Enhanced Krill Herd Algorithm for Chemical Engineering Problems

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Abstract

Krill Herd algorithm, Meta-Heuristic optimization, was introduced and wildly applied to many fields. However, Meta-heuristic sometimes got stuck in the local trapped. This article proposes a new technique to enhance the Krill Herd algorithm to apply to various chemical engineering problems. It focuses on balancing between the exploration and exploitation operator for escaping the optimum trapped by using the genetic algorithm named crossover operator to update a new position of the krill and also use the checking method to prevent the unexpectable error from running program. This new technique is the so-called Enhanced Krill Herd algorithm (EKHA). In this research, seven benchmark problems have validated the performance of the developed algorithm. In addition, EKHA also brought to solve the real working field. Four chemical engineering problems with different design conditions were selected to test the performance. The obtained results from the proposed method and standard krill herd algorithm show the achievements reaching the optimum results. This EKHA gave more accuracy comparing with the exact solution from the exact algorithm of the problem. The only weakness of the proposed algorithm is required more computational time for operating because of the checking method. The comparison between the two methods can prove the efficiency and superiority of the proposed algorithm.

Keywords:

Krill Herd algorithm; Meta-heuristic Optimization; Genetic algorithm; Exploration; Exploitation; Enhanced Krill Herd algorithm

1. Introduction

Nowadays, optimization is everywhere in the working field, such as mechanical design, financial markets, or computer science, to industrial applications [1]. People always intend to maximize or minimize to value or size of things they want, such as designing, construction, or maintenance. A decision making is made to the goal of a maximum benefit along with minimum effort. According to this, the several kinds of optimization algorithm was developed for dealing with this requirement. At present, there are three different algorithms for solving the optimization problems: exact algorithm, heuristic, and metaheuristic [2]. The Krill Herd algorithm is one of the metaheuristic methods that has been the nature inspirations. This method is the combination of local and global search. Both of them can adjust the contribution in the initial step and searching process [3]. Meta-heuristic can solve several optimization problems and reach a real solution to the problem. Some methods are using only pure local searches. For instance, Hill climbing is one of those methods that have highly capable of dealing with a specific problem, but it is difficult to approach the global solution. Other ways in a searching method are a random search without considering a landscape sign and record the results on the previous step, then random or blinding to looking for the global solution [3]. However, it still hard to succeed in finding the global solution from aimless finding.

According to this, metaheuristic was developed to overcome the significant weakness of it. The ability of metaheuristic is the combination of exploration and exploitation so that this property can create and adjust the contribution of local and random searching on the initial process [2,3]. However, the standard Krill Herd algorithm still has a risk of getting stuck from accelerating in the global search. So, the purpose of the report is to give another procedure to improve the performance of the standard Krill Herd algorithm by using the genetic operator and checking method to examine a result. This modification would update the new krill position result by the genetic operator named "Crossover" method after the processing of KHA had been finished. In general, the personal computer that is used for running a MATLAB program is different, so a performance to reach the global solution is different. However, repeating optimizing with the same problem can give a chance to get an output result by far different from other consequences. This is a so-called truncation error which caused by MATLAB software malfunctioned. Hence, an alternative method is required to prevent an unpredictable error by repeating an operation and then compare a range percentage between those results to address the stable output results. In the improved algorithm, the percentage of the range will be accepted if the value is less than 10 percent. Operation details will be described later. The proposed algorithm was applied with 7 benchmark and 4 chemical engineering problems.

At rest of the paper will organize as follow, the next section will introduce the background of the standard Krill Herd algorithm and deep detail of the equation and factor used. Then section 3 is described the modify krill herd. Section 4 will show the result and validating. Last, giving the conclusion of this work in section 5.

2. Background of Krill herd algorithm

Krill herd algorithm (KHA) is a metaheuristic population-based optimization algorithm proposed by Gondomi and Alavi in 2012 [1,4]. It is based on the herding behavior of krill individuals in order to increase krill density and reaching foods. It has three factors of individual krill position [5].

i. Movement induced by other krill individuals.

ii. Foraging activity.

iii. Random diffusion

The Lagrangian model of KH is generalized to an n dimensions decision space

$$\frac{dX_i}{dt} = N_i + F_i + D_i \qquad (1)$$

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.

