A Comprehensive Review of Krill Herd Algorithm: Variants, Hybrids and Applications

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Abstract

Krill herd (KH) is a novel swarm-based metaheuristic optimization algorithm inspired by the krill herding behavior. The objective function in the KH optimization process is based on the least distance between the food location and position of a krill. The KH method has been proven to outperform several state-of-the-art metaheuristic algorithms on many benchmarks and engineering cases. This paper presents a comprehensive review of different versions of the KH algorithm and their engineering applications. The study is divided into the following general parts: KH variants, engineering optimization/application, and theoretical analysis. In addition, specific features of KH and future directions are discussed.

Keywords

Krill herd; Engineering optimization; Swarm intelligence; Metaheuristic; Nature-inspired algorithm

1. Introduction

Optimization is the process of minimizing/maximizing an objective function within a given domain. With the increment of the complexity of the optimization problems, the traditional mathematical methods sometimes fail to address them. Inspired by nature, modern metaheuristic algorithms have been developed and applied to deal with these complicated problems. Some well-known methods in this context are particle swarm optimization (PSO) [1-4], monarch butterfly optimization (MBO) [5-9], earthworm optimization algorithm (EWA) [10], artificial bee colony (ABC) [11], ant colony optimization (ACO) [12], elephant herding optimization (EHO) [13,14], differential evolution (DE) [15-17], firefly algorithm (FA) [18-23], simulated annealing (SA) [24], intelligent water drop (IWD) algorithm [25], monkey algorithm (MA) [26], genetic algorithm (GA) [27], biogeography-based optimization (BBO) [28-31], evolutionary strategy (ES) [32], krill herd (KH) [33], water cycle algorithm (WCA) [34], cuckoo search (CS) [35-40], free search (FS) [41], probability-based incremental learning (PBIL) [42], moth search (MS) algorithm [43], dragonfly algorithm (DA) [44], interior search algorithm (ISA) [45], bat algorithm (BA) [46-54], chicken swarm optimization (CSO) [55], fireworks algorithm (FWA) [56], brain storm optimization (BSO) [57,58], harmony search (HS) [59-62], and stud GA (SGA) [63].

After studying the herding behavior of the krill in seas, Gandomi and Alavi [33] proposed a new swarm intelligence-based [64] global optimization algorithm, called krill herd (KH). The whole optimization process in KH can be divided into three movements. Each krill individual is then updated considering these movements. The objective function is the distance of food location and the position of the krill. KH has drawn many attentions from scholars and engineers due to its excellent performance. In this paper, the current research on the KH algorithm is comprehensively reviewed. The paper is structured as follows. Section 2 reviews the main steps of the KH algorithm. Section 3 presents different improved KH algorithms. This is followed by a review of the KH applications for solving engineering optimization/application of KH in Section 4. A theoretical analysis of KH is provided in Section 5. Section 6 presents some concluding remarks and suggestions for further work.

2. Krill Herd Algorithm: The Development History

2.1 Krill Herd Research Trends

The original KH algorithm is simple in concept and easy for implementation. There are three movements in this algorithm: motion induced by other krill, foraging motion, and physical diffusion. The krill individuals in the population are updated according to the three movements.

KH has received significant attention from scholars and engineers owing to its advantages over other optimization methods. The original paper has been cited 421 times according to Google Scholar (https://scholar.google.com/) till February 12, 2017. Since the development of the KH algorithm in 2012, 77 related studies have been published in conferences/journals/dissertation till

February 12, 2017. Among these 77 papers, 8 papers are published in 2012 and 2013, 24 papers are published in 2014, 22 papers are published in 2015, 22 papers are published in 2016, and the remained one paper is published in this year. Fig. 1 gives the number of the KH related papers since 2012. While many papers may be still in press, it is not possible to get hold of all these papers. These 64 papers can build a solid foundation for the future KH research.

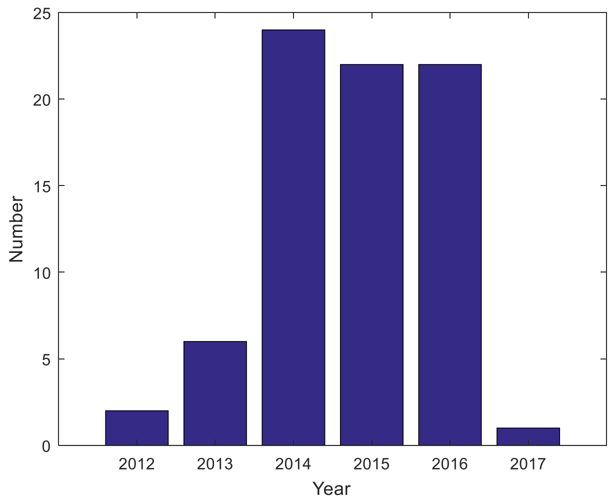

Fig. 1 The number of KH related publications since 2012

It should be mentioned that among KH-related papers, the original study in Dec 2012 was selected as the most cited articles published since 2012, extracted from Scopus[1], and the most downloaded articles from Communications in Nonlinear Science and Numerical Simulation in the last 90 days[2]. In addition, three papers, titled "Chaotic Krill Herd Algorithm" (Information Sciences, 2014, 274: 17-34), "Stud Krill Herd Algorithm" (Neurocomputing, 2014, 128: 363-370), and "Incorporating Mutation Scheme into Krill Herd Algorithm for Global Numerical Optimization" (Neural Computing & Applications, 2014, 24(3): 853-871), were selected as the top 1% highly cited paper by Web of Science[3,4,5] and Scopus[6,7,8]; three papers regarding KH algorithm were selected as

[1] https://www.journals.elsevier.com/communications-in-nonlinear-science-and-numerical-simulation/most-cited-articles. It can be accessed on February 12, 2017

[2] https://www.journals.elsevier.com/communications-in-nonlinear-science-and-numerical-simulation/most-downloaded-articles. It can be accessed on February 12, 2017

[3] http://apps.webofknowledge.com/summary.do?locale=en_US&errorKey=&viewType=summary&SID=2AgwI9sC7bg8xd5t2JR&product=UA&parentQid=1&qid=2&search_mode=GeneralSearch&mode=refine. It can be accessed on February 12, 2017

[4] http://apps.webofknowledge.com/full_record.do?product=UA&search_mode=GeneralSearch&qid=1&SID=4FoLnhGbN5R13GuUEGD&page=1&doc=1. It can be accessed on February 12, 2017

[5] http://apps.webofknowledge.com/full_record.do?product=UA&search_mode=GeneralSearch&qid=6&SID=4FoLnhGbN5R13GuUEGD&page=1&doc=2. It can be accessed on February 12, 2017

[6] http://www.scopus.com/record/pubmetrics.uri?eid=2-s2.0-84899913398&origin=recordpage#tabs=0. It can be accessed on February 12, 2017

[7] https://www-scopus-com.scopeesprx.elsevier.com/record/pubmetrics.uri?eid=2-s2.0-84893641121&origin=recordpage. It can be accessed on February 12, 2017

[8] https://www-scopus-com.scopeesprx.elsevier.com/record/pubmetrics.uri?eid=2-s2.0-84884521545&origin=recordpage. It can be accessed on February 12, 2017

the top 1% highly cited papers by Scopus, which are (we get the information from Web of Science and Scopus on February 12, 2017, and this information will be updated.):

- An effective krill herd algorithm with migration operator in biogeography-based optimization. *Applied Mathematical Modelling*, 2014, 38(9-10): 2454-2462[9]
- Hybrid krill herd algorithm with differential evolution for global numerical optimization. *Neural Computing and Applications*, 2014, 25(2): 297-308[10]
- A new improved krill herd algorithm for global numerical optimization. *Neurocomputing*, 2014, 138: 392-402[11]

2.2 Krill Herd Algorithm

In KH, the distance between the food location and the position of the krill individuals is considered as objective. The optimization process of the KH can be divided into the three following steps [33]:

i. movement induced by other krill individuals;
ii. foraging action; and
iii. random diffusion

The three actions mentioned above can be mathematically represented as follows.

