Design of Optimal localization Model for Wireless Sensor Network Nodes Using Improved Krill Herd Algorithm

Jafarsadegh Kamfar¹, Hessam Zandhessami²*, Mahmood Alborzi³

¹,²,³ Department of Information Technology Management, Science and Research branch, Islamic Azad University, Tehran, Iran

¹js.kamfar@srbiau.ac.ir, ²zandhessami@srbiau.ac.ir, ³mahmood_alborzi@yahoo.com

Abstract

Nowadays, Wireless Sensor Networks (WSNs) are significantly applied in engineering and scientific research. WSNs consist of a group of distributed space sensors that track the environment's physical conditions and control the collected data at one central location. Examples of these sensors' applications are smart cities, transport, volcano surveillance and environmental activity, earthquake monitoring, medicine, post-disaster response, and military control. Wireless sensor networks have a lot of research issues like access to the media, implementation, time synchronization, network security and localization of the nodes. One of the most critical problems in this network research is the optimum position of the sensors to have access to maximum coverage and increase network life span to decrease maintenance costs, develop and manage the network. One of the main causes of the failure in these networks is running out of sensor battery and replacing them which impose high costs to maintenance and managing of the network. In order to solve the issues related to optimization and localization, researchers have focused on the algorithms like Swarm Intelligence (SI), because they enable us to solve complicated issues of optimization and NP-Hard issues to solve optimization. However, most of these algorithms are specialized for a purpose or a special program, and the majority of the solutions are not compatible with most of the wireless network sensors. The DV-Hop is one of the most popular node algorithms. But the main problem of the DV-Hop is the possibility of error in calculating the assessed distance between the unknown node and the nodes of anchor. Therefore, minimizing this error is the key to improve this algorithm. To reduce the problem of high localization error, two meta-heuristic algorithms have been proposed based on a combination. In this paper, a new optimization method based on a combination of Krill Herd Algorithm (KHA) and Particle Swarm Optimization (PSO) called KHAPSO is suggested to improve DV-Hop. Simulation results in MATLAB 2016 show that the KHAPSO model has a lower mean error compared to the DV-Hop, DV-Hop-KHA and DV-Hop-PSO models. Also, energy consumption in the KHAPSO model is less in comparison to the other models. The KHAPSO model with 400 unknown nodes and 30 anchor nodes was able to reduce energy consumption by about 35% and at the same time 27% reduction in Average Localization Error (ALE) compared to DV-Hop.

Keywords: Wireless Sensor Networks, Node, Localization, Swarm Intelligence, Krill Herd Algorithm, Particle Swarm Optimization Algorithm

1. Introduction

* Corresponding Author E-Mail: Zandhessami@srbiau.ac.ir
WSNs are developed according to the IEEE 802.15.4 standard, which include a large number of sensor nodes that are used to collect and process environmental information with low power consumption, small size and reasonable price. WSNs have different applications in fields such as medicine, multimedia telecommunications, surveillance, military and building [1]. The main advantage of WSNs is the ability to be located in small and large independent points without any prefabricated infrastructure. WSNs must consume little energy, be intelligently programmed, and be able to receive and transmit data with high speed and accuracy [2]. By WSNs, different data such as temperature, pressure, motion, humidity, and pollution are collected from different environments. Having this information without knowing the location of sensor nodes is incomprehensible and useless [3].

One of the most challenging issues on WSNs technology is the issue of sensor nodes localization [4]. Because the localization of sensor nodes is a key issue in WSNs, the localization process has been considered by many researchers, which this has led to the design and development of various algorithms [5, 6]. Localization algorithms are divided into two categories: range-based algorithms [7] and range-free algorithms [8].

Range-based Localization algorithms use point to point distance, Received Signal Strength Index (RSSI) [9], Time of Arrival (TOA) [10], Angle of Arrival (AOA) [11], and Time Difference of Arrival (TDOA) [12] for calculating the localization of sensor nodes. The accuracy of the estimation in range-based algorithms depends on the transmission environment and generally on the complex hardware. Range-based algorithms use the trilateration method to determine the position of unknown nodes.

Range-free localization algorithms rely on sensor node connection information and network topology. A limited number of nodes, called anchor nodes, are aware of their geographical location information because they are equipped with GPS. In this way, they are a reference for unknown nodes to estimate their position based on connection information to anchor nodes. Anchor nodes assist unknown nodes determine their position. Anchor nodes distribute their position in the network, and other nodes can estimate their position by counting the number of steps of the anchor nodes. The approximate distance in this method is not perfect and the network must be dense and uniform for its accuracy. More steps and irregularities in the network cause high error estimation distance and as a result, a positioning error occurs. DV-Hop [13, 14], Centroid [15], Amorphous [16] and Approximate Point-In-Triangle (APIT) [17] are some range-free algorithms. Regardless of free-range algorithms' lower accuracy when compared to range-based algorithms, plainness of operation, low power consumption, no need to measure distances and angles that require additional and expensive equipment, have made these algorithms more efficient.

The biggest downside of DV-Hop is the fact that its accuracy is affected by the distances between unknown nodes and anchor nodes, and changes in anchor position [18]. The DV-Hop is not appropriate for non-convergent networks in which nodes are unevenly distributed, and it shows the required performance at the time that the network has dense and uniform topologies. When the number of steps between unknown nodes and anchor nodes increases, or there is malformation in the network, the distance between the steps varies, and the localization accuracy decreases.

WSNs require a localization algorithm to sensor nodes localization, which includes ease of execution, low complexity, and low computation time, and they do not need extra hardware for implementation [19]. These factors are usually provided by meta-heuristic algorithms that have optimal solutions, discover important points of search space and parallel search [20]. In this paper, a hybrid model based on KHA [21] and PSO [22] is proposed as KHAPSO for localization of sensor nodes. The goal of the KHAPSO model is to reduce localization error and energy consumption. The PSO algorithm is used to reinforce the KHA and is used to improve the position of community members. The main contributions of this paper are as follows: 1) Providing a hybrid model based on KHA and PSO for localization of nodes. 2) Updating positions in KHA are updated by the PSO.
3) Localization error and energy consumption in KHAPSO model are less than other methods. 4) Improving the DV-Hop by changing the number of steps to reduce localization error

The assessment results display that KHAPSO model has less localization error compared to the DV-Hop, DV-Hop-PSO, and DV-Hop-KHA models and it has a good performance in detecting the position of unknown nodes.

The paper is organized as follows: In Section 2, we will review the literature on DV-Hop and previous studies. In Section 3, we will discuss basic concepts such as the Krill Herd Algorithm and Particle Swarm Optimization. In Section 4, we will describe the steps of the KHAPSO model. In Section 5, we explain the evaluation criteria. In Section 6, we will evaluate and compare the results of the KHAPSO model and its comparison with other models, and finally, in Section 7, we will discuss the conclusions and future work.

2. Literature Review

2.1. DV-Hop

The DV-Hop is a distributed model that uses a method similar to classical distance vector routing. In this method, anchor nodes broadcast a flooding message across the network that includes the location of the anchor nodes and the number of hop size. Each receiving sensor node stores the message with the least number of hop sizes to the node of anchor and ignores the messages with the highest number of hop size.