2.1 Movement induced by other krill individuals

The movement of krill individuals depends on the neighboring krill individuals and the mutual effects between them. The movement of the i^{th} krill individual N_i can be defined as:

$$N_i^{new} = N_{max}\alpha_i + \omega_n N_i^{old} \qquad (2)$$

Where N_{max} is the Maximum induced speed, ω_n is the Inertia weight of motion-induced in range of [0,1], N_i^{old} is the Previous motion-induced

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \qquad (3)$$

The direction of the krill movement, α_i is estimated from local effect provided by local krill density, target effect provided by target krill density, and repulsive effect provided by repulsive swarm density.

$$\alpha_i^{local} = \sum_{j=1}^{NN} K_{ij} X_{ij} \qquad (4)$$

$$X_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \qquad (5)$$

$$K_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}} \qquad (6)$$

Where

α_i^{local} is the local effect provided by the neighboring krill individuals,

K_i is the fitness value of the i^{th} krill individual,

K_j is the fitness value of the j^{th} neighbor, (j = 1, 2, …, NN)

; NN: total number of neighbors

X is the relative position of the krill,

ε is the small positive number,

K^{best} and K^{worst} are the best fitness and worst fitness values of the krill individuals.

$$\alpha_i^{target} = C^{best} K_{i,best} X_{i,best} \quad (7)$$

$$C^{best} = 2(rand + \frac{I}{I_{max}}) \quad (8)$$

Where

α_i^{target} is the direction of motion-induced due to the best krill individual,
C_{best} is the effective coefficient of best
fitness krill individual to the ith krill individual,
Ki, best is the best objective function of the i^{th} krill individual,
Xi, best is the best position of the i^{th} krill individual, a rand is a random number in the range of [0,1], I is the current iteration number, and I_{max} is the maximum number of iterations.

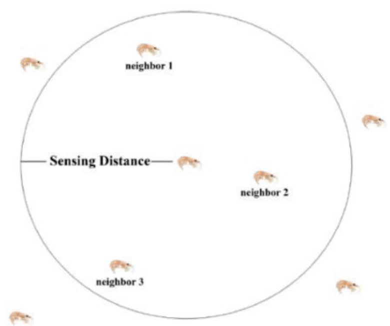

Figure 1 Schematic representation of Sensing Distance around a krill individual 'i'[6]

In order to evaluate the krill movement, it is necessary to identify the neighbors and their consideration. From all of the individuals in the local search space, only some krills are said to be a neighbor of i^{th} krill individual and vice versa. The identification of the neighbors is from the calculation of the "Neighborhood ratio" value. It is defined to determine the number of nearest krill individuals/neighbors present in the search space around the i^{th} krill individual located at position X_i. The sensing distance '$d_{s,i}$' is calculated from this individual, and all the neighbors located within this distance are said to be neighbors of krill individual 'i'.The sensing distance of i^{th} krill individual $d_{s,i}$ can define as :

$$d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \left\| x_i - x_j \right\| \quad (9)$$

Where N represents the number of krill individuals in the search space.

2.2 Foraging activity

Foraging motion is combined with two main factors: food location and previous food location.

$$F_i = V_f \beta_i + \omega_f F_i^{old} \quad (10)$$

$$\beta_i = \beta_i^{food} + \beta_i^{best} \quad (11)$$

Where

- V_f is the foraging speed which taken to be 0.02 ms^{-1},
- ω_f is the inertia weight of the foraging motion which calculated to be in the range of [0,1], F_i^{old} is the Last foraging motion value,
  β_i^{food} is the food attraction,β_i^{best} is the effect of current krill's best fitness value.

$$X_{food} = \frac{\sum_{i=1}^{N} \frac{X_i}{K_i}}{\sum_{i=1}^{N} \frac{1}{K_i}} \quad (12)$$

Where X_{food} is the center of the food.

$$\beta_i^{food} = C^{food} K_{i,food} X_{i,food} \qquad (13)$$

$$C^{food} = 2(1 + \frac{I}{I_{max}}) \qquad (14)$$

Where C^{food} is the food coefficient.

$$\beta_i^{best} = K_{i,best} X_{i,best} \qquad (15)$$

Where, $K_{i,best}$ is the best previous krill position.

