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Localization of Nodes in Wireless Sensor Networks using a Combination of Krill Herd Algorithm with Ant Colony Optimization

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***Abstract*- The industrial revolution and the spread of electronic technologies and wireless communications has led to the production of small smart sensors with low consumption and low-cost benefits. Sensor nodes work as autonomous low cost system, smaller size with wireless communication media but they work with low resources. The most significant item in the operation of Wireless Sensor Networks (WSNs) is finding the spatial information of objects, including retrieval and identification of events, routing according to geometric position, monitoring and tracking. Localization in WSNs is divided into two range-based and range-free categories. In this paper, in order to overcome the weaknesses of DV-Hop, a hybrid model based on the Krill Herd Algorithm and Ant Colony Optimization called KHAACO was proposed for locating unknown nodes. The aim of this study is to provide an approach for estimating the location of sensor nodes with minimal error and using KHAACO to estimate the location of unknown nodes and using the motion characteristics of other krill, foraging and spatial dispersion of the KHA and optimizing it with ACO. The evaluation of the hybrid model in the MATLAB environment has been done based on error criteria and energy consumption. The results showed that the hybrid model compared to DV-Hop, DV-Hop-ACO, and DV-Hop-PSO reduced the Localization error. The value of localization error reduction for 90 anchor nodes and 450 sensor nodes was equal to 9.95%.**

***Index Terms*-** Wireless Sensor Networks, Localization, DV-Hop, Krill Herd optimization, Ant Colony Optimization

I. INTRODUCTION

Wireless Sensor Networks (WSNs) include low cost, low power consumption, and automatic configuration sensor nodes [1]. Inexpensive sensor nodes provide intelligence and monitoring

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capabilities for many applications, such as monitoring and controlling various structures, from homes to cities [2]. In addition, WSNs are widely used in the field of measuring devices such as public infrastructure (street lamps, billboards, and etc.) [3].

The physical location of the sensor nodes is required to detect events. Event information received by the sink is meaningless and worthless without node location information [4]. Manual deployment of sensor nodes is one of the easiest ways to locate nodes [5], but it is practically impossible to deploy and cover on a large scale and out of reach. The Global Positioning System (GPS) is the most straightforward system for localization, but this method increases the cost of the network and at the same time consumes more energy [6].

Many methods have been proposed for positioning WSNs in the field of sensor position estimation. These methods are classified into two main classes [7]: range-based and range-free localization. Range-based localization techniques use accurate measurement techniques and usually require costly equipment to determine location information or accuracy between neighboring nodes. Some range-based location algorithms include RSSI [8], TOA [9], TDOA [10], and AOA [11]. Range-free methods use distance estimation algorithms to locate sensors without the need for expensive hardware. Range-free localization algorithms mainly use anchor nodes that are aware of their position. Anchor nodes are used to locate unknown nodes. There are many rage-free location algorithms, such as Centroid Algorithm [12], DV-Hop [13], Amorphous [14], Multidimensional Scaling (MDS) [15], and APIT [16]. Although range-based algorithms provide accurate results and rage-free location algorithms have a higher priority for large-scale wireless sensor networks due to their low cost and simplicity. In this paper, a new method based on the combination of the Krill Herd Algorithm (KHA) and the ACO algorithm called KHAACO is proposed to improve DV-Hop localization. [17, 18].

The DV-Hop has some features such as simplicity and low cost and is more popular. However the DV-Hop algorithm has some limitations, including low location accuracy, high power consumption, and high communication overhead .The paper aims to solve the shortcomings of KHA by using the ACO algorithm. KHA has some disadvantages like slow convergence and low accuracy during evolution. In this paper, a hybrid model is proposed to improve the position of krill based on the ACO algorithm. The main contributions of this paper are as follows:

- A review of the work done in the field of localization based on various factors.
- Improving the DV-Hop algorithm based on estimated distance and number of steps.
- Presenting the KHAACO model to estimate the position of unknown nodes accurately.
- Using the ACO algorithm to improve KHA in order to increase the accuracy of detecting the position of unknown nodes& Analysis and evaluation of KHAACO model with DV-Hop, KHA, ACO, and PSO models.

This paper is organized as follow: In Section 2, related works are reviewed.Section 3, we describe proposed model.Section 4, evaluation and results are analyzed, and finally conclusion and future works are showed in Section 5.

II. RELATED WORKS

Over the past few decades, extensive research into DV-Hop improvement has been proposed, and each has its advantages and disadvantages. The criterion for reducing location error is the most essential criterion to be considered in location. An advanced design of DV-Hop called 3DeDV-Hop was proposed to localize nodes [19]. The DV-Hop algorithm was modified based on the average number of weighted steps. The simulation was performed on OMNET++ and in the 500×500 environment based on the positioning error factor. The results showed that the error rate in 3DeDV-Hop was lower compared to 3DDV-Hop. A hybrid model based on DV-Hop and runner-root optimization algorithm was proposed for localization [20]. The most important goals of the hybrid model are to calculate the number of steps in all unknown nodes, to reduce the number of messages transmitted between unknown nodes and anchor nodes. Considering the above-mentioned items, leads to a reduction in positioning time and energy, and minimizes the cost of hybrid model communications. The results showed that the computational time and energy consumption in the hybrid model were less compared to the genetic algorithm and particle community optimization.

The parallel whale optimization algorithm (PWOA) was used to locate the unknown nodes to achieve optimal number of steps [21]. The PWOA algorithm includes two strategies for exchanging information between groups and significantly increases the global search ability and population diversity in WOA. The results in the 100×100 environment showed that the PWOA error rate was lower than DV-Hop and PSO. Each localization method has certain advantages and limitations in terms of performance [22]. Four well-known positioning methods were analyzed, such as DV-Hop, 2D-Hyperbolic (2DH), Weighted Centroid Localization (WCL), and Concentric Anchor Based (CAB). Also, DV-Hop-based hybrid models have been proposed to reduce positioning error. The simulation was performed in a 500×500 environment with 1500 sensor nodes. A comparison between the DV-2D, DV-Weighted and DV-Cab models showed that the DV-2D model had less error.

The Grey-Wolf optimization algorithm is used to improve the DV-Hop algorithm [23]. The GWO-DV-Hop and Weighted GWODV-Hop models have been used to improve DV-Hop. In these models, the second step (estimating the distance between the anchorage and the unknown node) is changed. Unknown nodes calculate their position with all anchor nodes regarding the effect of mean distances. The results showed that the error rate of the models was less compared to DV-Hop, considering the number of sensor nodes and radio radius. In order to improve DV-Hop, a modified particle swarm algorithm optimization has been used for localization [24]. For creating equilibrium between local search and global search, particles inertia weight and acceleration coefficients are used adaptively. Particles in the search space look for the best positions for unknown nodes. The simulation in the 100×100 region showed that the MPDV-HOP model has less error compared to the DV-Hop and PDV-Hop models.

