Function Optimization and Parameter Performance Analysis Based on Krill Herd Algorithm

Xiao-Xu Ma, and Jie-Sheng Wang

***Abstract*—Krill herds (KH) algorithm is a new bionic intelligent algorithm which originates from the behavior of foraging krill. The parameter initialization of the discussed KH algorithm has the important influence on the convergence speed, convergence precision and good global searching ability of the KH. The convergence speed and algorithm searching precision are determined by the foraging speed, maximum induced speed and maximum diffusion speed. The simulation experiments are carried out by using the six typical test functions to discuss this influence. The simulation results show that the convergence speed of KH algorithm is relatively sensitive to the setting of the algorithm parameters, and the proper KH parameters can flexibly improve the algorithm's convergence velocity and improve the accuracy of the searched solutions.**

***Index Terms*—krill herd algorithm, function optimization, convergence rate**

I. Introduction

OPTIMIZATION is the selection of a best element from a set of some available alternatives with regard to some criterion. The optimization algorithm is a basic principle of nature, which shows many different advantages and disadvantages in computational efficiency and global search probability and has a vast variety of applications in research and industry [1]. The function optimization presents a formalized framework for modelling and solving some certain problems. Given an objective function, it takes a number of parameters as its inputs, whose goal is to find the combination of parameters and return the best value. This framework is abstract enough that a wide variety of different problems can be interpreted as function optimization problems [2].

However, the traditional function optimization algorithm is used to solve the typical problem with small dimension, often not applicable in practice. So people focus on the nature. Nature provides rich models to solve these problems (such as fireflies, bats, ants). People discovered the swarm intelligence optimization algorithm by simulating natural biological systems. These models could stimulate computer scientists using household non-traditional tools to solve the application problems [3]. Now a lot of swarm intelligence optimization algorithm is proposed, such as particle swarm optimization (PSO) [4], ant colony algorithm (ACO) [5], bat algorithm (BA) [6], social learning optimization algorithm (SLO) [7], chickens algorithm (CSO) [8], firefly algorithm [9] etc. They can be used in the dictionary learning remote sensing data, automotive safety integrity level positioning, economic dispatch, composition and examples of the Cloud Service Composition of QOS awareness. Obviously, the study of swarm intelligence optimization has become an important research direction.

Krill herds (KH) algorithm is a new kind of bionic intelligent algorithm based on the simulation of Antarctic krill group's movement in the marine environment. It is a global probabilistic search algorithm with simple operation, strong commonality, easy to parallel processing and strong robustness. At present many scholars are crazy about this algorithm. Krill herds algorithm is used to solve numerical function optimization problems and its application in data clustering [10], inverse radiation problems [11], phase equilibrium calculations[12], the optimal power flow [13], dynamic optimal power flow of combined heat and power system [14], optimal power flow with direct current link placement problem [15], model turbine heat rate by fast learning network with tuning [16], inverse geometry design of two-dimensional complex radiative enclosures [17]. In this paper, the function optimization problem is solved based on KH algorithm. Then the parameter performance comparison and analysis are carried out through the simulation experiments in order to verify its superiority. The paper is organized as follows. In section 2, principles and procedures of KH algorithm are introduced. The simulation experiments and results analysis are introduced in details in Section 3. Finally, the conclusion illustrates the last part.

II. Krill herd algorithm

A. Herding behavior of krill swarms

The groupings formation of various species of marine animals are under-dispersed and non-random. Many studies have focused on capturing the underlying mechanisms

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governing the development of these formations. The major mechanisms identified are related to the feeding ability, enhanced reproduction, protection from predators, and environmental conditions. Some mathematical models have been developed to evaluate the relative contribution of these mechanisms based on experimental observations.

Antarctic krill is one of the best-studied species of marine animal. The krill herds are aggregations with no parallel orientation existing on time scales of hours to days and space scales of 10 meters to 100 meters. One of the main characteristics of this specie is its ability to form large swarms. Over the last three decades, several studies have been conducted to understand the ecology and distribution of krill herds. Although there are yet notable uncertainties about the forces determining the distribution of the krill herd, the conceptual models have been proposed to explain the observed formation of the krill herds. The results obtained by such conceptual frameworks revealed that the krill swarms form the basic unit of organization for this species. In order to better understand the formation of the krill swarms, the proximate causes and the factors that are adaptive advantages of aggregation formation (ultimate effects) should be distinguished.

When predators, such as seals, penguins or seabirds, attack krill, they remove individual krill. This results in reducing the krill density. The formation of the krill herds after predation depends on many parameters. The herding of the krill individuals is a multi-objective process including two main goals: increasing krill density, and reaching food. In the present study, this process is taken into account to propose a new metaheuristic algorithm for solving global optimization problems. Density-dependent attraction of krill (increasing density) and finding food (areas of high food concentration) are used as objectives which finally lead the krill to herd around the global minima. In this process, an individual krill moves toward the best solution when it searches for the highest density and food. That is to say that the closer the distance to the high density and food, the less the objective function.

B. Principles and procedures of krill herd algorithm

Predation removes individuals, leads to reduction of the average krill density, and distances the krill swarm from the food location. This process is assumed to be the initialization phase in the KH algorithm. In the natural system, the fitness of each individual is supposed to be a combination of the distance from the food and from the highest density of the krill swarm. Therefore, the fitness (imaginary distances) is the value of the objective function. The time-dependent position of an individual krill in 2D surface is governed by the following three main actions [18]: Movement induced by other krill individuals; Foraging activity; Random diffusion.

It is known that an optimization algorithm should be capable of searching spaces of arbitrary dimension. Therefore, the following Lagrangian model is generalized to an n dimensional decision space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{1}$$

where N_i is the motion induced by other krill individuals, F_i is the foraging motion and D_i is the physical diffusion of the i th krill individuals.