2.3 Physical diffusion

Physical diffusion is a random process which effected by maximum diffusion speed and random directional vector. Physical diffusion equation can be defined as:

$$D_i = D^{max} \delta \qquad (16)$$

Where D_{max} is the maximum diffusion speed, which ranges between [0.002, 0.0010] (ms^{-1}), δ is the random directional vector which in range of [-1,1].

2.4 Motion process of KHA

Due to the three factors motion of krill-herd, the position vector of krill's individual during the time interval from t to t+Δt is defined, and the positions of krill will be updated.

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \qquad (17)$$

$$\Delta t = C_t \sum_{j=1}^{NV} (UB_j - LB_j) \qquad (18)$$

Where Δt is the scale factor, NV is the number of variables, UBj, LBJ is upper and lower bounds of the variable (j = 1,2,3,.., NV), Ct is the empirical constant which ranges between [0, 2].

2.5 Genetic operator: Crossover operator

The genetic reproduction mechanism is incorporated to increase the performance of a krill-herd algorithm. Crossover operator is used in the genetic algorithm as an effective strategy by generating a uniformly distributed random vector value between 0 and 1.

$$X_{i,m} = \begin{cases} X_{r,m} & rand_{i,m} < Cr \\ X_{i,m} & else \end{cases} \qquad (19)$$

$$Cr = 0.2 K_{i,best} \qquad (20)$$

Where C_r is the crossover probability, r ∈ {1, 2... i - 1, i + 1... N}.

3. Overview method of Enhance Krill Herd algorithm

According to the previous section, the Standard Krill Herd algorithm optimization can prove various design problems and finding the best solution in the field of optimization. The main significant point of the Krill Herd algorithm and other types of meta-heuristic algorithms is to utilize the combination of random search and local search. So, the meta-heuristic can create the satisfying properties that heuristic do not have. In the Krill Herd algorithm, the point is to control the parameters to determine the contribution amount of both exploration and exploitation to keep its balance. However, this method might lead to a failure evaluation due to too much to rely on the exploitation method. This method is the searching of optimal solution within the given region; consequently, more possibilities that solution will get stuck in a local area of search space [3].

To prevent this problem, the exploration method, which is the algorithm to reach different promising regions of the search space, can overcome the issue by escaping from the local area, then it will increase the possibility to reach the global result. For this reason, the additional genetic algorithm which can maintain a balance between exploitation and exploration is necessary to update the krill position after the Krill Herd process has done to improve the performance of the algorithm and obtain the surpass result. A crossover genetic operator is chosen to be added to the proposed algorithm. Although a crossover operator is more of an exploitation operator, a good crossover operator can generate individuals within the exploration zone. From this operation, it will generate an even better offspring. The potential number of ways in which an operator can create a new individual is called exploratory power [7,8]. Even the crossover operator will exchange the information between a good individual to get a better offspring after the Krill Herd process; it still cannot accelerate the convergence by itself. Hence, after the Krill Herd algorithm process and the exchange of position between individual krill by crossover operator is over, the proposed algorithm will select the most optimal solution to be base krill position in the next iteration to make accelerating the convergence.

Moreover, when using the standard Krill Herd optimization algorithm, sometimes output the astounding solution, which is by far different from the other previous solution. It is the nature of the stochastic method, which is a randomly determined variable so that it can provide the varying results from different runs. On the other hand, this problem may be caused by an operating malfunction in the MATLAB program. So, this Enhanced Krill Herd algorithm is invented to improve this unpredictable incidence by repeating an operation and calculate the percentage error between old and new results to make sure that the output solution is stable. The percentage error is fixed by 10 percent for acceptable. The sequence of procedures of the EKHA is presented in Figure 2