A hybrid localization algorithm using APIT and DV-Hop is proposed [25]. The APIT algorithm is used for DV-HOP shortcomings. The three main objectives of the hybrid model to achieve localization accuracy and network coverage are as follows: 1) Adopt angle detection to determine the exact direction of unknown nodes. 2) Triangle formation by APIT algorithm for all unknown nodes. 3) Assigning weight to nodes by DV-Hop algorithm for the minimum number of steps. The results in the 100×100 range with 100 sensor nodes show that the hybrid model improvement was about 49%. An improved DV-Hop algorithm based on RSSI is proposed, which was called RFDV-Hop [26]. The model is divided into two stages. In the first step, RSSI is used to replace the number of steps in DV-Hop to calculate the initial position of unknown nodes. In the second step, the difference between the actual location embedded in the anchor nodes and the estimated location calculated from DV-Hop is used as the adjustment factor, and the actual location of the unknown nodes is calculated by calculating the distance between the unknown nodes and the anchor. Simulations have shown that RFDV-Hop has been able to reduce localization error effectively. In irregular networks such as C-shaped and X-shaped, the position detection mechanism plays a significant role in network stability.

A hybrid DV-Hop based on a Modified Cuckoo Search algorithm has been proposed for localization [27]. The hybrid model can dynamically adjust the search step size and calculate the node coordinates instead of the estimation method using the Cuckoo Search algorithm. The simulation results in the 200-200 region showed that the HMCS-D model compared to DV-Hop and CS-D reduced the average positioning error by 39.7% and 10.6%, respectively. The improved Hop-DV algorithm based on the Mass-Spring Model is proposed for positioning [28]. In the DV-hop-MSO model, the sum of squares of error is used to bring the two nodes closer. The DV-hop-MSO model also uses sensor node energy as a measure of network stability. Position changes in sensor nodes are based on updates. Results in the 100×100 environment with 300 sensor nodes showed that the DV-hop-MSO model has a lower error rate than the DV-Hop.

A combined PSO-DV-Hop model has been proposed to improve DV-Hop for detecting the exact position of unknown nodes [29]. In this model, the position of the best particle is used to detect neighboring nodes. The evaluation function is based on the distance and the number of steps. Simulation in a 300-300 environment with 100 sensor nodes has been shown that the detection accuracy of PSO-DV-Hop is higher compared to DV-Hop. The improved DV-Hop algorithm based on the clustering strategy reduces the communication overhead in the first stage of the DV-Hop algorithm [30]. The RSSI method has been used to replace the distance measurement of the number of steps to detect the distance between anchor nodes and unknown nodes. For the position of the nodes,

Table I. Comparison of proposed models for Localization of sensor nodes.

Refs	Models	Area	Number of Unknown	Number of Beacon	Comparisons	Evaluations
[19]	3DeDV-Hop	500×500	400-800	100-140	3DDV-Hop	*Localization error *Localization coverage
[20]	RRA DV-Hop	100×100 300×300	100-350	25-150	*DV-Hop *GA DV-Hop *PSO DV-Hop	*Computation Time (s) *Localization Error *Localization Error Variance
[21]	PWOA	100×100	200	5-40	*DV-Hop *PSO	*average localization error
[22]	DV-2D	500×500	1500	100-450	DV-Weighted DV-CAB	*localization error
[23]	GWO-DV Hop	100×100	200-450	20-80	*DV-Hop	*Localization error
	Weighted GWO-DV Hop	300×300	200-450	20-80	*DV-Hop	*Localization error
[24]	MPSO (MPDV-HOP)	100×100	120	20	*DV-Hop *PDV-Hop	*Localization Error *Average Localization Error
[25]	APIT+DV-Hop	100×100	100	30	*APIT *DV-Hop	*Localization error
[26]	RFDV-Hop	100×100	100	5-40	*DV-Hop	*Average Localization Error
[27]	HMCS-D	200×200	150	5-40	*DV-Hop *CS-D	*Average position error
[28]	DV-hop-MSO	100×100	300	5-40	*DV-Hop	*The positioning error
[29]	PSO-DV-Hop	300×300	100	15	*DV-Hop	*Localization precision
[30]	Improved DV-Hop	100×100	200	10	*DV-Hop	*Localization Error *Number of Data Packets
[31]	VN-APIT	200×200	100	8-36	*APIT *PIT *Centroid *Amorphous	*Average localization error
[32]	DV-MAXHOP	100×100	150	20	*DV-Hop *SISR *MDS-MAP	*localization error
[33]	Improved DV-Hop	100×100	100	30	*DV-Hop *DDV-Hop	*Average position error
[34]	PSO-RSSI	100×100	100	4	*PSO *GA	*Average position error

the Newton-like optimization method is used instead of the least-squares method. The simulation results showed that the improved DV-Hop algorithm was able to reduce the location error without increasing the computational complexity significantly. Table (1) shows a general comparison of the proposed models for positioning and DV-Hop improvement.

A new virtual node-based range-free localization called VN-APIT is proposed to improve APIT. By logically deploying virtual nodes in the sensor network by the VN-APIT model, detecting unknown nodes inside or outside the triangle formed by the three anchor nodes is determined. Evaluation of the results shows that the VN-APIT model contains less localization error than the APIT algorithm [31]. The DV-MAX HOP model is proposed using multi-objective optimization functions to minimize positioning errors and the number of steps [32]. A multi-objective optimization was set up to minimize location error (or maximize accuracy) and minimizes convergence time (algorithm execution time). Convergence time (and therefore energy cost) is minimized by reducing communication overhead. During the localization process, the number of transfers is reduced so that the total energy consumption is reduced and leads to faster convergence. The results in O-shaped, Sshaped, and C-shaped modes showed that the DV-Hop was more accurate than other models and reduces energy consumption. An improved DV-Hop with a Multi-communication radius was presented [33]. In this method, based on the multi-communication radius localization algorithm, the cosine theorem is used to correct the number of steps and estimate the average distance. The algorithm uses multiple radii for the data broadcasting localization to obtain the minimum number of steps between the unknown node and the anchor node. After estimating the distance of the number of steps, it adjusts the estimated distance using the cosine theorem. Experimental results showed that compared to the DV-Hop and the DDV-Hop algorithm, the improved DV-Hop improved the position accuracy and reduced the average position error of unknown nodes. An RSSI-based PSO is proposed for positioning [34]. The model uses the weight factor of inertia for local and global search. High inertia weight is more favorable for global search and low inertia weight is more favorable for local search. For better balance in global and local search capability, the PSO algorithm has used the improved inertia weight coefficient. Evaluations in 100×100 area showed that the improved PSO had less error.