(1) Motion induced by other krill individuals

According to theoretical arguments, the krill individuals try to maintain a high density and move due to their mutual effects. The direction of motion induced, α_i , is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect). For a krill individual, this movement can be defined as:

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \tag{2}$$

where：

$$\alpha_i = \alpha_i^{local} + \alpha_i^{t\arg et} \tag{3}$$

and $N^{\max}$ is the maximum induced speed, ω_n is the inertia weight of the motion induced in the range [0,1], N_i^{old} is the last motion induced, α_i^{local} is the local effect provided by the neighbors and $\alpha_i^{t\arg et}$ is the target direction effect provided by the best krill individual. According to the measured values of the maximum induced speed.it is taken 0.01 (ms^{-1}).

The effect of the neighbors can be assumed as an attractive /repulsive tendency between the individuals for a local search. In this study, the effect of the neighbors in a krill movement individual is determined as follows:

$$\alpha_{\mathrm{i}}^{\mathrm{local}} = \sum_{\mathrm{j=1}}^{\mathrm{NN}} \hat{\mathrm{K}}_{\mathrm{ij}} \hat{\mathrm{X}}_{\mathrm{ij}} \tag{4}$$

$$\hat{X}_{ij} = \frac{X_j - X_i}{\left\| X_j - X_i \right\| + \varepsilon} \tag{5}$$

$$\hat{K}_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{6}$$

where K^{best} and K^{worst} are the best and the worst fitness values of the krill individuals so far; K_i represents the fitness or the objective function value of the i th krill individual; K_i is the fitness of j th $(j = 1, 2, \cdots, NN)$ neighbor; X represents the related positions; and NN is the number of the neighbors. For avoiding the singularities, a small positive number ε is added to the denominator.

The right sides of Eq. (4)-(6) contain some unit vectors and some normalized fitness values. The vectors show the induced directions by different neighbors and each value presents the effect of a neighbor. The neighbors' vector can be attractive or repulsive since the normalized value can be negative or positive. For choosing the neighbor, different strategies can be used. For instance, a neighborhood ratio can be simply defined to find the number of the closest krill individuals. Using the actual behavior of the krill individuals, a sensing distance (ds) should be determined around a krill individual (as shown in Fig. 1) and the neighbors should be found.

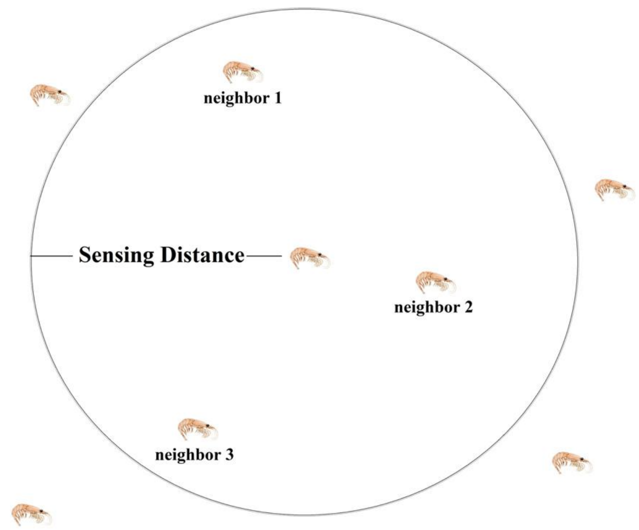


Fig. 1. A schematic representation of the sensing ambit around a krill individual.

The sensing distance for each krill individual can be determined using different heuristic methods. Here, it is determined using the following formula for each iteration:

$$d_{s,i}=\frac{1}{5N}\sum_{j-1}^{N}\left\|X_i-X_j\right\| \tag{7}$$

where $d_{s,i}$ is the sensing distance for the i th krill individual and N is the number of the krill individuals. The factor 5 in the denominator is empirically obtained. Using Eq.7, if the distance of two krill individuals is less than the defined sensing distance, they are neighbors.

The known target vector of each krill individual is the lowest fitness of an individual krill. The effect of the individual krill with the best fitness on the i th individual krill is taken into account using Eq. (8). This level leads it to the global optima and is formulated as:

$$\alpha_i^{target}=C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \tag{8}$$

where, C^{best} is the effective coefficient of the krill individual with the best fitness to the i th krill individual. This coefficient is defined since α_i^{target} leads the solution to the global optima and it should be more effective than other krill individuals such as neighbors. Herein, the value of C^{best} is defined as:

$$C^{best}=2\left(rand+\frac{I}{I_{\max}}\right) \tag{9}$$

where rand is a random values between 0 and 1 and it is for enhancing exploration, I is the actual iteration number and $I_{\max}$ is the maximum number of iterations.

(2) Foraging motion

The foraging motion is formulated in terms of two main effective parameters. The first one is the food location and the second one is the previous experience about the food location. This motion can be expressed for the ith krill individual as follows:

$$F=V_f\beta_i+\omega_f F_i^{old} \tag{10}$$

where：

$$\beta_i=\beta_i^{food}+\beta_i^{best} \tag{11}$$

and V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0,1], is the last foraging motion, β_i^{food} is the food attractive and β_i^{best} is the effect of the best fitness of the i th krill so far. According to the measured values of the foraging speed [30], it is taken 0.02 (ms^{-1}).

