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# Improved genetic algorithm for economic load dispatch in hydropower plants and comprehensive performance comparison with dynamic programming method

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ABSTRACT

This paper presents a practical genetic algorithm (GA)-based solution for solving the economic load dispatch problem (ELDP) and further compares the performance of the improved GA (IGA) with that of dynamic programming (DP). Specifically, their performance is comprehensively evaluated in terms of addressing the ELDP through a case study of 26 turbines in the Three Gorges Hydropower Plant with a focus on calculation accuracy, calculation time, and algorithm stability. Evaluation results show that the improved GA method can significantly reduce the ineffectiveness of the GA in current use and could avoid the running of the turbines in the cavitation/vibration zone, thereby ensuring the safety of the turbines during generating operations. Further, the analysis comparing the performance of the IGA and DP show that the IGA is superior to DP when a small number of turbines are involved. However, as the number of turbines increases, the IGA requires more calculation time than DP; moreover, its calculation accuracy and convergence rate are significantly reduced. It is difficult to guarantee the stability of IGA in high-dimension space even though the population grows, on account of the exponential expansion of the calculation dimension, the algorithm's premature convergence, and the lack of a local search capability. The improvement of the GA as well as the evaluation method proposed in this paper provide a new approach for choosing and improving optimization algorithms to solve the ELDP of large-scale hydropower plants.


## 1. Introduction

A hydropower plant usually has multiple turbines that are run side by side. Because of differences in the turbines' operating characteristics, the generation discharge varies sharply in different combinations of committed turbines. The purpose of an economic load dispatch problem (ELDP) study is to develop load-specific turbine operation strategies that clarify the number and timing of start and stop orders and the power load allocation of committed turbines (Ding et al., 2015). The ELDP study is of great importance for reducing the generation discharge of hydropower plants and improving their economy of operation (Kamboj, 2016). The economical operation of a hydropower plant has traditionally been based on algorithms for optimizing load dispatching. Improvements in the scheduling algorithm of the committed turbines are therefore able to generate significant economic benefits (Kumar et al., 2015). However, in practice, the operating ranges of the turbines are not always available for optimal load allocation on account of their physical operation limitations (Zhang et al., 2013). Turbines can have prohibited operating zones because of faults in the machines themselves or in the associated auxiliaries (He et al., 2008). Such faults usually lead to instabilities in certain ranges of the turbine load, rendering them unable to carry a load for any appreciable time in these operating zones (Niknam et al., 2012). Therefore, the input-output characteristics of large turbines are inherently highly nonlinear and probably non-convex (Séguin and Côté, 2016), which makes the economic load dispatch problem (ELDP) a large-scale highly nonlinear constrained optimization problem that is difficult to solve (Hidalgo et al., 2014).

The primary objective of the ELDP is to schedule the committed turbine outputs to meet the required load demand at the minimum discharge volume while satisfying the equality and inequality constraints for all turbines and for the system (Santra et al., 2016; Cheng et al., 2000). For this purpose, a continuous balance must be maintained between power generation and varying load demand (Lu et al., 2015). Meanwhile, the system frequency,

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## Nomenclature

| | |
|---|---|
| $dN, dN'$ | the discrete step lengths of DP and the GA (IGA), respectively |
| $Gen$ | the termination generation of the evolution process |
| $H$ | the average water head for the given period (m) |
| $i, j, k, l$ | the sequence number of the turbine, the sequence number of the cavitation/vibration zone of the turbine, the serial number of an individual in the GA (IGA) population, and the serial number of a state variable in DP, respectively |
| $ind_1, ind_2$ | two individuals involved in the crossover operation |
| $\text{int}[\cdot]$ | Gaussian rounding function |
| $INF$ | the maximum value of the penalty term |
| $n$ | the number of turbines |
| $n_T$, $n_S$ | the number of tests and the number of convergences, respectively |
| $N$ | the total number of turbines |
| $N_{DP}$ | a solution in the set of optimal DP solutions, $\Omega_{DP}$ |
| $N_i$ | the power output of turbine $i$ (MW) |
| $N_{i,IGA}$ | the optimal solution of IGA test $i$ |
| $N'_{\max_{k,i}}$, $N'_{\min_{k,i}}$ | the upper and lower limits, respectively, of the corresponding cumulative output |
| $N''_{\max_{k,i}}$, $N''_{\min_{k,i}}$ | the upper and lower limits, respectively, of the cumulative output variation |
| $Nd$ | the power grid load (MW) |
| $Ns_{i,l}$ | the variable value of state $l$ for phase $i$ |
| $NH_i$ | the expected output of turbine $i$ (MW) |
| $NY_t$ | the installed capacity of turbine $t$ (MW) |
| $\overline{N_{i,j}}$ | the upper output limit of turbine $i$ in zone $j$ with given water head $H$ (MW) |
| $\underline{N_{i,j}}$ | the lower output limit of turbine $i$ in zone $j$ with given water head $H$ (MW) |
| $\overline{Ntmp}$, $\overline{Ntmp}$ | $\max\{\sum_{t=1}^{i} N_t - NY_i, 0\}$ and $\min\{\sum_{t=1}^{i} N_t, \sum_{t=1}^{i-1} NY_t\}$, respectively |
| $OPT_{DP}$, $OPT_{IGA}$ | the optimal values obtained using the DP and the IGA approaches, respectively |
| $p_{k,i}$ | the cumulative output code of turbine $i$ of individual $k$ |
| $p''_{k,i}$ | the individual $p_{k,i}$ after variation |
| $p_m$ | the variation probability of the GA (IGA) |
| $p_{opdt}$ | the output discrete step length of IGA |
| $P$, $P'$, $P''$ | the parent population, the crossover population, and the mutant population in the GA (IGA), respectively |
| $Pop$ | the population size |
| $PS_{eps}$ | the threshold for completion of the IGA calculations (%) |
| $q_i(\cdot)$ | the generation discharge of turbine $i$ ($m^3/s$) |
| $Q$ | the generation discharge ($m^3/s$) |
| $Q_i^*(\sum_{t=1}^{i} N_t)$ | the optimal accumulated generation discharge in the remaining period |
| $Rnd, Rnd', Rnd'', Rndmut, \alpha$ | random numbers evenly distributed in the interval (Ding et al., 2015) |
| $Snum$ | the number of evolutionary generations |
| $t$ | time period |
| $Teps$ | the accuracy coefficient |
| $TC_{DP}$, $TC_{IGA}$ | the calculation times using DP and the IGA, respectively (s) |
| $\alpha_1$, $\alpha_2$ | the penalty coefficients for the operating constraint and the output domain constraint, respectively |
| $\Delta q_i$ | the penalty term to constraints on the operating condition |
| $\Delta qp_i$ | the penalty term to constraints on the output domain |
| $\Delta PC$, $\Delta TC$, $PS$ | the accuracy indicator, the calculation time indicator, and the algorithm stability indicator, respectively |
| $\varepsilon$ | the convergence threshold |
| $\Omega_i(H)$ | the cavitation/vibration zone of turbine $i$ |
| $\Omega_{DP}$ | the optimal state set |

voltage levels, and security must also be kept constant (Miao and Fan, 2016). In addition, the load dispatch has strict requirements on the calculation time because real-time ELDP is generally performed every 5 min and determines the active power output of all committed dispatchable turbines for the next 5-min interval (Bakirtzis et al., 2014). Therefore, the ELDP algorithm optimizes with the objective of minimizing the total amount of water discharged from the reservoir and completing the required operation in the shortest amount of time (Li et al., 2014).

