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Review Article

A comprehensive review: Krill Herd algorithm (KH) and its applications

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ABSTRACT

Krill Herd (KH) algorithm is a class of nature-inspired algorithm, which simulates the herding behavior of krill individuals. It has been successfully utilized to tackle many optimization problems in different domains and found to be very efficient. As a result, the studies has expanded significantly in the last 3 years. This paper presents the extensive (not exhaustive) review of KH algorithm in the area of applications, modifications, and hybridizations across these fields. The description of how KH algorithm was used in the approaches for solving these kinds of problems and further research directions are also discussed.

Contents

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1. Introduction

Research in optimization has remained active due to the fact that nearly all real-world problems belong to the class of complex optimization problems which are NP-hard in nature. Generally, the goal of problems' optimization is to find the best configuration of problem variables to optimize its objective function. These problems are sub-classified into constrained or unconstrained, continuous or discrete, single or multi-objective, and static or dynamic. Due to the challenging nature of these problems, several nature-inspired algorithmic techniques have been introduced by researchers to tackle wide range of optimization problems over the last four decades. The popularity of these algorithms is probably due to their robust search ability and optimization methodology in handling the problems of high dimensionality better than other calculus-based methods. Normally, these algorithms are derived from natural phenomena when some species are searching for better life. They can be classified into local-based algorithm, evolutionary algorithm, and swarm based algorithm. The local search-based algorithm begins with a single provisional solution, which will be iteratively improved until a stagnation point in the same area of the initial solution is reached. Examples include simulated annealing [1], tabu search [2], variable neighborhood search [3], hill climbing. The evolutionary algorithms begin with a set of random individual, which iteratively recombine the solutions and follow the survival of the fittest principle until the acceptable solution is reached. Examples include genetic algorithm [4], harmony search algorithm [5], genetic programming [6]. The last class is the swarm-based optimization method that basically starts with a set of points, and at each iteration the solutions are normally constructed based on historical information gained by previous generations. Some algorithms in this category are artificial bee colony algorithm [7], bacterial foraging algorithm [8], biogeographical-based optimization [9], cuckoo search algorithm [10], firefly algorithm [11], invasive weed optimization algorithm [12] and other studies can be found in [13,14].

In the recent time, the Krill Herd (KH) algorithm is proposed for solving global optimization function by Gandomi and Alavi in [15]. It is a swarm intelligence search algorithm that is motivated based on the herding behavior of krill individuals. In KH algorithm, the objective function for the movement of krill is measured by the shortest distance of each individual krill from food and highest density of the herd. Each individual in KH algorithm modifies its position based on three operational process: (1) motion induced by other individuals (2) foraging movement and (3) random physical diffusion. The KH algorithm is being referred to as a powerful search technique because it contains both exploration and exploitation strategies based on foraging movement and the motion induced by other individuals respectively. It is considered as one of the fast growing nature-inspired algorithmic solutions to solve the practical optimization problems [16]. This is as a result of its noticeable advantages in term of simplicity, flexibility, computationally efficiency as well as its stochastic nature which makes derivative information not to be essential [17]. In addition, as a swarm intelligence technique with a lot of advantages, it combines the efficient operations of evolutionary-based algorithm utilizing crossover and mutation components within its framework and thus makes the search framework stronger than other algorithms in terms of convergence rate. The success of KH algorithm has been recorded in many areas such as global optimization functions, network optimization, economic dispatch problem, optimum design truss, structural optimization, study of parameters and so on [15,18–25]. Similarly, studies have shown that the power of classical KH algorithm tends towards global exploration, but at times it may get stuck into some local optima and thus could not be able to implement global search fully. These shortcomings led to its modifications in terms of concepts and hybridizations with components from other metaheuristics when employed to tackle the problems of high dimensionality.

The main objectives of this review is to provide an extensive (though not exhaustive) summary of the related works on the applicability of KH algorithm to the different fields of optimization, as well as bringing out future challenges and possibilities. Note that this article classified the studies on KH algorithm based on five topics: applications, modifications, multi-objective-based, parameter-based and hybridizations. This classification aims at easing the understanding of the developmental trends in the KH algorithm.

This review paper is prepared by considering various publishers: ACM, ScienceDirect, Hindawi, IEEE Explorer, SpringerLink, Taylor & Francis, and others. Based on these publishers, Fig. 1 shows the number of published papers based on database classification in which KH algorithm is applied to different areas of optimization. The Figure shows clearly the fast growing interest in the utilization of KH algorithm and its applicability in different fields of research.

Fig. 2 shows the distribution of published articles related to KH algorithm with respect to years, which evidently shows that the number of published articles increases exponentially in the literature. However, as shown in this figure, the number articles published in the 2014 is higher than that of 2015 due to the fact many articles have not been updated.

The organization of this paper is as follows. A description general structure of KH algorithm is provided in Section 2 while the reviews of KH algorithm in relation to its modifications, hybridizations and application is given in Section 3. Finally, the discussion and conclusion in terms of its applications to optimization problems are outlined in Section 4.