The food effect is defined in terms of its location. The center of food should be found at first and then try to formulate food attraction. This cannot be determined but can be estimated. In this study, the virtual center of food concentration is estimated according to the fitness distribution of the krill individuals, which is inspired from ‘‘center of mass’’. The center of food for each iteration is formulated as:

$$X_i^{food}=\frac{\sum_{i=1}^{N}\frac{1}{K_i}X_i}{\sum_{i=1}^{N}\frac{1}{K_i}} \tag{12}$$

Therefore, the food attraction for the i th krill individual can be determined as follows:

$$\beta_i^{food}=C^{food}\hat{K}_{i,food}\hat{X}_{i,food} \tag{13}$$

where C^{food} is the food coefficient. Because the effect of food in the krill herding decreases during the time, the food coefficient is determined as:

$$C^{food}=2\left(1-\frac{I}{I_{\max}}\right) \tag{14}$$

The food attraction is defined to possibly attract the krill swarm to the global optima. Based on this definition, the krill individuals normally herd around the global optima after some iteration. This can be considered as an efficient global optimization strategy which helps improving the globality of the KH algorithm.

The effect of the best fitness of the i th krill individual is also handled using the following equation:

$$\beta_i^{best}=\hat{K}_{i,best}\hat{X}_{i,best} \tag{15}$$

where $\hat{K}_{i,best}$ is the best previously visited position of the i th krill individual.

(3) Physical diffusion

The physical diffusion of the krill individuals is considered to be a random process. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$D_i = D^{\max}\delta \tag{16}$$

where $D^{\max}$ is the maximum diffusion speed, and d is the random directional vector and its arrays are ranom values between -1 and 1.

Wolpert and Macready proposed a range for the maximum diffusion speed of the krill individuals as $D^{\max} \in [0.002, 0.010]$ (ms^{-1}) and a random number in this range is also used in this study. The better the position of the krill is, the less random the motion is. Thus, another term is added to the physical diffusion formula to consider this effect. The effects of the motion induced by other krill individuals and foraging motion gradually decrease with increasing the time (iterations). Referring to Eq. (16), the physical diffusion is a random vector and does not steadily reduce with the increases of the iteration number. Thus, another term (Eq. (17)) is added to Eq. (16). This term linearly decreases the random speed with the time and works on the basis of a geometrical annealing schedule:

$$D_i = D^{\max}\left(1 - \frac{I}{I_{\max}}\right)\delta \tag{17}$$

(4) Motion Process of the KH Algorithm

In general, the defined motions frequently change the position of a krill individual toward the best fitness. The foraging motion and the motion induced by other krill individuals contain two global and two local strategies. These are working in parallel which make KH a powerful algorithm. According to the formulations of these motions for the i th krill individual, if the related fitness value of each of the above mentioned effective factor (K_j ; K^{best} ; K^{food} or K_i^{best}) is better (less) than the fitness of the i th krill, it has an attractive effect; otherwise, it has a repulsive effect. It is also clear from the above formulations that a better fitness is more effective on the movement of i th krill individual. The physical diffusion performs a random search in the proposed method. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to $t+\Delta t$ is given by the following equation:

$$X(t+\Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \tag{18}$$

It should be noted that Δt is one of the most important constants and should be carefully set according to the optimization problem. This is because this parameter works as a scale factor of the speed vector. Δt completely depends on the search space and it seems it can be simply obtained from the following formula:

$$\Delta t = C_t \sum_{j=1}^{NV}\left(UB_j - LB_j\right) \tag{19}$$

where NV is the total number of variables, and LB_j and UB_j are lower and upper bounds of the j th variable ($j = 1, 2, \cdots, NV$),respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that C_t is a constant number between [0,2]. It is also obvious that low values of C_t let the krill individuals to search the space carefully.

III. Simulation Experiments and Results Analysis

A. Test Functions

In the simulation experiments, six typical functions are adopted to verify the performance of KH algorithm. The simulation environment adopts the Windows 10 operating system, Intel processor 2.40 GHz, 3G memory for Matlab 2014b simulation software. The testing functions are shown in Tab.1.

TABLE 1. Simulation testing functions

Function	Name	Expression	Range
f_1	Ackley	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}X_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	[-32,32]
f_1	Rotated Hyper-Ellipsoid	$f_2(x) = \sum_{i=1}^{d}\sum_{j=1}^{i}x_j^2$	[-5.536,65.536]
f_1	Schwefel	$f_3(x) = 418.9829d - \sum_{i=1}^{d}x_i\sin(\sqrt{\lvert x_i\rvert})$	[-100,100]
f_1	Michaelmas	$f_4(x) = -\sum_{i=1}^{d}\sin(x_i)\sin^{2m}(\frac{ix_i^2}{\pi})$	[0,π]
f_1	Drop-Wave	$f_5(x) = -\frac{1+\cos(12\sqrt{x_1^2+x_2^2})}{0.5(x_1^2+x_2^2)+2}$	[-5.12,5.12]
f_1	Rastrigin'	$f_6(x) = n*10 + \sum_{i=1}^{d}(x_i^2 - 10\cos(2\pi x_i))$	[-5.12,5.12]

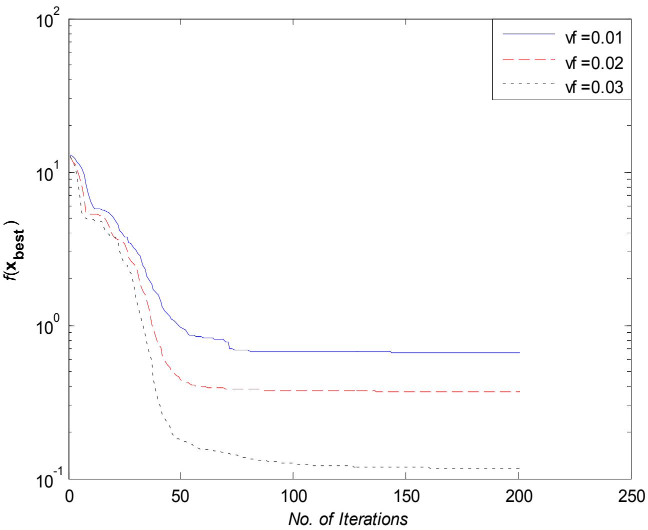
B. Simulation Experiments and Results Analysis

