Performance Analysis of HCEDV-Hop Localization Algorithm in Anisotropic Wireless Sensor Network

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Accurate and energy-efficient localization is an ongoing challenge in Anisotropic Wireless Sensor Networks (AWSNs), especially when AWSNs are deployed in irregular topologies (like valleys, coastlines, and mountainous terrain) versus regular topologies. This extended work presents additional performance evaluation of the previously introduced Hop-Correction and Energy-Efficient DV-Hop (HCEDV-Hop) algorithm. The HCEDV-Hop combines an error-correcting step with a hop-constrained broadcasting approach to improve localization accuracy and reduce energy consumption. In this study, we evaluate the HCEDV-Hop in anisotropic contexts where radio irregularities are direction-dependent and deployments in C-shaped fields are representative of real-world scenarios. The efficacy of the HCEDV-Hop is assessed using both regular and random deployments for a range of node densities, DOI values, and hop thresholds. Simulation results showed that localization errors increased in anisotropic fields but were still significantly reduced compared to conventional DV-Hop. While random deployment at DOI = 0.2 performed best, regular deployment maintained consistent accuracy. Broadcasting t hops decreased energy use without diminishing accuracy. Overall, the HCEDV-Hop performed better in ideal circumstances but remained reliable enough for real-world applications such as disaster management, environmental monitoring, and military surveillance.

Keywords: AWSN, Localization, DV-Hop, DOI, Accuracy.

Introduction:

Wireless Sensor Networks (WSNs) are becoming more prevalent for their ability to innovate various industries and revolutionize the way we live and work. As a versatile technology, they support a wide range of applications, including environmental monitoring, industrial automation, and military surveillance [1]. Sensor nodes collect data which is only useful if the location of the nodes is known exactly. Without accurate location information, the sensor data loses its significance, as the context of the event cannot be properly determined [2]. One of the primary challenges faced by WSN researchers is the accurate localization of sensor nodes. Most applications of WSNs critically depend on precise location information of these nodes to ensure the usefulness and reliability of the collected data [3]. Besides this, geographic routing protocols, fault management, and clustering all utilize location data [4]. Localization algorithms have become the most important research area in WSNs. This is because sensor node placement is essential to WSN functionality. Although numerous studies have recently addressed localization, many of them operate under the assumption that only a small fraction of nodes commonly referred to as anchor nodes have known positions, typically established using GPS technology or manual configuration [4][5].

In WSNs, other sensor nodes use multi-location techniques and estimate their distances to the anchor nodes to determine their positions. Even with a limited number of anchor nodes, these techniques offer a respectable degree of accuracy [6][7]. The cost-effectiveness of range-free localization techniques for large-scale WSN deployment has generated considerable research interest in recent years. AWSNs have directional dependencies or non-uniform wireless communication channels. Deliberate directional transmission, physical barriers, environmental factors, or antenna design can all lead to anisotropy. However, the widespread use of range-free localization techniques is hampered by the practical AWSNs, which operate with significantly reduced accuracy. The occurrence of large errors in distance estimation is the main cause of this decline in accuracy [8].

The drive to enhance localization accuracy has been a key motivation for the development of localization algorithms, most of which were initially designed and tested within two-dimensional (2D) square environments. Nevertheless, the real distribution of sensor nodes often varies for different kinds of terrains. For instance, some applications like air quality monitoring that need sensor deployment in flat 2D regions, military surveillance, and intelligent transportation need sensors in anisotropic and irregularly 2D-shaped shaped. Therefore, the problem of localizing sensors across such diverse terrains is a major issue [9]. When dealing with field anisotropy, the minimal ways between nodes are changed, which leads to inaccuracies in localization. Therefore, an in-depth investigation of how field features affect the behavior of localization algorithms is necessary.

Obstacles, noise, and signal fluctuations make the sensing environment complex, posing significant challenges for localization research. One widely used method to achieve an accurate geographic location of sensor nodes is using the Global Positioning System (GPS). The GPS is among the most precise and widely available positioning technologies. However, it is too expensive and energy-intensive to make it infeasible to install in every sensor node, where battery lifetime is a critical factor. Conversely, cellular signals can be interfered with under scenarios with extreme shadowing effects [10].