III. Proposed Model

The purpose of the localization problem in WSNs, which consists of M sensor nodes, is to estimate the location of N unknown nodes using the location information of anchor nodes; it means M-N with R transfer range. If the sensor node is within the transmission range of three anchor nodes or more, then positioning for the sensor node is calculated. Fig. (1) shows a hybrid model flowchart and Fig. (2) shows Pseudocode of the hybride model. The purpose of the hybrid model is to improve the KHA using ACO. The ACO has a high feedback and distribution mechanism in the problem space. ACO algorithm selects solutions in which the remaining pheromone intensity is higher and the ant population has converged towards them to discover solutions.The steps of the hybrid model are as follows.

Step 1 (Environment Deployment): Initially, m anchor nodes and n sensor nodes are randomly distributed in the environment. A set of unknown unknown sensor nodes $N = \{n_1, n_2, \dots, n_s\}$ are defined to cover the environment. Each anchor node is aware of its location and the nodes have an R transmission range. The value of R in the hybrid model is equal to 25 meters.

At this stage, the minimum number of hop count between anchor nodes and unknown nodes is calculated. Anchor nodes broadcast a message that includes identification code and a hop count to their neighbors, and the initial value of the hop counter is zero. The sensor that receives the message, increases the hop counter by one step and compares it with the value stored in its data table. If the number of steps is less than the previous value in the data table, this value is recorded for that node and the number of stored hop count is updated, otherwise, the message will be ignored and some hop

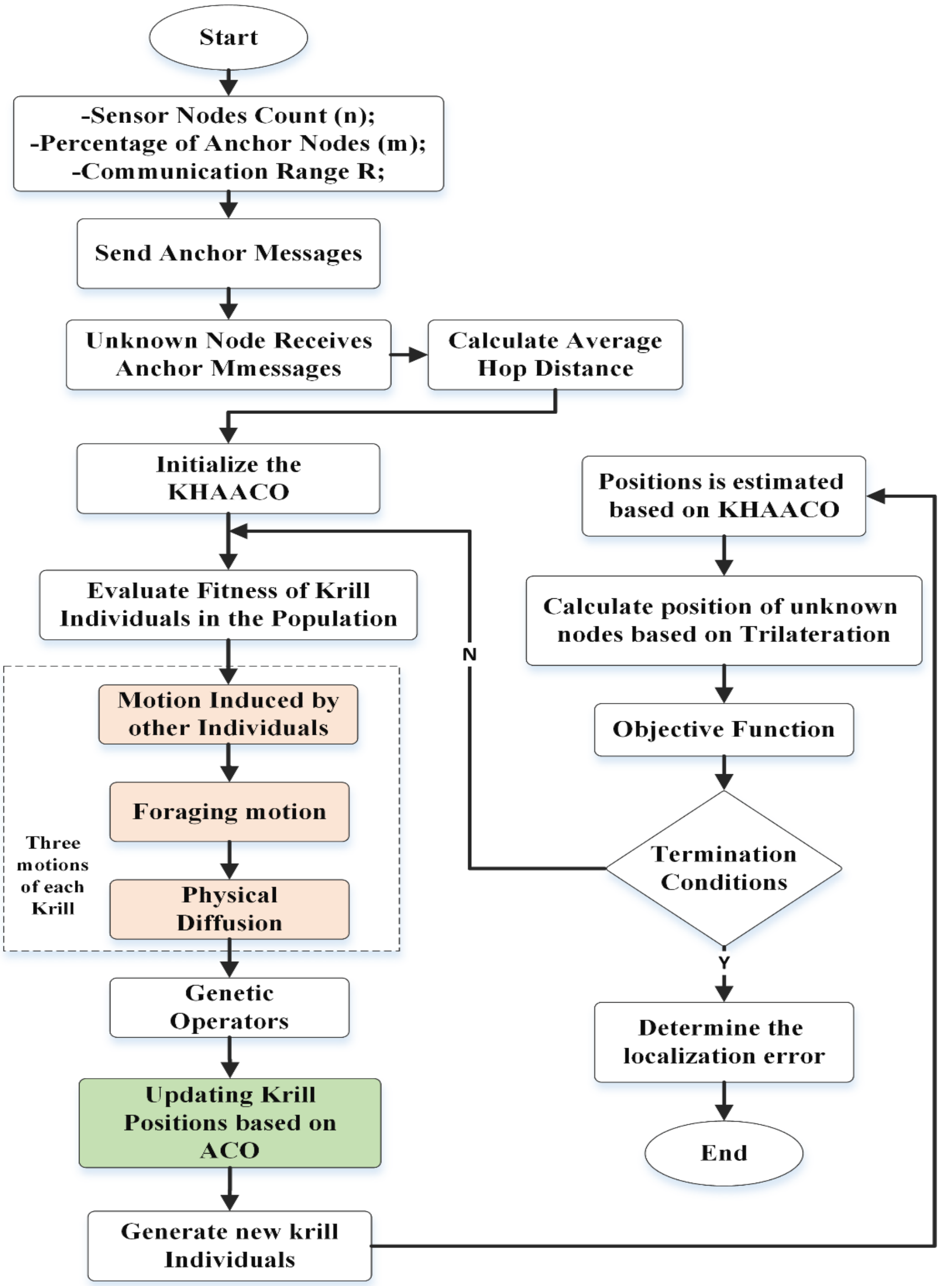

Fig. 1. Flow chart of hybrid model.

count will be sent to the next nodes by adding a unit to the hop counter. At the end of this step, all the unknown sensors have a number of hop count to the anchors.

