{N_{ij}}], \forall j \end{cases} \quad (7)$$

$$\alpha_2 = \begin{cases} 1 & N_i \in (-\infty, 0) \cup (NH_i, +\infty) \\ 0 & N_i \in [0, NH_i] \end{cases} \quad (8)$$

Where,  $\Delta q_i$  is the penalty term of constraint of operation condition zone and  $\Delta qp_i$  is the penalty term of constraint of output definition domain.  $\alpha_1$  and  $\alpha_2$  are the penalty coefficients and  $INF$  is the maximum.

### 2.2.1.3 State transition and state traversal

Using  $N_i$  as the decision variable, the state transition equation can be written as follows:

$$\sum_{t=1}^i N_t = \sum_{t=1}^{i-1} N_t + N_i \quad (9)$$

Recurrence equation:

$$Q_i^* \left( \sum_{t=1}^i N_t \right) = \min \left\{ f_i(N_i, N) + Q_{i-1}^* \left( \sum_{t=1}^{i-1} N_t \right) \right\} \quad (10)$$

Where,  $Q_i^* \left( \sum_{t=1}^i N_t \right)$  is the optimal cumulative power discharge in the remaining period.

### 2.2.2 Memetic algorithm

Local search is the root cause that the memetic algorithm is better than the genetic algorithm. Through local search, the search depth of the algorithm for the

solution space is increased a lot, further improving the solution quality. In this paper, the memetic algorithm using simplex optimization method for local search operation is called standard memetic algorithm. In the following, we will introduce how to use the memetic algorithm to solve the ELDP problem of hydropower plant and give emphasis on the improvement method of standard memetic algorithm for the ELDP problem of hydropower plant.

### 2.2.2.1 Standard memetic algorithm (SMA)

For the ELDP problem of hydropower station, the memetic algorithm applies integer encoding and establishes a corresponding relation between encoding and cumulative output value of unit. Details of encoding of memetic algorithm, initial population generation method, definition of fitness function and its main operators are as follows:

#### 2.2.2.1.1 Gene encoding

The cumulative output of  $i$  units ( $\sum_{t=1}^i N_t$ ) is defined as genes. Based on Formula (4) for discrete units with discrete step length defined as  $dN'$ , the genes are encoded as  $p_{k,i} = 0 \sim \left\lceil \min \left\{ \sum_{t=1}^i NY_t, Nd \right\} / dN' \right\rceil + 1$  to represent the element sequence of  $Ns_{i,j}$ .

The cumulative output of  $i$  units is decoded as  $Ns_{i,p_{k,i}}$  ( $k = 1 \sim Pop, i = 1 \sim n, Pop$  stands for population and  $n$  stands for number of units).

#### 2.2.2.1.2 Initial population generation

The linear constrained elimination method is used to generate the genes in reverse order under the conditions of load balance and output domain constraints.

When the cumulative output of  $i$  units is known as  $\sum_{t=1}^i N_t$ , then  $p_{k,i} = \text{int} \left\lceil \sum_{t=1}^i N_t / dN' \right\rceil$ .

The state transition equation (9) can be re-written as:

$$\sum_{t=1}^{i-1} N_t = \sum_{t=1}^i N_t - N_i \quad (11)$$

When the output feasible region constraint of unit  $N_i \in [0, NY_i]$  is integrated into Formula (11), then:

$$\sum_{t=1}^{i-1} N_t \in \left[ \sum_{t=1}^i N_t - NY_i, \sum_{t=1}^i N_t \right] \quad (12)$$

As the output is bound to be smaller than the installed capacity, i.e.  $N_t \in [0, NY_t]$ , to integrate it into Formula (11):

$$\sum_{t=1}^{i-1} N_t \in \left[ 0, \sum_{t=1}^{i-1} NY_t \right] \quad (13)$$

The common solution to Formulas (12) and (13) can satisfy the requirement for output domain, then:

$$\sum_{t=1}^{i-1} N_t \in \left[ \max \left\{ \sum_{t=1}^i N_t - NY_i, 0 \right\}, \min \left\{ \sum_{t=1}^i N_t, \sum_{t=1}^{i-1} NY_t \right\} \right] \quad (14)$$

Making  $\underline{Ntmp} = \max \left\{ \sum_{t=1}^i N_t - NY_i, 0 \right\}$ ,  $\overline{Ntmp} = \min \left\{ \sum_{t=1}^i N_t, \sum_{t=1}^{i-1} NY_t \right\}$ , the generating approach for gene  $p_{k,i-1}$  is expressed as:

$$p_{k,i-1} = \text{int} \left[ \underline{Ntmp} / dN' \right] + \text{int} \left[ Rnd \cdot \left( \text{int} \left[ \overline{Ntmp} / dN' \right] - \text{int} \left[ \underline{Ntmp} / dN' \right] \right) \right] \quad (15)$$

Where,  $Rnd$  indicates a random number evenly distributed in the interval  $[0,1]$ .