Using DV-Hop, all sensor nodes obtain the shortest distance based on the number of hop size to all anchor nodes. Since the DV-Hop has incorrect precision of positioning, it is mostly used in large applications due to its simplicity, achievability, stability, and fewer hardware equipment. Figure (1) displays the flowchart of the DV-Hop.
There are two types of sensor nodes in the network. Anchor nodes, normal sensor nodes. Anchor nodes are fixed-position nodes whose position is detected by the Global Positioning System (GPS). Normal sensor nodes are in unknown positions and their position is detected by anchor nodes. The DV-Hop consists of three main steps:

First Step (Communication Detection and Distribution): In this stage, the least number of hop size between anchor nodes and unknown nodes is calculated. Anchor nodes include a message code and a hop count counter to their neighbors, and the initial value of the hop size counter is zero. The sensor that receives the message increases the counter of the number of hop size by one unit and compares it with the value stored in its data table, if the counter of the number of hop size is less than the previous value in the data table, this value is recorded for that node and the number of the saved hop size is updated, otherwise the message will be ignored and a number of steps will be sent to the next nodes by adding a unit to the counter. At the end of this step, all the unknown sensors have a number of hop size to the anchors.

Second Step (Estimation of Distance): In the second stage, the number of hop size between anchor nodes is calculated using the number of hop size between each anchor node. In this step, based on the distance of the anchor nodes from each other and the number of hop size between them, the average number of hop size is calculated according to Eq. (1). In the DV-Hop [13], each anchor node calculates the Euclidean distance to the other anchor nodes and estimates the average length using the number of hop size information. In Eq. (1), the
parameters \( x \) and \( y \) are the points of geographic of the anchor nodes \( i \) and \( j \), and also the parameter \( h \) is the number of hop size between the anchor nodes.

\[
h_{Si} = \frac{\sum_{j \neq i}^N \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j \neq i}^N h_{ij}}
\]

(1)

Parameters \((x_i, y_i)\) and \((x_j, y_j)\) are the position of the anchor nodes of \( i \) and \( j \), \( N \) is the number of anchor nodes and \( h_{ij} \) is the number of hop size from the node of anchor \( i \) to the anchor node \( j \) and Trilateration is used to estimate the position of each node. Nodes calculate their guesstimated distance with more than three anchor nodes. Once all the distances have been determined, the nodes use Trilateration to estimate their location. The error in this method declines with increasing the number of nodes of anchor. The distance of each unknown node from all anchor node is calculated based on the number of hop size according to Eq. (2). In each sensor node, a table is stored as \( \{x_i, y_j, \text{hop count}\} \) for the number of hop size. The \( h_{ij} \) parameter is the count of the number of hop size between anchor node \( i \) and unknown node \( j \).

\[
d_{ij} = h_{Si} \times h_{ij}
\]

(2)

**Third Step (Estimating the Coordinates of Unknown Nodes):** In the third stage, the position of the unknown nodes is determined using Trilateration rule in which it was computed based on the distance of each anchor node in the second stage. The demonstration of the points of geographic of the anchor nodes \((x_i, y_i)\) and the coordinates of the unknown nodes \((x, y)\) are calculated according to Eq. (3).

\[
\begin{align*}
(x - x_1)^2 + (y - y_1)^2 & = d_1^2 \\
(x - x_2)^2 + (y - y_2)^2 & = d_2^2 \\
... & \\
(x - x_n)^2 + (y - y_n)^2 & = d_n^2
\end{align*}
\]

(3)

Where \((x, y)\) is an estimate of the node points of geographic is unknown. Eq. (3) can be developed as Eq. (4).

\[
\begin{align*}
x_1^2 + x_n^2 - 2(x_1^2 + x_n^2)x + y_1^2 + y_n^2 - 2(y_1^2 + y_n^2)y & = d_1^2 - d_n^2 \\
x_2^2 + x_n^2 - 2(x_2^2 + x_n^2)x + y_2^2 + y_n^2 - 2(y_2^2 + y_n^2)y & = d_2^2 - d_n^2 \\
... & \\
x_n^2 - x_n^2 - 2(x_n^2 + x_n^2)x + y_n^2 - 2(y_n^2 + y_n^2)y & = d_n^2 - d_n^2
\end{align*}
\]

(4)

By arranging Eq. (4), the linear equation system \( AX = B \) is defined according to Eq. (5).

\[
A = 2 \begin{pmatrix}
(x_n - x_1)(y_n - y_1) \\
(x_n - x_2)(y_n - y_2) \\
... \\
(x_n - x_{n-1})(y_n - y_{n-1})
\end{pmatrix}; 
X = \begin{pmatrix} x \\ y \end{pmatrix}; 
B = \begin{pmatrix} d_1^2 - d_n^2 + x_n^2 - x_1^2 + y_n^2 - y_1^2 \\
d_2^2 - d_n^2 + x_n^2 - x_2^2 + y_n^2 - y_2^2 \\
... \\
d_{n-1}^2 - d_n^2 + x_n^2 - x_{n-1}^2 + y_n^2 - y_{n-1}^2
\end{pmatrix}
\]

(5)

The position of the unknown nodes is determined using the least squares method, which is calculated according to Eq. (6). In Eq. (6) \( A^T \) is the transposition matrix \( A \) and \( A^{-1} \) is the reverse of the matrix \( A \). DV-Hop is straightforward to implement and unknown nodes positioning based on nodes anchorage is done, but must be improved DV-Hop positioning accuracy. According to Figure (2) the number of hop size between AB,
BC and AC is defined as follows: $hop_{AB} = 2$, $hop_{BC} = 5$ and $hop_{AC} = 6$. In the first step, the shortest number of steps between anchor nodes is identified. The value of $hs_A = (30 + 95)/(2 + 6) = 15.62m$, $hs_B = (30 + 70)/(2 + 5) = 14.28m$ and $hs_C = (70 + 95)/(5 + 6) = 15m$. In this example, node U receives the modified value from anchor B, and then estimates its distance from the three anchors. If node U obtains the average interval from node B, the interval between it and the three anchor nodes is equal to $d_{UA} = 14.28 \times 3 = 42.84$, $d_{UB} = 14.28 \times 2 = 28.56$ and $d_{UC} = 14.28 \times 3 = 42.84$. If node U obtains the average interval from node A, the interval between it and the three anchor nodes is $d_{UA} = 15.62 \times 3 = 46.86$, $d_{UB} = 15.62 \times 2 = 31.24$, and $d_{UC} = 15.62 \times 3 = 46.86$. If node U obtains the average distance from node C, the interval between it and the three anchor nodes is $d_{UA} = 15 \times 3 = 45$, $d_{UB} = 15 \times 2 = 30$ and $d_{UC} = 15 \times 3 = 45$, respectively.

The guesstimated distance between the U and B is equal to 28.56, and the interval between U of A is equal to 46.86 and the U of C is equal to 45. If the real distance between U and B is 55 and the guesstimated distance is 28.56, localization error for B is 55-28.56 = 26.44. Its accuracy with real interval is approximately equal to 51%. Due to this error, the guesstimated position of the node of unknown is inaccurate.

Fig. 2 View of the DV-hop based on Anchor and Unknown Nodes

2.2. Previous Works

A hybrid model based on DV-Hop and PSO has been suggested for localization of nodes of sensor [23]. The hybrid model reduces the relationship between unknown nodes and anchor nodes by calculating the number of hop size of all anchor nodes in unknown nodes, which significantly reduces the computational time and energy consumption of nodes. Nodes that have been displaced from their original position are guesstimated. The evaluation was performed in two areas with a size of 100×100 m$^2$ and 50×50 m$^2$. The number of sensor nodes, number of nodes of anchor and transmission range were 100-350, 10-60 and 25 m, respectively. In this paper, error positioning factors and energy consumed are taken into account. The results demonstrated that the hybrid model has improved by about 67%.

