Improved Whale Algorithm for Economic Load Dispatch Problem in Hydropower Plants and Comprehensive Performance Evaluation

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Abstract
A novel method for economic load dispatch problem (ELDP) based on improved whale optimization algorithm (IWOA) is presented, and the optimization performance of IWOA in ELDP was evaluated comprehensively. The search mechanism is modified to improve the ability of the algorithm to jump out of the local optimal. The adaptive nonlinear inertia weight is introduced to improve the convergence speed of the algorithm. A limited mutation mechanism is proposed to improve the convergence of the algorithm. The evaluation indicator of calculation time and calculation accuracy was established. Taking 26 units of the Three Gorges Hydropower Station as an example, limited adaptive genetic algorithm (LAGA), particle swarm optimization (PSO), whale optimization algorithm (WOA) and improved whale optimization algorithm (IWOA) were used to solve ELDP. The result shows that IWOA is superior to other algorithms in calculation results of various heads and loads. The calculation accuracy of IWOA was better than WOA when the number of units turned on was more than 6. The analysis results of IWOA and DP show that the calculation time of IWOA is better than that of DP when the number of units turned on is more than 6. The IWOA and the evaluation indicators proposed in this paper provide a new way for solving ELDP of large hydropower stations.

Keywords Economic load dispatch problem · Whale optimization algorithm · Adaptive inertia weight · Limited mutation mechanism · Evaluation indicator

1 Introduction

Hydropower station plays an important role in the connection between water resource and electricity (Pereira-Cardenal et al. 2016), and peak shaving in the power grid is usually carried out by hydropower stations (Feng et al. 2018). Therefore, the economic load dispatch
problem (ELDP) of hydropower plants is of great significance to economic development and the stable operation of the power system (Wu et al. 2015; Chang et al. 2017). The main purpose of ELDP is to minimize the water consumption of the hydropower unit by distributing the load to different units under a fixed total load (Cheng et al. 2000). In fact, ELDP is a multidimensional nonlinear problem because the operation of hydropower stations is limited by various constraints. The non-convex structure of this problem is one of the most difficult optimization problems, and it is difficult to obtain the global optimal solution.

At present, there are two categories of methods to solve the ELDP, one is traditional mathematical method, the other is heuristic algorithm (Xu et al. 2014). Traditional mathematical method include the Lagrange Relaxation (LR) (Li et al. 2013), linear programming (LP) (Nemati et al. 2018; Amani and Alizadeh 2021), nonlinear programming (NLP) (Catalao et al. 2009), dynamic programming (Shang et al. 2018) and quadratic programming (McLarty et al. 2019). The mathematical method is mature and has been used in many engineering applications. However, this traditional method has strict formulae and can only be used to solve non-convexity objective function (Zhang et al. 2010). For ELDP with non-convex objective function, the mathematical method is difficult to find the optimal solution (Secui 2015). With the increase of generator size and constraints, the phenomenon of “curse of the dimensionality” is inevitable (Zhao et al. 2012).

Instead, heuristic algorithms have been widely used to solving ELDP because of its strong robustness. Heuristic algorithms include genetic algorithm (GA) (Shang et al. 2017), particle swarm optimization (PSO) (Yuan et al. 2008), chicken swarm optimization (CSO) (Li et al. 2018), ant colony algorithm (ACO) (Vaisakh and Srinivas 2011), and bee colony optimization (Lu et al. 2015). However, genetic algorithm has low convergence rate in solving multi-constraint problems and has no advantage compared with novel heuristic algorithms. The performance of PSO and CSO deteriorates sharply when it is used to solve high dimensional problems (Zhai et al. 2020; Wu et al. 2016). Therefore, there are also many studies to improve the heuristic algorithm. Gholamghasemi et al. (2019) applied the phase particle swarm optimization algorithm (PPSO) to a large-scale units and successfully applied it to different types of ELDP. Younes and Benhamida (2011) proposed a GA-PSO hybrid algorithm, which improved the convergence accuracy and greatly shortened the running time.