Step 2 (Improve the estimation of the distance between the anchor and the unknown node): In the hybrid model to reduce the error between the estimated position and the actual position, a new method based on the weight value is used to calculate the number of steps. The aim is to reduce DV-Hop error and correctly detect the location of unknown nodes. All unknown nodes receive anchor

01. Sensory environment deployment
  *Sensor Nodes Count (n);
  *Percentage of Anchor Nodes (m);
  *Communication Range R;
02. DV-Hop: Hop Size Modification
03. Initialize the KHAACO
04. Initialize algorithm parameters V_f, D^{max}, N^{max}, NP, and minimum and maximum bounds
05. Randomly generate krill individuals (solutions)
06. Evaluate the objective function
06. **while** (stopping condition is not met) **do**
07. Store the pre-specified number of best krill
08. **For** each krill
  *Motion induced by the presence of other individuals
  *Calculate Foraging action
  *Calculate Physical diffusion
09. Implement crossover operator.
10. Updating Krill Positions based on ACO
  *Generate the new Positions (using probabilistic rule)
  *Evaluate new Positions
11. Positions is estimated based on KHAACO
12. Extracted the estimated position with best solution
13. Calculate position of unknown nodes based on Trilateration
14. The estimated position with lowest value of objective function;
15. **End if**
16. Evaluate the objective function value f and update the krill individual if necessary
17. **end for**
18. Replace the worst krill with the best krill stored before
19. **End while**
20. Determine the localization error
21. End

Fig. 2. Pseudocode of the hybride model.

node's messages, and an unknown node may receive multiple-step number messages from anchor nodes. If an anchor node is closer to an unknown node, then the average number of steps is less. Eq. (1) determines the average number of steps between anchor nodes.

$$\boldsymbol{w} = \frac{\left(\sum_{i=1}^{N} \frac{h_i}{\sum h_i} \times hs_i\right)}{N}; \quad \mathbf{hs}_i = \frac{\sum_{j \neq i}^{N} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum_{j \neq i}^{N} h_{ij}}, \tag{1}$$

In Eq. (1), the matrix of w is calculated as the average number of hop count, h_i is the number of hop counts, parameters (x_i, y_i) and (x_j, y_j) are the position of the anchor nodes i and j, N is the number of anchor nodes, hs_i is the shortest number of hop count between anchor nodes, and h_{ij} is the number of steps from the anchor node i to the anchor node j. In the new method, the value of ε is used to reduce the error. The mean error of the number of hop count between anchor nodes is defined according to Eq. (2).

$$\boldsymbol{\varepsilon} = \sum \left(\frac{\left| (\sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2}) - \boldsymbol{w} \times \boldsymbol{h_{ij}} \right|}{\boldsymbol{h_{ij}}} \right), \quad (2)$$

In Eq. (2), the parameters (x_i, y_i) and (x_j, y_j) are the position of the anchor nodes i and j, h_{ij} is the number of hop count from the anchor node i to the anchor node j. Within each sensor node a table is stored as $\{x_i, y_j, hop\ count\}$ for the number of hop count. Actual distance and estimated distance between anchor nodes are calculated by absolute value. Therefore, the value of the number of improved steps is defined based on Eq. (3).

$$\boldsymbol{hs_c} = \boldsymbol{hs_i} + \boldsymbol{\varepsilon}\,, \quad (3)$$

The distance between anchor node *i* and unknown node *t* is calculated as Eq. (4). In the new model, the estimated position of the nodes is much closer to the actual position compared to DV-Hop. This model reduces the number of hop count in positioning error and increases positioning accuracy.

$$\boldsymbol{\acute{d}_{it}} = \boldsymbol{hs_c} \times \boldsymbol{h_{ij}} \quad \boldsymbol{where\ i \neq j}\,, \quad (4)$$

Step 3 (estimating the position of the unknown node): To estimate the coordinates of unknown nodes, the KHAACO model is run independently. A population is generated with n krill, so that initially the position of each krill is randomly initialized. The position of the krill is then updated based on Eq. (5) and new points are found in the network space. The parameters $X_j^{max}$and $X_j^{min}$are the maximum and minimum values in the vector jth, respectively, and rand is a random function between 0 and 1. In Eq. (5), N^{max} is the maximum velocity and is usually considered to be 0.01 m/s.

$$\boldsymbol{X_i^{new}} = \boldsymbol{X_i^{t+1}} + \boldsymbol{N^{max}} + \frac{(\boldsymbol{X_j^{max}} - \boldsymbol{X_j^{min}})}{\boldsymbol{2}} \times \boldsymbol{rand}[\mathbf{0}.\mathbf{1}], \quad (5)$$

The initial population vector is defined based on the number of nodes. Whatever each node is selected, the x and y coordinates are calculated for it. Search is done by krill to find the coordinates of unknown nodes in the network environment. The ACO ensures that the hybrid model does not get stuck in the optimal local trap, and the best points based on ants is discover and assists the KHA in discovering the optimal position of the ith and jth members of the population. The path of the krill to the optimal points is stored by the ACO in vector η_{ij}. The vector η_{ij} is defined according to Eq. (6). As C is defined by the coordinates of the sensor nodes as $C_{ij}(t) = C_i(t) - C_j(t)$ and $D_{ij}(t)$ is the distance between krill ith and jth.

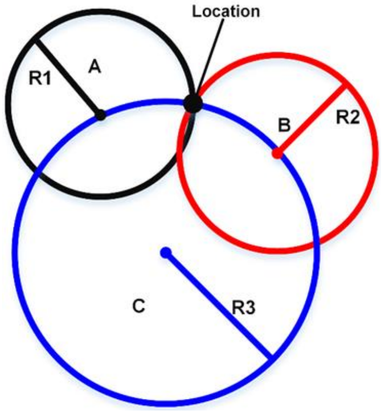

Fig. 3. The intersection of three nodes with transmission range R1, R2 and R3.

$$\eta_{ij}(t) = \begin{cases} e^{C_{ij}(t).D_{ij}(t)} & i \neq j \\ e^{C_i(t)} & i = j \end{cases}, \tag{6}$$

The aim of the new method to update the position of krill members in KHA is to accelerate the global convergence rate. Once the new krill is found, its suitability is assessed. If the fitness of the new krill is better than the fitness of the previous krill, the old position will be replaced with the new krill position. Otherwise, the old position is preserved. This step is repeated for all members of the krill. Finally, the elitist method is used to preserve the best krill in the population for the next generation. Using this method, krill members go to the best solution in the search space by a random jump. Therefore, local trouble is prevented and it converges quickly.

Step 4 (Calculate the position of unknown nodes): In this step, based on the Trilateration method, the position of the unknown nodes is determined. In the Trilateration method, the location is estimated by determining the intersection of three circles. Fig. (3) shows the intersection of three nodes with transmission ranges R1, R2, and R3.

According to the DV-Hop algorithm, the values d_1, d_2, and d_3 are calculated as Eq. (7). So d_1, d_2, and d_3 are the distances between unknown nodes and anchor nodes A (x_1, y_1), B (x_2, y_2), and C (x_3, y_3), respectively.

