Limited adaptive genetic algorithm for inner-plant economical operation of hydropower station

Jiao Zheng, Kan Yang and Xiuyuan Lu

ABSTRACT

A limited adaptive genetic algorithm (LAGA) is proposed in the paper for inner-plant economical operation of a hydropower station. In the LAGA, limited solution strategy, with the feasible solution generation method for generating an initial population and the limited perturbation mutation operator, is presented to avoid hydro units operating in cavitation–vibration regions. The adaptive probabilities of crossover and mutation are introduced to improve the convergence speed of the genetic algorithm (GA). Furthermore, the performance of the limited solution strategy and the adaptive parameter controlling improvement are checked against the historical methods, and the results of simulating inner-plant economical operation of the Three Gorges hydropower station demonstrate the effectiveness of the proposed approach. First, the limited solution strategy can support the safety operations of hydro units by avoiding cavitation–vibration region operations, and it achieves a better solution, because the non-negative fitness function is achieved. Second, the adaptive parameter method is shown to have better performance than other methods, because it realizes the twin goals of maintaining diversity in the population and advancing the convergence speed of GA. Thus, the LAGA is feasible and effective in optimizing inner-plant economical operation of hydropower stations.

Key words | cavitation–vibration regions, genetic algorithm, inner-plant economical operation of hydropower station, limited solution strategy, parameter controlling improvement

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INTRODUCTION

As one of the key issues for hydropower station economical operation, economic dispatch (ED) can cut unit maintenance costs and operational costs by reducing hydro units operating abrasion and water consumption. The main objective of the hydro units' ED problem is to determine the allocation of output power between the hydro generators so as to meet the power demand at minimum operating costs under various system and operating constraints (Das *et al.* 1999; Chandram *et al.* 2011). It is a large-scale highly non-linear constrained optimization problem. The minimization of costs for the ED problem of hydropower generation mainly depends on water consumption.

In the traditional ED model, maximum and minimum technical hydro generation output limits are considered, but serious limit issues affecting the turbine efficiency and service life such as cavitation and vibration are ignored (Baskar *et al.* 2003; Cai *et al.* 2007; Cheng *et al.* 2009; Nima & Hadi 2010; Christober 2011). However, ignoring limits in cavitation and vibration has led to terrible loss and serious disaster. At China's Lijiaxi hydropower station, the runner blade of turbine blades cracked and accidents to the hydro generator stator core occurred repeatedly, because hydro units operated in strong vibratory regions over a long period. At Russia's Sayano–Shushensk hydropower station, the vibration of one hydro unit led to sealing bolt and sealing plate cracking. This resulted in water being emitted and the hydro unit lifting, and damage to all hydro generators. To ensure the safe operation of a hydropower station, it is an important task to consider cavitation and vibration in

doi: 10.2166/nh.2012.198

the ED model and to find more effective approaches to optimize it.

Over many years, numerous researchers have developed various mathematical programming and optimization techniques, including equal increment method, branch and bound algorithm, mixed integer linear programming (MILP), decomposition approach, Lagrangian relaxation, and dynamic programming (DP) to solve inner-plant economical operation of hydropower stations (Allen & Bridgeman 1986; Cohen & Yoshimura 1987; Snyder *et al.* 1987; Oliveira *et al.* 1992; Guan *et al.* 1995; Georgakakos *et al.* 1997; Cheng *et al.* 2000; Martin 2000; Siu *et al.* 2001; Baltar *et al.* 2002; Yi *et al.* 2003). Among the different optimization approaches, DP has enjoyed much popularity, because it can offer convenient and efficient solutions for optimizing committed hydro units' load scheduling. However, DP faces the so-called 'curse of dimensionality', whose basic idea is that high dimensional data are difficult to work with when optimizing such large-scale highly non-linear constrained problems (Lamond *et al.* 1995). Recently, many modern intelligent heuristic approaches such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm, evolutionary programming (EP), chaotic optimization algorithm (COA) and combinations of the above methods have been developed for optimizing inner-plant economical operation (Kennedy & Eberhart 1995; Abido 2003; Cai *et al.* 2007; Christober 2011). Among them, GA is an adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics (Holland 1975). Its basic concept is to simulate processes in the natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest (Lian & Li 2006). As such, it represents an intelligent exploitation of a random search within a defined search space to solve complex problems.

However, with the increase of the larger problem scale of inner-plant economical operation of hydropower stations, especially when the number of units is more than 20 or the installed capacity is over 30,000 MW, GA is most frequently faced with the problems of premature convergence and local optimal deficiency. In the GA, the term of premature convergence means that a population for an optimization problem converged too early, resulting in it being suboptimal (Michalewicz 1996). In order to overcome these shortcomings, numerous researchers have developed various improvement strategies. To develop GA itself or to optimize other problems: first, the distribution property of the initial population is emphasized significantly, because it affects convergence performance of GA (Zalzala & Fleming 1997). Second, a GA with real-value coding is developed to improve low search efficiency of the algorithm. The results of reservoir optimal operation demonstrate that this improved GA had a better performance of convergence speed (Chang *et al.* 2005). Third, an adaptive genetic algorithm (AGA) with adaptive probabilities of crossover and mutation is defined. This efficient approach realized the twin goals of improving convergence speed and maintaining diversity in the population of GA (Srinivas & Patnaik 1994). Also, a hybrid optimization based on GA and simulated annealing (SA) is presented; the experimental results of TSP (travelling salesman problem) and VLSI (very large scale integration) floor planning proved that the combined method achieves high speed processing, while maintaining the quality of the solutions (Yoshikawa *et al.* 2008). However, the improvement strategies have rarely involved inner-plant economic operation of a hydropower station. As can be seen from the literature, individual coding has evolved from binary coding conversion to real-value coding (floating-point coding and decimal coding) on the one hand (Chang *et al.* 2005). The constant crossover probability and mutation probability have developed to a random one on the other hand (Nima & Hadi 2010). Therefore, it is time to find an advanced GA to optimize inner-plant economical operation of hydropower stations.

The remainder of the paper is structured as follows: next, the mathematical model for inner-plant economical operation of a hydropower station is introduced. This optimal model considers cavitation and vibration in ED, hence this is a complex model that includes linear and non-linear, equality and inequality constraints. In the following section, a limited adaptive genetic algorithm (LAGA) is proposed. In this new algorithm, first, the limited solution strategy, including the feasible solution generation method for generating initial population and the limited perturbation mutation operator, is adopted to avoid hydro units operating in cavitation–vibration regions. Second, the adaptive probabilities of crossover and mutation are introduced in order to improve the convergence speed of the GA. Then, a case study of the Three Gorges hydropower plant with 26 generating units is presented. Moreover, the performance of limited solution strategy is checked against the historical strategy and the adaptive parameter method is examined against the historical adaptive one and the random one. Finally, the main conclusions and future works are presented.

ANALYSIS OF MATHEMATICAL MODEL FOR HYDROPOWER STATION INNER-PLANT ECONOMICAL OPERATION

There are many different turbine generator units with different unit capacities and different efficiency curves in a hydropower station. In order to maximize overall hydropower station efficiency, it is urgently required to optimize its water allocation. The purpose of ED is to pursue minimum total water consumption of hydro units when the upstream water level and load requirement is ascertained for economical operation.