2. General structure of KH algorithm

Krill Herd algorithm is a swarm intelligence algorithm proposed for continuous optimization problems. It has been proven to have a better or comparable performance with some existing algorithmic techniques [26,27]. For instance, when compared with other swarm-intelligence methods, it is easy to implement, it is robust which makes it comparable to other nature-inspired algorithms and requires few control parameters, practically, only a single parameter δt (time interval) needs to be fine-tune [21,26]. In KH algorithm, the population of Krills search through a multi-dimensional search space for food and the locations of Krill individuals is represented as different decision variables while the distance between the Krill individuals and the rich food correspond to the value of the objective cost. Note that the time-dependent location of a Krill individual is measured by the three operational processes: (i) motion induced process, (ii) foraging movement and

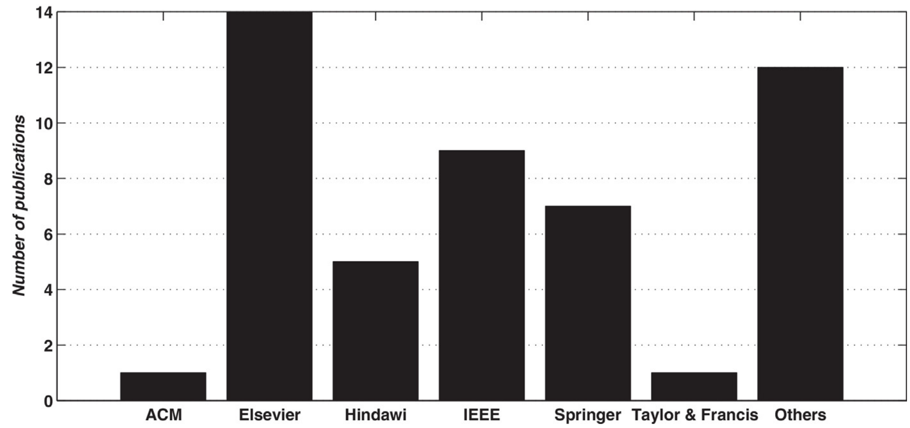

Fig. 1. Number of publications of KH algorithm per databases.

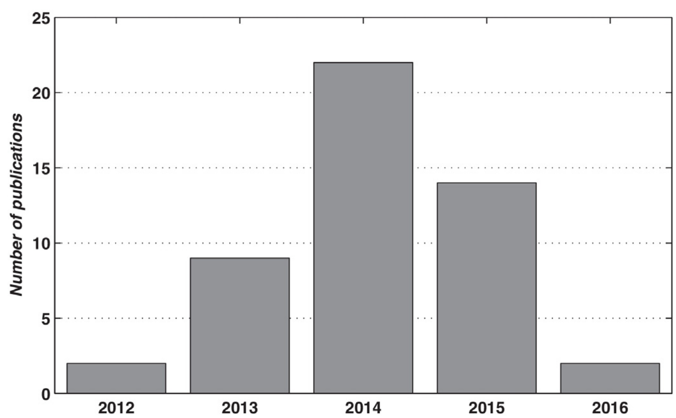

Fig. 2. Number of publications per year.

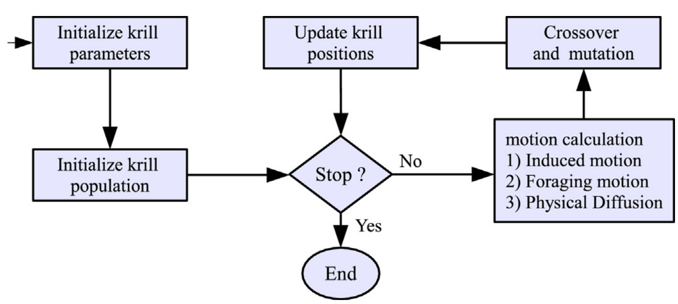

Fig. 3. A flowchart of the krill herd algorithm.

(iii) random physical diffusion. Fig. 3 shows the basic representation of the KH algorithm. The description and mathematical expression of these operational processes are provided in the following subsections:

2.1. Motion induced process

The velocity of individual Krill is influenced by the movement of other Krills in the multi-dimensional search space where its velocity is dynamically perturbed based on local effect, target swarm effect and repulsive swarm effect. The description of the movement of a Krill individual could be formulated as given in Eq. (1):

$$\theta_i^{new} = \epsilon_i \theta_i^{\max} + \mu_n \theta_i^{old} \tag{1}$$

where

$$\epsilon_i = \epsilon_i^{local} + \epsilon_i^{target} \tag{2}$$

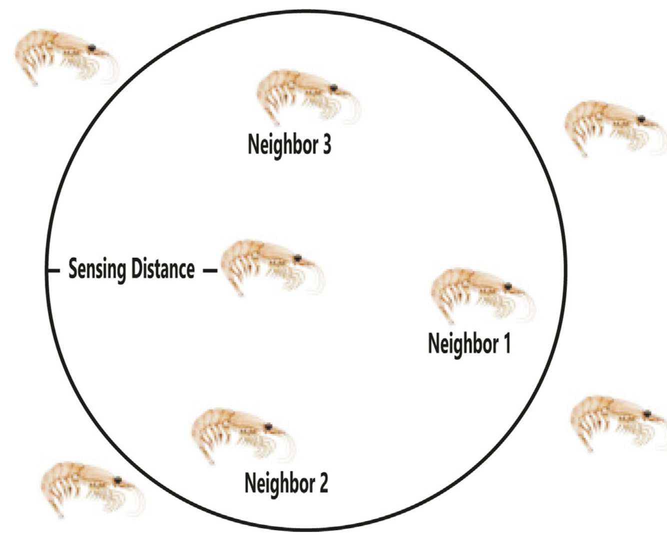

Fig. 4. A schematic representation of the sensing ambit around a krill individual.

