IJAIT (International Journal of Applied Information Technology)

http://journals.telkomuniversity.ac.id/ijait/

IWDSA: A Hybrid Intelligent Water Drops with a Simulated Annealing for The Localization Improvement in Wireless Sensor Networks

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A R T I C L E I N F O

Received August 6th, 2023
Revised August 25th, 2023
Accepted August 31th, 2023
Available online May 6th, 2024

Keywords
Wireless sensor networks, RSSI, ranging model, optimization techniques, intelligent water drops, simulated annealing

A B S T R A C T

Improving localization accuracy and reducing development costs are pivotal keys and main issues in managing and administrating wireless sensor networks (WSNs). This paper considers a modern and qualified algorithm that leverages advanced optimization techniques to localize nodes deployed in outdoor environments. The proposed algorithm, named Intelligent Water Drops with Simulated Annealing (IWDSA), combines two powerful optimization methods: Intelligent Water Drops (IWD) and Simulated Annealing (SA). IWD is a qualified stochastic optimization tool adept at minimizing objective functions. In IWDSA, SA is integrated to enhance solution quality and prevent IWD from getting trapped in local minima. This paper ensures that internal distances between nodes are calculated using Received Signal Strength Indicator (RSSI) measurements. The paper aims to achieve two primary goals. First, it addresses the challenge of low accuracy in RSSI measurements by employing IWDSA. Second, it aims to achieve highly accurate localization of unknown sensor nodes in WSNs. IWDSA enhances localization precision due to its flexible implementation of IWD and SA, combined with the cost-free utilization of RSSI. Simulation results demonstrate the reliable performance of the proposed algorithm in solving the low accuracy of RSSI measurements and localizing unknown nodes with high accuracy. Additionally, simulation results confirm that the proposed algorithm IWDSA exhibits outstanding performance compared to other algorithms utilizing optimization techniques, including genetic algorithms, bat algorithms, ant colony optimization, and swarm optimization. This exceptional performance is evident across various evaluation metrics, including localization error, localization rate, and simulation runtime.

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https://doi.org/10.25124/ijait.v8i1.6456
Paper_reg_number IJAIT000080102 2024

1. Introduction

Wireless sensor networks (WSNs) are scientifically described as networks comprising a few hundred to several thousand sensor nodes able to connect and communicate with each other wirelessly in an ad-hoc way [1]. These sensor nodes are installed randomly and sometimes methodically in the target environment to track the desired state or phenomena such as temperature, humidity, or fire. Each sensor is designed to observe a particular and specific condition of the target environment subjected to the sensor function and transmits the monitored information to the central node (sink) wirelessly and then finally to the main processing center.

The localization of WSNs is a considerably significant subject because WSNs applications, which comprise movement tracking, phenomena monitoring, and geographic routing, require a high level of precise verification of the target nodes' coordinates. The main job of localization algorithms is to add a label of geographic coordinates to the monitoring data generated from the sensor nodes in the target area. After that, the processing center handles and responds to the monitoring data [2].

A substantial number of algorithms have been assumed and invented to localize unknown sensor nodes in WSNs during the last two decades. These algorithms exploit and utilize the same idea that the positions' coordinates of unknown nodes in the target area could be determined by using the coordinates of anchor (beacon) nodes. These anchor nodes can obtain their positions using Global Position System (GPS) or manual pre-location in the target area [2]. The other sensor nodes installed in the target WSN area and do not have a function to get information about their positions are defined as unknown nodes (or non-anchor nodes). As a result of GPS's technical characteristics, such as its hardware's exorbitant cost and low precision in the non-line-of-sight application area, the performance of GPS may not be appropriate for the localization process of these unknown nodes [3]. Therefore, it was requisite for researchers to innovate and develop new ideas and algorithms for the localization process.

The scientific literature has a considerable number of localization algorithms. The researchers classified these algorithms into different categories, for example,

- Localization algorithms that differ in their dependence on anchors.
- Localization algorithms that differ in the way to calculate the position [4].

The first category is classified into anchor-based and anchor-free categories. In anchor-based algorithms, the sensor anchor nodes get information about their position coordinates using geographic location techniques such as GPS or traditional methods during the development of WSNs. Then trilateration approach is applied to the positions of anchors to calculate the locations coordinates of unknown nodes. On the other hand, in anchor free category, calculations utilized communication data transferred from unknown nodes to anchor nodes to estimate the positions of unknown nodes. The calculation result of this category presents the relative position coordinates of unknown nodes. Therefore, the anchor-based category is the best choice among these two categories to obtain high localization precision [5].

The second category is classified into a distributed category and a centralized category. In distributed category, the suggested localization algorithm is implemented internally by the unknown nodes to estimate their positions. This category has a disadvantage of the speed power consumption of the batteries of unknown sensor nodes. While in the centralized category, the main processing center processes and applies the localization algorithm to all gathered information to determine the coordinates of unknown nodes, thereby reducing the energy consumption of sensor node batteries. Hence, the centralized category has more advantages of saving power than the distributed category, therefore, it is the best choice when deploying nodes in harsh environments [6].

However, to implement a localization algorithm to achieve high accuracy, it is required to take into consideration some sensitive and significant points, such as the anchors' number required for localization and battery energy consumption. It is well known that localization algorithms implemented with a considerable number of anchors achieve high localization accuracy, which increases the running expense and energy consumption of WSNs. During the last few years, researchers have tended to replace traditional localization approaches, such as angulation and trilateration, with modern optimization techniques for the purpose to improve and achieve high position estimation accuracy.

During the last decade, researchers have invented and suggested several optimization techniques characterized by high degree of performance to enhance the precision of measurements calculated by the function of RSSI. These optimization techniques have proven their efficiency in enhancing the accuracy of localization based on RSSI. In the science literature, one of the highly qualified methods of optimization techniques is Meta-heuristics methods. Meta-heuristic is a global search method that is able to produce high-quality solutions for a specific problem within a reasonable time. These techniques belong to two categories. Methods relied on population solutions such as Differential Evolution (DE), Particle Swarm Optimization (PSO) and its variants [2], Pattern Search (PS), Local Unimodal Sampling (LUS), Ant Colony (ACO) [4], [7], Nelder Mead simplicial heuristic [8] and Intelligent Water Drops (IWD) [9] and Genetic Algorithm (GA) [10]. The other category of techniques relied on a single solution such as Variable Neighborhood Search (VNS) [11], Iterated Local Search (ILS) [12], Simulated Annealing (SA) [13], and Tabu Search (TS) [14].

In the literature, researchers suggested improving the performance of these optimization techniques by combining both categories to produce hybrid techniques. These hybrid techniques could gather the mother methods' best advantages, such as accelerating the search for the ideal solutions for the target problem and overcoming premature convergence. These ideas comprise a particle swarm optimization with local search (PSOLS) [15], differential evolution with local search (DE-LS) [16], a hybrid genetic algorithm with local search (GA-LS) [17], and evolutionary programming with local search (EP-LS) [18].

This work utilized a range-based centralized category to enhance localization accuracy for WSNs deployed in an outdoor environment. Figure 1 presents an illustration of the proposed scenario. This paper assumed to utilize an RSSI-based ranging technique to obtain the interior distance between anchor nodes and unknown nodes. The processing unit applies the proposed optimization techniques to the estimated information to get the position coordinates of the unknown nodes.

This paper suggested a hybrid of modern and highly qualified meta-heuristic optimization techniques, namely Intelligent Water Drops (IWD) and simulated annealing (SA), to intensify the precision of the final calculation for the position of unknown nodes. This hybrid algorithm is called Intelligent Water Drops with a Simulated Annealing for localization improvement in wireless sensor networks; in short, IWDSA. Indeed, IWD is a population-based optimization technique that is very simple and highly qualified. IWD uses a constructive manner to derive an optimal solution for a target problem [18], [19], [20].

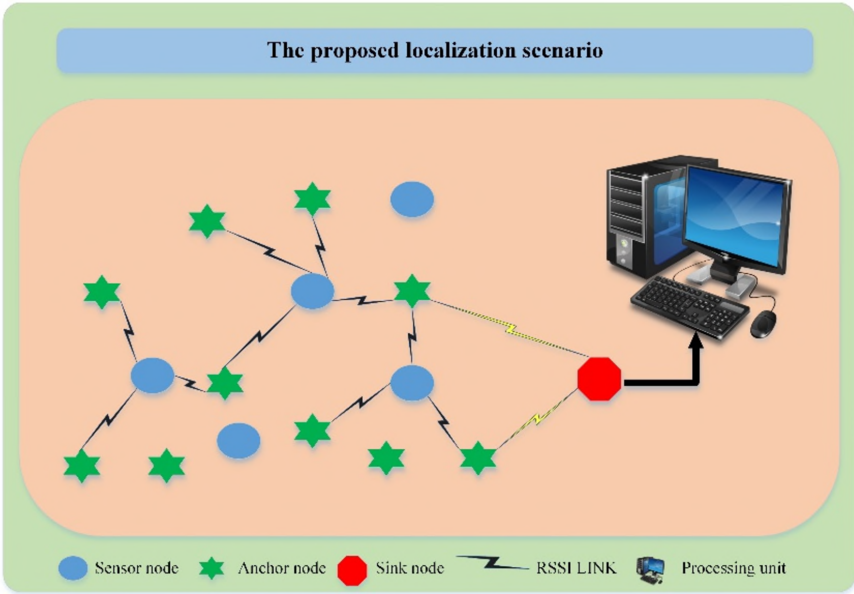

Figure 1 The Proposed Scenario

The SA technique has been utilized in the literature to derive a solution for several optimization problems; the results were fairly good in most cases [21]. SA is selected in this paper for its characteristics, such as high objective values, and its ability to escape from the current solution to the next better solutions. Therefore, IWD and SA characteristics can be considered the essential motivation for utilizing the proposed hybrid algorithm IWDSA to enhance localization accuracy. To date, it is the first time to use a hybrid algorithm between IWD and SA to improve localization accuracy in WSN.