The objective function of ED in one schedule period can be expressed as

$$\text{Min } Q = \sum_{j=1}^{n} u_j \cdot q_j(N_j, H) \tag{1}$$

Subject to the following constraints:

- Load balance constraint:

$$\sum_{j=1}^{n} u_j \cdot N_j = N \tag{2}$$

- Work water head constraint of turbine:

$$H_{\min_j} \leq H \leq H_{\max_j} \tag{3}$$

- Hydro unit capacity constraint:

$$N_{1,\min_j} \leq N_j \leq N_{1,\max_j} \tag{4}$$

- Hydro unit stable operation condition constraint:

$$N_{2,\min_j} \leq N_j \leq N_{2,\max_j} \tag{5}$$

where the notations used are as follows: Q is the total water consumption of hydropower plant for power generation; n represents the number of units; u_j is the symbol of the alternative unit, considering units maintenance. The value of u_j is 1 or 0, which denotes the unit participating or not participating in load distribution. N_j represents unit output; H represents water head in this schedule period; q_j is the water consumption of the jth hydro unit according to N_j and H; N is the load requirement of hydropower station; $H_{\min_j}$ and $H_{\max_j}$ represent bounds for work water head of the jth hydro unit in this schedule period; $N_{1,\min_j}$ and $N_{1,\max_j}$ are the allowable capacity of minimization and maximization for the jth hydro unit; $N_{2,\min_j}$ and $N_{2,\max_j}$ are bounds for stable operation output of the jth hydro unit according to H.

In this model, hydro unit cavitation–vibration regions are considered in Equation (5). Namely, the hydro unit stable operation output constraint means avoiding operating in the cavitation–vibration regions. By the intersection of stable operation output area and the allowable capacity area, the allowable hydro unit operation output constraint can be expressed by

$$N_{\min_j} \leq N_j \leq N_{\max_j} \tag{6}$$

Therefore, if H has been obtained by short-term optimal operation of a hydropower station, this inner-plant economical operation is a complex problem which includes linear and non-linear, equality and inequality constraints.

In the above hydropower station inner-plant economical operation model, the unit capacity and the requirement of avoiding cavitation–vibration regions are both taken into account in allowable hydro unit output constraints. Generally, a hydro unit operation area is classified into cavitation–vibration regions, including prohibition operation ranges and limited operation ranges, and stable operation regions. One outstanding example is the unit operation area of the Three Gorges left-bank ALSTOM (Figure 1). The division is based on hydro unit bracket vibration, water-guided swing, pressure fluctuation and other standards. Additionally, for different hydro units, their unit operation areas differ from one another.

There are big vibration and big noise in a hydro unit when it operates in a cavitation–vibration region. To ensure long-term security and stability, the hydro unit can only operate in stable operation regions. Thus, for

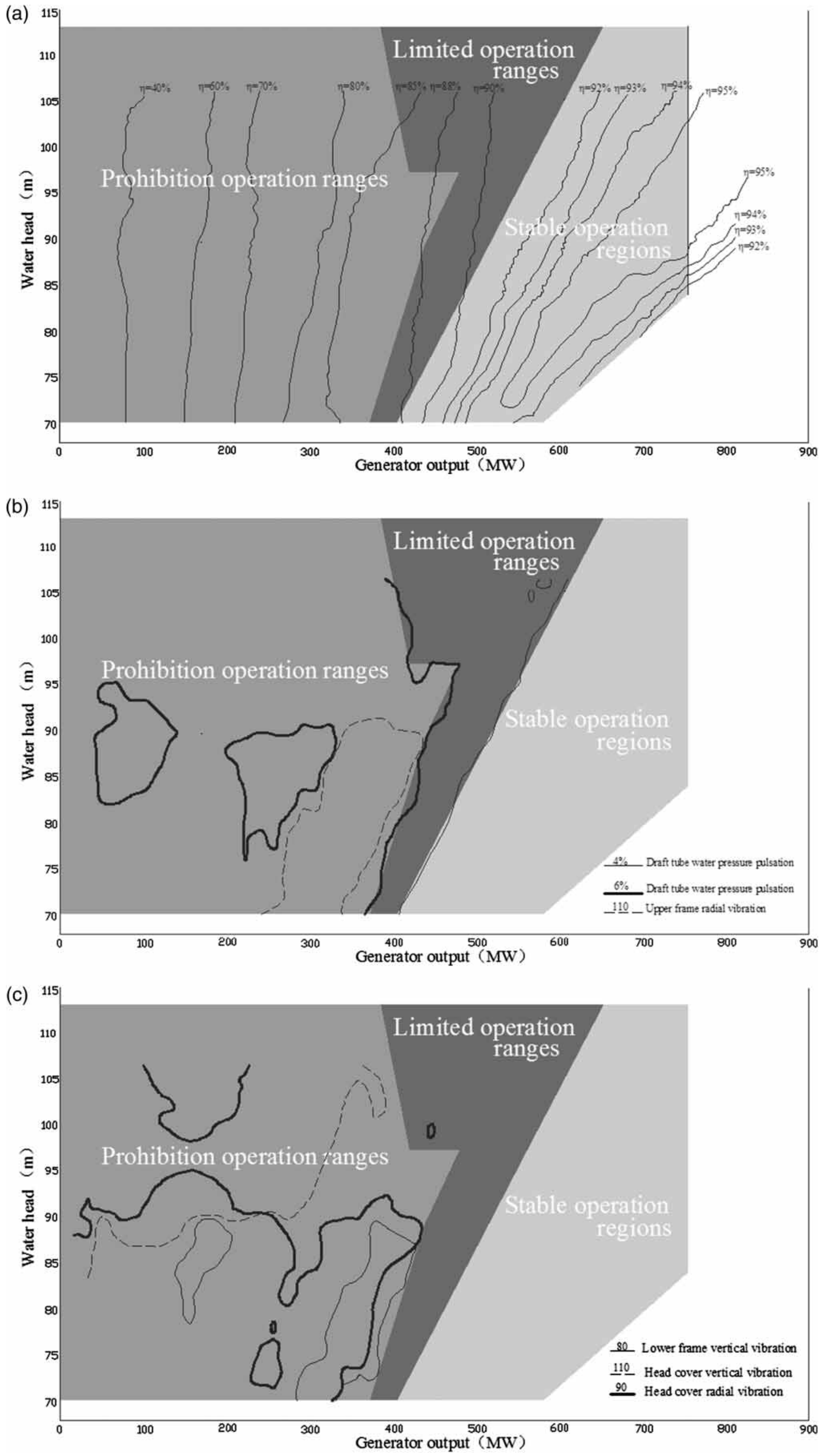

Figure 1 | Unit operation area of the Three Gorges left-bank ALSTOM unit.

hydropower station economical operation, it is important to avoid cavitation–vibration region operation and to keep operating in stable operation regions. The limits for hydro unit stable operation regions and the allowable hydro unit capacity are both associated with water head (H). Therefore, a feasible interval of allowable hydro unit operation output can be established by the intersection of hydro unit stable operation regions and the allowable hydro unit capacity.

LIMITED ADAPTIVE GENETIC ALGORITHM

GA is an adaptive heuristic search algorithm and represents an intelligent exploitation of a random search within a defined search space to solve complex problems. There are four advantages of GA compared with other traditional optimization methods: first, it works with a coding of the parameter set rather than the parameters themselves. Second, it searches from a population of points at any one time rather than a single point. Third, it uses fitness information rather than derivatives or other auxiliary knowledge. Finally, it uses probabilistic transition rules rather than a deterministic one (Goldberg *et al.* 1989; Chang 1990).

GA can be considered to consist of the following steps (Burn & Yulianti 2001):

1. Make the string of parameters codifying the variables.
2. Generate the initial population of strings.
3. Evaluate the fitness of each string.
4. Select excellent strings from the current population to mate.
5. Perform crossover and mutation for the selected strings.
6. Repeat steps 3–5 for the required number of iterations.

The genetic string for the hydropower station inner-plant economical operation is $(p_{i,1}, p_{i,2}, \ldots, p_{i,n})$, in which, $p_{i,j}$ is the real-value coding for the cumulative output of the jth hydro unit in the ith individual string; n represents the number of hydro units.