(1) Change of Variable v_f

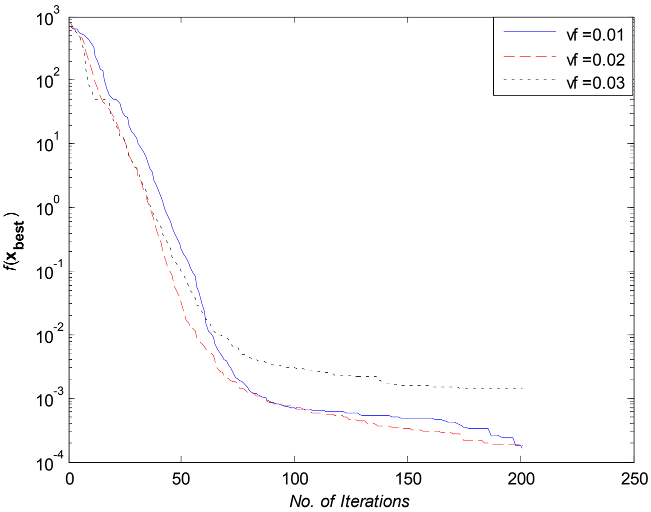
The initialization parameters of KH algorithm are set as: the population size n is 25, the number of iterations max_it is 200, D^{max} =0.003, N^{max} =0.01. In order to reduce the influence of random disturbance, the independent operating for each test function is carried out 10 times. The optimal value and average values of KH algorithm in different foraging speed are shown in Tab. 2. The simulation results of the six test functions are shown in Fig. 2.

TABLE 2. PERFORMANCE COMPARISON OF MFPA UNDER DIFFERENT

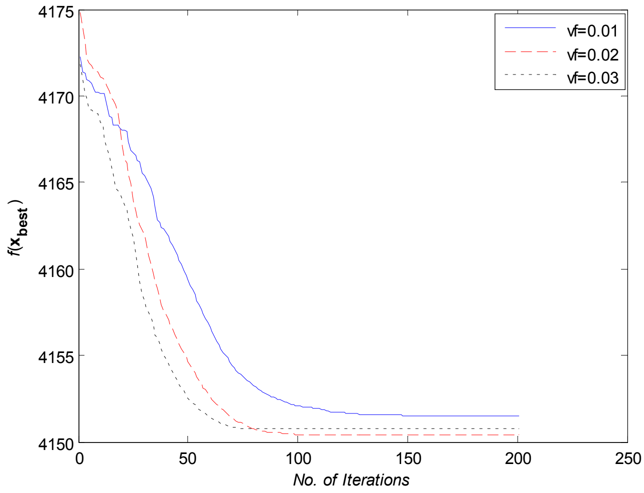
Function	Result	Simulation results of KH under different v_f		
		0.01	0.02	0.03
f_1	optimum	1.159214e-004	2.834541e-004	1.206518e-004
	average	0.664422	0.366695	0.116505
	std	0.923498	0.775967	0.365057
f_2	optimum	6.705122e-006	8.590074e-006	2.437952e-005
	average	1.637314e-004	1.832501e-004	0.001433
	std	3.084173e-004	3.638709e-004	0.003299
f_3	optimum	4150.376	4150.376	4150.376
	average	4151.498	4150.376	4150.750
	std	1.805951	6.643310e-005	1.182190
f_4	optimum	-1.987943	-1.967845	-1.957951
	average	-1.747110	-1.82092	-1.815117
	std	0.303825	0.135230	0.111534
f_5	optimum	-1.0	-1.0	-1.0
	average	-0.961747	-0.974497	-0.967409
	std	0.032923	0.032922	0.032906
f_6	optimum	4.169298e-009	1.592288e-008	3.685230e-009
	average	0.397984	0.198993	0.198996
	std	0.513795	0.419511	0.419510



