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Wireless Node Localization Based on Wild Goats Algorithm for Industrial Internet of Things

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ABSTRACT

In an industrial Internet of things (IIoT) environment, accurately determining the location of each sensor node is crucial for ensuring the data integrity of the network. Using the signal properties of the beacon nodes, an unknown node can calculate the distance to each beacon node and localize itself. Low computation time is important, particularly in an industrial environment, because many tasks need to be executed rapidly to maintain the timeliness of an industrial process. This paper proposes a node localization scheme based on the wild goats algorithm (WGA) to accurately and efficiently localize unknown nodes. The simulation results demonstrate the potential of the proposed localization algorithm to achieve better accuracy than other algorithms.

Key Words: beacon node, industrial wireless sensor network, node localization, Wild Goats Algorithm, unknown node

Ⅰ. Introduction

In recent years, rapid progress in the industrial Internet of things (IIoT) has led to advancements in various areas, such as industry, science, medicine, and military. The current ability of the wireless technology industry to produce devices of nearly all shapes and sizes enables applications to be more targeted and efficient under any condition or environment. Many IIoT networks are deployed in non stationary situations that require the ability to locate each wireless device to sustain the integrity of the data circulating in the network[1].

The IIoT refers to the use of Internet of things (IoT) technology in manufacturing, logistics, oil and gas, transportation, energy and utilities, mining and metals, aviation, and other industrial environments. The IIoT is defined by systems that link, monitor, and control complex industrial processes and applications[2]. This enables to share and analyze massive volumes of data to increase production, efficiency, and safety in industrial settings. IIoT systems frequently use machine learning, big data technology, sensor data, machine-to-machine (M2M) communication, and automation technologies, which have become ingrained in industrial processes. Numerous advantages, including higher productivity, enhanced safety, improved product quality, and lower operational costs,

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can be achieved using IIoT.

Several possible solutions are available for locating wireless devices in a network; however, two solutions are prominent. The first and most apparent solution is to equip the nodes with a positioning device, such as a global positioning system (GPS). This enables the network operator to retrieve each device in real time, without requiring excessive time for installation and testing. The disadvantage of this solution is that the procurement and maintenance costs of the positioning device can significantly affect the total implementation cost if the network is expandable.

The second solution is to use localization. Localization is a technique for estimating the location of a wireless device or node by utilizing wireless-network properties, such as signal strength, data transmission delay, average node distance, and communication range. Localization is less expensive than positioning devices, and in some cases, the initial system does not need to be modified.

The localization problem can be regarded as an optimization problem[3]. In a broad sense, optimization involves determining the optimal solution to a problem while considering one or more parameters. The general idea of optimizing localization is to search for the optimal location as the estimated location of an unknown node using the distance between the unknown node and several beacon nodes as well as the location of each beacon node. This problem is relatively easy, in theory, when all known distances between the unknown and beacon nodes are assumed to be accurate. However, more realistic models include measurement noise, which can affect the localization process. Optimization plays an important role in localizing the unknown nodes.

Mathematical optimization can be divided into two categories: deterministic and stochastic. The difference between the two methods is the involvement of random elements[4]. Deterministic optimization depends on rigorous mathematical computations, determined settings, and repeatable outputs. Stochastic optimization includes random variables that make every output unique.

Stochastic optimization is preferred for localization problems owing to its ability to provide immediate results with relatively low computational complexity[5]. Metaheuristic optimization is a type of stochastic optimization. The name originates from two words: 'meta' and 'heuristic'. A heuristic involves discovering or finding in a hit-and-miss manner. Meta is a prefix for a noun that specifies at a higher level than the original noun. Hence, metaheuristic optimization incorporates trial and error to determine the optimal value of an objective function.

Different types of metaheuristic algorithms have been proposed for wireless localization. Bio inspired algorithms are a recent trend in optimization. Several studies have implemented bio inspired metaheuristic algorithms for localization. Daely et al.[5] proposed a hybrid bio inspired optimization algorithm as a localization algorithm for (IWSNs). To achieve a low computing time and high accuracy, the proposed technique combines the dragonfly technique (DA) with particle swarm optimization (PSO). The proposed technique was compared with PSO and DA in a sensor network with a mesh topology considered The findings revealed that the proposed technique outperforms the other algorithms when both the localization error and computation time are considered.