In order to improve the convergence speed of the GA and to keep safe the operation of the hydro units, a LAGA is proposed. There are two differences between the LAGA and the traditional GA (TGA) which has been adopted in optimizing the inner-plant economical operation of a hydropower station. On the one hand, a limited solution strategy is proposed to avoid hydro units operating in cavitation–vibration regions in the LAGA. First, 'the feasible solution generation method' is substituted for 'a randomly generated method' to generate an initial population. Second, 'the limited perturbation mutation operator' is substituted for the 'perturbation mutation operator'. In the TGA, hydro units operate in both stable operation regions and cavitation–vibration regions (Baskar *et al.* 2003; Nima & Hadi 2010). 'The adaptive probabilities of crossover and mutation' are substituted for the 'random probabilities of crossover and mutation' (Nima & Hadi 2010) to improve the convergence speed of the GA.

Individual coding and fitness function

Individual coding not only decides the performance of solution space, but also affects the crossover and mutation operations indirectly. Real-value coding is used to avoid inefficient searching caused by long strings of binary coding (Chang & Chen 1998; Chang *et al.* 2005). Thus, discrete solution space is formulated via the control accuracy of step, and corresponding relation between the real-value coding and cumulative output is formed.

The fitness function of an individual reflects the objective function value. Designing a fitness function requires realizing the twin goals of keeping non-negative value and ensuring higher fitness corresponding to better individual. According to the purpose of ED and considering the computer bytes restriction for storing, the fitness function is expressed as

$$\text{fitness} = M/(Q + 0.001) \tag{7}$$

where M represents a large constant. In TGA, the allowable hydro unit operation output constraint is often met by imposing quantitative penalties in fitness function design. However, solution quality relies heavily on the penalty coefficient and it is difficult to control the value of the penalty coefficient at that time. If the value of the penalty coefficient is too small, GA may converge on an infeasible solution. In contrast, GA may converge on a local optimization solution when the value of the penalty coefficient is too large. In this research, a feasible solution is generated in the initial population to avoid imposing penalties in the fitness function.

Limited solution strategy

Feasible solution generation method

The distribution property of the initial population seriously affects convergence performance of the algorithm (Zalzala & Fleming 1997). The traditional method for generating an initial population is to use a randomly generated one. It is too difficult to search for a feasible solution by using a randomly generated one because the inner-plant economical operation of a hydropower station is a complex problem which includes linear and non-linear, equality and inequality constraints. The feasible solution generation method is proposed to keep hydro unit operation away from cavitation–vibration regions. It is also superior to the randomly generated method in terms of economical operation. In this new method, avoiding the cavitation–vibration regions, load balance constraint and others are all considered in generating the initial population.

The real-value coding for cumulative output

$$p_{i,j-1} = \frac{N'_{\min}i,j-1}{p_{opdt}} + \mathrm{int}\left[Rnd' \times \left(\frac{N'_{\max}i,j-1}{p_{opdt}} - \frac{N'_{\min}i,j-1}{p_{opdt}}\right)\right] \tag{8}$$

in which, $p_{i,j-1}$ is the real-value coding for cumulative output of the $(j-1)$th hydro unit in the ith individual; $N'_{\max_{i,j-1}}$ and $N'_{\min_{i,j-1}}$ are bounds for cumulative output of the $(j-1)$th hydro unit; p_{opdt} represents control accuracy of step; Rnd′ is a uniform random number in [0,1]; int is the rounding function.

For the ith individual, when all hydro units are operating:

Using load balance constraint

$$\sum_{j=1}^{n} N_j = N \tag{9}$$

gives the cumulative output of the nth unit

$$p_{i,n} = N/p_{opdt} \tag{10}$$

Applying cumulative output descending relation gives

$$\sum_{j=1}^{n-1} N_j = \sum_{j=1}^{n} N - N_n \tag{11}$$

According to Equations (11) and (6), gives

$$\sum_{j=1}^{n-1} N_{\min_j} \le \sum_{j=1}^{n-1} N_j \le \sum_{j=1}^{n-1} N_{\max_j} \tag{12}$$

$$\sum_{j=1}^{n} N - N_{\max_j} \le \sum_{j=1}^{n-1} N_j \le \sum_{j=1}^{n} N - N_{\min_j} \tag{13}$$

Hence, the coefficient $N'_{\min_{i,j-1}}$ and $N'_{\max_{i,j-1}}$ is obtained from

$$N'_{\min_{i,j-1}} = \max\left\{\sum_{t=1}^{j-1} N_{\min_t},\ \sum_{t=1}^{j} N_t - N_{\max_j}\right\} \tag{14}$$

$$N'_{\max_{i,j-1}} = \min\left\{\sum_{t=1}^{j-1} N_{\max_t},\ \sum_{t=1}^{j} N_t - N_{\min_j}\right\} \tag{15}$$

Therefore, the real-value coding for the cumulative output of the nth hydro unit is acquired via Equation (10), and others' real-value coding are obtained via Equations (14), (15) and (8) by contrary reverse order recurrence tactics. In the initial population, various model constraints are all met and cavitation–vibration regions are avoided according to this new method.

Limited perturbation mutation operator

In order to ensure that all hydro units operate away from the cavitation–vibration regions, the limited perturbation mutation operator is introduced. The picture showing the bound for cumulative output in the limited perturbation mutation operation is represented in Figure 2.

On the one hand, under the influence of the jth allowable hydro unit operation output constraint, mutation in the ith stage should neither be less than point A: $\sum_{t=1}^{j-1} N''_t + N_{\min_j}$ nor higher than point B: $\sum_{t=1}^{j-1} N''_t + N_{\max_j}$. On the other hand, under the influence

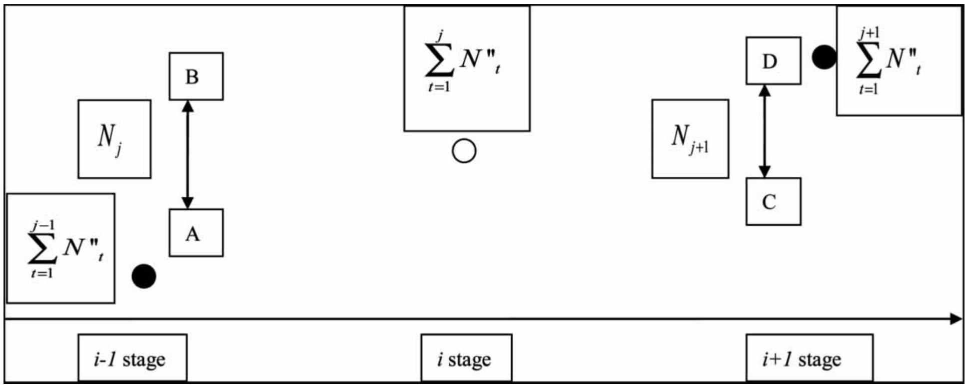

Figure 2 | The bound for cumulative output in the limited perturbation mutation operation.

of the $(j+1)$th allowable hydro unit operation output constraint, it should neither be less than point C: $\sum_{t=1}^{j+1} N''_t - N_{\max_j}$ nor higher than point D: $\sum_{t=1}^{j+1} N''_t - N_{\min_{j+1}}$. In which, N''_t is the output of the tth hydro unit after mutation operation; $N''_{\max_{i,j}}$ and $N''_{\min_{i,j}}$ are the bounds for cumulative output in mutation operation. They can be calculated by

$$N''_{\min_i} = \max\left\{\sum_{t=1}^{j-1} N''_t + N_{\min_j}, \sum_{t=1}^{j+1} N''_t - N_{\max_j}\right\} \tag{16}$$

$$N''_{\max_{i,j}} = \min\left\{\sum_{t=1}^{j-1} N''_t + N_{\max_j}, \sum_{t=1}^{j+1} N''_t - N_{\min_{j+1}}\right\} \tag{17}$$

Thus the limited perturbation mutation operator is expressed as:

$$p''_{i,j} = \begin{cases} \dfrac{N''_{\min_{i,j}}}{p_{opdt}} + \mathrm{int}\left[Rnd'' \times \left(\dfrac{N''_{\max_{i,j}}}{p_{opdt}} - \dfrac{N''_{\min_{i,j}}}{p_{opdt}}\right)\right] & if{:}Rnd \le p_m \\ p_{i,j} & if{:}Rnd > p_m \end{cases} \tag{18}$$

where Rnd'' and Rnd are both random numbers in [0,1]; p_m represents mutation probability; $p_{i,j}$ is translated into $p''_{i,j}$ after the perturbation mutation operation.

