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Parameter Identification of Pump Turbine Governing System Using an Improved Backtracking Search Algorithm

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Abstract: Accurate parameter identification of pump turbine governing system (PTGS) is of great importance to the precise modeling of pumped storage unit. As PTGS is characterized by uncertainties and strong nonlinear characteristics, it is difficult to identify its parameters. To solve the parameter identification problem for PTGS, an improved backtracking search algorithm (IBSA) is proposed by combining the original BSA with the orthogonal initialization technique, the chaotic local search operator, the elastic boundary processing strategy and the adaptive mutation scale factor. The proposed IBSA algorithm for parameter identification of PTGS was applied on an illustrative example to demonstrate its accuracy and efficiency. The simulation results have shown that IBSA performed better compared with the particle swarm optimization, the gravitational search algorithm and the original BSA in regard to solution quality and parameter identification accuracy.

Keywords: pump turbine governing system; parameter identification; improved backtracking search algorithm; orthogonal initialization; chaotic local search; elastic boundary processing; adaptive mutation scale factor

1. Introduction

Pumped storage unit (PSU) is an efficient tool for peak shaving, valley filling, frequency and phase adjustment, rotation and emergency reserve in a power grid, which makes it important in guaranteeing power supply quality, operation flexibility and reliability of the power grid [1,2]. Pump turbine governing system (PTGS) is the terminal actuator for the automatic generation control of PSU. It is mainly composed of a penstock system, a servomechanism, a pump turbine, a generator and a controller. PSU generally has the characteristics of high head, large inertia and frequent changing of working conditions. The structure of the penstock system is complex and the water hammer effect of the long water diversion pipelines is obvious. The servomechanism system is featured by the nonlinear characteristics of clearance, dead zone, limiting amplitude, etc. The pump turbine is likely to be encountered with the “S” characteristic area or the “hump area” problem while the rotation speed changes rapidly. All these characteristics of the different parts of PTGS are important sources of instability in the process of power generating.

In the actual optimal control and stability analysis of PSU, it is necessary to know the time constant of the servomechanism system, the inertial time constant, adjustment coefficient of the generator, and the flow inertial time constant of the penstock system. However, there is little opportunity to test these parameters on actual units. On the other hand, with the increasing operating life of the...
unit, it is often accompanied by the wear and performance degradation of the mechanical structure, thus the actual parameters of the system are often different from the initial parameters. Therefore, it is necessary to research on parameter identification strategies for the accurate modeling of PSU and to support for the stability analysis of power system.

Although the parameter identification of PTGS is important and difficult, study on this subject is inadequate [3]. As the difference between the model of PTGS and that of traditional hydraulic turbine governing system (HTGS) is not very significant, the related works for parameter identification of traditional HTGS can provide meaningful reference for the research on that of PTGS [4,5]. However, due to the time-varying parameters and the complex nonlinearity of the different parts of PTGS, the physical model of PTGS cannot be accurately described using mathematical expressions. Thus, the classical time-domain and frequency-domain identification methods based on linear identification theory including the frequency response method, the step response method, the impulse response method [6–8], the least square method [9] and system identification based on spectral methods [10–12] are no longer applicable. Moreover, due to the non-differentiation of the objective functions of the gradient or two-step gradient based optimization methods, the employment of these methods for parameter identification is limited. The current research on parameter identification of nonlinear HTGS or PTGS usually employs a heuristic non-gradient optimization algorithm. The basic idea of the heuristic algorithms for parameter identification of PTGS is to convert the parameter identification problem into a parameter optimization problem by defining the error between the system output and the model output as the fitness function. The unknown parameters are obtained along with the iterations of the intelligent optimization algorithms. The parameter identification methods for HTGS or PTGS based on intelligent optimization algorithms have received extensive attention in recent years [13].

Li et al. [14] and Chen et al. [15] established a HTGS that truly reflects the nonlinearity of the hydraulic turbine, the hydraulic actuator and the water hammer effect of the penstock system. An improved gravitational search algorithm (GSA) that combined the original GSA with the search strategy of the particle swarm optimization (PSO) was developed to obtain the most accurate parameters of the nonlinear HTGS. Zhang et al. [16] proposed a mixed-strategy based GSA (MS-GSA) based on the elite agent’s guidance, the adaptive gravitational constant function and the Gaussian and Cauchy mutations to enhance the exploitation ability of GSA. Experimental results of this paper have demonstrated that the MS-GSA can achieve significantly better exploration and exploitation ability compared with the seven other popular meta-heuristics algorithms. Xu et al. [17] developed an improved GSA (IGSA) algorithm based on the chemotaxis operator of the bacterial foraging algorithm for parameter identification of PTGS. A self-adaptive parameter identification model combining the IGSA is constructed to realize the self-adaptive adjusting of the parameters. Chen et al. [18] made a comparative analysis on the performance of three novel parameter identification methods for an integrated model of HTGS with uncertainties. The three methods are referred as the unknown parameter observer, the synchronization-based parameter observer and the ant lion optimizer (ALO) based estimator. Results have shown that the ALO-based estimator has the best system independence.