The processing details relating to the MATLAB code is presented on:

https://www.youtube.com/watch?v=sYKyzismYlI&feature=youtu.be

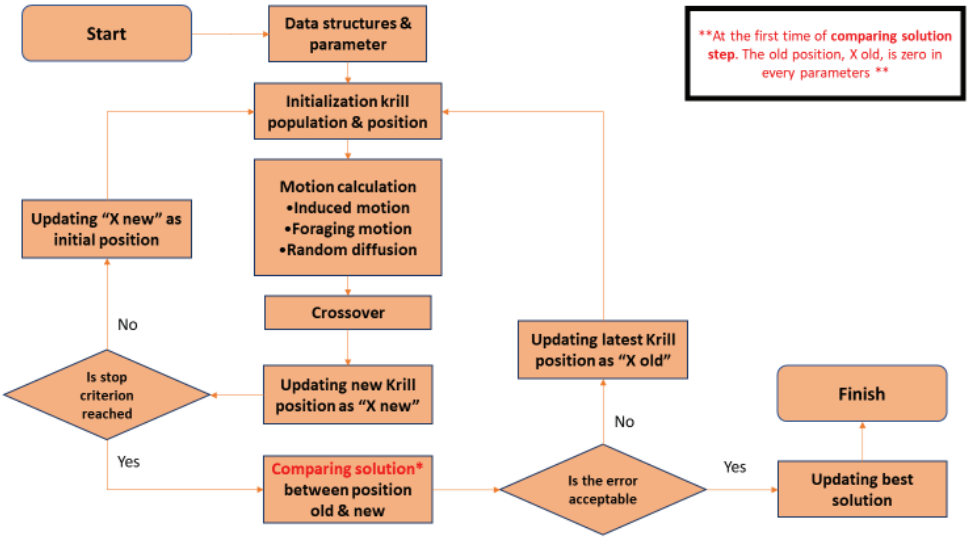

Figure 2 The processing flowchart of Enhanced Krill Herd algorithm

4. Experiment Results and Discussion

This section represents the performance of the Krill Herd algorithm. It can solve various experiments on design and chemical engineering problems, which has the purpose of finding the optimal solution and comparing performance with the Enhanced Krill Herd algorithm. To make a fair comparison, both optimization methods that are used to solve all solutions will be conducted using the same personal computer (i.e., Windows 10 environment using MATLAB (9.0.0) software computer programming with RAM 8GB).

According to all optimization problems, seven different functions of benchmark problems and four chemical engineering problems are used to evaluate the efficiency of the algorithm. The method name, function detail, and characteristic of these problems are represented in Table 1, letter "B" stands for benchmark, and "C" stands for chemical engineering; both of them are followed by problem number. The comparing result between information is made for proving the surprising of EKHA is presented in Table 2 for benchmark problems and chemical engineering problems.

For both algorithms in this research, all problems have the same defined parameter by 50 Number of krill populations (NP), 200 Iteration (MI), and 20 Runs time (NR). For additional parameter, Acceptable range (AR), which exists only on EKHA, can be defined as 10 percent of error compared with the previous one.

Code and running results can be obtained:

https://drive.google.com/drive/folders/1ZUtia7HKKkgjujdWzPy8MjxH8cDi7jWz

Table 1 The benchmark and chemical engineering functions

No.	Name	Defined functions
B01	Compressional and tensional spring	$f(x) = x_1^2 x_2 (2 + x_3)$
B02	Ackley	$f(x) = -20\exp\left((-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)\right) + 20 + \exp(1)$
B03	Cross-in-Tray	$f(x) = -0.0001\left(\left\|\sin(x_1)\sin(x_2)\exp\left(\left\|100 - \frac{\sqrt{x_1^2+x_2^2}}{\pi}\right\|\right)\right\| + 1\right)^{0.1}$
B04	Michalewicz	$f(x) = -\sum_{i=1}^{d}\sin(x_i)\sin^{20}\left(\frac{ix_i^2}{\pi}\right)$
B05	Keane's bump	$f(x) = -\left\|\left\{\sum_{i=1}^{d}\cos^4(x_i) - 2\prod_{i=1}^{d}\cos^2(x_i)\right\} \Big/ \left(\sum_{i=1}^{d} ix_i^2\right)^{0.5}\right\|$
B06	Three-bar truss design	$f(x) = \left(2\sqrt{2}x_1 + x_2\right) 100$
B7	Welded beam design	$f(x) = 1.10471 x_1^2 x_2 + 0.04811 x_3 x_4 (14 + x_2)$
C01	Heat Exchanger Network	$f(x) = \frac{2500}{3}\left(\frac{x_1-100}{300-x_1}\right) + 1250\left(\frac{x_2-x_1}{400-x_2}\right) + 25(500 - x_2)$
C02	Reactor Sequence	$f(x) = -\frac{1}{(1+k_3x_1)(1+k_4x_2)} - \frac{1}{(1+k_1x_1)(1+k_3x_1)(1+k_4x_2)} - \frac{1}{(1+k_2x_2)(1+k_1x_1)(1+k_4x_2)} + \frac{1}{(1+k_1x_1)(1+k_4x_2)}$
C03	Three-Stage Process System with Recycle	$f(x) = x_1^{0.6} + x_2^{0.6} + x_3^{0.4} - 4x_3 + 2x_4 + 5x_5 - x_6$
C04	Alkylation Process	$f(x) = 5.04x_1 + 0.035x_1 + 10x_3 + 3.35x_5 - 0.063x_2x_7$