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

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

2.2.1. Motion induced by other krill

For the first motion, the direction of motion, α_i, can loosely be divided into the following three components: the target effect, the local effect, and the repulsive effect [33]. For the krill *i*, it can mathematically be represented as:

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

where

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{3}$$

and $N^{\max}$ is the maximum induced speed, ω_n is the inertia weight in [0, 1], N_i^{old} is the last motion induced, α_i^{local} is the local effect and α_i^{target} is the target direction effect.

Moreover, α_i^{local} can be calculated as follows:

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

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

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

where K^{worst} and K^{best} are, respectively, the best and the worst fitness of the krill; K_i and K_j represent the fitness of the *i*th and *j*th krill, respectively; K_j is the fitness of *j*th (j=1,2,…, NN) neighbor; X represents the related positions, and NN is the number of the neighbors.

In addition, α_i^{target} can be given as:

$$\alpha_i^{target} = C^{best} \hat{K}_{i,best} \hat{X}_{i,best} \tag{7}$$

where, C^{best} is the effective coefficient of the krill individual with the best fitness to the *i*th krill individual.

2.2.2. Foraging motion

The second action can be represented as two parts: food location and its previous experience. For the *i*th krill, it can be expressed below:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \tag{8}$$

where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{9}$$

and V_f is the foraging speed, ω_f is the inertia weight in [0, 1], F_i^{old} 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.

2.2.3. Physical diffusion

Physical diffusion is essentially a random process. It can be formulated as follows:

$$D_i = D^{\max} \delta \tag{10}$$

where $D^{\max}$ is the maximum diffusion speed, and δ is the random vector in [-1, 1].

Inspired by the evolutionary computation, two genetic reproduction mechanisms, crossover operator and mutation operator, are further added the basic KH algorithm [33]. More detailed information about two genetic reproduction operators and KH algorithms can be found in [33].

According to the analyzes mentioned before, the main steps of the KH algorithm is represented in Fig. 2. The corresponding flowchart can also be seen in Fig. 3. In Fig. 2, G^{max} is the maximum generation. The MATLAB code of the KH can be found in the website: http://www.mathworks.com/matlabcentral/fileexchange/55486-krill-herd-algorithm.

Krill herd algorithm

Begin

Step 1: Initialization. Set the generation counter G=1; initialize the population P of N_P krill individuals randomly; set the foraging speed V_f, the maximum diffusion speed D^{max}, and the maximum induced speed N^{max}.

Step 2: While the termination criteria is not satisfied **or** $G<G^{max}$ **do**

Sort the population/krill from best to worst.

for i=1:N_P (all krill) **do**

Perform the following motion calculation.

Motion induced by the presence of other individuals

Foraging motion

Physical diffusion

Implement the genetic operators.

Update the krill individual position in the search space.

Evaluate each krill individual according to its position.

end for i

Sort the population/krill from best to worst and find the current best.

G=G+1.

Step 3: end while

Step 4: Post-processing the results and visualization.

End.

Fig. 2 The KH algorithm

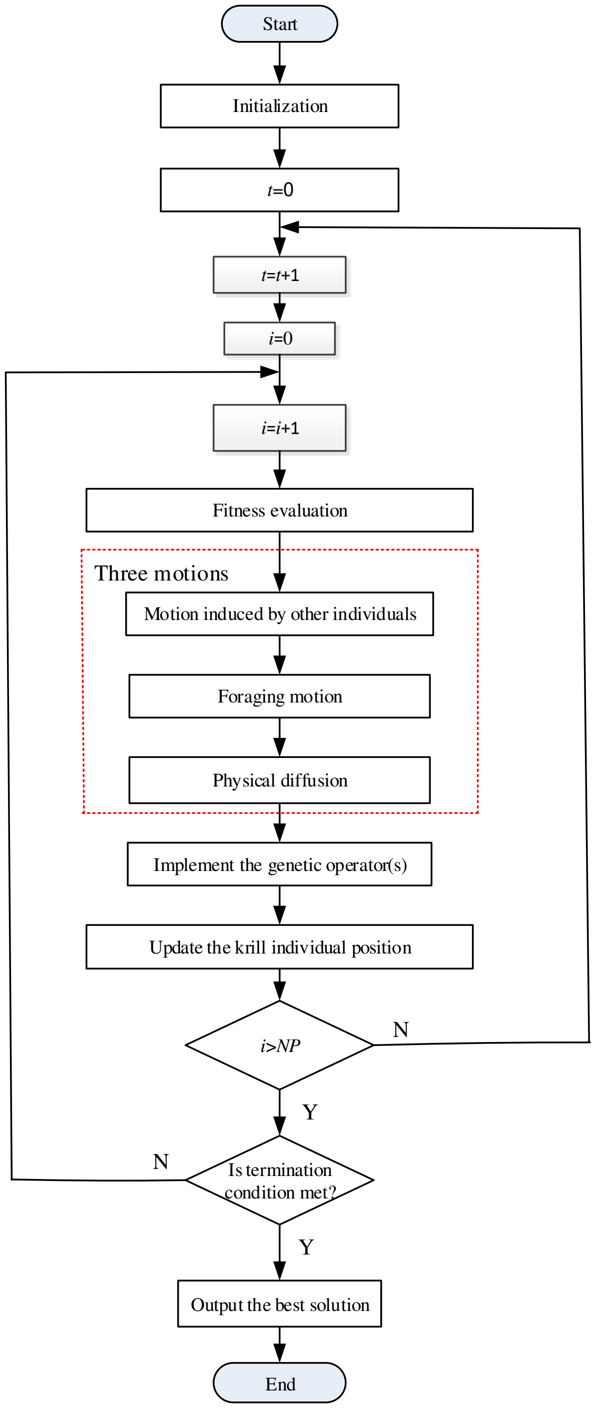

Fig. 3 Flowchart of the KH algorithm

3. Different Variants of KH

A recent study on the performance the KH algorithm was carried out by Madamanchi [65]. Five different benchmark functions (Alpine, Ackley, Griewank, Rastrigin and Sphere) are considered. The obtained results proved the efficiency of KH in solving the optimization problems [65]. However, the variants of KHs can be generally divided into the following three groups.