Given load balance  $\sum_{i=1}^n N_i = Nd$ , the reverse recursion of Formulas (14) and (15) from the last gene is performed to obtain individuals that satisfy output domain and load balancing constraints.

#### 2.2.2.1.3 Fitness function

According to the objective function, the fitness formula is constructed:

$$Fitness = \frac{INF}{\sum_{i=1}^n f_i \left( Ns_{i,p_{k,i}} - Ns_{i-1,p_{k,i-1}}, H \right)} \quad (16)$$

#### 2.2.2.1.4 Crossover operator

For  $Pop$  individuals initially generated, select two individuals as per the preset crossover probability for crossover operation and generate a new generation of group (two new individuals).

$$X_1^{new} = \omega_1 \cdot X_1 + (1 - \omega_1) \cdot X_2 \quad (17)$$

$$X_2^{new} = \omega_2 \cdot X_2 + (1 - \omega_2) \cdot X_1 \quad (18)$$

$X_1$  and  $X_2$  are two parent individuals selected from the population at random;  $X_1^{new}$  and  $X_2^{new}$  are new offspring individuals generated by crossover operation; and  $\omega_1$  and  $\omega_2$  are parameters selected from  $[0,1]$  at random.

#### 2.2.2.1.5 Mutation operator

Among new individuals generated by crossover operation, select several individuals as per a certain mutation probability and conduct mutation operation as per the mutation operator in the following formula:

$$V'_{ij} = \begin{cases} X_{ij} + (b_{sup} - X_{ij}) \left[ r \cdot (1 - t)^2 \right], & sign = 0 \\ X_{ij} - (X_{ij} - b_{inf}) \left[ r \cdot (1 - t)^2 \right], & sign = 1 \end{cases} \quad (19)$$

Where,  $X_{ij}$  is the component  $j$  of selected mutation individual  $X_i$ ;  $V'_{ij}$  is the individual after mutation;  $sign$  is 0 or 1 at random;  $b_{sup}$  and  $b_{inf}$  are the upper and lower limits of parameters respectively;  $r$  is the random number from  $[0,1]$ ; and  $t$  is the population evolution mark and  $t = g_c / G_{max}$ , where  $g_c$  is the current evolution algebra of population while  $G_{max}$  is the maximum evolution algebra of population.



#### 2.2.2.1.6 Selection operator

Select *Pop* excellent individuals from the current population, make them have the chance to be selected to the next iteration process, and abandon individuals with low fitness. The probability of each individual to be selected is in direct proportion to its fitness and the selection probability is as shown in Formula (20):

$$p'_i = \frac{\frac{1}{f_i}}{\sum \frac{1}{f_i}} \quad (20)$$

#### 2.2.2.1.7 Local search operation

The simplex method is used for local search operation, namely, for the convex polyhedron consisting of  $n + 1$  peaks ( $X_1, X_2, \dots, X_n, X_{n+1}$ ) in  $n$ -dimensional space, calculate function values of  $n + 1$  peaks and confirm the worst peak  $X_w$ , secondary bad peak  $X_s$  and optimal peak  $X_b$  and the centroid  $X_m$  of all points other than the worst peak in the simplex:

$$X_m = (X_1 + X_2 + \dots + X_n + X_{n+1} - X_w)/n \quad (21)$$

Then, calculate the reflection point  $X_r$  passing  $X_m$  and  $X_w$ :

$$X_r = X_m + (X_m - X_w) \quad (22)$$

There are three possible conditions for the reflection point:

- If  $X_r$  is better than  $X_b$ , calculate the extension point  $X_c$  along the reflection direction,  $X_c = X_m - \alpha \cdot (X_m - X_w)$ , where,  $\alpha > 1$  is the extension coefficient. If  $X_c$  is better than  $X_b$ , use  $X_c$  to replace  $X_w$  and generate a new simplex; or use  $X_r$  to replace  $X_w$  and generate a new simplex.
- If  $X_r$  is worse than  $X_b$  but not worse than  $X_s$ , use  $X_r$  to replace  $X_w$  and generate a new simplex.
- If  $X_r$  is worse than  $X_s$ , it indicates that  $X_r$  is too far and it shall be compressed along directions of  $X_r$  and  $X_m$ . Making  $X_h$  be the relatively optimal point between  $X_r$  and  $X_w$ , calculate the compression point  $X_c$ ,  $X_c = X_m - \beta \cdot (X_h - X_m)$ , where,  $0 < \beta < 1$  is the compression coefficient. If  $X_c$  is not worse than  $X_h$ , use  $X_c$  to replace  $X_w$  and generate a new simplex. Or conduct compression of simplex, namely, use  $X$  as the base point and cut the initial simplex into a half.

In all the above conditions, the new simplex must have a peak better than certain peak of the initial simplex; the simplex is subject to reflection, extension and compression through circulation; and the search process may converge to certain locally optimal solution or may be completed till meeting the termination condition.