To obtain accurate dispatch results in a timely manner, a demand exists for techniques that have no restrictions on characteristics of the turbines (Bortoni et al., 2015). A variety of optimization techniques have been tried, including mixed-integer, linear, and nonlinear programming approaches (Lu et al., 2010). The mixed-integer linear programming (MILP) technique circumvents the nonlinearity by assuming a constant net water head and a fixed power load (Chen et al., 2016). This assumption simplifies the modeling process; however, it can lead to remarkable inaccuracy because of the inevitable errors and uncertainties that are induced by the use of piecewise linear approximation and the introduction of discreteness to the problem via the addition of integer variables or constraints (Cheng et al., 2016). Furthermore, this approach may not be precise enough for a large hydropower plant when long-term scheduling is considered. On the other hand, both lambda-iteration and gradient-technique methods in conventional approaches to solving these problems are calculus-based techniques (Subramanian et al., 2016) that require a smooth and convex function and strict continuity of the search space (Suman et al., 2016). The dynamic programming (DP) approach (Li et al., 2014) imposes no restrictions on the nature of the turbine operating curves; therefore, it can solve ELDPs that have inherently nonlinear and discontinuous physical operation limitations (Nanda et al., 1994).

Evolutionary computation is one such tool that has demonstrated its ability to solve these complex problems (Nahas and Abouheaf, 2016; Yang et al., 2012). Evolutionary computation methods mimic biological population genetics in a search for the optimal solution (Abido, 2006). They can be implemented in various forms, such as a genetic algorithm (GA) (Gen and Cheng, 2000), evolutionary programming (EP) (Lai, 1998), or an evolution strategy (ES) (Miranda et al., 1998). The GA approach has immense potential for applications in the field of power systems. The GA approach addresses all types of problems that typically present significant challenges for researchers (Sivaraj and Ravichandran, 2011): integer variables, non-convex functions, non-differentiable functions, unconnected domains, poorly behaving functions, multiple local optima, and multiple objectives. It has been successfully applied to solve various problems in electric power systems, such as economic load dispatch (Lee et al., 2011), unit commitment (Pavez-Lazo and Soto-Cartes, 2011), reactive power control (Devaraj and Preetha Roselyn, 2010), hydrothermal scheduling (Senthil Kumar and Mohan, 2011), and distribution system planning (Guimaraes et al., 2010). Some situations exist in which simple GA does not perform particularly well (Fadaee and Radzi, 2012). Nonetheless, GAs have proven to be a versatile and effective approach for solving optimization problems (Yokota et al., 1996). It is believed that, with the development of artificial intelligence, modern optimization algorithms, such as GAs, will be more commonly used in unit load allocation (Younes and Rahli, 2006).

So far, GA and DP are still two representative algorithms for solving the economic load dispatch problem (ELDP), although DP may suffer from the "curse of dimensionality" or local optimality (Srikrishna and Sivarajan, 2010). Despite the above advancements, no unified conclusion has emerged on the advantages and disadvantages of the two algorithms because of their very different structures and working principles (Salazar et al., 2016). This makes it difficult for a hydropower plant to select the optimal algorithm for creating a real-time scheduling scheme, thus hindering the practical application of the optimization algorithm in projects. Baskar et al. (2003) used a two-phase hybrid real-coded GA and DP to solve a 10-generation-unit ELDP, and they concluded that GA has a higher accuracy than DP. Orero and Irving (1996)) integrated binary-coded GA into the crowding mechanism to highlight the individual differences. However, the improved GA approach was found to be less accurate than DP in the performance comparison of 15 experimental turbines involved in load distribution. In addition, Kazarlis et al. (1996) analyzed the performance of GA and DP approaches to a load commitment of 72 units. They determined that GA consistently requires less calculation time than DP; however, the accuracy and rate of convergence are significantly decreased when 18 or more units are involved. The above-mentioned conclusions require further verification because the algorithm efficiency comparison must account for calculation accuracy and time in addition to convergence rate. Otherwise, the schemes are not comparable. To date, research on calculation accuracy and time has been rare. Chen et al. (2000) integrated the indicator of calculation time when comparing the convergence and speed of DP algorithms and GAs. Nevertheless, they did not consider accuracy. Abdelaziz et al. (2012) studied the effectiveness of GA improvement and showed that the optimal solution quality was improved. However, the study failed to consider the calculation time efficiency.

In general, research on a DP and GA performance comparison has been inadequate. Existing studies are only clustered on one aspect of the algorithms; they do not provide a comprehensive evaluation. In short, previous research is deficient in the following three aspects. First, the benchmarks are not unified, leading to different conclusions. DP and GA are two different approaches, and the experiment scheme must be comparable to ensure the objectivity of the conclusions. Second, the evaluation indicators are not sufficiently comprehensive to cover the time efficiency, stability, and accuracy of the algorithms in certain experimental schemes. Third, the experimental conditions are not identical. The algorithm performance is subject to the step length and convergence threshold (DP), as well as the coding method, operator structure, parameter selection, and improvement operation (GA). Different forms and calculation parameters of algorithms result in variance in the conclusions.

The Three Gorges hydropower project, which spans the Yangtze River in Yichang, Hubei Province, China, has the world's largest hydropower plant (Huang and Yan, 2009). The issues of the Three Gorges Hydropower Plant, such as multiple turbines, different models, and nonlinear output, have presented new challenges for the ELDP (Zheng et al., 2013). The ELDP of these turbines is recognized as one of the world's most complex problems. Twenty-six turbines of five types that have sharply different output curves were installed on both banks. In recent years, the Three Gorges Hydropower Plant has been attempting to use GA to optimize the load allocation on these 26 units. The GA-based solution in current use relies on the penalty of the fitness function to avoid operation in the prohibited zone. However, for the ELDP of the 26 turbines, neither a quantitative nor a variable penalty factor can be found to guarantee a non-negative solution of the fitness function. As a result, the GA always converges prematurely (to local optima), and the load allocation results often make units run in the cavitation/vibration zone. Therefore, there is an urgent need to develop an applicable algorithm for solving the ELDP of the 26 turbines. In order to provide solid technical support for the Three Gorges Hydropower Plant, this study aimed to address the following two questions: 1) How can the GA be improved to solve the problems of premature convergence and vibration? 2) Of the DP and GA approaches, which type of algorithm is more applicable for the special case of the Three Gorges Hydropower Plant? This study proposed an approach to improve the performance of the GA in current use and compared the performance of DP and improved GA (IGA) with a focus on calculation accuracy, calculation time, and algorithm stability. We believe this study makes contributions to the existing body of knowledge since the improvement of the GA as well as the evaluation method proposed in this study provide a new approach for choosing and improving optimization algorithms to solve the ELDP of large-scale hydropower plants.

The remainder of this paper is structured as follows. Section 2 presents the methodology: Section 2.1 defines the ELDP, Section 2.2 presents the improved GA method as well as the optimization processes of the DP, and Section 2.3 focuses on performance evaluation indicators. Section 3 describes the case study: Section 3.1 briefly describes the ELDP case of 26 turbines in the Three Gorges Hydropower Plant, Section 3.2 presents the experiment designed for testing GA and IGA, and Section 3.3 presents the test scheme and parameter settings for the comparison of the IGA and DP performance. Section 4 provides the results and analysis: Section 4.1 gives the results of IGA implementation, and Section 4.2 gives an analysis of the performance of IGA and DP. Finally, an overall summary is given in Section 5.

