An Optimized K-Nearest Neighbor Algorithm for Extending Wireless Sensor Network Lifetime

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Abstract. This paper presents an optimized K-nearest neighbors (KNNs) classification algorithm using the metaheuristic whale optimization to searches for sink node in wireless sensor networks. Sink node aggregate data from all sensor nodes and reducing the energy consumption network to prolong network lifetime. To reach aforementioned, a fitness function has formulated to choose the best location of sink node with high residual neighbor's sensor nodes energy to leads to maximizing the network lifetime. Eventually, the experimental results have been conducted whereas sensor nodes are propagated in a random location within the desired network area. The system has 11% improvement on the network's energy consumption that increases the lifetime of the network.

Keywords: *K-Nearest Neighbor Algorithm, energy-efficient, classification, Wireless sensor networks, swarm optimization.*

1 Introduction

In recent advances, the development of Wireless Sensor Networks (WSNs) [1] is expanding rapidly. It consists of huge number of sensor nodes that are with low cost, small volume, wireless communication, data processing ability, sensing, storage, and energy resources. There are various applications of WSNs, such as home security, surveillance, disaster relief, healthcare, and environmental monitoring [2]. WSN contains base-station with one or more sinks that aggregate data from all sensor nodes and send to sink node. Sink node location can actively decreases the energy consumption and increase the lifetime of the network by reducing the distance between the sensor and sink node [3], [4] have proposed an approach to finding positions of multiple stationary sink nodes. Sensor nodes allow communicating with one or multiple sinks through multiple paths in order to improve the network lifetime. A sink node was designated device similar to the regular sensor nodes but with more power. The main task of the sink node in wireless sensor networks (WSNs) is forwarding the messages directly to both of the sink nodes and the farthest one to save their energy. Many sensor nodes will become quickly unable to communicate with the base station, and the network becomes nonoperational. Consequently, the choice of the best location of sink node to receive all messages from sensor nodes without consuming their energies suddenly is a big challenge in WSNs.

Network energy and lifetime introduced by many of authors such as Chen and Li superior the energy-oriented strategy presented by Hou et al., [5] regarding networks lifetime that have developed an efficient polynomial-time heuristic algorithm (SPINDS), which attempted to increase the network lifetime by iteratively moving a relay node to another enhanced location. A single objective swarm such as a discrete version of the whale optimization algorithm was presented in [6] to determine the active nodes which cover all nodes and inactive nodes in network topology to prolong the WSNs lifetime. Also, in [7] introduced an algorithm to solve the multiple base station locations. To achieve the balance among clusters over which existing sink location for small to medium scale WSNs, Slama et al. have utilized a graph partitioning techniques [8], in [9] proposed a hybrid algorithm of both Simulated Annealing and Bee Algorithm for a weighted minimal spanning tree (BASA-WMST) and another bio-inspired techniques to build that topology such as the PSO-minimum spanning tree-based topology control scheme [10], which called the non-dominated discrete particle swarm optimization (NDPSO) also in [11] proposed method to determine position of sink node with reduce the number of active nodes to prolong network's lifetime via PSO. Most of simulations of WSN use the sink node that is placed at the center of the region. Estimation of nodes physical coordinates in a 2-dimensional deployment area though a number of previously located beacon nodes using PSO and bacterial foraging algorithm (BFA) [12], or solving coverage problem related to the dynamic sensors deployment using Artificial Bee Colony (ABC) [13].

Some paper focus on Centralized approaches such as [14], [15], [16] that provide accurate global information and implementation of these approaches are expensive in practice due to significant communication overheads required for gathering information. These approaches are unfeasible for WSNs that typically have a large number of sensor nodes. For this reason, distributed approaches are preferable to centralized approaches. in [17] propose an approach for optimizing the lifetime of sensors network by divide network into disjoint sets that each set represents a tree to optimize the lifetime of network by using an efficient algorithm for balancing weight between trees in the network. Rafael Asorey-Cacheda in [18] addresses concern of network's lifetime and proposes some techniques to plan an arbitrary WSN, presents an algorithm that approaches the results of the optimization framework to calculate the optimal assignment of renewable energy supplies to maximize network lifetime.

Most studies and simulations were executed based on this placement strategy. Efrat et al. [19] and Jun and Hubaux [20] have proposed model that called the P-Median Problem (PMP) to determine the sink node placement. Also, in [20] has proved that the center of the circle is the optimal position for a base station in WSNs, but the conclusion is only suitable for the uniform deployment of nodes. In [21] is proposed method to choose position of sink node to maximize the weight of data flows to reduce the energy consumption. In [22] proposed joint routing and compressed aggregation to minimize the network energy consumption that characterize the optimal solution to this optimization problem, and propose a mixedinteger programming formulation along with a greedy heuristic, from which both the optimal and the near-optimal aggregation trees are obtained.

There are two types of localization of WSNs algorithms are range-based algorithms [23] and range-free algorithms [24] that depend on physical attributes of the wireless signals transmitted between antennas. The base station (sink node) utilizes information that receives from other nodes to build a map of the network and estimate the position of the sensor, a sink node address in self-configuration topology raises another issue that influences the performance of the WSN in terms of energy, delay, and network lifetime. Consequently, the location of sink node should be accurately selected in order to maximize the networks lifetime.