#### 2.2.2.2 The improvement to SMA (improved MA, IMA)

Differential Evolution Algorithm is also an effective technique to solve complex optimization problems, which is widely used in the fields of parameter optimization, neural network training, robot, energy and so on [39–42]. The Differential Evolution Algorithm in essence is a kind of greedy genetic algorithm based on real

number encoding with the idea of guaranteeing optimality, which solves the optimization problems through the cooperation and competition among individuals in the population [43]. In this paper, the optimization idea of Differential Evolution Algorithm is used for reference to improve the mutation operators and selection operators of Standard Memetic Algorithm (SMA). The improvement methods for the mutation operators and selection operators of SMA are as follows:

#### 2.2.2.2.1 Improvement to mutation operator

In differential evolution, the mutation operation uses the linear combination of multiple individuals in the parent population to generate new individuals, of which the most standard mutation component is the difference vector of the parent individual. For any target individual  $X_i$  in the parent population, the mutation individual  $V_i$  is generated according to the formula (23):

$$V_i = X_{r_1} + F(X_{r_2} - X_{r_3}), i = 1, 2, \dots, Pop \quad (23)$$

Where,  $\{X_{r_1}, X_{r_2}, X_{r_3}\}$  are three different individuals randomly selected from the parent population, and  $r_1 \neq r_2 \neq r_3 \neq i$ , in which  $F$  is the zoom factor and the value range is  $[0, 2]$ , which is used to control the influence of the difference vector  $(X_{r_2} - X_{r_3})$ .

#### 2.2.2.2.2 Improvement to selection operator

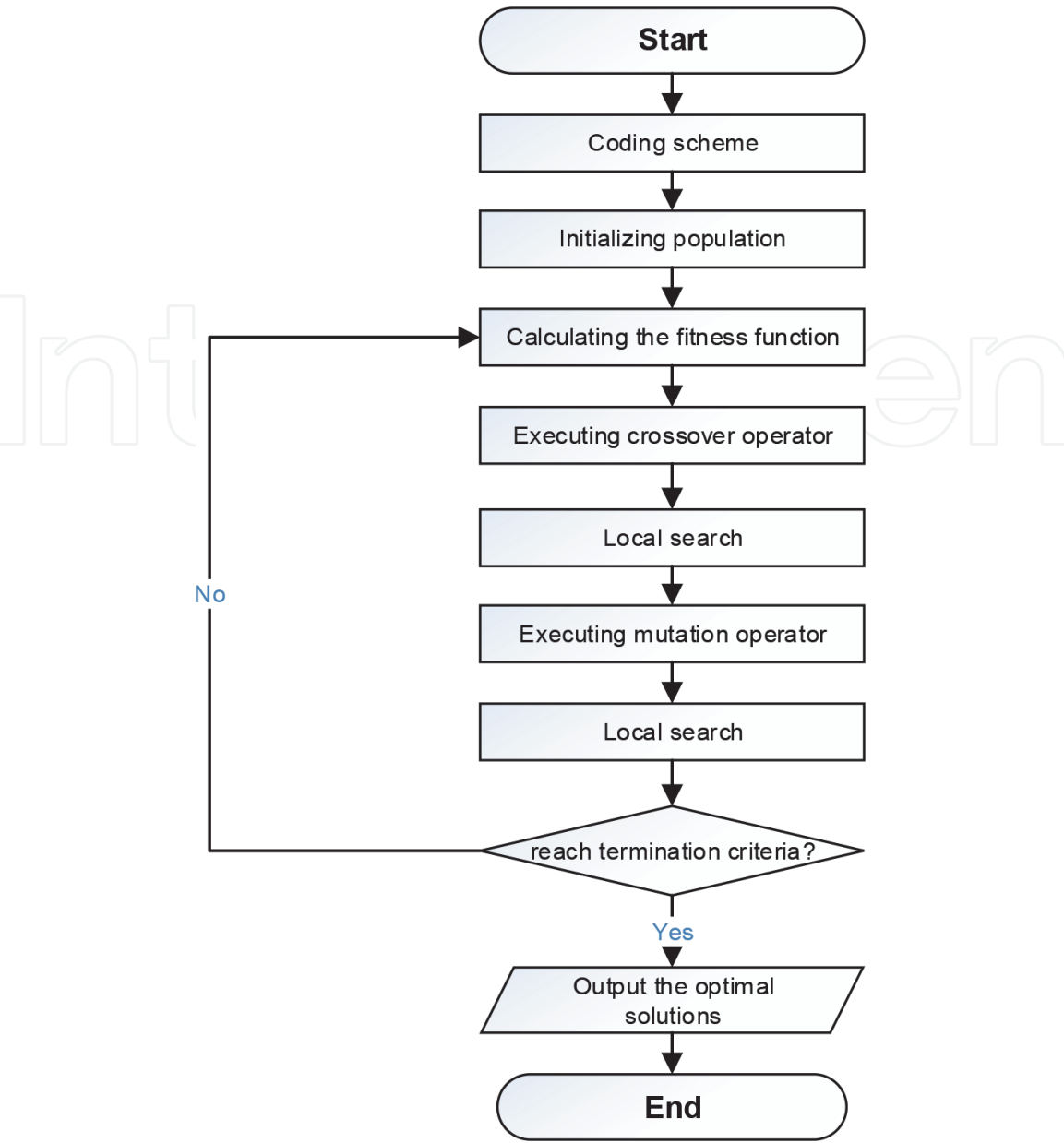
The “greedy” selection method [44] is adopted in the selection operation, and  $V_i$  is accepted by the population if and only if the fitness value of the new vector individual  $V_i$  is better than that of the target vector individual  $X_i$ . Otherwise,  $X_i$  will remain in the next generation population and continue to perform mutation and crossover operations as the target vector in the next iterative computation. For the minimization problem:

$$X_i^{t+1} = \begin{cases} V_i & f(V_i) < f(X_i^t) \\ X_i^t & \text{Other} \end{cases} \quad (24)$$

The selection operation is the one-to-one competition between the parent individuals and the newly generated candidate individuals to select the superior and eliminate the inferior, so that the offspring individuals are always superior to or equal to the parent individuals and thus the population can always evolve towards the optimal solution.

#### 2.2.2.3 Workflow of memetic algorithm

**Figure 1** shows the flow diagram of the Memetic Algorithm. The execution steps of the Memetic Algorithm are as follows: ① to determine the coding scheme of the problem and set the relevant parameters; ② to initialize the population; ③ to execute the crossover operator; ④ to use the local search algorithm to conduct neighborhood search for individuals, and update all individuals. ⑤ To execute the mutation operator to generate new individuals. ⑥ To use the local search algorithm to conduct neighborhood search for individuals again, and update all individuals. ⑦ To calculate the fitness value of all individuals in the population through the fitness function. ⑧ To execute the selection operator for the population screening as per the natural law of “survival of the fittest” to abandon the individuals with poor fitness and retain the individuals with high fitness. ⑨ To determine whether the



**Figure 1.**  
Flow diagram of the memetic algorithm.

termination conditions are met. To determine whether the optimization criteria or the termination conditions of the algorithm have been met; if met, terminate the operation, otherwise continue to execute step ③.

### 3. Experiment, results and analysis

#### 3.1 Experimental setup

The Three Gorges Hydropower Station is equipped with 14 generating units on the left bank and 12 on the right bank. Currently, 26 units of the power plants on the left and right banks have been automatically put into the power grid operation. The configuration of these units in the Three Gorges Hydropower Station is shown in **Figure 2**. Those 26 units can be classified into 5 categories: # 1 - # 3 and # 7 - # 9 are VGS; # 4 - # 6 and # 10 - # 14 are ALSTOM I; # 15 - # 18 are ORIENTAL I; # 19 - # 22 are ALSTOM II; and # 23 - # 26 are HARBIN. The output curves of the five types of units differ greatly. The unit output curves are shown in **Figure 3**.

Under the operating condition that the head of Three Gorges Hydropower Station is at 108 m, the unit load distribution performance of Memetic Algorithm before and after the improvement are tested in this paper. The overall water consumption of the hydropower station is mainly analyzed in the circumstance that the power grid load is increased step by step from 8GW to 16GW and the load distribution is carried out as per the unit load distribution results by Memetic Algorithm. Whether the algorithm performance is good or bad is determined by analyzing the water consumption under a given load. And it is believed that the smaller the total water consumption, the better the algorithm load distribution results, and the better the algorithm performance. In this analysis, 26 units that are automatically put into the power grid operation are taken as the research object in this paper, and the result of the DP algorithm is used as the benchmark for comparison.

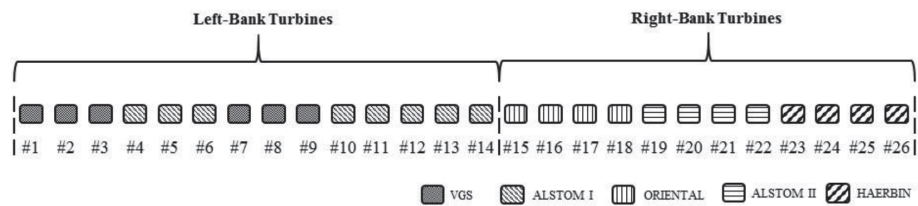
The population size of the Memetic Algorithm is set to be 100, then the cross-over probability  $P_c = 0.6$ , the mutation probability  $P_m = 0.5$ , the penalty factor  $\lambda = 4000$ , and the maximum generation  $G_{\max} = 300$ . Considering that the Memetic Algorithm is a stochastic optimization algorithm, the solution has a certain degree of uncertainty. In order to eliminate the influence of the randomness of initial solution on the calculation results, two kinds of Memetic Algorithms before and after the improvement are used in this paper to respectively carry out 10 operations for each load level, from which the best results are selected as the final optimal solution, and the average value of the operation results is used as the final result for analysis.