A model based on the hybrid of DV-Hop-GA based on random topology, C-Shaped, and W-Shaped topology has been proposed for Positioning [24]. The Positioning process saves computing time and energy consumption. Genetic Algorithm (GA) is used to estimate the interval between unknown nodes and the anchor. The assessment was performed in an environment with a size of 100-100 m$^2$, 100 sensor nodes, 15 nodes of anchor and a
transmission range of 25m. The results demonstrated that DV-Hop-GA had better performance and less positioning error compared to DV-Hop.

The Self-Adaptive Mutation and Crossover operators based Differential Evolution (SA-MCDE) model includes a hybrid of DE and GA based on RSSI method for Positioning [25]. Crossover and mutation operators are used to better explore the solution space. The number of unknown nodes and anchor nodes were 100 and 20, respectively. The assessment results demonstrated that the percentage of Positioning accuracy in the SA-MCDE model was about 40 to 90%.

In order to solve the problem of locating unknown nodes, the hybrid DV-Hop-PSO model has been used [26]. The PSO algorithm has fast search speed, high accuracy, good memory and easy use in engineering. In order to speed up convergence in the DV-Hop-PSO model, dynamic learning factors are updated. The results of experiments with 200 unknown nodes and 30 anchor nodes with a communication radius of 15 meters demonstrated that the PSO had a faster convergence speed and higher spatial accuracy than the DV-Hop non-optimization algorithm.

In [27], the PSO-based PSODV-Hop model is proposed for WSNs. The proposed model reduces the connection between nodes; hence it significantly reduces the energy consumption of the nodes. It also increases positioning accuracy without any additional hardware. Various tests have been performed to confirm the usefulness of the PSODV-Hop algorithm in 100-100 m environment with 100 sensor nodes and 10 anchor nodes. The amount of positioning error in PSODV-Hop was less compared to DV-Hop.

The IDV-Hop model has been proposed to correct the distance between unknown nodes and nodes of anchor based on the Teaching Learning Based Optimization (TLBO) [28]. The purpose of the TLBO algorithm is to correct the distance in order to reduce energy consumption packet transfers. The convergence rate of the TLBO to obtain the solutions is very low. The assessment results with 100 sensor nodes and 25 anchor nodes indicated that the average localization error in IDV-Hop model was low compared to GADV-Hop and DV-Hop-PSO.

Accurate positioning of sensor nodes has a major impact on the performance of WSNs. In [29] a localization method using Butterfly optimization algorithm (BOA) is presented. In order to simulate and validate the DV-Hop-BOA model, different sensor sizes from 25 to 150 nodes have been used for measurement. The performance of the DV-Hop-BOA was compared with those of the PSO and the Firefly Algorithm (FA). The assessment results demonstrated that DV-Hop-BOA had lower error and high accuracy in detecting the location of unknown nodes.

A new optimization method based on intelligent water drops (IWD) algorithm and RSSI has been proposed to average the square error of anchor nodes [30]. RSSI is applied to determine the internal distances between sensor nodes. The IWD algorithm is a high-performance global optimization method that helps minimize the objective function without getting caught up in local optimizations. The assessment results with 100 sensor nodes and 20 anchor nodes confirmed that the proposed algorithm could perform better than optimization algorithms such as Ant Colony Optimization, GA and PSO.

In order to increase the positioning accuracy of nodes in the three-dimensional space of WSNs, two positioning algorithms based on Bacterial Foraging Optimization (BFO) and Invasive Weed Optimization (IWO) have been proposed [31]. In the hybrid method, RSSI is used to estimate the positioning of unknown nodes. A fuzzy logic system is used to overcome the nonlinear relationship between RSSI and node location. BFO and IWO algorithms have been used to further optimize the lateral weights of anchor nodes to increase the positioning accuracy of the nodes. The simulations performed on 100 sensor nodes and 20 anchor nodes demonstrated higher accuracy of the hybrid model by 10%, stability and optimal performance of the hybrid model. Of course, the disadvantage of this method is its high cost and low speed in convergence.
The FA Positioning algorithm has been proposed due to good convergence to estimate the location information of sensor nodes [32]. FA has less computation time and a distributed positioning algorithm and it requires less spatial information exchange between the sensor nodes and the sink node. Compared to conventional algorithms, FA reduces the energy consumption of nodes. Therefore, FA increases the lifespan and reliability of WSNs. Parameters such as absorption coefficient, initial attractiveness; numbers of initial populations are set correctly for optimal convergence. Simulations with 40 sensor nodes and 8 anchor nodes demonstrated that the mean error had a rapid downward slope.

In [33], GA, PSO and SFLA models have been used to improve DV-Hop in the second and third steps. In the second phase of DV-Hop, SFLA was used to correct the HopSize error. In addition, the PSO-GA model in the last step of the DV-Hop algorithm is used to minimize the Root Mean Square Error (RMSE) instead of the trilateration method. The simulations were conducted with 100 sensor nodes, 10 anchor nodes and a transmission range of 40 meters. The combined PSO-GA improves the performance of the DV-Hop by being able to minimize errors between the guessed and actual points of geographic.

Three intelligent algorithms, namely the DE algorithm, the FA algorithm and the hybrid FA-DE model for the positioning problem are presented in [34]. Algorithms are analyzed and compared according to the complexity of time, convergence and accuracy of spatial information. The results with 40 sensor nodes and 10 anchor nodes demonstrated that the hybrid model had less error compared to FA and DE. The accuracy percentage of the hybrid model was 98%.

A new hybrid optimization model based on PSO and Variable Neighborhood Search (VNS) called HPSOVNS has been proposed for positioning [35]. The Mean Squared Error (MSE) and error of all neighboring anchor nodes are used as the objective function in the HPSOVNS model. Internal distances between sensor nodes are calculated using RSSI. HPSOVNS is a hybrid optimization method that has a high performance in finding the best solutions and minimizing the objective function without getting caught up in local optimizations. The hybrid model has increased positioning accuracy because the positive features and effective capabilities of PSO and VNS are combined with RSSI. The assessment results show that HPSOVNS performed better than PSO algorithms, and advanced positioning algorithms such as GEPM, NLLE and RSSI-LSSVR.

An improved version of the Modified Shuffled Frog Leaping Algorithm (MSFLA) is proposed for accurate positioning of sensors [36]. MSFLA results are compared with Trilateration, ABC and PSO algorithms. The assessment results show that MSFLA improved the positioning estimate by more than 30% compared to trilateration. The main disadvantage of MSFLA is that it has a high computational cost.

Table (1) compares the proposed models for positioning based on different factors.

| Refs | Models | Area (m²) | Anchor Nodes | Unknown Nodes | Radius (Meter) | Category | Evaluation Factors |
|------|--------|-----------|--------------|---------------|----------------|----------|---------------------|
| [23] | DV-Hop-PSO | 100×100 | 10-60 | 100-350 | 25 | range-free | -Localization Error; -Energy Consumption; |
| [24] | DV-Hop-GA | 100×100 | 15 | 100 | 25 | range-free | -Localization Error; -Energy Consumption; |
| [25] | SA-MCDE | 100×100 | 20 | 100 | - | range-based | -Localization Error; -Least Square Distance Error; |
| [26] | DV-Hop-PSO | 100×100 | 30 | 200 | 15-40 | range-free | -Influences of beacon node; -Influences of |
3. Basic Concepts
In this section, we describe the KHA and the PSO algorithm.