Some of the researchers introduced strategies for determining the location of sink nodes such as the proposed strategy by Chen and Li [25] which contain the energy-oriented and lifetime oriented strategies in both the single-hop and multiple-hop WSNs. Sensor nodes allow communicating with one or multiple sinks through multiple paths in order to improve the network lifetime. The optimal placement for a given number of sinks is equivalent to the clustering problem and should be solved using a clustering algorithm, and other works focus on single sink node is introduced by Oyman, E.I., Ersoy [26].

Other researches focus on power control, for example, authors in [27], [28], [29] use technique that controls the nodes transmission power but it does not aim to achieve the energy efficiency of an entire network and power control as a technique that nodes transmit power to achieve a node such as energy efficient algorithms of the wireless transceiver. Another power control technique mentioned in [30] is the technique that aims to select the best transmit power level for a single wireless transmission. Techniques that aim to achieve the energy efficiency of the entire network instead of a node-wide or channel-wide perspective are considered to power control.

This work proposes whale optimization algorithm based KNN to better solve some the problem of finding the best location of single sink node in with reducing energy consumption to prolong network lifetime in WSNs environment. Moreover, after choosing the location of sink node in the network determines best of nearest neighbors nodes. Finally, the performance of the proposed WOA-KNN is compared with another algorithm such as particle swarm optimization based k-nearest neighbor (PSO-KNN).

The structure of the paper is organized as follows: we present the network model and assumptions and methods that used In Section 2, overview proposed algorithm, in Section 3 the proposed Whale optimization based topology control algorithm, In Section 4, simulation results are considered, and we conclude the paper in Section 5.

2 Preliminaries

2.1 Network Model and Assumptions

Assume wireless sensor network with a set of sensor nodes that consists of an active and inactive node and a single sink node that gather data from all sensor nodes in a network. Sensor nodes are randomly distributed in a given area $R = L \times L$, where L is the side length. The sensor nodes have a power source, bandwidth and memory, and they might sensor down from the network at any time due to limited battery lifetime. We assume that the sink node (base station) is far away from the nodes, but it is connected with a set of sensor nodes. In Figure 1 illustrate Network Model and assumptions that used in this work.

Assumptions We consider the following assumptions about the sensor network model N:

- Let S be a set of sensor nodes that are distributed randomly and uniformly in a given area R. All sensor nodes have the same capabilities such as mobility, homogeneous, limited memory and power.
- Let $AN = AN, ..., AN_n$be the set of active nodes. All active nodes have the amount of memory, power, and bandwidth.
- Let Sk be the sink node that collects data from all sensor nodes.

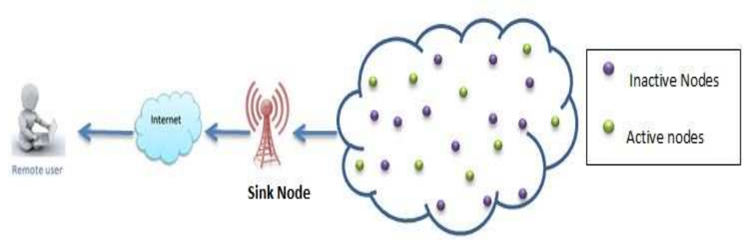


Figure 1: Network Model architecture of wireless sensor network.

2.2 Whale Optimization Algorithm

Mirjalili et al. proposed Whale Optimization Algorithm (WOA) [31], is considered one of swam intelligent application [32,33] that is a novel nature-inspired meta-heuristic optimization algorithm, the whales movement are considered to be intelligent animals. The WOA is inspired by the unique hunting behavior of humpback whales. Usually the humpback whales prefer to hunt small fishes or krills which are close to the surface of sea. Whales swim around prey within a shrinking circle and along a spiral-shaped path simultaneously in order to create bubbles along a circle or '9'-shaped path.The mathematical model of WOA is described in the following sections encircling prey, bubble net hunting method, search the prey. To simulate this behavior in WOA, their formulations are designed as follows:

Shrinking encircling preys: The target prey and the other search agents try to update their positions towards it. This behavior is represented by the following formula:

$$\overrightarrow{X}(t+1) = \overrightarrow{X}(t) - A.\overrightarrow{D} \tag{1}$$

$$\overrightarrow{D} = |C\overrightarrow{X}^*(t) - \overrightarrow{X}(t)| \tag{2}$$

$$A = 2.a.r - a \tag{3}$$

$$C = 2.r \tag{4}$$

Where$\overrightarrow{X}$ is the historically best position, $\overrightarrow{X}$ is a whale position and t indicates the current iteration. a is linearly reduced from 2 to 0 and r is a random in the range of [0,1]. The sign || denotes the absolute value.

Spiral bubble-net feeding maneuver: A spiral equation is used between the position of whale and prey as follows:

$$\overrightarrow{X}(t+1) = e^{bk}.cos(2\pi k).D' - \overrightarrow{X}^*(t) \tag{5}$$

$$D' = |\overrightarrow{X^*}(t) - \overrightarrow{X}(t)| \tag{6}$$

Where b is a constant, and k is a random in the range of [-1,1].

Search for prey: The search agent is updated according to a randomly chosen search agent instead of the best search agent:

$$\overrightarrow{D''} = |C.\overrightarrow{X(t)}_{rand} - \overrightarrow{X}(t)| \tag{7}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X(t)}_{rand} - A.\overrightarrow{D''}| \tag{8}$$

Where $\overrightarrow{X(t)}_{rand}$ is selected randomly from whales in the current iteration. Finally, follows these conditions:

- $|A| > 1$ enforces exploration to WOA algorithm to find out global optimum avoids local optima.