$$\epsilon_i^{local} = \sum_{i=0}^{Ns-1} f_{ij} x_{ij} \tag{3}$$

Note that

$$f_{ij} = \frac{f_i - f_j}{f_w - f_b} \tag{4}$$

$$x_{ij} = \frac{x_i - x_j}{|x_i - x_j| rand(0, 1)} \tag{5}$$

$$\epsilon_i^{target} = 2\left(rand(0, 1) + \frac{i}{i_{\max}}\right) f_i^{best} x_i^{best} \tag{6}$$

where $\theta_i^{\max}$ denotes the maximum induced motion; θ_i^{old} is the last induced motion; μ_n represents the inertia weight of the motion induced while the local and target effects are respectively represented by ϵ_i^{local} and ϵ_i^{target}; f_w and f_b are the worst and best position of the population; f_i and f_j represent the fitness values of the i_{th} and the j_{th} krill individual respectively; the current and maximum generation number are given by i and i_{max} respectively.

In order to identify the neighboring members of each krill individual, a sensing distance (SD_i) parameter is employed as shown in Fig. 4, which is adopted from [15]. Note that if the distance between the two krill individuals is lower than the sensing distance, that particular krill is regarded as neighbor of the other krill. The formulation of the sensing distance is given in Eq. (7):

$$SD_i = \frac{1}{5n_p}\sum_{i=0}^{n_p-1}|x_i - x_j| \tag{7}$$

As described in Eq. (7), n_p denotes the number of krill individuals in the population while x_i and x_j represent the position of the i_{th} and the j_{th} krill, respectively.

2.2. Foraging movement

The foraging movement of each individual krill is formulated in terms of the current food location and the previous knowledge about the food location which could be expressed as shown in Eq. (8):

$$F_m = V_f a_i + \mu_f F_m^{old} \tag{8}$$

where

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

F_m is the first movement; V_f represents the foraging velocity; μ_f is the inertia weight of the foraging movement in (0,1); F_m^{old} is the previous foraging movement, a_i^{food} is the food attractive and a_i^{best} describe the effect of the best fitness of the each individual krill so far.

2.3. Random physical diffusion

In KH algorithm, the population diversity is enhanced with the aid of random diffusion process that is integrated in krill individuals. The mathematical expression of the random diffusion process in terms of a maximum diffusion speed and a random directional factor is given in Eq. (10) as follows:

$$RD_i = RD^{\max}\vartheta \tag{10}$$

RD^{max} in the Eq. (10) represents the maximum diffusion speed and ϑ is the random vector between (−1,1).

2.4. Position update

In line with the three above analyzed process, the defined motions frequently modify the position of a krill individual toward the best solution. The time dependent position from time t to δt is formulated in Eq. (11) as:

$$x_i(t+\delta t) = x_i(t) + \delta t\frac{dx_i}{dt} \tag{11}$$

where the definition of the δt which is one of the most important constant is described by Eq. (12) as:

$$\delta t = C_t\sum_{j=0}^{nv-1}(UB_j - LB_j) \tag{12}$$

It is worthy to mention that nv is the total number of variables; UB_j and LB_j are upper and lower bounds of the j_{th} variables; and C_t is the position constant.

Generally, the expression of the classical KH algorithm may be given by Lagrangian model (i.e. approximation) in a dimensional decision space as provided in Eq. (13)

$$\frac{dx_i}{dt} = N_i + F_i + D_i \tag{13}$$

As shown in Eq. (13), N_i is the motion induced by other krill individuals; F_i represents the foraging movement; D_i is the random physical diffusion i_{th} krill [15].

The performance of the KH algorithm during the update process is enhanced in term of generating better solution and increase the rate of convergence using the genetic components: the crossover and mutation. The description of the operational process of these components as integrated into KH algorithm is given as follows:

2.4.1. Crossover component

In this phase, each member of krill update its current position using the position of others in accordance with the position update equation. The j_{th} elements of the i_{th} krill may be updated based on Eq. (14)

$$x_{ij} = \begin{cases} x_{rj} & \text{if} \quad rand(0,1) < C_{R_i} \\ & \text{where} \quad r = 1, 2, \ldots, n_p; r \neq i \\ x_{ij} & otherwise \end{cases} \tag{14}$$

where C_{R_i} is the crossover rate which is defined as $C_{R_i} = 0.2f_i^{best}$ in [15]

2.4.2. Mutation component

The usage of the mutation operator is determined by a mutation rate parameter (M_R). The mutant solutions x_{ij} changing the solution x_{BESTj} with the difference of two other randomly selected vectors x_{nj} and x_{pj} with the aid of Eq. (15) as follows:

$$x_{ij}^{mutant} = x_{BESTj} + M_R(x_{nj} - x_{pj}) \tag{15}$$

The modified value of x_{ij}^{mod} based on mutation rate (M_R) is chosen from x_{ij}^{mutant} and x_{ij} which can be expressed mathematically as:

$$x_{ij}^{\mathrm{mod}} = \begin{cases} x_{ij}^{mutant} & \text{if} \quad rand(0,1) \leq M_R \\ x_{ij} & \text{otherwise} \end{cases} \tag{16}$$

Note that $M_R = \frac{0.05}{F_i^{BEST}}$. Algorithm 1 shows the representation of the search process of KH algorithm.

