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An Improved Mayfly Optimization Algorithm Based on Median Position and Its Application in the Optimization of PID Parameters of Hydro-Turbine Governor

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ABSTRACT Mayfly algorithm is a new intelligent optimization algorithm with unique optimization capabilities recently proposed. It has strong research value, but there are also insufficient explorations, and it is easy to fall into the problem of local optimization. This paper aims to improve the optimization performance of the mayfly algorithm and explore its application value in practical engineering optimization problems. An improved mayfly algorithm based on the median position of the group is proposed. In its velocity update, the median position of the group is introduced with emphasis, and a non-linear gravity coefficient is introduced at the same time. Through the benchmark test function, its superiority in exploitation, convergence speed and accuracy and the improvement of exploration are verified. At the same time, the simulation model of the hydro-turbine governor using MATLAB/Simulink is established, and 10% frequency disturbance experiments of this model are carried out separately in two typical working conditions. The experiments results show that the optimal ITAE index value of the system obtained by the improved mayfly algorithm is smaller, and 16.5 and 18.1 iterations to complete on average. In addition, the experiments results reveal that the PID parameters optimized by the improved mayfly algorithm can make the dynamic performance of the regulation system better than other popular swarm intelligence algorithms, where the overshoot decreased by more than 3.1%, and the adjustment time also decreased in different degrees. The proposal of the median position of the group provides a new idea for the improvement of the swarm intelligence optimization algorithm. Meanwhile, a new effective method for optimizing the PID parameters of the hydro-turbine governor has been found.

INDEX TERMS Mayfly algorithm, swarm intelligence optimization algorithm, median position, group diversity, hydro-turbine governor, PID parameters.

ABBREVIATIONS

MA	Mayfly Algorithm
MMA	Mayfly Algorithm Based on Median Position
PSO	Particle Swarm Optimization
SSA	Salvia Swarm Algorithm
WOA	Whale Optimization Algorithm
GA	Genetic Algorithm
FA	Firefly Algorithm
PID	Proportional Integral Differential
FEs	Function Evaluations
std	standard deviation

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I. INTRODUCTION

With the rapid development of the economy and technology, a large number of optimization problems have appeared in scientific research and actual industrial production, such as the transportation field [1], [2], the power field [3], [4], the material field [5], [6], the communication field [7], [8], the mechanical field [9], [10] and e-commerce field [11], [12], and etc. These problems are usually inferior in nature, that is, non-differentiable, non-linear, etc. Therefore, traditional numerical optimization methods are difficult to solve these problems, but swarm intelligence optimization algorithms show strong effectiveness in solving these problems. Swarm intelligence algorithm has become one of hot spots in the fields of artificial intelligence and intelligent computing due to its strong versatility, high solving efficiency, and it is easy to understand and master, etc. Besides, it has also become one of the important solutions for solving optimization problems in actual production. In addition, in the past few decades, many swarm intelligence algorithms based on various biological groups have been proposed. Among them, the most famous swarm intelligence algorithms are ant colony algorithm [13] and particle swarm algorithm [14]. There are also many swarm intelligence algorithms based on bionics, such as bacteria foraging algorithm [15], Artificial fish swarm algorithm [16], artificial bee colony algorithm [17], cat colony algorithm [18], firefly algorithm [19], cuckoo search algorithm [20], bat algorithm [21], krill swarm algorithm [22], gray wolf algorithm [23], whale algorithm [24], antlion algorithm [25], moth fighting fire algorithm [26], dragonfly algorithm [27], harris hawk optimization [28], locust algorithm [29], satin blue gardener bird algorithm [30], black tern optimization algorithm [31], seagull optimization algorithm [32], sailfish optimization algorithm [33], sparrow algorithm [34], etc. In addition, there are some algorithms based on swarm intelligence theory, such as differential evolution algorithm [35], firework algorithm [36], acoustic search algorithm [37], brainstorming optimization algorithm [38], etc. The openness of the swarm intelligence optimization algorithm allows various optimization algorithms to complement each other to optimize the performance of the algorithm, so that the algorithm has stronger adaptability and flexibility when dealing with different problems. However, the convergence, search efficiency and parameter settings of the algorithm in specific applications still need to be developed and improved by researchers.

Mayfly optimization algorithm is a new intelligent optimization algorithm proposed by Zervoudakis and Tsafarakis in 2020 [39]. And the algorithm is inspired by mayfly flight behavior and mating process, including mayfly crossing, mutation, group gathering, wedding dance, and random walking. Besides, the algorithm combines the main advantages of swarm intelligence and evolutionary algorithms. Mayfly optimization algorithm has attracted more and more attention because of its special advantages in convergence accuracy, speed and exploitation. However, like other algorithms, MA also suffers from some disadvantages, i.e. weak exploration, stagnation in local optima with a low convergence accuracy, and lack of proper balance between exploration and exploitation. At present, a few researchers have carried out in-depth research on the improvement of the MA and its application. Generally, there are two methods to enhance the performance of MA in the literatures. The first way is that some researchers try to combine MA with other optimization theories and methods. For instance, to solve the global optimization problems, Gupta *et al.* [40] proposed a new improved mayfly optimization algorithm by combining chaos theory and mayfly algorithm. Similarly, Shaheen *et al.* [41] proposed a newly developed optimization method "Chaotic Mayfly optimization algorithm" for obtaining the proton exchange membrane fuel cell parameters. Moreover, Adnan *et al.* [42] proposed a new improved mayfly optimization algorithm by combining the simulated annealing algorithm with the mayfly optimization algorithm to determine the optimal hyper-parameters of support vector regression to overcome the exploration weakness of the mayfly optimization algorithm method. From the above it can be concluded that combining multiple algorithms can make up for the shortcomings of a single algorithm to a certain extent and improve the performance of the algorithm, but there are also some shortcomings. For example, the hybrid algorithm will increase the computational cost and increase the complexity due to the number of parameters involved. Therefore, if the computational cost of the hybrid algorithm could be effectively reduced, combining two or more other algorithms into one algorithm will be one of the effective ways to improve the performance of the algorithm. The other way toward the improvement of MA performance is to add some operators into the standard MA. For example, Wei *et al.* [43] used a new policy for updating the position that is derived from the bubble-net searching mechanism in the whale optimization algorithm. Besides, Liu *et al.* [44] proposed a multi-objective version of the improved MA by adding an archive mechanism, non-dominated sorting strategy, and roulette wheel selection. It can be observed that designing some improved MA is feasible and the above-mentioned implementation is also a good indication of this ability. However, these improved MA seem to be difficult to promote the capability of the algorithm in simultaneously attaining the balance between exploration and exploitation. Therefore, the mayfly algorithm still has a large space for exploration, which is also the main motivation of this paper to study it and introduce engineering applications.

The hydro-turbine governor is the most important part of the turbine regulating system, and it is also a significant control device to ensure the stable operation of hydropower generating units [45], [46]. The stable operation and regulation quality of the turbine regulating system are directly affected by the parameters of the hydro-turbine governor, which in turn affects the electric energy quality. At present, the PID control method is adopted by most hydropower stations. Therefore, it is critical to select the three parameters of the governor (K_p, K_i and K_d) correctly, which makes the turbine regulating system have superior dynamic quality, and which guarantees the safe operation of the units and the electric energy quality. In recent years, many experts and scholars have successively introduced different swarm intelligence optimization algorithms into the PID parameter optimization of the governor and conducted a lot of extensive and in-depth research, such as particle swarm algorithm [47], [48], bacterial foraging algorithm [49], moth-killing algorithm [50], fruit fly algorithm [51], beetle search algorithm [52] and cuckoo search algorithm [53], etc. Furthermore, these methods have their advantages, but there are also common problems such as long calculation time, easy to fall into the local optimum, and premature convergence, which are especially obvious in large-scale and complex problems. Therefore, it is necessary to introduce an optimization algorithm with better performance into the turbine regulating system.