3.1. Krill Herd Algorithm
Krill Herd Algorithm (KHA) [21] is a nature-inspired algorithm based on krill life that has been proposed to solve optimization problems. This algorithm was presented by Ghandomi and Alavi in 2012. This algorithm is based on the feeding behavior of krill. The shortest distance of each krill from the food and the gathering center of the other krill is the objective function for the krill movement. In the KHA, the KRILL movement is formulated by three main factors:
- Movement induced by other krill individuals
- Foraging
- Random diffusion

When predators such as guinea pigs, penguins or seabirds attack krill, they reduce their density by hunting krill. The formation of a group of krill after the attack depends on many factors. Crowds of krill are formed for the following purposes: to increase the density of krill and to find food. These features have been used in the construction of the KHA.
Attracting krill to crowded places and searching for food causes krill to gather around the optimal global. In this process, krill at the time of looking for food and the highest density are moving towards the best solution. In natural systems, the fit of each krill is an integration of the distance from the food and the maximum density of the krill. In multi-dimensional spaces, the algorithm must be able to search multiple dimensions; Therefore, the Lagrange model is used for the next n decision space. In this algorithm, *Lagrangian* model according to Eq. (7) is used to search for space (position).

\[
\frac{dX_i}{dt} = N_i + F_i + D_i
\]  

(7)

In Eq. (7) \(N_i\) is the motion induced by other krill individuals, \(F_i\) is the foraging motion, and \(D_i\) is the physical scattering of the krill. Each krill will impress others to maintain high density and high speed by movement.  

**Motion induced by other krill individuals:** According to theoretical discussions, krill individuals try to move towards the center of group density. To move through the local swarm density (local effect), the destination of the swarm movement (target effect) and the factors that the swarm avoid are approximated. The motion of other krill is defined according to Eq. (8).

\[
N_i^{\text{new}} = N_i^{\text{max}} \alpha_i + \omega_n N_i^{\text{old}}
\]  

(8)

\[
\alpha_i = \sum_{j=1}^{NN} \frac{K_i - K_j}{K_{\text{worst}} - K_{\text{best}}} \times \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} + 2 \left( \text{rand} + \frac{I}{I_{\text{max}}} \right) \times \hat{R}_{i,\text{best}} \times \hat{X}_{i,\text{best}}
\]  

(9)

In Eq. (8) \(N_i^{\text{max}}\) is the maximum speed and is usually considered to be equal to 0.01 m / s. In Eq. (8) \(\alpha_i\) is the direction of movement, which consists of two parameters: The local effect created by the neighbors (movement due to local density determined by the neighbors) and the directional effect (movement due to the density of the destination determined by the best member of the population) determined by the best krill. Neighbor influence can be considered as a ratio of attractiveness to repulsion among other krill individuals for local search.  

In Eq. (9) \(NN\) is the number of neighbors, \(K_i\) indicates the suitability or value of the target function of the \(i\) member of the population. The parameter \(K_j\) is the suitability value of \(j\)th neighbor, which is \(j = 1, 2, ..., NN\). \(X_i\) and \(X_j\) represent the position of the \(i\) and \(j\) members of a population. \(\varepsilon\) is a small positive value so that the denominator is not zero. In Eq. (9), \(K_{\text{best}}\) and \(K_{\text{worst}}\) are the values of the best and the worst members of the population. These vectors represent the directions of various neighbors, and each value represents the influence of that neighbor. The neighbor vector can be absorbing or repelling. The rand parameter has a random value between 0 and 1 and is intended to increase exploration. Parameter \(I\) is the number of iterations and \(I_{\text{max}}\) is the maximum number of iterations.  

There are several methods for selecting a member’s neighbors from the population, one of which is to use the closest members as neighbors. To do this, a criterion is needed to measure the proximity of members to each other. Eq. (10) is used as the measurement distance to determine neighbors.

\[
d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \|X_i - X_j\|
\]  

(10)

In Eq. (10) \(d_{s,i}\) is the measurement distance for the \(i\)th member of the population and \(N\) is the number of members of the population. The coefficient 5 in the denominator is obtained experimentally. Using Eq. (10), if
the distance is less than two members of the population of the distance measurement, these two are considered together as neighbors. Vector purpose of each krill follows the krill with the best fitness value.

**Foraging Motion:** Foraging motion is expressed with two essential effective parameters. The first is the food situation and the second is the prior experience about the food situation. Foraging motion is defined according to Eq. (11).

\[
F_i = 0.02 \times \left( 2 \left( 1 - \frac{l}{I_{\text{max}}} \right) \times \bar{R}_{i,\text{food}} \times \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \right) + \left( \bar{R}_{i,\text{ibest}} \times X_{i,\text{ibest}} \right) + \omega_f F_{i,\text{old}}
\]

(11)

In Eq. (11) \(V_f\) is equal to the feed rate (value of feed rate is 0.02), \(\omega_f\) is the inertial weight of the foraging motion in the interval [0,1], \(F_{i,\text{old}}\) is the last foraging motion (previous move). The effect of food depends on its position. At first, the food center must be found and its amount should be approximated. As \(K_{i,\text{ibest}}\) position seen by the i member of the population.

**Physical Diffusion (random movement):** The physical diffusion of krill can be considered a random process. This motion is defined as Eq. (12).

\[
D_i = D_{\text{max}} \left( 1 - \frac{l}{I_{\text{max}}} \right) \delta
\]

(12)

\(D_{\text{max}}\) is the maximum scattering velocity and \(\delta\) is the vector of random direction whose values are randomly assigned between -1 and 1. The effect of other of members and foraging motion decreases over time with increasing repetition.

**Motion Process of the KHA (Position Update):** The foraging motion and the movement created by other krill have two local and global techniques. The two work in parallel to power the KHA. According to the formulations of these movements for the first member, if the amount of fit for each of the above positions is better than the fit of the first member, that position has the effect of gravity, otherwise it has a repulsive effect. Using various effective parameters of motion over time, the position vector of a krill during the interval \(t\) to \(t + \Delta t\) is defined by Eq. (13).

\[
X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt}
\]

(13)

\[
\Delta t = C_t \sum_{i=1}^{NV} (UB_j - LB_j)
\]

(14)

Eq. (13) and Eq. (14) are obtained from Eq. (15), which is used to improve the situation.

\[
X_i(t + \Delta t) = X_i(t) + C_t \sum_{i=1}^{NV} (UB_j - LB_j) \times (N_i + F_i + D_i)
\]

(15)

\(NV\) parameter is the total number of variables, \(UB\) and \(LB\) parameters are the upper limit and the lower limit of the j variable, respectively. The \(C_t\) parameter is selected in the range [0,2]. It is clear that the small value of this parameter allows accurate exploration of the search space. To increase the efficiency of the search process, the reproduction operators of the GA have been added to the optimization of the krill group, which include the
crossover and mutation operator. The crossover operator is defined by the probability \( C_r \), the control, and \( m \) after \( X_i \) according to Eq. (16). \( rand_{i,m} \) parameter is a random number in the range [1, 0].

\[
X_{i,m} = \begin{cases} 
    x_{r,m} & \text{rand}_{i,m} < C_r; \\
    x_{i,m} & \text{else}
\end{cases}
\]

Using Eq. (16), the probability of crossover for the global optimization increases to zero with decreasing fit. The mutation operator in the KH algorithm is defined by the control \( Mu \) probability and the second \( m \) after \( X_i \) according to Eq. (17).