The Backtracking Search Algorithm (BSA) proposed by Civicioglu [19] is an optimization algorithm that generates a search direction matrix using the difference vector between the historical populations. Civicioglu verified the effectiveness of BSA by comparing it with six other intelligent optimization algorithms, including the PSO, the artificial bee colony, the adaptive differential evolution, etc. Because of its simple structure, the BSA has gained extensive attention from various researchers. In the last few years, it has been successfully employed in many fields such as shop scheduling [20], turning operation [21], economic dispatch [22,23], forecasting [24], controller optimization [25,26] and proportional-integral-derivative (PID) controller tuning [27]. Although BSA performs well compared with some other algorithms, many studies have demonstrated that there still exists much room for improving the performance of BSA [28,29]. In this study, the BSA algorithm is employed to solve the parameter identification problem of PTGS. To enhance the convergence speed and solution quality of
the original BSA algorithm, the orthogonal initialization technique, the chaotic local search operator, the elastic boundary processing strategy and the adaptive mutation scale factor are introduced and combined with the BSA.

The rest of this study is arranged as follows: Section 2 introduces the four different parts of PTGS. Section 3 introduces the original BSA algorithm and the strategies for improving its performance. Section 4 illustrates the parameter identification strategy for PTGS using IBSA. Section 5 presents the experiments and compares the results. Section 6 presents conclusions to the experiment results.

2. Model of Pump Turbine Governing System

PTGS is a complex nonlinear feedback control system which consists of a pump turbine speed governor and four controlled objects. The speed governor consists of two parts, namely, a controller and a servomechanism to realize the control of the guide vane opening. The controlled objects of the pump turbine include a speed governor, a penstock system, a pump turbine and a generator with a load. A simple structure of PTGS is illustrated in Figure 1.

![Figure 1. A simple structure of PTGS.](image)

2.1. Model of the Speed Governor

2.1.1. Model of the Controller

A parallel PID controller is usually exploited in the controller of PTGS. The structure of the parallel PID controller is similar to the conventional controller of which the functions are frequency regulation and opening adjustment. The transfer function of the turbine controller is described as follows:

\[
\sigma_{\text{PID}}(s) = \left( K_p + \frac{K_d s}{1 + T_d s} + \frac{K_i}{s} \right) (x_c - x) + b_p (y_c - \sigma_{\text{PID}}) \frac{K_i}{s}
\]  

(1)

where \( \sigma_{\text{PID}} \) denotes the output of the controller; \( x_c \) represents the given speed; \( x \) represents the turbine speed; \( y_c \) is the given opening; \( b_p \) denotes the permanent transition coefficient; \( T_d \) represents the differential time constant; and \( K_p, K_i \) and \( K_d \) represent the proportional gain, the integral gain and the differential gain, respectively.

2.1.2. Model of the Servomechanism

A servomechanism is the physical actuator of the pumped turbine speed governor. It receives the electrical output signal from the controller and converts it into the displacement of the governor relay displacement to realize the control and adjustment of the guide vane opening of the pump turbine. The servomechanism mainly includes a main pressure valve and a main relay. The transfer functions of these two parts are expressed as follows:

\[
G(s) = \frac{K_v}{1 + T_p s}
\]

(2)

\[
G_v(s) = \frac{1}{T_y s}
\]

(3)
where $T_{yl}$ denotes the inertial time constant of the main pressure valve; $K_v$ represents the proportional coefficient; and $T_{y}$ is the open-loop time constant of the main relay.

Combined with the above description about the transfer function of the controller, the block diagram of the transfer functions of the speed governor (Figure 2) can be expressed as:

![Figure 2. The block diagram of the speed governor.](image)

2.2. Model of the Penstock System

Considering the real-time computation and the parameterization characteristics of the penstock system, a second-order elastic water hammer model [1] is adopted in this study. The transfer function of the penstock system can be calculated by:

$$G_h(s) = \frac{H(s)}{Q(s)} = \frac{-T_{ws}s}{1 + \frac{1}{2}fT_{r}s + \frac{1}{8}T_{r}^2s^2}$$

(4)

where $T_{ws}$ is flow inertia time constant of the diversion system; $f$ denotes the head loss coefficient; and $T_{r}$ represents water hammer pressure wave time constant.

2.3. Model of the Pump Turbine

Accurate modeling of the pump turbine is the key to the modeling and simulation of PTGS. In the current research of the nonlinear pump turbine modeling, the characteristic curves are usually adopted. The pump turbine model based on characteristic curves can be described as follows:

$$\begin{align*}
M_{11} &= f_M(a, N_{11}) \\
Q_{11} &= f_Q(a, N_{11})
\end{align*}$$