In light of the fact mentioned above, in this study, an improved mayfly optimization algorithm is proposed and applied to the PID parameter optimization of the hydro-turbine governor. The key contribution of this paper is outlined below:

1) A concept of the median position of the group is proposed and introduced into the speed update of the basic mayfly optimization algorithm to form a new improved mayfly optimization algorithm. The introduced median position of the group enables each mayfly to make more use of group information to decide its own behavior, which ensures the diversity of the group, thereby promoting the balance between exploration and exploitation stages and the search efficiency of the algorithm.
2) Through the tests of three sets of benchmark functions, it is verified that the improved mayfly algorithm has superior performance in exploitation, convergence speed and accuracy. At the same time, the exploration of the algorithm is also improved.
3) The improved mayfly optimization algorithm is applied to an example of the PID parameter optimization of a hydro-turbine governor, and the results are compared with other swarm intelligence algorithms through digital simulation, which proves its superiority in the application of the PID parameter optimization of hydro-turbine governor.

The rest of this paper is organized as follows: Section 2 briefly describes the basic mayfly algorithm, an improved mayfly algorithm based on the median position is proposed, and the benchmark functions, test program and performance comparison results are listed. In section 3, a typical turbine governing system is described, and the simulation calculation steps and test results are shown. Section 4 gives the conclusion.

II. IMPROVED MAYFLY OPTIMIZATION ALGORITHM BASED ON MEDIAN POSITION

A. MAYFLY ALGORITHM

Mayfly algorithm, as a new type of intelligent optimization algorithm, has the characteristics of strong optimization ability and strong research value. Besides, it is inspired by the social behavior of mayfly, especially their mating process. The mayfly is assumed to be an adult after hatching from the egg, and the most suitable mayfly will survive. Moreover, the position of each mayfly in the search space represents a potential solution to the problem. The working principle of the algorithm is as follows: initially, two groups of mayfly were randomly generated, representing male and female populations. Each mayfly is randomly placed in the problem space as a candidate solution $x = (x_1, \ldots\ldots, x_d)$ represented by a d-dimensional vector, and its performance is evaluated according to a predetermined objective function $f(x)$. Furthermore, the velocity of the mayfly $v = (v_1, \ldots\ldots, v_d)$ is defined as the change of its position. The flight direction of each mayfly is the dynamic interaction between the individual and the social flight experience. Finally, each mayfly will continuously adjust its trajectory to the personal best position ($pbest$) so far and the best position obtained by all mayfly in the group ($gbest$) so far.

1) MOVEMENT OF MALE MAYFLY

Male mayflies gather in groups, and their positions are adjusted based on the experience of themselves and their neighbors. Assuming that x_i^t is the current position of the mayfly i in the search space at the time step t, the position update is the sum of the $t + 1$th iteration velocity plus the tth iteration position, and its position expression is:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{1}$$

Considering that male mayflies always dance a few meters above the water, suppose they cannot have a fast speed, and they will move constantly. Thus, the velocity of the male mayfly is updated to:

$$v_{ij}^{t+1} = v_{ij}^t + a_1 e^{-\beta r_p^2}(pbest_{ij} - x_{ij}^t) + a_2 e^{-\beta r_g^2}(gbest_j - x_{ij}^t) \tag{2}$$

where v_{ij}^t is the velocity of the mayfly i in dimension j at time step t. x_{ij}^t is the position of the mayfly i in dimension j at time step t. a_1 and a_2 are the positive attraction constants. $pbest_i$ is the best position in the history of mayfly i. $gbest$ is the best mayfly position at time step t. β is a fixed visibility coefficient of the mayfly, which controls the visibility of the mayfly. r_p is the cartesian distance between the current position and $pbest_i$. r_g is the Cartesian distance between the current position and $gbest$. The distance is calculated as follows:

$$\|x_i - X_i\| = \sqrt{\sum\nolimits_{j=1}^{n} (x_{ij} - X_{ij})^2} \tag{3}$$

where x_{ij} is the j^{th} element of mayfly i and X_i corresponds to $pbest_i$ or $gbest$.

The best mayfly in the group must continue to perform their unique up and down dance. Thus, the best mayfly must constantly change their speed. The velocity is updated as follows:

$$v_{ij}^{t+1} = v_{ij}^t + d \cdot r \tag{4}$$

where d is the nuptial dance coefficient and r is a random value in the range $[-1, 1]$.

2) MOVEMENT OF FEMALE MAYFLY

Unlike male mayfly, there is no gathering phenomenon for female mayfly which will fly to the male groups to reproduce. Suppose y_i^t is the position of mayfly i at time step t, and its position is updated by increasing the speed. Therefore, the calculation is as follows:

$$y_i^{t+1} = y_i^t + v_i^{t+1} \tag{5}$$

According to the principle that the best females should be attracted to the best males, and the second-best females should be attracted to the second-best males, and so on, the issue of minimization should be considered at the same time. Therefore, the velocity is calculated as follows:

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + a_2 e^{-\beta r_{mf}^2}(x_{ij}^t - y_{ij}^t), & \text{if } f(y_i) > f(x_i) \\ v_{ij}^t + fl \cdot r, & \text{if } f(y_i) \le f(x_i) \end{cases} \tag{6}$$

where v_{ij}^t is the velocity of female mayfly i in dimension j at the time step t, y_{ij}^t is the position of female mayfly i in dimension j at the time step t. fl is a random walk coefficient that works when the female is not attacked by the male. r is a random value in the range $[-1, 1]$. r_{mf} is the cartesian distance between female and male mayflies. r_{mf} was calculated by using equation (3).

3) MAYFLY MATING

The female and male mayfly select pairs for mating based on the fitness function. Moreover, the male mayfly and the female mayfly which are both with the best fitness value get mating, and so on. Besides, the result of mating is to produce two offspring, and the formula is as follows:

$$offspring\ 1 = L \cdot male + (1 - L) \cdot female \tag{7}$$

$$offspring\ 2 = L \cdot female + (1 - L) \cdot male \tag{8}$$

where L is a random value within a specific range, and the initial velocities of the offspring are set to be zero.

4) MAYFLY VARIATION

In order to deal with the possible premature convergence that the optimal value is the local optimal rather than the global optimal, a normal distribution random number is added to the selected progeny mayfly for mutation. The progeny mayfly mutation formula is as follows:

$$offspring_n = offspring_n + \sigma \cdot N(0, 1) \tag{9}$$

where σ is the standard deviation of the normal distribution. $N(0, 1)$ is a standard normal distribution with an average value of zero and a variance of one. The number of mutant individuals is *round* (0.05 times the number of male mayfly). The wedding dance coefficient and random flight coefficient will also be decreased with the number of iterations, and the formula is as follows:

$$d_t = d_0 \cdot d_{damp}^t \tag{10}$$

$$fl_t = fl_0 \cdot fl_{damp}^t \tag{11}$$

where d_t and fl_t are the wedding dance coefficient and random flight coefficient at time t separately; d_{damp} and fl_{damp} are the wedding dance coefficient and the attenuation parameter of random flight respectively.

B. PROPOSED MMY ALGORITHM

Compared with other swarm intelligence algorithms, the basic mayfly optimization algorithm has better good convergence speed and accuracy. However, there are also local optimum and lag phenomena in the search process of the solution. In order to improve the overall search performance and accuracy of the algorithm, an improved method is proposed below in this paper.