Rajashree et al.[6] proposed localization using a range-based technique such as the received signal strength indicator. The received signal strength indicator can assess the signal strength; however, it has a large localization error. In this study, a new approach called spider monkey optimization was employed to address large localization errors.

Mihoubi et al.[7] proposed a multicriteria optimization approach based on the Harris Hawk optimization algorithm (HHOA), which is a bio inspired algorithm. The study demonstrated that the proposed paradigm may increase the pace of localization and reduce node energy usage. To determine the position of the trigger, HHOA populations share information using a multi agent method. The performance of this technique in a large with millions of nodes is remarkable. Several tests were conducted under various scenarios in a decentralized WSN environment. Finally, a comparative study was conducted using several current bio inspired algorithms.

Rani et al.[8] aimed to improve localization using a swarm intelligence algorithm. To achieve this, a range-free and distributed method using the salp swarm algorithm for moving target nodes in maritime rescue networks was proposed. The results are compared with those of existing algorithms: PSO and the Butterfly Optimization Algorithm (BOA). The proposed method has a lower localization error than the PSO and BOA. The vast number of metaheuristic optimization implementations for localization showed that metaheuristic optimization is a promising direction for finding a novel, accurate, and efficient wireless localization method.

In this study, we propose the wild goat algorithm (WGA). The WGA is a metaheuristic algorithm that mimics the herding behavior of wild goats when exploring a mountain[9]. Wild goats form multiple small groups at the bottom of the mountain and move upward in different ways. When two or more groups meet and are attracted by food, they unite into a larger group, and this process continues until a single group of wild goats is formed.

This behavior was used to model the movements of search agents in the search space. Our contributions are summarized as follows:

1. WGA based localization algorithm for range-based wireless localization in IIoT was developed.
2. Cooperative localization scheme that details the information exchange between nodes to cooperatively estimate the locations of unknown nodes was implemented.
3. The proposed algorithm was compared with other algorithms in scenarios with varying node degrees.

The remainder of this paper is organized as follows: Section Ⅱ describes range-based localization and several distance-estimation techniques for localization. Section Ⅲ explains the proposed localization scheme based on WGA. Section Ⅳ discusses the simulation scenarios and results. Finally, section Ⅴ concludes the paper and discusses future work.

Ⅱ. Range-Based Localization

2.1 Overview of Wireless Localization

Most of the time, wireless localization is critically needed in a IIoT network, particularly when the location information affects the processes inside the network. Several works have shown the importance of localization, e.g., indoor facility services[10,11], network security[12,13], patient monitoring[14], robot path-planning[15,16], athlete's movement tracking[17], and environment monitoring[18-20]. The relevance and integrity of the data are enhanced when the location of the acquired data is known.

Wireless localization algorithms, in their applications, can be divided into centralized and distributed localization. In centralized localization, a single node localizes all the other nodes. To perform this localization, good processing resources and power supplies are needed, particularly if the network is large. Distributed localization is much preferred in networks with limited resources. Each unknown node will localize itself with the help of neighboring beacon nodes.

Wireless-localization algorithms can also be grouped into range-based and range-free categories. A range-based wireless localization algorithm incorporates the distance measurement or angle measurement between nodes. The measurement is possible when two nodes are within communication range of each other; hence, the name. In contrast, range-free wireless localization does not measure the distance or angle; rather, it uses a rough estimation.

In this study, the proposed algorithm is designed for distributed range-based wireless localization. Each unknown node will localize itself, with assistance from neighboring beacon nodes. Each beacon node will broadcast its location, to enable the unknown nodes in its vicinity to use its location as a reference and to measure their distance from it.

2.2 Distance Measurement Methods

Distance measurement is pivotal in range-based wireless localization. Several wireless-transmission properties can be used to determine the distance between two wireless nodes. In the following, the properties used most to calculate distance are described briefly.