- $|A| < 1$ For updating the position of best current search agent selected.

The algorithm for standard whale optimization algorithm is given below in Algorithm 1:

Algorithm 1 pseudo code of standard whale algorithm.

Input: Objective function f(x) and algorithm parameters a; A, C, p and l
Output: Minimized function value position
Randomly Initialize the whales population.
Initialize the number of maximum iteration Max_{iter}.
Calculate fitness value using the objective function
while $t <= Max_{iter}$ **do**
    ForEach search agent
    Calculate and Update a; A, C, p and l.
    if $p < 0.5$ **then**
        if $(|A| < 1)$ **then**
            Update the position of the current agent by Eq.1
        else$(|A| \geq 1)$
            Select a random search agent (X_{rand})
            Update the position of the current agent by Eq.8
        end if
    else$(p \geq 0.5)$
        Update the position of the current agent by Eq.5
    end if
    End ForEach
    Calculate fitness of each search agent
    t=t+1
end while
Return the current best whale.

2.3 K-Nearest Neighbor (K-NN)

The K-nearest neighbor (K-NN) method proposed by Fix and Hodges [34] that was considered of the nonparametric methods used for classification of new object based on training samples and attributes. The K-NN is considered a supervised learning algorithm that a new instance query result is classified based on the K-nearest neighbor category [35]. The K-NN method applied in many areas: artificial intelligence, pattern recognition, statistical estimation, feature selection and categorical problems. The advantage of KNN is east to implement and simple. K-NN is not negatively affected when training data are large, and indifferent to noisy training data. The need to determine parameter K is regard disadvantage of the K-NN method, calculate the distances between the query instance and all the training samples, sort the distances and determine the nearest neighbors based on the Kth minimum distance, additionally determine the categories of the nearest neighbors

The KNN search problem compose of searching the k nearest neighbors of each point in the reference. Commonly, the Euclidean or the Manhattan distance is used but any other distance can be used instead such as the Chebyshev norm or the Mahalanobis distance. The brute force algorithm (BF) also called exhaustive search is considered method to search the KNN. the BF algorithm is the following:

- 1. Compute all the distances.
- 2. Sort the computed distances.
- 3. Select the k reference points corresponding to the k smallest distances.
- 4. Repeat steps 1. to 3.

When k is equal 1, this case is considered The simplest case of k-nearest neighbor algorithm, where the class assigned to the unseen tuple is the class of most nearest tuple to it. Another property of KNN is that it can be employed not only for predicting a categorical attribute but also for predicting a continuous valued attribute. The later one is called regression. In regression, the value of class attribute of an unseen tuple will be the average of the class attribute values of the k nearest tuples to the unseen tuple.

The aim from this technique KNN algorithm is to optimized by whale optimization algorithm in order to determine best location of sink node with best high residual neighbor's sensor nodes.

3 The Proposed WOA-KNN Algorithm

Improving the accuracy of k-NN classifier algorithm is the target of this study. To improve the k-NN classification the best solution is that best of k-nearest neighbors for sink node that selected through WOA. For this propose, first contribution of the paper has focused on the WOA. WOA is one of the best and popular search tools.

Firstly, the data set of network has been split to the active nodes and inactive nodes. Next, maximum of iteration has been determined to validate the k-NN so. Then in each iteration, the WOA procedure is called. In WOA algorithm, a population of N Whales has been produced randomly and the fitness function of population (Whales) is computed. Note that each whale introduces a real values in range [0,1] for each dimension. After that, fitness value of each whale is calculated. Then evaluated whales are used in evolutionary progress. The cycle of WOA approach described in previous section 2.2. The evolutionary process has continued until the conditions are satisfied. For this propose, Whales returns a vector with the best real values in range [0,1]. After that, the weighted are stored to the k-NN algorithm for classification. Note that all weights will be computed the distances. After 100 iterations, best solution are given and have been used in the k-NN.

This section describes the design and the implementation of Whale optimization algorithm based K-nearest neighbors algorithm for wirless sensor networks as shown in Figure 2 and Algorithm 2illustrate in detailed . During implementation of WOA according to fitness function that clarify in equation 9 after choose best of k parameter that clarify number of nearest neighbors of sink node position with high residual energy in order to Maintain on power of network.

$$f(w_i) = \alpha_1 d_w + \alpha_2 \sum_{i=1}^{N_w} E_{w_i} \tag{9}$$

Where N_w is the set of neighbors of a node w, E_{w_i} refers to the the residual energy within a neighbor node w and d_w is the Euclidean distance between the position of the node w and the center of network. One drawback of equation 9 is the fairness between nodes; since the nodes with low energy with a high number of nodes that covered from it.

4 Experimental Results

The performance of the proposed optimized KNN tested on ten data sets of different sizes network that was implemented and evaluated using a Java-based simulation tool called Atarraya [36]. The proposed WOA-KNN model was implemented using MATLAB. In Table 1 obtained simulation parameters that were adjusted for the experimental scenarios.

The simulations of nodes are assumed to mimic the characteristics of simple sensors with the energy model that defined in [37]. The performance analysis calculated the mean of average of NRuns = 10 different runs of the algorithm that is calculated for both algorithms PSO-KNN and the WOA-KNN, Tables 3 and 2 summarizes all obtained results, where N, AN, K, L, EC and T means the

Algorithm 2 pseudo code of WOA-KNN algorithm.