1) A NON-LINEAR GRAVITY COEFFICIENT

The gravity coefficient of the mayfly algorithm is similar to the gravity coefficient of PSO, it helps to achieve a balance between exploitation and exploration [39]. Thus, a non-linear gravity coefficient is used in this paper to make the gravity coefficient slowly decrease at the beginning of the iteration, so that it has better exploration, which could avoid falling into the local optimum, and it could achieve a certain convergence accuracy faster. In the later stages of the iteration, the gravity coefficient is accelerated reduced, thereby improving exploitation to find the optimal solution. Furthermore, the introduction of a non-linear gravity coefficient can better balance exploration and exploitation. The formula of the non-linear gravity coefficient is:

$$g(t) = 0.5 \times \sqrt{1 - (t/Maxt)^2} + 0.4 \tag{12}$$

where, t is the number of iterations, and $Maxt$ is the maximum number of iterations. Introducing this non-linear gravity coefficient into the mayfly algorithm, the formula for the velocity update of the male mayfly is:

$$v_{ij}^{t+1} = g(t)v_{ij}^t + a_1 e^{-\beta r_p^2}(pbest_{ij} - x_{ij}^t) + a_2 e^{-\beta r_g^2}(gbest_{ij} - x_{ij}^t) \tag{13}$$

The formula for the velocity update of the male mayfly is:

$$v_{ij}^{t+1} = \begin{cases} g(t)v_{ij}^t + a_2 e^{-\beta r_{mf}^2}(x_{ij}^t - y_{ij}^t), & \text{if } f(y_i) > f(x_i) \\ g(t)v_{ij}^t + fl \cdot r, & \text{if } f(y_i) \le f(x_i) \end{cases} \tag{14}$$

2) THE INTRODUCTION OF THE MEDIAN POSITION OF THE GROUP

From the basic principles of the above mayfly algorithm, it is not difficult to recognize that the mayfly algorithm can be regarded as an improvement of the particle swarm optimization algorithm, which combines the advantages of the particle swarm algorithm (PSO), genetic algorithm (GA) and firefly algorithm (FA). Besides, the mayfly algorithm has many similarities with the particle swarm algorithm in the position and velocity update of the mayfly. Therefore, the adjustment of the mayfly movement in the mayfly algorithm is also based on the social sharing of the same biological information to form an evolutionary advantage. This information mainly includes individual memory and overall cognition. Individual memory can get the best position of each individual, and overall cognition can get the best position of the entire group, which is the best solution.

From the update formula of the male mayfly algorithm velocity, it can be found that the new velocity is determined by three parts. The first part is the velocity v_{ij}^t of the mayfly i in the previous iteration; The second part is the distance $(pbest_{ij} - x_{ij}^t)$ between the current position of the mayfly i and the individual's optimal position, which is the 'perception' part, which indicates that the individual thinks about itself; The third part is the distance $(gbest_{ij} - x_{ij}^t)$ between the current position of the mayfly i and the best position of the group, which is the 'social' part, which represents the sharing and cooperation of the mayfly with the group information, and which guides the mayfly to the best position the group passed. Therefore, it can be recognized that the flight process of the mayfly is not only influenced by the best position it has experienced, but also by other individuals in the group. However, the information transmission and sharing between the populations is realized only through $gbest$ and $pbest$, and there is no other way to exchange information between the mayflies. Hence, this leads to a single source of information and a small amount of information exchange among the mayflies. Moreover, the diversity of the population is easy to lose during the movement. Besides, because the mayfly clusters rapidly, premature convergence occurs, which often results in the group being trapped in a local optimum. Thus, if only the best individual in the whole is emphasized in the process of group optimization, it is easy to overlook some important information. Furthermore, it is not enough to rely solely on the information of $gbest$ and $pbest$. Every member of the group, whether good or bad, can contribute its information to influence the overall movement. In addition to $gbest$ and $pbest$, the information of other individuals should also be considered and used in the search process. And the search space of the group should not be limited to the area defined by the above two points.

As an important feature of the group, the diversity of the group is closely related to the early convergence in the evolution process, the slow speed in the later evolution and the poor convergence performance. Therefore, group diversity is crucial to the global convergence of the algorithm. In addition, there is no doubt that the diversity of the group could be increased through increasing the personal experience information and the sharing of group information. Based on the above, a group average position based on $gbest$ and $pbest$ is added in this paper. In statistics, the median and average are often used to reflect the overall average level, where the average is easily affected by extreme values. Nevertheless, in the swarm intelligence algorithm, in the initial stage of spatial search, the distribution of individuals in the group is relatively scattered, and there are a small number of individuals whose positions are extremely poor. Hence, taking the average as the group average position may not accurately reflect the overall average position. Therefore, the concept of the median position of the group based on the median concept is brought up in this paper, which sorts all the mayfly individuals according to their objective function value, and which takes the median position of the mayfly as the median position of the group. The specific expression is:

$$pm = \begin{cases} x_{(n+1)/2}, & if\ n\ is\ odd \\ (x_{n/2} + x_{n/2+1})/2, & if\ n\ is\ even \end{cases} \tag{15}$$

where, n is the number of groups. The median position is used as the average position of the group into the velocity update formula of the male mayfly, and the expression is:

$$\begin{aligned} v_{ij}^{t+1} &= g(t)v_{ij}^t + a_1 e^{-\beta r_p^2}(pbest_{ij} - x_{ij}^t) \\ &\quad + a_2 e^{-\beta r_g^2}(gbest_{ij} - x_{ij}^t) + a_4 e^{-\beta r_m^2}(pm_{ij} - x_{ij}^t) \end{aligned} \tag{16}$$

where a_4 is the positive attraction coefficient of social effects, and r_m is the distance between the current position and the median position. r_m was calculated by using equation (3).

C. VALIDATION AND COMPARISON

Matlab is a very powerful mathematical software, which is widely used in data analysis, image processing, control systems and other fields. To verify the effectiveness of the proposed mayfly optimization algorithm based on the median position, Matlab is used to optimize and calculate a certain number of selected benchmark functions in this paper, and the test results of several popular swarm intelligence optimization algorithms on the benchmark functions are compared and analyzed, all the simulations have been carried out on an AMD Ryzen eight core processor, 3.40 GHz desktop computer with 8 GB of RAM.

1) BENCHMARK FUNCTION

The selection of the benchmark function is very important for the performance test and comparison of the tested optimization algorithm. Besides, according to the actual needs of this paper, three types of functions were selected from the classic benchmark functions which include 5 unimodal functions, 4 multimodal functions, and 9 low-dimensional multimodal functions, totaling 18 functions. Furthermore, unimodal functions are mostly used to examine the convergence speed, convergence accuracy and exploitation of algorithms in high-dimensional situations; Multimodal functions have multiple local optimums, which can effectively test the explorations of the algorithm; Low-dimensional multimodal functions are used to check the effectiveness of the algorithm in a specific low-dimensional state. And the 18 benchmark functions of these three categories are listed in Tables 1, 2 and 3.

TABLE 1. Unimodal test functions.

Function ID	Name	Function	D	Range	Optimum
F1	Sphere	$f_1(x)=\Sigma_{i=1}^{D}x_i^2$	30	[-100,100]	0
F2	Schwefel 1.2	$f_2(x)=\sum_{i=1}^{D}(\Sigma_{j=1}^{i}x_j)^2$	30	[-100,100]	0
F3	Schwefel 2.21	$f_3(x)=max_i\{\lvert x_i\rvert,1\le i\le D\}$	30	[-100,100]	0
F4	Rosenbrock	$f_4(x)=\sum_{i=1}^{D}100(x_{i+1}-x_i)^2+(x_i-1)^2$	30	[-30,30]	0
F5	Step	$f_5(x)=\sum_{i=1}^{D}(x_i+0.5)^2$	30	[-100,100]	0

TABLE 2. Multimodal test functions.

Function ID	Name	Function	D	Range	Optimum
F6	Schwefel	$f_6(x)=-\sum_{i=1}^{D}\left(x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$	30	[-500,500]	-12569.5
F7	Griewank	$f_7(x)=(1/4000)\sum_{i=1}^{D}(x_i^2)-\left(\prod_{i=1}^{D}\cos\left(x_i/\sqrt{i}\right)\right)+1$	30	[-600,600]	0
F8	Penalized	$f_8(x)=(\pi/D)\{10\sin^2(\pi y_i)+\sum_{i=1}^{D-1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})]+(y_D-1)^2\}+\sum_{i=1}^{D}u(x_i,10,100,4)$	30	[-50,50]	0
F9	Penalized 2	$f_9(x)=0.1\{\sin^2(3\pi x_i)+\sum_{i=1}^{29}(x_i-1)^2 p[1+\sin^2(3\pi x_{i+1})]+(x_D-1)^2[1+\sin^2(2\pi x_D)]\}+\sum_{i=1}^{D}u(x_i,5,100,4)$	30	[-50,50]	0

TABLE 3. Low-dimension multimodal test functions.