In general, heuristic algorithm has gradually replaced traditional mathematical methods with its advantages of high precision and high efficiency. The improved algorithm improves the optimization effect and attracts more and more attention. However, the convergence, stability and dependence on more parameters of the heuristic algorithm are common problems (Bahos et al. 2011). Because of this, whale optimization algorithm (WOA) with strong optimization ability and less parameter dependence is proposed and applied to various research fields (Mirjalili and Lewis 2016). There are also many improvements to WOA proposed for solving different problems. Global contraction probability is adopted to ensure the global optimization capability of the algorithm in the late iteration (Tian et al. 2020; Yang and Yang 2021). Nonlinear adaptive weights are used to improve the speed of optimization (Zhang and Wang 2020). Therefore, an improved whale optimization algorithm (IWOA) is proposed in this paper to solve ELDP in this paper. The search mechanism of whale algorithm is improved, adaptive nonlinear inertia weight is introduced, and a limited mutation mechanism is proposed.

There are many kinds of algorithms proposed for ELDP, but there is no unified evaluation system. The previous literatures are only comparative results, which is not comprehensive.
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Shang et al. (2017) constructed evaluation indicator of algorithm time efficiency and calculation accuracy, but lacked evaluation of algorithm optimization ability. In this paper, IWOA algorithm is applied to the Three Gorges Hydropower station, and a series of evaluation indicators are constructed to prove the performance of the algorithm. The results of IWOA are compared with many heuristic algorithms, and the results show that IWOA algorithm is effective and feasible.

The rest of this paper is organized as follows: Sect. 2 introduces the constraints and formulation of the ELDP; Sect. 3 introduces the basic concept of the method of solving the ELDP and the structure of evaluation indicators; Sect. 4 takes Three Gorges Hydropower Station as an example for case application; Sect. 5 analyzes the calculation results; Finally, conclusions are drawn in Sect. 6.

2 Methodology

2.1 The Economic Load dispatch Problem Formulation

2.1.1 Objective Function

The goal of economic load dispatch problem of hydropower station is to minimize water consumption, and the objective function is as follows:

\[
Q = \text{Min} \sum_{i=1}^{I} q_i(p_i, H) + f_i(p_i, H)
\]

(1)

\[
f_i(p_i, H) = \sum_{p_i \notin R} M_1 * q_i(p_i, H) + \sum_{p_i \in R} M_2 * (\sum_{i=1}^{I} p_i, H - P)^2
\]

(2)

where Q denotes the total water consumption of the power station corresponding to the total load P; \(q_i(p_i, H)\) denotes the water consumption of unit i under output \(p_i\) and head H; I denotes the total number of units; \(f_i(p_i, H)\) denotes the penalty value if the total load of the unit does not meet the total load constraint, or the unit I does not meet the unit safety operation zone constraints; P denotes the total load requirement; \(M_1\) and \(M_2\) represent the parameters of the penalty function respectively; R denotes unit stable operation region.

2.1.2 Constraints

(1) Total load constraint

\[
P = \sum_{i=1}^{n} p_i
\]

(3)

where P denotes the total load requirement; \(p_i\) denotes output of the ith turbine.

(2) Output constraint
where $N_{i,\text{min}}$ and $N_{i,\text{max}}$ represent the lower and upper output limit of the $i$th turbine, respectively.

(3) Unit safety operation zone constraints

\[ N_{i,j,\text{low}} \leq p_i \leq N_{i,j,\text{up}} \quad j = 1, 2, 3 \ldots, n_k \]  

where $N_{i,j,\text{low}}$ and $N_{i,j,\text{up}}$ represent the upper and lower limits of the $j$th safe operation zone of turbine $I$, respectively; $n_k$ denotes the number of safe operating zones of the turbine.

2.2 Solution Method

2.2.1 Dynamic Programming

The DP is used to solve the ELDP. The output of the turbine needs to be discretized with equal step length, and the turbine number is regarded as a stage variable. The formula of dynamic programming includes the state transfer equation and the recursive equation. The formula is as follows:

(1) The state transfer equation:

\[ \sum_{i=1}^{I} p_i = \sum_{i=1}^{I-1} p_i + p_I \]  

where $\sum_{i=1}^{I} p_i$ represents the total load of the previous $I$ turbines; $p_I$ represents the load of the turbine opened at stage $I$.