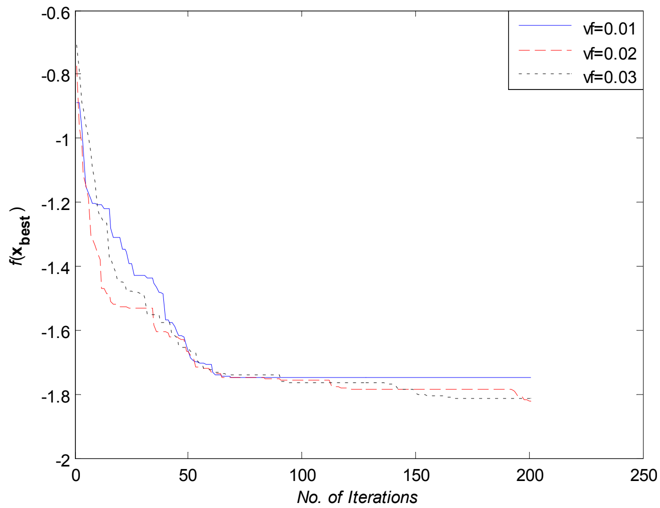
(a) Function f_1



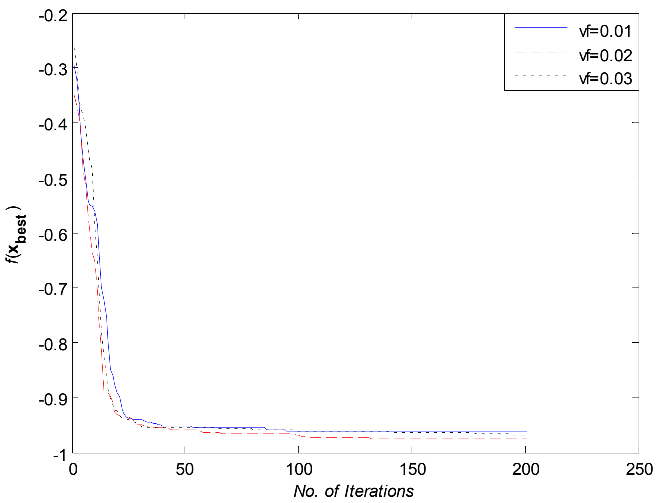
(b) Function f_2



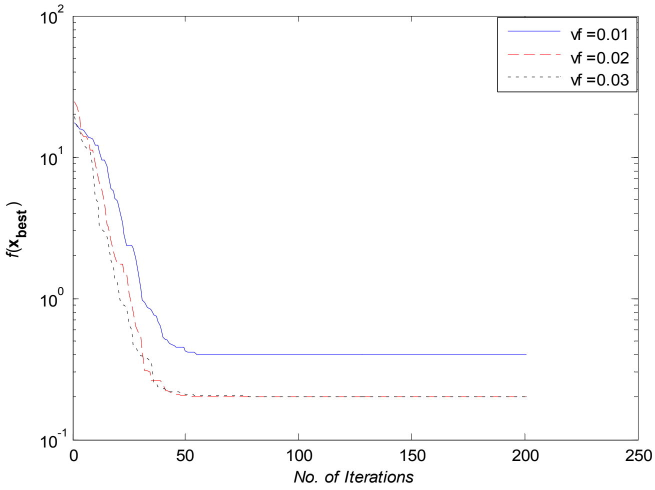
(c) Function f_3



(d) Function f_4



(e) Function f_5



(f) Function f_6

Fig. 2 Simulation results of KH algorithm under different v_f .

It can be seen from the convergence curves and the numerical results of six functions after 200 iterations and 10 times running independently that the v_f is from 0.01 to 0.03, and the function f_1 and f_2 get the optimal value when v_f =0.01. The optimization ability of function f_3 and f_5 remains the same. The optimization ability of function f_4 increases gradually. Function f_6 get the optimal value when v_f =0.03. The most obvious convergence curve is f_1 and the worst convergence curve function is f_5 . Compared with other convergence curves, the function f_3 has the most volatile. It can be seen from all convergence trends, the convergence rate did not increase or decrease regularity with the increase of v_f . Meanwhile, it has a certain relationship with the solution space. It is different of the function optimization performance impacted by the maximum or minimum values of parameter v_f . Hence, each function is corresponding to the optimal value of v_f . When v_f is 0.01, the optimization effect of function f_1 and f_2 is the best. When v_f is 0.03, the optimization effect of function f_6 is the best. With the change of v_f function f_3 and optimization effect remained constant and function f_5 and f_4 was gradually enhanced.

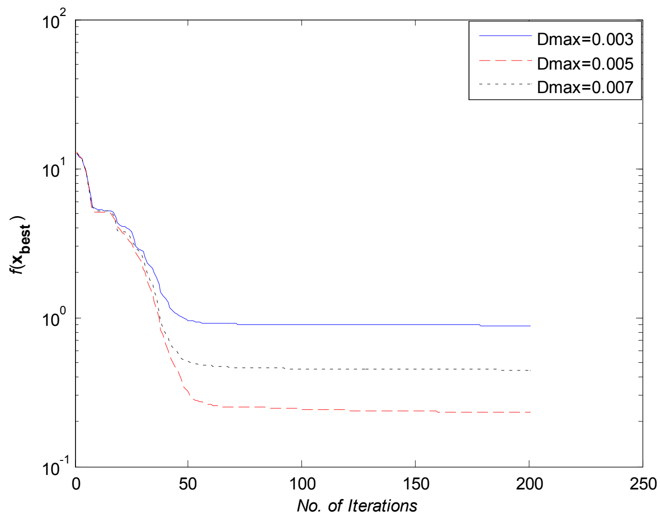
(2) Change of Variable $D^{\max}$

The initialization parameters of KH algorithm are set as: the population size n is 25, the number of iterations max_it is 200, v_f =0.02 and $N^{\max}$ =0.01. In order to reduce the influence of random disturbance, the independent operating for each test function is carried out 10 times. The optimal value and average values of KH algorithm in different maximum diffusion speed are shown in Tab. 3. The simulation results of the six test functions are shown in Fig. 3.

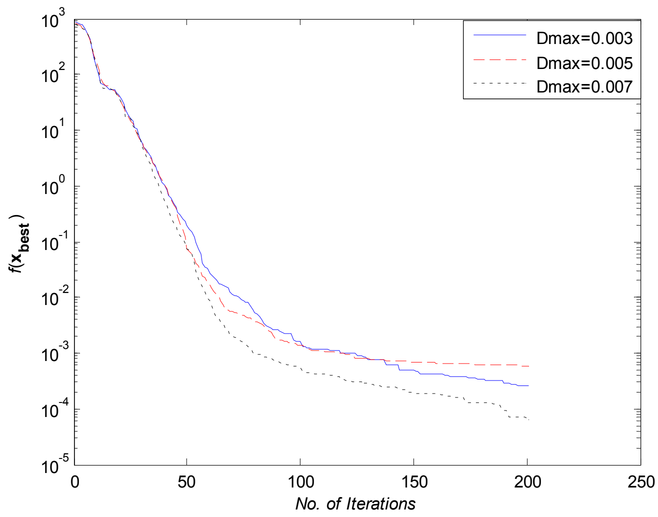
It can be seen from the convergence curves and the numerical results of six functions after 200 iterations and 10 times running independently that the $D^{\max}$ is from 0.003 to 0.007, and the optimization ability of function f_1 , f_2 and f_4 increases gradually. The optimization ability of function f_3 and f_5 remains the same. The function f_1 and f_2 get the optimal value when $D^{\max}$ =0.007. The most obvious convergence curve is f_1 and the worst convergence curve function is f_5. Compared with other convergence curves, function f_3 has the most volatile. It can be seen from all convergence trends, the convergence rate did not increase or decrease regularity with the increase of $D^{\max}$. Meanwhile, it has a certain relationship with the solution space. It is different of the function optimization performance impacted by the maximum or minimum values of parameter $D^{\max}$. Hence, each function is corresponding to the optimal value of $D^{\max}$. When $D^{\max}$ is 0.007, the optimization effect of function f_6 is the best. With the change of $D^{\max}$ function f_3 and f_5 optimization effect remained constant and function f_1, f_2 and f_4 was gradually enhanced.