Input: A graph represents the nodes and their neighbors in the input WSN
Output: The final topology with sink node position
Randomly Initialize the whales population X[i](i = 1, 2, ..., n).
Initialize the number of maximum iteration Max_{iter}.
Calculate the fitness for each network By Eq.9
the best network
while $t <= Max_{iter}$ **do**
    ForEach candidate network solution Xi do
    Calculate and Update a; A, C, p and l.
    ForEach Network Topology X[i] do
    if $p < 0.5$ **then**
        if $(|A| < 1)$ **then**
            Update status of the current node by Eq.1
        else$(|A| \geq 1)$
            Select a random search agent (X_{rand})
            Update status of the current node by Eq.8
        end if
    else$(p \geq 0.5)$
        Update status of the current node by Eq.5
    end if
    End ForEach
    Produce sink node with k nearest neighbors according to fitness function By Eq.9
    t=t+1
end while
Return network with best location of sink node have k-nearest neighbor high residual energy.

Table 1
Atarraya simulation parameter.

Parameter	**Value**
Deployment area	600m * 600m
Number of nodes	200,400,600...,2000
Sensor node model	Simple
Node communication	range 100m
Node sensing	range 20m
Node location distribution	Uniform
Node energy distribution	Uniform
Max energy	1000 milliamperes-hour(mA-h)
α_1	0.5
α_2	0.3

network size, number of active nodes, number of nearest neighbors for sink node

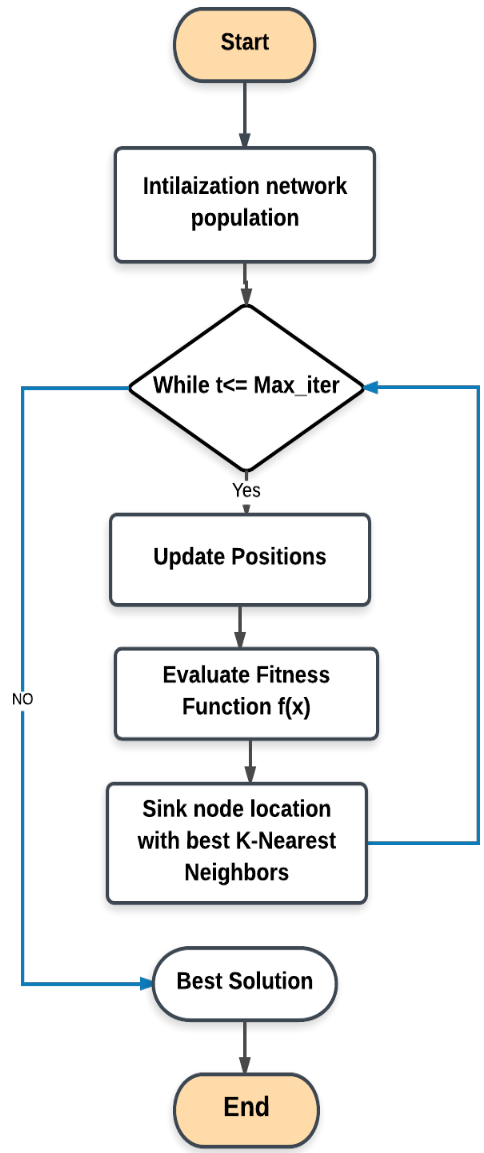


Figure 2: The flowchart of Optimized K-Nearest Neighbor based Whale Optimization Algorithm (WOA-KNN).

that selected, Lifetime network, Energy consumption and total network energy respectively.

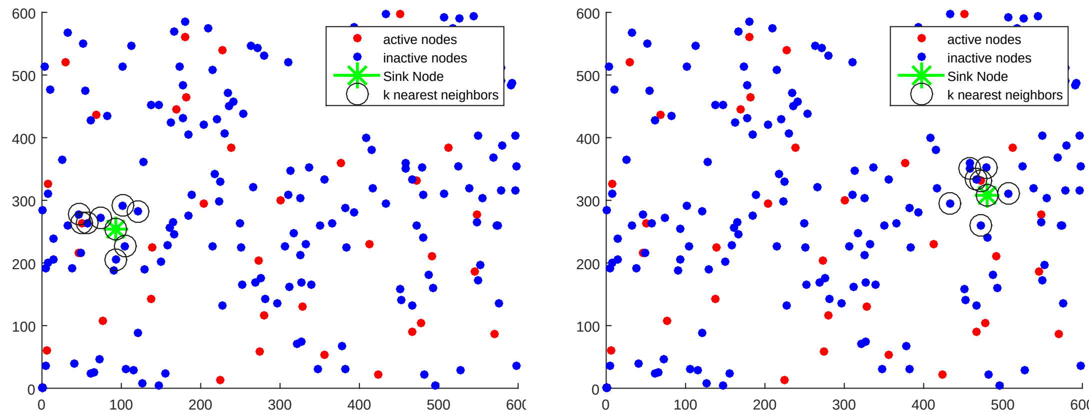
Table 2
Results obtained from the WOA-KNN algorithm.

N	**AN**	**K**	**L**	**EC**	**T**
200	39	8	1453	10546	95823
400	38	9	1632	13684	98357
600	40	7	1475	12568	106354
800	48	9	1524	13476	127862
1000	42	8	1624	16245	131425
1200	46	12	1538	18456	157332
1400	45	11	1504	17896	149652
1600	49	12	1425	16972	173589
1800	47	14	1684	19564	163471
2000	48	13	1614	18674	182463

Table 3
Results obtained from the PSO-KNN algorithm.