Function ID	Name	Function	D	Range	Optimum
F10	Foxholes	$f_{10}(x)=\left[(1/500)+\sum_{j=1}^{25}1/j+\sum_{i=1}^{2}(x_i-a_{ij})^6\right]^{-1}$	2	[65.536,65.536]	0.998
F11	Kowalik	$f_{11}(x)=\sum_{i=1}^{11}\lvert a_i-(x_1(b_i^2+b_ix_2)/b_i^2+b_ix_3+x_4)\rvert^2$	4	[-5,5]	3.075×10^{-4}
F12	Six Hump Camel	$f_{12}(x)=4x_1^2-2.1x_1^4+x_1^6/3+x_1x_2-4x_2^2+4x_2^4$	2	[-5,5]	-1.0316
F13	Branin	$f_{13}(x)=(x_2-(5.1/4\pi^2)x_1^2+(5/\pi)x_1-6)^2+10(1-(1/8\pi))\cos x_1+10$	2	[-5,10]×[0,15]	0.398
F14	GoldStein-Price	$f_{14}(x)=[1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]\times[30+(2x_1-3x_2)^2(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	2	[-2,2]	3
F15	Hartman 3	$f_{15}(x)=-\sum_{i=1}^{4}\exp\left[-\sum_{j=1}^{3}a_{ij}(x_i-p_{ij})^2\right]$	3	[0,1]	-3.86
F16	Hartman 6	$f_{16}(x)=-\sum_{i=1}^{4}\exp\left[-\sum_{j=1}^{6}a_{ij}(x_i-p_{ij})^2\right]$	6	[0,1]	-3.322
F17	Shekel 5	$f_{17}(x)=-\sum_{i=1}^{5}\lvert(x_i-a_i)(x_i-a_i)^T+c_i\rvert^{-1}$	4	[0,10]	-10.1532
F18	Shekel 7	$f_{18}(x)=-\sum_{i=1}^{7}\lvert(x_i-a_i)(x_i-a_i)^T+c_i\rvert^{-1}$	4	[0,10]	-10.4028

2) COMPARISON WITH OTHER ALGORITHMS

To test the superiority of MMA, it is compared with selected several popular swarm intelligence algorithms including particle swarm optimization (PSO), salvia swarm algorithm (SSA), whale optimization algorithm (WOA) and basic mayfly algorithm(MA), and the selected parameters of each algorithm are shown in Table 4.

3) EXPERIMENTAL RESULTS AND ANALYSIS

The test calculation of all algorithms is limited to the specified maximum number of function evaluations (FEs) according to the convergence speed, where the FEs of F1-F10 are 10^5, F11 is 10^4, F12-F15 are 10^3, and the remaining functions are 2000. Besides, each algorithm was independently run 30 times with each benchmark function. Therefore, the experimental results are based on the analysis of these performance indicators of 30 independent runs, including the average value, the median position value, the standard deviation (std), the best value and the worst value of the best function value for 30 independent runs, as shown in Tables 5, 6 and 7. At the same time, the convergence curve of each algorithm in the optimization calculation of different functions is obtained, as shown in Figs 1, 2 and 3.

a: ASSESSMENT OF EXPLOITATION

Table 5 shows that MMA has reached the optimal value in F5, and the average value in F1, F2 and F3 are very close to the optimal value. Moreover, the test results for 4 out of

TABLE 4. Parameter values used in MMA, MA, PSO, SSA and WOA.

Algorithm	Parameter	Value
MMA	Population size	Male：20，female：20
	Inertia weight	Non-linear reduction from 0.9 to 0.4
	Personal Learning Coefficient	1
	Global Learning Coefficient	1.5
	Distance sight Coefficient	2
	Nuptial Dance	5
	Random flight	1
MA	Inertia weight	Linear reduction from 0.9 to 0.4
PSO	Population size	30
	Inertia weight	0.9
	Cognitive coefficient	2
	Social coefficient	2
SSA	Population size	30
	Control parameter	[0, 1] random number
WOA	Population size	30

TABLE 5. Comparison of different methods in solving the unimodal test functions in Table 1 at 30 dimensions.

F	Statistics	MMA	MA	PSO	SSA	WOA
F1	Best	1.0804E-43	1.3152E-19	0.00785	4.23689E-09	0
	Worst	1.3864E-36	2.5969E-14	3.0326	7.518E-09	0
	Average	6.21894E-38	3.55787E-15	0.819787667	5.70419E-09	0
	Median	7.6066E-40	2.7236E-16	0.5725	5.6308E-09	0
	Std	2.53562E-37	6.23887E-15	0.793838767	9.03197E-10	0
F2	Best	2.6675E-13	0.000020096	46.91901853	3.27673E-05	31.52883091
	Worst	8.0789E-10	0.021304	15656.42461	0.003086114	9642.870038
	Average	8.58719E-11	0.002519778	3980.871535	0.000506796	2231.41243
	Median	9.51475E-12	0.000762015	821.1663791	0.000176195	1480.276835
	Std	2.04735E-10	0.005360501	5137.648097	0.000760249	2270.59927
F3	Best	0.00321	0.72647	0.22555239	0.373936278	0.003729804
	Worst	0.1339	1.3748	3.956135902	6.257500067	78.13697621
	Average	0.069699367	1.036569667	1.907880565	2.162639125	19.70535172
	Median	0.0668895	1.06545	1.865291302	1.813538084	5.140532627
	Std	0.031902923	0.2029999	0.834492236	1.652617767	25.53898926
F4	Best	0.9458	7.693	48.73863828	24.37030385	25.02522296
	Worst	21.369	84.4044	3096.883705	393.8485759	27.84851731
	Average	13.03488333	29.59747667	346.7075383	58.96656903	25.76330666
	Median	13.698	25.1382	113.3884127	28.12432049	25.79266426
	Std	3.814522529	18.06454502	697.1310721	74.65349915	0.479790858
F5	Best	0	2.2508E-19	1.479391765	3.12744E-09	0.000121015
	Worst	0	1.7919E-14	15.03831574	1.03146E-08	0.00067978
	Average	0	2.18874E-15	6.84564955	6.19712E-09	0.000318591
	Median	0	2.00585E-16	5.870975287	6.36171E-09	0.000289628
	Std	0	4.7414E-15	3.570723192	1.37929E-09	0.000136645

the 5 functions show that performance indicators such as the best value, average value, worst value or std are significantly better than other algorithms, which proves that MMA has better exploitation.

b: ASSESSMENT OF EXPLORATION

Multimodal functions are widely applied to test the explorations of optimization algorithms. Table 6 and Figure 2 show that in the four multimodal function tests of MMA, three test results are better than other algorithms in terms of performance indicators such as the best value, average value, worst value or std, but one test result is weaker than the WOA algorithm. Among them, the best value and average value in F5 and F7 are theoretical optimal values, which proves its good stability and can effectively jump out of the local optimum. Thus, it is proved that MMA has good exploration in the optimization calculation of high-dimensional multimodal function, and its overall performance is the best. Additionally, it can be seen from Table 7 that MMA is overall better than other algorithms in the low-dimensional multimodal function test. At the same time, within the specified FEs range, the rate of MMA converging to the optimal value is much higher than other algorithms, and the specific convergence rate is shown in Figure 4. Therefore, it can be seen that after the improvement of the basic MA, the convergence of MMA has been substantially promoted, especially for the low-dimensional multi-peak test function. On the one hand, it is because the basic mayfly algorithm promotes explorations through

TABLE 6. Comparison of different methods in solving the multimodal test functions in Table 2 at 30 dimensions.