Selection operator and arithmetic crossover operator

In the LAGA, traditional selection operators can be adopted in solving hydropower station inner-plant economical operation because the fitness function meets the requirement of being non-negative. The roulette wheel selection operator is most commonly used, so it is adopted in this research. In this method, the higher fitness ones will be reserved to be descendants and the others will be out according to the fitness size of proportion selection.

Arithmetic crossover operator is introduced as follows

$$p'_{i,j} = \alpha.p_{i_1,j} + (1-\alpha).p_{i_2,j} \tag{19}$$

$$p'_{i+1,j} = (1-\alpha).p_{i_1,j} + \alpha.p_{i_2,j} \tag{20}$$

where, α represents weight, the i_1th and the i_2th are two individuals for crossover operation; the ith and the $(i+1)$th are the new individuals through crossover operation. Thus $p_{i_1,j}$ and $p_{i_2,j}$ are translated into $p'_{i,j}$ and $p'_{i+1,j}$ after crossover operation. Arithmetic crossover operation is a linear search between two solution individuals, so the load balance constraint is still met after crossover operation and the hydro unit operation condition constraint is also met when $\alpha \in [0, 1]$ is satisfied.

Adaptive parameter controlling improvements

The first adaptive parameter controlling improvement

The significance of P_c (crossover probability) and P_m (mutation probability) for controlling GA performance has long been acknowledged in the literature (DeJong 1985; Goldberg 1989). The higher value of P_c, the greater is the chance of damaging genetic pattern. As P_c decreases, however, the search can become slow. The choice of P_m is critical to GA performance, and a large value of P_m transforms GA into a purely random search algorithm. However, it is difficult to produce a new individual by using a small value of P_m. TGA usually uses a constant P_c and P_m (Chang *et al.* 2005). It is very tedious work to define the value of P_c and P_m by repeated experiments, for different optimization issues. It is also hard work to find the best value of P_c and P_m for each question. The adaptive probabilities of crossover and mutation depending on the fitness value of individuals were proposed by Srinivas & Patnaik (1994) and can be expressed as:

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f')}{f_{\max} - f_{avg}} & if\colon f \geq f_{\mathrm{avg}} \\ k_2 & if\colon f < f_{\mathrm{avg}} \end{cases} \tag{21}$$

$$P_m = \begin{cases} \dfrac{k_3(f_{\max} - f)}{f_{\max} - f_{avg}} & if\colon f \geq f_{\mathrm{avg}} \\ k_4 & if\colon f < f_{\mathrm{avg}} \end{cases} \tag{22}$$

where $f_{\max}$ is the highest value of fitness in the population; f_{avg} represents the average value of fitness in the population; f' denotes the one which has higher fitness between two crossover individuals; f is fitness value of the mutation individual; and k_1, k_2, k_3, k_4 are adaptive parameters with values between 0 and 1.

However, this improvement is ineffective in early evolution, because $P_c = 0$ and $P_m = 0$ when the individual's fitness value is the highest one in the population. In order to overcome this flaw, the developed adaptive P_c and P_m (the first adaptive parameter controlling improvement) can be expressed as:

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})(f' - f_{\mathrm{avg}})}{f_{\max} - f_{\mathrm{avg}}} & if\colon f_{\mathrm{avg}} \leq f' \\ P_{c1} & if\colon f' < f_{\mathrm{avg}} \end{cases} \tag{23}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f_{\max} - f)}{f_{\max} - f_{\mathrm{avg}}} & if\colon f_{\mathrm{avg}} \leq f \\ P_{m1} & if\colon f < f_{\mathrm{avg}} \end{cases} \tag{24}$$

in which, $P_{c1} = 0.9$, $P_{c2} = 0.6$, $P_{m1} = 0.1$, $P_{m2} = 0.001$.

This adaptive improvement not only gives lower values of P_c and P_m for high fitness individuals and higher values of P_c and P_m for low fitness individuals, but also gives the individual the maximum fitness P_{c2} and P_{m2}. The lower values of P_c and P_m aid in the convergence of the GA, and the higher values of P_c and P_m prevent GA from getting stuck at a local optimum. This developed controlling improvement depends on the fitness value of an individual and the dispersion degree of population to deliver the best P_c and P_m relative to each individual. Thus it achieves the twin goals of maintaining diversity in the population and sustaining the convergence capacity of the GA.

The second adaptive parameter controlling improvement

In China, Lian & Li (2006) proposed an adaptive parameter controlling improvement based on evolving algebra and the fitness value of an individual, and employed it in the Lijiaxia hydropower station inner-plant economic operation. The improvement (the second adaptive parameter controlling) can be represented as:

$$P_c = \begin{cases} m_1 & m_1 \geq P_{c,\min} \\ P_{c,\min} & m_1 < P_{c,\min} \end{cases} \tag{25}$$

$$m_1 = P_{c,\max} \times 2^{(-t/T)} \tag{26}$$

$$P_m^n = \begin{cases} m_2 & m_2 \geq P_{m,\min} \\ P_{m,\min} & m_2 < P_{m,\min} \end{cases} \tag{27}$$

$$m_2 = \exp\left(\frac{R_n}{p_{opsize}} - 1\right) \times \frac{1}{1 + t/T} \times P_{m,\max} \tag{28}$$

where $P_{c,\max}$ $P_{c,\min}$ denote the crossover probability of minimization and maximization; $P_{m,\min}$ and $P_{m,\max}$ are bounds for mutation probability; t represents current evolution generation; T defines maximum evolution generation; p_m^n represents the mutation probability of the nth individual; R_n is the descending sequence number of the nth individual p_{opsize} denotes the size of population, namely containing number of individuals.

In this parameter controlling improvement, P_c decreases via t increasing, and it remains unchanged after reducing to a given minimum value ($P_{c,min}$). While, mutation probability decreases with t increasing, and for different individual fitness values, their mutation probabilities differ from one another at the same evolution generation. This improvement achieves lower values of P_m for high fitness individuals.

As can be seen from other research about economic operation, Nima & Hadi (2010) adopted a random parameter between the maximum value and the minimum value to optimize inner-plant economic operation of a complex hydropower station.

CASE STUDY: INNER-PLANT ECONOMICAL OPERATION OF THE THREE GORGES HYDROPOWER STATION

The Three Gorges hydropower station, located on the Yangtze River in China, is used as a case study. The station currently consists of 26 hydro units. Among them, there are six left-bank VGS units, eight left-bank ALSTOM units, four right-bank ALSTOM units, four right-bank Orient power units and four right-bank HEC units. In other words, there are five kinds of hydro units, and total installed capacity is 18,200 MW. Due to the large numbers, types and diversity condition combinations of units, the inner-plant economical operation of the Three Gorges hydropower station is a high dimensional and non-linear combinatorial optimization problem.