TABLE 3. PERFORMANCE COMPARISON OF MFPA UNDER DIFFERENT

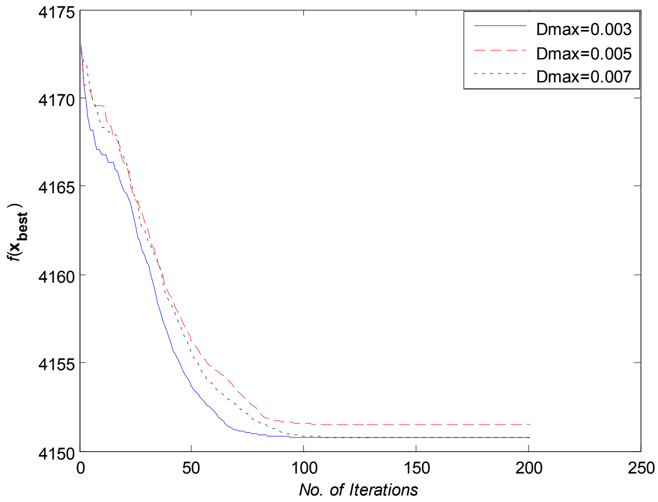
Function	Result	Simulation results of KH under different $D^{\max}$		
		0.003	0.005	0.007
	optimum	4.073356e-004	2.416538e-004	8.354039e-005
f_1	average	0.885024	0.231437	0.445285
	std	0.964666	0.486905	0.728154
	optimum	1.200277e-005	1.161213e-005	7.114425e-006
f_2	average	2.583204e-004	5.908937e-004	6.502112e-005
	std	3.853848e-004	0.001106	6.112197e-005
	optimum	4150.377	4150.376	4150.376
f_3	average	4150.750	4151.499	4150.750
	std	1.182174	2.522636	1.182191
	optimum	-1.987951	-1.967850	-1.967848
f_4	average	-1.843193	-1.802331	-1.621005
	std	0.127519	0.129911	0.268727
	optimum	-1.0	-1.0	-1.0
f_5	average	-0.961745	-0.974495	-0.980871
	std	0.032920	0.032920	0.030795
	optimum	3.177220e-008	1.562952e-007	2.899656e-008
f_6	average	0.211694	0.397988	0.497482
	std	0.414713	0.513795	0.845553