This paper intends to achieve the following technical contributions:

- Take advantage of the ability of optimization techniques to build a highly qualified localization algorithm.
- Design, implement and evaluate a hybrid algorithm of Intelligent Water Drops (IWD) and simulated annealing to enhance the estimation accuracy of localization in WSN.
- Build a typical localization model utilizing the proposed hybrid algorithm IWDSA and compare its efficiency with other localization models that suggested optimization techniques for improving localization accuracy.

This paper is structured in several sections. Section 2 presents a summary of the related works that have been done on localization algorithms. This section is followed by a Network Model and Background in Section 3. A description of IWD and SA is approaching in Section 4. The implementation of the proposed hybrid algorithm IWDSA is presented in Section 5. Simulation experiments and extensive discussions of the final results are introduced clearly in Section 6. Section 7 is the final part of the paper and it presented the concluding remarks and future works of the study.

2. Related Works

During the last two decades, researchers published a significant number of surveys in WSN. These surveys included WSN applications, issues, protocols and algorithms. These surveys can be found, not limited to, in [10], [22]–[28]. In [29], the authors utilized ant colony optimization approach with mobile anchor for the path planning, and they proposed a centroid-weighted localization algorithm for location estimation of unknown nodes. Evaluation of simulation results demonstrated an appropriate localization accuracy compared to the traditional centroid approaches. In [30], the authors took advantage of Genetic Algorithm to deal with the low positioning accuracy while utilizing minimum anchor nodes. The experiment results of their proposed algorithm indicate that three beacon (anchor nodes) were adequate to get an appropriate localization accuracy. The authors in [31] exploited RSSI-Least Squares Support Vector Regression (RSSI-LSSVR) to optimize the localization precision and to lower the deployment charge. The evaluation of their algorithm showed that their method could enhance the localization precision and lessen the deployment charge with more reliability. In [32], the authors utilized a new method of graph embedding with polynomial mapping called (GEPM) for localization in WSN. They used evaluation factors such as the range, the number of installed anchors, and the noise to evaluate their method. Generally, the authors proved that GEPM could achieve high localization accuracy in conditions of small area and low noise. In [33], the authors proposed an advanced version of DV-Hop algorithm called Hop-correction and energy efficient DV-Hop (HCEDV-Hop) to improve the localization accuracy. The results showed that the proposed algorithm outperforms the basic DV-hop in terms of localization accuracy and energy consumption.

In [34], the authors utilized a technique called Particle Swarm Optimization (PSO) to enhance localization accuracy at outdoor WSN application. They evaluated their proposed algorithm that utilized PSO with other algorithms utilized simulated annealing approach, proving their algorithm produces higher localization accuracy. In [35], the authors optimized the performance of the DV-Hop algorithm by utilizing PSO technique. The evaluation results proved that the improved DV-Hop algorithm with PSO technique presented a high localization coverage rate compared to the traditional DV-Hop approach. In [36], the authors developed their localization algorithm accommodating the advantages of the basic PSO version with RSSI to optimize localization accuracy. They developed their algorithm in the same way as the DV-distance algorithm to improve localization success ratios. The evaluation of the proposed algorithm depicted that it is capable of optimizing the localization accuracy and produce high access ratio of the nodes. In [37], the authors built their localization algorithm by combining two optimization techniques, namely fuzzy logic and an extreme Learning machine (FELM) with a vector particle swarm optimization (HVP), and they called their algorithm HVP_FELM. Their study was limited by the average localization error and its relationship with the anchor's density and the communication range. The best result of localization accuracy is about 1.5m. This study ignored the noise effect on localization accuracy. In [38], the authors utilized an upgraded version of PSO called Cooperative Distributed Particle Swarm Optimization (CDPSO) for the localization process in WSN. The authors proved that the efficiency of CDPSO outperformed other basic algorithms considering the result of localization accuracy. The authors confined localization error and complexity for the evaluation and ignored other influencing factors including the noise of the environment and the anchors' number. The work in [39] relied on a modified version of the bat algorithm called MBA to improve the original version's localization performance.

The authors concluded that the proposed algorithm outperformed the original algorithm in several aspects, such as localization rate and speed convergence. However, they found that the localization accuracy is lower than the original version. In the science literature, several studies considered and took advantages of optimization techniques for the localization process. These studies can be found in works such as [1], and [40]–[44].

This paper developed a hybrid localization algorithm that combines modern and highly qualified optimization techniques, namely Intelligent Water Drops (IWD) and simulated annealing (SA), called IWDSA. The evaluation of simulation results proved the high performance of IWDSA to optimize localization accuracy. The high performance of IWDSA seemed obvious in several evaluation factors, including localization accuracy, localization rate and localization processing time. An evaluation comparison was handled between IWDSA and other localization algorithms, including traditional localization techniques (e.g., HCEDV-Hop and RSSI-LSSVR) and other localization algorithms that utilized optimization techniques (e.g., IWD, ACO, MPA, and HSPPSO). The simulation experiment considered several parameters for implementation, including the number of anchors (*N*), noise which is represented by standard deviation (σ), communication range and complexity which is represented localization time.

3. Network Model and Localization Background

3.1. Network Model

This paper suggested a WSN comprises a group of sensor nodes (unknown nodes) and beacon (anchor) nodes deployed in an outdoor target area. This work assumed to install the sensor nodes in a random way in the target area where these nodes have a function to receive signals from anchor nodes. The anchor nodes have predefined fixed locations, and their fundamental responsibility is to broadcast anchor signals which will be received and treated by sensor nodes for the localization process. The sensor nodes release the received anchor signals after extracting RSSI information.

This model assumed the following conditions.

- The network covers the target area and cannot change after deployment. This network comprises a considerable quantity of sensor nodes deployed in random approach in a two-dimensional geographic space in the target area. After deployment, these nodes could not move or change their position.
- The network has one primary node deployed at a fixed position outside the border of the target area and has a way of directly connection to the processing unit.
- The network has N static beacon (anchor) nodes and M unknown nodes. The anchors have a function to determine their positions by GPS or by manual pre-programming during installation.
- The suggested mode of radio propagation is not completely spherical, and RSS has a random variation. The random variation of RSS is formulated as a Gaussian distributed random variable (in dB) with zero mean and σ standard deviation in (dB).

This paper suggested a common type of nodes communication: nodes can discover and connect with other nodes in the network if the inter-distance measured between them is smaller than the communication range *r*.

3.2. Stages of Localization System

There are four distinct stages in the localization system as drawn in Figure 2.

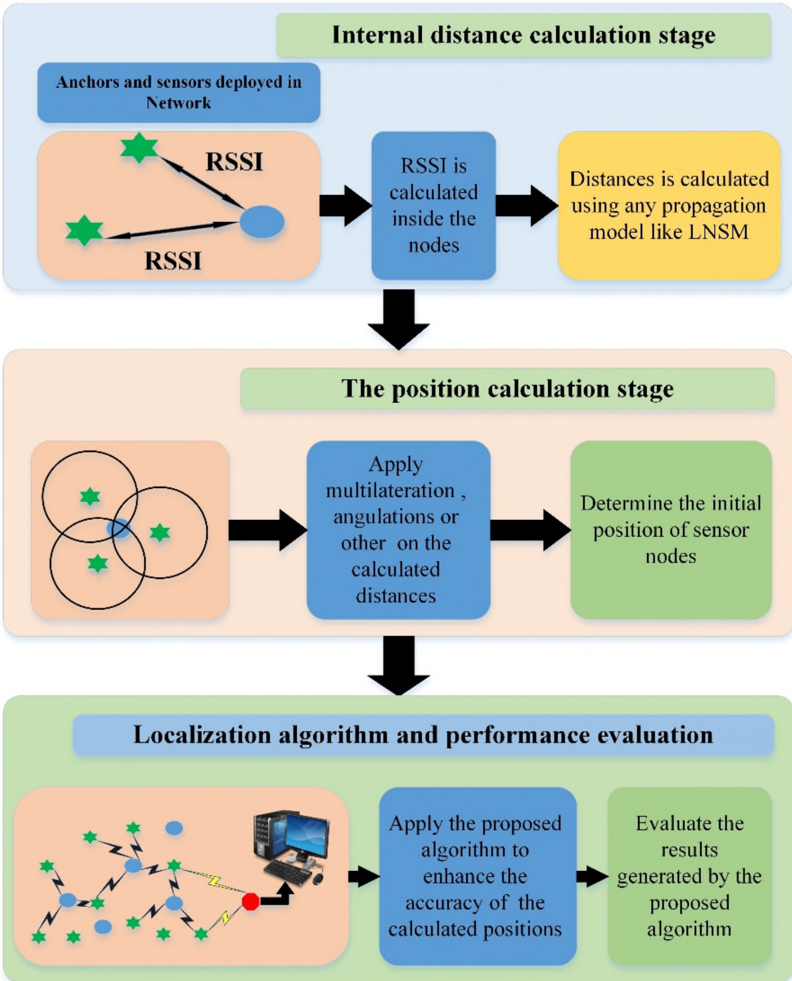

Figure 2 Stages of Localization System

1. The internal distances measurement stage: In this stage, there are several techniques of ranging utilized to calculate the inter-distances between anchors and unknown nodes. Generally, these techniques include several techniques, such as those utilized angle of arrival (AOA) technique, received signal strength (RSS) technique, and time-based techniques like time of arrival (TOA), time difference of arrival (TDOA) or round trip time (RTT). Then, any suggested Radio propagation model will treat the signal measurement resulting from ranging techniques to calculate the final inter-space between WSN nodes.
2. The position calculation stage: In this stage, traditional techniques such as multilateration /angulations or modern techniques process the previous stage measurements to determine the initial positions coordinates of unknown nodes installed in WSNs.
3. Localization algorithm applying stage: This is the fundamental stage in the localization process. This stage explains how the information from the previous two stages can be handled and exploited to improve the position accuracy of unknown nodes by utilizing the proposed

hybrid algorithm that combines Intelligent Water Drops (IWD) and simulated annealing.