N	**AN**	**K**	**L**	**EC**	**T**
200	39	7	1354	12548	95823
400	38	6	1573	14625	98357
600	40	8	1374	12934	106354
800	48	7	1354	14022	127862
1000	42	10	1397	16834	131425
1200	46	11	1426	20045	157332
1400	45	13	1398	19357	149652
1600	49	11	1243	20279	173589
1800	47	12	1425	22687	163471
2000	48	11	1375	23745	182463

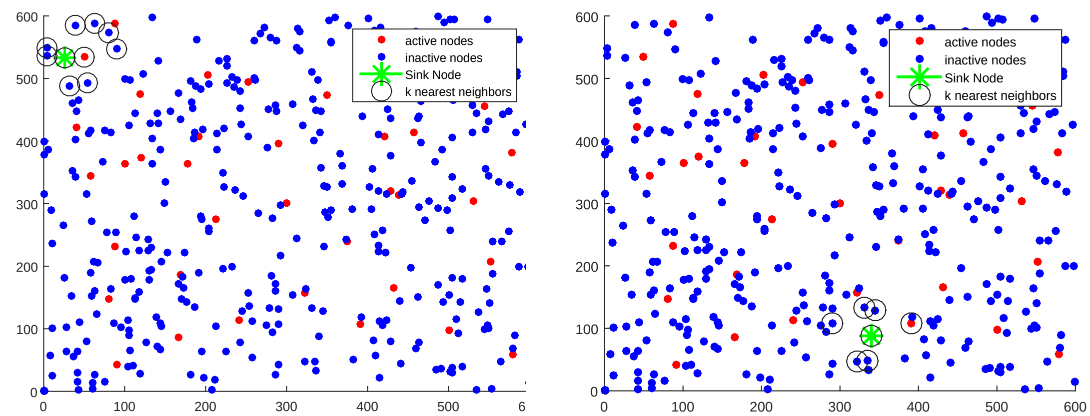
Results of the WOA-KNN algorithm compared to PSO-KNN are shown from Figure 3 to Figure 12 for network sizes 200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000 nodes respectively, active nodes and inactive nodes clarify by a red color and a blue color in graph respectively and green color represents sink node for network. The main target of constructing a reduced network energy has been achieved where determine best location of sink node using the proposed algorithm WOA-KNN compared to the PSO-KNN algorithm. Figure 13 shows the number of K nearest neighbors for WOA-KNN and PSO-KNN. Figure 14 illustrates energy consumption for a network and Figure 15 illustrates the lifetime between both algorithms.



(a) WOA-KNN algorithm for 200 nodes.

(b) PSO-KNN algorithm for 200 nodes.

Figure 3: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 200 nodes.



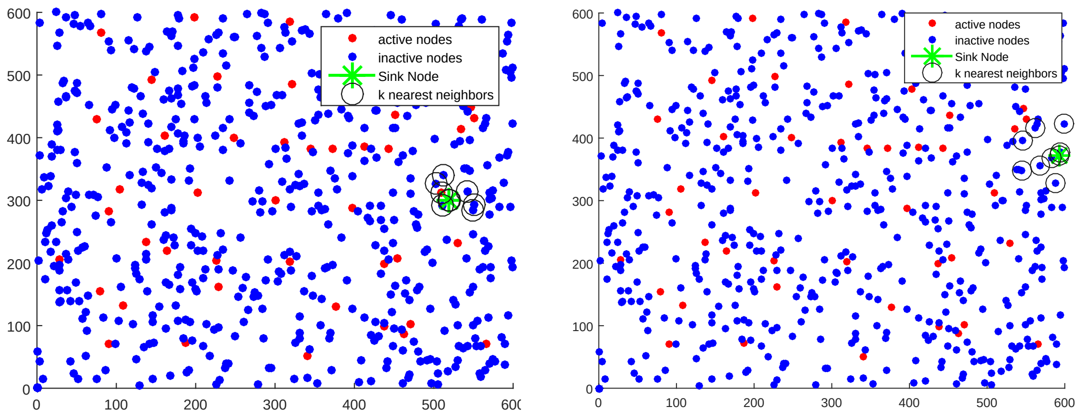
(a) WOA-KNN algorithm for 400 nodes.

(b) PSO-KNN algorithm for 400 nodes.

Figure 4: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 400 nodes.

5 Conclusion

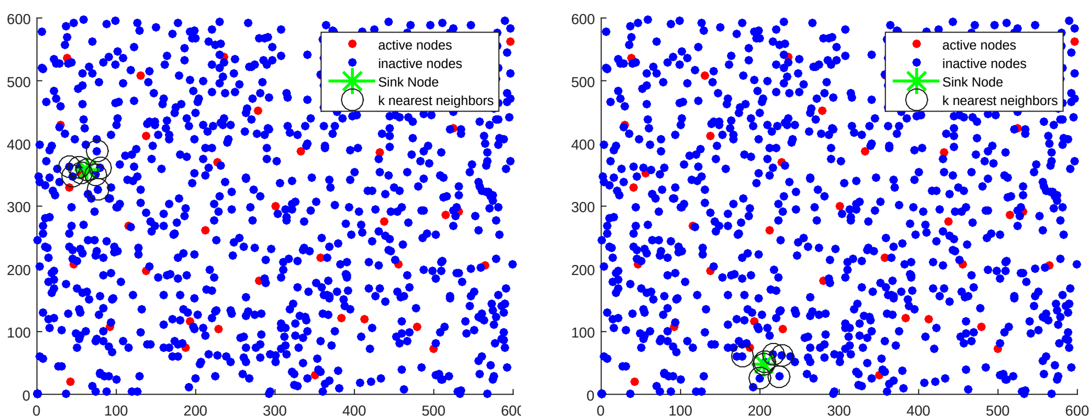
This work proposed method to improve K-nearest Neighbor via whale optimization algorithm that used it in Wireless Sensor Networks (WSNs) sink node location problem. To solve this problem of finding the best location of single sink node with optimal number of k parameter that determines best of neighbor's sink



(a) WOA-KNN algorithm for 600 nodes.