In this research, hydro units of the Three Gorges hydropower station are sequentially numbered. To illustrate the results of comparison between the proposed improvement and the traditional one, load distribution corresponding to 70, 74 and 77 m water heads are used as a sample. Zero load flow is taken into account to simulate practical economical operation. The control accuracy is 10^4 KW. Stable operation regions of each hydro unit in the Three Gorges corresponding to each water head are shown in Table 1 and the power–water head–flow characteristic curves (NHQ curves) of the five kinds of hydro unit corresponding to each water head are demonstrated in Figure 3.

The comparison between the limited solution strategy and the historical strategy

To illustrate the advantage of the limited solution strategy, including the feasible solution generation method for generating an initial population and the limited perturbation mutation operator, a comparison between GA with limited solution strategy (LAGA) and TGA is made by optimal load distribution. In the comparison, the first adaptive parameter controlling improvement, with the adaptive probabilities of crossover and mutation, is applied to improve convergence speed. In addition, evolutionary generation 500 is adopted as the termination condition of the two algorithms. In order to compare the characteristics of the two algorithms, three-level magnitude loads (large, medium and small) are considered. Because GA is an optimization method imitating biological evolution based on stochastic theory, this research studies 10 simulation operations for each algorithm, and selects the best result as the optimal scheduling for comparison.

Case 1: optimal load distribution corresponding to a 70 m water head

The results of comparison between the two algorithms for optimal load distribution under three three-level

Table 1 | Stable operation region of each unit in the Three Gorges corresponding to each water head (unit: 10^4 KW)

Water head	Left-bank VGS units 1–6	Left-bank ALSTOM units 7–14	Right-bank ALSTOM units 15–18	Right-bank Orient power units 19–22	Right-bank HEC units 23–26
70 m	38.5–57	40.5–58	36–55.5	40.5–61	35.5–52
74 m	40.5–63	43–63.5	38.5–60.5	42.5–65.5	38–56.5
77 m	42–67.5	44.5–67	40–63.5	44–68.5	40–60

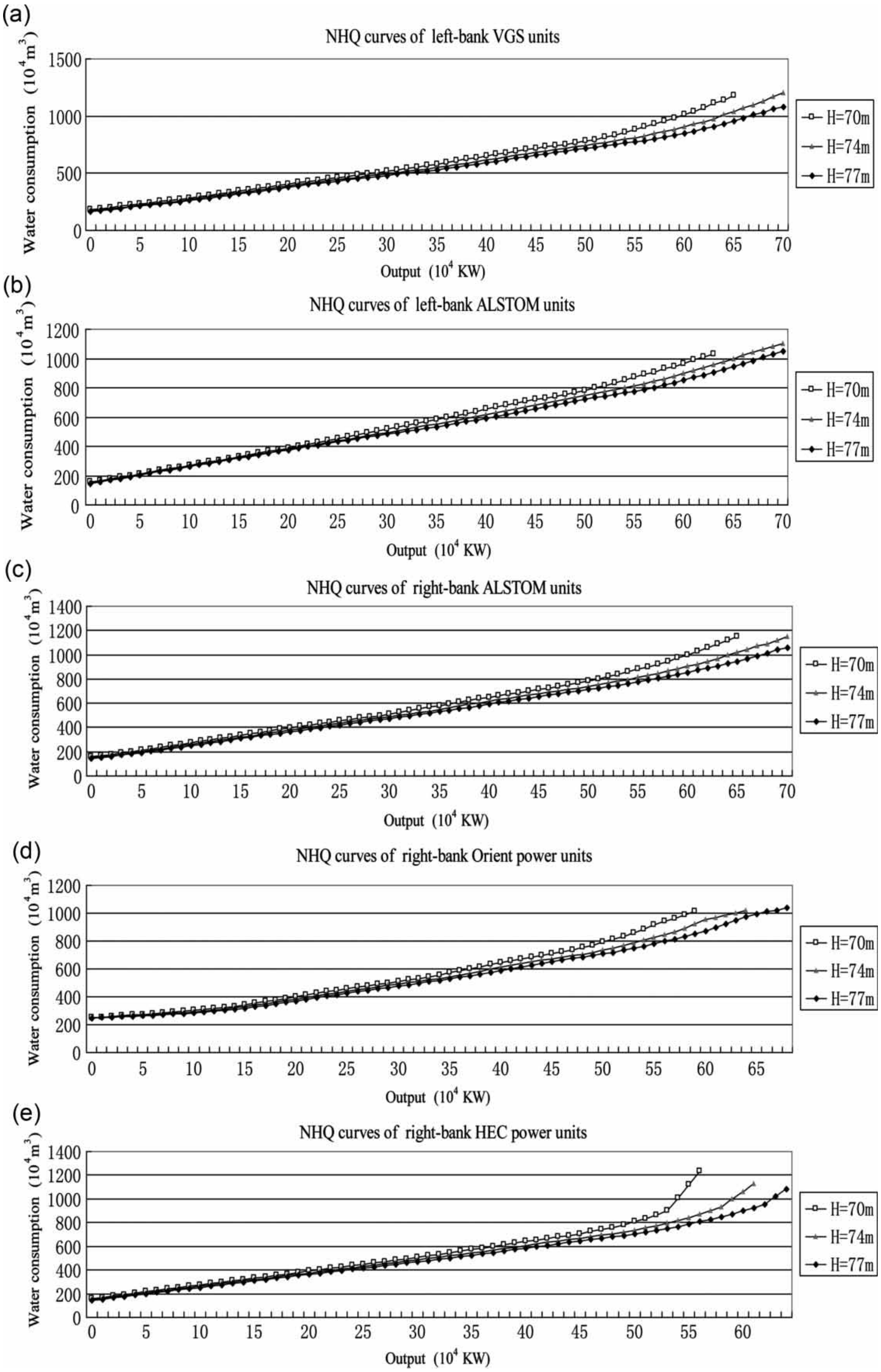

Figure 3 | The NHQ curves of five kinds of hydro unit corresponding to each water head.

magnitude loads corresponding to a 70 m water head are shown in Figure 4, where minimum value and maximum value limits are in terms of the stable operation area for a 70 m water head.

Minimum water consumption, maximum water consumption and the average consumption are three evaluation indexes adopted in this research to fully illustrate the results of comparison. The minimum water consumption represents the best optimal result, the maximum one denotes the worst optimal result, and the average one defines the average optimal result in 10 simulation operations. The contrasting results between the LAGA and TGA corresponding to a 70 m water head are illustrated in Table 2.

From Table 2, when there is a 70 m water head, it is seen that the LAGA has a better performance than TGA whether the load is large or small. Taking the best result (the minimum water consumption) as the optimal scheduling for comparison, Table 2 demonstrates that the LAGA saves $250 \times 10^4\,m^3$, $733 \times 10^4\,m^3$ and $398 \times 10^4\,m^3$, respectively, when the load is $1{,}100 \times 10^4$ KW, $1{,}250 \times 10^4$ KW, $1{,}450 \times 10^4$ KW. Furthermore, Figure 4 shows that the LAGA keeps all hydro units operating away from cavitation–vibration regions while saving water consumption in the case of a 70 m water head.