4. The performance evaluation stage: This is the final stage in the localization system, where several evaluation metrics compromised localization error and final localization rate are utilized to evaluate the localization results.

3.3. Radio Propagation Models

In the scientific literature, propagation models refer to the methods that study and predict the average strength of the received signal at a specific point from the transmitter. They also refer to the means that study the signal strength variability in a specific location [2]. In the scientific literature, several studies have supposed several models of propagation for different environments, either outdoor or indoor [4] and [45]. Generally, RSSI-based techniques utilize a common propagation model called Lognormal shadowing model (LNSM). LNSM is characterized as a simple model and has a fair achievement in formulating the relationship between the measured distance and the degree of signal attenuation. LNSM formulate the relationship between RSSI and distance as in Equation 1.

$$RSSI_d(dBm) = RSSI_{d_0}(dBm) - 10n\log\frac{d}{d_0} + X_\sigma \qquad \text{Equation 1}$$

Where

- $RSSI_d$: It indicates the power of the signal received by the antenna of sensor node (unknown node) from the surrounding anchors.
- $RSSI_{d0}$: It indicates the power of the signal received by the antenna of sensor node (unknown node) at reference distance d_0 from an anchor node, often 1m. Some factories of WSN devices refer to the $RSSI_{d0}$ value in the product datasheet, for example (-45 dBm) [46].
- d: refers to the distance between anchor node and the studied unknown node.
- **(10n log d/d_0)**: It indicates the Pathloss.
- n: It refers to the Path Loss exponent. It has an STD value that ranges from 2 to 6.5 and is to be determined based on the propagation media of the signal or surrounding environment (see Table 1) of the WSNs.
- X_σ: It refers to the shadowing factor or by other meaning, it express the random variation in RSS. Scientifically, it can be defined as a Gaussian distributed random variable (in dB) with zero mean and σ standard deviation (in dB).

Table 1 Path Loss Exponent Rang

Environment	n
Urban macro cells	3.7 - 6.5
Urban micro cells	2.7 - 3.5
Office building (same floor)	1.6 - 3.5
Office building (multiple floors)	2 - 6
Store	1.8 - 2.2
Factory	1.6 - 3.3
Home	3

Then the distance *(d)* from any anchor node to the studied unknown node is calculated as in Equation 2.

$$d = 10^{\frac{RSSI_{d0} - RSSI_d + X_\sigma}{10n}} \qquad \text{Equation 2}$$

Practically, the position of the studied unknown node could be calculated after determining the distances to three anchors at least. The distance to any anchor is calculated by Equation 2. Then, the coordinate of the studied unknown node could be obtained by applying trilateration. Generally, there will be measurement errors for any models of ranging technique. These errors often result from noise during range estimations and adversely affect the localization accuracy in the position estimation stage. To overcome the errors resulting from geometric approaches (trilateration), the researchers developed other approaches to estimate the position of the unknown nodes, such as optimization techniques that could minimize measurement errors.

As previously explained in the introduction, the purpose of localization algorithms is to determine the locations of unknown nodes by processing the location information of anchor nodes. The localization process can be expressed as an optimization problem that requires finding the best solution by developing an objective function.

This paper formulated the objective function, which will guide the solution of the optimization problem by taking advantage of the circular positioning algorithm. This algorithm aims to extract the (x, y) position of the unknown node that reduces the sum of squared errors of the estimated distances set. Assume that (X_i, Y_i) is the position of anchor node i, $(i = 1, 2 \ldots N)$, where (N is the number of anchor nodes) and (d_i) is the distances between anchor nodes and the studied unknown node calculated by the suggested model of ranging, LNSM, then the squared error in the set of the calculated distances (Equation 3).

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(X_i - x)^2 + (Y_i - y)^2} - d_i\right)^2 \qquad \text{Equation 3}$$

This paper assumes to utilize Equation 3 as the fitness function of the objective function $f(x, y)$ (Equation 4).

$$f(x, y) = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(X_i - x)^2 + (Y_i - y)^2} - d_i\right)^2 \qquad \text{Equation 4}$$

Where

- $N \geq 3$ is the number of anchor nodes within the transmission range of unknown node.
- (X_i, Y_i) is the coordinate of i_{th} beacon (anchor) node.
- (x, y) is the coordinate of the studied unknown node.
- d_i is the determined distance between anchors and the studied unknown node.

4. Intelligent Water Drops

The idea of Intelligent Water Drops (IWD) was inspired by rivers in nature. When a massive swarm of water drops are stirring in the natural river, they create a path the river follows. This river path changes dramatically with time due to water drops movement. In addition, the natural environment has a direct effect on the path of the river. These effects have been compiled in an algorithm called Intelligent Water Drop. Figure 3 shows a river's natural path where water drops move without stopping.

Figure 3 Natural River

It can be observed from Figure 3, that the river paths in nature ordinarily have a lot of twists and turns. Axiomatically, water drops navigate their way to their target destination without eyes; the destination is often a lake or sea. The water drops are driven by a gravitational force that pulls everything in a straight line toward the earth's center. Therefore, in the ideal case where the path has no barriers or obstacles, the swarm of water drops transfer through a straight line toward the target destination. This straight line is the shortest route that water drops can take from the source to the destination.

As mentioned, the water drops route is not ideal, so it is not perfectly straight due to natural obstacles and barriers along the whole path. In addition, water drops constantly try to create a new path similar to the ideal one; therefore, the river's path continually changes with time.

Water drop velocity in the river is a significant characteristic to study. The IWD algorithm assumes that each water drop able to carry a specific volume of soil from one point to another along its movement path. Usually, water drops load the soil from fast to slow parts of the path. As a result, the fast part becomes deeper because water drops already transferred a significant amounts of soil; therefore, the fast part attracts more water drops. As long as its movement path, water drops unloaded the carried soil in the river's slower beds. Typically, during movement from the river source to the target destination, water drops prioritize the easier path when several branches with various difficulties exist. The degree of difficulty of any path can be selected by the volume of the accumulated soil on that path. Therefore, as long as the volume of the accumulated soil in that path is less, it will be considered an easy path; conversely, as long as the volume of the accumulated soil in that path is more, it will be regarded as a hard path.

IWD algorithm was developed by Shah-Hosseini in 2007. He explained several remarkable characteristics of a water drop that transfer in the natural rivers. Two significant characteristics characterize this Intelligent Water Drop [47]:

1. The existing volume of soil transferred by IWD, shortly (Soil IWD).
2. The existing velocity of IWD, shortly (Velocity IWD).

The IWD algorithm assumes that the amount of (Soil IWD) and the value of (Velocity IWD) for each water drops vary while they move in the surrounding environment. IWD algorithm considered the surrounding environment of water drops as the problem that required solving. Generally, the IWD drops can transfer in several paths, starting from a specific source and reaching a target destination in the surrounding environment. Each path can be considered a unique solution. In most cases, the target destination is unknown. In the case that the target destination is well known, the shortest route starting from the origin to reach the target destination is considered the solution. However, in the other cases where the target destination is unspecific, the solution is extracted by searching for an optimum target destination by applying several terms of measurement to the given problem.

In the beginning, the developer of IWD algorithm used it to find the best solution of the Travelling Salesman Problem (TSP) [47]. Then, successively IWD algorithm was used to solve several problems, such as n-queen puzzle [9], the Multidimensional Knapsack Problem (MKP) [48], and Robot Path Planning [49]. Generally, Intelligent Water Drop algorithm is considered the appropriate method to deal with optimization problems. This paper suggested utilizing an improved variation of IWD named (IWD for continuous optimization), shortly IWD-CO**,** to solve the continuous optimization problem. In this case, the solution requires several continuous parameters that can minimize or maximize the objective function. The continuous variables are expressed as binary strings in the IWD-CO algorithm. Also, the target problem is defined as a binary representation. Finally, the best solution among the optimized solutions generated by IWD-CO is selected as the final solution.

This paper planned to utilize the version of IWD-CO to enhance the localization accuracy in WSNs by hybridizing it with simulated annealing. Equation 4 is considered the objective function, which will be a guide to solve the optimization problem and find the best solution in the searching space.

5. IWD for Optimizing Continuous Problem

This part of paper demonstrates the steps that IWD-CO follows to enhance the solution of a target problem or for the objective function. The solution generated by IWD-CO is designed based on a theory graph, which represents a distributed memory for IWD-CO for processing data. The implementation steps of IWD-CO are clarified in the subsequent subsections.