Table 2 The benchmark and chemical engineering constraints

No.	Name	Constraints
B01	Compressional and tensional spring	$g_1(x) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \leq 0$ $g_2(x) = \frac{4x_2^2 - x_1x_2}{12566(x_1^3x_2 - x_1^4)} + \frac{1}{5108x_1^2} - 1 \leq 0$ $g_3(x) = 1 - \frac{140.45x_1}{x_2^3 x_3} \leq 0$ $g_4(x) = \frac{x_1 + x_2}{1.5} - 1 \leq 0$
B02	Ackley	-
B03	Cross-in-Tray	-
B04	Michalewicz	-
B05	Keane's bump	$g_1(x) : 0.75 - \prod_{i=1}^{m} x_1\text{-}7.5m<0$ $0 < x_i < 10$
B06	Three-bar truss design	$g_1(x) = \frac{\sqrt{2}x_1 + x_2}{\sqrt{2}x_1^2 + 2x_1x_2} P - \sigma \leq 0$ $g_2(x) = \frac{x_2}{\sqrt{2}x_1^2 + 2x_1x_2} P - \sigma \leq 0$ $g_3(x) = \frac{1}{\sqrt{2}x_2 + x_1} P - \sigma \leq 0$
B07	Welded beam design	$g_1(x) = \tau(x) - \tau_{max} \leq 0$ $g_2(x) = \sigma(x) - \sigma_{max} \leq 0$ $g_3(x) = x_1 - x_4 \leq 0$ $g_4(x) = 0.10471x_1^2 + 0.04811x_3x_4(14 + x_2) - 5 \leq 0$ $g_5(x) = 0.125 - x_1 \leq 0$ $g_6(x) = \delta(x) - \delta_{max} \leq 0$ $g_7(x) = P - P_c(x) \leq 0$
C01	Heat Exchanger Network	$x_4 - 100 = 0.0012(x_1)(300 - x_4)$ $x_5 - x_4 = 0.0008(x_2)(400 - x_5)$ $500 - x_5 = 0.04(x_3)$ $(0, 0, 0, 100, 100) \leq x_i \leq (15834, 36250, 10000, 300, 400)$
C02	Reactor Sequence	$(x_1 - 1) + k_1x_1x_5 = 0$ $(x_2 - x_1) + k_2x_2x_6 = 0$ $(x_3 + x_1 - 1) + k_3x_3x_5 = 0$ $(x_4 - x_3 + x_2 - x_1) + k_4x_4x_6 = 0$ $x_5^{0.5} + x_6^{0.5} \leq 4$ $0 \leq x_i \leq (1, 1, 1, 1, 16, 16)$
C03	Three-Stage Process System with Recycle	$-3x_1 + x_2 - 3x_4 = 0$ $-2x_2 + x_3 - 2x_5 = 0$ $4x_4 - x_6 = 0$ $x_1 + 2x_4 \leq 4$ $x_2 + x_5 \leq 4$ $x_3 + x_6 \leq 6$ $0 \leq x_i \leq (3, 4, 4, 2, 2, 6)$
C04	Alkylation Process	$x_1 = 1.22x_4 - x_5$ $x_9 + 0.222x_{10} = 35.82$ $3x_7 - x_{10} = 133$ $x_7 = 86.35 + 1.098x_8 - 0.038x_8^2 + 0.325(x_6 - 89)$ $x_4x_9 + 1000x_3 = 98000x_3/x_6$ $x_2 + x_5 = x_1x_8$ $1.12 + 0.13167x_8 - 0.00667x_8^2 \geq x_4/x_1$ $(1, 1, 0, 1, 85, 90, 3, 1, 2, 145) \leq x_i \leq (2000, 16000, 120, 5000, 2000, 93, 95, 12, 4, 162)$