Case 2: optimal load distribution corresponding to a 74 m water head

The results of comparison between two algorithms for optimal load distribution under three three-level magnitude loads corresponding to a 74 m water head are demonstrated

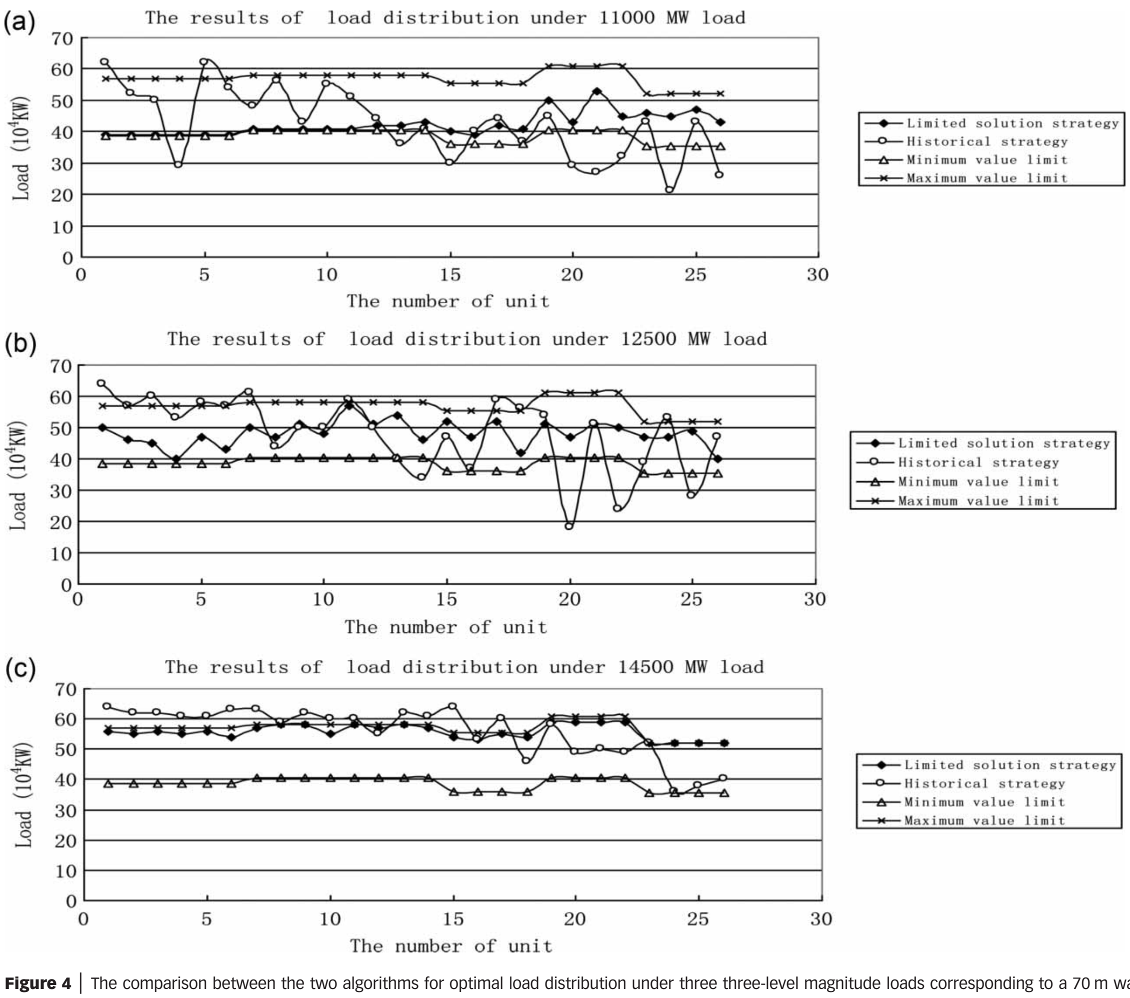

Figure 4 | The comparison between the two algorithms for optimal load distribution under three three-level magnitude loads corresponding to a 70 m water head.

Table 2 | The contrasting results between the LAGA and TGA corresponding to a 70 m water head (unit: 10^4 m^3)

Load (10^4 KW)	Algorithm	The minimum water consumption	The maximum water consumption	The average water consumption
1,100	LAGA	17,724	17,856	17,772
	TGA	17,974	18,431	18,240
	Save water	250	575	468
1,250	LAGA	19,775	19,908	19,857
	TGA	20,508	20,819	20,646
	Save water	733	911	789
1,450	LAGA	23,563	23,580	23,573
	TGA	23,961	24,262	24,176
	Save water	398	682	603

in Figure 5, where minimum value and maximum value limits are in terms of the stable operation area for a 74 m water head.

Minimum water consumption, maximum water consumption and the average consumption are three evaluation indexes adopted in this research to fully illustrate the results of comparison. The minimum water consumption represents the best optimal result, the maximum one denotes the worst optimal result, and the average one defines the average optimal result in 10 simulation operations. The contrasting results between the LAGA and TGA corresponding to a 74 m water head are illustrated in Table 3.

From Table 3, corresponding to a 74 m water head, it can be seen that the LAGA has a better performance than TGA whether the load is large or small. Taking the best result (the minimum water consumption) as the optimal scheduling for comparison, Table 3 shows that the LAGA saves 478×10^4 m^3, 851×10^4 m^3 and 574×10^4 m^3, respectively, when the load is $1{,}170 \times 10^4$ KW, $1{,}350 \times 10^4$ KW and $1{,}550 \times 10^4$ KW. Furthermore, Figure 5 demonstrates that the LAGA keeps all hydro units operating away from cavitation–vibration regions while saving water consumption.

Case 3: optimal load distribution corresponding to a 77 m water head

The results of comparison between the two algorithms for optimal load distribution under three three-level magnitude loads corresponding to a 77 m water head are shown in Figure 6, where the minimum value and the maximum value limits are in terms of the stable operation area for a 77 m water head.

The minimum water consumption, the maximum water consumption and the average consumption are three evaluation indexes adopted in this research to fully illustrate the results of comparison. The minimum water consumption represents the best optimal result, the maximum one denotes the worst optimal result, and the average one defines the average optimal result in 10 simulation operations. The contrasting results between the LAGA and TGA corresponding to a 77 m water head are illustrated in Table 4.

From Table 4, corresponding to a 77 m water head, the LAGA once again has a better performance than TGA whether the load is large or small. Taking the best result (the minimum water consumption) as the optimal scheduling for comparison, Table 4 shows that the LAGA saves 260×10^4 m^3, 357×10^4 m^3 and 132×10^4 m^3, respectively, when the load is $1{,}200 \times 10^4$ KW, $1{,}450 \times 10^4$ KW and $1{,}650 \times 10^4$ KW. Moreover, Figure 6 demonstrates that the LAGA keeps all hydro units operating away from cavitation–vibration regions while saving water consumption.

Tables 2–4 show the LAGA has a better performance than TGA whether the load is large or small in the same environment. Namely, LAGA finds a better solution to reducing water consumption by avoiding infeasible solution area searching in the same environment. It is noted from Figures 4–6 that all hydro units operate in stable operation regions from the distribution scheme in the LAGA. In