F	Statistics	MMA	MA	PSO	SSA	WOA
F6	Best	-12489.2368	-11236.2789	-10169.36685	-8900.669031	-12569.47227
	Worst	-8656.8406	-9667.7018	-4204.179769	-6395.343659	-8916.847889
	Average	-11043.75613	-10370.55279	-7930.321793	-7632.040312	-11734.4916
	Median	-11226.37685	-10375.3619	-7959.666506	-7601.480857	-12274.41359
	Std	1071.345463	352.4171212	1383.960783	551.365438	1124.277749
F7	Best	0	0	0.659519903	1.44793E-08	0
	Worst	0	0.15668	1.220045364	0.041738471	0
	Average	0	0.02035666	1.021702566	0.015261914	0
	Median	0	0.0013739	1.051420983	0.014776107	0
	Std	0	0.034714843	0.117200128	0.010420067	0
F8	Best	1.5705E-32	1.2789E-18	0.07338245	0.076996645	1.5961E-05
	Worst	8.6731E-22	5.6369E-17	2.275358357	10.92694292	0.006026397
	Average	2.89113E-23	2.62117E-17	0.857928294	3.286830762	0.000246121
	Median	1.6028E-32	3.22765E-17	0.731750998	2.950832785	4.7564E-05
	Std	1.58348E-22	1.86493E-17	0.645590577	2.543357587	0.001091807
F9	Best	1.3498E-32	1.1119E-17	1.174201345	1.98222E-10	0.00032422
	Worst	9.2384E-32	3.2356E-11	4.166790135	4.63724E-10	0.08693565
	Average	1.74423E-32	1.15846E-12	2.43609001	3.31522E-10	0.010761517
	Median	1.3498E-32	2.36655E-16	2.277783987	3.34472E-10	0.001418724
	Std	1.58789E-32	5.90811E-12	0.708567006	7.08162E-11	0.018622491

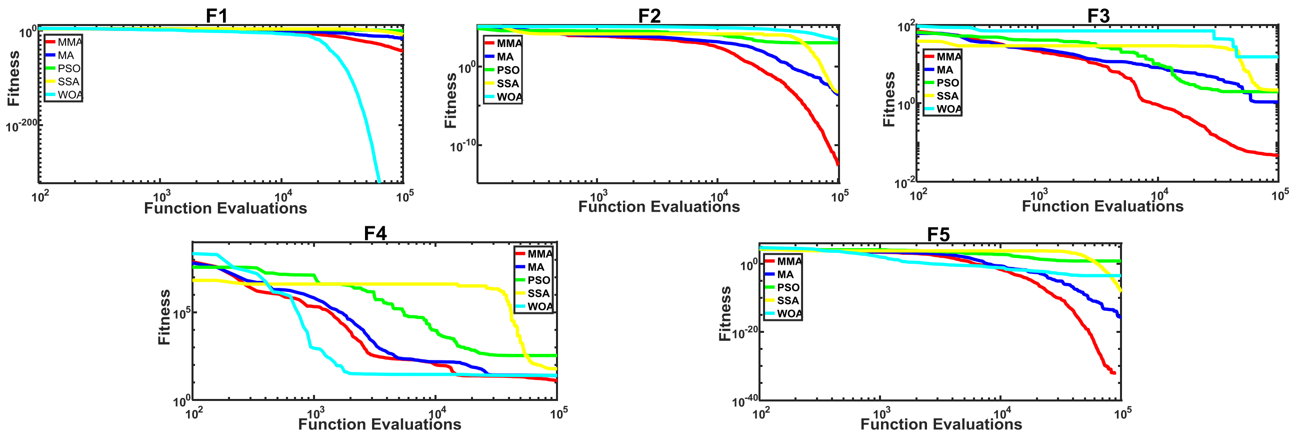

FIGURE 1. Convergence characteristic curves for MMA, MA, PSO, HAS, SSA and WOA in solving the unimodal test functions in Table 1 at 30 dimensions.

mating and selecting better offspring to replace the parents. More importantly, the median position of group is introduced into MMA, which enhances the sharing of group information, increases the group diversity, and to a certain extent improves the situation where the original algorithm is easy to fall into the local optimum.

c: ASSESSMENT OF CONVERGENCE SPEED AND ACCURACY

The convergence curve of the algorithm can reflect its convergence speed and accuracy intuitively. Figs 1 and 2 indicates that among the test results of 9 test functions of MMA, 7 test results show that its convergence speed and convergence accuracy are significantly better than other algorithms. Furthermore, in Fig 3, for low-dimensional multimodal functions, the performance of MMA is more prominent in terms of convergence speed, in the 9 low-dimensional multimodal test functions, the convergence speed of MMA is much higher than other algorithms, which is manifested in the faster convergence speed of the algorithm in the early stage and higher search accuracy.

III. APPLICATION OF MMA IN THE OPTIMIZATION OF PID PARAMETERS OF HYDRO-TURBINE GOVERNOR

The turbine regulating system is composed of the controlled object and the regulating system. The controlled objects include a turbine system and a generator system. The governor of the regulating system mainly includes a regulator and an electro-hydraulic servo system, and the governor generally adopts the parallel PID form [54], [55], [56]. The composition of the turbine regulating system is shown in Fig 5.

Where c is turbine speed relative deviation set point, ce is the speed deviation, u is the control signal output by the regulator, mt is turbine torque relative deviation, m_{g0} is the

TABLE 7. Comparison of different methods in solving the low-dimension multimodal test functions in Table 3.

F	Statistics	MMA	MA	PSO	SSA	WOA
	Best	0.998	0.998	0.998	0.998	0.998003838
	Worst	0.998	0.998	0.998	0.998	2.982105157
F10	Average	0.998	0.998	0.998	0.998	1.26255068
	Median	0.998	0.998	0.998	0.998	0.998003838
	Std	0	0	0	0	0.685994903
	Best	0.00030749	0.00087202	0.000307486	0.000497591	0.000309837
	Worst	0.00030749	0.0025372	0.022553327	0.020531732	0.002251949
F11	Average	0.00030749	0.001272223	0.01035776	0.003548586	0.000769913
	Median	0.00030749	0.001041	0.005292826	0.000993185	0.000607594
	Std	0	0.000500031	0.00952492	0.006739592	0.000581353
	Best	-1.0316	-1.0316	-1.03162816	-1.031628453	-1.031628442
	Worst	-1.0316	-1.0316	-1.030301879	-1.031628453	-1.031044422
F12	Average	-1.0316	-1.0316	-1.031344355	-1.031628453	-1.0315728
	Median	-1.0316	-1.0316	-1.031457416	-1.031628453	-1.031625096
	Std	0	0	0.000315786	2.59856E-12	0.000136578
	Best	0.39789	0.39789	0.397887517	0.397887358	0.397888674
	Worst	0.39789	0.39789	0.398850933	0.398308086	0.54195458
F13	Average	0.39789	0.39789	0.397956088	0.397902684	0.417879236
	Median	0.39789	0.39789	0.397901114	0.397887358	0.399750473
	Std	0	0	0.000182828	7.67195E-05	0.037831264
	Best	3	3	3.000002126	3	3.000001848
	Worst	3	3	3.014178597	3	32.03979487
F14	Average	3	3	3.00282678	3	8.549896665
	Median	3	3	3.001217911	3	3.003992263
	Std	0	0	0.003889213	0	11.26411524
	Best	-3.862789763	-3.86278914	-3.862773467	-3.862781825	-3.862764308
	Worst	-3.862776763	-3.86277514	-3.85485095	-3.633741994	-2.983347546
F15	Average	-3.862780033	-3.862781306	-3.859895135	-3.818666217	-3.750536198
	Median	-3.862779263	-3.86278164	-3.862177656	-3.845133956	-3.829590992
	Std	2.80829E-06	3.81543E-06	0.003572534	0.062514035	0.210808345
	Best	-3.321996147	-3.321995179	-3.321981691	-3.321995168	-3.260443996
	Worst	-3.321988758	-3.203102007	-2.638085802	-2.887026173	-2.497674148
F16	Average	-3.321994303	-3.30614275	-3.18180043	-3.233817969	-3.077714231
	Median	-3.321994936	-3.32199517	-3.200052712	-3.321661884	-3.115302039
	Std	1.51728E-06	0.041106823	0.176045168	0.120105776	0.19727405
	Best	-10.15319969	-10.15319968	-10.1531653	-10.15319968	-10.05727653
	Worst	-2.682860392	-2.682860392	-0.497301243	-2.630471668	-1.753161814
F17	Average	-9.05913182	-8.908143102	-6.778706021	-7.15457837	-7.12404592
	Median	-10.15319967	-10.15319963	-5.100599684	-10.15319965	-8.062127945
	Std	2.404293121	2.831624786	3.237082506	3.553225524	2.583581948
	Best	-10.40280066	-10.40294066	-10.40285721	-10.40294057	-10.24985686
	Worst	-2.765897324	-2.765897324	-1.837592586	-2.751933564	-1.678737941
F18	Average	-9.292606962	-8.303508175	-6.948151229	-7.70943481	-5.414264004
	Median	-10.40294052	-10.40294052	-5.096864661	-10.40294056	-4.965438738
	Std	2.551279479	3.271455487	3.404375848	3.408483558	2.287612725