2.2.1 Time of Arrival (TOA)

TOA is time when a signal from a transmitter arrives at a receiver. The TOA of a signal can be expressed as

$$t_{Rx}=\frac{d}{v}+t_{Tx}, \tag{1}$$

where d denotes the distance between nodes, v denotes the signal-propagation speed (equal to the speed of light for radio-frequency (RF) signal), and t_{Tx} denotes the time when the signal was transmitted. From (1), the distance between the two nodes can be derived as

$$d=v(t_{Rx}-t_{Tx}). \tag{2}$$

The t_{Tx} information is usually included in the transmitted signal to ease the calculation for the receiving node. This calculation assumes that all nodes are synchronized with each other and that no other delay source exists.

2.2.2 Time Difference of Arrival (TDOA)

TDOA covers the weakness of TOA, which is the need to synchronize all nodes. As the name suggests, it uses the difference in the signals' arrivals. To use this method, the signals must travel over different frequencies, e.g., RF and audio frequency (AF). Using (1), the TDOA of two signals between two nodes can be expressed as

$$t_{Rx,AF}-t_{Rx,RF}= \left(\frac{d}{v_{AF}}+t_{Tx,AF}\right)-\left(\frac{d}{v_{RF}}+t_{Tx,RF}\right). \tag{3}$$

Assuming that the difference between $t_{Tx,AF}$ and $t_{Tx,RF}$ is insignificant and can be ignored, (3) can be simplified as

$$t_{Rx,AF}-t_{Rx,RF}=\frac{d}{v_{AF}}-\frac{d}{v_{RF}}. \tag{4}$$

As shown in (4), the time when the signal was transmitted is not necessary; thus, the nodes do not need to be synchronized. The distance can then be calculated as

$$d=\frac{v_{RF}v_{AF}\left(t_{Rx,AF}-t_{Rx,RF}\right)}{v_{RF}-v_{AF}}. \tag{5}$$

2.2.3 Received Signal Strength (RSS)

TOA and TDOA are good techniques with high accuracy in line-of-sight (LOS) situations; however, the need to synchronize all nodes or add new instruments for distance measurement is sometimes inconvenient. Moreover, these methods do not perform well in non-LOS (NLOS) scenarios. Measuring the RSS is another method for estimating the distance between two nodes. The RSS is the power of the received radio signal.

In logarithmic units, the RSS of a signal can be expressed as

$$P_{Rx}=P_{Tx}+G_{Tx}+G_{Rx}-PL, \tag{6}$$

where P_{Tx} is the transmission power, G_{Tx} is the transmitter antenna gain, G_{Rx} is the receiver antenna gain, and PL is the path loss of the link between two nodes. Generally, PL can be assumed to follow the log-distance path-loss model, such as

$$PL=PL_0+10\gamma\log_{10}\left(\frac{d}{d_0}\right)+X, \tag{7}$$

where PL_0 denotes the reference path loss, γ denotes the path-loss exponent, d_0 denotes the reference distance, and $X=X_{SF}+X_{FF}$ denotes the flat fading element from two random numbers: X_{SF} is derived from a zero-mean Gaussian distribution to represent slow fading and X_{FF} is derived from a Rayleigh distribution for NLOS condition or Rician distribution for LOS condition. Usually, PL_0 and γ need to be estimated empirically before being used for distance measurement, which is the disadvantage of using RSS. XFrom (6) and (7), the distance between two nodes can be calculated as

$$d = d_0 10^{\frac{P_{Rx} - P_{Tx} - G_{Tx} - G_{Rx} - PL_0}{10\gamma}}. \tag{8}$$

2.3 Objective Function Formulation

In this study, we assume that a network consists of nodes with identical networking properties. The measured distance between two nodes can be modeled as

$$\check{d} = d + n, \tag{9}$$

where d denotes the actual distance between the two nodes and n denotes the measurement noise (usually a random value from a normal distribution). Fig. 1 provides an illustration of distance measurement.