Algorithm 1. Basic Krill-inspired algorithm

Initialization of Krill parameters: V_f, RD^{max}, θ^{max}, C_R, M_R, and n_p.
for j = 1 to n_p **do**
  for i = 1 to d **do**
    $x_{ij} = LB_i + (UB_i - LB_i) \times U(1, d)$ {Initialization of krill population}
  end for
  Compute f_j {Evaluate each krill}
end for
Sort the krill and find $\boldsymbol{x}^{best}$, where $best \in (1, 2, \ldots, n_p)$
while $t < Max\_iterations$ **do**
  for j = 1 to n_p **do**
    Perform the three motion calculation using Eqs (1), (8) and (10)
    $x_j(t+\delta t) = x_j(t) + \delta t\frac{dx_j}{dt}$ {Update each krill}
    Fine-tune x_{j+1} by using krill operators: Crossover and mutation
    Evaluate each krill by x_{j+1}
  end for
  Replace the worst krill with the best krill.
  Sort the krill and find $\boldsymbol{x}^{best}$, where $best \in (1, 2, \ldots, n_p)$
  t=t+1
end while
Return $\boldsymbol{x}^{best}$

3. Applications of KH algorithm

Studies have reported numerous applications of KH algorithm to real-world and benchmark optimization problems in which many publications investigated its performance with other nature-inspired and optimization algorithms. Gandomi and Alavi in [15] proposed the original KH algorithm for global benchmark function in 2012 in which its performance was compared against eight well-known state-of-the-arts algorithmic techniques. Experimental results proved that KH algorithm outperforms the existing algorithms and has the capability of solving wide range of benchmark optimization function efficiently. The next subsections provide exhaustive summary of the applicability of KH algorithm to different areas.

3.1. Application to electric and power system problem

The presentation of new and efficient KH algorithm to solve both convex and non-convex ELD problems is proposed in [21], where the overall performance and effectiveness of the KH algorithm is enhanced with the crossover and mutation operator of DE. The authors observed that different versions of KH algorithm have been successfully applied to small, medium, and large-scale power systems for solving six different ELD problems. They compared the simulation results obtained by their KH algorithms with those obtained by other recently developed methods from the literature. The simulation results showed that KH algorithm is robust and able to provide better solution than other existing techniques in terms of fuel cost. The usage of bio-inspired KH algorithm to tackle the combined heat and power economic dispatch (CHPED) optimization is carried out by Adhvaryyu et al. in [22], in which the transmission loss that computed through the loss coefficients utilization is considered in their study. These scholars compared the performance of the proposed KH algorithm with existing methods like PSO, EP and DE that worked on the same test system. In another development, a similar bio-inspired KH algorithm is adopted to solve the hybrid system consisting of cogeneration units integrated with wind power unit in [28], where the objective is to simultaneously minimize the production cost and emission level of the system.

Younesi and Tohidi [29] designed a new sensorless control scheme based on KH algorithm for a permanent magnet synchronous motor (PMSM). The parameters of the speed and torque PI-Controllers are optimized by the authors to minimize the speed tracking error in steady state. They utilized the discrete-time model which does not depend on initial conditions of integrators and tested under variable operating conditions. The results of the simulation demonstrated that their proposed KH algorithm has a satisfactory performance against load disturbances and robustness against machine parameters' variations. Tackling the proportional integral derivative (PID) control system in order to obtain optimal PID parameters using KH algorithm is presented by Alikhani et al. [30]. Note that in their work, the plant error over the time is defined via three cost functions and the KH algorithm is utilized to obtain the optimal solution to cost functions. This is achieved by searching the PID parameter space for global minimum as well as fine-tuning the controller effectively. The numerical results showed that their strategy solved the problem effectively.

Gandomi and Alavi [26] studied the performance of the KH algorithm when applied to solve engineering optimization problems, comprising six design problems that have been reported in the literature. When the performance of the KH algorithm is compared against the series of the state-of-the-arts algorithms, it is found that the algorithm achieved the best known solution from the literature. Khalil et al. [31] investigated the performance of three nature-inspired algorithms such as monkey algorithm (MA), gravitational search algorithm (GSA) and krill herd algorithm, when employed to solve phase stability, phase equilibrium and chemical equilibrium problems. The authors in their research studied the effect of integrating a local search optimizer at the end of the stochastic optimizer search and compared the results of the each algorithm in order to determine their strength. They discovered that the KH algorithm had comparable performance with other existing methods.