load torque relative deviation, and x is turbine speed relative deviation.

Figure 5 shows that when the system frequency is disturbed, the turbine regulating system adjusts according to the speed deviation ce formed by the given speed signal c and the actual speed x of the hydroelectric generating unit. Specifically, the PID control law is formed by the PID regulator controlling the PID parameters (K_p, K_i and K_d), which converts the speed deviation ce into the adjustment signal u. And then electro-hydraulic servo system converts the adjustment signal u into the hydraulic signal to operate the hydraulic device which can adjust the opening of the guide vane and change turbine torque relative deviation mt. Thus, the new unit speed x is generated by the change of the difference between turbine torque relative deviation mt and the system load.

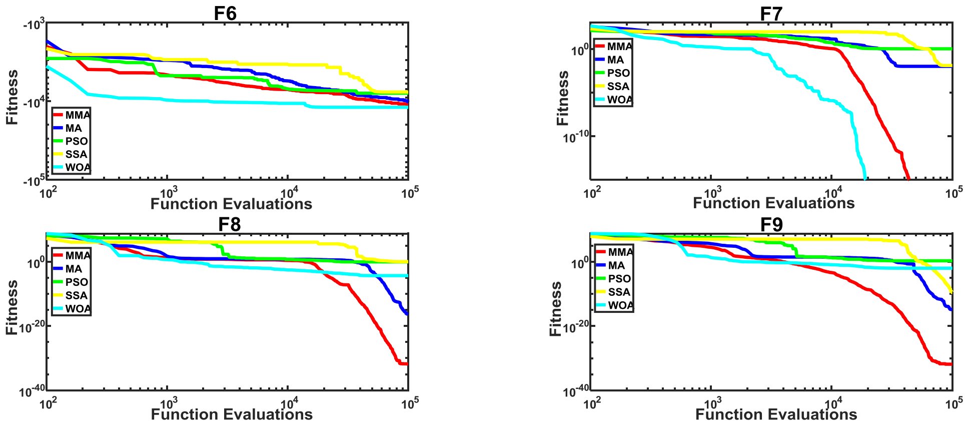

FIGURE 2. Convergence characteristic curves for MMA, MA, PSO, HAS, SSA and WOA in solving the multimodal test functions in Table 2 at 30 dimensions.

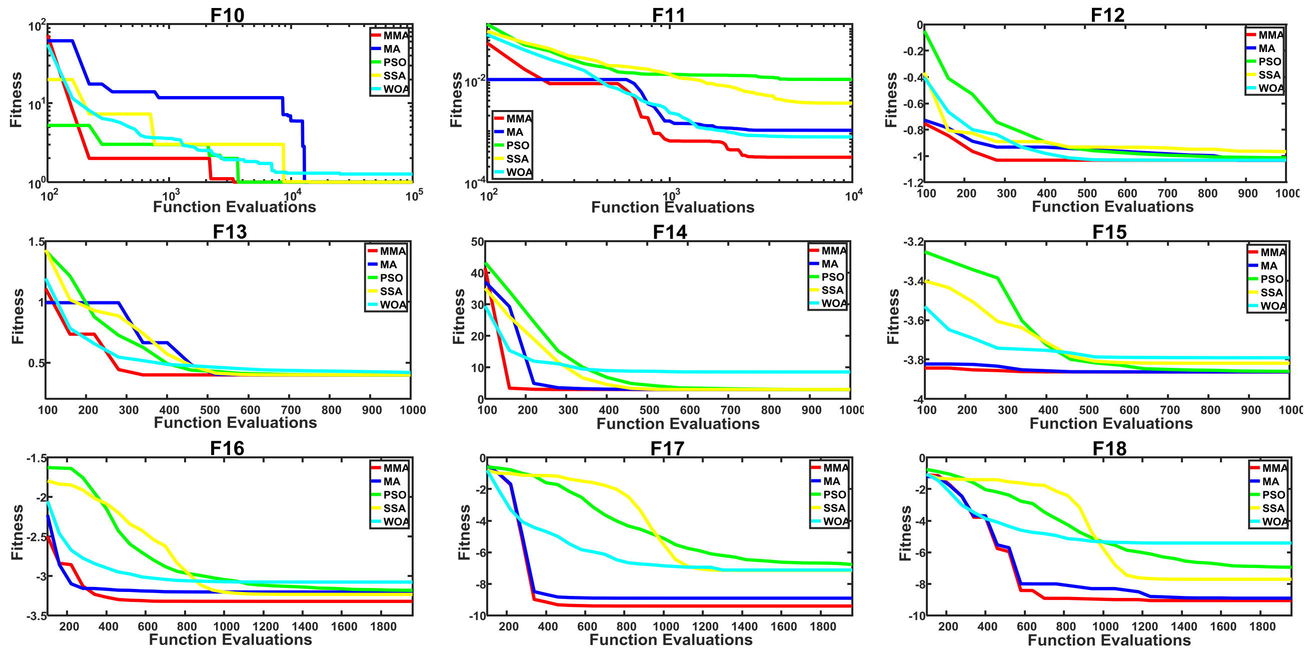

FIGURE 3. Convergence characteristic curves for MMA, MA, PSO, HAS, SSA and WOA in solving the Low-dimension multimodal test functions in Table 3.

A. TRANSFER FUNCTIONS OF HYDRO-TURBINE GOVERNOR SYSTEM

The transfer function of water turbine speed governor PID controller is:

$$G_r(s) = (K_p + K_i/s + K_d s)/(1 + T_n s) \tag{17}$$

where K_p is the proportional gain; K_i the integral gain; K_d the derivative gain; s is the Laplace operator; and T_n is the derivative filter time constant, in seconds; the transfer function of electro-hydraulic servo system is:

$$G_y(s) = 1/(1 + T_y s) \tag{18}$$

where T_y is the wicket gate servomotor response time.

Water and penstock are taken to be incompressible, if penstock is short or medium in length, therefore, inelastic water hammer effect is considered. From Fig.5, the transfer function of turbine and water diversion system is:

$$G_t(s) = (e_y - eT_w s)/(1 + e_{qh} T_w s) \tag{19}$$

$$e = e_{qy} e_h - e_{qh} e_y \tag{20}$$

where T_w is the water inertia time, in seconds; e_y, e_{qy}, e_h, e_{qh} are partial derivatives of water turbine; the transfer function of generator and load is:

$$G_g(s) = 1/(T_a s + e_n) \tag{21}$$

where T_a is the generator unit mechanical time, in seconds and e_n is the load self-regulation factor.