3.1 Improved KH Algorithms

A list of the improved KH algorithms is shown in Table 1. The details for each of these methods are as given below.

3.1.1. Chaotic KH

Wang *et al.* [66] introduced the chaos theory into the KH optimization process. The range of a chaotic map is always between 0 and 1 through normalization. Twelve chaotic maps are used to tune the inertia weights (ω_n, ω_f) used in KH on fourteen benchmarks. The best chaotic map (Singer map) is selected to generate the chaotic KH (CKH) algorithm [66], and it is further compared with other eight state-of-the-art metaheuristic algorithms (ACO [12], BA [49], CS [35], DE [15], ES [32], GA [27], PBIL [42], and PSO [1]).

Wang *et al.* [67] proposed a chaotic particle-swarm krill herd (CPKH) algorithm. In CPKH, thirteen different chaotic maps are used to tune the parameters, and the best chaotic map (singer map) is selected to form CPKH algorithm. The formed CPKH algorithm is verified by thirty-two different benchmarks and a gear train design problem in comparison with other six metaheuristic algorithms (ABC [11], DE [15], ES [32], HS [59], PBIL [42], and PSO [1]).

Saremi *et al.* [68] incorporated three 1-D chaotic maps (Circle, Sine, and Tent) into the basic KH algorithm to overcome the stagnation in local optima and slow convergence. Comparing with the basic KH, the proposed method can avoid local optima and has much faster convergence speed on four benchmarks [68].

Mukherjee *et al.* [69] used various chaotic maps to generate chaotic KH (CKH) with the aim of improving the performance of the basic KH method. It is observed that Logistic map-based CKHA offers better results as compared other chaotic maps.

Bidar *et al.* [70] proposed another version of chaotic KH optimization algorithm by adopting chaos theory in KH algorithm. In this method, chaos theory brings dynamism and instability properties to the algorithm so that by strengthening the performance of random search, it helps the algorithm to escape from local optimum traps. The results showed that this improved method had a better performance than the standard KH method.

3.1.2. OKH

The opposition-based learning (OBL) is an important learning strategy. OBL has been successfully used to guide the search capability of the metaheuristic algorithms. The studies that use this strategy to improve KH are listed below.

Wang *et al.* [71] proposed an improved version of KH based on OBL namely Opposition Krill Herd (OKH). In OKH, two other important optimization strategies called position clamping (PC) and heavy-tailed Cauchy mutation (CM) are also added with the aim of avoiding getting stuck in local optima.

Li *et al.* [72] proposed another version of the KH algorithm based on the OBL strategy and free search operator called opposition-based free search krill herd optimization algorithm (FSKH). In FSKH, each krill individual can search according to its own perception and scope of activities.

The free search strategy highly encourages the individuals to escape from being trapped in local optimal solution. Compared to PSO [1], DE [15], HS [59], FS [41], and BA [49], the FSKH algorithm shows a better optimization performance and robustness.

Sultana and Roy [73] introduced the idea of OBL into KH to minimize annual energy losses when different renewable resources are used. Also, the OKH is used to solve optimal capacitor allocation problem (33-bus and 69-bus) in reconfigured distribution network [74].

Mukherjee *et al*. [75] proposed opposition-based KHA (OKHA). In OKHA, the concept of opposition-based population initialization and generation jumping are introduced into the basic KH with the aim of accelerating the convergence speed.

3.1.3. Lévy flights

Wang *et al*. [76] proposed an improved krill herd (IKH). The main improvement pertains to the exchange of information between top krill during motion calculation process to generate better candidate solutions. Furthermore, the IKH method uses a new Lévy flight distribution and elitism scheme to update the KH motion calculation. Several standard benchmark functions are used to verify the efficiency of IKH. Based on the results, the performance of IKH is superior to or highly competitive with the standard KH and other population-based optimization methods (GA [27], BA [49], CS [35], DE [15], HS [59], PSO [1]).

Wang *et al.* [77] introduced Lévy flights into the basic KH algorithm, which significantly improved the performance of the KH. A local Lévy flights (LLF) operator was added to the krill updating process, and the updating strategies of the krill individuals were then modified [77]. The LLF operator encourages the exploitation and makes the krill individuals search the space carefully at the end of the search. The elitism scheme is also applied to keep the best krill during the process when updating the krill.

3.1.4. Multi-stage krill herd

Wang *et al*. [78] highlighted the exploration stage and exploitation stage separately, and proposed a multi-stage krill herd (MSKH) algorithm. In MSKH, the basic KH and a focused local mutation and crossover (LMC) operator are used to implement global search and local search, respectively. That is to say, the exploration stage uses a basic KH algorithm to select a good candidate solution set. It is followed by fine-tuning a good candidate solution in the exploitation stage with a focused local mutation and crossover (LMC) operator in order to enhance its efficiency and reliability when solving global numerical optimization problems.

3.1.5. Krill herd with linear decreasing step

Li *et al*. [79] proposed an improved KH with linear decreasing step (KHLD). KHLD tackles the deficiency of KH in achieving the excellent balance between exploration and exploitation in optimization processing. Twenty benchmark functions are used to verify the effectiveness of these improvements. It is illustrated that, in most cases, the performance of KHLD is superior to the standard KH [79].

3.1.6. KH clustering algorithm

Singh and Sood [80] introduced the concept of clustering into the KH algorithm to develop a new krill herd clustering (KHC) algorithm. In the basic KH, the krill follow the shortest path to search for the solutions, while KHC employs density-based spatial clustering of applications with noise (DBSCAN) technique to find the shortest path for the krill individuals.

Table 1. The improved KH algorithms

Name	*Author*	*Reference*
Chaotic krill herd algorithm	Wang *et al.*	[66]
Chaotic particle-swarm krill herd	Wang *et al.*	[67]
Chaotic KH optimization algorithm	Saremi *et al.*	[68]
Chaotic KH (CKH)	Mukherjee *et al.*	[69]
Chaotic KH optimization algorithm	Bidar *et al.*	[70]
Opposition krill herd (OKH)	Wang *et al.*	[71]
Opposition-based free search KH (FSKH)	Li *et al.*	[72]
Oppositional krill herd (OKH)	Sultana and Roy	[73]
Opposition based KHA (OKHA)	Mukherjee *et al.*	[75]
Improved krill herd (IKH)	Wang *et al.*	[76].
Lévy-flight krill herd (LKH)	Wang *et al.*	[77]
Multi-stage krill herd (MSKH)	Wang *et al.*	[78]
Krill herd with linear decreasing step (KHLD)	Li *et al.*	[79]
Krill herd clustering (KHC) algorithm	Singh and Sood	[80]

3.2 Hybrid KH Algorithms

Table 2 presents the hybrid KH algorithms. The details for each of these methods are presented in the following sections.

3.2.1. CSKH

Wang *et al.* [35] proposed a hybrid metaheuristic algorithm namely CSKH by a combination of the advantages of cuckoo search (CS) and KH. In CSKH, two operators inspired by the CS algorithm, krill updating (KU) and krill abandoning (KA) were introduced into the basic KH [81]. The KU operator inspires the intensive exploitation and makes the krill individuals search the space carefully in the later run phase of the search. This is while the KA operator is used to further enhance the exploration of the CSKH in place of a fraction of the worse krill at the end of each generation.