\[
X_{i,m} = \begin{cases} 
    x_{gbest,m} + \mu(x_{p,m} - x_{q,m}) & \text{rand}_{i,m} < Mu; \\
    x_{i,m} & \text{else}
\end{cases}
\]

3.2. Particle Swarm Optimization

In the PSO algorithm [22], first group members are randomly generated in the problem space, and the search for the optimal solution begins. In the general structure of the search, each individual follows the individual who has the best fit function, while not forgetting his own experience and follows the situation in which he has the best fit function. Therefore, in each iteration of the algorithm, each individual changes their next position according to two values, one is the best position that the individual has ever had (\( p_{best} \)) and the other is the best position that has ever been created by the entire population and it is actually the best \( p_{best} \) in the whole population (\( g_{best} \)). Conceptually, \( p_{best} \) for each individual in fact is that person's biological memory. \( g_{best} \) is the general knowledge of the population, and when people change their position based on \( g_{best} \), they are actually trying to bring their level of knowledge to the level of knowledge of the population. Conceptually, the best particle in a group binds all the particles in a group together. The next position for each particle is determined by Eq. (18) and Eq. (19).

\[
v_{i+1} = w. v_i + c_1.r_1 \cdot (P_{best_i} - x_i) + c_2.r_2 \cdot (g_{best_i} - x_i)
\]

\[
x_{i+1} = x_i + v_{i+1}
\]

In Eq. (18) \( c_1 \) and \( c_2 \) are learning parameters. \( Rand() \) is a function for generating random numbers in the range [0, 1]. \( Xi \) Parameter is the current position and \( vi \) is the speed of movement of individuals. \( W \) is a control parameter in the range of 0.4 to 0.9, which controls the current velocity (\( vi \)) with the effect of the next velocity, creating a balance between the algorithm's ability to search locally and global search. Large values \( w \) lead to global search and small values lead to local search. In order to balance local and global search, it is necessary to reduce the weight of inertia uniformly during the implementation of the algorithm. If the value of \( w \) decreases, the search is mostly done locally around the optimal answer.

4. KHAPSO Model

In this section, the steps of the KHAPSO model are described step by step. Unknown nodes are considered members of the krill population. The position of unknown nodes is embedded in each vector. The position vector is defined based on Eq. (20). Each vector row represents the solutions and \( S \) demonstrates the number of solutions. The objective function is defined in the proposed model based on error minimization. The matrix \( X \) is
a vector space of size $S \times n$, such a way that $S$ is the number of solutions and $n$ is the length of each solution. The initialization of the vectors is based on a random population of natural numbers (number of sensor nodes), so that each factor contains two variables $x$ and $y$ corresponding to the coordinates of the nodes of unknown.

$$X = \begin{bmatrix}
  x_{1,1} & x_{1,2} & \cdots & x_{1,n-1} & x_{1,n} \\
  \vdots & \vdots & \ddots & \vdots & \vdots \\
  x_{S-1,1} & x_{S-1,2} & \cdots & x_{S-1,n-1} & x_{S-1,n} \\
  x_{S,1} & x_{S,2} & \cdots & x_{S,n-1} & x_{S,n}
\end{bmatrix} \begin{bmatrix}
  f(e) \\
  \vdots \\
  f(e)
\end{bmatrix}
$$

(20)

Using KHA causes each sensor node to constantly change its position to the optimal position. After determining the optimal position for unknown nodes by KHAPSO model, DV-Hop is used to calculate the position of unknown nodes. The network is based on a 2D area with $m$ nodes of anchor and $n$ sensor nodes. Figure (3) displays the KHAPSO model flowchart.
In Figure (4) is shown KHAPSO pseudocode for the localization.

1) Sensory environment deployment
- Sensor Nodes Count (n);
- Percentage of Anchor Nodes (m);
- Communication Range R;

2) DV-Hop: Hop Size Modification

3) Initialize the KHAPSO

Fig. 3 KHAPSO model flowchart for positioning
-The constant value of the variables, such as maximum induced speed, inertia weight, foraging speed
-Initial krill population and searching speed $Ni, Fi, and Di$ are randomly made in the searching space

4. Repeat
5) Evaluate Fitness of Krill Individuals in the Population
- The fitness of each krill is computed, and the global best and worst krill members are defined and saved
6) Main operations in KHA
- Motion Induced by other Individuals
- Foraging motion
- Physical Diffusion
7) Genetic Operators
- Crossover
- Mutation
8) Updating Krill Positions based on PSO ($Gbest \& Pbest$):
- Modify the position of each krill individual using Eq. (24)
- $Gbest$ is the best global solution in the swarm.
- $Pbest$ is the best local solution in the swarm.
9) Generate new krill Individuals
10) Positions is estimated based on KHAPSO
11) Extracted the estimated position with best solution
12) Calculate position of unknown nodes based on Trilateration
13) The estimated position with lowest value of objective function;
14) Until: Termination Conditions
15) Determine the localization error
16) End

Fig. 4 KHAPSO model pseudocode for localization

The steps of the KHAPSO model are described below.

The First Stage (Area Deployment): The anchor nodes $m$ and $n$ sensor nodes are randomly distributed environment. Each anchor node is aware of its location, and each anchor node and unknown node has an R-range. The value of $R$ in the proposed model is equal to 25 meters.

Second Step (Improved distance estimation): In the DV-Hop, the minimum number of hop size between unknown nodes and anchor nodes must be computed. In this step, the distance between all anchor nodes is computed using their actual distance according to Eq. (21). In Eq. (21), the parameters $(x_i - y_i)$ and $(x_j - y_j)$ are the coordinates of the anchor nodes $i$ and $j$, respectively, and $\hat{d}_{ij}$ is the actual distance between the two anchor nodes $i$ and $j$.

\[
\hat{d}_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}
\] (21)

Also, the distance between two anchor nodes is computed by multiplying the number of hop size and $HopSize_i$ of each anchor node. The $d_{ij}$ parameter is the computed distance between the two anchor nodes $i$ and $j$, which is computed according to the definition of Eq. (22).

\[
d_{ij} = h s_i \times h_{ij} \quad \text{where } i \neq j
\] (22)

Based on Eq. (21) and Eq. (22), the error between the calculated distance ($d_{ij}$) and the actual distance ($\hat{d}_{ij}$) of the anchor nodes is obtained. Anchor node distance error is used to compute the correction ratio of an anchor sensor node $i$. 
\[ \text{err}_{ij} = |d_{ij} - \hat{d}_{ij}| \]  

(23)

Dividing the calculated distance error (err) by the number of steps is used to correct the HopSize accuracy of anchor nodes. The distance between anchor node \( i \) and unknown node \( t \) is calculated according to the definition of Eq. (24). The \( h_{it} \) parameter is the number of hop size between anchor node \( i \) and unknown node \( t \).

\[ \hat{d}_{it} = (h_{si} + \frac{\sum_{i \neq j} \text{err}_{ij}}{\sum_{i \neq j} h_{ij}}) \times h_{it} \]  

(24)

Third Step (Estimating the Position of the Unknown Node): In the third stage, the position of the sensors is determined using the KHAPSO model. Foraging motion and movement created by other krill have two strategies, local and global. The strategies work in parallel to make the KH algorithm powerful in discovering optimal points. The main step in the KH algorithm is the motion created by the other krill. The solutions are generated based on updating the current status of each solution using three operators: movement induced by other krill individuals, foraging motion, and random physical diffusion. The first operator is used to encourage members to sustain a high density to find the best anchor node (this operator is used to move members to anchor nodes). The second operator is defined for the members' desire for global optimization, and it is considered a global optimization strategy for the KH algorithm (this operator is defined to attract unknown nodes to the best anchor node). The third factor is used to randomly move each member from a high-density area to a low-density area or vice versa.