(2) The recursive equation:

\[ Q_s(\sum_{i=1}^{I} p_i) = \min_{p_i \in R} \left\{ q_i(p_i, H) + Q_s(\sum_{i=1}^{I-1} p_i) \right\} \]  

where $Q_s(\sum_{i=1}^{I} p_i)$ represents the minimum total water consumption of all turbines when the total load is $\sum_{i=1}^{I} p_i$; $q_i(p_i, H)$ refers the water consumption of the new startup unit at stage $i$; $R$ is unit stable operation region.

2.2.2 Traditional WOA

The optimization method of WOA is to simulate the predation process of humpback whale. Traditional WOA algorithm has three optimization methods. The first method is encircling prey: the whale with the highest fitness in the population is selected as the target, and all the whales move closer to the target at a faster rate. This method makes the algorithm close to the current optimal value quickly and improves the convergence speed of the algorithm. The second method is the bubble-net attacking method: when all the whales are close to the solution with the highest fitness, a part of the whales choose this method, which can spiral
search the surrounding space of the current solution and improve the convergence accuracy of the algorithm. The third method is search for prey: a whale is randomly selected as the target in the population, and then all the whales approach the target. This method can make the algorithm search in a large range, but also can make the algorithm away from the local optimal. Mathematical models are established as follows:

(1) Encircling Prey

\[ X(t+1) = X^*(t) - A \cdot D \]  
\[ D = |C \cdot X^*(t) - X(t)| \]  
\[ A = 2a \cdot r - a \]  
\[ C = 2 \cdot r \]  
\[ a = 2 - 2 \cdot t/T \]  

where \( X^*(t) \) represents the best location when the number of iterations is \( t \); \( X(t) \) represents the current location of the individual when the number of iterations is \( t \); \( r \) is random numbers between 0 and 1; \( T \) is the maximum number of iterations.

(2) Bubble-Net Attacking Method

\[ X(t+1) = D \cdot e^b \cdot \cos(2\pi l) + X^*(t) \]  
\[ D = |X^*(t) - X(t)| \]  

where \( D \) represents the difference between the current location and the best location; \( b \) is control parameters; \( l \) is random numbers between \(-1 \) and \( 1 \).

(3) Search for Prey

\[ X(t+1) = X_{\text{rand}} - A \cdot D \]  
\[ D = |C \cdot X_{\text{rand}} - X(t)| \]  

where \( X_{\text{rand}} \) is an individual chosen at random. If \( A \geq 1 \), all the whales will move toward \( X_{\text{rand}} \).

2.2.3 Methodology of IWOA

(1) Improved Search for Prey.

The three predation behaviors of WOA interact with each other. If the weights of the encircling prey and the bubble-net attacking method are significant, the algorithm will be precocious. If the weight of the search for prey is significant, the optimization ability of the algorithm will be reduced. So how to balance these three methods is very important to improve the algorithm. For the traditional WOA, when \( t \) is greater than \( 2/M \), the method of search for prey will be abandoned. Therefore, the algorithm will lose the ability to jump
out of the local optimum in the late iteration. This paper improves the condition of search theory. The formula is as follows:

\[ k = k_{\text{min}} - (k_{\text{max}} - k_{\text{min}}) \left( \frac{t}{T} \right) \]  

(17)

where \( k \) is search for prey probability; \( k_{\text{max}} \) and \( k_{\text{min}} \) are the maximum and minimum values of parameter \( k \), respectively. Each iteration of the algorithm will generate a random number \( p \) from 0 to 1. If \( p < 0.5 \), the value of parameter of A determines whether to search for prey. Otherwise, calculate parameter \( k \) according to Eq. (16) and the algorithm conducts the search for prey when \( p \geq q \). This method improves the shortcoming of WOA which loses the global optimization ability in the late iteration.

(2) Adaptive Nonlinear Inertia Weight.

Adaptive nonlinear inertia weight is a commonly used method to improve the algorithm. Therefore, an adaptive nonlinear inertial weight is proposed to balance the early mining capability and the later optimization capability of the algorithm in this paper. The formula is as follows:

\[ w = w_{\text{max}} - (w_{\text{max}} - w_{\text{min}}) \left( \frac{t}{T} \right)^{1/t} \]  

(18)

\[ X(t+1) = \begin{cases} 
X^*(t) - w \cdot A \cdot D & p < 0.5 \\
 w \cdot D \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & p \geq 0.5
\end{cases} \]  

(19)

Where \( w_{\text{max}} \) and \( w_{\text{min}} \) are the maximum and minimum values of the parameter \( w \); \( X(t+1) \) represents the location of the individual when the number of iterations is \( t+1 \); \( X^*(t) \) represents the best location when the number of iterations is \( t \). 