3.2.2. HSKH

Wang *et al*. [59] improved the performance of the KH by incorporating harmony search (HS) into the basic KH algorithm. In the proposed HSKH approach, the mutation operator originated from HS is to mutate between krill instead of physical diffusion used in KH [82]. In fact, HSKH combines the exploration of HS with the exploitation of KH effectively. Hence, it can generate the promising candidate solutions. Fourteen standard benchmark functions are applied to verify the effects of these improvements. It is demonstrated that, in most cases, the performance of the HSKH is superior to, or at least highly competitive with, the standard KH and other population-based optimization methods, such as ACO [12], BBO [28], DE [15], ES [32], GA [27], HS [59], PSO [1], and SGA [63].

3.2.3. SKH

Wang *et al*. [83] added an updated version of reproduction schemes called stud selection and crossover (SSC) operator to the basic KH algorithm. Accordingly, a new version of the KH algorithm termed as Stud Krill Herd (SKH) was proposed. The added SSC operator is inspired by the Stud genetic algorithm [63]. It selects the best krill (Stud) to perform the crossover operator. This approach appears to be well capable of solving various functions. Several problems are used to test the SKH method. In addition, the influence of the different crossover types on convergence and performance is carefully studied.

Pulluri *et al.* [84] used SKH algorithm to tackle the optimal power flow (OPF) problems in a power system network. In order to investigate the performance, SKH algorithm is demonstrated on the optimal power flow problems of IEEE 14-bus, IEEE 30-bus and IEEE 57-bus systems. The different objective functions considered are minimization of total production cost with and without valve-point loading effect, minimization of active power loss, minimization of L-index and minimization of emission pollution. The OPF results obtained with SKH are compared with the other evolutionary algorithms recently reported in the literature.

Pulluri *et al.* [85] used SKH algorithm to solve another kind of OPF problem. The SKH algorithm has been demonstrated on the OPF problems of IEEE 30-bus, Algerian 59-bus, and IEEE 118-bus systems considering various objective functions such as total production cost, L-index, power loss, and emission pollution to be minimized.

3.2.4. BBKH

Wang *et al*. [28] proposed a biogeography-based krill herd (BBKH) algorithm inspired by biogeography-based optimization (BBO). In BBKH, a new krill migration (KM) operator is used to update the krill individuals, especially at the stage of the exploitative stage [86]. The KM operator emphasizes the exploitation and lets the krill cluster around the best solutions at the later run phase of the search. The effects of these enhancements are tested by various well-defined benchmark functions. Based on the experimental results, this novel BBKH approach performs better than the basic KH and other twelve optimization algorithms, which are ABC [11], ACO [12], BA [49], BBO

[28], CS [35], DE [15], ES [32], GA [27], HS [59], PBIL [42], PSO [1], and SGA [63].

3.2.5. DEKH

Wang *et al.* [87] incorporated the idea of differential evolution [15] into the KH algorithm. The derived hybrid method is called differential evolution KH (DEKH). In DEKH, the hybrid differential evolution (HDE) operator is used to search for the promising solutions with the given region. DEKH is validated by twenty-six benchmark functions. From the results, the proposed methods are able to find a more accurate solution than the KH and other methods. In addition, the robustness of the DEKH algorithm and the influence of the initial population size on convergence and performance are investigated by a series of experiments. This is another good paradigm of the combination of swarm intelligence algorithm and evolutionary computation.

3.2.6. KH-QPSO

Wang *et al.* [88] introduced quantum-behaved particle swarm optimization (QPSO) [3] into KH algorithm. The so-called KH-QPSO algorithm is capable of avoiding the premature convergence and eventually finding the function minimum. More especially, KH-QPSO can make all the individuals proceed to the true global optimum without introducing additional operators to the basic KH and QPSO algorithms. To verify the performance of KH-QPSO, various experiments are carried out on an array of test problems as well as an engineering case.

3.2.7. SAKH

Wang *et al.* [89] proposed a hybrid KH algorithm called simulated annealing-based krill herd (SAKH) by a combination of simulated annealing (SA) [24] and KH. In SAKH, a krill selecting (KS) operator is an improved version of greedy strategy and accepts few not-so-good solutions with a low probability originally used in SA. In addition, a kind of elitism scheme is used to save the best individuals in the population in the process of the krill updating. The merits of these improvements are verified by an array of standard functions. The experimental results show that the performance of the SAKH method is superior to, or at least highly competitive with, the standard KH and other optimization methods (ABC [11], BA [49], CS [35], DE [15], ES [32], GA [27], HS [59], PBIL [42], PSO [1], and SA [24]).

3.2.8. PBILKH

Wang *et al.* [42] proposed a hybrid algorithm called PBILKH by introducing the population-based incremental learning (PBIL) into the KH optimization process. In PBILKH, a new KU operator is used to implement local search at the exploitation stage in terms of probability updating (PU) operator [90]. In addition, a type of elitism is applied to memorize the krill with the best fitness when finding the best solution. The effectiveness of the PBILKH is verified by various benchmarks. The experimental results demonstrate that the PBILKH is well capable of overtaking the KH algorithm and other optimization methods such as ABC [11], DE [15], ES [32], GA [27], HS [59], PBIL [42], and PSO.

3.2.9. FiKH

Wang *et al.* [20] combined the advantage of KH and FA and proposed a hybrid firefly-inspired KH (FiKH) [91]. In order to improve the ability of the local search, an attractiveness and light intensity updating (ALIU) operator inspired by FA is implemented at the later of the search process. Moreover, an elitism strategy is adopted to maintain the optimal krill with the best fitness when updating the krill. The results indicated that FKH performs more accurate and effective than the basic KH and other optimization algorithms.

3.2.10. MAKHA

Khalil *et al.* [92] developed a reliable and efficient optimization method via the hybridization of two bio-inspired swarm intelligence optimization algorithms, namely, monkey (MA) [26] and KH algorithms. The hybridization made use of the efficient steps in each of the two original algorithms and provided a better balance between the exploration/diversification steps and the exploitation/intensification steps. The new hybrid algorithm, MAKHA, is rigorously tested with twenty-several benchmark problems. The results were compared with the results of the two original algorithms. MAKHA proved to be considerably more reliable and more efficient in tested problems.

Table 2. The hybrid KH algorithms

Name	*Author*	*Reference*
Cuckoo search	Wang *et al.*	[81]
Harmony search	Wang *et al.*	[82]
Stud genetic algorithm	Wang *et al.*	[83]
Biogeography-based optimization	Wang *et al.*	[86]
Differential evolution	Wang *et al.*	[87]
Quantum-behaved particle swarm optimization	Wang *et al.*	[88]
Simulated annealing	Wang *et al.*	[89]
Population-based incremental learning	Wang *et al.*	[90]
Monkey algorithm	Khalil *et al.*	[92]

3.3 Variants of KHs

Table 2 presents different variants of the KH algorithm. The details for each of these methods are presented herein.