The PSO ensures that the hybrid model does not fall into the local optimal trap and discovers the best points based on \( g_{best} \) and \( p_{best} \), and assists the KHA in discovering the optimal positions of members \( i \) and \( j \) from the population. A new method is to update the position of krill members in KHA with the aim of accelerating the global convergence rate. In Eq. (25) \( X_{g_{best}} \) is the position of the best member of the krill in the total particles of the PSO group and \( \text{rand} \) is a generator of random numbers that is uniformly generated in the range [0,1] and \( c \) is a learning parameter in the range 0 to 2.

\[ X_{i}(t + \Delta t) = X_{i}(t + \Delta t) + (X_{p_{best}} - X_{i}(t + \Delta t)) + (X_{g_{best}} - X_{i}(t + \Delta t)) + c \times (\text{rand} - \frac{1}{2}) \]  

(25)

Fourth Step (Calculate the Position of Unknown Nodes): In this step, based on the Trilateration method, the position of unknown nodes is determined. A hypothetical example according to Figure (5) by the Trilateration method to estimate the point \( (x_0, y_0) \) based on three anchor nodes \( (x_1 = 0.1, y_1 = 0.3), (x_2 = 1.1, y_2 = 2) \) and \( (x_3 = 2.2, y_3 = 0.3) \) is solved. The estimate of the unknown node position that is its located in the area of Anchor B should be close to the actual value \( (x_0 = 1.5, y_0 = 1) \).
According to the third step in the DV-Hop, the values \(d_1\), \(d_2\) and \(d_3\) are calculated as Eq. (26). In this step, the value of \(d\) is calculated for anchor nodes A, B and C.

\[
\begin{align*}
(x - x_1)^2 + (y - y_1)^2 &= d_1^2 \
(x - x_2)^2 + (y - y_2)^2 &= d_2^2 \
\vdots \
(x - x_n)^2 + (y - y_n)^2 &= d_n^2
\end{align*}
\]

\[
\begin{align*}
d_1^2 &= \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} = 1.56 \
d_2^2 &= \sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2} = 1.07 \
\vdots \
d_n^2 &= \sqrt{(x_0 - x_n)^2 + (y_0 - y_n)^2} = 0.98
\end{align*}
\]

Vectors A and B are calculated by Eq. (27) and Eq. (28). The values of the anchor points are calculated by vector A and then the value of points of the anchor nodes and the distance between them are determined by vector B.

\[
A = \begin{bmatrix} -2x_1 + 2x_2 & -2y_1 + 2y_2 \\ -2x_2 + 2x_3 & -2y_2 + 2y_3 \end{bmatrix} = \begin{bmatrix} -2(0.1) + 2(1.1) & -2(0.3) + 2(2) \\ -2(1.1) + 2(0.3) & -2(2) + 2(2.2) \end{bmatrix} = \begin{bmatrix} 2 & 3.4 \\ 2.2 & -3.4 \end{bmatrix}
\]

\[
B = \begin{bmatrix} d_1^2 - d_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2 \\ d_2^2 - d_3^2 - x_2^2 + x_3^2 - y_2^2 + y_3^2 \end{bmatrix} = \begin{bmatrix} 5.59 \\ -0.19 \end{bmatrix}
\]

\[
P = (A^T A)^{-1} A^T B = \begin{bmatrix} 1.28 \\ 0.88 \end{bmatrix}
\]

**Fifth Step (Objective Function):** In Eq. (30), the parameters \(x\) and \(y\) are the points of geographic of the unknown nodes (position of the krill population members) and \((x_i,y_i)\) are the points of geographic of the anchor nodes. The parameter \(\hat{d}_{it}\) is calculated by the DV-HOP based on Eq. (24). Since distance is a guesstimated value, it may be prone to error. Therefore, the fundamental purpose of the KHAPSO model is to reduce positioning error. The objective function is defined in the KHAPSO model according to Eq. (30). The objective function is used to evaluate the quality of the position of krill population members and to guide the search algorithm. The optimal solution of the best vector with the minimum amount of fit is considered as the optimal position for unknown nodes.
\[ f(x, y) = \min \left[ \sum_{i=1}^{N} \left| \sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}_{i\ell} \right| \right] \]  

(30)

### 5. Evaluation Criteria

Important factors such as Average Localization Error (ALE) and energy consumption were used for evaluation. The minimum ALE and energy consumption indicate the quality of the KHAPSO model.

#### 5.1. Average Localization Error

Positioning error calculates the difference between the actual coordinates and the guesstimated coordinates of unknown nodes [37]. The ALE is calculated according to Eq. (31). Eq. (31) \((\bar{x}_i, \bar{y}_i)\) shows the guesstimated coordinates of unknown nodes and \((x_i, y_i)\) shows the actual coordinates of unknown nodes. The parameters \(R\) and \(N\) are equal to the transmission range and the total number of unknown nodes, respectively.

\[
\text{ALE} = \sum_{i=1}^{N} \frac{\sqrt{(\bar{x}_i - x_i)^2 + (\bar{y}_i - y_i)^2}}{N \times R} 
\]

(31)

#### 5.2. Energy Consumption in Localization Process

Since WSNs performance and coverage depends heavily on network lifetime, so in terms of energy storage is critical in the design of WSNs. The power supply is limited at the nodes and in practice, it is not possible to replace or recharge it; therefore, the available energy should be used in the best possible way. Energy consumption is a major issue in locating sensor nodes. Energy is mainly used in transmitting the message, receiving the message and the computational process in positioning. Two different types of nodes are deployed in the sensor environment, anchor nodes and unknown nodes that can be informed of their position with the help of anchor nodes. The total energy consumed during the positioning process is calculated by anchor nodes and unknown nodes according to Eq. (33) [38].

\[
E_A = 2 \times E_T + E_c 
\]

(32)

\[
E_U = E_R (1 + M) + E_T (1 + M) + 2 \times E_c 
\]

(33)

In Eq. (33) \(E_T\) is the energy consumed in transmission, \(E_R\) is the energy consumed in reception and \(E_c\) is the energy consumed in computational operations. The average energy consumption by the grid is calculated according to Eq. (34). \(N\) is the number of unknown nodes and \(M\) is the number of anchor nodes.

\[
E_{Average} = \frac{\sum_{i=0}^{M} E_{Ai} + \sum_{i=0}^{N} E_{Ui}}{M + N} 
\]

(34)