The noise in a measurement can impair the localization performance. To lessen the impact of noise on the localization, the average of multiple measurements is used, rather than the distance from one measurement, as the average might be more accurate. The average of M distance measurements is calculated as

$$\bar{d} = \frac{1}{M} \sum_{m=1}^{M} \check{d}_m, \tag{10}$$

where m denotes the index of distance measurement. The problem of localization in two-dimensional square area with side length ℓ, with aid from $B \geq 3$ neighboring beacon nodes, can be considered as an optimization problem with an objective function such as

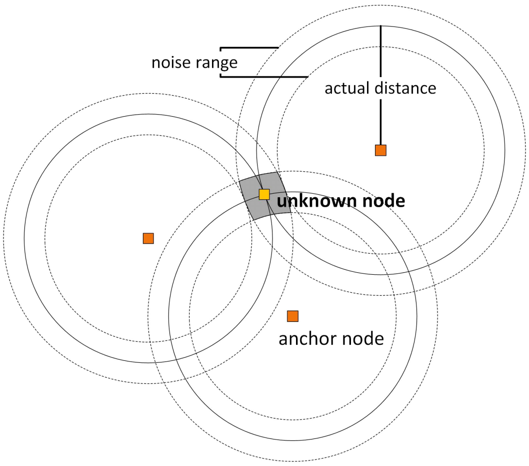


Fig. 1. Distance measurement scheme in localization.

$$F_{obj}(\mathbf{x}) = \sqrt{\frac{1}{B} \sum_{b=1}^{B} \left(\left\| \mathbf{x} - \tilde{\mathbf{x}}_b \right\| - \bar{d}_b \right)^2}, \tag{11}$$

where $\mathbf{x}$ denotes the location of unknown node and $\tilde{\mathbf{x}}_b$ denotes the location of beacon node b. The estimated location of the unknown node can thus be found in the manner of

$$\begin{aligned} \hat{\mathbf{x}} = \arg\min \quad & F_{obj}(\mathbf{x}), \\ \text{s.t.} \quad & 0 \leq x, y \leq \ell, \\ & B \geq 3. \end{aligned} \tag{12}$$

Ⅲ. Proposed Localization Algorithm

In this study, we use WGA as the basis of our proposed algorithm. WGA incorporates the herding behavior of wild goats to provide an immediate solution for optimization problems[9]. Wild goats climb up and down the mountain in groups, seeking food. Each group has a leader and several followers. The groups' movements are initially based on each group leader; however, along the way, other leaders' movements will also be considered to determine the next move.

WGA starts by generating n_X wild goats or search agents. These search agents then are evaluated using the objective function (11). The objective function value of a search agent $i \in \{1, ..., n_X\}$ is then used to determine its weight, using formula as follows

$$w_i = \exp\left(-n_{dim} \frac{F_{obj}(\mathbf{x}_i) - \min F_{obj}(\mathbf{X})}{\sum_{j=1}^{n_X} F_{obj}(\mathbf{x}_j) - n_X \min F_{obj}(\mathbf{X})} \right), \tag{13}$$

where n_{dim} is the dimension of the problem and $\mathbf{X} = [\mathbf{x}_1, ..., \mathbf{x}_{n_X}]$ is the set of all search agents' locations.

When the weights of all search agents are calculated, the n_G search agents with the highest weight value are selected as group leaders. A group initially will have group weight w_G that is equal to its leader's weight w_L. The number of followers for group i is determined as follows

$$n_{F_i} = \text{round}\left(\frac{w_{G_i}}{\sum_{j=1}^{n_G} w_{G_j}} \times n_{Fol}\right), \qquad (14)$$

$$n_{Fol} = n_X - n_G, \qquad (15)$$

where n_{Fol} is the number of remaining search agents that will be followers of the chosen leaders.