## 2. Methodology

### 2.1. ELDP formulation

The ELDP can be described as an optimization process based on the following objective function and operation constraints.

#### 2.1.1. Objective function

The objective of the ELDP is to minimize the water discharge of the turbines when the upstream water level of the reservoir and the power grid load are given:

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

where $Q$ represents the generation discharge and $n$ is the number of turbines. In addition, $q_i(\cdot)$ represents the generation discharge of turbine $i$, $N_i$ denotes the power output of turbine $i$, and $H$ represents the average water head for the given period.

*2.1.2. Nonlinear constraints related to turbine cavitation/vibration*

The turbines are subject to the following load balancing and turbine operating constraints:

$$\sum_{i=1}^{n} N_i = Nd \tag{2}$$

$$0 \leqslant N_i \leqslant NH_i, \quad \text{and} \quad N_i \notin [\underline{N_{i,j}}, \overline{N_{i,j}}]; j \in \Omega_i \tag{3}$$

where $Nd$ is the power grid load, $NH_i$ characterizes the expected output of turbine $i$ (MW), and $\Omega_i(H)$ denotes the cavitation/vibration zone of turbine $i$; $\overline{N_{i,j}}$ and $\underline{N_{i,j}}$, respectively, denote the demonstrated upper and lower output limits of turbine $i$ in zone $j$ with given water head $H$.

Fundamentally, the ELDP problem is a high-dimension, discrete, and non-convex nonlinear programming problem, one that is difficult to solve directly using existing linearization techniques. Errors would inevitably be introduced by the rough linearization of such nonlinear constraints as safety turbine operation constraints and water head changes, while piecewise linear approximation would lead to a drastic increase in computational dimension as well as a rapid decline in calculation efficiency.

*2.2. Solution approaches*

DP and GA are two representative algorithms for solving the ELDP.

*2.2.1. DP-based solution: Overview*

There are two steps to the DP-based solution to ELDP: 1) Sequentially obtain the optimal function of each phase according to the recursion formula; 2) obtain the load of each turbine and the corresponding water discharge, turbine number, and combination based on backward generation of the optimal function, i.e., the best operation mode. The variables, constraints, and process of solving ELDP using the DP algorithm are detailed as follows:

*2.2.1.1. Phase and state variables.* The serial number of turbine $i$ is defined as the phase variable, and the cumulative output $\sum_{t=1}^{i} N_t$ is the state variable. The state discrete step length is $dN$, and the cumulative state discrete output is written as

$$Ns_{i,l} = \begin{cases} \min\{l \cdot dN, \sum_{t=1}^{i} NY_t, Nd\}, & \text{when } i \neq n \\ Nd, & \text{when } i = n \end{cases} \tag{4}$$

where $l \in [0, \text{int}[\min\{\sum_{t=1}^{i} NY_t, Nd\}/dN] + 1]$, $Ns_{i,j}$ represents the variable value of state $l$ for phase $i$, $NY_t$ represents the installed capacity of turbine $t$, and $\text{int}[\cdot]$ is the Gaussian rounding function.

*2.2.1.2. Constraints.* A penalty function is used to handle the constraints of the output conditions. The objective function $f_i(N_i, H)$ of the penalty variable in phase $i$ is written as

$$f_i(N_i, H) = q_i(N_i, H) + \Delta q_i + \Delta qp_i \tag{5}$$

$$\Delta q_i = \alpha_1 \cdot INF, \Delta qp_i = \alpha_2 \cdot INF \tag{6}$$

wherein

$$\alpha_1 = \begin{cases} 1 & N_i \in [\underline{N_{i,j}}, \overline{N_{i,j}}], \exists j \\ 0 & N_i \notin [\underline{N_{i,j}}, \overline{N_{i,j}}], \forall j \end{cases} \tag{7}$$

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

where $\Delta q_i$ represents the penalty term to constraints on the operating conditions, and $\Delta qp_i$ denotes the penalty term to constraints on the output domain. In addition, $\alpha_1$ and $\alpha_2$ are penalty coefficients, and $INF$ represents the maximum value of the penalty term.

*2.2.1.3. State transition and state traversal.* With output $N_i$ defined as a decision variable, the state transition equation can be written as

$$\sum_{t=1}^{i} N_t = \sum_{t=1}^{i-1} N_t + N_i \tag{9}$$

The recursive equation is written as

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

where $Q_i^*(\sum_{t=1}^{i} N_t)$ represents the optimal accumulated generation discharge in the remaining period.

DP state traversal is shown in Fig. 1. The DP solution to space is made stage by stage. Owing to the output domain constraint, $N_i \in [0, NY_i]$, the DP calculation of cumulative power flow in state $j$ and phase $i$ requires simply searching state $j - \text{int}[NY_i/dN]$ to state $j$ in phase $i - 1$, as shown in Fig. 1. When there are multiple optimal solutions to the problem, the optimal set of states $\Omega_{DP}$ is recorded.

*2.2.1.4. State backtracking.* All the optimal strategies are obtained by backtracking the final state of phase $n$, and the solution is completed.

*2.2.2. GA and improved GA (IGA)*

*2.2.2.1. GA-based solution: Overview.* The GA has been adopted by the Three Gorges Hydropower Plant. The operator correction method and penalty function method are two typical methods of processing constraints in the GA approach. The former is mainly used to solve linear constrained optimization problems. Based on linear processing, the elimination of linear constraints and operator adjustment can quickly and efficiently generate a feasible solution. The safety constraints describing the output of the unit are nonlinear equations. For the GA in current use, a penalty function is adopted to deal with nonlinear constraints. It constructs nonlinear constraints as a penalty term to be added to the fitness function. Using this method, the constrained optimization problem is converted into an unconstrained optimization problem. Out of

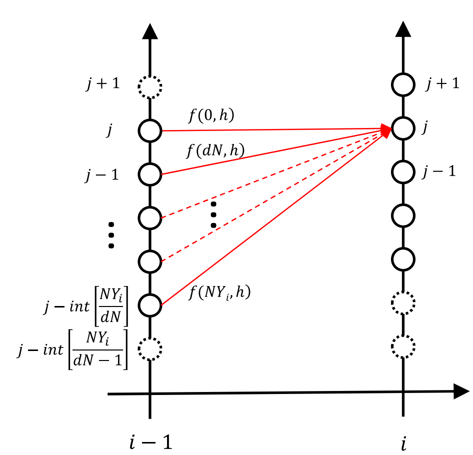


**Fig. 1.** Schematic view of the dynamic programming (DP) state traversal.

combined consideration, the operator correction method is applied to address constraints on the load balance and output domain. The penalty function is constructed in Formula (5) for constraints on operating conditions.

*2.2.2.1.1. Encoding and decoding.* The cumulative output of the $i$th turbine, $\sum_{t=1}^{i} N_t$, is defined as a gene. Based on Formula (4) for discrete units with a discrete step length defined as $dN'$, the genes are encoded as $p_{k,i} \in [0, [\min\{\sum_{t=1}^{i} NY_t, Nd\}/dN'] + 1]$ to represent the sequence of elements in the term $Ns_{i,l}$. The cumulative output of turbine $i$ is decoded as $Ns_{i,p_{k,i}}$ ($k \in [1, Pop]$, $i \in [1, n]$, where $Pop$ denotes the population size and $n$ is the number of turbines).