3.3.1. Discrete KH

Wang *et al.* [93] incorporated some optimization strategies into the basic KH algorithm to generate a discrete version called discrete krill herd (DKH). The intention has been to use DKH towards solving the discrete optimization problem.

Sur and Shukla [94] described different kinds of the creature activities, and then proposed a discrete version of the KH. This method is further used to solve graph network based search and optimization problems.

3.3.2. Binary KH

Rodrigues *et al.* [95] proposed a binary version of KH algorithm. This algorithm is used to solve feature selection purposes problem in several datasets. The experiments showed that the proposed technique outperforms three other metaheuristic algorithms for this task.

3.3.3. Fuzzy KH

Fattahi *et al.* [96] proposed a fuzzy KH (FKH) which can dynamically adjust the participation amount of exploration and exploitation by looking the progress of solving the problem at each step. Some standard benchmark functions and the Inventory Control Problem was used to evaluate the FKH algorithm. The experimental results indicate the superiority of the FKH algorithm in comparison with the standard KH optimization algorithm.

Fattahi *et al.* [97] used a fuzzy system as a parameter tuner to adjust the participation amount of the global and local search and proposed a fuzzy KH. The higher performance of the fuzzy KH method is verified on different benchmarks.

3.3.5. Multi-objective KH

Ayala *et al.* [98] proposed a new multi-objective KH (MKH) algorithm to solve multi-objective optimization problems. The modified MKH approach uses the beta distribution in the inertia weight tuning.

Table 3. Different variants of KH

Name	*Author*	*Reference*
Discrete krill herd	Wang *et al.*	[93]
Discrete krill herd	Sur and Shukla	[94]
Binary krill herd	Rodrigues *et al.*	[95]
Fuzzy krill herd	Fattahi *et al.*	[96]
Fuzzy krill herd	Fattahi *et al.*	[97]

Multi-objective KH	Ayala *et al.*	[98]

4. Engineering Optimization/Applications

Different engineering optimization and applications of the KH algorithm are classified into the following categories: continuous optimization, combinatorial optimization, constrained optimization, mluti-objective optimization, dynamic and noisy environment, and other engineering applications. Table 4 presents a summary of the applications of KH in engineering optimization.

4.1 Continuous optimization

4.1.1. Neural networks

Kowalski and Łukasik [99] used the KH algorithm to train artificial neural network (ANN). The trained network is used for the classification of examples drawn from the UCI Machine Learning Repository. It has been concluded that the application of KH improves the accuracy of ANN as well as the time needed for its training.

Lari and Abadeh [100] used the KH method to help ANNs select the best structure and weights. The task of optimizing the network structure was on the three components of this algorithm (movement induced by the other krill, random diffusion, and foraging motion) along with a genetic operator. Five UCI data sets are used to evaluate the proposed method. The results indicated that KH considerably improved the classification accuracy of ANN.

Faris *et al.* [101] used the KH algorithm to train the feed-forward neural network and optimize its connection weights. The trained networks are used to solve E-mail spam detection problem. The results showed that this KH-ANN approach outperforms the Back propagation and GA.

Stasinakis *et al.* [102] proposed a KH Support Vector Regression (KH-νSVR) [103,104] model. The KH optimizes the SVR parameters by balancing the search between local and global optima. The proposed model is applied to the task of forecasting and trading three commodity exchange traded funds on a daily basis over the period 2012-2014. The inputs of the KH-νSVR models are selected through the model confidence set from a large pool of linear predictors. The KH-νSVR's statistical and trading performance is benchmarked against traditionally adjusted SVR structures and the best linear predictor.

Wang *et al.* [105] used support vector machine (SVM) [106] to distinguish indoor pollutant gases. An effective enhanced KH algorithm (EKH) based on a novel decision weighting factor computing method is proposed to optimize the SVM parameters. In EKH, an updated crossover operator is added. The research results showed that EKH significantly improves the performance of our electronic nose (E-nose) system. The study done by Wang *et al.* [105] revealed the potential of improved KH-based methods in E-nose research area.

4.1.2. Clustering problem

Li *et al*. [107] proposed a new version of KH in combination with elitism strategy namely KHE. This method is then used to solve clustering problem. Elitism strategy has a strong ability to prevent the krill population from degrading. In addition, the well-selected parameters are used in the KHE method instead of originating from nature. The clustering results showed that KHE performs better than fuzzy C-means (FCM) clustering algorithm [108].

Jensi *et al.* [109] proposed another improved KH algorithm by adding global search operator for exploration around the defined search region. The elitism strategy is also applied to maintain the best krill during the krill update steps. The proposed method is tested on a set of twenty-six well-known benchmark functions and is compared with thirteen popular optimization algorithms. In addition, the proposed method has high convergence rate. The high performance of the proposed algorithm is then employed for data clustering problems and is tested using six real datasets available from UCI machine learning laboratory [110]. The experimental results thus show that the proposed algorithm is efficient for solving data clustering problems.

4.1.3. Phase equilibrium calculation

Moodley *et al*. [111] used the KH algorithm and the modified Lévy-flight KH algorithm (LKH) [77] to phase stability (PS) and phase equilibrium calculations phase stability (PS) and phase equilibrium calculations, where global minimization of the total Gibbs energy is necessary. Several phase stability and phase equilibrium systems are considered for the analysis of the performance of the technique.

4.1.4. Control

Younesi and Tohidi [112] used the KH algorithm to adjust the parameters of the sensorless controllers for a permanent magnet synchronous motor (PMSM). A frequency-adaptive disturbance observer has been proposed to remove the disturbances in estimating the stator flux and to enhance the accuracy of the rotor angle estimation [112]. The design and utilization of the proposed observer are detailed under the consideration of its application to the practical system driving PMSM. The performance of the proposed sensorless method is assessed through experiments at low-speed operations, where the sensorless drive of PMSM is regarded as being extremely difficult without the signal injection.

Yaghoobi *et al.* [113] presented an improved version of KH algorithm. The proposed algorithm has been applied to determine coefficients of PID controller to achieve desired system response. For this purpose, a cost function based on weighted sum of step response characteristics is considered to be minimized. Simulation results compare the performance of the ICKH algorithm with many other optimization algorithms.

4.1.5. Inverse radiation problem

Ren *et al*. [114] proposed three improved versions of the KH algorithm to solve inverse radiation problems. Additionally, the extinction coefficient and scattering albedo in a parallel slab with short pulse laser incident are retrieved using the improved algorithms. Consequent numerical simulations indicated that radiative properties can be retrieved accurately even with measurement errors.

4.1.6. Channel equalization problem

Pandey *et al.* [115] described the design of an adaptive channel equalizer based on the KH algorithm. The designed KH-based equalizer has better channel equalization than other metaheuristic algorithms, e.g., PSO [1] and DE [15].

4.1.7. Dual-cluster routing in UWSNs

Aimed at the limited energy of nodes in underwater wireless sensor networks (UWSNs) [116] and the heavy load of cluster heads in clustering routing algorithms, Jiang *et al.* [117] proposed a dynamic layered dual-cluster routing algorithm based on KH algorithm in UWSNs. Cluster size is first decided by the distance between the cluster head nodes and sink node, and a dynamic layered mechanism is established to avoid the repeated selection of the same cluster head nodes. The simulation results show that the proposed algorithm can effectively decrease cluster energy consumption, balance the network energy consumption, and prolong the network lifetime.