### 6. Evaluation and Results

The evaluation of the proposed model, which is a combination of KHA and PSO, was performed in MATLAB 2016 environment. Table (2) illustrates the value of the parameters for evaluation. The network consists of 100-400 unknown nodes that are randomly distributed in a 100x100 area. The sensor nodes communicate with each other via a wireless radio channel and they transmit information in a multi-way mode.
### Table 2 Value of parameters for evaluation

| Parameters                        | Mark  | Value                | Type   |
|-----------------------------------|-------|----------------------|--------|
| Size                              | S     | 100x100 m^2          | WSN    |
| Nodes Deployment                  | -     | Random Distribution  | WSN    |
| Type of Sensor                    | -     | Anchor and Unknown   | WSN    |
| Number of Unknown Node            | m     | 100-400              | WSN    |
| Number of Anchor Node             | n     | 10-80                | WSN    |
| Round                             | -     | 500                  | WSN    |
| Transmission Range                | R     | 25 meters            | WSN    |
| initial energy of the nodes       | $E_{initial}$ | 0.5 Joules           | WSN    |
| Transmitting energy consumption   | $E_T$ | 1.5 mJ               | WSN    |
| Receiving energy consumption      | $E_R$ | 1.15 mJ              | WSN    |
| Computational energy consumption  | $E_c$ | 0.2 mJ               | WSN    |
| Initial population                | Pop   | 30                   | KHAPSO |
| inertia weight                    | $\varnothing$ | 0.6                  | KHAPSO |
| $V_f$                             | foraging speed | 0.02                | KHA    |
| $D^{max}$                         | diffusion speed | 0.008               | KHA    |
| $N^{max}$                         | induced speed | 0.01                | KHA    |
| Learning factor                   | $c_1$ | 1.5                  | PSO    |
| Learning factor                   | $c_2$ | 1.5                  | PSO    |
| Min inertia                       | $\varnothing$ | 0.4                 | PSO    |
| Max inertia                       | $\varnothing$ | 0.9                 | PSO    |
| Maximum iterations                | -     | 200                  | KHAPSO |

### 6.1. The Effect of The Number of Unknown Nodes on Localization Error

Figure (6) illustrates that the Average Localization Error decreased with increasing number of unknown nodes since if the number of nodes is more, they are placed on each other's radio range and discover the anchor node. For assessment, 100x100 area with 30 anchor nodes and 25m transmission range has been used. Unknown nodes range from 50 to 400. According to Figure (6), it can be concluded that the KHAPSO model has a lower Average Localization Error compared to other models. The DV-Hop model has more errors than other models. Also, DV-Hop-KHA and DV-Hop-PSO models have more errors compared to KHAPSO model.
6.2. The Effect of the Number of Anchor Nodes on Average Localization Error

Figure (7) illustrates that the ALE decreased with increasing number of anchor nodes. For simulation, an area of 100×100 with 100 sensor nodes and a transmission range of 25 meters was used. Anchor nodes are variables from 10 to 80. The KHAPSO model has less error compared to the DV-Hop-KHA and DV-Hop-PSO models. If the number of anchor nodes is 80, hence the value of ALE is 0.1648. The DV-Hop model has been able to reduce the amount of error by increasing the number of anchor nodes, but the amount of reduction is very small compared to other models especially KHAPSO.
In Figure (8) for the simulation, an area 100×100 m² has been considered with 400 sensor nodes and 25 m transmission range. Anchor nodes are variables from 10 to 80. From Figure (8), it has been observed that if the number of anchor nodes is equal to 10, then the error value is high. Because the unknown nodes in their sensory range are without anchor nodes, it will be difficult for them to detect the position. The KHAPSO model with about 400 unknown nodes and 80 anchor nodes has improved by about 36% compared to DV-Hop. Also, a comparison of the diagram in Figure (8) shows that the error of DV-Hop-KHA and DV-Hop-PSO models is less than that of DV-Hop model.
6.3. The Effect of the Number of Unknown Nodes on Energy Consumption

As presented in Figure (9), energy consumption increases as the number of unknown nodes raises. Because with increasing the number of sensor nodes, the computation time also increases and so, the frequency of sending and receiving in the environment increases. For simulation, an area of 100×100 square meters with 30 anchor nodes and a transmission range of 25 meters is used. Unknown nodes range from 100 to 400. Energy consumption in the DV-Hop model is higher than other models. The KHAPSO model consumes less energy compared to the DV-Hop-KHA and DV-Hop-PSO models. Because in less time it can find the location of unknown nodes and prevent additional calculations.
6.4. The effect of number of anchor nodes on energy consumption

Figure (10) shows the effect of the number of anchor nodes on energy consumption. As shown in Figure (10), with increasing number of anchor nodes, energy consumption has increased. Because as the number of anchor nodes increases, the distribution of multicast messages across the network environment between unknown nodes in order to find the minimum number of hop size and store in the routing table increases. For simulation, an area of 100×100 square meters with 400 sensor nodes and a transmission range of 25 meters have been used. Anchor nodes are variable from 10 to 80. Energy consumption in the DV-Hop model is higher than other models. The KHAPSO model consumes less energy compared to the DV-Hop-KHA and DV-Hop-PSO models.
The results of evaluations demonstrated that the KHAPSO model had better performance compared to the DV-Hop, DV-Hop-KHA and DV-Hop-PSO models.

7. Conclusion and Future Research

Recent developments in wireless communications and electromechanical equipment innovations have expanded the use of WSNs. Localization of sensor nodes has become one of the necessities in WSNs applications. In WSNs, some sensor nodes are aware of their position and play important roles in locating other nodes, and the location of these nodes, usually determined by GPS, is known as anchor nodes. Using anchor nodes, the location of unknown nodes can be found. But a precise localization mechanism must be used for the location of unknown nodes. In this paper, a model based on KHA and PSO for sensor node localization is proposed. PSO was used to optimize KHA. KHA solutions were optimized by PSO and KHA exploration power was increased. The results demonstrated based on different criteria that the performance of the KHAPSO model was better compared with other models. The KHAPSO model was evaluated based on the number of different unknown nodes as well as the number of anchor nodes. Evaluations demonstrated that if the number of anchor nodes is more, then the error value is less. Compared to the DV-Hop model, the KHAPSO model was able to reduce energy consumption by about 35% for 400 sensor nodes and 30 anchor nodes. A decrease in average error and at the same time, the 35 percent reduction in energy consumption means an increase in stability and life span of the network which leads to a reduction in maintenance cost and network management. Therefore, with these successful results, we concluded that the KHAPSO model was better than the DV-Hop, DV-Hop-KHA and, DV-Hop-PSO models.

Issues such as optimal placement of anchor nodes in the sensor area, finding the best position for the mobile sink, and examining the optimal coverage of anchor nodes due to lack of scalability, incompatibility, and increase of computational cost should be considered as localization problems. To direction future researches, we can use a hybrid of different meta-heuristic algorithms to expressed problems. Meta-heuristic algorithms using two factors of exploration and extraction can learn in search environments and can find the best solution.
conflicts of interest: Jafarsadegh Kamfar, Hessam Zandhessami, and Mahmood Alborzi declare that they have no conflict of interest.

References

[1] J. Jiang, G. Han, H. Wang, and M. Guizani, "A survey on location privacy protection in Wireless Sensor Networks," *Journal of Network and Computer Applications*, vol. 125, pp. 93-114, 2019/01/01/ 2019.

[2] F. T. Zuhra, K. A. Bakar, A. Ahmed, and M. A. Tunio, "Routing protocols in wireless body sensor networks: A comprehensive survey," *Journal of Network and Computer Applications*, vol. 99, pp. 73-97, 2017/12/01/ 2017.

[3] B. M. Sahoo, H. M. Pandey, and T. Amgoth, "GAPSO-H: A hybrid approach towards optimizing the cluster based routing in wireless sensor network," *Swarm and Evolutionary Computation*, vol. 60, p. 100772, 2021/02/01/ 2021.

[4] G. Han, H. Xu, T. Q. Duong, J. Jiang, and T. Hara, "Localization algorithms of Wireless Sensor Networks: a survey," *Telecommunication Systems*, vol. 52, pp. 2419-2436, 2013/04/01 2013.

[5] W. Liu, E. Dong, and Y. Song, "Robustness analysis for node multilateration localization in wireless sensor networks," *Wireless Networks*, vol. 21, pp. 1473-1483, 2015/07/01 2015.