### 3.2 Results and analysis

For the nine load levels of 8GW, 9GW, 10GW, 11GW, 12GW, 13GW, 14GW, 15GW and 16GW, the load distribution schemes of the Memetic Algorithm before improvement (SMA) and of the Improved SMA (ISMA) are used respectively to calculate the total water consumption of 26 generating units of the Three Gorges Hydropower Station, which is shown in **Figure 4**.

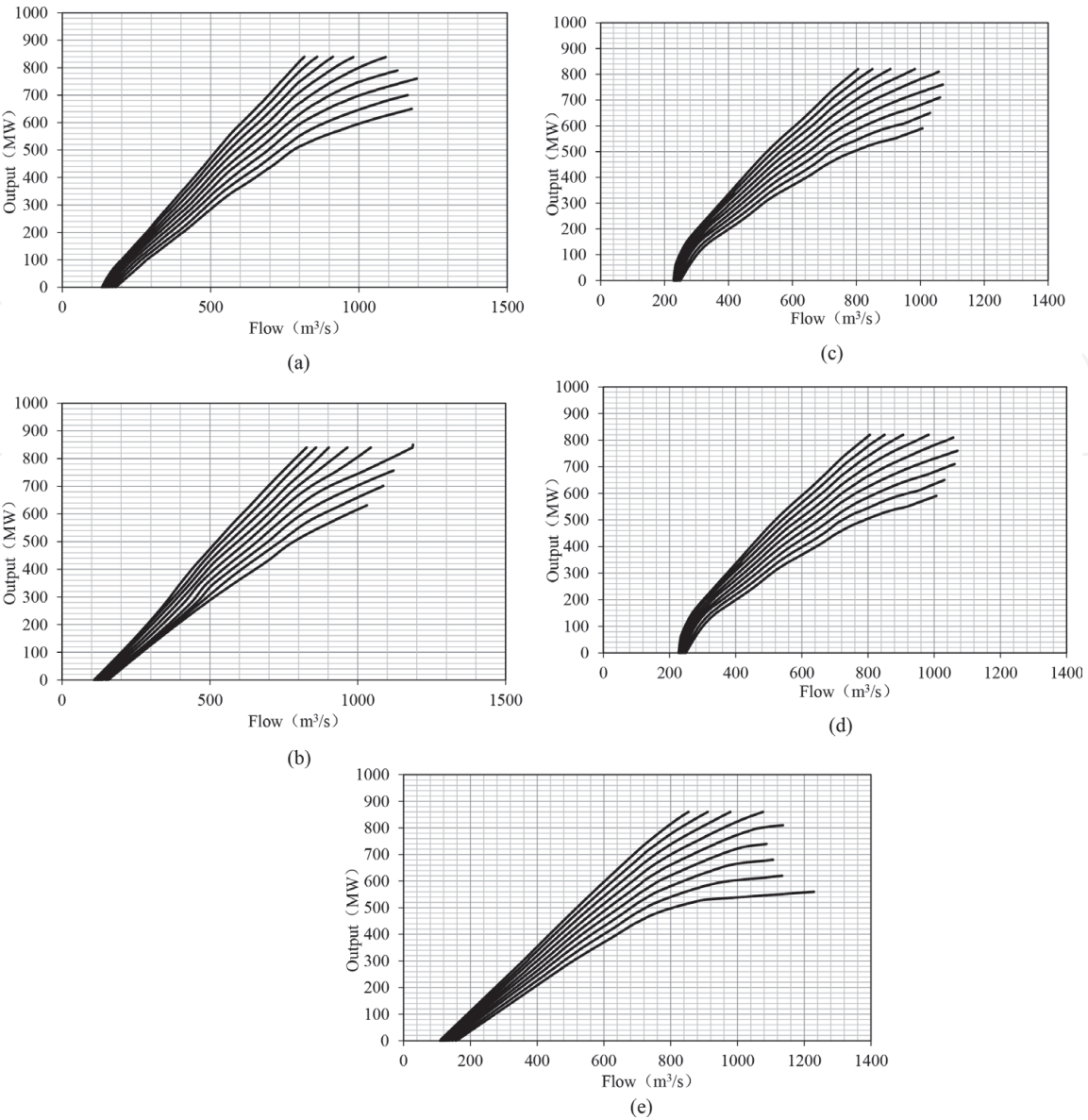
It can be seen from **Figure 4** that with the increase of the total load of the hydropower station, the total water consumption of the hydropower station is always on the rise no matter whether the load distribution scheme of the Standard Memetic Algorithm (SMA) or of the improved Memetic Algorithm (ISMA) is adopted. However, on the whole, the average water consumption in the improved Memetic Algorithm is always lower than that of the standard Memetic Algorithm, which shows that the improved Memetic Algorithm reduces the water consumption rate of power generation and improves the utilization efficiency to water resources. **Figure 5** shows the reduction of the water consumption of the Three Gorges Hydropower Plant by ISMA compared with that by SMA.