4.1.8. Model turbine heat rate

To improve the solution quality and to quicken the global convergence speed of KH, Niu *et al.* [118] proposed an ameliorated KH algorithm (A-KH) to solve the global optimization problems. Compared with other several state-of-art algorithms, A-KH shows better search performance. Furthermore, A-KH is adopted to adjust the parameters of the fast learning network (FLN) so as to build the turbine heat rate model of a 600MW supercritical steam and obtain a high-precision prediction model. Experimental results show that, compared with other several turbine heat rate models, the tuned FLN model by A-KH has better regression precision and generalization capability.

4.2 Combinatorial optimization

4.2.1. Scheduling

Wang *et al.* [93] used a multilayer coding strategy in the preprocessing stage and then the DKH method to solve the flexible job-shop scheduling problem (FJSSP) [93]. In addition, elitism strategy is integrated into DKH with the aim of making the krill swarm move towards the better solutions all the time. The performance of the DKH algorithm is verified by two FJSSP instances. Based on the results, the developed approach is able to find the better scheduling in most cases than some existing state-of-the-art algorithms, e.g., ABC [11], ACO [12], and GA [27].

Puongyeam *et al.* [119] proposed a modified KH (MKH) algorithm and used it to solve production scheduling problem. The computational experiments were carried out using various sizes of scheduling problem obtained from a capital goods company. The analysis of the computational results indicated that the MKH algorithm significantly performs better than the conventional KH algorithm for all problems.

Roy *et al.* [120] combined DE with the KH algorithm to solve the short-term hydrothermal scheduling (HTS) problem. The potentialities of DE are used in the KH technique to improve the convergence speed and robustness. The practical short-term HTS problem is solved using the KH technique in which the crossover and mutation operations of the DE algorithm are employed to efficiently control the local and global search. The quality and usefulness of this approach is demonstrated through its application to two standard test systems. The simulation results revealed that the method is better in comparison with the other existing techniques in terms of computational time and the quality of the obtained solutions.

4.2.2. QoS Routing

Kalaiselvi and Radhakrishnan [121] proposed a differentially guided krill herd based algorithm called DGKH. In DGKH, the krill individuals are updated by using the information from various krill individuals instead of the corresponding previous one. Also, the DGKH is used to solve multi-constrained QoS Routing problem in Mobile Ad Hoc Networks. It is demonstrated that the proposed DGKH algorithm is an effective approximation algorithm exhibiting satisfactory performance than the KH and existing algorithms in the literature by determining an optimum path that satisfies more than one QoS constraint in MANETs.

4.2.3. Portfolio optimization

Bacanin *et al.* [122] solved the constrained portfolio optimization problem using the KH algorithm. Comparing with the traditional methods, the experimental results indicated that KH is a promising algorithm for tackling portfolio optimization problems.

Moreover, Tuba *et al.* [123]used the KH to solve the constrained portfolio selection problem. The results showed that the KH algorithm is a promising technique for portfolio optimization problem and can outperform other optimization metaheuristics such as GA [27] and FA [20].

4.2.4. Feature selection

Rodrigues *et al.* [95] proposed a binary version of KH algorithm for feature selection in several datasets. The experiments showed that the proposed technique outperforms three other metaheuristic algorithms, *i.e.*, FA [20], HS [59] and PSO [1], for this task.

4.2.5. Optimal power flow

Mukherjee *et al.* [69] used the best Logistic map from a set of chaotic maps to generate chaotic KH (CKH). In addition, the proposed method is applied to standard 26-bus and IEEE 57-bus test power systems for the solution of optimal power flow of power system with different objectives that reflect minimization of fuel cost or active power loss or sum of total voltage deviation. The obtained results showed that the CKH algorithm outperforms other evolutionary optimization techniques in terms of convergence rate and global search ability.

Mukherjee *et al.* [75] proposed opposition based KHA (OKHA) to solve the optimal power flow (OPF) problem of power systems. The potential of the proposed OKH is successfully assessed on modified IEEE-30 bus and IEEE-57 bus test power systems. The simulation results indicated that the proposed approach yields a better solution than the other popular methods. The effectiveness of OKH for tackling the OPF problem of power system equipped with flexible AC transmission systems (FACTS) devices is also verified.

As mentioned before, Pulluri *et al.* [84] used SKH algorithm to tackle the optimal power flow (OPF) problems in a power system network on the optimal power flow problems of IEEE 14-bus, IEEE 30-bus and IEEE 57-bus systems. Later, Pulluri *et al.* [85] used SKH algorithm to solve the OPF problems of IEEE 30-bus, Algerian 59-bus, and IEEE 118-bus systems considering various objective functions.

4.2.6. Mobility tracking

Vincylloyd and Anand [124] used the KH algorithm to solve mobility tracking problems in wireless communication systems. They presented a novel hybrid method using a krill herd algorithm designed to optimize the location area (LA) within available spectrum such that total network cost, comprising location update (LU) cost and cost for paging, is minimized without compromise. Based on various mobility patterns of users and network architecture, the design of the LR area is formulated as a combinatorial optimization problem [124]. The numerical results indicated that the proposed model provides a more accurate update boundary in a real environment than that derived from a hexagonal cell configuration with a random walk movement pattern. The proposed model allows the network to maintain a better balance between the processing incurred due to location update and the radio bandwidth utilized for paging between call arrivals [124].

4.2.7. Four-bar linkage

Bulatović *et al.* [125] presented two modifications for the KH algorithm, which are the initialization of food location and the replacement of the crossover operator with the combination of columns of fitness functions obtained in one iteration. The modified KH (MKH) was used to solve four benchmark examples from the synthesis of a four-bar linkage.

4.2.8. Optimal capacitor allocation problem

Sultana and Roy [74] used the basic KH and oppositional KH (OKH) to solve optimal capacitor allocation problem (33-bus and 69-bus) in reconfigured distribution network. They presented the KH algorithm to find optimal location of the capacitor and optimal reconfiguration in order to minimize real power loss of radial distribution systems. Moreover, the opposition based learning (OBL) concept is integrated with KH algorithm for improving the convergence speed and simulation results. The conventional KH and OKH algorithms are tested on 33-bus and 69-bus radial distribution networks. The solution results showed that OKH technique can generate better quality solutions and better convergence characteristics than those obtained by conventional KH algorithm and other existing optimization techniques.

4.2.9. Inverse geometry design

Sun *et al*. [126] incorporated the discrete ordinate method and Akima cubic interpolation into five kinds of KH algorithms to solve the inverse geometry design of a two-dimensional radiative enclosure filling with participating media. The retrieval results showed that the KH algorithm can be applied successfully to inverse geometry design problems. KH is proved to be more efficient than the micro GA and PSO. The influences of radiative properties of the media and the number of control points on the retrieval geometry design results are also investigated by Sun *et al*. [126].