*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 turbine $i$ is known ($\sum_{t=1}^{i} N_t$), then $p_{k,i} = \text{int}[\sum_{t=1}^{i} N_t/dN']$. Formula (9) can be rewritten as

$$\sum_{t=1}^{i-1} N_t = \sum_{t=1}^{i} N_t - N_i \tag{11}$$

When the output domain constraint $N_i \in [0, NY_i]$ is integrated into Formula (11), then

$$\sum_{t=1}^{i-1} N_t \in [\sum_{t=1}^{i} N_t - NY_i, \sum_{t=1}^{i} N_t] \tag{12}$$

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

$$\sum_{t=1}^{i-1} N_t \in [0, \sum_{t=1}^{i-1} NY_t] \tag{13}$$

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

$$\sum_{t=1}^{i-1} N_t \in [\max\{\sum_{t=1}^{i} N_t - NY_i, 0\}, \min\{\sum_{t=1}^{i} N_t, \sum_{t=1}^{i-1} NY_t\}] \tag{14}$$

Letting $\underline{Ntmp} = \max\{\sum_{t=1}^{i} N_t - NY_i, 0\}$ and $\overline{Ntmp} = \min\{\sum_{t=1}^{i} N_t, \sum_{t=1}^{i-1} NY_t\}$, the approach for generating gene $p_{k,i-1}$ can be expressed as

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

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 the output domain and load balance requirements.

*2.2.2.1.3. Fitness function.* According to the objective function, the fitness formula is constructed as

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

*2.2.2.1.4. Crossover operator.* An arithmetic crossover is used, and assuming that only the two individuals in the population $k = 1$ and $k = 2$ are crossed, the genes after crossover can be calculated using the following formulas:

$$p'_{k,i} = \alpha \cdot p_{1,i} + (1-\alpha) \cdot p_{2,i}, p'_{k+1,i} = (1-\alpha) \cdot p_{ind_1,i} + \alpha \cdot p_{ind_2,i} \tag{17}$$

where $\alpha$ indicates a random number evenly distributed in the interval [0,1], and $ind_1$ and $ind_2$ represent the individuals involved in the crossover operation.

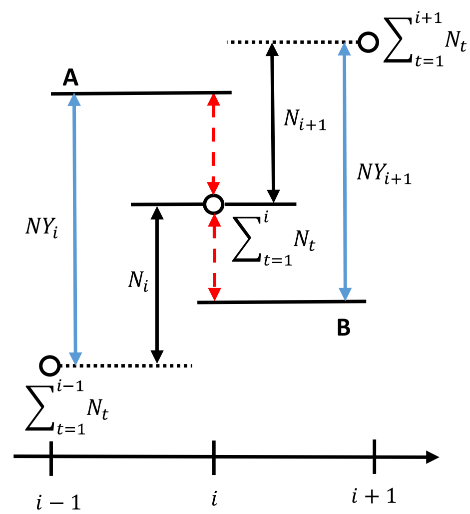


**Fig. 2.** Schematic diagram of variation.

Arithmetic crossover satisfies the load balance constraints and output domain constraints. Taking the crossover probability as 1, $P'$ with a size of $Pop$ is formed after the crossover.

*2.2.2.1.5. Variation operator.* The variation probability $p_m$ is introduced to control gene variation: the mutant gene is replaced, and the variation operator is used with the new random gene, as shown in Fig. 2.

The gene variation in point $i$ also affects the output and turbines $i$ and $i+1$. Given the output domain constraint, $N_i \in [0, NY_i]$, the post-variation point $i$ will not be higher than point A, $\sum_{t=1}^{i-1} N_t + NY_i$. In the same way, when $N_{i+1} \in [0, NY_{i+1}]$, the post-variation point $i$ will not be lower than point B, $\sum_{t=1}^{i+1} N_t - NY_{i+1}$. Hence, the domain of mutant genes is

$$\sum_{t=1}^{i} N_t \in [\max\{\sum_{t=1}^{i-1} N_t, \sum_{t=1}^{i+1} N_t - NY_{i+1}\}, \min\{\sum_{t=1}^{i-1} N_t + NY_i, \sum_{t=1}^{i+1} N_t\}] \tag{18}$$

Letting $\underline{Ntmp} = \max\{\sum_{t=1}^{i-1} N_t, \sum_{t=1}^{i+1} N_t - NY_{i+1}\}$ and $\overline{Ntmp} = \min\{\sum_{t=1}^{i-1} N_t + NY_i, \sum_{t=1}^{i+1} N_t\}$, the mutant genes are calculated as follows:

$$p''_{k,i} = \begin{cases} \text{int}[\underline{Ntmp}/dN'] + \text{int}[Rndmut \cdot (\text{int}[\overline{Ntmp}/dN'])], & \text{if } Rnd \leqslant p_m \\ p_{k,i}, & \text{if } Rnd > p_m \end{cases} \tag{19}$$

where $Rnd$ and $Rndmut$ are random numbers that are evenly distributed in the interval [0,1], and $P''$ represents the size of the mutant population.

*2.2.2.1.6. Selection operator.* Using the tournament selection method (Yang and Soh, 1997), the highest-scoring individuals in three populations—namely parent population $P$, crossover population $P'$, and mutant population $P''$—are taken as a new parent population for the next generation's evolution.

*2.2.2.1.7. Termination condition.* The algorithm terminates when the optimal solution remains unchanged over $Snum$ generations or the GA reaches the termination generation $Gen$. Then the GA outputs the optimal individual.

*2.2.2.2. Improvements to method.* To improve the performance and efficiency of the GA, a feasible solution space was constructed in this study. A means of generating the initial population and performing the variation operation in solution space is also proposed so that the generated solutions are convergent while the turbines are prevented from running in the cavitation/vibration zone. The technical details of the algorithm improvements are as follows:

*2.2.2.2.1. Method of initial population generation.* The distribution of the initial population affects the convergence of the GA. The convergence will be slower or the GA may not even be able to converge to a local optimum if the initial population is biased and decentralized. An initial population generation method is thus herein presented to ensure that the initial population satisfies the load balance and domain output constraints while avoiding turbine cavitation/vibration. The improved approach is given as follows:

The cumulative output is encoded:

$$p_{k,i-1} = \frac{N'_{\min_{k,i-1}}}{p_{\text{opdt}}} + \text{int}\left[Rnd' \times \left(\frac{N'_{\max_{k,i-1}}}{p_{\text{opdt}}} - \frac{N'_{\min_{k,i-1}}}{p_{\text{opdt}}}\right)\right] \tag{20}$$

where $p_{k,i-1}$ represents the cumulative output code of turbine $i-1$ of individual $k$; $N'_{\max_{k,i-1}}$ and $N'_{\min_{k,i-1}}$ indicate, respectively, the upper and lower limits of the corresponding cumulative output; $p_{\text{opdt}}$ denotes the output discrete step length; $Rnd'$ is a random number evenly distributed in the interval [0,1], and $\text{int}[\cdot]$ is the Gaussian rounding function.

