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# A mixed-strategy based gravitational search algorithm for parameter identification of hydraulic turbine governing system

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ABSTRACT

A Mixed-Strategy based Gravitational Search Algorithm (MS-GSA) is proposed in this paper, in which three improvement strategies are mixed and integrated in the standard GSA to enhance the optimization ability. The first improvement strategy is introducing elite agent's guidance into movement function to accelerate convergence speed. The second one is designing an adaptive gravitational constant function to keep a balance between the exploration and exploitation in the searching process. And the third improvement strategy is the mutation strategy based on the Cauchy and Gaussian mutations for overcoming the shortages of premature. The MS-GSA has been verified by comparing with 7 popular meta-heuristics algorithms on 23 typical basic benchmark functions and 7 CEC2005 composite benchmark functions. The results on these benchmark functions show that the MS-GSA has achieved significantly better performance than other algorithms. The effectiveness and significance of the results have been verified by Wilcoxon's test. Finally, the MS-GSA is employed to solve the parameter identification problem of Hydraulic turbine governing system (HTGS). It is shown that the MS-GSA is able to identify the parameters of HTGS effectively with higher accuracy compared with existing methods.



## 1. Introduction

Hydraulic turbine governing system (HTGS) is one of the most important systems in hydropower plant, which plays a key role in maintaining safety, stability and economical operation of the hydropower plant [1]. The HTGS is a complicated non-minimum phase system [2–11], and parameter identification of this kind of system is a challenging task. Parameter identification problem of the HTGS can be considered to be an optimization problem, and meta-heuristic algorithms which have been used as important methods to obtain the optimal solutions for practical engineering design optimization problems are widely applied in this task [12–19]. For example, the genetic algorithm (GA) and particle swarm optimization (PSO) have been used to identify the parameter of HTGS and get a good result [20,21]. However, because of the HTGS is a complicated non-minimum phase system, there still exits some shortcomings when these methods are applied for the complicated characters of HTGS [22]. More effective meta-heuristics are in desperate need for complicated engineering optimization problem, like parameter identification of HTGS.

Recently, the development of meta-heuristics is blooming. A lot of methods have been proposed and studied, including Moth-Flame Optimization (MFO) [23], Gravitational Search Algorithm (GSA) [24], Sine Cosine algorithm (SCA) [25], Grey Wolf Optimizer (GWO) [27], Black Hole(BH) [28], Social Spider Algorithm (SSA) [29], Search Group Algorithm(SGA) [30], etc. Among these recently developed meta-heuristics, GSA is one of the most popular classes of nature-inspired optimizers, which is inspired by the well-known law of gravity and mass interactions. Although many researches have proved that the GSA is more effective than traditional meta-heuristics such as GA and PSO in solving various problems, there are still some shortcomings in the standard GSA, which mainly focus on the following respects: imbalance of exploration and exploitation, shortage of convergence, and the premature. Although many researches have studied one or two kinds of these shortcomings and improved the GSA accordingly, few of them have tried to solve these shortcomings comprehensively.

The movement strategy is crucial in determining the search ability of GSA. In standard GSA, agents are driven by gravitational force, and the agent's movement is not guided by elite agents or historical information, which is completely differently with some other meta-heuristics. Researchers have noticed that introduction and combination of different movement strategies would probably be beneficial to improve the search performance of GSA. Li et al. [2] modified the movement function of GSA by introducing searching strategy of PSO, and found that information about individual's best position and the population's best position were useful to guide the move of an agent and accelerate the convergence speed of the population. The follow-up researches [3,31,32,34]

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confirmed the effectiveness of improvement of movement's function by combing search strategy of PSO, and it's found that this improvement is able to enhance the global exploration ability of GSA. A novel hybrid algorithm of GSA with Kepler algorithm was proposed to provide much stronger specialization in intensification and diversification [33]. Combination of different movement strategies endow GSA many merits and enhance the search performance.

The gravitational constant function is important in accelerating the convergence speed of GSA. In the standard GSA a decaying exponential function with fixed attenuation factor is used to calculate the gravitational constant at different time. Many researchers have also tried to define new gravitational constant function to improve the convergence speed of GSA. Fuzzy adaptive gravitational search algorithm (FAGSA) was proposed for the first time to tune the gravitational constant using fuzzy "IF/THEN" rules [35]. And a piecewise function based gravitational search algorithm (PFGSA) was proposed to select the better gravitational constant [36]. In [37], the gravitational constant was set as a function of individual optimum fitness instead of the fixed step sequence in original GSA.