3.2. Application to wireless and network system problems

Amudhavel et al. [19] adopted the KH algorithm to tackle some issues in the peer-to-peer network (P2P) where the n-grams technique that splits the query strings into the substrings is employed for searching the nodes based on the query that has the data. The authors concluded that reduction in the search process led to decreases in high bandwidth and thus reduction of the congestion in network and network traffic. The challenges in the Smart Phone Ad Hoc Network (SPAN) such as synchronization, bandwidth, power conservation is tackled with the KH algorithm in [20], where the intensification strategy of the algorithm is employed to resolve the issues in the SPAN. The bandwidth and power consumption were respectively reduced and efficiently influenced with the aid of intensification strength of the KH algorithm. The presentation of the KH algorithm to solve the challenges faced in wireless network (i.e. standardization and routing) is given in [32] where the issues to enhance the efficiency of the wireless ad hoc network are resolved. In their method, routing delay was side-stepped by updating the forward table placed in the nodes, whenever a message is passed through the node. The updating is carried out in order to determine the shortest path to reach the destination with minimum time and cost constraint. Experimental simulation showed that their method enhanced the efficiency of wireless ad hoc network. Similarly, the performance of the KH algorithm is investigated for the Mobile ad hoc network (MANET) in which the problem encountered during the dynamic nature of MANET were addressed [33]. The presentation of the KH algorithm for the design of an adaptive channel equalizer is discussed in [34], in which the channel equalization problem is formulated as an optimization task. They compared the performance of their proposed system with other EC based equalizer methods and found that the KH algorithm based equalizer produced an improved channel equalization over the other schemes. Lastly, the KH algorithm is applied to tackle cluster related problem in [35].

3.3. Application to neural network training

The emergence of artificial neural networks as an important tool in the domain of artificial intelligence and optimization could not be over emphasized. Kowalski and Lukasik in [36] studied the performance of the KH algorithm for the training of artificial neural networks and evaluate its obtained results with other stochastic methods that worked on the same problem instances drawn from the UCI machine learning repository. They concluded that the KH algorithm produced promising results in terms of classification error (CE), sum of square errors (SSE) and time taken for the training of the ANN. In another development, Lari and Abadel [37] employed KH algorithm to improve the network structure of the ANN in which the process was based on three components (i.e. induced movement by the other krill, random diffusion, and foraging motion) along with a genetic operator. The authors proved that their method produced a better performance in terms of high classification accuracy and low mean square error when compared their results with the previous methods that worked on the same instances of the UCI dataset. Similar study that adapted KH algorithm for training of ANN is proposed by the same authors in [38].

4. Modifications of KH algorithm

The different variants of the classical KH algorithm in terms of modifications and parameter tuning, in order to improve its performance, have been proposed by the researchers in the domain and the discussion of these variants is provided in this section

4.1. Binary-based KH algorithm

The modification of the KH algorithm based on binary concept is presented for tackling feature selection problem by Rodrigues et al. [39] in which the krill individuals are position to the binary coordinates. The proposed technique outperforms three other approaches when evaluated on several feature selection datasets by the authors.

4.2. Chaotic-based KH algorithm

The motivation to improve the performance of the KH algorithm led to the modification of its components using chaotic theory concept by some researchers in the domain. Wang et al. [40] improved the performance of the KH algorithm with a series of chaotic particle-swarm named (CPKH) for solving numerical optimization problems within limited time frames. They integrated chaos sequence into the KH algorithm in order to enhance its global search capability. The results of the experiment show that their method can accelerate the global convergence speed as well as maintaining the strong robustness of the classical KH algorithm. In another development, the acceleration of the global convergence speed of the KH algorithm using chaos theory was proposed by Wang et al. [41]. In their study, the various chaotic maps are utilized to change the three main movements of the KH algorithm during the search process. The experimental results showed that the modification with an appropriate chaotic map performs better than the original KH and obtained comparable results with other existing approaches. The combinations of chaos theory with the KH algorithm is employed to tackle the global optimization problems in [18], where the logistic chaotic mapping is employed in the physical diffusion operator and acts on random specifications of the KH algorithm. When the authors evaluated the performance of their proposed method on global optimization problems. It is found that modified KH (i.e. chaotic) algorithm performs better than the classical KH algorithm. Similarly, Saremi et al. [42] tackled the limitations of the KH algorithm in term of its in ability to avoid local optimal and premature convergence with the aid of chaos theory. The induced movement of the KH algorithm is modified in order to provide the chaotic behavior. Computational experiment proved that the chaotic map is able to enhance the KH algorithm's performance when tested on four benchmark function. Mukherjee and Mukherjee [16] improved the performance of the basic KH algorithm using various chaotic maps for optimal power flow and named chaotic KH algorithm (CKH). The authors observed that logistic map based on CKH offers better results when compared with other chaotic maps.

Other modification that employed the chaotic sequence to fine-tune the parameters of the KH algorithm is presented for the global optimization function in [43]. In this work, the authors generate and allocate chaotic sequence in order to control parameters of the standard KH algorithm and dynamic behavior was introduced to enhance the performance of the KH algorithm when dealing with the problems. The results of the experiment on eight benchmark problems proved the superiority of their method over standard KH algorithm and PSO algorithm. Amudhavel et al. [44] solved Vehicular Ad-Hoc Network (VANET) with chaotic KH algorithm where the original KH algorithm is modified using the three chaotic maps, namely circle, sine and sinusoidal. The introduction of chaotic maps by the authors is to provide chaotic behaviors and thus allow a group of krill individuals with chaotic induced movements. The performance of their chaotic method led to reduction in congestion greatly.