Assuming that all turbines are put into operation, given the load balance constraint, i.e., $\sum_{i=1}^{n} N_i = N$, the cumulative output of turbine $n$ is encoded as

$$p_{i,n} = N/p_{\text{opdt}} \tag{21}$$

The decreasing relation of the cumulative output is expressed as

$$\sum_{i=1}^{n-1} N_i = \sum_{i=1}^{n} N - N_n \tag{22}$$

Considering Formulas (21) and (3), the following formula can be obtained:

$$\sum_{i=1}^{n-1} N_{\min_i} \leqslant \sum_{i=1}^{n-1} N_i \leqslant \sum_{i=1}^{n-1} N_{\max_i}, \quad \sum_{i=1}^{n} N - N_{\max_i} \leqslant \sum_{i=1}^{n-1} N_i \leqslant \sum_{i=1}^{n} N - N_{\min_i} \tag{23}$$

Then, $N'_{\min_{k,i-1}}$ and $N'_{\max_{k,i-1}}$ in Formula (20) can be respectively written as

$$N'_{\min_{k,i-1}} = \max\{\sum_{t=1}^{i-1} N_{\min_t}, \sum_{t=1}^{i} N_t - N_{\max_i}\} N'_{\max_{k,i-1}} = \min\{\sum_{t=1}^{i-1} N_{\max_t}, \sum_{t=1}^{i} N_t - N_{\min_i}\} \tag{24}$$

The cumulative output code for turbine $n$ is obtained by Formula (21) and for other turbines by employing Formulas (23) and (20). The initial population generated by this model can simultaneously satisfy the constraints and effectively avoid the cavitation/vibration zone.

*2.2.2.2.2. Population variation control.* The coding variation at point $i$ will affect the size of the output of turbines $i$ and $i+1$. To effectively avoid the cavitation/vibration zone, a perturbation variation operator based on the feasible solution space is herein introduced. It requires the position of variation to be controlled within the given interval and a variation-based individual to effectively avoid the running of the turbines in the cavitation/vibration zone. As shown in Fig. 3, the $i$-point variation should not be positioned below point B or point D, nor should it be higher than point A or point C.

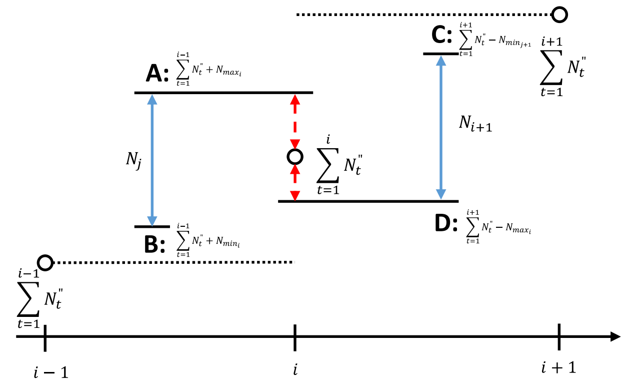


**Fig. 3.** Schematic view of solution space perturbation variation.

As shown in Fig. 3, $N''_{\max_{k,i}}$ and $N''_{\min_{k,i}}$ represent, respectively, the upper and lower limits of the cumulative output variation. They can be obtained using the following formulas:

$$N''_{\min_{k,i}} = \max\{\sum_{t=1}^{i-1} N''_t + N_{\min_i}, \sum_{t=1}^{i+1} N''_t - N_{\max_i}\} N''_{\max_{k,i}} = \min\{\sum_{t=1}^{i-1} N''_t + N_{\max_i}, \sum_{t=1}^{i+1} N''_t - N_{\min_{i+1}}\}. \tag{25}$$

Hence, the solution space perturbation variation operator can be expressed as

$$p''_{k,i} = \begin{cases} \frac{N''_{\min_{k,i}}}{p_{\text{opdt}}} + \text{int}\left[Rnd'' \times \left(\frac{N''_{\max_{k,i}}}{p_{\text{opdt}}} - \frac{N''_{\min_{k,i}}}{p_{\text{opdt}}}\right)\right] & Rnd \leqslant p_{\text{m}} \\ p_{k,i} & Rnd > p_{\text{m}} \end{cases} \tag{26}$$

where $Rnd''$ and $Rnd$ are random numbers in the interval [0,1], $p_{\text{m}}$ denotes the variation probability, and $p_{k,i}$ and $p''_{k,i}$ represent individuals before and after variation, respectively.

## 2.3. Performance evaluation indicators

Accuracy, calculation time, and algorithm stability are the three indicators for evaluating algorithm performance.

### 2.3.1. Accuracy

Using the DP calculation results, the accuracy indicator is constructed as

$$\Delta PC = OPT_{\text{IGA}} - OPT_{\text{DP}} \tag{27}$$

where $OPT_{\text{DP}}$ and $OPT_{\text{IGA}}$ represent the optimal values obtained using the DP and the IGA approaches, respectively. $\Delta PC > 0$ means that the IGA has a lower accuracy than the DP; $\Delta PC < 0$ means that the IGA is more accurate than the DP.

Note that, as the minimum discharge for power generation is taken as the objective of the ELDP, the accuracy of the algorithm that presents a smaller discharge is deemed higher.

### 2.3.2. Calculation time

The difference in calculation time is expressed as

$$\Delta TC = TC_{\text{IGA}} - TC_{\text{DP}} \tag{28}$$

where $TC_{\text{DP}}$ and $TC_{\text{IGA}}$ respectively represent the calculation times of the DP and IGA approaches.

#### 2.3.3. Stability

The convergence rate *PS* reflects the stability of stochastic algorithm IGA. Under the condition of repeated tests, the probability that the algorithm will converge to the global optimal solution is

$$PS = n_S/n_T \tag{29}$$

where $n_T$ represents the number of tests, and $n_S$ is the number of convergences. The IGA is deemed to have reached convergence when its solution is similar to any of the optimal DP solutions.

$$|N_{i,IGA} - N_{DP}| \leqslant \varepsilon, \forall i; \quad N_{DP} \in \Omega_{DP} \tag{30}$$

where $N_{DP}$ represents any solution in the set of optimal DP solutions, $\Omega_{DP}$. In addition, $N_{i,IGA}$ represents the optimal solution of the IGA test *i*, and $\varepsilon \leqslant 1$ is the convergence threshold.

## 3. Case study

### 3.1. Experimental setup

Twenty-six turbines with a total installed capacity of 18,200 MW are installed on the left bank (14 turbines) and right bank (12 turbines) of the Three Gorges Hydropower Plant, as outlined in Table 1. The turbines are depicted in Fig. 4.

Although each of these turbines has the same generating capacity, the output characteristics vary sharply on account of the different manufacturers. The turbines can be classified into five categories according to their manufacturers: VGS: 1–3 and 7–9; ALSTOM I: 4–6 and 10–14; ORIENTAL I: 15–18; ALSTOM II: 19–22; HARBIN: 23–26.