It can be seen from **Figure 5** that the average water consumption for simulation of the improved Memetic Algorithm is less than that for simulation of the standard Memetic Algorithm by 1.35%–16.19%. The improved Memetic Algorithm saves more than 10% of the water consumption compared with the standard Memetic Algorithm when the total load of the power station is relatively low (8GW-10GW)



**Figure 2.**  
*Layout of generating units on the left and right banks of the Three Gorges Hydropower Plant.*



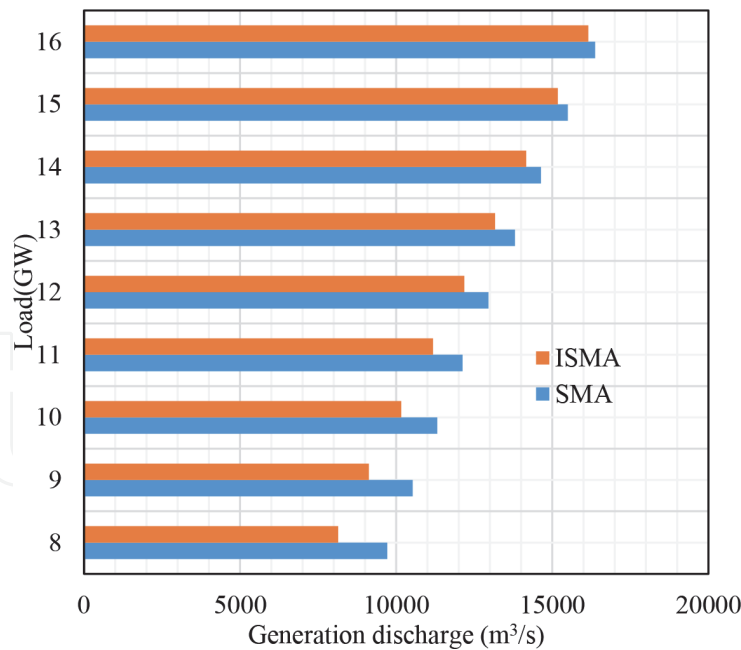


**Figure 3.** Output curve graphs of the five types of units of the Three Gorges Hydropower Plant (head at 70–110 m, variation interval of water level at 5 m). (a) VGS. (b) ALSTOM I. (c) ORIENTAL. (d) ALSTOM II. (e) HAERBIN.

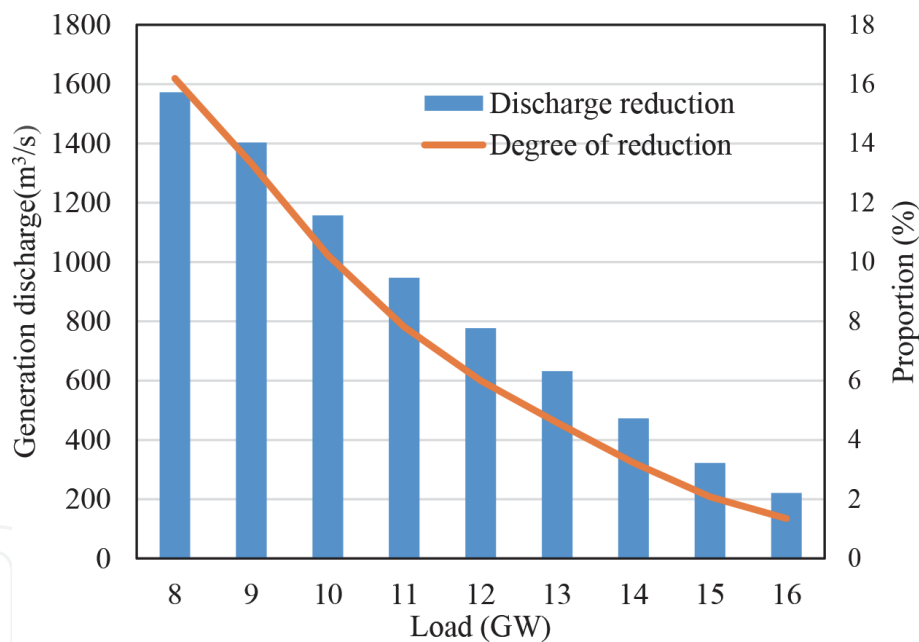
and also saves more than 1% of water consumption when the total load of the power station is relatively high (11GW-16GW). This shows that the Memetic Algorithm which improves the mutation operation and the selection operation enhances the global and local optimization capacities of the Memetic Algorithm.

In order to further compare the performances of the two algorithms, the evolutionary processes of the two algorithms at the total load of the Three Gorges Hydropower Station of 8GW, 10 GW, 12GW and 14 GW are analyzed in this paper, which is shown in **Figure 6**. As shown in **Figure 6**, the optimal water consumption obtained by the Standard Memetic Algorithm stimulation decreases in smaller range with the increase of the evolution algebra; the optimal water consumption obtained by the improved Memetic Algorithm stimulation decreases obviously with the increase of the evolution algebra, which shows that the improved Memetic Algorithm can perform an effective global search at the early stage of evolution and make the individuals in the population move closer to the globally optimal solution quickly, compared to which the Standard Memetic Algorithm has a weak global searching ability.