For every iteration in the WGA, leaders and followers of every group will move according to their set behaviors. The group leader with the highest weight value (the best group leader) will move by considering its movement vector and best location (location which gives the best objective function value). The other leaders will also consider the same thing, with the addition of location of the best group leader. The followers in each group will move by considering their respective movement vector, best location, group leader's position, and other follower' location in the same group with the highest weight value. The calculated movement vectors of all leaders and followers are added to their location to determine their next location in the next iteration. Each group then compares the weight value of the leader and followers, and the one with the highest weight value will become the group leader. The weight of group i is determined as follows

$$w_{G_i} = \frac{w_{L_i} + \sum_{j=1}^{n_{F_i}} w_{F_{i,j}}}{n_{F_i} + 1} \qquad (16)$$

where $w_{F_{i,j}}$ denotes the weight of follower j in group i

All groups also cooperate with each other in every iteration. Between two groups, a search agent from the group with lower weight value will be attracted and move out to the other group with higher group weight value, to gain better information for its own movement update. This cooperation is going for all pairs of groups, for every iteration, until one big group is formed at the end. During this cooperation process, some search agents may undergo mutation process. Each mutated search agents can replace any group leader if its weight value is higher than the matched group leader's weight value. The concise pseudocode of WGA is shown in Algorithm 1. Full explanation of WGA is provided in [9].

Given an IIoT network consisting of sensor nodes, some know their locations while the others do not know (we called them unknown nodes). Every unknown node will try to identify its one-hop neighbor(s). When it can identify more than two beacon nodes, request for their location will be sent. The beacon nodes will reply with their location and the unknown node will also measure the distance between itself and beacon nodes using methods mentioned in Section II. When an unknown node has two or less neighboring beacon nodes, it will wait for a set amount of time before repeating again the process of identification.

The localization process uses WGA to estimate the unknown node's location. The inputs for this process

Algorithm 1. Pseudocode of WGA

```
function WGA(objective function, number of iterations, population size)
    Initialize population of search agents
        Evaluate all search agents using objective function
    Calculate weight of each search agent
    Determine the group leaders
    Determine followers for each group
    Calculate weight of each group
    for every iteration until the last iteration do
    for every group do
        Update the leader's movement and location
        Update the followers' movements and locations
    Evaluate the leader and followers
    end for
    Perform group cooperation
    Perform mutation for some search agents
    Evaluate mutated search agents
    for every mutated search agent do
        if its weight is higher than a group leader then
        Replace the group leader with the mutated search agent
        Put the ex-group leader in the mutated search agent's old group
    end if
    end for
    end for
 return location of group leader with the highest weight
 end function
```

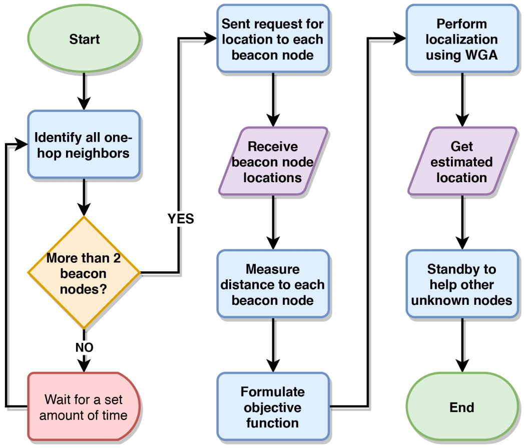


Fig. 2. Flowchart of proposed localization scheme.

are the beacon nodes' locations and distances between unknown node and all beacon nodes. Both of these inputs are used to formulate the objective function in (11). The objective function then is used for WGA, with number of iterations and population size set at the beginning. After WGA returns the estimated location of unknown node, the unknown node become a beacon node and ready to aid localization of other neighboring unknown nodes. The flowchart of the proposed localization scheme is shown in Fig. 2.

Ⅳ. Simulation Results and Discussion

In this section, the simulation results of the proposed algorithm and other algorithms are compared and discussed. The environment for simulation is described in Table 1. Performance metrics are also explained compactly to highlight the improvement and loss of the proposed algorithm against other compared algorithms.