(3) Limited Mutation Mechanism.

The improved strategy mentioned above can make IWOA converge to the better solution quickly. However, all the populations in the late iteration of the algorithm meet the load constraint. If the optimization continues, the load will be changed, but the total load will not meet the load constraint, so that the algorithm loses the ability of local optimization. To this end, a limited mutation mechanism was introduced. The mechanism applies a small range of random disturbances to the two units, which have the same size and opposite direction. Because the sum of the load of the two changes is 0, it not only meets the load balancing requirements, but also enables the algorithm to continue to search for optimization. The limited mutation mechanism formula is as follows:

1) When the output of the unit is not 0:

\[ \begin{cases} 
 p_{t+1}^{l,j} = p_{t,j}^{l} + r_1 \ast E \\
 p_{t+1}^{l+r_2,j} = p_{t,j}^{l} - r_1 \ast E \\
 1 \leq t + r_2 \leq G_T
\end{cases} \]  

(20)
where $p_{t,j}^{i,t}$ and $p_{t+1,j}^{i,t}$ are the output of unit $i$ of unit $j$ at time $t$ and $t+1$ respectively; $r_1$ is a random number between $-1$ and $1$; $E$ is the range of mutations; $i + r_2$ is another corresponding unit generated randomly; $G_T$ is the total number of units. When the output of unit $I$ is not zero, its load is increased by $r_1 \ast E$, and at the same time, another unit whose output is not zero is randomly found, and its load is subtracted by the same value.

2) When the output of the unit is 0:

$$\begin{align*}
C_h &= p_{t,j}^{i+1} \\
p_{t+1,j}^{i+1} &= p_{t+1,j}^{i+r_3,j} \\
N_{t+r_3,j} &= C_h \\
i + r_3 &\leq G_T
\end{align*}$$

(21)

where $C_h$ is the intermediate value of the exchange; $i + r_3$ is another corresponding unit generated randomly. When the output of unit $I$ is 0, its load value is exchanged with another unit whose load value is not 0.

### 2.3 Evaluation Indicators

The quality of the algorithm needs to construct some evaluation indexes. The index of traditional algorithm is to construct multiple objective functions to solve, but this method cannot represent the quality of specific problems. Therefore, a series of evaluation indicators should be developed for ELD problem.

#### 2.3.1 Accuracy

Accuracy represents the ability of the algorithm to optimize to the global best. We use the result of DP calculation as the global optimal result to evaluate the accuracy of the algorithm. The function is constructed as follows:

$$A_{c_k} = O_k - O_{DP}$$

(22)

where $A_{c_k}$ is the accuracy of algorithm $k$; $O_k$ and $O_{DP}$ are the calculation results of algorithms $k$ and DP, respectively.

#### 2.3.2 Time Efficiency

The time efficiency represents the solving speed of the algorithm. When the solution meets the accuracy requirement, the faster the time, the higher the efficiency. The time efficiency function is constructed as follows:

$$T_{c_k} = T_k - T_{DP}$$

(23)

where $T_{c_k}$ is the difference in calculation time of algorithm $k$; $T_k$ and $T_{DP}$ are the calculation time of algorithms $k$ and DP, respectively.
2.3.3 Tests to Evaluate Performance

(1) Tests to evaluate performance of IWOA in ELDP.

In order to evaluate the performance of IWOA, LAGA, PSO, WOA and IWOA were used to solve ELDP in the case of the Three Gorges Hydropower Station. Using a variety of heads and loads, the calculated water consumption is compared.

(2) Tests to evaluate performance of WOA and IWOA.

The WOA and IWOA are used to optimize the load dispatch of 26 units at 75 m head of three gorges hydropower station. The influence of cavitation vibration in actual economic operation is considered in this study. In order to compare the performance of the two algorithms, the parameter $b$ of the two algorithms is set to 2. The iteration termination condition is set to 100 generations. In order to evaluate the performance of the two algorithms under different loads, the loads of the hydropower station are set as 14.26 million kilowatts, 9.51 million kilowatts and 2.35 million kilowatts respectively. These three conditions are used to describe the large, medium and small power load levels of the 26 units respectively. In order to eliminate the influence of random factors, IWOA and WOA were solved 10 times for ELDP, and the optimal result was selected as the final result.