(5)

where $M_{11}$ denotes the unit moment; $Q_{11}$ represents the unit flow; $N_{11}$ denotes the unit speed; $a$ represents the guide vane opening; and the nonlinear functions $f_M$ and $f_Q$ can be described using the moment characteristic curve and the flow characteristic curve of the pump turbine, respectively. Taking a pumped storage power station in China as an example, the characteristic curves of the pump turbine (Figure 3) are shown as follows:
Due to the multi-value of the characteristic curve in the “S” area, the interpolation error of it is great and the derivative is not continuous, which may lead to calculation error in the iterations. In this study, the improved Suter transform [30] is introduced to convert the original characteristic curves to the \( WH \) and \( WM \) characteristic curves through the dimensionless parameters. The converting equations are expressed as follows:

\[
\begin{align*}
WH(x, y) &= \frac{h}{v^2 + q^2 + C_h^2} \\
WM(x, y) &= \frac{(m + w_1 h) R_y}{v^2 + q^2 + R_h^2}
\end{align*}
\]

whilst \( v \geq 0 \)

\[
\begin{align*}
x &= \arctan \left( \frac{q + w_2 \sqrt{h}}{v} \right) \quad \text{while} \quad v < 0
\end{align*}
\]

where \( v, q, h, m, \) and \( y \) represent the values of the unit speed, the flow, the head, the moment and the opening, respectively; \( x \) is the relative flow angle; \( w_1 > |M_{11\max}| / M_{11r}; w_2 \in [0.5, 1.2]; R_y \in [0.1, 0.3]; R_h \in [0.4, 0.6]. \) The \( WH(x, y) \) and \( WM(x, y) \) curves obtained using the improved Suter transform (Figure 4) are described as follows:

![Figure 3. The characteristic curves of a pump turbine: (a) flow characteristic curve; and (b) moment characteristic curve.](image1)

![Figure 4. The \( WH \) and \( WM \) curves obtained using the improved Suter transform: (a) \( WH \) curve; and (b) \( WM \) curve.](image2)
2.4. Model of the Generator with a Load

The modeling of PTGS usually uses a first-order model that reflects the dynamics characteristics and the self-adjusting properties of the generator. Considering the balance between the pump turbine moment and the generator torque, the transfer function of the generator with a load can be expressed as follows:

\[ G_g(s) = \frac{1}{\frac{T_a}{s} + en} \]  

(7)

where \( T_a \) and \( en \) represent the inertial time constant and the adjusting coefficient that considers both the generator and the load, respectively.

3. Improved Backtracking Search Algorithm

3.1. Overview of the Backtracking Search Algorithm

BSA developed by Civicioglu is a swarm-intelligence optimization algorithm which was designed to be a global optimizer to solve real-valued numerical optimization problems [19]. One advantage of BSA compared with other evolutionary algorithms is that it has only one control parameter, which improves its generalization ability. Another advantage of the algorithm is that it sets up a memory to preserve a historical population to generate a good search direction. The step-by-step description of BSA can be summarized as below:

**Step 1: Initialization.** Randomly generate an initial population \( P \) according to Equation (8):

\[ P_{i,j} = \text{rand} \times (\text{up}_j - \text{low}_j) + \text{low}_j, \quad i = 1, 2, \ldots, N, \quad j = 1, 2, \ldots, D \]  

(8)

where \( N \) denotes the population size; \( D \) represents the dimension of the decision matrix of the optimization problem; \( P_{i,j} \) represents the value of the \( j \)-th dimension of the \( i \)-th individual; \( \text{up}_j \) and \( \text{low}_j \) denote the maximum and minimum values of the \( j \)-th dimension, respectively; and \( \text{rand} = U(0, 1) \), \( U(\cdot) \) is a uniform distribution of which the mean is 0 and the variance is 1.

**Step 2: Selection-I.** Selection-I first generates a historical population \( \text{oldP} \) randomly to prevent the historical population from being empty, and thus the feasibility of the algorithm is guaranteed. The random generated historical population is initialized as follows:

\[ \text{oldP}_{i,j} = \text{rand} \times (\text{up}_j - \text{low}_j) + \text{low}_j \]  

(9)

Secondly, the historical population \( \text{oldP} \) is updated according to the following equations:

\[ \text{if } a < b \text{ then } \text{oldP} = P, \text{else } \text{oldP} = \text{oldP} \]  

(10)

\[ \text{oldP} = \text{randshuffle}(\text{oldP}) \]  

(11)

where \( a \) and \( b \) represent two random variables that obey uniform distribution; and \( \text{randshuffle}(\cdot) \) denotes a random selection function. According to Equation (10), a population of the previous generations is randomly selected to replace the current population such that the memory function of the BSA is realized.

**Step 3: Mutation.** Firstly, the individuals of the parent population are sorted according to Equation (12), and then the offspring population is generated according to Equation (13):

\[ \text{oldP} = \text{Permuting}(\text{oldP}) \]  

(12)

\[ \text{Mutant} = P + F \times (\text{oldP} - P) \]  

(13)
where $\text{Permuting}(\cdot)$ represents the random ranking function; $F$ denotes the mutation scale factor which controls the variation amplitude of the search direction matrix, $F = 3 \cdot \text{rand, rand} \sim N(0, 1)$; and $N(\cdot)$ denotes the standard normal distribution.

**Step 4: Crossover.** The crossover operation of the BSA algorithm mainly consists of two steps. In the first step, a $N \times D$ dimensional binary matrix is generated. Two pre-determined crossover strategies are called with equal probability by comparing two randomly generated numbers. The first step of the crossover step is as follows:

\[
\text{if } \text{rand}1 < \text{rand}2 \text{ then } \text{map}(i, u(1 : \text{mixrate} \times \text{rand} \times D)) = 0, \\
\text{else } \text{map}(i, \text{randi}(D)) = 0
\]  

(14)

where $\text{mixrate}$ denotes the cross probability; and $\text{rand}$, $\text{rand}1$ and $\text{rand}2$ denote random numbers that obey the uniform distribution.