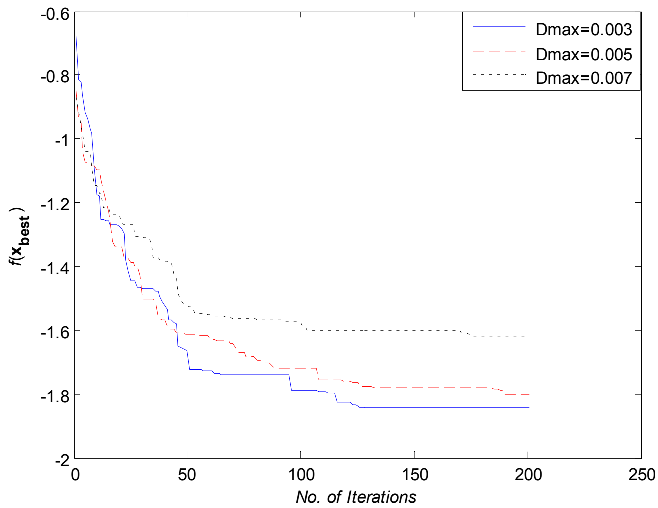
(a) Function f_1



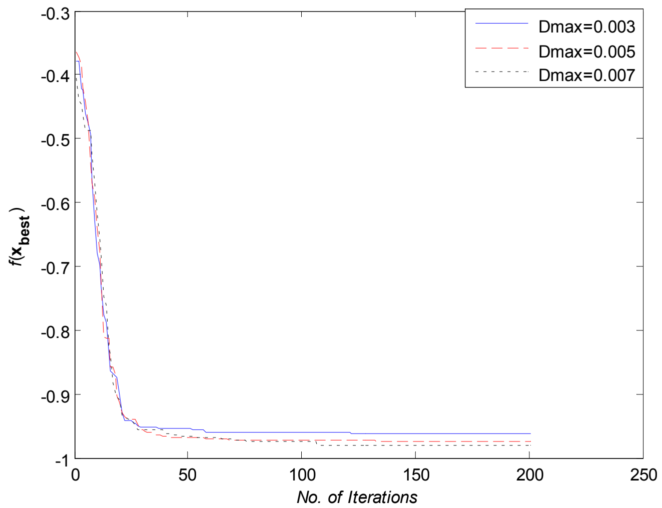
(b) Function f_2



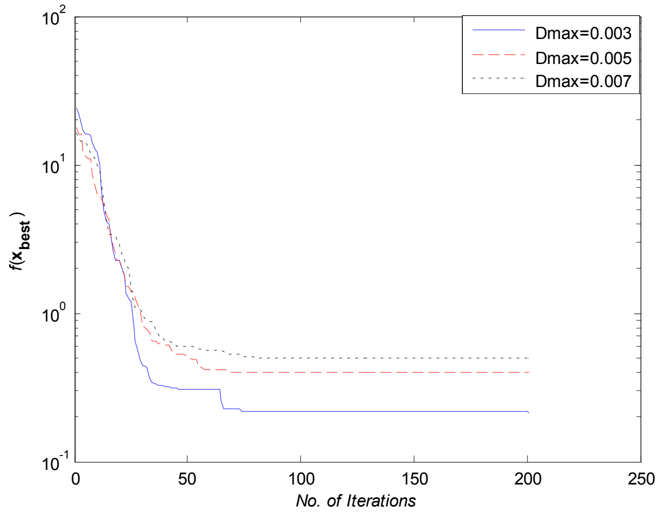
(c) Function f_3



(d) Function f_4



(e) Function f_5



(f) Function f_6

Fig. 3 Simulation results of KH under different $D^{\max}$.

(3) Change of Variable $N^{\max}$

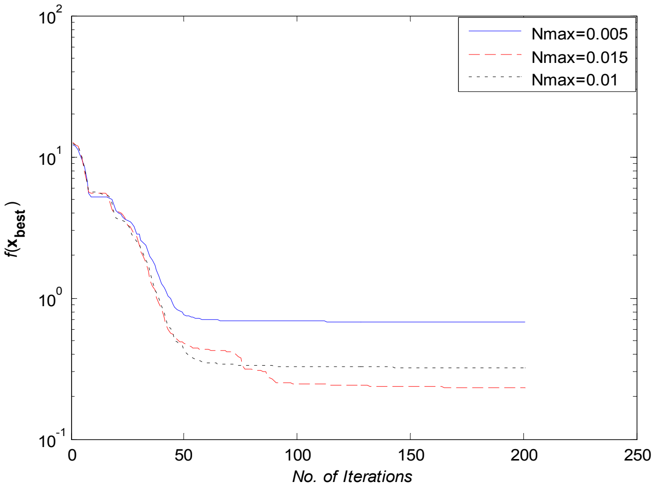
The initialization parameters of KH algorithm are set as: the population size n is 25, the number of iterations max_it for 200, v_f =0.02, $D^{\max}$ =0.003. In order to reduce the influence of random disturbance, the independent operating for each test function is carried out 10 times. The optimal value and average values of KH algorithm in different maximum induced speed are shown in Tab. 4. The simulation results of the six test functions are shown in Fig. 4.

It can be seen from the convergence curves and the numerical results of six functions after 200 iterations and 10 times running independently that the $N^{\max}$ is from 0.005 to 0.01, and the function f_1 and f_6 get the optimal value when $N^{\max}$ =0.015. The function f_2 get the optimal value when $N^{\max}$ =0.005. The optimization ability of f_3 function f_3 , f_4 and f_5 remains the same. Compared with other convergence curves, function f_3 has the most volatile. It can be seen from all convergence trends, the convergence rate did not increase or decrease regularity with the increase of $N^{\max}$. Meanwhile, it has a certain relationship with the solution space. It is different of the function optimization performance impacted by the maximum or minimum values of parameter $N^{\max}$. Hence, each function is corresponding to the optimal value of $N^{\max}$. When $N^{\max}$ is 0.015, the optimization effect of function f_1 and f_6 is the best. When $N^{\max}$ is 0.005, the optimization effect of function f_2 is the best. With the change of $N^{\max}$ function f_3 , f_4 and f_5 optimization effect remained constant.

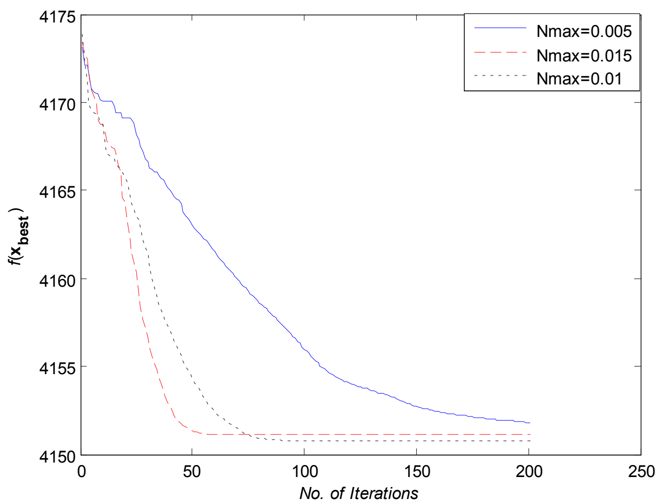
TABLE 4. PERFORMANCE COMPARISON OF MFPA UNDER DIFFERENT

Function	Result	Simulation results of KH under different $N^{\max}$		
		0.005	0.015	0.01
f_1	optimum	2.852422e-004	2.295210e-004	2.872100e-004
	average	0.676072	0.231780	0.318885