Table 1. Specification of simulation environment

Specification	Description
Processor	Intel Core i5-8500
Operating frequency	3.0 GHz
Operating system	Windows 10
Simulation software	MATLAB R2022a

4.1 Simulation Scenarios

The performance of the proposed algorithm was evaluated in two simulation scenarios, called Scenario 1 and Scenario 2. The parameters of both scenarios are described in Table 2 and 3 respectively. Scenario 1 is used to compare algorithms where all the nodes assisting in localization know their location prior to unknown node localization. In Scenario 2, the localization of each unknown node will be assisted

Table 2. Simulation parameters of Scenario 1

Parameter	Description
Network size	5 nodes
Number of initial beacon nodes	4 nodes
Number of initial unknown nodes	1 node
Communication range	100 m
Standard deviation of distance measurement	1 m

Table 3. Simulation parameters of Scenario 2

Parameter	Description
Network size	100 nodes
Number of initial beacon nodes	10 nodes
Number of initial unknown nodes	40 node
Communication range	25 m
Average node degree	8, 12, 16, 20, 24
Pathloss exponent	3.0
Gaussian standard deviation	7
Rician distribution's scale	1
Rayleigh scale	1

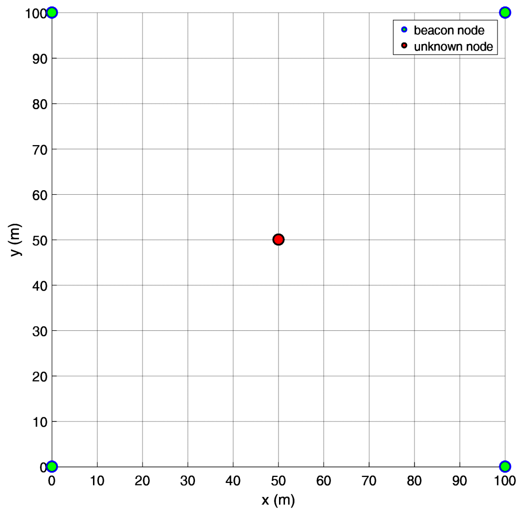
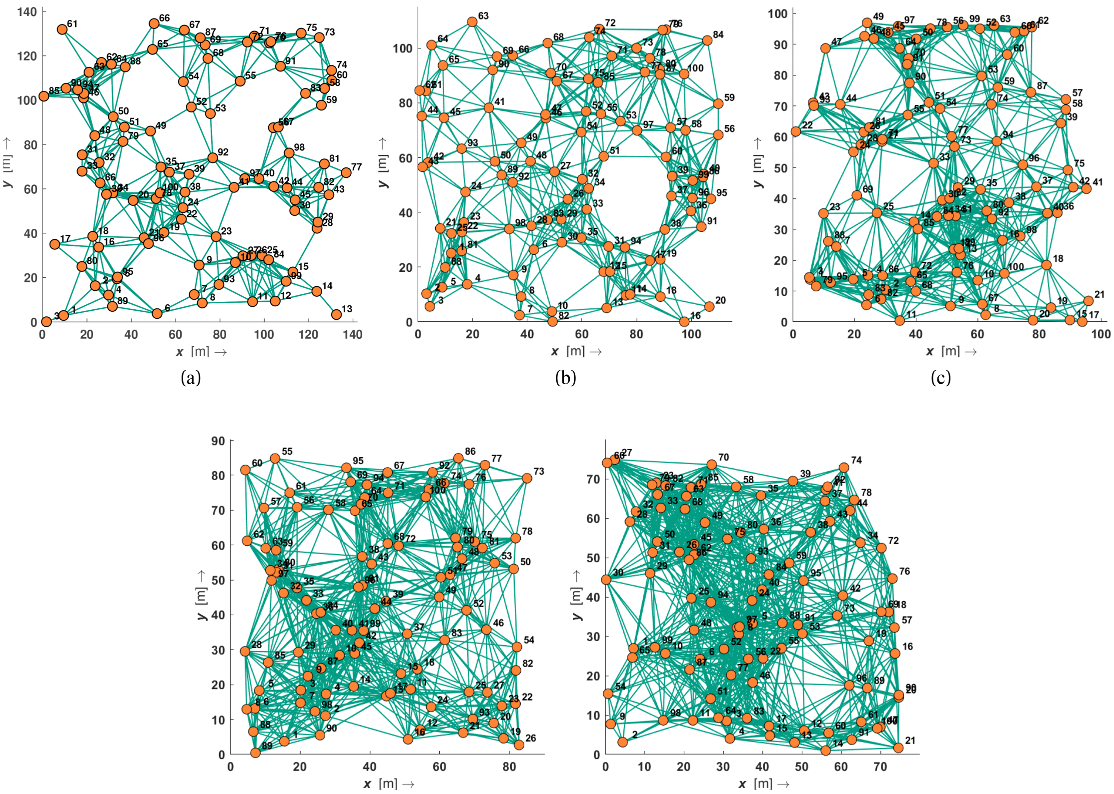