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 = d_2^2 \\ \vdots \\ (x - x_n)^2 + (y - y_n)^2 = d_n^2 \end{cases}, \tag{7}$$

The position of the unknown nodes is determined using the least-squares method, which is calculated according to Eq. (8). In Eq. (8) A^T is the transposition matrix A and A^{-1} is the inverse of the matrix A. In Eq. (8), the value of *P* is equal to the values of *x* and *y* of the unknown node. The values of the anchor points are calculated by vector *A* and then the values of the points of the anchor nodes and the distance between them are determined by vector *B*. In Eq. (8), the transposition of matrix *A* is calculated and multiplied by matrix A. Then, the inverse of matrix *A* is calculated.

$$\boldsymbol{P} = (\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A})^{-\boldsymbol{1}}\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{B}\ , \tag{8}$$

Step 5 (objective function): In Eq. (9), the parameters x and y are the coordinates of the unknown nodes (position of the krill population members) and (xi, yi) are the coordinates of the anchor nodes. The $\acute{d}_{it}$ parameter is calculated by the modified DV-HOP. The primary purpose of the KHAACO model is to reduce positioning errors. The objective function is defined in the KHAACO model according to Eq. (9). The objective function is used to evaluate the quality of the position of krill population members and to guide the search algorithm. 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 least amount of fitting is considered as the optimal position for unknown nodes.

$$\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{min}\left[\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{N}}\left|\sqrt{(\boldsymbol{x}-\boldsymbol{x}_{\boldsymbol{i}})^{\boldsymbol{2}} + (\boldsymbol{y}-\boldsymbol{y}_{\boldsymbol{i}})^{\boldsymbol{2}}} - \acute{\boldsymbol{d}}_{\boldsymbol{it}}\right|\right], \tag{9}$$

N≥3 indicates the number of anchor nodes in the unknown node transfer range. The distance between anchor nodes and unknown sensor nodes is modeled using modified DV-Hop. The distance of each unknown node is calculated using $\acute{d}$. The sub-radical value is the distance between the coordinates of the unknown nodes (y, x) and the coordinates of the anchor nodes(xi, yi).

A. Time Complexity

1) KHA

The complexity of meta-heuristic algorithms depends on their structure. Therefore, the complexity of the proposed model depends on the size of the population, the number of solutions, the dimensions of the decision and the maximum number of iterations. The time complexity of the KH algorithm depends on two main steps, which are the calculation of motion and the updating of krill positions. Thus, the time complexity of KHA is defined as Eq. (11). The KHA termination criterion is the number of iterations during optimization (T is the number of iterations). For each individual in the population (N is the number of individual), the fitness function assessments are equal to O (T×N). In Eq. (11), T the maximum number of iterations is N, the number of krill, and D is the dimension of the problem.

$$\boldsymbol{O}(\boldsymbol{KH}) = \boldsymbol{O}\left(\boldsymbol{t}\big(\boldsymbol{O}(\boldsymbol{motion\ neighbors}) + \boldsymbol{O}(\boldsymbol{position\ update})\big)\right), \tag{10}$$

$$\boldsymbol{O}(\boldsymbol{KH}) = \boldsymbol{O}\left(\boldsymbol{t}\big(\boldsymbol{N}^{\boldsymbol{2}} \times \boldsymbol{D} + \boldsymbol{N} \times \boldsymbol{D}\big)\right) = \boldsymbol{O}\big(\boldsymbol{TN}^{\boldsymbol{2}}\boldsymbol{D} + \boldsymbol{TND}\big) = \boldsymbol{O}\big(\boldsymbol{TN}^{\boldsymbol{2}}\boldsymbol{D}\big), \tag{11}$$

2) ACO

The most important factors in the ACO algorithm are the number of initial populations, pheromone updates and the number of iterations. The complexity of this algorithm at its best equals to $O(T \times N^3)$. A value of N^2 represents the process of pheromone evaporation, value of N represents the process of pheromone update, and a T represents the number of iterations.

3) KHAACO

The computational complexity of KHAACO is crucial in determining runtime. The complexity of KHAACO depends primarily on the structure of the algorithms. Thus, the complexity of KHAACO depends on the size of the solution population, the dimensions of the decision variables, and the maximum number of iterations. The time complexity of KHAACO consists of three main components: the computational complexity of the movement of the krill, the computational complexity of updating the krill, and the pheromone operation. The complexity of the proposed model in terms of big-O is defined as Eq. (12).

$$\boldsymbol{O}(\boldsymbol{KHAACO}) = \boldsymbol{O}\left(\boldsymbol{TN^2D} + \boldsymbol{TN^3}\right), \tag{12}$$

IV. Evaluation and Results

The evaluation of the proposed model, which is a combination of KHA and ACO, was performed in MATLAB 2018 environment with 20 independent times run. Table (2) shows the value of the parameters for evaluation. The sensor nodes communicate via a wireless radio channel and transmit information in a multi-channel mode.

WSNs require fine-tuning to increase detection performance and accuracy. It is necessary to prepare the following items in order to launch the hybrid model:

- Several sensor nodes are located in a two-dimensional environment in a square area of size L×L. Each node is sound and has the ability to receive and send information and has primary energy.
- Some fixed unknown sensor nodes are randomly placed in a uniformly distributed environment.
- Unknown nodes are not aware of their geographical location. Therefore, in order to send data, they must first discover their location.
- Each sensor node in the network has a fixed transmission range (R).
- There are several anchor nodes in the network environment. Anchor nodes send messages to other sensor nodes in their transmission range.
- Unknown nodes can calculate the localization process if they receive three different message.

Table II. Value of Parameters for Evaluation.

Parameter	Abbreviation	Type	Value
Network size	S	WSN	200×200 m^2
Arrange the nodes	-	WSN	random distribution
Kind of nodes	-	WSN	Anchorage & unknown
Number of unknown nodes	U	WSN	100-450
Number of anchor nodes	A	WSN	10-90
The number of repetitions	-	WSN	500
transmission range	R	WSN	25 meters
The initial energy of the nodes	I_{nitial}	WSN	0.5 Joules
Transmitting energy consumption	E_T	WSN	1.5 mJ
Receiving energy consumption	E_R	WSN	1.15 mJ
Computational energy consumption	E_c	WSN	0.2 mJ
Initial population	Pop	ACO	30
pheromone rate	α	ACO	1
pheromone rate	β	ACO	5
V_f	foraging speed	KHA	0.02
D^{max}	diffusion speed	KHA	0.008
N^{max}	induced speed	KHA	0.01
Maximum iterations	-	KHAACO	200

B. Evaluation Criteria

Essential factors such as mean localization error and energy consumption were used for evaluation. The minimum average positioning error and energy consumption indicate the quality of the KHAACO model.