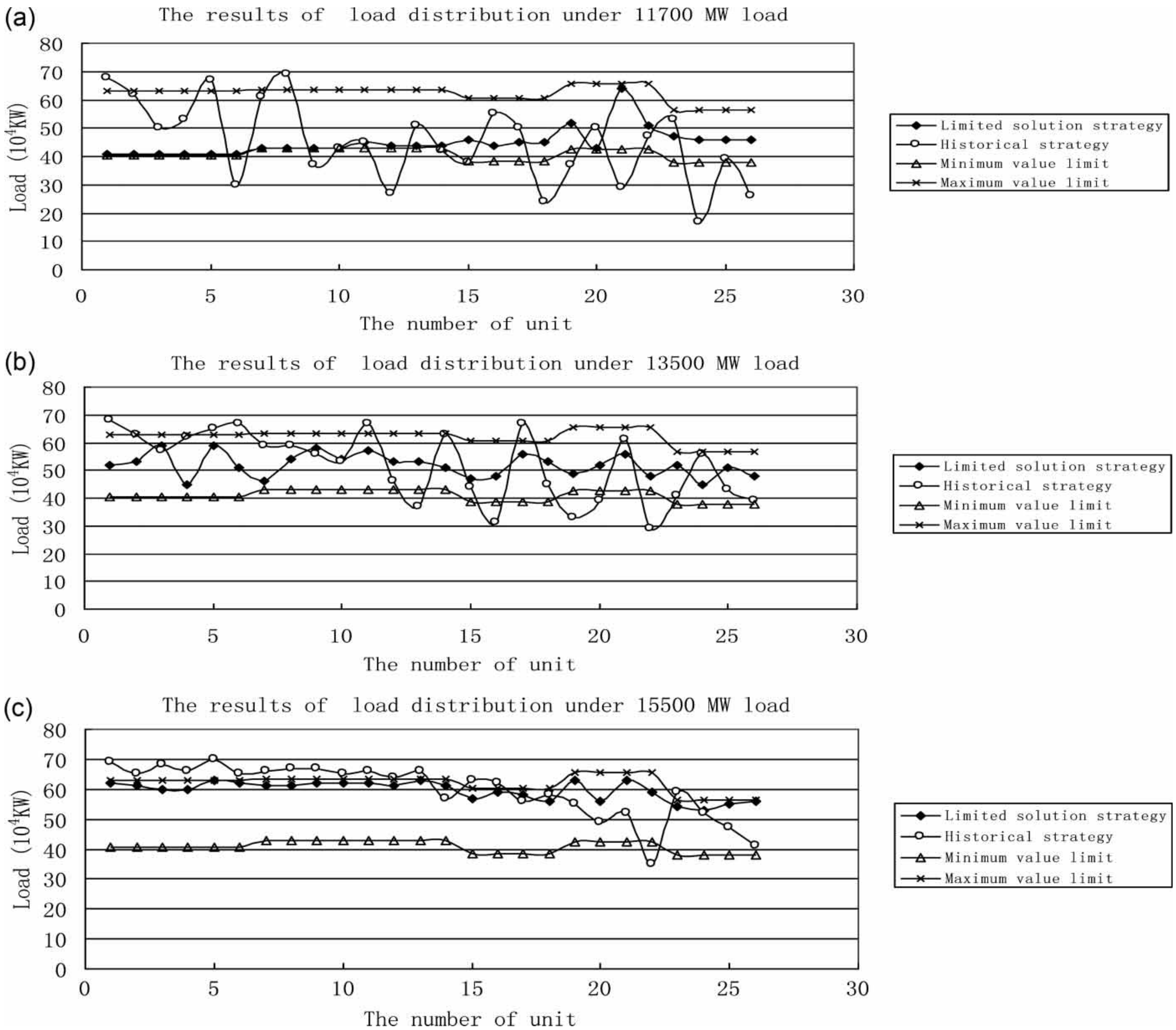

Figure 5 | The comparison between the two algorithms for optimal load distribution under three three-level magnitude loads corresponding to a 74 m water head.

contrast, some hydro units operate in cavitation–vibration regions from the distribution scheme in the TGA. TGA cannot keep all hydro units operating away from cavitation–vibration regions which will cause a great deal of harm to the hydro units. The LAGA can overcome this, and can guarantee that all hydro units operate in stable operation regions. Therefore, not only can the LAGA cut unit maintenance costs via reducing unit operating losses, but can also cut unit operational costs by reducing water consumption. Although using the limited solution strategy, the penalty in fitness function is avoided and the diversity of population is maintained in the LAGA. Thus, the LAGA is a superior algorithm for solving hydropower station inner-plant economical operation, to a certain degree.

Comparison of parameter controlling improvements

To compare the parameter controlling improvements, limited solution strategies, including the feasible solution generation method for generating initial population and the limited perturbation mutation operator, are adopted in the GA. The first adaptive parameter controlling improvement, the second adaptive parameter controlling improvement and random controlling improvement are

Table 3 | The contrasting results between the LAGA and TGA corresponding to a 74 m water head (unit: 10^4 m^3)

Load (10^4 KW)	Algorithm	The minimum water consumption	The maximum water consumption	The average water consumption
1,170	LAGA	17,704	17,773	17,727
	TGA	18,182	19,070	18,444
	Save water	478	1,297	717
1,350	LAGA	20,044	20,240	20,170
	TGA	20,895	21,377	21,078
	Save water	851	1,137	908
1,550	LAGA	23,582	23,639	23,614
	TGA	24,156	24,514	24,389
	Save water	574	875	775

compared in this research. Of these, the second adaptive parameter controlling improvement is proposed by Lian & Li (2006) for the Lijiaxia hydropower station inner-plant economical operation, and the random controlling improvement is proposed by Nima & Hadi (2010). The value of, $P_{c,\max}$, $P_{m,\min}$ and $P_{m,\max}$ denote 0.5, 1, 0.005 and 0.05

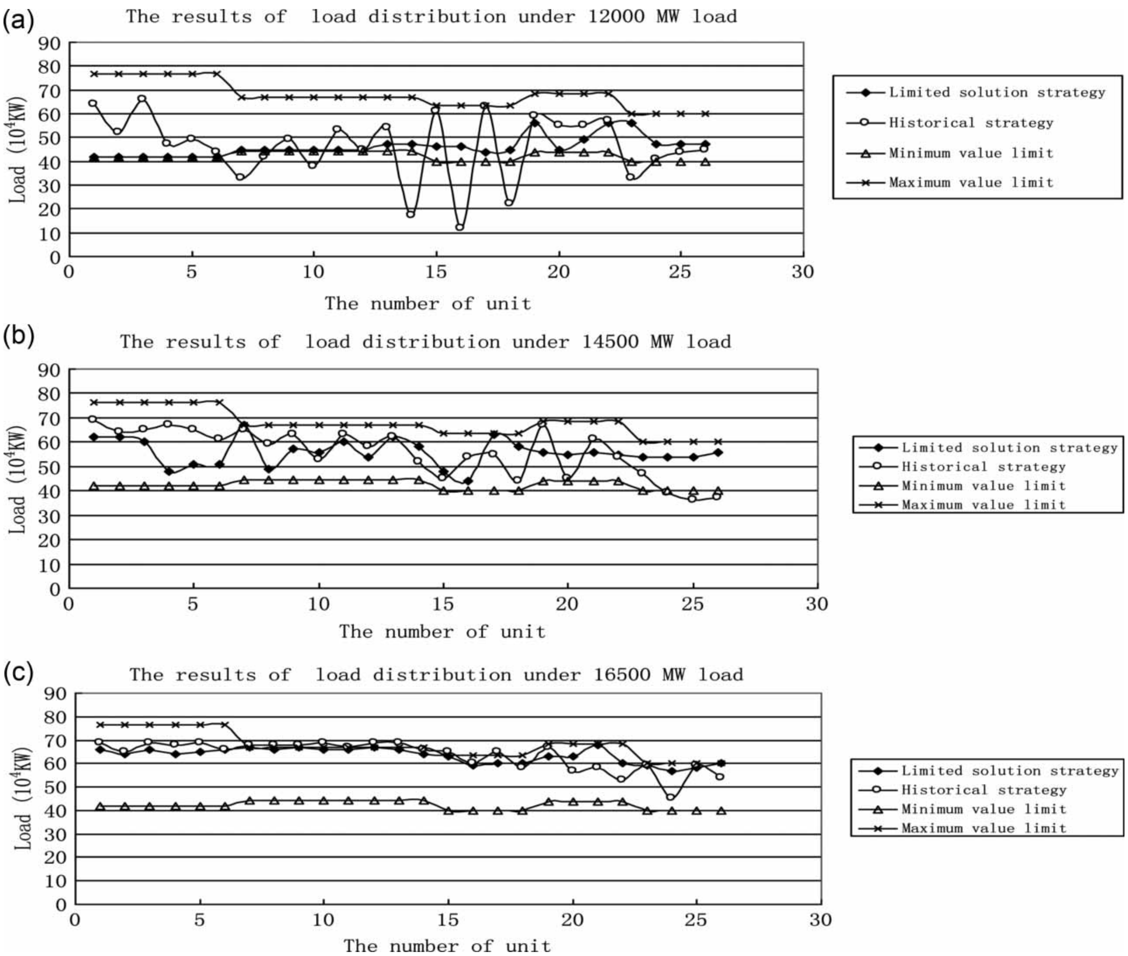

Figure 6 | The comparison between the two algorithms for optimal load distribution under three three-level magnitude loads corresponding to a 77 m water head.