3 Case Study

3.1 Introduction of Three Gorges Hydropower Station

The Three Gorges Hydropower Station, the largest in the world, is located on the upper reaches of the Yangtze River in Yichang, Hubei Province. Its location is shown in Fig. 1. It consists of 32 mixed-current generating sets with a load of 700 MW and 2 power supply...
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The three Gorges Hydropower Station has a total installed capacity of 22,500 megawatts and a variety of turbines, so it is suitable for studying the ELDP. Among these hydropower units, 26 were first put into operation, which has been studied by most scholars because of detailed data. In order to compare with previous studies, this paper only studies these 26 hydroelectric generating units. There are five types in these 26 units, all with a maximum load of 700 MW (Yang et al. 2018). Figure 2 shows the characteristic curves of five types of units under different water heads. Table 1 shows the stable operating zones corresponding to different types of units.

### 3.2 Tests to Evaluate Performance of IW OA and DP

#### 3.2.1 Scene Settings

When the calculation time is not considered, the result of DP is undoubtedly optimal. However, because the power load of hydropower station is variable, the time efficiency of solving ELDP is an important factor, which also brings great challenges to the application of heuristic algorithm in practice. In order to comprehensively evaluate the reliability of the algorithm, the following two scenarios are set up to comprehensively evaluate the calculation accuracy and calculation time efficiency of the algorithm.

**Scenario 1: Comparison of calculation times with the same calculation accuracy.**

In order to ensure the rationality of the comparison results, the accuracy of IW OA and DP algorithms must meet the same requirements. In this scenario, the solution of DP applied to solving ELDP is considered optimal. Set a sufficiently small parameter $\epsilon$. When
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\begin{align*}
|P_{IWOA} - P_{DP}| & \leq \varepsilon, \text{ IWOA is considered to have the same accuracy as DP, and then we can compare the calculation time of the two algorithms.}
\end{align*}

**Scenario 2: Compare the calculation accuracy with the same calculation time.**

The computation time $T_{DP}$ for solving ELDP is regarded as the benchmark. When the IWOA computation time $T_{IWOA}$ satisfies $|T_{IWOA} - T_{DP}| \leq T_{eps}$, the iteration is terminated, and then precision comparison is performed.

### 3.2.2 Parameter Setting

The algorithm parameters are set as follows: the number of population is set to 100, the number of water turbines is set to 26, and the maximum iteration was set to 200. The crossover rate $p_c$ and mutation rate $p_m$ of LAGA are set as 0.9 and 0.08, respectively. The inertia weight $w$ of PSO was set as 1, and the learning factors $c_1$ and $c_2$ were also set as 1, respectively. Parameter $b$ of both WOA and IWOA was set as 2. The maximum value $w_{\text{max}}$ and minimum value $w_{\text{min}}$ of inertia weights of IWOA were set as 1 and 0.1, respectively. The maximum value $k_{\text{max}}$ and minimum value $k_{\text{min}}$ of random probability are set to 0.95 and 0.01, respectively. The perturbation variation probability $P_m$ is set to 0.01.

### 4 Results and Discussion

#### 4.1 Performance of IWOA in ELDP

The ELDP was calculated by LAGA, PSO, WOA, and IWOA. Each algorithm is calculated when the gross water head is 75 m, 88 and 107 m, and the algorithm was run 20 times in each case. The calculated water consumption results are shown in Table 2.

As shown in Table 2, when the head is 75 m, the water consumption calculated by IWOA is 6673.7 m$^3$/s, 5817.4 m$^3$/s, and 12926.1 m$^3$/s respectively when the load is low, medium and high. When the head is 88 m, the water consumption calculated by IWOA is 5817.4 m$^3$/s, 17772.7 m$^3$/s and 15008.9 m$^3$/s respectively when the load is low, medium and high. As shown in 36
water consumption calculation results, 8 out of 9 water consumption calculation results of WOA are lower than that of PSO and LAGA. The calculation results of water consumption of IWOA are lower than those of other algorithms.