C. Average Localization Error

Localization error calculates the difference between the actual coordinates and the estimated coordinates of unknown nodes. The average localization error is calculated according to Eq. (13) [35]. Eq. (13) $(\bar{x}_i, \bar{y}_i)$ shows the estimated coordinates of the unknown nodes and (x_i, y_i) the actual coordinates of the unknown nodes. The parameters R and N are equal to the transmission range and the total number of unknown nodes, respectively.

$$\mathbf{ALE} = \sum_{\mathbf{i=1}}^{\mathbf{N}} \frac{\sqrt{(\bar{\mathbf{x}}_\mathbf{i} - \mathbf{x}_\mathbf{i})^2 + (\bar{\mathbf{y}}_\mathbf{i} - \mathbf{y}_\mathbf{i})^2}}{\mathbf{N} * \mathbf{R}}, \tag{13}$$

D. Energy Consumed

Since the performance of WSNs is highly dependent on the life of the network and its network coverage, it is critical to consider energy storage in the design of WSNs. The power supply in the nodes is limited 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 localization. In the sensor environment, two different types of nodes are deployed, anchor nodes and unknown nodes that can be informed of their location 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. (14) and Eq. (15) [36].

$$\boldsymbol{E_A = 2 \times E_T + E_c}, \tag{14}$$

$$\boldsymbol{E_U = E_R(1+M) + E_T(1+M) + 2 \times E_c}, \tag{15}$$

Energy is an important criterion for determining the position of nodes. It is not possible to detect the position if the nodes do not have enough energy. In Eq. (15), 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. (16). *N* is the number of unknown nodes and *M* is the number of anchor nodes.

$$\boldsymbol{E_{Average} = \frac{\sum_{i=0}^{M} E_{Ai} + \sum_{i=0}^{N} E_{Ui}}{M+N}}, \tag{16}$$

E. The effect of the number of unknown nodes on localization error

Fig. (4) shows the effect of the number of unknown nodes on positioning error. The number of anchor nodes is equal to 90. As shown in Fig. (4), the KHAACO model contains a smaller amount of positioning error compared to other models. The localization error value for 450 sensor nodes in the KHAACO model is 0.2805 and in the DV-Hop model is 0.3084. Also, the DV-Hop-ACO and DV-Hop-KHA models have lower error rates than the DV-Hop.

F. The effect of the number of anchor nodes on the average localization error

In Fig. (5), the effect of the number of anchor nodes on positioning error is shown. The number of unknown nodes is 450. It is clear from Fig. (5) that if the number of anchor nodes is 10, then the localization error value for the 450 sensor nodes in the KHAACO model will be 0.3792 and in the DV-Hop model is 0.4587. Also, if the number of anchor nodes is equal to 50, then the amount of localization error in the KHAACO model is equal to 0.3568 and in the DV-Hop model is equal to

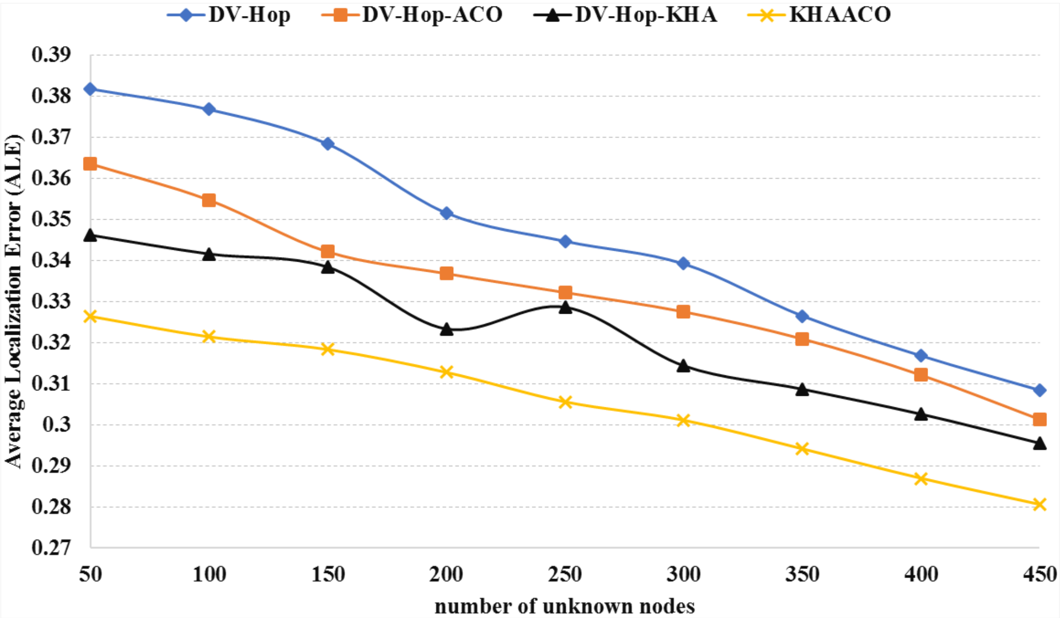

Fig. 4. The effect of the number of unknown nodes on localization error.

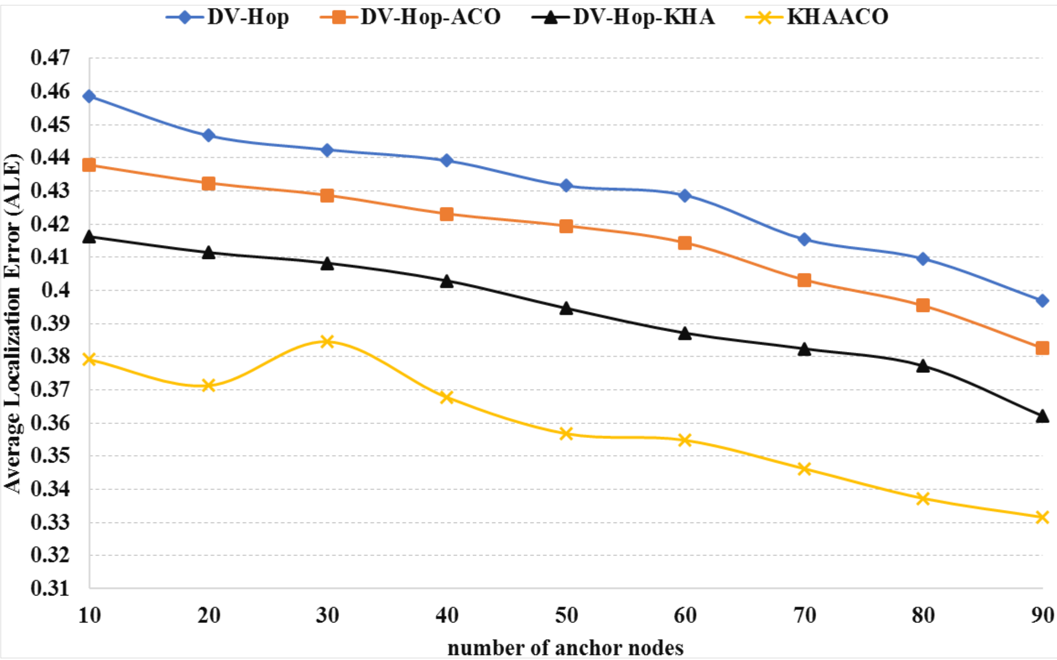

Fig. 5. The effect of the number of anchor nodes on localization error.