5.1. Problem Illustration

Suppose that $f(X)$: R^M is the function required to be minimized or maximized by IWD-CO. $f(X)$: R^M has N elements $Z = [z_1, z_2, \ldots z_N]^T$, where these elements are the input of IWC-CO. A graph is built with N nodes, hence there will be $2(N * P)$ directed edges. The IWD-CO utilizes this graph to generate solutions for the target objective function of the problem. The allowed scope of each element is divided by a precision factor equal to P. Assume that the search space has a range of component (i) from minimum (i) to maximum (i), where each following node (P) in the graph is represented by P bits in the shape of a binary string. This paper planned to evaluate a value of P equal to two. Initially, this paper proposed that the edges linking the graph nodes carry the same volume of soil. The journey of every water drop takes a path starting from node one and ending at the last node. In the graph, there are two directed edges $ed_{i,i+1}(k)$ linking between node (i) and the next node $i + 1$. k is a one-bit with zero or one value, each value of k represents one directed graph-edge to the node.

5.2. Edge Determination

Assume that a water drop launches its trip from node with number (i) and crosses the $edge_{i,i+1}(k)$ to reach the next node with number $(i + 1)$. The probability $Pr_{iwd}(ed_{i,i+1}(k))$ for choosing an edge in the graph is calculated Equation 5 to Equation 7.

$$\boldsymbol{Pr_{iwd}}(\boldsymbol{ed_{i,i+1}(k)}) = \frac{f(soil\ (ed_{i,i+1}(k)))}{\sum_{l=0}^{1} f(soil\ (ed_{i,i+1}(l)))}, \qquad \text{Equation 5}$$

where

$$f(soil(\boldsymbol{ed_{i,i+1}(k)}) = \frac{1}{0.0001 + g(soil(\boldsymbol{ed_{i,i+1}(k)})}, \qquad \text{Equation 6}$$

and

$$g(soil\left(\boldsymbol{ed_{i,i+1}(k)}\right) = \begin{cases} soil\ \left(ed_{i,i+1}(k)\right)\ if\ min_{l=0.1}\left(soil\ \left(ed_{i,i+1}(l)\right)\right) \geq 0, \\ soil\ \left(ed_{i,i+1}(k)\right) - min_{l=0.1}\left(soil\ \left(ed_{i,i+1}(l)\right)\right)\ else. \end{cases} \qquad \text{Equation 7}$$

Along its journey path and the different operation of replacing nodes with others and choosing the next edges, the water drop updates its carried soil and transfers soil from the current choosing edge. The local soil updating process is demonstrated in the following subsection.

5.3. Local Soil Updating

Assume that a water drop is transferred from node number (i) to the next node number $(i + 1)$ by crossing edge $y_{i,i+1}(k)$. Sequentially the suggested algorithm updates the volume of soil $(soil_{iwd})$ that IWD water drop carried out, and the volume of soil replacing from the selected edge between the neighboring nodes, $soil(ed_{i,i+1}(k))$ (Equation 8 and Equation 9).

$$soil\left(\boldsymbol{ed_{i,i+1}(k)}\right) = 1.1 * soil\left(\boldsymbol{ed_{i,i+1}(k)}\right) - 0.01 * \Delta soil\left(\boldsymbol{ed_{i,i+1}(k)}\right), soil_{iwd} = soil_{iwd} + \Delta soil\left(\boldsymbol{ed_{i,i+1}(k)}\right). \qquad \text{Equation 8}$$

Where

$$\Delta soil\left(\boldsymbol{ed_{i,i+1}(k)}\right) = 0.001 \qquad \text{Equation 9}$$

As a result, IWD, which selects an edge with a small amount of soil, acquires more speed than IWD, which chooses an edge with a large amount of soil. The IWD creates solutions by completing their journey to the node in the end of the problem graph. Then these solutions are utilized by a local search algorithm.

5.4. Mutation-Based Local Search Stage

The solutions generated by the IWD in the previous stage undergo a mutation operation. Initially, a mutation process starts by randomly electing any edge $ed_{i,i+1}(k)$ from the graph. The selected edge is changed by any neighbor edge that connects the same nodes i and $i + 1$ in case replacement improves the selected solution's fitness value. The replacement process is repeated over a fixed period. As mentioned, all the generated solutions by the IWD in the current iteration undergo this stage of mutation-based local search. In the final stage of the mutation process, the edges that represent the best solution are selected and they will undergo the process of global soil updating. The following subsection demonstrates that.

5.5. Global Soil Updating

The best generated solution T^B from the mutation stage will undergo Global soil updating. The best solution T^B is extracted from among the solutions generated by IWD in the final iteration. This solution is characterized by the best value of (fitness) among all the solutions developed by IWD. In this stage, the soil's volume of graph-edges shaping the best generated solution T^B undergoes an update as follows (Equation 10 and Equation 11).

$$soil\left(\boldsymbol{ed_{i,i+1}(k)}\right) = min\left(max\left(Tempsoil\left(ed_{i,i+1}(k)\right), MinSoil\right), MaxSoil\right)\ \forall\ ed_{i,i+1}(k) \in\ T^B, \qquad \text{Equation 10}$$

where,

$$Tempsoil\left(ed_{i,i+1}(k)\right) = 1.1\ * soil\ \left(ed_{i,i+1}(k)\right) - 0.01 * \frac{soil_B^{iwd}}{(N*P)}, \qquad \forall\ ed_{i,i+1}(k) \in\ T^B, \qquad \text{Equation 11}$$

MinSoil and *MaxSoil* are the upper and lower limits for the amount of soil that the global soil updating relies on to stop unacceptable use of the edges. The simulation experiment sets these boundaries as *MinSoil* = 2000 and *MaxSoil* = 10000. N represent the function components number, whereas P is the precision factor. The term $soil_B^{iwd}$ is the volume of soil accumulated by the IWD-best generated solution from the graph-edges during the journey in the graph. Briefly, $soil_B^{iwd}$ represents the fitness cost of the best generated solution within the current iteration group, T^B. After the current iteration of the process of global soil updating, a process with new iteration will start with a new IWD group. The updating is repeated with new IWD until the implementation reached the final number of iterations.

6. Simulated Annealing

Since Simulated Annealing was innovated and utilized as a solving method for optimization problems, it has been used to improve the solutions for a considerable number of algorithms. SA has been utilized either as an original version with its essential functions or as a hybrid algorithm with other metaheuristics methods. SA technique proved its ability to introduce good application results compared to other local search metaheuristics techniques [50][51]. The scientific literature has excellent reviews and studies about SA and its application to solve optimization problems [52].

The main goal of combining SA with IWD is to improve the quality of the final solutions generated by the IWD. Another fundamental goal in suggesting the hybrid algorithm between these two techniques is to build a robust local search method that assists IWD algorithm to overcome trapping into local minima. SA is considered an intelligent search method that can pass from the current solution to another among the neighborhood solutions. Therefore, SA has the advantage of producing objective values that support IWD to solve the localization problem efficiently. SA has more advantages than the hill climbing method, where it has the potential to crossover local minima trapping by selecting worse moves (low quality) or uphill steps randomly in some time. SA follows a specific movement procedure to choose the best solution, so if the expected move could produce a solution better than its current position solution, then SA will follow that movement. If the expected move creates a worse solution, SA could accept that movement based on specific probability selection criteria.

For the localization process, the SA starts its procedure by evaluating the construction of the best IWD solutions, represented by T_i^{iwd} *(i = 1, 2... n)*, for a set of specific elements with updated solutions T_i^{iwd} +1 generated by switching the orders of two elements randomly. The cost of fitness function represents the quality of solution T_i^{iwd}, and it is indicated by $f(T_i^{iwd})$. The difference in cost Δf between the original solution T_i^{iwd} and the updated solution T_i^{iwd} +1 is denoted by Equation 12.

$$\Delta f = f\left(T_{i+1}^{iwd}\right) - f\left(T_i^{iwd}\right) \qquad \text{Equation 12}$$

The cost of fitness functions is calculated repeatedly; hence, the average evaluation of the function costs presents a good indication of the quality of the generated solutions. In some specific cases, it should consider following a simple evaluation of the fitness functions to reduce the implementation time of SA.

SA starts the optimization process with the initial solution generated by IWDCO. The new solution is only accepted if its fitness cost is smaller than the previous solution. More clearly, the new solution is accepted when its fitness cost achieves the following (Equation 13):

$$f\left(T_{i+1}^{iwd}\right) < f\left(T_i^{iwd}\right) \qquad \text{Equation 13}$$

However, in some cases, SA algorithm to accept or reject any new solution f (T_i^{iwd} +1) which has a higher fitness cost is based on the following acceptance criteria probability (Equation 14):

$$p(f, t_\tau) = \exp\left(-\frac{f\left(T_{i+1}^{iwd}\right) - f\left(T_i^{iwd}\right)}{k t_\tau}\right) \qquad \text{Equation 14}$$

To enhance the efficiency of SA, Eq 14 will be replaced by the following equation in the case the size of the target problem is large (Equation 15):

$$p(f, t_\tau) = \exp\left(-\frac{f\left(T_{i+1}^{iwd}\right) - f\left(T_i^{iwd}\right)}{t_\tau}\right) \qquad \text{Equation 15}$$

In the purpose of lessening the implementation time of the SA procedure, an approximation process is applied on Equation 16.

$$p(f, t_\tau) = \left(1 - \frac{f\left(T_{i+1}^{iwd}\right) - f\left(T_i^{iwd}\right)}{t_\tau}\right) \qquad \text{Equation 16}$$

t_τ denotes the temperature factor at the τth iteration during the evaluation process of the new solution by applying Eq 15 or Eq 16. Hence, the new solution's acceptance probability relates to the temperature t_τ and the difference in the fitness cost between the previous solution and the new solution. Several researchers approved that the acceptance probability of any new solution, that is worse than the previous solution, declines as the temperature t_τ decreases. Briefly, only the best solutions are accepted when the temperature t_τ deteriorates to zero. This paper adopted the following cooling formula (Equation 17).

$$t_\tau + 1 = \alpha t_\tau \qquad \text{Equation 17}$$

Where α represents the deteriorate rate of the temperature t_τ at each time SA discovers a new solution.