Fig. 3. Illustration of Scenario 1.



(a) (b) (c) (d) (e)

Fig. 4. Illustration of Scenario 2 with the network's average node degree of (a) 8, (b) 12, (c) 16, (d) 20, and (e) 24.

by the neighboring beacon nodes and other unknown nodes that already estimated their location. Measured distance for localization is simulated using 7 and distance is measure for 10 times and average as depicted in 10. The The location of all nodes are determined beforehand to achieve the intended average network degree. This scenario will add another error source to localization, which is the accumulation of localization error of assisting localized nodes. Illustrations of both scenarios are shown in Fig. 3 and Fig. 4 respectively.

4.2 Localization Error

The first simulation was run for Scenario 1. compared the localization error of the proposed algorithm against PSO, CS, CSO, and Artificial Bee Colony (ABC) algorithm. The simulation was performed 100 times for each algorithm and the average errors of localization are compared in Fig. 5. It shows the proposed algorithm can outperform other algorithms. Similar result is also derived from the empirical cumulative distribution function (CDF) of each algorithm's sample, presented in Fig. 6. The proposed algorithm is proved to be superior for localization when compared with other bio-inspired algorithms. The group movements, cooperation, and individual mutation give WGA advantage in providing a more extensive search capability in the search area.

Scenario 2 was also simulated to compare the localization error of each algorithm. The simulations were executed 100 times for each algorithm in networks with different average node degree. The average node degree is the average number of edges connected to each node in a network. The larger the degree means, the higher the network density becomes. The result is shown in Fig. 7 and Fig. 8. Both figures shows that WGA has competitive performance in LOS and NLOS condition, especially in sparse network

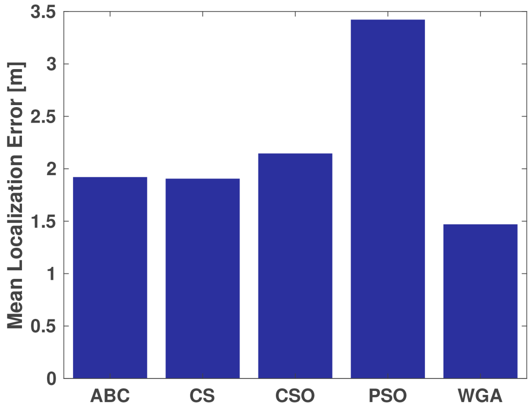


Fig. 5. Comparison of mean localization errors between WGA and other algorithms in Scenario 1.

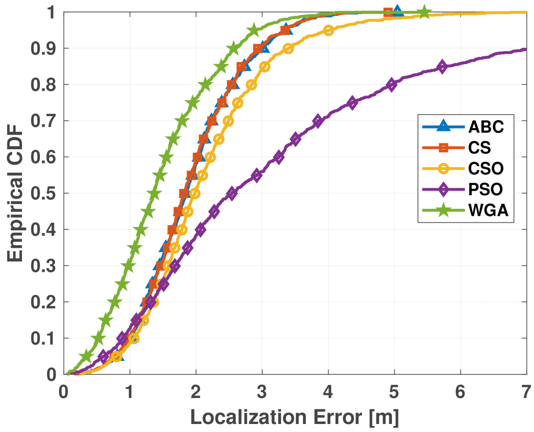


Fig. 6. Comparison of empirical CDF between WGA and other algorithms in Scenario 1.