0.4316. According to the results, it can be concluded that the hybrid model has been able to reduce the amount of error.

G. The effect of radio range on the average localization error

The effect of radio range on positioning error is shown in Fig. (6). The numbers of anchor nodes and unknown nodes are 90 and 450, respectively. Fig. (6) indicates that if the radio range is 20,

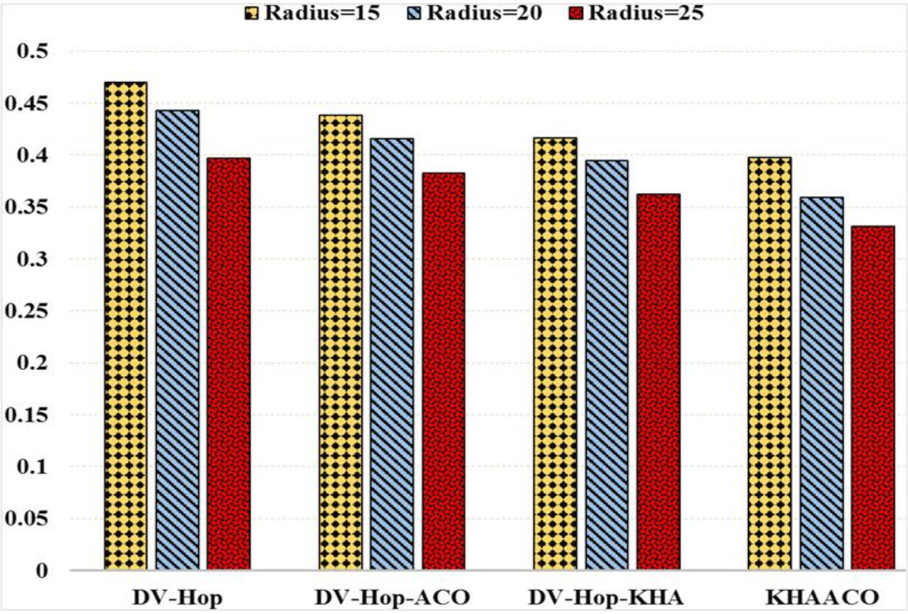

Fig. 6. The effect of radio range on localization error.

then the localization error values in the KHAACO and DV-Hop models are 0.4698 and 0.3978, respectively. In DV-Hop-ACO and DV-Hop-KHA models, it is equal to 0.4381 and 0.4165, respectively. Also, if the radio range is equal to 20, then the localization error values in the KHAACO and DV-Hop models are 0.4426 and 0.3591, respectively. The hybrid model has a higher recovery rate compared to other models and the error rate has decreased with increasing radio range.

H. The effect of the number of unknown nodes on energy consumption

The effect of the number of unknown nodes on energy consumption is shown in Fig. (7). The number of anchor nodes is equal to 90. It is clear from Fig. (7) that if the number of unknown nodes is greater, then the energy consumption will be higher. Because as the number of nodes increases, the network environment will include sending and receiving many packets, and therefore the energy consumption of nodes will increase due to communication. If the number of unknown nodes is 450, then the power consumption of the KHAACO and DV-Hop models will be 68.55 and 48.94, respectively.

I. The effect of the number of anchorage nodes on energy consumption

The effect of the number of anchor nodes on energy consumption is shown in Fig. (8). The number of unknown nodes is 450. According to Fig. (7) if the number of anchor nodes increase, then the energy consumption will act the same. The hybrid model uses less energy compared to the DV-Hop, DV-Hop-ACO and DV-Hop-KHA. The energy consumed in the case of the number of anchor nodes in the KHAACO model and DV-Hop model is equal to 68.47 and 42.61, respectively.

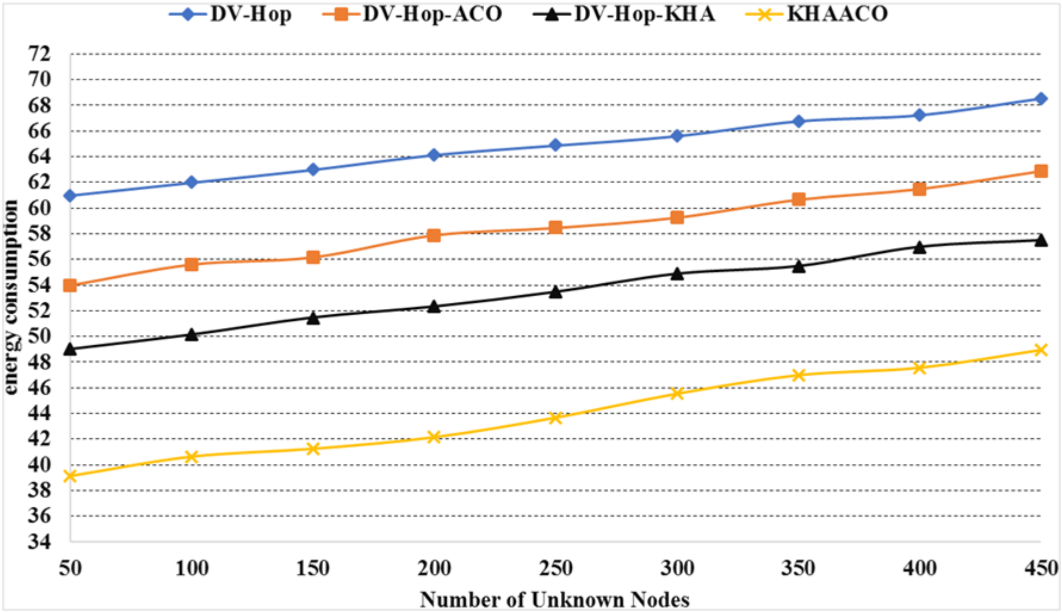

Fig. 7. The effect of the number of unknown nodes on energy consumption.