4.3. Fuzzy-based KH algorithm

The performance of the KH algorithm could be more powerful, if it is integrated with fuzzy sets theory. Fattahi et al. [45] proposed fuzzy-based KH algorithm where fuzzy system is utilized to fine-tune the parameters during the search cycle to strike a balance between the exploration and exploitation capabilities while solving the problems. The utilization of the fuzzy system is to assign suitable values to the respective variables that control amount of local exploitation and global exploration in order to enhance the search capability of the algorithm while solving the problems. When the authors tested the proposed fuzzy-based KH algorithm on different benchmark functions, it showed the higher performance of the proposed method.

4.4. Discrete-based KH algorithm

Application of discrete KH algorithm for graph-based network search and optimization problems is proposed in [46] where the continuous nature of the algorithm was modified to cope with the optimization problems of discrete variables. The results of the experiment showed that the performance of the KH algorithm is better when it comes to decision making and path planning for graph-based network and other discrete event based optimization problems. The flexible job-shop scheduling problem (FJSSP) is solved with discrete KH method in [47] where some heuristic strategies are incorporated in order to develop an effective solution approach. The solution approach is divided into two stages: in the first stage, the multilayer coding strategy is employed in preprocessing phase which enables the KH method to deal with FJSSP. Then the proposed DKH method is utilized to find the best scheduling sequence within the promising domain. They also introduced elitism strategy into their proposed method to drive the krill swarm towards the better solutions during the search. When the performance of the proposed discrete KH algorithm is evaluated using two FJSSP instances, the results clearly demonstrate that the approach outperformed some existing state-of-the-art algorithms.

4.5. Opposition-based KH algorithm

The concept of opposition-based learning strategy is employed in the modification of the classical KH algorithm for tackling the optimal location of capacitor in [48]. The modification is aimed at improving the performance of the algorithm in terms of generating good results as well as enhancing the speed of convergence. The authors employed 33-bus and 69-bus radial distribution networks to test the performance of their modified KH algorithm. The experimental results showed that their proposed technique achieved good quality convergence characteristics and obtained better quality results when compared with those achieved by the classical KH algorithm and other existing nature-inspired techniques available from the literature. Similar strategy is implemented to tackle the same problem by Sultana and Roy in [49]. The introduction of opposition based learning (OBL) strategy and free search operator into the KH algorithm (FSKH) for numerical benchmark function is presented in [50]. In FSKH, each krill member can explore the space based on its own perception and scope of activities. The usage of free search strategy is to aid the individuals from being trapped in local optima, assists in the improvement of exploration capability and the diversity of the krill population. Thus the modification aided the FSKH to strike a right balance between local exploitation and global exploration. The authors proved that their proposed method is robust and perform better than existing nature-inspired algorithms when applied to solve fourteen global optimization benchmark functions. An application of the opposition-based KH algorithm was presented for the minimization of the power loss in the transmission lines in power system and/or the voltage deviation minimization at the load buses by controlling the reactive power that is referred to as optimal reactive power dispatch (ORPD) is presented by Dutta et al. [51]. In their work, an optimal steady-state performance of the power systems is obtained using an improved evolutionary algorithm based on oppositional KH algorithm (OKHA). Furthermore, the effect of UPFC location in steady-state analysis to show its capabilities in controlling active and reactive power flow within any electrical network is studied. The effectiveness of the KH algorithm and OKH algorithm were verified using two different single objective a multi-objective datasets through standard IEEE 57-bus and 118-bus test systems. The results of the study showed that the proposed KH algorithm and OKH approach are feasible and efficient.

4.6. Other modifications

Li et al. [52] presented the modification of the KH algorithm using linear decreasing step to strike a balance between exploration and exploitation when employed to solve the optimization problem. When authors verified the effectiveness of their improved KH algorithm with 20 benchmark functions. It is discovered that the performance of their modified version is better than the original KH algorithm.

An improved KH algorithm is presented to tackle global optimization function by Guo et al. [27], in which better solutions were generated based on exchange of information between top krill motion calculation process. The authors utilized a new Levy flight distribution and elitism scheme to update the motion calculation of the KH algorithm and accelerate the global convergence speed as well as preserving the robustness of the basic KH algorithm. When several standard benchmark functions are employed to verify the efficiency of their method, it was found that the proposed algorithm has a superior performance with the original KH algorithm and highly competitive with other robust population-based methods.

A modified KH algorithm with dual populations, named double herd krill algorithm (DHKA) is proposed for location area optimization in mobile wireless cellular network in [53]. The krill herd is divided in their research based on the concept of global search and local search strategies derived from DE [54]. Numerical experiment showed that the DHKA proved to be a better alternative for solving complex optimization problem like location area optimization.

A multi constrained quality-of-service routing (QOSR) in mobile ad hoc networks (MANETs) was tackled by differentially guided KH algorithm (DGKH) in [55]. In their research, the position of krill individuals is not updated at each cycle, but uses the information from other krill individuals to determine a feasible path. The experimental results of the DGKH algorithm using MANETs with different number nodes (routes) and three constraints: maximum allowed delay, maximum allowed jitter, and minimum requested bandwidth, showed that the proposed algorithm is very effective than the classical KH algorithm and other existing algorithms.