In the second step, a new experimental population is generated according to Equation (15). $T_{ij}$ is replaced by $P_{ij}$ in the experimental population when $\text{map}_{ij} = 1$. The second step is as follows:

\[
T = \text{map.} \times P + ( \sim \text{map}) \times \text{Mutant}
\]  

(15)

**Step 5: Selection-II.** Calculate the fitness values of the individuals in the experimental population $T$ and the current population $P$. Update the current population $T$ using the greedy algorithm, such that the individual with the minimum fitness value is obtained. For minimization problems, the current population is updated according to the following equation:

\[
P_i = \begin{cases} 
T_i, & \text{fitness}(T_i) < \text{fitness}(P_i) \\
P_i, & \text{else}
\end{cases}
\]  

(16)

where $\text{fitness}(\cdot)$ represents the function to calculate the fitness value.

**Step 6:** If the termination criteria are met, stop iterating and output the optimal solution; else skip to Step 2.

3.2. Improvements of the Backtracking Search Algorithm

Due to the simple structure of the BSA algorithm, it is easy to combine the BSA algorithm with other strategies to improve its performance [31]. In this study, an improved backtracking search algorithm (IBSA) is developed by combining the orthogonal initialization technique, the chaotic local search operator, the elastic boundary processing strategy and the adaptive mutation scale factor with the original BSA algorithm. The IBSA algorithm generates the initial population according to the orthogonal initialization technology, which can enhance the population diversity and improve the algorithm’s ability to explore the feasible domain. At the same time, the chaotic local search operator and the elastic boundary processing strategy are exploited to generate the offspring individuals. The variation amplitude of the search direction matrix can be adjusted using the adaptive mutation scale factor, which can prevent the algorithm from falling into local optimal solutions and thus approximate the global optimal solution.

3.2.1. The Orthogonal Initialization Technique

The distribution of the individuals in the initial population can affect the convergence rate and the quality of the final solution of the algorithm. With the help of the orthogonal table, the orthogonal initialization technology can generate a uniform-distributed initial population in the feasible domain, such that the algorithm can explore the feasible domain thoroughly. The steps of the orthogonal initialization technique are as follows:
**Step 1:** Assuming that $x_i$ is the $i$-th decision variable of the continuous optimization problem. The range of $x_i$ can be quantified into $Q$ discrete levels $r_{i1}, r_{i2}, \ldots, r_{iQ}$. $r_{ij}$ can be expressed as follows:

$$r_{ij} = \begin{cases} x_{i \text{, min}} & j = 1 \\ x_{i \text{, min}} + (j - 1) \cdot \frac{x_{i \text{, max}} - x_{i \text{, min}}}{Q-1} & 1 < j < Q \\ x_{i \text{, max}} & j = Q \end{cases}$$ (17)

where $Q$ is an odd number.

**Step 2:** The orthogonal table $L_M(Q^N)$ is designed according to [32], where $M$ represents the number of elements in the orthogonal table, $N$ represents the number of the decision variables, and $M = Q^J$. $J$ should satisfy the following condition:

$$\min M = Q^J \quad \text{st} \quad \left\{ \begin{array}{l} B = \frac{M-1}{M-2} \geq N \\ M \geq NP \end{array} \right.$$ (18)

where $NP$ denotes the size of the initial population; the orthogonal table $L_M(Q^N)$ can be expressed as $L_M(Q^N) = [a_{ij}]_{M \times N^J}$ and $a_{ij}$ represents the $i$-th level of the $j$-th decision variable.

**Step 3:** A uniform-distributed orthogonal population can be generated in the feasible domain according to the orthogonal table designed in Step 2. Generally, the number of the individuals in the orthogonal population is slightly larger than the population size of the algorithm, so that the best $NP$ individuals are retained according to the elite reservation strategy.

### 3.2.2. The Chaotic Local Search Operator

BSA generates the search direction matrix for crossover and mutation through the difference vector between the historical population and the parent population. The difference between the individuals within the initial iteration population is great, thus the algorithm can maintain a strong global search ability. However, as the iteration processes, the differences between the historical population and the parent population and among the individuals within the population become smaller, and the information entropy contained in the difference vector also decreases, which in turn affects the global search performance of the algorithm.

Chaotic local search is one of the most effective ways to prevent the intelligent evolutionary algorithms from falling into local minimum. The ergodicity and randomness of the chaotic system can make the chaotic sequence go through all the search space without repetition [33]. The chaotic local search can reduce the blindness and disorder of the random local search and improve its efficiency. The IBSA algorithm proposed in this study employs the chaotic local search operator to improve BSA’s Selection-II operator.