Table 4 | The contrasting results between the LAGA and TGA corresponding to a 77 m water head (unit: 10^4 m^3)

Load (10^4 KW)	Algorithm	The minimum water consumption	The maximum water consumption	The average water consumption
1,200	LAGA	17,399	17,493	17,439.6
	TGA	17,659	17,931	17,770.1
	Save water	260	438	330.5
1,450	LAGA	20,709	20,808	20,773.3
	TGA	21,066	21,407	21,243.9
	Save water	357	599	470.6
1,650	LAGA	24,225	24,271	24,250.1
	TGA	24,357	24,621	24,452.8
	Save water	132	350	202.7

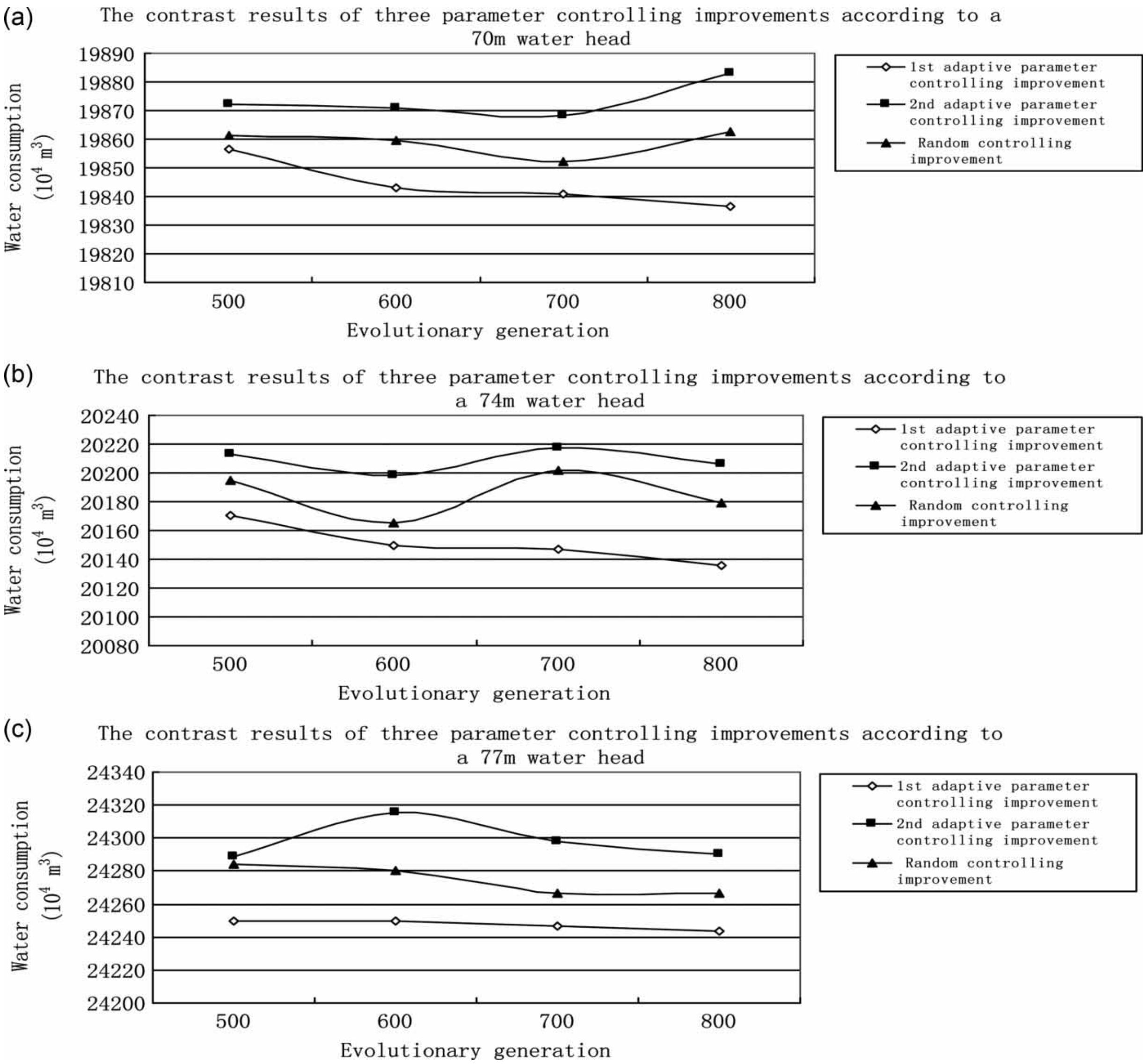

Figure 7 | The contrasting results of the three parameter controlling improvements.

(Srinivas & Patnaik 1994). In order to compare the characteristics of these improvements, GA optimizing load distribution of the Three Gorges under 70, 74 and 77 m water heads, medium magnitude loads are considered. As well, evolutionary generations 100, 150, 200, 250 and 300 are adopted as termination conditions of the GA to compare the performance better. This research studies 10 simulation operations for GA with each parameter controlling improvement in each evolutionary generation, and selects the average result as the optimal scheduling for comparison. The contrasting results of the three parameter controlling improvements are shown in Figure 7.

Figure 7 demonstrates that the first adaptive parameter controlling improvement shows better performance than the others. To maintain diversity in the population, in the first adaptive parameter controlling improvement, P_c and P_m increase as the fitness value of the population became equal or reached local optimization value. However, P_c and P_m decrease as the fitness value of the population dispersed. Meanwhile, the higher fitness individuals are corresponding to larger P_c and P_m, and lower fitness individuals are corresponding to smaller P_c and P_m. Thus this improvement strategy obtains the best P_c and P_m relative to each individual and keeps diversity in the population and advances convergence speed by taking advantage of the fitness value of individuals and dispersion degree of population.

CONCLUSIONS AND FUTURE WORK

There is no reasonable application method to avoid hydro units operating in cavitation–vibration regions in GA optimizing hydropower station economical operation. Negative fitness function has often occurred by imposing penalties in the traditional method, thus early maturity in the selection process of TGA is caused. Namely, TGA often converges to a locally optimal solution.

In this paper, the LAGA has been successfully introduced to optimize hydropower station inner-plant economical operation. The limited solution strategy and the adaptive parameter controlling improvement have been demonstrated to be superior in terms of avoiding a hydro unit operating in cavitation–vibration regions and in improving convergence speed. The LAGA has an important reference value for an improved GA applied in the inner-plant economical operation of a hydropower station. It can reduce hydro unit operating losses and maintain normal operation of hydro units by avoiding cavitation–vibration regions. Furthermore, it can reduce water consumption and achieve a better solution by avoiding infeasible solution area searching.

Inner-plant economical operation of a hydropower station is a complex problem which includes linear and non-linear, equality and inequality constraints. There are still many problems in inner-plant economical operation of hydropower stations, such as start-up and shut-down costs, minimum start-off time constraints and Automatic Generation Control (AGC), which need to be studied in the future.

ACKNOWLEDGEMENTS

This research was funded by the National Key Basic Research Program of China (973 Program) (2012CB417006), the National Science Support Plan Project of China (2009BAC56B03) and the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD).

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First received 20 December 2011; accepted in revised form 28 June 2012. Available online 4 December 2012