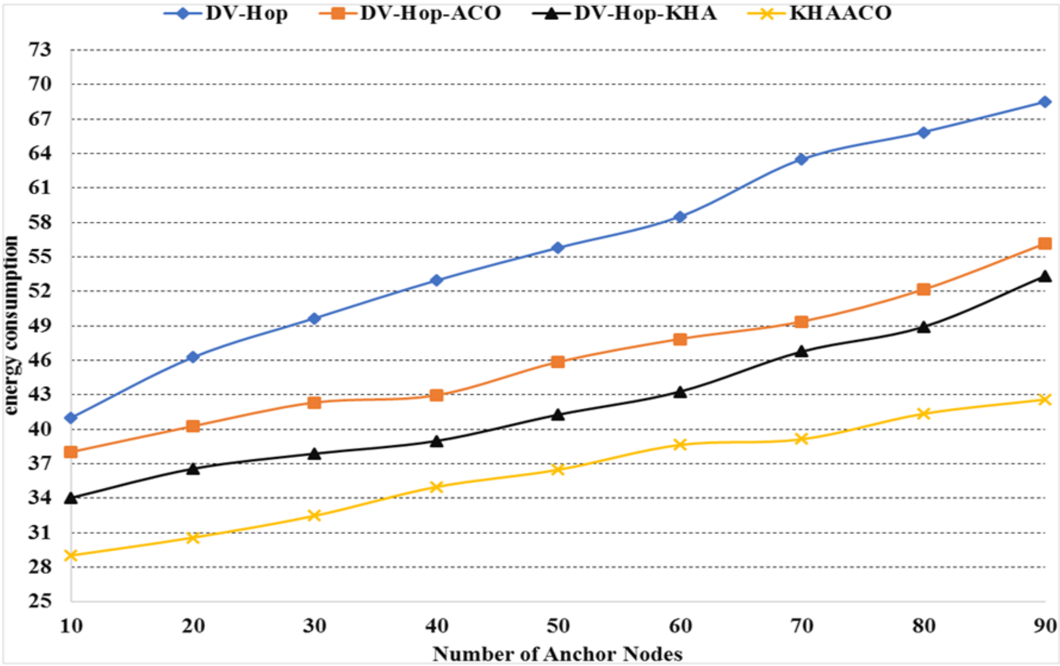

Fig. 8. The effect of the number of anchorage nodes on energy consumption.

Comparison of localization error of the models was performed in the same communication radius and based on different densities of anchorage nodes. The communication radius *R* was adjusted to 25 m and the number of anchor nodes gradually increased from 10 to 90. The DV-Hop positioning error was 0.4587 for 10 anchor nodes and 0.3968 for 90 anchor nodes. In contrast, the localization model of the hybrid model was 0.3792 for 10 anchor nodes and 0.33.15 for 90 anchor nodes.

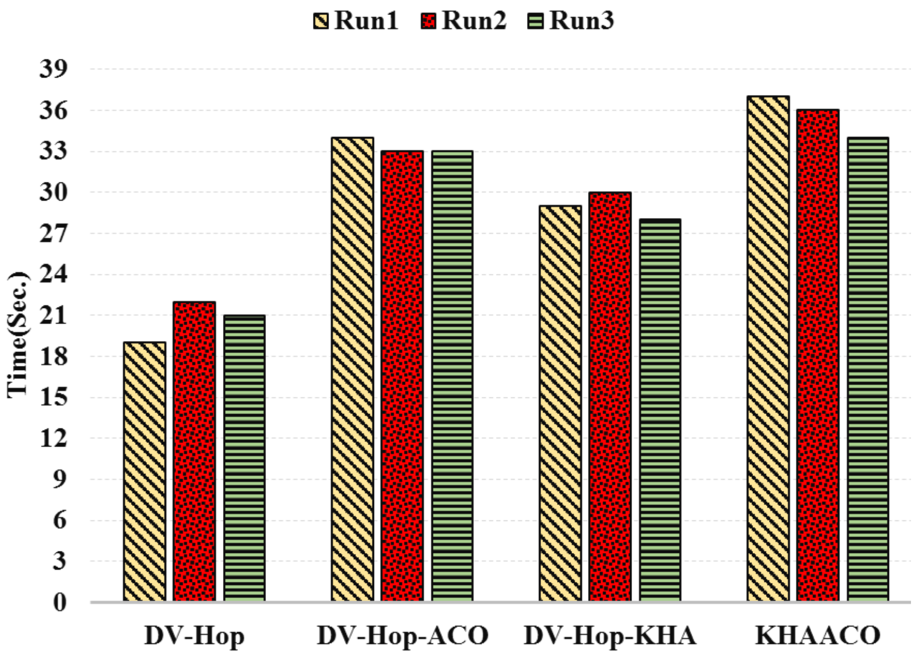

Fig. 9. Chart of time complexity of models.

J. Complexity comparison

Fig. (9) shows the time complexity diagram of the models for 450 unknown nodes and 90 anchor nodes. Comparisons show that the KHAACO model has a longer time compared to other models. However, evaluations have shown that the error rate and power consumption are lower in the KHAACO model. The results show that KHA has a shorter execution time than ACO.

V. CONCLUSION AND FUTURE WORKS

Due to the disadvantages of the DV-Hop, and in some other disadvantages mentioned in this article, such as high localization error and number of step error, DV-Hop is not a suitable and efficient method for localizing WSNs. In this paper, a new method based on KH and ACO algorithms, which are meta-heuristic algorithms, is proposed for localization. The ACO was used to optimize the KH algorithm and the goal was to increase the detection accuracy of the KHA. The ACO enhances the localization of the krill. The hybrid model was evaluated based on criteria such as localization error, number of anchor nodes and energy consumed. The experiments showed that the hybrid model had a significant improvement compared to the DV-Hop and other models. The reduction of localization error in the hybrid model with 90 anchor nodes and 450 sensor nodes compared to DV-Hop was 9.95%. Also, the percentage of energy reduction in the combined model with 90 anchor nodes and 450 sensor nodes compared to DV-Hop was equal to 37.77%. The comparison of the localization error means with the DV-Hop was performed under different radio communication radius. 450 knots were performed by increasing the communication radius R from 15 meters to 25 meters. In the hybrid model, when the communication radius of the nodes increased, the positioning error was less and the positioning performance was better. For future studies, localization error using the same hybrid algorithms for moving sensors with variable speed in wider geographical environments can be investigated.

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