5. Hybridizations of KH algorithm

The popularity of hybrid approach in the domain of optimization is fast growing and focus is on improving the performance of classical algorithms based on idea of hybridizing the components from other optimization techniques. Studies have shown that the performance of the KH algorithm have been enhanced through the incorporations of other operators from metaheuristic techniques. The section provides the review of the hybridization of the KH algorithm with other operators from another metaheuristic techniques

5.1. Hybridization with local search-based algorithm

Normally, the population-based approaches likes KH algorithm are strong in the scanning the search space of multiple regions at the same time. However, it is not that efficient in navigating each region deeply. In contrast, local search-based algorithm is very efficient in deeply navigating a single search space region but cannot scan the whole search space regions. Therefore, the hybridization of local search within the population search algorithm is very promising to complement the advantages of both types in a single optimization algorithm [13]. The main aim of this type of hybridization is to strike the right balance between a wide range exploration and nearby exploitation of the problem search space.

Wang et al. [56] presented a hybrid method, called the simulated annealing-based Krill Herd (SKH) for optimization problems. The authors enhanced the reliability and robustness of the KH algorithm when tackling the optimization using a new krill selection (KS) operator which is employed to refine krill behavior during the position update. Note that the introduction of KS operator involves greedy strategy and accepting few worst solutions with a low probability originally used in simulated annealing (SA). The experimental results showed that the proposed method is better than standard KH and other optimization methods.

5.2. Hybridization with population-based algorithm

This section summarizes the hybridization of KH algorithm with operators of other population-based algorithms in order to improve its performance when utilized for complex optimization problems. Wang et al. [57] proposed a hybrid algorithm termed a biogeography-based krill herd (BBKH) algorithm for solving complex optimization tasks. The authors in their work improved the performance KH algorithm with introduction of a new krill migration (KM) operator during update process in order to tackled the problems efficiently. The usage of KM operator is to enhance the exploitation capability by allows the krill to cluster around the best solutions at the later run of the search. The performance of a novel BBKH approach is better than the basic KH and other optimization algorithms in accordance with experimental results. The tackling of numerical optimization problems with an updated genetic reproduction schemes of the KH algorithm using stud selection and crossover (SSC) operator during the krill updating process is proposed by Wang et al. [58]. The idea of SSC that based on stud genetic algorithm is that the best krill and stud generates an optimal information for all other members in the population by genetic operator instead of stochastic selection. The authors carefully studied the performance of their method on several benchmark problems and found that it is has better or comparable performance than the standard KH algorithm and other state-of-the-art methods. The drive to strike a good balance between the global exploration and local exploitation capability of the classical KH algorithm while tackling the production scheduling problems led to introduction of modified KH algorithm in [59]. The authors in their research combined the exploitation of the employed bee component from global best artificial bee colony (GABC) [60] with the exploration capability of the KH algorithm in order to generate the good solutions during the search process. They investigated their algorithm with various sizes of scheduling problem obtained from a capital goods company. The analysis on the obtained results showed that the hybrid algorithm significantly performed better than the basic KH algorithm for all problems. The performance of the KH algorithm for solving global optimization is recently improved with harmony search (HS) in [17], where the HS is employed instead of physical diffusion to alter krill movement during the process of krill updating in the KH algorithm. It is worthy to mention that the proposed hybrid method effectively combined the global exploration of the HS with the local exploitation of the KH algorithm, in order to generate the desired solutions. The authors verified the performance of their method on fourteen standard benchmark functions and found that the hybrid method (i.e. HS/KH) is highly competitive when compared with other population-based algorithms. Wang et al. [61] addressed the poor exploitation of the KH algorithm with hybridization of differential evolution operator when applied to tackle optimization functions. The integration is achieved with addition of a new hybrid differential evolution (HDE) operator into the krill, during the updating process and thus aided the intensification and lets the krill perform as local search within the defined region. The proposed method is validated by the authors using 26 functions and discovered that it was able to find more accurate solution than the KH and other methods. A novel hybridization of KH algorithm with quantum-behaved particle swarm optimization (QPSO) is presented for benchmark and engineering optimization [62], where the QPSO is utilized to enhanced local search capability as well as increasing the individual diversity in the population. The performance of the hybrid method is tested on an array of test problems as well as an engineering case. Based on the simulation results, it showed that the hybrid method is more efficient than other optimization methods.

5.3. Hybridization with other components

Wang et al. [63] improved the performance of the KH algorithm with a Lèvy-flight mechanism for tackling the optimization tasks within limited computing time. The authors integrated a new local Lèvy-flight (LLF) operator during the updating krill process in order to improve its efficiency and reliability while solving global numerical optimization problems. The usage of LLF operator is to enhance the exploitation and allows individuals to carefully exploits the search space. In addition, they also applied elitism scheme in order to maintain the best krill during the updating process. The performance of their LKH version was tested on fourteen standard benchmark functions which showed that the algorithm is superior to the standard KH algorithm and it is found to be highly competitive with other existing population-based methods.

6. Multi-objective KH algorithm

Literature has shown the achievement of the KH algorithm as a single-objective optimization algorithm when applied to tackle problems with continuous search space. This has led to the motivation of the researchers to extend its usage to multi-objective areas. Mohammedi et al. [64] developed a multi-objective binary KH algorithm for the classification problems in which the classical KH algorithm was converted to binary algorithm. The breast cancer datatet was employed by the authors to test the performance of their methods and found that a accuracy achieved by their algorithm was higher than existing ones with few rules and little sum of the rules lengths. Ayala et al. [65] developed a new multi-objective KH (MOKH) algorithm and a modified MKH approach with the beta distribution in the tuning of inertia weight for electromagnetic optimization. Similar study is evaluated on a brushless direct current (DC) wheel motor benchmark in [66], it was found that MKH algorithms showed a promising performance on a multi-objective constrained brushless DC motor design problem.