### 3.2. Tests to evaluate performance of GA and IGA

The study applied IGA and GA to optimize the load allocation of the 26 turbines in the Three Gorges Hydropower Plant with the water level of the reservoir below 77 m. For the study, the no-load discharge in actual economical operation was considered, and the precision benchmark for the calculation of load allocation was set to 10,000 kW. For comparison purposes, the selection probability and the variation probability were set to 0.7 and 0.08, respectively, for both algorithms. The iteration termination condition was 500 generations. To evaluate the optimal allocation

**Table 1**
Turbine parameters.

| Three Gorges Hydropower Plant | Left bank | | | Right bank | | |
|---|---|---|---|---|---|---|
| Type | VGS | ALSTOM | | ORIENTAL | ALSTOM | HARBIN |
| Number | 6 | 8 | | 4 | 4 | 4 |
| Rated head (m) | 80.6 | | | 85 | | |
| Max. head (m) | | | 113 | | | |
| Min. head (m) | | | 71 | | | |
| Rated flow capacity ($m^3/s$) | | | 996 | | | |
| Unit capacity (MW) | | | 700 | | | |

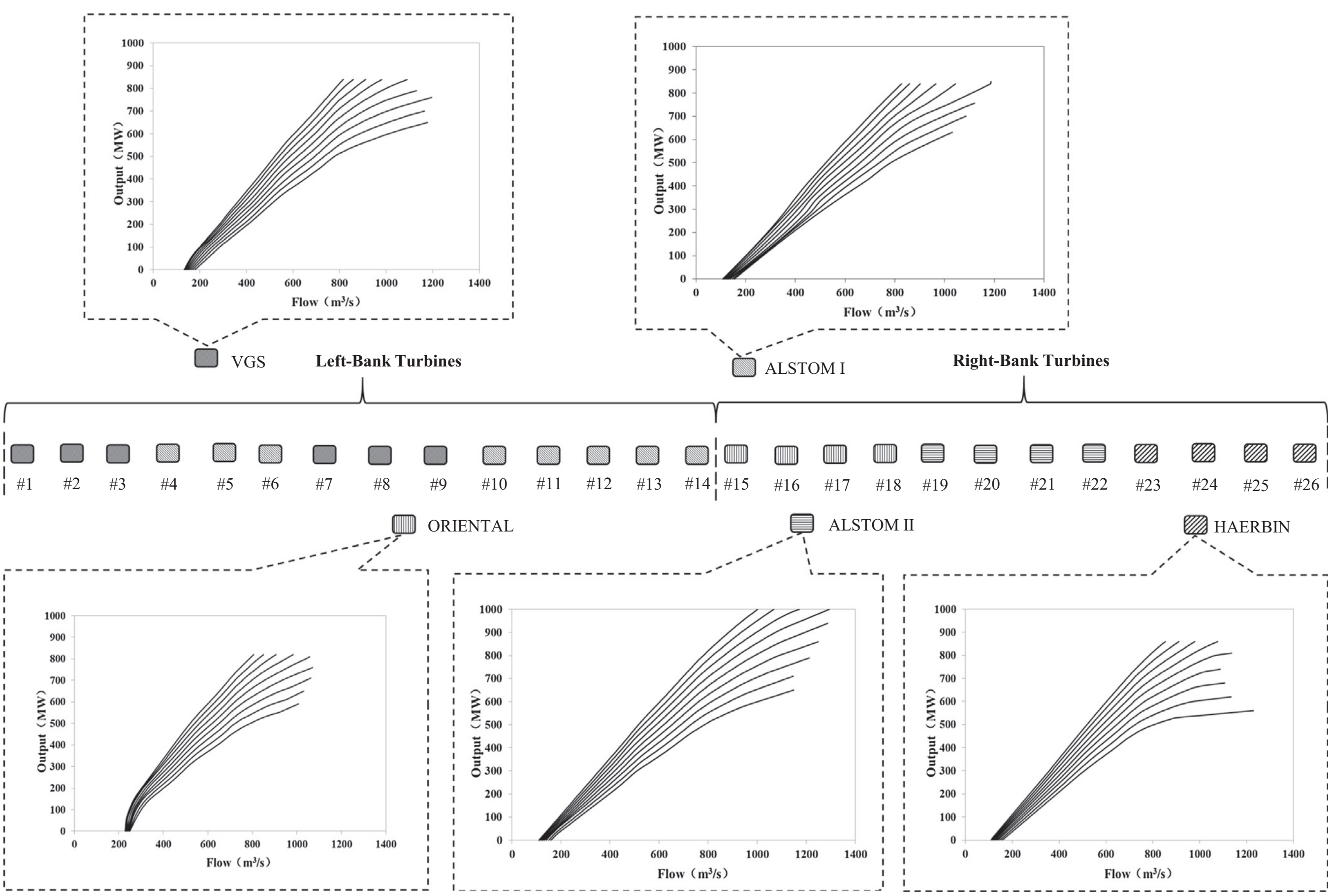


**Fig. 4.** Distribution of the 26 turbines installed in the Three Gorges Hydropower Plant.

performance of the two algorithms under different loads, test cases were run at the upper limit, mean value, and lower limit of the load for the Three Gorges Hydropower Plant, namely 16.5 million kW, 14.5 million kW, and 12 million kW, respectively. These three cases were used to characterize large, medium, and small power load levels, respectively, for the 26 units.

The GA is a stochastic algorithm that was developed as a mimicking of genetic changes and the evolutionary mechanism of organisms in the natural environment. In order to eliminate the influence of stochastic factors, in this study the ELDP was repeatedly solved many times using IGA and GA, and the optimal result out of ten results was taken as the final result for each.

### 3.3. Tests to compare performance of IGA and DP

#### 3.3.1. Testing scheme

The power load changes over time along with the power load distribution. The time-varying characteristics of the ELDP determine the importance of the calculation time required for power load allocation. The need for decision timeliness requires that the computational program be able to make the correct decisions in a very short time; otherwise, the algorithm will not have value in a practical application. In order to comprehensively evaluate the possibility of applying the algorithm, this section presents two scenarios that consider both computational precision and computation time:

**Scenario I: Comparison of calculation time under the condition of the same calculation accuracy.** To ensure comparability, the calculation accuracy of the IGA and DP algorithms must be the same. In this scenario, the optimal DP solution is employed as a benchmark. The DP algorithm is used to solve the ELDP. The optimal solution is set as the threshold $PS_{eps}$ for completing the IGA calculations. When $PS \geqslant PS_{eps}$, IGA and DP are considered to have the same accuracy, and then the calculation time is compared between the two algorithms.

**Scenario II: Comparison of calculation accuracy under the condition of the same calculation time.** The DP calculation time $TC_{DP}$ is taken as a benchmark. When the IGA calculation time $TC_{IGA}$ meets the requirement $|TC_{IGA} - TC_{DP}| \leqslant Teps$, the calculation is terminated, and then the accuracies are compared. To ensure that IGA has a higher accuracy than DP, the discrete step length of IGA should be made smaller than that of DP.

#### 3.3.2. Parameter settings

The IGA performance is affected by a variety of factors, including the selection operator, crossover operator, variation operator, initial population base, crossover rate, variation rate, and termination condition. To ensure an objective and fair comparison, the IGA parameters and operators are optimized, and only the optimal performance parameters are used. The parameters for the test scheme are as follows:

(1) The water head of the 26 turbines installed in the Three Gorges Hydropower Plant is set to 100 m.
(2) Thirteen turbine subsets (numbered 2, 4,...,26) are randomly selected from the 26 turbines to perform the load dispatch experiment.
(3) Ten groups of load are randomly generated for each subset of turbines to carry out ten independent tests to observe the statistical performance of the algorithm.
(4) The DP discrete step length $dN = 14$ MW and the IGA discrete step length $dN' = 14$ MW are used in Scenario I, and $dN' = dN/10 = 1.4$ MW is used in Scenario II.
(5) The preferred IGA parameters are set as follows: crossover rate of 1, variation rate of 0.1, $Snum = 5$, $Gen = 100$, $\varepsilon = 2$. In Scenario I, the lower limit for convergence rate $PS_{eps} = 50\%$. In Scenario II, when $n \leqslant 16$, the time difference should be $Teps = 0.3$ s, and when $n > 16$, $Teps = 1.5$ s.