(b) PSO-KNN algorithm for 600 nodes.

Figure 5: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 600 nodes.

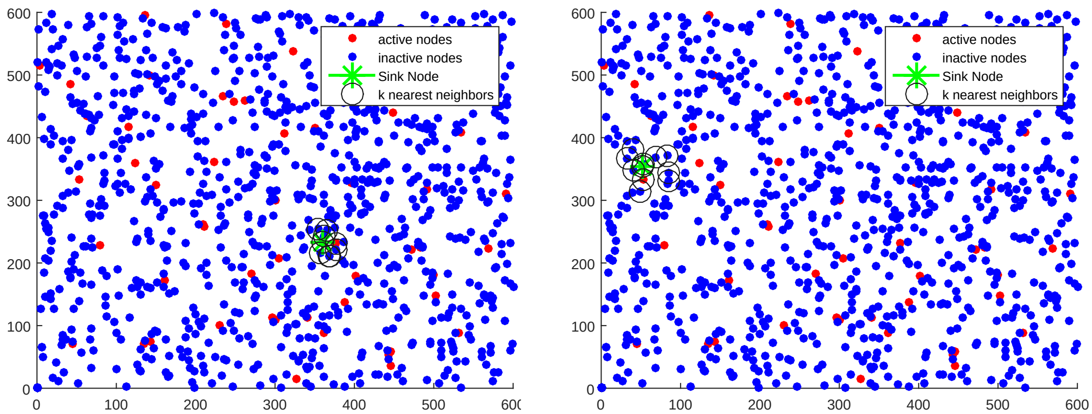


(a) WOA-KNN algorithm for 800 nodes.

(b) PSO-KNN algorithm for 800 nodes.

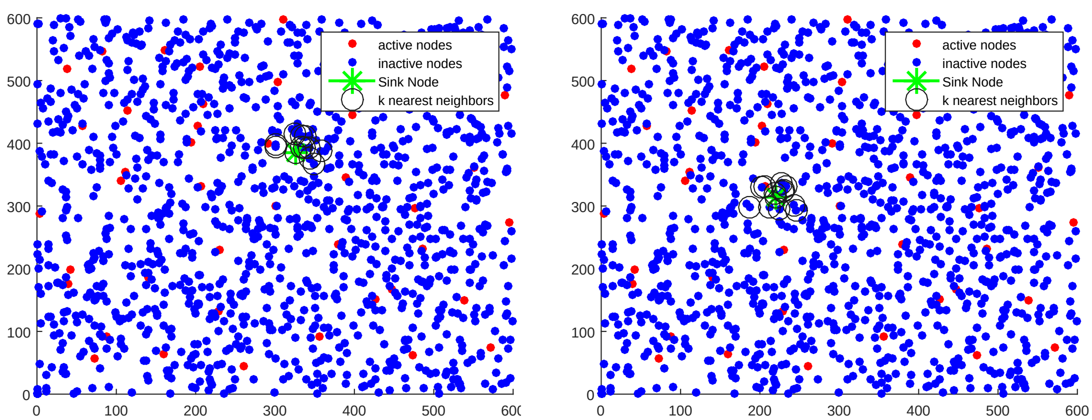
Figure 6: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 800 nodes.

node that has high residual energy in order to reducing energy consumption to extending network lifetime in WSNs environment. We proposed WOA-KNN to choose optimal location of single sink node with neighbor's high residual energy that gathers data from all active nodes in network, After getting the location of the sink node using the proposed WOA-KNN reconstructs network accord-



(a) WOA-KNN algorithm for 1000 nodes. **(b)** PSO-KNN algorithm for 1000 nodes.

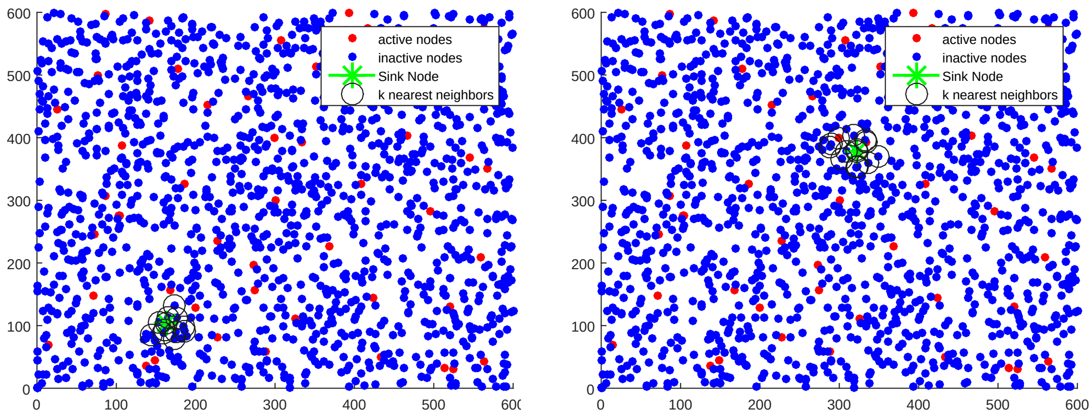
Figure 7: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN from 1000 nodes.