7. Parameter-less KH algorithm

Wang et al. [67] studied a systematic method for the selection of the best parameter values for the KH algorithm based on arrays of high-dimensional benchmark problems which aimed at determining the optimal values for its five main parameters. The authors divided their research into two where the KH algorithm without genetic operators is selected to investigate the first set of parameters i.e. C_{best}, C_{food}, D_{max} which are defined in their paper as the effective coefficient, the food coefficient, and the maximum diffusion speed respectively. The parametric analysis of C_R and M_R is carried out with the KH algorithm with two genetic operators: crossover and mutation operator. They concluded that the KH would perform best for most high-dimensional test functions by setting the Lagrangian parameters of *i*, *jand k* respectively to 4.00, 4.25 and 0.014 in C_{best}, C_{food} and D_{max} while the best genetic parameters, C_R and M_R, are also found to be 0.225, and 0.025 respectively. Similarly, the influence parameter related to the effect of the herd movement as induced by krill individuals: maximum induced speed and inertia weight are studied in [25].

8. Discussion and conclusion

This section summarizes the review of the studies on KH algorithm as given in Tables 1–3 where the publications related to the KH algorithm in terms of various areas of application, modification and hybridization to different formulations of combinatorial optimization problems are studied. Based on these tables, it can be seen that, the growth of this algorithm is on the increasing, despite the fact that its proposition is about three years. In accordance to the reviewed articles, it can be observed that the burk of the study on this algorithm focused on algorithmic applications and modifications to several area of discipline, yet there is still much more to do in this direction. Further studies of this algorithm in terms of its adaptation to other domain, self-adaptation of control parameters and theoretical studies needs to be investigated in the nearest future. Literature have shown that no much works have been carried out on theoretical aspect of the KH algorithm in general, it would be interesting to perform a theoretical study of the run-time and convergence properties of this algorithm as well as fitness landscapes and its dynamics nature. The design of parameter-less KH algorithm where there will be no parameters to be tuned by the user and population structured of the KH algorithm are another aspect theoretical research area that worth investigating. Finally, forces on krill are overwhelming in nature, therefore, effects of other environmental factors such as water/ocean speed, tides and turbulence, etc., which may often larger than the speed of individual krill in the KH algorithm needs further investigation to improve the search process of the original KH algorithm.

Furthermore, this study conducted a systematic, extensive (not exhaustive) review to obtain the relevant literature on the applications, modifications and hybridizations of the KH algorithm when employed to solve problems of high dimensionality in different domain. According to the reviewed articles, it can be seen that KH algorithm has been mostly utilized in solving global optimization problems. Hence, the need for its applicability to tackle other problems is still an open subject to the researchers. Complex optimization problems in these domains could be solved effectively and efficiently by taking the advantages of the KH algorithm. Lastly, it is of the opinion that this survey paper will be useful to the community as well as the researchers who are currently working or will work in this direction by guiding them about how the KH algorithm can be employed to tackle the problems in these domains. Conclusively, it can be seen from the studies, there still many interesting

Table 1
Application areas of KH algorithm.

Area	Publication
Electrical and power system	Mandal et al. [21], Adhvaryyu et al. [22], Adhvaryyu et al. [28], Gandomi and Alavi [26], Younesi and Tohidi [29], Alikhani et al. [30], Khalil et al. [31],
Wireless and network system	Amudhavel et al. [19], Amudhavel et al. [20], Amudhavel et al. [32], Amudhavel et al. [33], Pandey et al. [34], Singh and Sood [35].
Neural network training	Kowalski and Łukasik [36], Lari and Abadel [38,37]

Table 2
Modified versions of KH algorithm.

KH	Studies
Binary-based KH algorithm	Rodrigues et al. [39]
Chaotic-based KH algorithm	Wang et al. [40], Wang et al. [41], Gharavian et al. [18], Saremi et al. [42], Mukherjee and Mukherjee [16], Bidar et al. [43] Amudhavel et al. [44]
Fuzzy-based KH algorithm	Fattahi et al. [45]
Discrete-based KH algorithm	Sur and Shukla [46] Wang et al. [47]
Opposition-based KH algorithm	Sultana and Roy [49,48], Dutta et al. [51]
Multi-objective based KH algorithm	Mohammedi et al. [64], Ayala et al. [65], Brisset and Brochet [66]
Parameter-based KH algorithm	Kowalski and Łukasik [25], Wang et al. [67]
Other Modification	Li et al. [52], Guo et al. [27], Vincylloyd and Anand [53], Kalaiselvi and Radhakrishnan [55]

Table 3
Hybridization of KH algorithm.

KH	Studies
Hybridization with local search-based algorithm	Wang et al. [56]
Hybridization with population-based algorithm	Wang et al. [17], Wang et al. [57], Wang et al. [58], Puongyeam et al. [59], Wang et al. [61], Wang et al. [62]
Hybridization with components from other algorithm	Wang et al. [63]

research directions ahead that can be conquer by the utilization of the KH algorithm.

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