As shown in Table 2, comparing the water consumption results calculated by IWOA, WOA, PSO and LAGA, we found that the calculation result of IWOA was the smallest. Under 75 m water head, water consumption of IWOA at low, medium and high loads decreased by 1.19%, 0.18% and 0.73% compared with that of WOA. Under 88 m water head, water consumption of IWOA at low, medium and high loads decreased by 0.63%, 0.11% and 0.23% compared with that of WOA. Under 107 m water head, water consumption of IWOA at low, medium and high loads decreased by 1.80%, 0.39% and 0.36% compared with that of WOA.

The calculation results of water consumption of IWOA and DP are shown in Table 3. When the head is 75 m and the load is low, medium and high, the difference between the calculation results of IWOA and DP is 0.76%, 0.54% and 0.06%, respectively. When the head is 88 m and the load is low, medium and high, the difference between the calculation results of IWOA and DP is 0.36%, 0.43% and 0.17%, respectively. When the head is 107 m and the load is low, medium and high, the difference between the calculation results of IWOA and DP is 0.01%, 0.51% and 0.18%, respectively.

### 4.2 Performance Evaluation of IWOA and WOA

The comparison results of IWOA and WOA are shown in Fig. 3, where the black line and red line represent the upper limit and lower limit of stable operation area respectively. If the load allocated by the unit is lower than the black line, it indicates that the unit is operating in cavitation erosion vibration zone, which will cause serious damage to the unit. According to Fig. 3(a) and Fig. 3(b), the number of started units calculated by WOA and IWOA is the same as DP. The distribution of WOA units is relatively random, while the distribution of IWOA results is concentrated in the units with small water consumption. This shows that WOA has high optimization capability, but it has certain limitations when facing the nonlinear combination problem of multiple units. According to Fig. 3(c), in the case of high load, all units are on, and the optimal solution of IWOA is almost the same as that of DP, with better optimization capability.
4.3 Performance Evaluation of IWOA and DP

Fig. 3 Comparison of load dispatch schemes of WOA, IWOA and DP: (a) load dispatch results when the total load is 2.35 million kW; (b) Load dispatch results when the total load is 9.51 million kW; (c) The result of load dispatch when the total load is 14.26 million kW
The ELDP was calculated by WOA and IWOA in two scenarios respectively. Each algorithm is calculated when the gross water head is 100 m, and the algorithm was run 20 times in each scenario. To evaluate the performance of the algorithm, the comparison of calculation accuracy between IGA (Shang et al. 2017), IWOA and WOA is shown in Fig. 4. The greater the number of open units, the greater the difference between the result of heuristic algorithm and the optimal value. When the number of units turned on is less than 6, the accuracy of IWOA and WOA is similar. When the number of units turned on is greater than 6, the result of WOA is worse than that of IGA and IWOA; when the number of units turned on is greater than 10, the result of IWOA is better than that of IGA and WOA. Therefore, the calculation accuracy of IWOA is better than that of IGA and WOA when more units turned on.

The comparison of computational time performance between IGA (Shang et al. 2017), IWOA, WOA and DP is shown in Fig. 5. Considering the difference in computer performance, we scaled the IGA results with the DP results calculated in this paper as the standard, and this adjustment did not affect the comparison between IGA and DP. As shown in Fig. 5, the larger the number of units turned on, the more time it takes to solve ELDP. The increasing trend of DP and IGA time is obvious, which proves that DP and GA are not suitable for solving complex ELDP. When the number of units turned on is greater than 6, the computation time of WOA and IWOA is smaller than DP, and the computation time of IWOA is
better than WOA. Therefore, the calculation time of IWOA is better than that of IGA and WOA when more units turned on.

5 Conclusion

In this paper, taking the Three Gorges Hydropower Station as an example, various optimization algorithms are applied to the mathematical model of ELDP. LAGA, PSO, WOA and IWOA were applied and the evaluation indicators of ELDP was constructed. The performance of intelligent optimization algorithm was analyzed from the aspects of convergence ability, optimization ability, stability and accuracy. Based on the comprehensive results of three typical loads and three typical head analysis algorithms, the economic benefits of the improved algorithm for the economic operation model in the hydropower station are analyzed. The improved whale algorithm improves the problem that the traditional whale algorithm lacks the optimization speed and is easy to fall into the local optimal solution. The optimization result is the best among the above intelligent algorithms, which provides a new idea for solving the ELDP.

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Declarations

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