(a) WOA-KNN algorithm for 1200 nodes. **(b)** PSO-KNN algorithm for 1200 nodes.

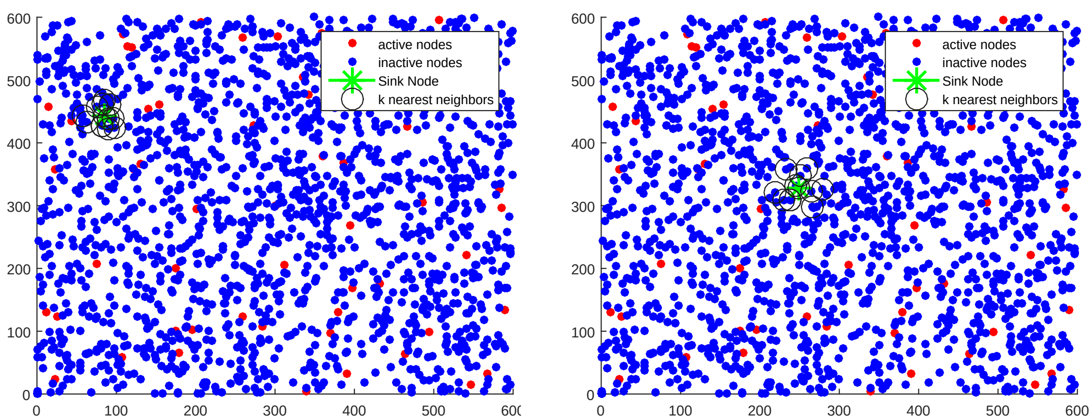
Figure 8: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN from 1200 nodes.

ing to sink node position. The proposed algorithm save the energy consumption approximately by 11% compared with the well-known algorithm PSO-KNN.



(a) WOA-KNN algorithm for 1400 nodes. **(b)** PSO-KNN algorithm for 1400 nodes.

Figure 9: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 1400 nodes.



(a) WOA-KNN algorithm for 1600 nodes. **(b)** PSO-KNN algorithm for 1600 nodes.

Figure 10: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 1600 nodes.

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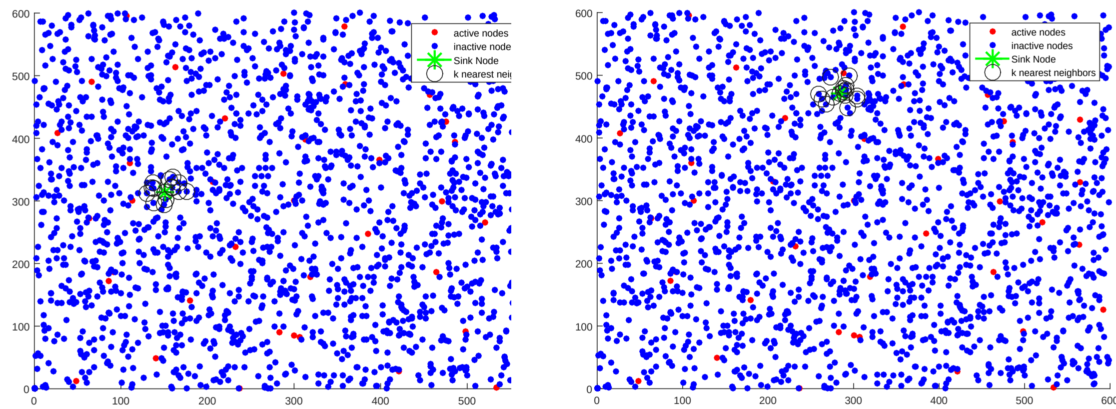
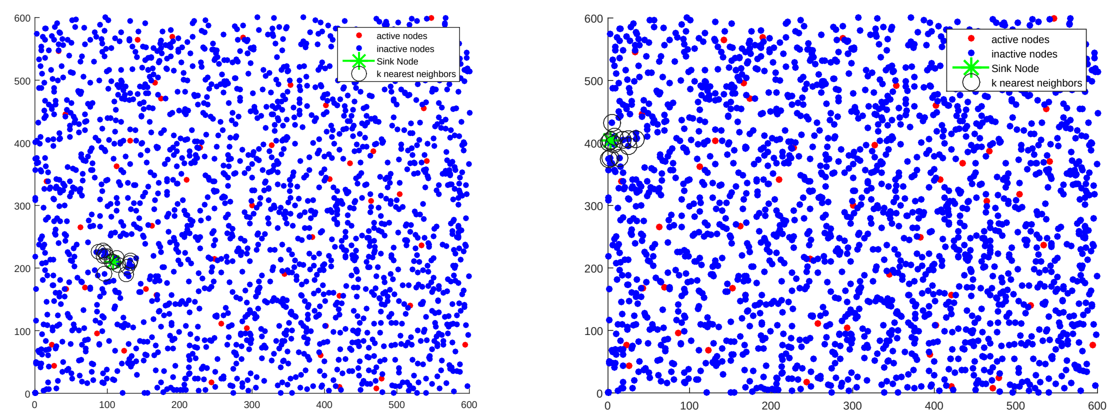


(a) WOA-KNN algorithm for 1800 nodes. **(b)** PSO-KNN algorithm for 1800 nodes.