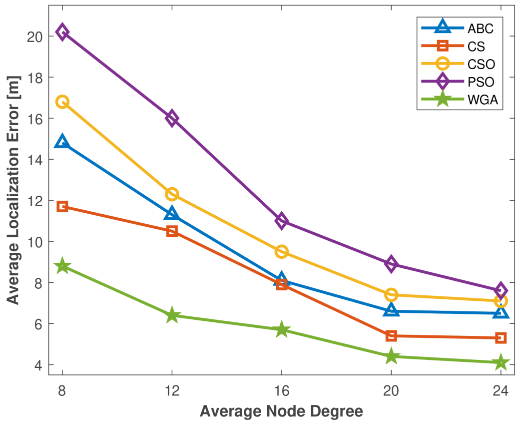


Fig. 7. The comparison of each algorithm's average localization error with varying average node degree in LOS condition.

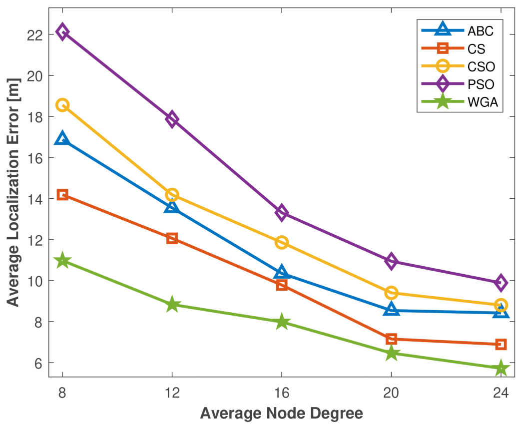


Fig. 8. The comparison of each algorithm's average localization error with varying average node degree in NLOS condition.

condition, with localization error much lower than other algorithms. Localization errors are higher in NLOS condition as the signal strength attenuate more with obstacles in between nodes thus adding error in localization.

4.3 Computation Time

The computation time is another metric to assess the performance of a localization algorithm. By using Scenario 1, each algorithm was run for 100 times, and the average of computation times is plotted in Fig. 9. The figure shows that WGA requires longer time to compute compared with other algorithms, but the difference is not really far apart. The movement update for every leader and follower at each group do take time because every update of a search agent

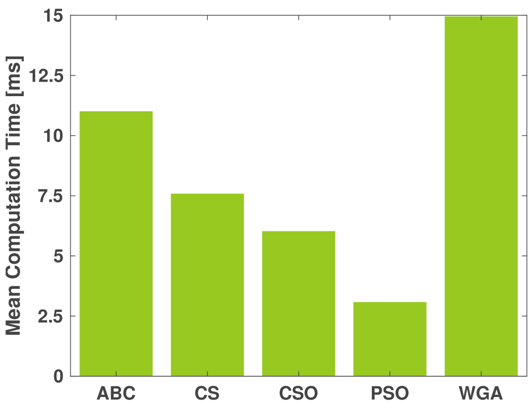


Fig. 9. Comparison of computation time between WGA and other algorithms.

calls for observation of other search agents. We believe that in overall, WGA still performs better than other algorithms in comparison, because it can achieve less error with just minimum increase in computation time.

Ⅴ. Conclusion

Wireless localization is a critical network technique. The data that enter and exit a wireless node lose integrity if they do not match the location information. Many applications of IIoT depends on the accountability of the localization scheme in the network. The unknown node cannot be localized using the exact method because the prior distance measurements contain noise, which may worsen the localization performance.

To address the problem of range-based localization for the distributed IIoT, WGA was proposed. Simulation results showed that WGA exhibit excellent performance. It outperformed the other algorithms in both scenarios used in the simulation. Although WGA requires more computation time, considering its accuracy level, we believe WGA still trumps other algorithms . Thus, the proposed localization scheme has potential for implementation in industrial environments.

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