7. The Proposed Hybrid Algorithm

The proposed hybrid algorithm IWDSA utilizes the SA acceptance probability criteria to compare the cost of fitness function between the current and the new solution, then selects one for the updating process. The proposed algorithm performs this process by computing the fitness function of the solutions generated by the old and new IWD drops and comparing their quality. Generally, the generated solutions' quality revolves around T^M and T^B. The proposed algorithm follows several factors to evaluate the acceptance method of the solutions. These factors mainly include the fitness function (solution quality) and the working temperature t_τ. The main advantage of acceptance criteria is to give an ability for the IWD algorithm to escape from the trap in local minima; hence that leads to increasing the rate of both exploration and convergence of the algorithm.

7.1. Implementation Steps of the IWDSA

The implementation method of the proposed algorithm IWDSA for the process of localization in the target WSNs follows the pseudo code shown in Algorithm 1. Each unknown node in the target network is undergoing the implementation of the subsequent steps:

Step 1: The majority of metaheuristic optimization techniques initiate the implementation process with an initial solution. Hence, in the beginning of the localization process, the deployed unknown nodes have to extract the initial estimated position. Therefore, in this paper, the centroid of the anchor nodes located under the unknown node coverage range is considered a perfect initial calculated position. Step 1 is demonstrated as follows (Equation 18).

$$X_{init} = \frac{1}{N}\sum_{i=1}^{N} X_i\,, \qquad Y_{init} = \frac{1}{N}\sum_{i=1}^{N} Y_i\,, \qquad \text{Equation 18}$$

where

- (X_{init}, Y_{init}) is the initial position of i_{th} unknown deployed node.
- (X_i, Y_i) is the position coordinate of i_{th} beacon (anchor) node.
- N denotes the density of anchors located under the coverage area of unknown deployed node in the target WSNs.

Step 2: The positions of the N components, $Z = [z_1, z_2, \ldots, z_N]^T$, which represent the objective function $f(x, y)$, are assigned randomly throughout the polar coordinates system. The initial position obtained from step 1 (Equation 12) is selected as the origin point in the graph.

Step 3: In this step, the algorithm divides the search space assigned to each component, Z_i, into P different positions with coordinate (x, y) where each position denotes a single node in the target graph, and also represents initial generated position of the unknown deployed node which will undergo evaluation by using

Equation 4. Hence, the problem's graph has number of nodes equal to ($N * P$) and $2 * N * P$ number of edges, where each node has a connection to the neighbor nodes by two edges. The proposed algorithm assigned the same amount of soil for all edges forming the graph; this amount is equal to 5000.

Step 4: IWDSA starts the implementation cycle by distributing all water drops randomly on the graph nodes.

Step 5: Every water drop determines the next graph $edge_{i,i+1}(k)$, which is a link connected node with number (i) and node with number ($i + 1$) based on Equations 5, 6 & 7.

Step 6: During the implementation, the soil volume carried by IWD ($soil_{iwd}$), and the soil accumulated in the selected edge, $soil(ed_{i,i+1}(k))$, are updating by applying Equations 8 & 9.

Step 7: At this step, the mutation process is applied to all solutions generated by IWD as nominated in the mutation local search stage. Then, the edges are chosen depending on the fitness cost of the suggested objective function. Equation 4 represent the objective function.

Step 8: In this step, the best generated solution T^B is extracted from all solutions generated by water drops in **Step 6**. The best generated solution T^B is characterized by the lowest cost of fitness of the objective function, as shown in Equation 4.

Step 9: SA algorithm starts its process from this step by creating new solution T_{i+1}^{iwd} from T_i^{iwd}, where T_i^{iwd} is equal to T^B from step 8.

Step 10: The fitness value of both T_{i+1}^{iwd} and T_i^{iwd} is calculated, and a comparison between their values is handled to determine the solution T^M with the lowest fitness value.

Step 11: The global soil updating will be applied to the best final solution T^M resulted from the previous step by implementing Equations 10 & 11, and then updates the global best solution T^B based on SA algorithm process.

Step 12: Update working temperature $t_{k+1} = \alpha t_k$.

Step 13: The proposed algorithm IWDSA repeats steps from **Step 4** to **Step 12** until the termination condition or the last value of iterations number is implemented. In the final stage, the best estimated location of the target unknown sensor node is determined by exploring the nodes which created the best solution T^B. Then, the solution with the lowest value of the objective function is the final position of the target unknown sensor node, Equation 4.

7.2. IWDSA Pseudo Code

Algorithm 1 depicts the pseudo code of the proposed algorithm IWDSA.

Algorithm 1 Pseudo code of the IWDSA

Require : Unknown nodes deployed in outdoor environment.
Parameters initialization: Determine the position of anchors using GPS, maximum iteration number, amount of initial soil and update parameters for both soil and velocity.
Output : The estimated position of unknown nodes.
1: **ForEach** unknown node
2: Calculate the initial estimated position using Eq 12;
3: Initialized the N components of $f(x, y)$ randomly using polar coordinate with the initial in last step as the origin;
4: Divide search space of each component to P position, thus, totally $N * P$ nodes construct the graph with $2 * N * P$ edges;
5: **End For**
6: **ForEach** IWD
7: Assign amount of soil to all edges of the graph, e.g., 5000;

8: **End For**
9: **Repeat** until reach termination condition;
10: Distribute IWD randomly on the of graph's nodes;
11: Start the cycle of IWD-CO;
12: Each node selects appropriate edge to next node by Eq 5, 6, & 7;
13: Update $Soil_{iwd}$ and $Soil(ed_{i,i+1}(k))$, using Eq 8 & 9;
14: Apply the mutation process on the solutions generated by IWD;
15: Extract the best Solution T^B which is related to the lowest value of fitness function Eq 4;
16: *********Hybrid with SA start from this point*******
17: T_i^{iwd} is equal to T^B from last step;
18: Create a new solution T_{i+1}^{iwd} from T_i^{iwd} .
19: Calculate the fitness functions $f(T_{i+1}^{iwd})$ and $f(T_i^{iwd})$.
20: **If** $f(T_i^{iwd}) \leq f(T_i^{iwd})$ **Then**
21: $T_i^{iwd} = T_{i+1}^{iwd}$;
22: **Else**
23: Calculate $p(f, t_\tau)$ with Eq 14 or Eq 15;
24: **If** $p \geq r(0, 1)$ **Then ; r is random number**
25: : $T_i^{iwd} = T_{i+1}^{iwd}$
26: **END IF**
27: $T^M = T_i^{iwd}$, T^M *is the current best solution.*
28: Apply soil updating on the best current solution using Eq 10 & 11 and update the Global best solution T^B as follow
29: **If** $f(T^B) \geq f(T^M)$ **Then**
30: $T^B = T^M$
31: **Else**
32: $T^B = T^M$
33: **End IF**
34: Update working temperature $t_{k+1} = \alpha t_k$
35: **End Repeat**
36: Extracted the position from the graph's nodes that represented the best generated solution T^B;
37: The final position of the studied node is the graph's node has the lowest cost of the suggested objective function;

8. Simulation Experiment and Performance Analysis

The performance of the proposed algorithm IWDSA was analyzed by launching Simulation experiments. These experiments were carried out using Matlab™16. The simulation experiments were handled with a wireless sensor network comprising a specific number of unknown sensor nodes and a fixed number of anchor nodes. The target WSN was installed outdoors with dimensions 20m $*$ 20m. The unknown wireless sensor nodes were deployed randomly in the target WSN. In contrast, the beacon (anchor) nodes took fixed places in the simulation area.

An evaluation comparison was handled between IWDSA and other localization algorithms, including algorithms that used traditional localization techniques (e.g., HCEDV-Hop and RSSI-LSSVR) and other algorithms of localization that utilized optimization approaches (e.g., IWD, ACO, MPA, and HSPPSO). The simulation experiment considered several influencing factors for implementation, including the number of anchors (N), communication range and noise that expressed by standard deviation **(σ)**. Table 2 lists the setting of parameters values for the simulation experiment.

Table 2 Simulation Experiment Parameters.

Parameter	value
Network size	*20 $*$ 20* (m)
Number of nodes	*100*

Parameter	value
Percentage of anchor nodes	*5%* to *20 %*
Transmission range	*r = 5 - 20m*
Path loss exponent *n*	*2*
Noise σ	*0.1 - 1.5*

8.1. Simulation Environment

To carry out the simulation, we developed a MATLAB-based program, as previously mentioned. This program is characterized by a user interface that facilitates the input of settings and parameters. The user interface depicts the results as illustrated in Figure 4.