Figure 11: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 1800 nodes.



(a) WOA-KNN algorithm for 2000 nodes. **(b)** PSO-KNN algorithm for 2000 nodes.

Figure 12: Sink node location with best nearest neighbors of the WOA-KNN and PSO-KNN 2000 nodes.

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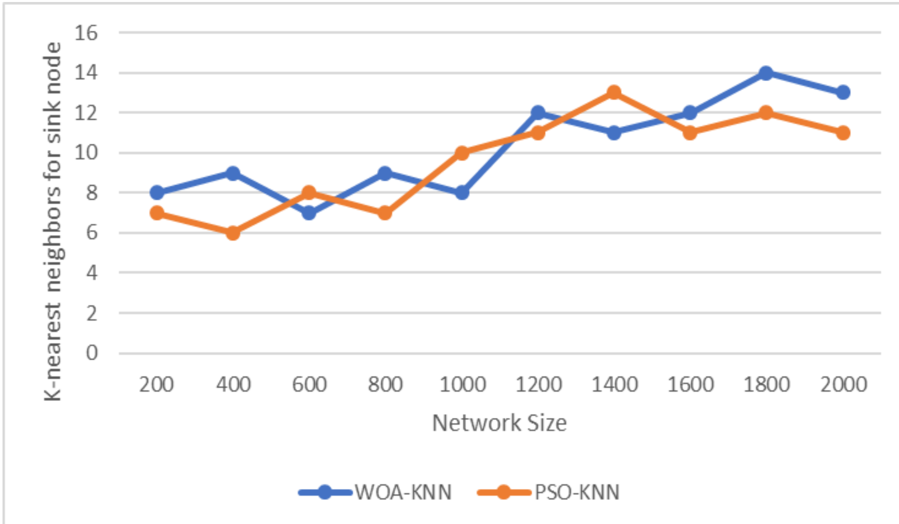

Figure 13: No of K-nearest neghbors.

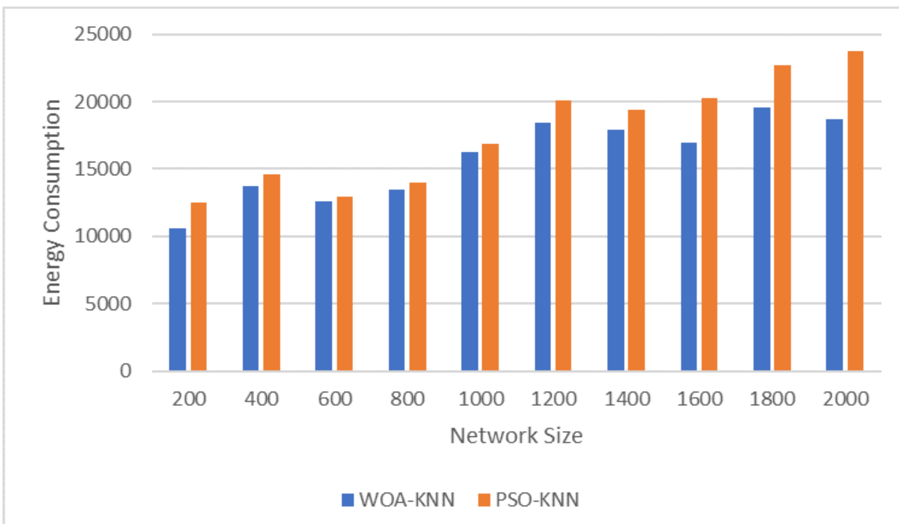

Figure 14: Energy consumption.

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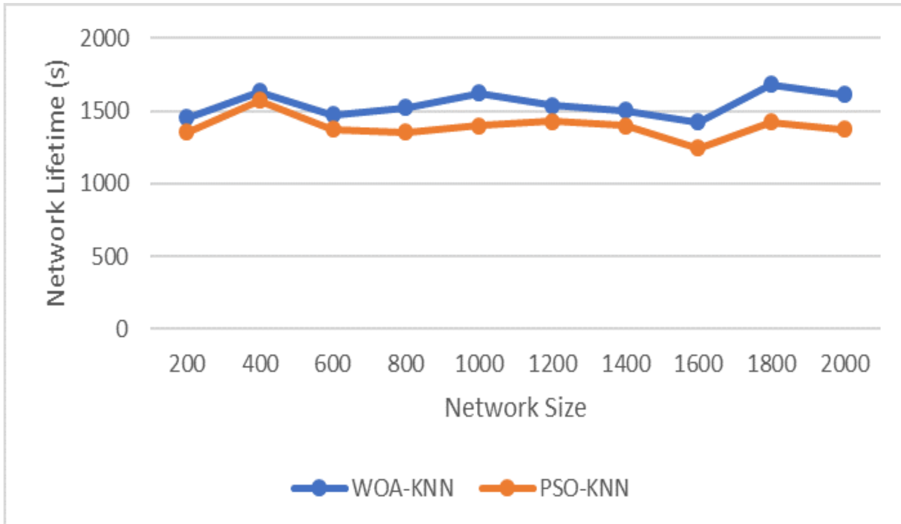

Figure 15: Lifetime Network.

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