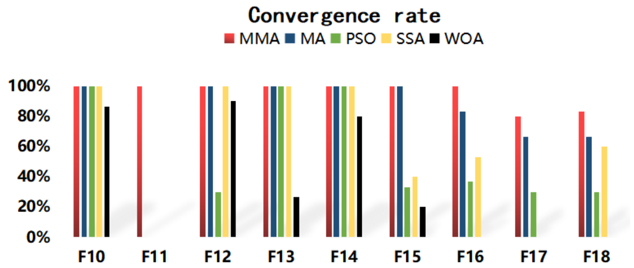

FIGURE 4. Convergence rate to the optimal value for MMA, MA, PSO, SSA and WOA in solving the low-dimension multimodal test functions in Table 3.

B. ALGORITHM FLOW OF MMA IN THE OPTIMIZATION OF PID PARAMETERS OF HYDRO-TURBINE GOVERNOR

According to the optimization process of MMA described above, the algorithm flow of MMA in the optimization of PID parameters of hydro-turbine governor is shown in Fig 6, and the specific steps are as follows:

Step 1: Set the number of male mayflies, female mayflies, and the number of offspring, and set the learning factor, visibility coefficient and dance coefficient, and other parameters at the same time; Based on the parameters set above, initialize the positions and velocities of the population. Use the integrated time and absolute error (ITAE) index of the speed deviation of the hydropower unit as the fitness function of the optimization algorithm.

Step 2: Establish a simulation model of the turbine regulating system with the Simulink tool in Matlab, as shown in Fig 7. Then start to enter the iteration, and calculate the fitness function value of each mayfly, then the values are sorted. And while *gbest*, *pbest* and *pm* are calculated.

Step 3: Update the speed and position of the male and female mayfly with the formulas, and male and female mayfly mating.

Step 4: Calculate the fitness function values of the offspring and variants, update the individual fitness which is compared with the global fitness, then update the global optimum.

Step 5: If the number of iterations reaches the maximum, end the algorithm and output the result. If not, return to step 2 for another iteration.

The expression of ITAE index is:

$$J_{ITAE} = \int_0^{T_s} t\,|e(t)|dt \tag{22}$$

where $e(t)$ is the system deviation, and T_s is the adjustment time.

C. EXPERIMENTAL RESULTS AND ANALYSIS

To verify the effectiveness of MMA in the parameter optimization of the turbine regulating system, a PID parameter optimization simulation test of the governor is carried out in

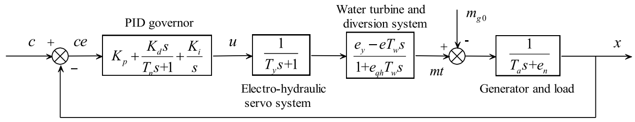

FIGURE 5. Composition diagram of hydraulic turbine regulating system.

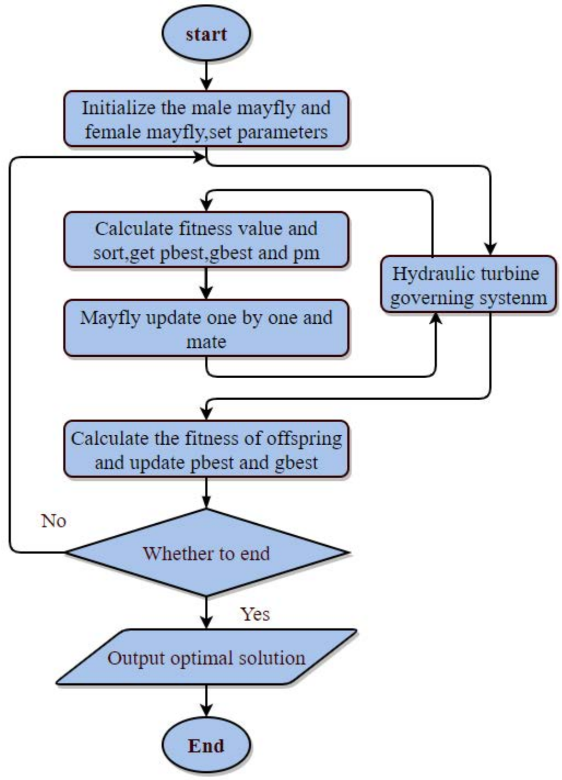

FIGURE 6. Flow chart of MMA.

this paper. In the simulation process, to test the robustness of the optimization algorithm, two typical working conditions are selected. Furthermore, 10% frequency disturbance experiments were carried out under the two working conditions respectively [47], [48]. Besides, Table 8 shows the characteristic parameters of the unit under two specific working conditions.

In the case of ensuring that the results of parameters optimization are correct, to improve the calculation efficiency, the boundaries of K_p, K_i and K_d are all set as [0, 5]. And T_s is 20 seconds. Besides, the maximum number of iterations is set to 50. In addition, the results are based on 35 independent runs for each algorithm. Furthermore, MMA is compared with MA, PSO, SSA, and WOA, where the specific parameter settings of each algorithm are consistent with those in Table 4.

Table 9 shows the experimental results of each algorithm under 10% frequency disturbance under two working conditions. And it lists the best value, worst value, average value, median value and std of ITAE index value after 35 independent runs. Furthermore, there are also the maximum, minimum, and average number of iterations to the optimal value (the error is not greater than 0.1%), and the success rate of

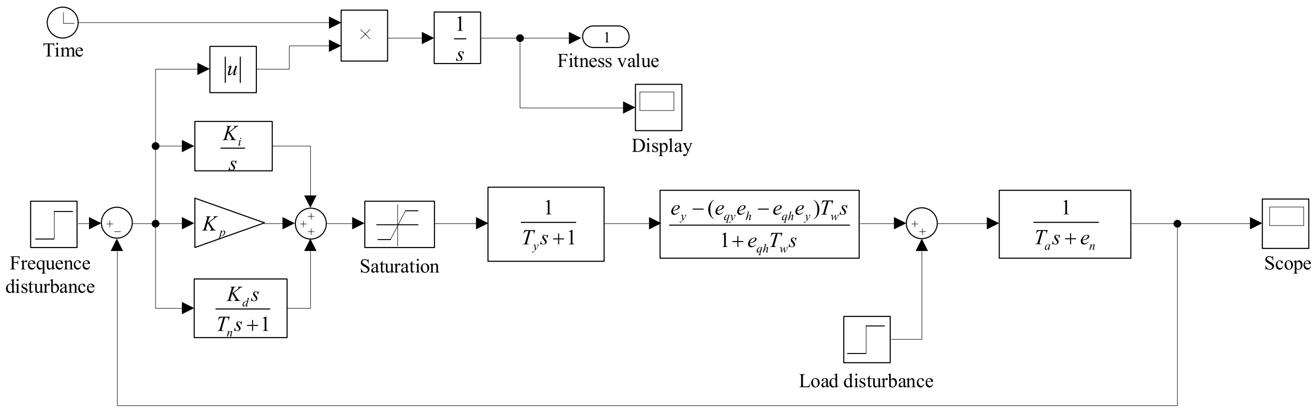

FIGURE 7. Simulation model of the hydro-turbine governor.

TABLE 8. Parameters of hydro-turbine regulating system.

Parameters	T_y	T_a	T_w	e_n	e_h	e_y	e_{qh}	e_{qy}
Working condition 1	0.05	10.54	1.6	1.3	0.86	1.12	0.18	1.4
Working condition 2	0.05	10.54	2.2	1.6	1.43	0.65	0.4	0.85

TABLE 9. Experimental results of 10% frequency disturbance under two working conditions by different algorithms.