When the quality of the optimal solution remains unchanged in a certain iteration $Lim_{Gen}$, generate a chaotic sequence near $X_{\text{best}}$. If the number of search times of the chaotic sequence is $K$, $K$ individuals are obtained. Calculate the fitness values of the $K$ individuals, the individual with the best fitness value is identified as $X_{K_{\text{best}}}$. If fitness($X_{K_{\text{best}}}$) < fitness($X_{\text{best}}$), replace with $X_{K_{\text{best}}}$ and a new population is obtained, otherwise the individuals in the population remain unchanged. The process of the chaotic local search centered on $X_{\text{best}}$ can be expressed as:

$$cx^{(1)} = (X_{\text{best}, j} - X_{\min, j}) / (X_{\max, j} - X_{\min, j})$$

$$X_{k, j} = X_{\min, j} + cx^{(k)} \cdot (X_{\max, j} - X_{\min, j})$$ (19)

where $(X_{\min, j}, X_{\max, j})$ represents the search domain of the local search, and a new individual $X_{k, j}$ is obtained by projecting the chaotic sequence $cx^{(k)}$ into the interval of the optimal variable.
The chaotic sequence is generated using the chaotic map. In this section, a chaotic sequence is generated using Tent map of a uniform probability density distribution \[34\]. The generation process is as follows:

\[
\begin{align*}
    cx^{(k+1)} &= \begin{cases} 
        \frac{cx^{(k)}}{0.5} & cx^{(k)} < 0.5 \\
        2(1 - cx^{(k)}) & \text{else}
    \end{cases} \\
\end{align*}
\]

where \(cx^{(k)}\) represents the \(k\)-th chaotic variable, and the range of each element of the chaotic variable is \((0, 1)\). Considering the existence of small cycles and unstable points in the iteration process of the Tent map, a random equation is introduced to adjust the iterations \[35\].

3.2.3. The Elastic Boundary Processing Strategy

After generating a new population using the crossover and mutation operators of BSA, the individuals of the new population may exceed the feasible region. The original BSA algorithm will directly replace the individuals beyond the feasible region with the boundary of the feasible region, making the transboundary individuals gather around the boundaries of the feasible region massively, and thus the quality of the individuals and the diversity of the population decreases. At the same time, if there is a local optimal solution at the boundary, the algorithm’s probability to fall into the local optimal solution increases. To get rid of this drawback of the BSA algorithm, the IBSA algorithm introduces the elastic boundary processing strategy to the crossover and mutation operators of the BSA algorithm to rebound the individuals beyond the boundary of the feasible region into the feasible region. The elastic boundary processing strategy can be described as follows:

\[
\begin{align*}
    T_{ij} &= \begin{cases} 
        up_j - rand \times (T_{ij} - up_j) & T_{ij} \geq up_j \\
        low_j + rand \times (low_j - T_{ij}) & T_{ij} \leq low_j
    \end{cases}
\end{align*}
\]

where \(T_{ij}\) represents the value of the \(j\)-th dimension of the \(i\)-th individual in the population; \(up_j\) and \(low_j\) represent the upper and lower bounds of the \(j\)-th dimension, respectively; and \(rand\) represents a random number of uniform distribution in \((0,1)\).

Most of the transboundary individuals will be rebounded into the feasible region using the elastic boundary processing strategy shown in Equation (21). However, if there still exists transboundary individuals, reset them according to the following equation:

\[
\begin{align*}
    \text{if } T_{ij} \geq up_j \text{ or } T_{ij} \leq low_j, \text{ then } T_{ij} &= rand \times (up_j - low_j) + low_j
\end{align*}
\]

3.2.4. The Adaptive Mutation Scale Factor

The variation magnitude of the search direction matrix of BSA is controlled using the mutation scale factor \(F\). In the original BSA, \(F = 3 \cdot rand, \text{ rand } \sim N(0, 1)\) and \(N(\cdot)\) is the standard normal distribution. The value of \(F\) has a great influence on the population diversity and the convergence speed of the algorithm. The larger \(F\) value will enhance the diversity of the population while not conducive to the fast convergence of the algorithm. The smaller \(F\) value, in the other way, can accelerate the convergence speed of the algorithm and reduce the diversity of the population. In addition, different stages of population evolution require different crossover mutation probabilities. The appropriate way to adjust \(F\) is crucial to the quality of the optimal solution of the algorithm. In the early stage of the algorithm progress, larger \(F\) value can be employed to obtain powerful global search ability. In the later stage of the iteration, smaller \(F\) value can be employed to accelerate the convergence of the algorithm. Adjusting the coefficient adaptively can find a balance between the global search performance and the local optimization ability of the algorithm.
Tian et al. [36] demonstrated that a random number $F$ that obeys the chi-square distribution can produce better disturbances. The IBSA algorithm introduces an adaptive mutation scale factor based on the chi-square distribution to adjust $F$. The $F$ value is generated according to the following equation:

$$F = e^{at} \cdot \frac{1}{t_{\text{max}}} \cdot \sqrt{CH3}, \quad CH3 \sim \chi^2(3)$$

where $CH3$ represents a random number that obeys $\chi^2(3)$, which is a chi-square distribution with degree of freedom 3; $t$ represents the number of iterations; and $a$ is an adjustment coefficient to control the variation magnitude of $F$.