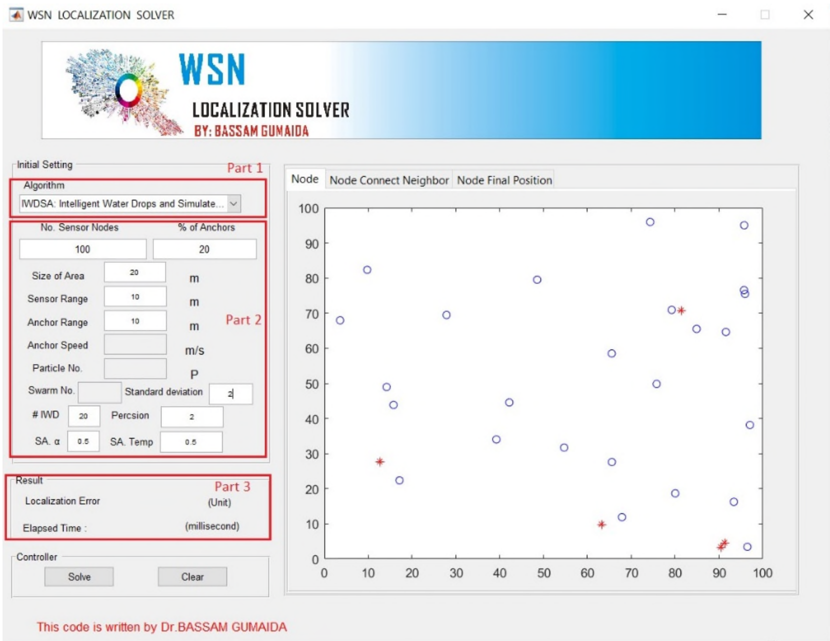

Figure 4 Simulation Interface

where:

- Part 1: select the localization algorithm.
- Part 2: determine the number of sensor nodes and anchors, and to select the way of deployment and set up the value of the influencing factors such as standard deviation, communication range, set up IWD parameters and set up SA parameters.
- Part 3 to show the simulation results including the localization error and implementation time.

The simulation program is executed through the subsequent steps.

1. Determine the initial settings included (the number of anchors, sensor nodes, and the value of standard deviation, number of IWD, parameters of simulated annealing).
2. Deploy the sensor nodes and anchors in the simulation area (assign the coordinates).
3. Estimate the distances between anchors and sensor nodes by utilizing the formula of RSSI.
4. The position estimation of sensor nodes by applying multilateration.

5. Executing the proposed hybrid algorithm IWDSA on the positions estimated in the previous step for optimization purposes by following the outlined pseudo code to identify the best solution.
6. Calculate the localization error and implantation time and show them in the user interface as depict in Figure 5.
7. Repeat the previous steps with different parameter values and settings.
8. Organize the final outcomes within appropriate tables and subsequently present them through a corresponding figure.

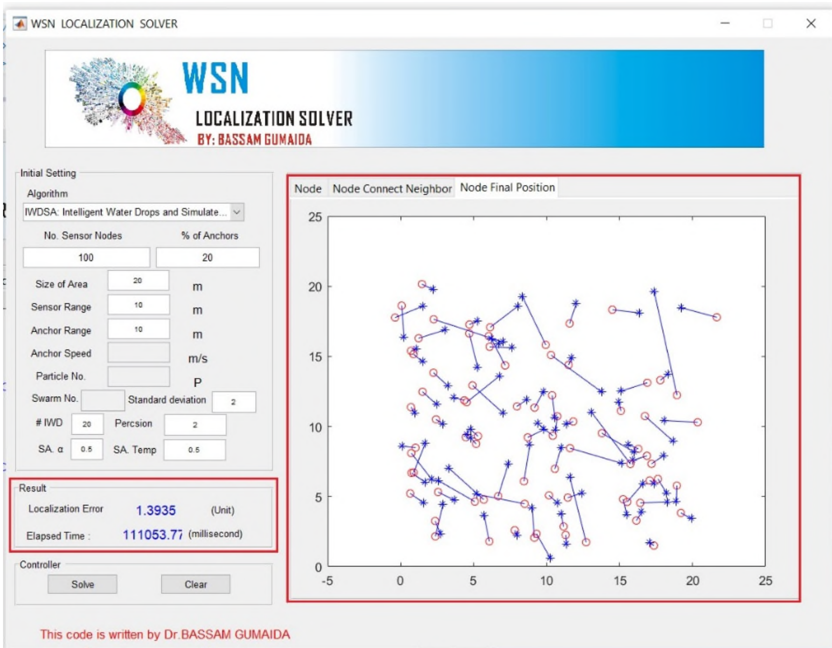

Figure 5 Interface with Result

8.2. Metrics of Performance Evaluation

This paper utilized several factors to rate the performance of the assumed algorithm IWDSA and measure its ability to enhance localization error. The evaluation studies the effect of the density of anchors, communication or transmission range, and noise represented by standard deviation on the algorithm performance. This paper utilized three metrics to evaluate the performance of IWDSA, namely localization error (represents the localization accuracy), localization success and complexity.

Localization error (LE): is the Mean Square Error (MSE) of the proportional between the generated position by IWDSA and the actual position of the unknown wireless sensor node, as shown in Equation 19.

$$LE = \frac{1}{N}\sum_{i=1}^{k}\sqrt{\left(X_{est_i} - X_{real_i}\right)^2 + \left(Y_{est_i} - Y_{real_i}\right)^2} \qquad \text{Equation 19}$$

where

- K is the total number of the deployed sensor (unknown) nodes.
- (X_{est_i}, Y_{est_i}) are the generated coordinates of wireless sensor (unknown) nodes i.
- (X_{real_i}, Y_{real_i}) are the actual coordinates of wireless sensor (unknown) nodes i deployed in the target WSNs.

Localization success: is expressed as the ratio of successfully localized nodes to the network's total number of wireless sensor nodes (Equation 20).

$$LS = \frac{number\ of\ localized\ nodes}{number\ of\ all\ unknown\ nodes} \qquad \text{Equation 20}$$

Complexity: or in other words, the localization time. It can be expressed as the time spent by the algorithms to conduct the localization processes in the target WSNs. This metric is considered as essential metric for the performance analysis among all evaluated algorithms.

8.3. Experiment Results Evaluation

This paper follows a specific methodology to present performance evaluation of the proposed algorithm by analyzing the experimental results as the following two stages.

1. Firstly, this paper evaluated the performance of IWD before hybrid with SA. The evaluation has been carried out, taking into consideration three affecting parameters. These parameters are the number of water drops, the precision value (P), and the function's components (N).
2. Secondly, this paper studied the performance of the suggested hybrid algorithm, IWDSA, and evaluated the performance at the optimum point compared to other algorithms' performance using localization evaluation metrics.

8.3.1. Localization Error Against the Number of Water Drops

Figure 6 illustrates the direct effect of increasing the density of water drops on localization accuracy.

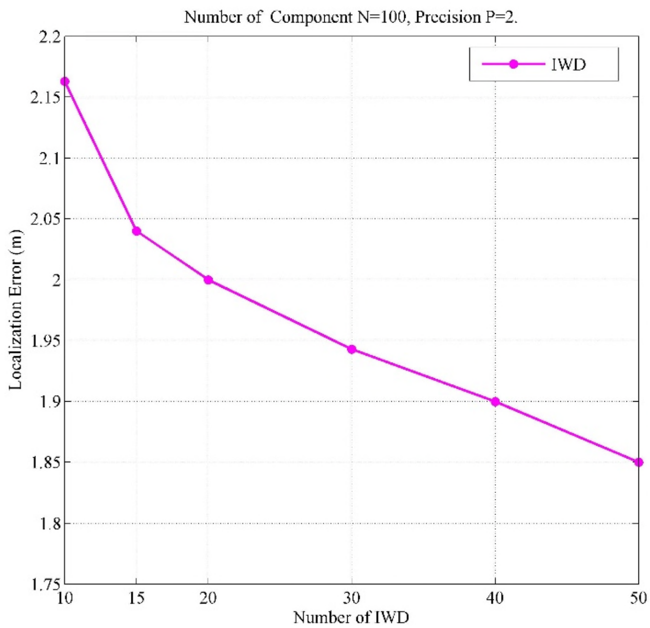

Figure 6 Localization Error vs. IWD

The simulation results demonstrate the degradation of the localization error when the density of IWD is increasing in the problem graph. This degradation of localization error is a direct result of increasing the number of solutions generated by IWD, which in turn leads to increasing the probability of obtaining the best solution for the objective function. Therefore, as a final result, increasing the number of IWD improves the localization precision.

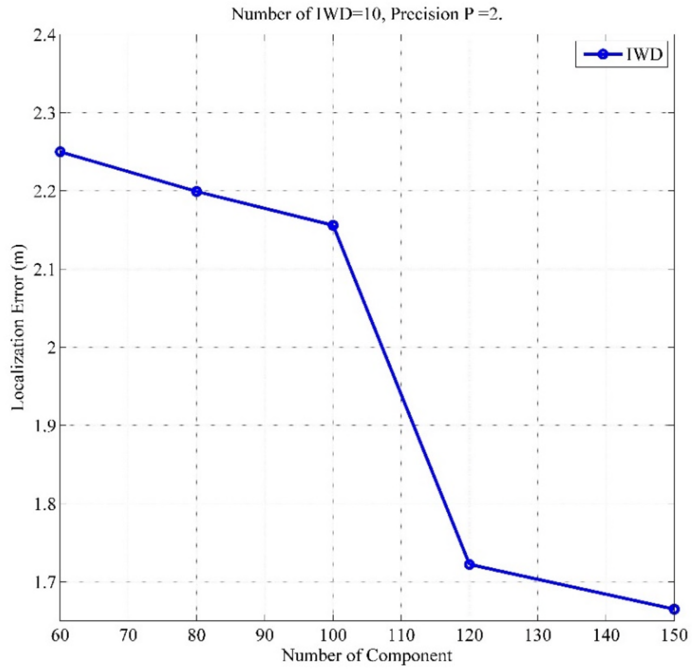

Figure 7 Localization Error vs. Number of Components

8.3.2. Localization Error against the Number of Components (N)

The impact of rising the density of the function's components (*N*) appears clearly in Figure 7. It demonstrates that the localization error declines when increase the density of components (*N*). This decline in localization error is attributed to expanding search space that surround the initial solution, which increases the probability of obtaining the best solution characterized by the smallest value of fitness function briefly, the localization accuracy presented by IWD increases while rising the density of components (*N*). Figure 6 and Figure 7 proved the same result that expanding the search space that surrounds the initial point will inevitably enhance the localization accuracy.