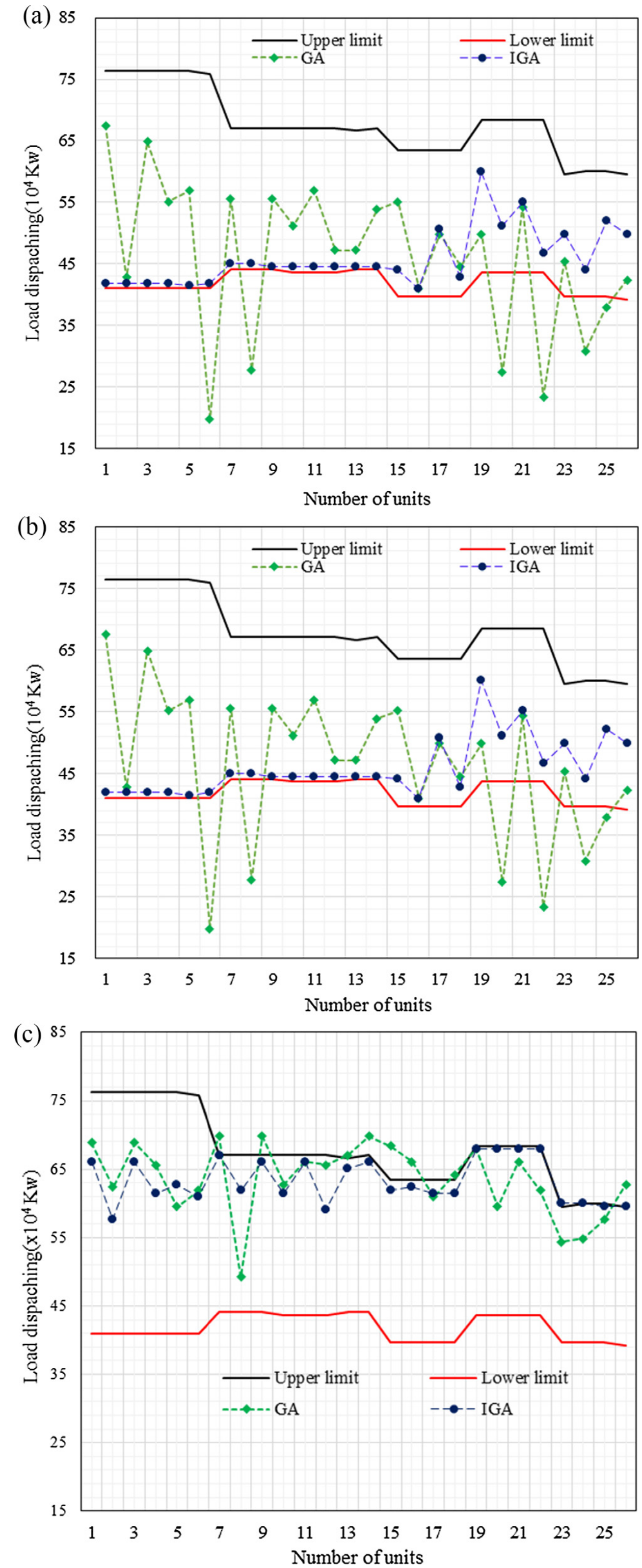


**Fig. 5.** Comparison of genetic algorithm (GA) and improved GA (IGA) load allocation schemes under different loads: (a) load allocation results with a total load of 12 million kW; (b) load allocation results with a total load of 14.5 million kW; (c) load allocation results with a total load of 16.5 million kW.

(6) IGA will be terminated when either of the following requirements is met:
- The number of algorithm generations reaches *Gen*.
- For Scenario I: The optimal solution is used to maintain *Snum* at the same value, or the objective function value corresponding to the optimal individual is equal to the DP objective function value. For Scenario II: $|TC_{IGA} - TC_{DP}| \leqslant Teps$.

(7) The computer parameters include a) CPU: Intel(R) Core(TM) i7-4810MQ; b) frequency: 2.80 GHz; c) memory: 32 GB; d) software: Microsoft Visual Studio 2010 under the Windows 7 operating system.

## 4. Results and discussion

### *4.1. Analysis of performance of GA and IGA*

The optimal results obtained are compared in Fig. 5, where the upper limit and lower limit represent the upper and lower limits of the safe operation zone, respectively. If the load is higher than the upper limit or lower than the lower limit, the turbines will enter the cavitation/vibration zone. In the figure, GA represents the GA in current use, and IGA represents the improved GA developed in the study.

As shown in Fig. 5, the scheme obtained by IGA makes all the turbines run in the stable operation zone. On the other hand, in the GA-based scheme, some turbines run in the cavitation/vibration zone, causing significant damage to the turbine. The IGA is conducive to the safe operation of turbines and can therefore reduce the operating loss and maintenance costs. In addition, as shown in Table 1, the solution can reduce the amount of generation discharge and thereby reduce the operating costs of power plants. This is because IGA reduces the search scope and improves the efficiency of searching by avoiding the infeasible zone, which makes it easier to find the optimal solution than with GA.

To fully compare the performance of the two algorithms, the minimum, maximum, and average flows are considered. These flows respectively represent the best, worst, and average results among the ten simulations for finding an optimal solution. The ten simulation results for the two algorithms are summarized in Table 2.

Table 2 shows that the IGA is more effective than the GA. The GA randomly generates the initial population, which is composed of solvable and unsolvable parts. The unsolvable population can be eliminated in the evolution by reducing the fitness through the penalty in the fitness function. The variation operation also occurs in the space of solvable and unsolvable populations, and the post-variation unsolvable population is also eliminated by penalty. However, the penalty-based treatment cannot guarantee non-negative fitness, leading to prematurity in the operations selected by GA. Its ELDP result makes turbines run in the cavitation/vibration zone. The IGA, on the other hand, enables initial population generation and perturbation variance in the feasible solution space, which ensures

**Table 2**
Simulation results for GA and IGA.

| Load N/ ($10^4$kW) | Algorithm | Minimum flow ($10^4$ m$^3$) | Maximum flow ($10^4$ m$^3$) | Average flow ($10^4$ m$^3$) |
|---|---|---|---|---|
| 1200 | IGA | 17,385 | 17,500 | 17,440.6 |
| | GA | 17,569 | 18,392 | 17,931.4 |
| | Flow savings | 184 | 892 | 490.8 |
| 1450 | IGA | 20,779 | 20,993 | 20,862 |
| | GA | 20,946 | 21,597 | 21,313 |
| | Flow savings | 167 | 604 | 451 |
| 1650 | IGA | 24,214 | 24,298 | 24,262 |
| | GA | 24,396 | 24,647 | 24,499.5 |
| | Flow savings | 182 | 349 | 237.5 |