Premature is the potential defect of almost all population-based meta-heuristics. Researchers have also tried to introduce some new mutation operators to prevent premature. Nezamabadi-pour et al. [38] proposed a novel operator called "Disruption" inspiring from astrophysics to improve the exploration and exploitation abilities of the standard GSA. In [39], the opposition-based learning was employed for population initialization and also for generation jumping to improve the convergence rate of the GSA. Doraghinejad et al. [40] hybridized the Black Hole theory with GSA in order to prevent premature convergence and to improve the abilities of GSA in exploration and exploitation. In [26], a locally information was introduced in GSA to improve premature convergence, in which each agent learns from its unique neighborhood formed by k local neighbors and the historically global best agent rather than from just the single elite group. In order to improve algorithm's performance in preventing premature, a quantum-inspired gravitational search algorithm (QIGSA) [41] was proposed inspired by quantum phenomenon [42]. In [3], the chaotic mutation was brought into the GSA to avoid the trap of local optima. Gaussian mutation [43] and Cauchy mutation [44] have also shown the ability to improve swarm-based algorithms. Researches results have proved that bringing in a new operator is one of the effective approaches to overcome premature and local convergence.

Although the above mentioned improving strategies are useful to improve the performance of standard GSA, one particular strategy may only promote GSA on one aspect. As we have discussed, the combination with searching model of PSO mainly contribute to speed up the exploitation phase. The optimal design of gravitational constant function is aiming at accelerating the convergence speed. And the mutation operator is mainly effective on improving the ability of escaping from poor local optima. If we want to enhance the searching ability of GSA further, multiple improvement strategies would be necessary. Then, the following questions are very interesting and worth to study: (1) how will the mixtures of multiple improvement strategies promote GSA; (2) which improvement strategy is more important and contributes the most if they are mixed and integrated in the standard GSA.

Motivated by the above questions, a novel mixed strategy based gravitational search algorithm (MS-GSA) is proposed to improve the performance of GSA from different aspects, while elite guided movement strategy, adaptive gravitational constant function and combined mutation strategy are designed and integrated. In order to test the performance of the proposed algorithm, the MS-GSA was evaluated by 23 standard benchmark functions and 7 challenging composite functions [40]. The contributions of these strategies on the improvement have been evaluated and analyzed. In this end, the proposed MS-GSA was used for the parameter identification of HTGS. The main contributions of this paper are: an improve GSA was proposed by designing multiple improvement strategies with a comprehensive perspective, and the contribution of different strategy in promoting GSA was evaluated.

The rest of this paper is organized as follows: Section 2 introduces the three improvement strategies and proposes the MS-GSA. In Section 3, the performance of the MS-GSA is compared with 7 other meta-heuristics algorithms by using benchmark functions, and the three strategies are evaluated. The model of the HTGS is described and parameter identification of HTGS is conducted by using MS-GSA in Section 4. Section 5 presents the conclusions of this study.

## 2. The mixed-strategy based gravitational search algorithm

### 2.1. Brief introduction of GSA

The gravitational search algorithm (GSA) is a recently developed meta-heuristic optimization algorithm that is inspired by the Newtonian Laws of Gravity and mass interaction. As a stochastic population-based algorithm, the GSA was introduced by Rashedi et al. [24] for the first time. In the GSA, the every particle in the universe is considered to be an object with mass. The one object is attracted by others objects through the gravity, so all of the objects will be attracted to objects with heavier masses. The detailed information about the GSA is described as following:

There are $N$ agents in the search space, we define the position of the $i_{th}$ agent by Eq. (1).

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^D), \ \ for\ i = 1, .., .N, \tag{1}$$

where $x_i^d$ is the position of the $i_{th}$ agent in the $d_{th}$ dimension.

The acting force of agent $i$ from agent $j$ at the time $t$ is defined by the following equation:

$$F_{ij}^d(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{2}$$

where $M_j(t)$ and $M_i(t)$ are the mass which are related to agent $i$ and $j$ at time $t$, respectively. The Euclidian distance between agent $i$ and $j$ $R_{ij}(t)$ is defined as $R_{ij}(t)=\|X_i(t),X_j(t)\|_2$. $\varepsilon$ is a small constant and the gravitational constant $G(t)$ is defined as following equation:

$$G(t) = G_0 \cdot \exp\left(-\alpha \cdot \frac{t}{max\_it}\right) \tag{3}$$

where $G_0$ is the initial gravitational constant, $max\_it$ is the maximum iterations, $t$ is the current iteration, and $\alpha$ is a constant, named as the attenuation factor.

The mass of the $i_{th}$ agent is defined by the fitness evaluation as Eq. (12):

$$\begin{cases} m_i(t)\dfrac{fit_i(t) - worst(t)}{best(t) - worst(t)} \\ M_i(t) = m_i(t)/\sum_{j=1}^N m_j(t) \end{cases} \tag{4}$$

where $fit_i(t)$ is the fitness value of the agent $i$ at time $t$. For a minimization problem, $worst(t)$ and $best(t)$ are calculated by the following equation:

$$\begin{cases} best(t) = \min\limits_{j\in\{1,...,N\}} fit_j(t) \\ worst(t) = \max\limits_{j\in\{1,...,N\}} fit_j(t) \end{cases} \tag{5}$$

In order to increase the random characteristic of algorithm, the total force acted on agent $i$ in the direction $d$ is a randomly composition of the forces of from the other agents:

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} rand_j F_{ij}^d(t) \tag{6}$$