### 3.2.5. The Flowchart of the Improved Backtracking Search Algorithm

Combined with the above description about the orthogonal initialization technique, the chaotic local search operator, the elastic boundary processing technique and the adaptive mutation scale factor, the flowchart of the IBSA algorithm is shown in Figure 5.

![Figure 5. The flowchart of the improved backtracking search algorithm.](image)

### 4. Parameter Identification Strategy

#### 4.1. Parameter Identification of PTGS Based on IBSA

The basic idea of the parameter identification of PTGS based on intelligent optimization algorithms can be expressed as: the unknown parameters vector for PTGS is usually taken as the decision variable of the optimization algorithm. The objective is to minimize the deviation between the simulation output and the measured value. The optimal parameters are obtained through iterations of the populations of the algorithm. The general structure of the parameter identification model for PTGS system based on IBSA is given Figure 6.
4.2. Objective Function

As described in Section 2, the parameters to be identified of the model of PTGS are $\hat{\theta} = [K_p, K_i, K_d, T_y, T_y, T_w, T_a, \text{en}]$. The original and the identification systems are provided with a same excitation input. The turbine speed $\sigma$, the guide vane opening $y$ and the controller output $x$ of the original system are obtained according to the parameters of the original system while the outputs $\hat{\sigma}, \hat{y}, \hat{x}$ of the identification system are obtained by optimizing $\hat{\theta}$ using IBSA. The objective function is adopted as:

$$
\text{Fitness}(\hat{\theta}) = w_1(\sigma - \hat{\sigma})^2 + w_2(y - \hat{y})^2 + w_3(x - \hat{x})^2
$$

where $w_1, w_2,$ and $w_3$ denote the weight coefficients of different parts. It should be pointed out that the contribution of the outputs of each part to the parameter identification results is different. The weight coefficients of different parts are determined through the parameter perturbation method [37].

5. Experiments and Results Analysis

5.1. Case Study

To test the performance of the proposed IBSA algorithm in identifying the parameters of PTGS, set a group of $\theta = [K_p, K_i, K_d, T_y, T_y, T_w, T_a, \text{en}]$ as the actual value and record the dynamic process of the output of the original system for experiment and analysis. The parameter accuracy ($\text{PE}$) and the average parameter error ($\text{APE}$) are employed in this study to evaluate the parameter identification accuracy of PTGS. The $\text{PE}$ and $\text{APE}$ are calculated as follows:

$$
\text{PE}_i = \frac{|\theta_i - \hat{\theta}_i|}{\theta_i} \times 100\%, \ i = 1, 2, \ldots, m
$$

$$
\text{APE} = \frac{1}{m} \sum_{i=1}^{m} (\text{PE})_i
$$

Two typical test conditions under the frequency disturbance and the load disturbance of PTGS are selected to do the experiment. To verify the integrity and effectiveness of the proposed identification strategy, the PID controller parameters are included in the parameter set to be identified. The frequency and load disturbance of unit step are applied when the unit is in stable operation. The simulation time is set as 50 s and the sampling frequency is set as 100 Hz. The real parameters of the two
operating conditions are set as \([8.7, 0.35, 1.9, 0.2, 0.02, 1.3, 10.8, 1.0]\) and \([6.7, 0.45, 0.5, 0.18, 0.02, 1.3, 10.8, 0.9]\), respectively.

The measured data of PTGS collected in the actual engineering project usually contains environmental interference and measurement noise. These noise data cannot be ignored because they influence the accuracy and robustness of the parameter identification of PTGS. In this study, the parameter identification experiments under different signal to noise ratio (SNR) are carried out by adding the environment and measuring noise in the outputs of the governor, the guide vane opening and the turbine speed of the system using the awgn function.

5.2. Parameter Identification under Frequency and Load Disturbances

To make the effectiveness of IBSA more convincing, three other optimization algorithms, PSO, GSA and BSA, are used as the control groups for parameter identification of PTGS. The parameters of the algorithms are set as follows: the population size of PSO, GSA, BSA and IBSA is set as 40; and the number of iterations is set as 200. The coefficients of PSO are set as: \(w = 0.5\) and \(c_1 = c_2 = 2.0\). The coefficients of GSA are set as: \(G_0 = 30\) and \(b = 10\). BSA uses the default mutation scale factor \(F = 3 \cdot \text{randn}\). The range of the parameters to be identified is set as \((50\%, 150\%)\) of the actual value, and the SNR is set as 90 dB. Considering the randomness of the intelligent optimization algorithms, each group of experiments contains 10 independent repeated experiments and the final result is obtained by averaging the 10 experiments.

The parameter identification error of different optimization algorithms under two different working conditions are shown in Tables 1 and 2, respectively. In Tables 1 and 2, the BSA has achieved similar or better identification results compared with those of GSA, and the identification accuracy of BSA and GSA are obviously better than those of PSO. Due to the strong nonlinearity and the signal noise of PTGS, the PSO may not successfully identify the related parameters of the servomechanism. The identification accuracy of IBSA is much greater than that of the traditional BSA, which indicates that the improved strategies such as the orthogonal initialization and the chaotic local search can enhance the global search performance and the convergence accuracy of the algorithm effectively. Especially, the maximum PE of the identification results of IBSA is only 1.7% under the frequency disturbance, which is far lower than the 12.7% of GSA and the 7.2% of BSA. Although the PE for \(T_y\) of IBSA has increased under the load disturbance condition compared with that under the frequency disturbance, it is still much smaller than of the other algorithms.