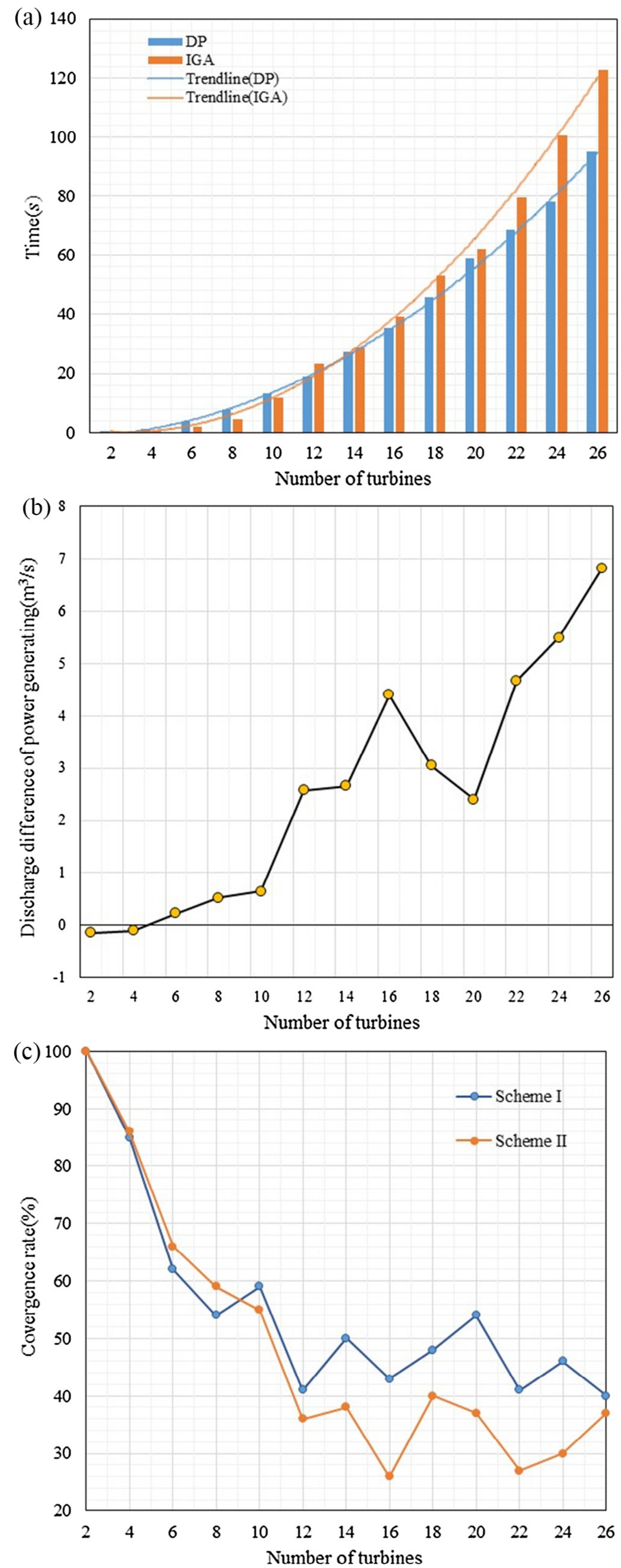


**Fig. 6.** Comparison of DP and IGA performance against number of turbines: (a) calculation time; (b) calculation accuracy; (c) IGA convergence rate.

that all the turbines operate in the safe zone. Thus, the ELDP objective is better achieved using the IGA. When the upstream water level of the reservoir and the load required by the power grid are determined, the IGA can minimize the total volume of water discharge through the rational allocation of the power load.

### 4.2. Comparative analysis of IGA and DP

The test results are shown in Fig. 6. Fig. 6 (a) shows the result of the IGA and DP calculation time comparison under the condition of the same calculation accuracy. When there are ten or fewer units, the IGA calculation time is less than that of DP; when the number of units exceeds ten, the IGA calculation time is greater than that of DP. This means that the calculation time will significantly increase with the involvement of more turbines, undermining the computational efficiency advantage of the IGA. Moreover, in terms of the large-scale load dispatch problem, it implies that the GA-based algorithms play a very limited role in avoiding the "curse of dimensionality" of the DP algorithm and in improving the computational efficiency.

Fig. 6 (b) shows the accuracy comparison result when the calculation times are equal. When there are fewer than four units, the IGA displays higher calculation accuracy than the DP algorithm. However, the GA calculation accuracy decreases as the number of turbines increases, particularly when there are more than ten units. Fig. 6 (c) shows the convergence rate of the IGA in Scenarios I and II. With the increase in the number of turbines, the algorithm convergence rate significantly decreases and finally stabilizes between 25% and 55%. This result can be attributed to the exponential expansion of the calculation dimension in the ELDP, the algorithm prematurity problem, and the lack of local search capability.

It is should be noted that 26 turbines in the Three Gorges Hydropower Plant were considered for the study. Since 2012, six other turbines have been put into operation; these are installed underground. Now the Three Gorges Hydropower Plant has 32 turbines with a stand-alone rated power of 700 MW, including 14 turbines on the left bank, 12 on the right bank, and 6 in the underground plant. Regardless of the isolated operation of the 6 turbines, the calculations for the 32 turbines performed by assuming unified scheduling management of the Three Gorges Hydropower Plant arrived at similar conclusions.

## 5. Conclusions

The GA transforms the ELDP into an unconstrained optimization problem through constructing nonlinear constraints as a penalty to be added to the fitness function. However, this algorithm was found to be infeasible for the committed turbines in the Three Gorges Hydropower Plant, which have sharply different output curves. For the ELDP case of 26 turbines in this plant, neither quantitative nor variable penalties can satisfy the non-negativity requirement of the fitness function, leading to GA convergence prematurity and reducing the search efficiency of the algorithm. More seriously, the load dispatch result of the ELDP always makes the turbines run in prohibited zones. In order to solve these problems, this study proposed an IGA that addresses the problems of the GA currently being used. The IGA constructs a feasible solution space, to which the actions of the initial population generation and the perturbation variance are restricted. Test results show that the IGA ensures that all the turbines operate in the safe zone and thus avoids the cavitation/vibration of the turbines.

This study further compared the performance of DP and the IGA in addressing the ELDP through a case study of 26 turbines of the Three Gorges Hydropower Plant. The results show the following: 1) Given the same accuracy, when there are fewer than ten turbines, the IGA needs less calculation time than DP, but when the number of turbines exceeds ten, the IGA calculation time is longer than that of DP. This indicates that the IGA has a very limited role in overcoming the "curse of dimensionality." 2) Given the same calculation time, the IGA is more accurate than DP when there are fewer than four turbines; nonetheless, the IGA accuracy shows a downward trend with an increase in the number of turbines, falling below that of DP when the number of turbines exceeds ten. 3) IGA convergence rates decrease as the number of turbines increases. This implies that it is difficult to guarantee IGA stability in high-dimension space even though the population grows, on account of the exponential expansion of the calculation dimension, the algorithm's tendency to converge prematurely, and the lack of local search capability.

As demonstrated by the study's results, the proposed improvement method can significantly reduce the ineffectiveness of the traditional GA and ensure the safety of turbines during the generating operation. Thus, the IGA provides a new approach to the GA-based solution to nonlinear constrained optimization problems. Furthermore, the evaluation method proposed in this study provides a novel approach for comparing optimization algorithms for the ELDP of large-scale hydropower plants.

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