4.3 Constrained Optimization

4.3.1. Economic dispatch problem

1) Economic dispatch problem

Kavousi-Fard *et al*. [127] proposed a new modified KH (MKH) algorithm by using Lévy flights motion and crossover operator. This method is further applied to address the practical economic dispatch (ED) problem incorporating different types of constraints, such as valve-loading effects, prohibited operating zone, spinning reserve and multi-fuel option. The proposed MKH algorithm is examined on three test systems to validate its satisfying performance [127].

2) Dynamic economic dispatch

Ashouri and Hosseini [128] used the KH algorithm and water cycle algorithm (WCA) [34] to solve Dynamic economic dispatch (DED) problem. Also, several comparative studies have been done based on two above methods. Two common case studies considering various constraints have been used to show the effectiveness of these methods. The results and convergence characteristics showed that the proposed methods are capable of giving high-quality results which are better than many other previously applied algorithms [127].

3) Combined heat and power economic dispatch problem

Adhvaryyu *et al*. [129] used the KH algorithm to solve combined heat and power economic dispatch (CHPED) problem. The algorithm has been illustrated simulating on a test system and the result has been compared with those obtained from PSO [1] and DE [15]. The comparison showed that the solution obtained by this KH method is of better quality than other methods.

4) Annual energy losses

Sultana and Roy [73] proposed oppositional krill herd (OKH) to minimize annual energy losses when different renewable resources are used. In order to show the effectiveness of the OKH algorithm, it is implemented on 33-bus, 69-bus, and 118-bus radial distribution networks to find optimal location and the optimal size of RDGs (renewable distributed generators) to optimize energy losses [73]. Moreover, the OKH algorithm is compared with the basic KH algorithm and a recently developed analytical approach. It is observed from the test results that the proposed OKH algorithm is more efficient in terms of simulation results of energy loss and convergence property than the other reported algorithms [73].

5) Distributed generator (DG)

Sultana and Roy [130] used the KH algorithm to solve the optimal DG allocation problem of distribution networks. The algorithm is evaluated on standard 33-bus, 69-bus and 118-bus radial distribution networks. The simulation results indicated that installing DG in the optimal location can significantly reduce the power loss of distributed power system. Moreover, the numerical results, compared with other stochastic search algorithms, show that KH could find better quality solutions [130].

Davodi *et al.* [131] proposed an effective intelligent optimization method to solve the multi-objective distribution feeder reconfiguration (DFR) problem considering generators (DGs). In this regard, they introduced a novel population-based algorithm based on KH algorithm to solve the multi-objective distribution feeder reconfiguration problem considering DG units. In order to improve the search ability of the algorithm, a new modification process is further proposed. This modification enhanced the overall outcome of the KH algorithm in both search and convergence area [131]. During the search process of the proposed modified KH (MKH) algorithm, the achieved non-dominated solutions are stored in an external repository. Owing to distinctive objective functions, a fuzzy clustering technique is applied to control the size of the repository within the restrictions. The objective functions considered in this paper are power losses, voltage deviation of buses and total cost of the active power produced by DG units and distribution companies. In order to evaluate the feasibility and effectiveness of the method, the proposed approach is tested on a distribution test system.

Rostami *et al.* [132] proposed a novel optimal stochastic reconfiguration methodology to moderate the charging effect of PHEVs (plug-in hybrid electric vehicles) by changing the topology of the grid using some remote controlled switches. Uncertainties associated with network demand, energy price, and PHEV charging behavior in different charging frameworks are handled with Monte Carlo simulation and the proposed stochastic problem is solved with the KH optimization algorithm [132]. The numerical studies on Tai-power distribution system verify the efficacy of proposed reconfiguration to improve the system performance considering PHEV charging loads.

6) Optimal reactive power dispatch

Dutta *et al.* [133] presented an improved evolutionary algorithm based on the OKH algorithm for obtaining optimal steady-state performance of power systems. They also proposed the effect of UPFC location in steady-state analysis and to demonstrate the capabilities of UPFC in controlling active and reactive power flow within any electrical network. To verify the effectiveness of KH and OKH, two different single objective functions such as minimization of real power losses and improvement of voltage profile and a multi-objective function that simultaneously minimizes transmission loss and voltage deviation has been studied through standard IEEE 57-bus and 118-

bus test systems. The study results showed that the proposed KH and OKH approaches are feasible and efficient.

Mukherjee *et al.* [134] presented the chaotic krill herd (CKH) algorithm (CKHA), for the solution of the optimal reactive power dispatch (ORPD) problem of power system incorporating flexible AC transmission systems (FACTS) devices on standard IEEE 30-bus test power system. The considered power system models are equipped with two types of FACTS controllers (namely, thyristor controlled series capacitor and thyristor controlled phase shifter). Simulation results indicate that CKH yields superior solution over other popular methods. The obtained results indicate the effectiveness of the solution of ORPD problem of power system considering FACTS devices. Finally, simulation is extended to some large-scale power system models like IEEE 57-bus and IEEE 118-bus test power systems for the same objectives to emphasis on the scalability of the proposed CKHA technique.

7) Optimal VAR dispatch problem

Mukherjee *et al.* [135] used chaotic krill herd (CKH) algorithm is to solve the optimal VAR dispatch problem of power system considering either minimization of real power loss or that of absolute value of total voltage deviation or improvements of voltage profile as an objective while satisfying all the equality and the inequality constraints of the power system network. Detailed studies of different chaotic maps are illustrated. Among these, Logistic map is considered in the proposed technique to improve the performance of the basic KHA. The performance of the proposed CKH is implemented on standard IEEE 14- and IEEE 118-bus test power systems in which the control of bus voltages, tap position of transformers and reactive power sources are involved. The results offered by CKH are compared with other evolutionary optimization based techniques.

8) Transient stability constrained optimal power flow

Transient stability constrained optimal power flow (TSCOPF) is a nonlinear optimization problem with both algebraic and differential equations which is difficult to solve even for small power network. In order to solve the TSCOPF problem efficiently, Mukherjee *et al.* [136] used KH algorithm to solve it. To accelerate the convergence speed and to improve the simulation results, opposition based learning (OBL) is also incorporated in the basic KH method. The simulation results, obtained by the basic KH method and the oppositional KH algorithm, are compared to those obtained by using some other recently developed methods available in the literature. In this paper, case studies conducted on 10 generator New England 39-bus system and 17 generator 162-bus system indicate that OKH approach is much more, computationally, efficient than the other reported popular state-of-the-art algorithms and OKH is found to be a promising tool to solve the TSCOPF problem of power systems.

4.4 Multi-objective optimization

4.4.1. Electromagnetic optimization

Ayala *et al.* [98] proposed a new multi-objective KH (MKH) algorithm and a modified MKH approach to address the electromagnetic optimization problems. The numerical results on a multiobjective constrained brushless direct current motor design problem showed that the evaluated MKH algorithms provide a promising performance.