Table 1. Parameter identification error of the four algorithms under frequency disturbance.

<table>
<thead>
<tr>
<th>(\theta_i)</th>
<th>Actual Value</th>
<th>PSO</th>
<th>PE</th>
<th>GSA</th>
<th>PE</th>
<th>BSA</th>
<th>PE</th>
<th>IBSA</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>(K_p)</td>
<td>8.7</td>
<td>8.428</td>
<td>0.031</td>
<td>8.617</td>
<td>0.010</td>
<td>8.687</td>
<td>0.001</td>
<td>8.703</td>
<td>0.000</td>
</tr>
<tr>
<td>(K_i)</td>
<td>0.35</td>
<td>0.463</td>
<td>0.323</td>
<td>0.32</td>
<td>0.086</td>
<td>0.331</td>
<td>0.054</td>
<td>0.356</td>
<td>0.017</td>
</tr>
<tr>
<td>(K_d)</td>
<td>1.9</td>
<td>2.35</td>
<td>0.237</td>
<td>1.936</td>
<td>0.019</td>
<td>1.908</td>
<td>0.004</td>
<td>1.917</td>
<td>0.009</td>
</tr>
<tr>
<td>(T_y)</td>
<td>0.2</td>
<td>0.277</td>
<td>0.385</td>
<td>0.199</td>
<td>0.005</td>
<td>0.2</td>
<td>0.000</td>
<td>0.198</td>
<td>0.010</td>
</tr>
<tr>
<td>(T_{y, d})</td>
<td>0.02</td>
<td>0.01</td>
<td>0.500</td>
<td>0.021</td>
<td>0.050</td>
<td>0.019</td>
<td>0.050</td>
<td>0.02</td>
<td>0.000</td>
</tr>
<tr>
<td>(T_{w})</td>
<td>1.3</td>
<td>1.445</td>
<td>0.112</td>
<td>1.135</td>
<td>0.127</td>
<td>1.207</td>
<td>0.072</td>
<td>1.293</td>
<td>0.005</td>
</tr>
<tr>
<td>(T_a)</td>
<td>10.8</td>
<td>9.523</td>
<td>0.118</td>
<td>11.457</td>
<td>0.061</td>
<td>11.54</td>
<td>0.069</td>
<td>10.883</td>
<td>0.008</td>
</tr>
<tr>
<td>(en)</td>
<td>1</td>
<td>1.205</td>
<td>0.205</td>
<td>0.918</td>
<td>0.082</td>
<td>0.958</td>
<td>0.042</td>
<td>0.996</td>
<td>0.004</td>
</tr>
<tr>
<td>APE</td>
<td>0.239</td>
<td>0.055</td>
<td>0.037</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The dynamic response of the turbine speed, the guide vane opening and the controller outputs of the original and the identification systems using IBSA under two different working conditions are shown in Figures 7a–c and 8a–c, respectively. The identification errors of the three parts under two different working conditions are exhibited in Figures 7d–f and 8d–f, respectively. It is shown in Figures 7 and 8 that the error between the dynamic response of the identification system using IBSA...
and the original system is very small, which demonstrates that the identification accuracy of IBSA for PTGS is very high.

Table 2. Parameter identification error of the four algorithms under load disturbance.

<table>
<thead>
<tr>
<th>$\theta_i$</th>
<th>Actual Value</th>
<th>PSO PE</th>
<th>GSA PE</th>
<th>BSA PE</th>
<th>IBSA PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_p$</td>
<td>6.7</td>
<td>7.351</td>
<td>0.097</td>
<td>6.638</td>
<td>0.009</td>
</tr>
<tr>
<td>$K_i$</td>
<td>0.45</td>
<td>0.415</td>
<td>0.078</td>
<td>0.448</td>
<td>0.004</td>
</tr>
<tr>
<td>$K_d$</td>
<td>0.5</td>
<td>0.45</td>
<td>0.100</td>
<td>0.412</td>
<td>0.176</td>
</tr>
<tr>
<td>$T_y$</td>
<td>0.18</td>
<td>0.197</td>
<td>0.094</td>
<td>0.183</td>
<td>0.017</td>
</tr>
<tr>
<td>$T_{yl}$</td>
<td>0.02</td>
<td>0.03</td>
<td>0.500</td>
<td>0.027</td>
<td>0.350</td>
</tr>
<tr>
<td>$T_w$</td>
<td>1.3</td>
<td>1.469</td>
<td>0.130</td>
<td>1.451</td>
<td>0.116</td>
</tr>
<tr>
<td>$T_a$</td>
<td>10.8</td>
<td>11.44</td>
<td>0.059</td>
<td>10.873</td>
<td>0.007</td>
</tr>
<tr>
<td>$en$</td>
<td>0.9</td>
<td>1.259</td>
<td>0.399</td>
<td>0.96</td>
<td>0.067</td>
</tr>
</tbody>
</table>

| APE        | 0.182        | 0.093  | 0.090  | 0.040  |

Figure 7. Comparison between the outputs of the three parts of the original and the identification systems under frequency disturbance: (a) outputs of the turbine speed; (b) outputs of the guide vane opening; (c) outputs of the controller output; (d) identification error of the turbine speed; (e) identification error of the guide vane opening; and (f) identification error of the controller output.
Figure 8. Comparison between the outputs of the three parts of the original and the identification systems under load disturbance: (a) outputs of the turbine speed; (b) outputs of the guide vane opening; (c) outputs of the controller output; (d) identification error of the turbine speed; (e) identification error of the guide vane opening; and (f) identification error of the controller output.