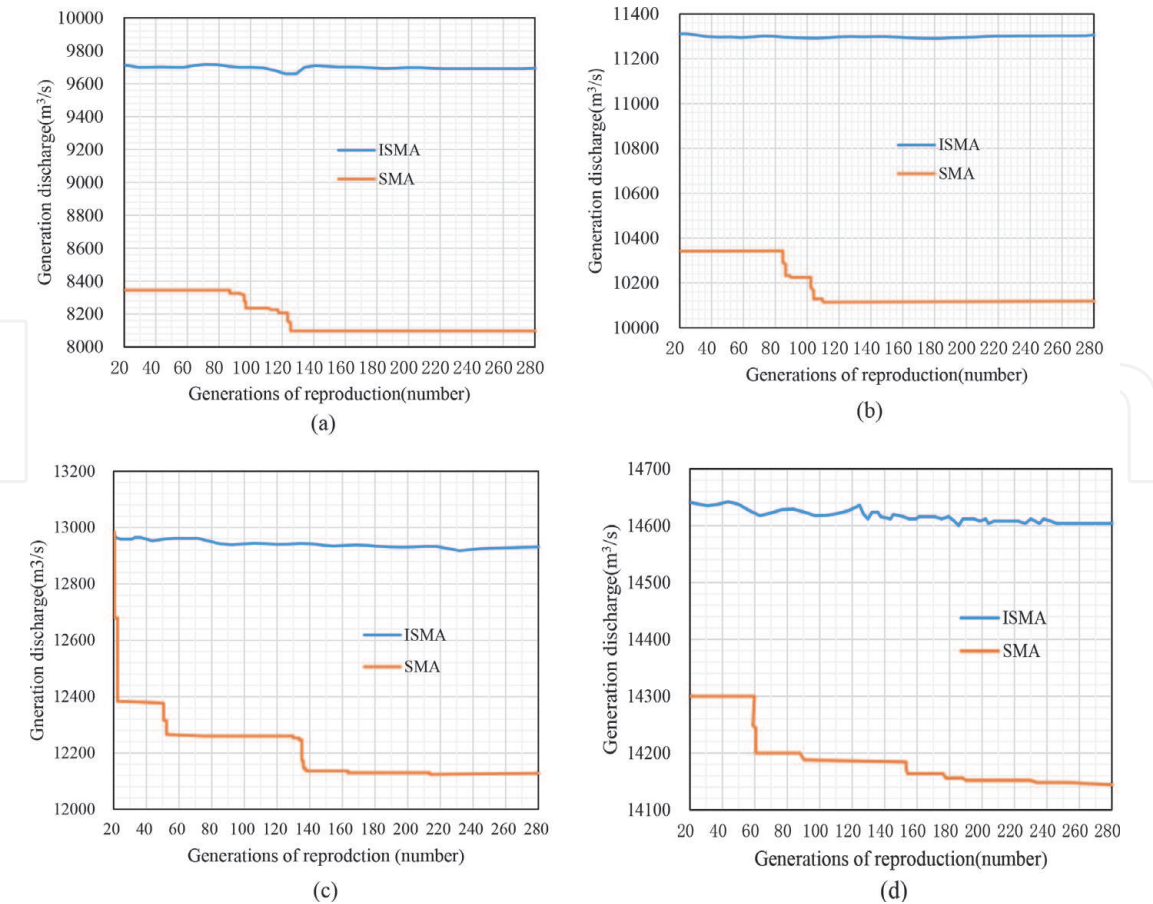


**Figure 4.**  
Total water consumption of the Three Gorges Hydropower Station under the load distribution carried out respectively as per SMA and ISMA calculation schemes.