		Statistics	MMA	MA	PSO	SSA	WOA
Working condition 1	ITAE	Best	0.205412036	0.205412404	0.205433764	0.20543367	0.205439801
		worst	0.205412056	0.205588129	1.342903231	0.29531497	0.436886118
		Average	0.205412047	0.205440535	0.294346252	0.229306974	0.254227361
		Median	0.205412046	0.205417357	0.205694024	0.218653655	0.235597729
		Std.	4.68968E-09	3.70757E-05	0.212754341	0.025207301	0.073597422
	Iterations of the optimal value	MinIter	12	13	38	33	15
		MaxIter	20	22	50	43	47
		Average	16.53	17.267	47.33	40.267	30.8
Working condition 2	ITAE	Best	0.713073506	0.713073838	0.713081775	0.713835332	0.713076574
		worst	0.713075526	0.713079983	0.717433996	1.582311305	1.520777141
		Average	0.713074031	0.713075402	0.713521675	0.882654393	0.793828236
		Median	0.713073523	0.713074385	0.713124365	0.74475663	0.721617996
		Std.	8.02469E-07	1.63091E-06	0.001093351	0.265061925	0.178383544
	Iterations of the optimal value	MinIter	13	15	39	28	15
		MaxIter	21	23	50	50	50
		Average	18.143	19.229	47.829	42.371	34.8

converging to the optimal ITAE index value where the error is not more than 0.1% as the standard.

Shown as in the table 9, the best value and average value of ITAE for MMA and MA are obviously better than other algorithms, while MMA is slightly better than MA, which proves that these two algorithms have good convergence accuracy. Moreover, the best value, worst value and average value of ITAE for MMA are almost the same, and the std value is very small. Besides, the ITAE value obtained in each run can converge near the best value, indicating that MMA has better exploration and good stability, it can avoid falling into the local optimal value. However, there is a certain degree of falling into the local optimal solution for all of the other algorithms, which cannot achieve stable optimization. Therefore, according to the number of iterations converging to the optimal value, whether it is the minimum number of iterations or the average number of iterations, the number of MMA is much smaller than that of other algorithms, which proves that MMA has an excellent convergence speed.

Figure 8 shows the average best fitness convergence curve for different algorithms under two working conditions with 10% frequency disturbance. As shown in the figure, the optimal solution is quickly found in the early stage by MMA. Moreover, it is much faster than other algorithms, and its optimal solution accuracy is also better than the others, showing excellent exploitation.

TABLE 10. Performance of 10% frequency disturbance under two working conditions by different algorithms.

	Statistics	MMA	MA	PSO	SSA	WOA
Working condition 1	Overshoot	3.10%	3.20%	3.30%	10.20%	3.40%
	Adjustment time	5.35	5.37	5.4	7.15	6.4
Working condition 2	Overshoot	3.20%	3.20%	4.17%	11.40%	5.20%
	Adjustment time	8.135	8.136	8.165	7.608	7.86

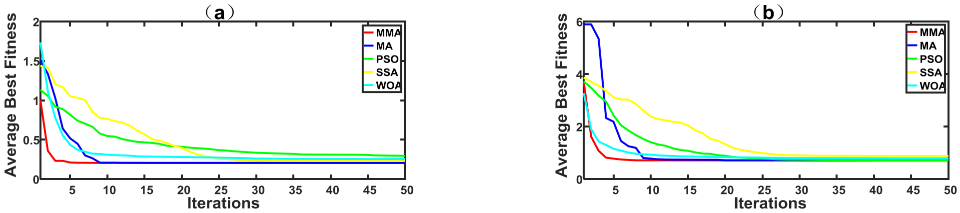

FIGURE 8. Convergence curves of average best fitness with 10% frequency disturbance under two working conditions provided by different algorithms.

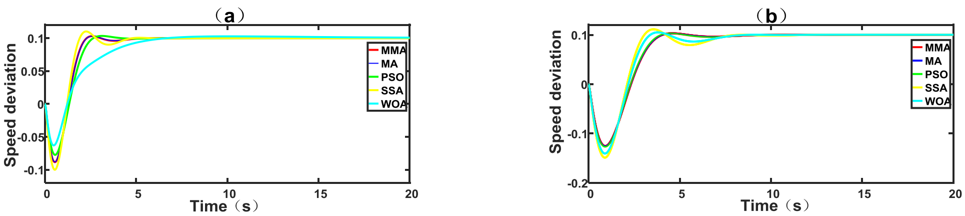

FIGURE 9. Response curves with 10% frequency disturbance under two working conditions provided by different algorithms.

Figure 9 shows the response curves with 10% frequency disturbance under two working conditions provided by different algorithms. Besides, in Table 10, the specific performance index values of the speed response curve of the turbine regulation system under two working conditions with 10% frequency disturbance are listed, including the overshoot and the adjustment time. As shown in the Figure 9, the speed response curve corresponding to the optimization result of MMA is relatively better than other curves. According to the performance index values, MMA has the smallest overshoot and the shortest adjustment time under working condition 1. And under working condition 2, although the adjustment time of MMA is slightly longer than SSA and WOA, its overshoot is also the smallest. However, the overshoot corresponding to SSA and WOA is too large, which shows that the oscillation amplitude of the curve is too large in the early transition process.

Through the frequency disturbance experiment analysis and comparison of different algorithms under two working conditions, it is proved that the PID parameters optimized by the MMA can make the turbine regulating system have better overall dynamic performance. Furthermore, the optimization process of MMA under both working conditions can stably and quickly converge to a better ITAE index value. MMA not only guarantees its original features of fast convergence speed and strong exploitation, but also effectively improves exploration. This is mainly because the median position of the group is introduced into the basic mayfly algorithm, where the problem of insufficient group diversity in the optimization process has been solved in a better way. In this paper, the importance of the median position in the group for swarm intelligence algorithm is described theoretically, where its effectiveness has been proved through practical application in engineering. The concept of group median position can not only be used in the mayfly optimization algorithm but also can be extended to other similar swarm intelligence algorithms, showing its wide applicability and good application value.

IV. CONCLUSION

The paper improves the current situation of the basic mayfly optimization algorithm where the global search ability is insufficient and the local optimum is easy to fall into. On the one hand, inspired by the improvement of the inertia weight factor in the particle swarm algorithm, a decreasing nonlinear inertia weight factor that is slow first and then fast is introduced. On the other hand, the concept of the median position of the group is proposed and introduced into the speed update of the mayfly algorithm. The optimization performance of MMA and the other four swarm intelligence algorithms is compared and analyzed through three sets of benchmark functions. And the experimental results show that

MMA performs better in 16 of the 18 test functions. Besides, the superior performance of MMA in local search, global search and convergence speed and accuracy is confirmed by the experiments. Moreover, MMA is applied to the optimization of PID parameters of hydro-turbine governor, and the frequency disturbance simulation experiment under two different working conditions is carried out by constructing a simulation module, which is compared with several popular swarm intelligence algorithms. The experimental results indicate that MMA can make the system obtain a smaller ITAE value, and there are only takes 16.5 and 18.1 iterations to complete on average. Furthermore, compared with other algorithms, the PID parameters optimized by MMA can reduce the overshoot of the regulation system by more than 3.1%, and the adjustment time also decrease to varying degrees. Therefore, the experimental results prove that MMA not only has faster convergence speed, higher convergence accuracy and stronger stability in the optimization process but also has the better balance between exploration and exploitation. In conclusion, the PID parameters obtained through MMA can enable the turbine regulating system to have better overall dynamic performance.

In the future, there are still the following issues to be further studied:

1) The introduction of the median position of the group still needs to be further demonstrated mathematically for its effectiveness on the swarm intelligence algorithm, which will play a vital role in the further promotion and application of the median position in the swarm intelligence algorithm.
2) The introduction of the median position of the group can improve exploration of the mayfly algorithm to a certain extent, but compared with its super exploitation, its exploration still has huge room for improvement. Besides, improving the overall performance of the algorithm by setting more reasonable parameters will be one of the important research directions in the future.
3) The efficiency and effectiveness of the MMA in tackling constrained problems need further investigation. The MMA should be widely used in other engineering optimization problems, and it should be compared with more optimization algorithms to verify its effectiveness and adaptability.

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