Figure 9 shows the convergence curves of different optimization algorithms under the frequency and load disturbances. In Figure 9, under the frequency disturbance, PSO falls into a local optimum in the 20th iteration and converges in advance; the convergence curves of GSA and BSA tend to be stable in the first 80 generations and the fitness value approximates to the global optimum. IBSA has achieved better convergence speed and identification accuracy compared with BSA. Under the load disturbance, PSO converges to the local optimal solution in advance and it is difficult to obtain the global optimal parameters. The convergence curve of GSA decreases rapidly in the early stage, but it decreases much slower when it reaches the $10^{-3}$ level. The performance of the initial solution of BSA is poor, however, due to its appropriate crossover and mutation strategies, the convergence curve can still maintain a declining trend. The convergence curve of IBSA shows a steady and rapid decline, which reflects the good global exploration and local search ability of the proposed IBSA for parameter identification of PTGS.
5.3. Influence of Signal-To-Noise Ratio (SNR) on Identification Accuracy

The measurement data of PTGS in practical engineering applications usually contains environmental and measurement noise. It is worth further research to investigate the parameter identification performance under different levels of noise. In this section, the noise signals with different signal-to-noise ratios (SNR) (90 dB, 50 dB, and 20 dB) are added to the turbine speed, the guide vane opening and the controller output of PTGS. The IBSA algorithm of which the performance is the best in Section 5.2 is selected as the optimization algorithm for the experiments. The parameter identification results of PTGS with different SNR are listed in Table 3.

Table 3. Parameter identification results of PTGS with three different signal-to-noise ratios.

<table>
<thead>
<tr>
<th>$\theta_i$</th>
<th>Actual Value</th>
<th>90 dB</th>
<th>50 dB</th>
<th>20 dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_p$</td>
<td>8.7</td>
<td>8.703</td>
<td>0.000</td>
<td>8.65</td>
</tr>
<tr>
<td>$K_i$</td>
<td>0.35</td>
<td>0.356</td>
<td>0.017</td>
<td>0.35</td>
</tr>
<tr>
<td>$K_d$</td>
<td>1.9</td>
<td>1.917</td>
<td>0.009</td>
<td>1.887</td>
</tr>
<tr>
<td>$T_y$</td>
<td>0.2</td>
<td>0.198</td>
<td>0.010</td>
<td>0.195</td>
</tr>
<tr>
<td>$T_{yl}$</td>
<td>0.02</td>
<td>0.02</td>
<td>0.000</td>
<td>0.0193</td>
</tr>
<tr>
<td>$T_w$</td>
<td>1.3</td>
<td>1.293</td>
<td>0.005</td>
<td>1.28</td>
</tr>
<tr>
<td>$T_a$</td>
<td>10.8</td>
<td>10.883</td>
<td>0.008</td>
<td>10.92</td>
</tr>
<tr>
<td>$en$</td>
<td>1</td>
<td>0.996</td>
<td>0.004</td>
<td>0.983</td>
</tr>
</tbody>
</table>

It is shown in Table 3 that the parameter identification error with 50 dB is much greater than that with 90 dB, which might be caused by the existence of the nonlinear parts such as the dead zone, the clearance and the limit amplitude of the servomechanism and the penstock system. The identification error increases significantly when the SNR is 20 dB. However, the identification accuracy of some of the parameters under 20 dB is still good and can meet the requirements of practical engineering applications.

6. Conclusions

This study proposes a novel swarm-intelligence optimization algorithm named BSA for the parameter identification of the nonlinear PTGS system. To improve the performance of the BSA, four improvement strategies including the orthogonal initialization technique, the chaotic local search operator, the elastic boundary processing strategy and the adaptive mutation scale factor have been introduced and combined with the original structure of BSA. The proposed IBSA was applied on an illustrative example to verify its feasibility and effectiveness. The experiment results
have demonstrated that the IBSA algorithm can enhance the global search performance and the convergence speed of the original BSA effectively. The identification accuracy of PTGS based on IBSA is much better than that based on the PSO, GSA and original BSA algorithms. The proposed IBSA can be employed as an effective tool for the accurate parameter identification of the nonlinear PTGS system. The identification experiments of PTGS with different SNR ratio have shown that, with the increasing of the SNR ratio, the identification accuracy decreases. However, the parameter identification accuracy of PTGS using IBSA can still satisfy the requirements of practical engineering applications. The online identification and tracking of the parameters of PTGS under dynamic environment is still worth further research.

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Conflicts of Interest: The authors declare no conflict of interest.

References