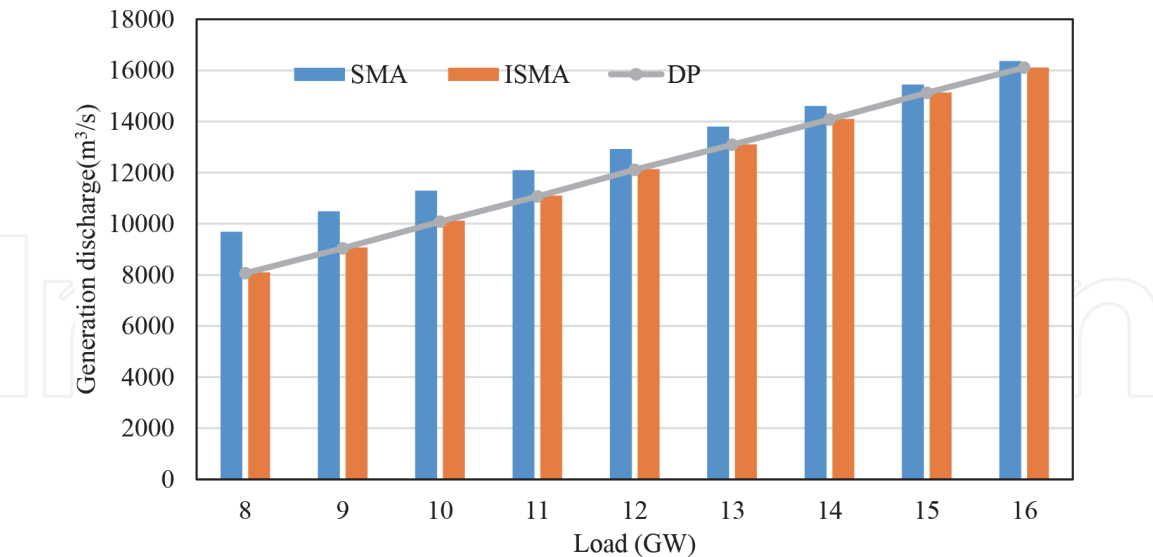


**Figure 5.**  
Analysis of performance improvement degree of ISMA compared with that of SMA.

In this paper, the optimal simulation results of the two Memetic Algorithms are compared with the DP optimization results under the same load discrete interval. See **Figure 7** for the comparison results. As can be seen from **Figure 7**, the optimization result of the improved Memetic Algorithm is almost identical with the DP calculation accuracy, while the result of the Standard Memetic Algorithm stimulation is poorer, which shows that compared with the Standard Memetic Algorithm, the improved Memetic Algorithm can effectively search the globally optimal solution. The comparison results indicate that it is feasible to use the improved Memetic Algorithm to solve the problem of economic operation in a large hydropower station.



**Figure 6.** Evolutionary processes of SMA and ISMA. (a) At the load of 8GW. (b) At the load of 10GW. (c) At the load of 12GW. (d) At the load of 14GW.



**Figure 7.** Diagram of comparison between the optimal simulation results of the two memetic algorithms and the optimization results of DP algorithm.

4. Conclusion and discussion

Through the in-depth study of biology, scientists gradually find that individuals in the nature behave in a simple manner and with very limited ability, but when they work together, what they show is not a simple superposition of individual capabilities but very shocking and complex behavior characteristics. Inspired by

this, scientists are paying more and more attention to the study of swarm intelligence algorithm, which also includes the study of the Memetic Algorithm. The combination of excellent global searching ability and fast local searching ability can produce enormous energy, therefore, the Memetic Algorithm has been paid more and more attention and has been recognized by more scientists. With the continuous in-depth study, Memetic Algorithm has not only improved the genetic algorithm but also has developed into a loose framework of the optimization algorithm.

In order to solve the problem of economic operation in hydropower plant, a new Memetic Algorithm is presented in this paper. Through the combination with the local search strategy, the Memetic Algorithm not only inherits the global optimization capacity of genetic algorithm itself, but also greatly improves the local searching ability of the algorithm by locally adjusting the new individuals generated by evolution. The framework and operational process similar with that of the genetic algorithm are used in Memetic Algorithm, but the Memetic Algorithm has an additional local search optimization process after crossover and mutation. Memetic Algorithm fully absorbs the advantages of genetic algorithm and local search algorithm and adopts the operational process of genetic algorithm, but after each crossover and mutation, local search is carried out, where the bad population will be removed early by optimizing the population distribution, thus reducing the iterations and speeding up the rate of convergence of the algorithm.

Taking China Three Gorges Hydropower Station, the largest hydropower station in the world, as an example, this paper studies the method of using Memetic Algorithm to solve the problem of economic operation in hydropower plant. The experiment result shows that it is feasible to use the Memetic Algorithm to solve the problem of economic operation in a large hydropower station. The experiment result also shows that the Memetic Algorithm improved by the idea of differential evolution demonstrates a better load distribution performance when compared with that before improvement. When the total load of the hydropower station is relatively low (8GW-10GW), the water consumption for the improved Memetic Algorithm is less than that for the standard Memetic Algorithm by more than 10%. When the total load of the hydropower station is relatively high (11GW-16GW), the water consumption for the improved Memetic Algorithm is also less than that for the standard Memetic Algorithm by more than 1%. This shows that the improvement of mutation operation and selection operation can greatly enhance the global and local optimization capacity of Memetic Algorithm.

As an intelligent algorithm of high efficiency, Memetic Algorithm has obvious advantages in solving large-scale, complex, high-dimensional and dynamic problems. However, the Memetic Algorithm needs a lot of improvements, for example, how to choose global search operators and local search operators, how to determine the control parameters such as population size, crossover probability and mutation probability, etc. All of these problems need to be further improved. In the future research work, the emphasis will be focused on the following aspects for in-depth study: ① How to further optimize the Memetic Algorithm framework to make the algorithm more flexible. ② To carry out in-depth study for the key control parameters to find out the setting rules of the control parameters. ③ To apply the optimized Memetic Algorithm to a wider field.

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