Figures 3, 4, 5, and 6 showed the process of each chemical engineering problem (i.e., C01, C02, C03, C04) that covered with all variables such as heat transfer, amount of substance flowrate, and area of each machinery batch. Letter "X" that is followed by a number is the desired variable needed to get the optimization solution.

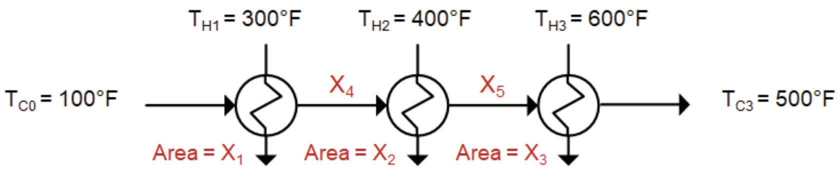

Figure 3 Design of the minimum heat exchangers area on Heat Exchanger Network design

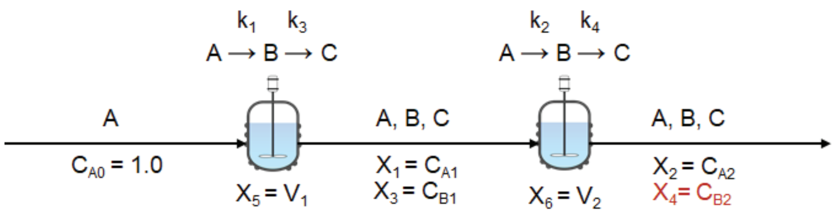

Figure 4 Designing a sequence of two reactors with a capital cost constraint

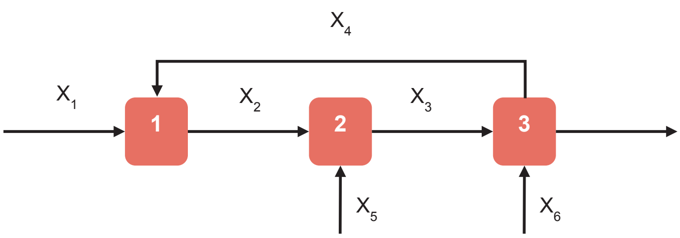

Figure 5 Design of Three-Stage Process System with Recycle

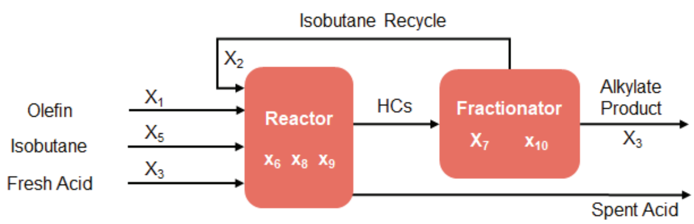

Figure 6 Determining the optimum set operating conditions for the Alkylation process to get maximum profit

Table 3 shows the output results of all problems for each comparative algorithm. According to this result, It can prove that Enhance Krill Herd Algorithm has higher performance than standard Krill Herd Algorithm to solve the optimization problem on 7 benchmark and 4 chemical engineering solutions (i.e., B01, B02, B03, B04, B05, B06, B07, C01, C02, C03, and C04). Figure 7 is shown the comparison between standard and enhanced one of benchmark function B07 with full convergence behavior. This graph is representing the best optimum value from parameters: 10 Number of runs, 50 Krill population, and 200 Iteration times. It obviously is seen that the developed algorithm is better than the standard. Then the percentage error of each problem was calculated by using an equation:

Percentage error =

$$[(X_{exact} - X_{EKHA})/X_{exact}] \times 100 \quad (21)$$

Table 3 The comparison between Krill Herd Algorithm and Enhance Krill Herd Algorithm

No.	Dimension	Exact solution	Krill Herd Algorithm	Enhanced Krill Herd algorithm	Error (%)	Improve from KHA (%)
B01	3	0.0127	0.0127	0.0127	0	0
B02	2	0	2.1669e-06	2.9961e-10	-2.9961e-8	99.9861
	5	0	9.6998e-05	5.5938e-11	-5.593e-9	99.9999
B03	2	-2.0626	-2.0626	-2.0626	0	0
B04	2	-1.8013	-1.9936	-1.8013	0	9.6459
	5	-4.6877	-3.8150	-4.3714	6.7474	-14.5845
	10	-9.6602	-6.4647	-7.7375	19.9033	-19.6885
B05	2	-0.3650	-0.3650	-0.3649	0.02739	0.0274
	5	-0.6737	-0.4373	-0.5960	11.5333	-36.2909
	20	-0.76	-0.1792	-0.3650	51.9736	-103.683
B06	2	263.8933	275.6835	265.4421	-0.5869	3.714912
B07	4	1.7249	1.9039	1.6068	6.84677	15.60481
C01	2	7049.2	7049.2	7049.2	0	0
C02	2	-0.3888	-0.3888	-0.3888	0	0
C03	3	-13.4019	-13.3988	-13.4018	7.4616e-4	-0.02239
C04	4	-1768.75	-1026.7	-1226.3	30.6	-19.4409

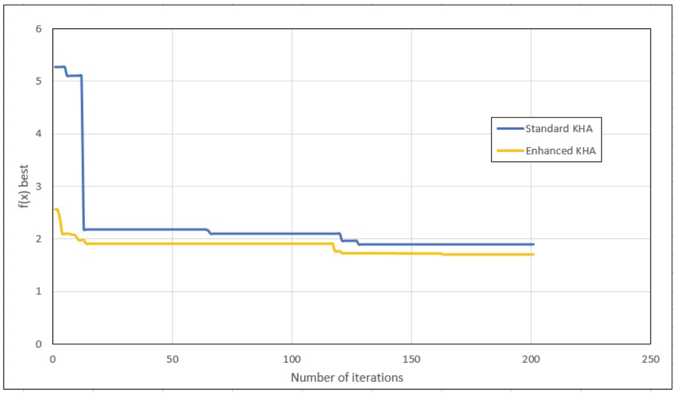

Figure 7 The convergence comparison of the best value between Enhanced KHA and standard KHA in benchmark B07

5. Conclusion

Various types and functions of benchmark problems are used to validate the performance of the proposed method. However, sometimes it still found some error happened from computer performance or MATLAB program. This problem could lead to getting the wrong solution. This article proposed a new technique called Enhanced Krill Herd algorithm optimization, EKHA. The Enhance Krill Herd Algorithm is using two additional methods in the standard KHA. It can increase the possibility of reaching the optimal result. First, the crossover method, which is employed to update a new position of krill after the KHA process is finished. Second, the checking method, which necessary to used after the whole process is completed. This method is needed to be added in the algorithm for preventing the truncation error happened from a program that was sometimes determining the wrong result. This processing will re-check the results by repeating a process, then compare a percent of range between them before output the suitable solution. This will improve the performance of the algorithm to deal with a difficult solution, though it requires more computational time from checking the method to get a suitable result. The time required depends on the complexity of equations. According to the results from 7 benchmark and 4 chemical engineering problems, all problem results show that the Enhanced method could determine the optimum result that closer than the standard Krill Herd algorithm or equal to the exact result. Even though the Enhance Krill Herd algorithm has excellent efficiency to reach the optimal value, but it is not suitable for dealing with the high dimensional problems or many constraint equations. Refer to benchmark number B05 running with 20 dimensions and chemical engineering problem number C04, which have complex constraints; the results show that there is still a high percentage error but not much as standard KHA. As a consequence, for this reason, it can prove that this Enhanced method is superiority comparing with the standard Krill Herd algorithm.

6. Acknowledgment

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7. References

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