[6] Y. Wei, W. Li, and T. Chen, "Node localization algorithm for wireless sensor networks using compressive sensing theory," *Personal and Ubiquitous Computing*, vol. 20, pp. 809-819, 2016/10/01 2016.

[7] C. Poellabauer, "Range-Free Localization Techniques," in *The Art of Wireless Sensor Networks: Volume I: Fundamentals*, H. M. Ammari, Ed., ed Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 353-384.

[8] D. Ma, M. J. Er, B. Wang, and H. B. Lim, "Range-free wireless sensor networks localization based on hop-count quantization," *Telecommunication Systems*, vol. 50, pp. 199-213, 2012/07/01 2012.

[9] A. S. Paul and E. A. Wan, "RSSI-Based Indoor Localization and Tracking Using Sigma-Point Kalman Smoothers," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, pp. 860-873, 2009.

[10] E. Xu, Z. Ding, and S. Dasgupta, "Source Localization in Wireless Sensor Networks From Signal Time-of-Arrival Measurements," *IEEE Transactions on Signal Processing*, vol. 59, pp. 2887-2897, 2011.

[11] Z. Yanping, H. Daqing, and J. Aimin, "Network localization using angle of arrival," in *2008 IEEE International Conference on Electro/Information Technology*, 2008, pp. 205-210.

[12] T.-X. Cong, E.-C. Kim, and I. Koo, "RSS Based Localization Scheme Using Angle-Referred Calibration in Wireless Sensor Networks," in *Advanced Intelligent Computing Theories and Applications. With Aspects of Theoretical and Methodological Issues*, Berlin, Heidelberg, 2008, pp. 1222-1233.

[13] D. Niculescu and N. Badri, "Ad hoc positioning system (APS) using AOA," in *IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No.03CH37428)*, 2003, pp. 1734-1743 vol.3.

[14] D. Niculescu and B. Nath, "Ad hoc positioning system (APS)," in *GLOBECOM'01. IEEE Global Telecommunications Conference (Cat. No.01CH37270)*, 2001, pp. 2926-2931 vol.5.

[15] S. Čapkun, M. Hamdi, and J.-P. Hubaux, "GPS-free Positioning in Mobile Ad Hoc Networks," *Cluster Computing*, vol. 5, pp. 157-167, 2002/04/01 2002.

[16] R. Nagpal, "Organizing a global coordinate system from local information on an amorphous computer," *AIM-1666*, vol. 1, pp. 1-12, 1999.

[17] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. Abdelzaher, "Range-free localization schemes for large scale sensor networks," presented at the Proceedings of the 9th annual international conference on Mobile computing and networking, San Diego, CA, USA, 2003.

[18] Y. Huang and L. Zhang, "Weighted DV-Hop Localization Algorithm for Wireless Sensor Network based on Differential Evolution Algorithm," in *2019 IEEE 2nd International Conference on Information and Computer Technologies (ICICT)*, 2019, pp. 14-18.

[19] L. Gui, T. Val, A. Wei, and R. Dalce, "Improvement of range-free localization technology by a novel DV-hop protocol in wireless sensor networks," *Ad Hoc Networks*, vol. 24, pp. 55-73, 2015/01/01/ 2015.
A. L. a. Bolaji, M. A. Al-Betar, M. A. Awadallah, A. T. Khader, and L. M. Abualigah, "A comprehensive review: Krill Herd algorithm (KH) and its applications," Applied Soft Computing, vol. 49, pp. 437-446, 2016/12/01/2016.

A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," Communications in Nonlinear Science and Numerical Simulation, vol. 17, pp. 4831-4845, 2012/12/01/2012.

J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proceedings of ICNN'95 - International Conference on Neural Networks, 1995, pp. 1942-1948 vol.4.

V. Kanwar and A. Kumar, "DV-Hop localization methods for displaced sensor nodes in wireless sensor network using PSO," Wireless Networks, 2020/08/10 2020.

V. Kanwar and A. Kumar, "DV-Hop based localization methods for additionally deployed nodes in wireless sensor network using genetic algorithm," Journal of Ambient Intelligence and Humanized Computing, 2020/03/30 2020.

V. Annepu and A. Rajesh, "Implementation of self adaptive mutation factor and cross-over probability based differential evolution algorithm for node localization in wireless sensor networks," Evolutionary Intelligence, vol. 12, pp. 469-478, 2019/09/01 2019.

D. Xue, "Research on range-free location algorithm for wireless sensor network based on particle swarm optimization," EURASIP Journal on Wireless Communications and Networking, vol. 2019, p. 221, 2019/09/03 2019.

S. P. Singh and S. C. Sharma, "A PSO Based Improved Localization Algorithm for Wireless Sensor Network," Wireless Personal Communications, vol. 98, pp. 487-503, 2018/01/01 2018.

G. Sharma and A. Kumar, "Improved DV-Hop localization algorithm using teaching learning based optimization for wireless sensor networks," Telecommunication Systems, vol. 67, pp. 163-178, 2018/02/01 2018.

S. Arora and S. Singh, "Node Localization in Wireless Sensor Networks Using Butterfly Optimization Algorithm," Arabian Journal for Science and Engineering, vol. 42, pp. 3325-3335, 2017/08/01 2017.

B. F. Gumaida and J. Luo, "Novel localization algorithm for wireless sensor network based on intelligent water drops," Wireless Networks, vol. 25, pp. 597-609, 2019/02/01 2019.

G. Sharma and A. Kumar, "Fuzzy logic based 3D localization in wireless sensor networks using invasive weed and bacterial foraging optimization," Telecommunication Systems, vol. 67, pp. 149-162, 2018/02/01 2018.

R. Harikrishnan, V. Jawahar Senthil Kumar, and P. Sridevi Ponmalar, "Firefly Algorithm Approach for Localization in Wireless Sensor Networks," in Proceedings of 3rd International Conference on Advanced Computing, Networking and Informatics, New Delhi, 2016, pp. 209-214.

M. Mehrabi, H. Taheri, and P. Taghdiri, "An improved DV-Hop localization algorithm based on evolutionary algorithms," Telecommunication Systems, vol. 64, pp. 639-647, 2017/04/01 2017.

R. Harikrishnan, V. Jawahar Senthil Kumar, and P. Sridevi Ponmalar, "A Comparative Analysis of Intelligent Algorithms for Localization in Wireless Sensor Networks," Wireless Personal Communications, vol. 87, pp. 1057-1069, 2016/04/01 2016.

B. F. Gumaida and J. Luo, "A hybrid particle swarm optimization with a variable neighborhood search for the localization enhancement in wireless sensor networks," Applied Intelligence, vol. 49, pp. 3539-3557, 2019/10/01 2019.

V. R. Kulkarni, V. Desai, and R. V. Kulkarni, "A comparative investigation of deterministic and metaheuristic algorithms for node localization in wireless sensor networks," Wireless Networks, vol. 25, pp. 2789-2803, 2019/07/01 2019.

F. Zeng, W. Li, and X. Guo, "An Improved DV-Hop Localization Algorithm Based on Average Hop and Node Distance Optimization," in 2018 2nd IEEE Advanced Information Management,Communicates,Electronic and Automation Control Conference (IMCEC), 2018, pp. 1336-1339.
F. Khelifi, A. Bradai, A. Benslimane, M. L. Kaddachi, and M. Atri, "Energy-Saving Performance of an Improved DV-Hop Localization Algorithm for Wireless Sensor Networks," in *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, 2017, pp. 1-6.