4.5 Dynamic and noisy environment

4.5.1. Graph-based network route optimization

Sur and Shukla [94] described different kinds of the creature activities, and then proposed a discrete version of the KH, which is further used to solve graph network based search and optimization problems. KH is operated on a multi-parametric road graph for the search of the optimized path with respect to some parameters and evaluation function and the convergence rate is compared with Ant ACO [12] and IWD [25] algorithms. Due to the dynamicity of the road network with several dynamic parameters, the optimized path tends to change with intervals, the optimized path changes and will bring about a near fair distribution of vehicles in the road network and withdraw the excessive pressure on the busy roads and pave the way for proper exploitation of the underutilized.

4.6 Civil engineering

4.6.1. Optimum design of truss structures

Gandomi *et al*. [137] used the KH algorithm to solve three truss design optimization problems. The performance of KH is further compared with various classical and advanced algorithms.

4.6.2. Structural Optimization

Gandomi and Alavi [138] introduced KH for solving engineering optimization problems. For more verification, KH is applied to six design problems. Further, the performance of the KH algorithm is compared with that of various algorithms representative of the state-of-the-art in the area. The comparisons show that the results obtained by KH are better than the best solutions obtained by the existing methods.

Gandomi *et al*. [139] introduced the KH algorithm into structural optimization, and the KH was used to solve three design problems. The performance of the KH algorithm is further compared with various algorithms representative of the state of the art in the area. The comparisons showed that the results obtained by KH can be better than the best solutions obtained by the existing methods in these three case studies.

4.7 Fuzzy rule-based systems

Shanghooshabad and Abadeh [140] used the KH algorithm to generate fuzzy rule based systems (FRBSs). In FRBSs, there are three objectives: accuracy, interpretability, and robustness. The proposed algorithm consists of two stages based on the KH algorithm; in the first stage the candidate rules are generated intelligently so in the second stage, the fuzzy rules will be selected that get closer to the objectives. Stage 2 of the proposed algorithm can be used as a post-processing algorithm on other algorithms and converts those to robust algorithms. The generated systems by KH have better performance than other strategies.

Table 4. A summary of the KH applications in engineering optimization

Category	*Problem/Application*	*Author*	*Ref.*
Continuous optimization	Training artificial neural network	Kowalski and Łukasik	[99]
	Selecting structure and weights for neural networks	Lari and Abadeh	[100]
	Training the Feedforward neural network	Faris *et al.*	[101]
	Optimizing Support Vector Regression	Stasinakis *et al.*	[102]
	Optimizing Support vector machine	Wang *et al.*	[105]
	Clustering problem	Li *et al.*	[107]
		Jensi *et al.*	[109]
	Phase equilibrium calculations	Moodley *et al.*	[111]
	Sensorless control	Younesi and Tohidi	[112]
	PID control	Yaghoobi *et al.*	[113]
	Inverse radiation problem	Ren *et al.*	[114]
	Channel equalization problem	Pandey *et al.*	[115]
	Dual-cluster routing in UWSNs	Jiang *et al.*	[117]
	Model turbine heat rate	Niu *et al.*	[118]
Combinatorial optimization	Flexible job-shop scheduling problem (FJSSP)	Wang *et al.*	[93]
	Production scheduling problem	Puongyeam *et al.*	[119]
	Short-term hydrothermal scheduling	Roy *et al.*	[120]
	QoS Routing	Kalaiselvi and Radhakrishnan	[121]
	Portfolio optimization	Bacanin *et al.*	[122]
	Portfolio selection problem	Tuba *et al.*	[123]

	Feature selection	Rodrigues *et al.*	[95]
	Optimal power flow problem	Mukherjee *et al.*	[69]
		Mukherjee *et al.*	[75]
		Pulluri *et al.*	[84]
		Pulluri *et al.*	[85]
	Mobility tracking problem	Vincylloyd and Anand	[124]
	Four-bar linkage	Bulatović *et al.*	[125]
	Optimal capacitor allocation problem	Sultana and Roy	[74]
	Inverse geometry design	Sun *et al.*	[126]
Constrained Optimization	Economic dispatch problem	Kavousi-Fard *et al.*	[127]
	Dynamic economic dispatch	Ashouri and Hosseini	[128]
	CHPED problem	Adhvaryyu *et al.*	[129]
	Annual energy losses	Sultana and Roy	[73]
	Distributed generator (DG)	Sultana and Roy	[130]
	Distribution feeder reconfiguration (DFR)	Davodi *et al.*	[131]
	Optimal distribution feeder reconfiguration	Rostami *et al.*	[132]
	Optimal reactive power dispatch (ORPD)	Dutta *et al.*	[133]
		Mukherjee *et al.*	[134]
	Optimal VAR dispatch problem	Mukherjee *et al.*	[135]
	Transient stability constrained optimal power flow (TSCOPF)	Mukherjee *et al.*	[136]
MOO[1]	Electromagnetic optimization	Ayala *et al.*	[98]
DNE[2]	Graph-based network route optimization	Sur and Shukla	[94]
Civil engineering	Optimum design of truss structures	Gandomi *et al.*	[137]
	Structural optimization	Gandomi and Alavi	[138]
	Structural optimization	Gandomi *et al.*	[139]
Fuzzy system	Fuzzy rule-based systems	Shanghooshabad & Abadeh	[140]

[1]MOO is short for Multi-objective optimization.
[2]DNE is short for Dynamic and noisy environment.

5. Theoretical Analysis

5.1 Convergence

Aiming to the failure of the balance of global search and local search, the reason was explained by using a 2-D Ackley function in [79].

5.2 Parametric study

Wang *et al*. [141] studied the five of the most important parameters used in the KH algorithm through benchmark evaluation on twenty-four benchmarks. For most benchmarks, KH performs the best when the coefficient of the krill individual, food coefficient, maximum diffusion speed, crossover probability and mutation probability parameters are set to 4.00, 4.25, 0.014, 0.225, and 0.025, respectively.

Kowalski and Lukasik [142] described numerous basic parameters impact upon the quality of selected solutions, by examining empirically the influence of two parameters of the KH Algorithm, i.e., maximum induced speed and inertia weight.

5.2 Other studies

Singh *et al*. [143] have conducted a series of experiments on KH, FA, and CS through benchmark evaluation. The performance of these algorithms on the basis of efficiency, convergence, time are fully explored. For both unimodal and multimodal optimization, CS via Lévy flight has outperformed others. While for multimodal optimization, the KH algorithm is superior to FA, FA is superior to KH for unimodal optimization.

6. Conclusion and Future Direction

The KH algorithm is a new, attractive, and promising swarm-based metaheuristic algorithm. It has drawn great attention from scholars to engineers since it was proposed in 2012. This study reviewed the recent research about the KH algorithm in the literature. The collected papers have been classified into three categories, which are improved, hybrid, and variants of KH, engineering optimization applications, and theoretical analysis. However, there are some issues that should be clarified for the future research in this domain. More research needs to be done on the theoretical analysis of KH for a more stable implementation and more reliable solutions. Also, new optimization strategies can be incorporated into the basic KH. The improved KH variants may be tested through benchmark evaluation and can be applied to solve other practical engineering optimization/application problems. In addition, selection of the KH parameters is still a challenging problem when dealing with new problems. Another issue is that most researchers studied the KH algorithm for single-objective problems. Accordingly, multi-objective and many-objective optimization with KH can be a good topic for future research.

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