8.3.3. Localization Error against Anchor Density

Table 3 and Figure 8 compare the performance and strength of the proposed algorithm IWDSA with other algorithms. The comparison demonstrates the direct effect of increasing the density of anchors on the localization errors. The comparison proved the capability of IWDSA to enhance and improve the localization accuracy compared to the original IWD and other localization algorithm.

Table 3 Localization Errors Against The Density of Anchors

Metric	Localization Algorithms						
Number of Anchors	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
4	2.5	6.145	2.335	2.458	3.7	1.807	1.51
8	2.32	5.5	1.8	1.876	3.105	1.575	1.27
12	2.155	5.3	1.67	1.736	2.855	1.46	0.98

Metric	Localization Algorithms						
Number of Anchors	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
16	2.05	4.93	1.59	1.648	2.745	1.418	0.91
20	1.92	4.9	1.32	1.567	2.6	1.379	0.86

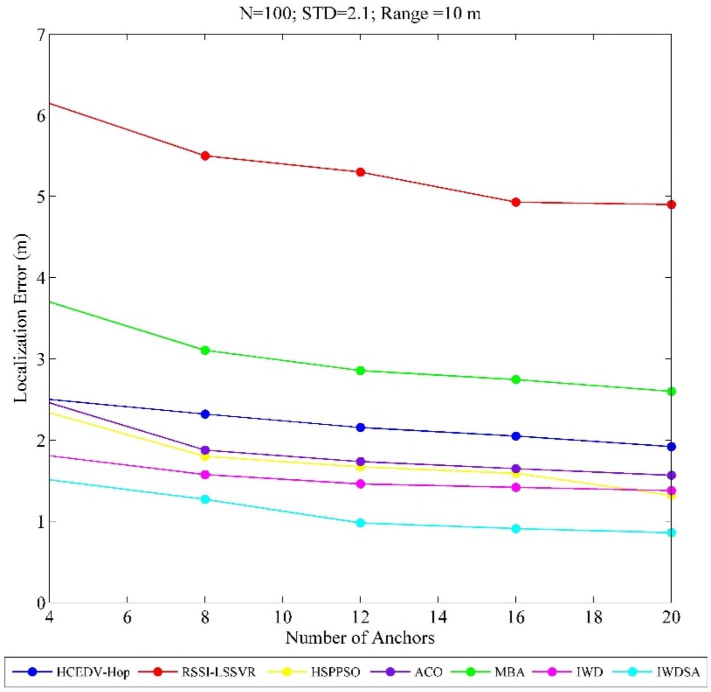

Figure 8 Localization Error against Anchor Density

The experiment's results emphasize the capability of IWDSA to improve localization accuracy with fewer anchors, which perfectly reduces the cost of sensor network developments. It is evident from the experiment result that when the number of anchors distributed in the deployment area is 20, the hybrid algorithm IWDSA boosts the localization accuracy by 38% compared to the original IWD (before hybrid with SA). Table 3 gives information of the localization error against several values of the number of anchors. For example, from the results in the table, when the value is 8, the localization error resulting from IWDSA is equal to 1.27 m, whereas, for HCEDV-Hop, RSSI-LSSVR, HSPPSO, ACO, MBA and IWD, the error value is equal to 2.32 m, 5.5 m, 1.8 m, 1.876 m, 3.105 m and 1.575 m respectively. When the value of the number of anchors is equal to 20, the value of localization error resulted by IWDSA just with 0.86 m compared to 4.9 m resulted by RSSI-LSSVR. Eventually, the overall result proved that the proposed hybrid algorithm IWDSA could achieve and present high localization accuracy with fewer anchors.

8.3.4. Robustness under the influence of noise

Based on this work's suggested radio propagation approach, the error of distance measurement between the deployed sensor nodes is represented as $X\sigma$. Gaussian distributed random variable (in dB) characterized by zero mean and standard deviation σ (in dB). Hence, the standard deviation value could be considered a perfect metric to evaluate the performance of IWDSA in a noisy environment.

Table 4 Localization Error Against Noise.

Metric	Localization Algorithms						
Noise (σ)	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
1	4.12	5.07	0.8756	1.3	2.77	1.2	0.81
2	4.65	5.441	1.13	1.34	3	1.38	1
3	5.23	5.68	1.285	2.5	3.77	1.56	1.5
4	5.45	6.06	3.02	3.2	4.25	3.56	2.41

The experiment results shown in Figure 9 and Table 4 illustrate the effect of the noise σ on localization errors. The results demonstrated the slight impact of noise on the performance and robustness of the proposed hybrid algorithm. Despite the slight effect, the results showed the robustness and perfect performance of the hybrid algorithm in the noisy environment; simultaneously, the results proved the capability of the IWDSA to present a high degree of localization accuracy when comparing with other algorithms. It can be noted from the results when the noise value σ equal to 3, the value of localization error results from the hybrid algorithm is 1.5 m compared to localization error value larger than 3 m resulted by HCEDV-Hop, RSSI-LSSVR and MBA. Under the exact terms of noise, the localization error of HSPPOS and IWD are 1.285 m and 1.56 m, respectively. Eventually, the experiment results proved the robustness of the proposed hybrid algorithm IWDSA under harsh noise conditions.

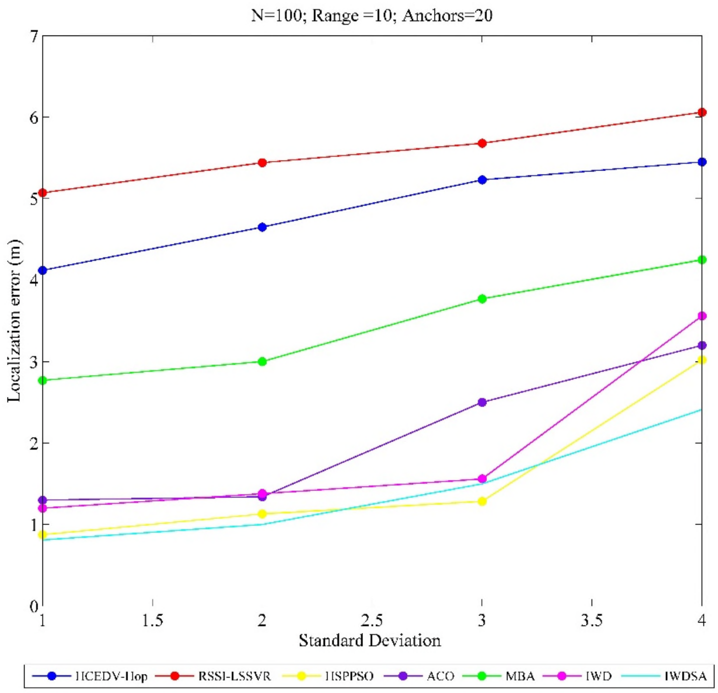

Figure 9 Localization Error against Noise

8.3.5. Localization rate against anchor density

This section outlines how the anchor density has an influence on the localization rate. Figure 10 and Table 5 introduce a comparison among the hybrid algorithm IWDSA and other studied algorithms. Experiment results assured and revealed an improvement in the localization rate by IWDSA while increasing the density of anchors for all studied algorithms.

Table 5 Localization Rate Against Anchor Density.

Metric	Localization Algorithms						
Anchors density	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
4	0.104	0.095	0.145	0.128	0.099	0.135	0.155
8	0.168	0.15	0.195	0.1875	0.125	0.19	0.255
12	0.3214	0.3451	0.3928	0.3571	0.3571	0.3214	0.5653
16	0.6667	0.355	0.7083	0.625	0.425	0.6667	0.8569
20	0.72	0.58	1	0.78	0.69	0.82	1

The results revealed that the hybrid localization algorithm obtained the highest localization rate. In addition, the results disclosed that IWDSA requires less numbers of anchors to achieve the localization process; hence, IWDSA can save the deployment cost.

Finally, the experiment result proved that the proposed algorithm was able to achieve 100% localization rate with just twenty anchors.