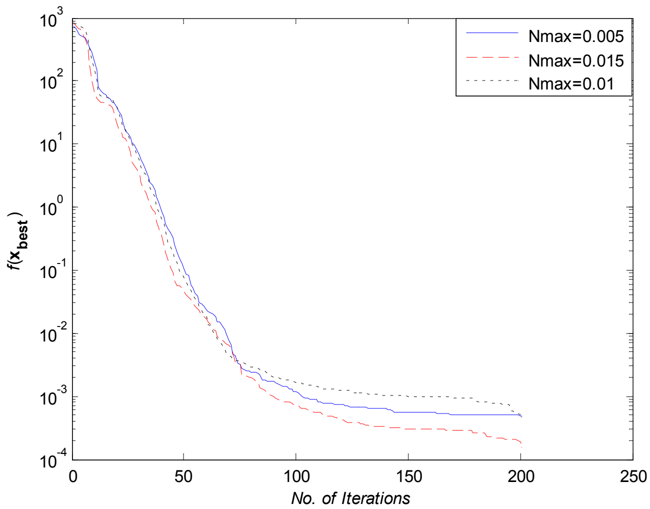
	std	0.734369	0.486896	0.696915
f_2	optimum	6.339941e-006	9.027443e-006	1.324295e-005
	average	4.827832e-004	1.600327e-004	4.544999e-004
	std	9.462522e-004	3.145845e-004	7.737618e-004
f_3	optimum	4150.376	4150.376	4150.376
	average	4152.792	4151.124	4151.750
	std	2.609708	1.576272	1.182177
f_4	optimum	-1.987	-1.987	-1.987
	average	-1.625992	-1.790188	-1.843584
	std	0.228600	0.092997	0.145720
f_5	optimum	-1.0	-1.0	-1.0
	average	-0.961046	-0.987246	-0.974494
	std	0.032041	0.026880	0.0329191
f_6	optimum	1.478529e-006	5.406166e-008	1.961675e-007
	average	0.366102	0.298494	0.596979
	std	0.468728	0.480619	0.695683



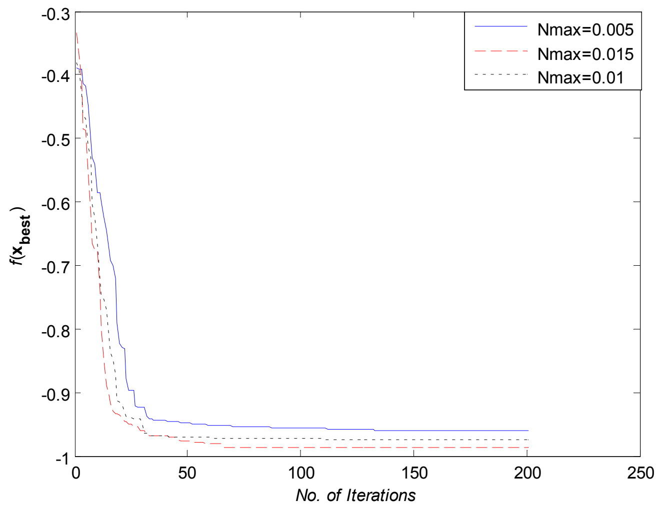
(a) Function f_1



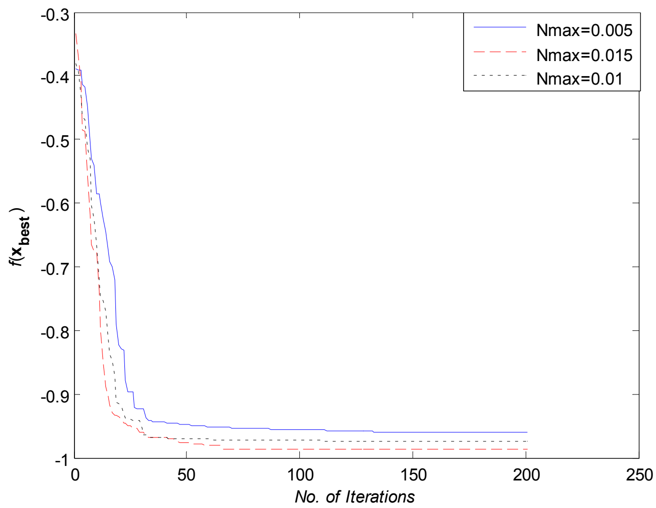
(c) Function f_3



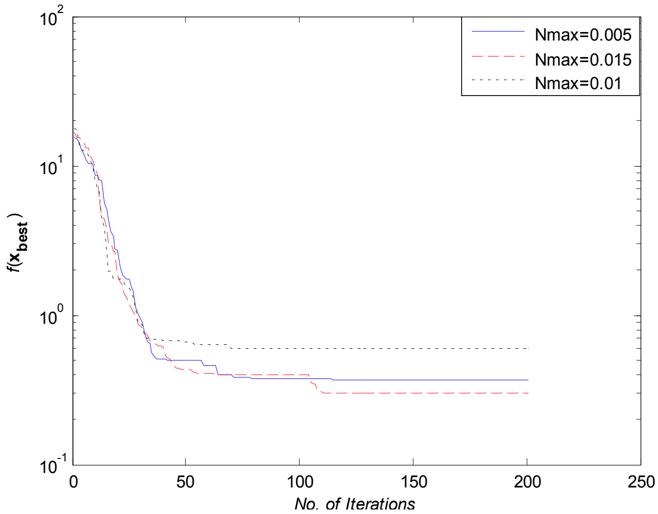
(b) Function f_2



(d) Function f_4



(e) Function f_5



(f) Function f_6

Fig. 4 Simulation results of KH algorithm under different $N^{\max}$.

IV. CONCLUSION

Based on the basic principle of KH algorithm, the optimization performance is verified by carrying out the simulation experiments on six test functions. v_f , $D^{\max}$ and $N^{\max}$ have contact with the convergence precision. The values for different parameters are different. Therefore, for different functions the simulation experiments should be carried out in order to obtain the appropriate parameter setting. The parameters have some influence on the convergence speed. The simulation results show that the convergence speed and convergence precision of the algorithm is relatively sensitive to the setting of the algorithm parameters.

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