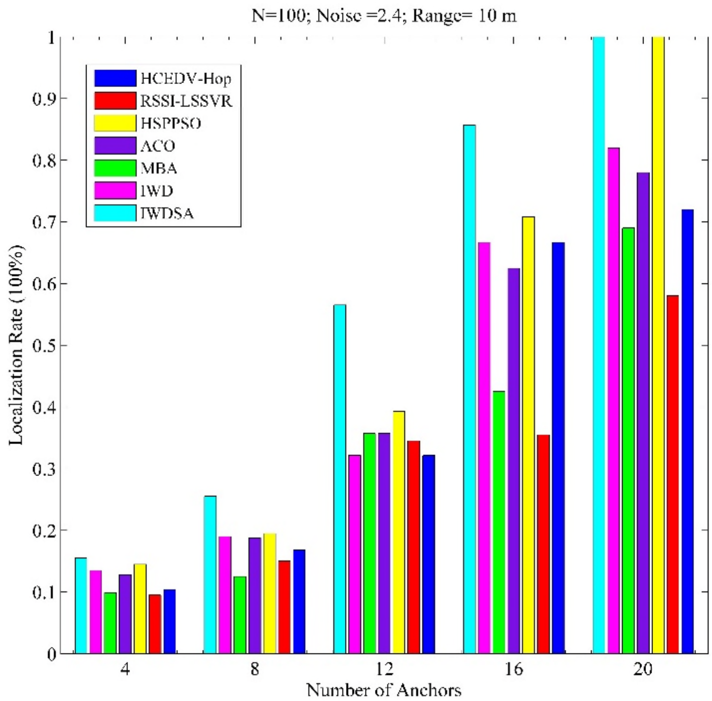

Figure 10 Localization Rate Against Anchor Density

8.3.6. Localization time against anchor density.

Table 6 and Figure 11 explain the direct influence of the anchors' density on the time required for localization process. They address a comparison among the hybrid algorithm IWDSA and other studied algorithms. The localization time was selected as a fair metric to determine the complexity associated with each algorithm while executing. The results demonstrated that the required time for the process of localization declines while increasing the number of anchors. The time decreases because the trilateration process takes a shorter time due to the availability of the required number of anchors. Eventually, the hybrid algorithm IWDSA presented a perfect efficiency compared to the other models.

Table 6 Localization time against anchor density

Metric	Localization Algorithms						
Anchors density	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
4	65.6	91.0	47.9	47.8	81.9	55.3	45.6
8	64.5	76.6	42.0	36.2	68.7	54.6	35.4
12	45.8	64.8	25.0	35.1	60.0	42.9	15.9
16	39.1	49.9	20.0	29.7	42.0	31.1	14.6
20	33.8	49.5	17.5	24.7	41.8	30.5	9.1

A computer featuring i7 processor and 12 Gigabytes of memory was used to handle the simulation experiment. The results in Table 6 demonstrated the required time to localize all sensor nodes deployed in the simulation area. It is evident that the suggested hybrid algorithm IWDSA reached the best-estimated positions of sensor nodes in short time compared to other algorithms. This convergence to the best position appears clearly when the number of anchors exceeds twelve. Implementing the localization process in a short time prolongs the sensor nodes' battery life and thus reduces the final cost of WSN. Eventually, the results proved that a hybrid between IWD algorithm and SA algorithm contributes to overcoming the time problem that may occur when utilizing IWD algorithm alone.

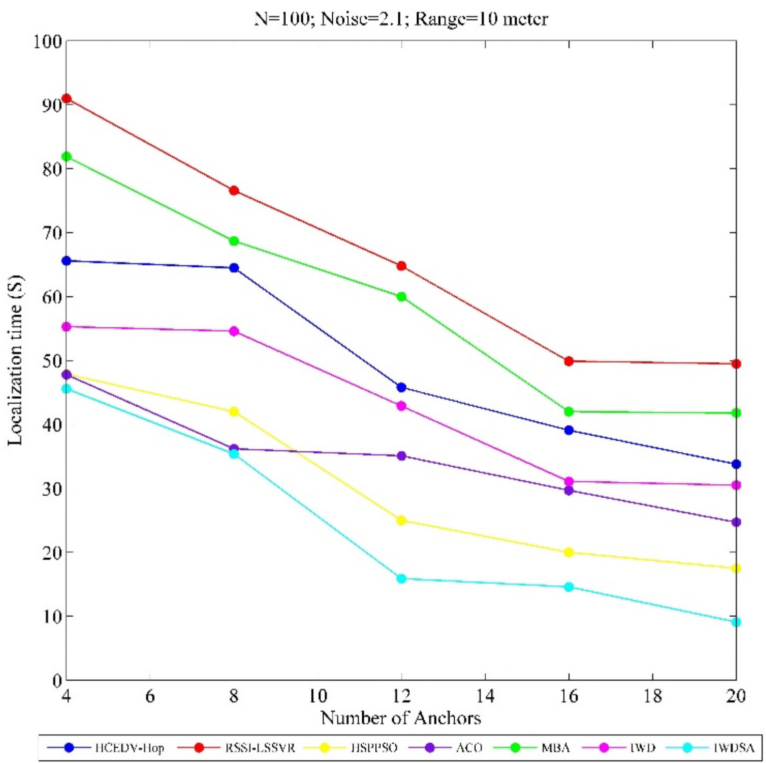

Figure 11 Localization Time Against Anchor Density

8.3.7. Localization Error Against Transmission Range

Sensor nodes' transmission/ coverage range has a direct and positive relationship with the transmission power. Empirically, it has been proven that the wider the transmission range, the more accurate localization for any algorithm. This enhancement in localization accuracy is attributed to the increase in the number of the neighbor anchors located under the coverage area of the sensor node, which in return contributes to reducing the calculation error when estimating the position of the sensor node.

Table 7 Localization Errors Against Transmission Range

Metric	Localization Algorithms						
Transmission range	HCEDV-Hop	RSSI-LSSVR	HSPPSO	ACO	MBA	IWD	IWDSA
10	2.3	5.12	2.12	2.4	2.36	2.2	1.48
15	1.95	4.8	1.64	1.86	2.23	1.67	1.302
20	1.83	4.52	1.13	1.36	1.96	1.17	1.101
25	1.632	3.86	1.01	1.16	1.75	0.92	0.8569
30	1.62	3.35	0.92	1.2	1.26	1	0.65

The experiment results proved the efficiency of the proposed hybrid algorithm, as shown in Figure 12 and Table 7. The results demonstrated the localization error with different transmission ranges; for example, when the transmission range equal to 30 m, the error of localization resulting from the hybrid algorithm IWDSA is just 0.65 m compared to 1 m resulting from IWD without hybrid. In addition, the localization error is 1.62 m, 3.35 m, 0.92 m, 1.2 m, and 1.26 m for HCEDV-Hop, RSSI-LSSVR, HSPPSO, ACO, and MBA, respectively.

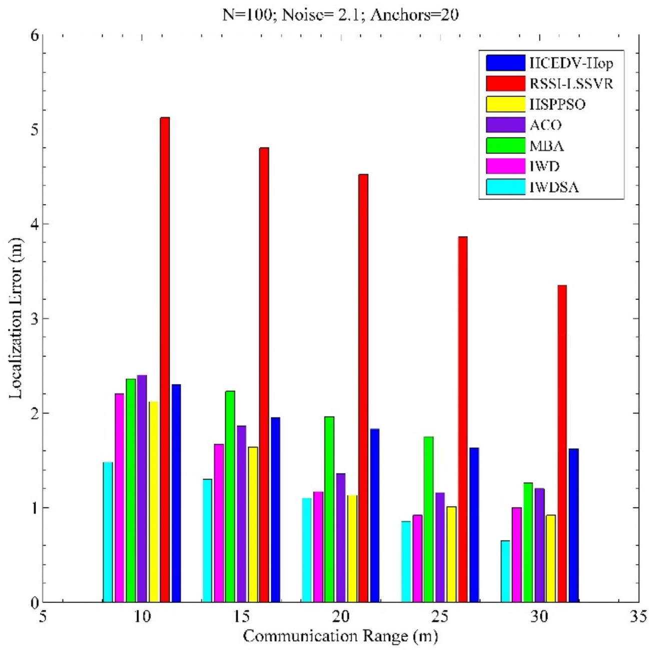

Figure 12 Localization Errors Against Transmission Range

9. Summary and Conclusions

Manufacturing WSN devices comprises several imposed restrictions, such as the battery size and extra functions, including the navigation tool GPS. In addition, WSN applications and projects usually require high localization accuracy in order to achieve or implement specific tasks. Due to the reasons mentioned above, the centralized localization approaches, which utilize RSSI technique, are preferable and considerable as a satisfactory and economically effective solution for several applications and projects of WSN that require high localization accuracy and low deployment cost simultaneously.

In the literature, an enormous number of scientific works in research and experimental means, affirmed that the generated error by the localization algorithms which utilized RSSI is an outcome of the weak accuracy of RSSI measurements when applied it to obtain the inter-distance between sensor nodes.

Firstly, this paper drew the implementation steps of the suggested hybrid localization algorithm IWDSA to localize the sensor nodes deployed in the target WSN networks. Secondly, this paper introduced a perfect method to evaluate the proposed localization algorithm considering several metrics, including localization accuracy and complexity. It was assured that the RSSI technique is utilized to calculate the inter-distances between nodes deployed in the target area. Several simulation experiments were handled to evaluate the proposed hybrid algorithm. Simulation results demonstrated that IWDSA could achieve perfect localization accuracy regardless of the error resulting from RSSI measurement. Considering the complexity, the results demonstrated the performance of IWDSA under the effects of several factors, including anchors density and transmission range. The results proved that IWDSA reached the best solution in a short time compared to basic IWD and other algorithms, which contributed to achieving the localization process in a short time that will contribute to extend the lifetime of the nodes' battery.

The advantages of two categories of localization approached, specifically range-based and centralized-based, have been exploited by the proposed hybrid algorithm to enhance localization accuracy and improve localization rate. The critical contribution of this research was to enhance the performance of the basic IWD by hybridizing it with SA. Our plan for future work is to study, evaluate, and investigate the performance of the assumed hybrid algorithm IWDSA with other categories of localization approaches, including range-free and distributed categories.

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