Although GPS can offer precise location information, it is not feasible to add GPS to all micro sensor nodes of WSNs because of its high cost and low performance in some special environments. In addition, GPS might not work as well in localized indoor and complex environments [11]. It is a difficult task to design a localization algorithm that is as smart as well as efficient in restricted conditions. Recent studies are directed towards leveraging the communication and relationship among sensor nodes to obtain localization [12][13].

Only a limited number of nodes—referred to as anchors—have GPS modules since they are the only ones with the extra cost of installing GPS modules to save money and minimize energy consumption. The other nodes use localization methods to find their locations. Locating the position of the sensor nodes is the primary goal of WSNs, which are composed of many low-cost nodes that are highly distributed in a specific region to gauge diverse phenomena. There exist two forms of node self-localization: range-free and range-based. Range-free localization employs connectivity or pattern matching to estimate location, while range-based localization employs measured distance/angle.

WSN localization techniques generally fall into two categories: range-based and range-free systems [14][15]. Range-based algorithms require information about the distances or angles between nodes, which can be estimated through methods such as time-of-flight (ToF) measurements, received signal strength indicator (RSSI), and angle of arrival (AoA). Some of them include trilateration, maximum likelihood, and multidimensional scaling [16][17][18]. Distance-related metrics in WSN localization can be estimated using a variety of techniques, including Angle of Arrival, Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Received Signal Strength Indicator (RSSI). These methods provide the necessary measurements for range-based localization by leveraging signal properties such as propagation time, arrival angle, or signal attenuation [19][20][21].

Connectivity- based localization, known as binary measurement, assumes that sensor nodes are connected if they fall within each other's radio transmission range. Algorithms of range-free measurements, such as Centroid [22], DV-Hop [23], Amorphous [24], MDS-MAP [25], and APIT [26], are gaining popularity due to low cost, low power consumption, robustness to measurement noise, and simple hardware requirements.

These algorithms can provide a reasonable level of localization accuracy [27]. DV-Hop, a distance vector routing and localization-based distributed method, is one of the algorithms having many research due to its simplicity and low hardware requirements [28].

Combining different range-based techniques, or hybrid positioning, is one of the most classical techniques to improve precision and coverage in localization in multiple applications. For distributed localization in WSN, the estimation of positions of the sensors with the neighboring sensors is influenced by hardware defects, environment changes, topology of the network, density of the sensors, or other distortions [29]. These factors are critical to the precision of estimation in realistic multi-hop scenarios. There exists a multitude of algorithms and methodologies developed to address different problems in different applications [4][30].

The DV-HOP protocol [27] is a popular localization protocol that uses a distance vector approach to estimate the location of the nodes. However, the traditional DV-HOP protocol assumes that the network is isotropic, which means that the network has the same characteristics in all directions. In reality, many WSNs have anisotropic characteristics, which means that the network has different characteristics in different directions. This can be caused by factors such as obstacles, terrain, and human activity. Generally, multi-hop range-free localization algorithms are quite effective in topology-independent networks that are isotropic with evenly and densely distributed sensor nodes. Nevertheless, these algorithms can still be influenced by the layout of the network, which resulted in a notable drop of accuracy in the locating process.

Range-free localization algorithms are purely non-deterministic, and they are sensitive to the node heterogeneity and field anisotropy [31][32][33][34]. Most range-free localization techniques currently in use assume that all sensor nodes are uniform, possessing the same communication ranges and transmission powers. Nodes may operate at varying transmission powers and communication ranges, though, if the manufacturer's specifications and battery condition. The earlier work, which focused on DV-Hop and its variants, had limitations that prompted us to create the HCEDV-Hop localization algorithm. This research is essentially an extension of the initial study to understand how the HCEDV-Hop method manages the C-shaped AWNs, hence, by initially measuring the algorithm's accuracy and reliability in the deployment of such an irregular environment.

Objectives of the Study:

The main objectives of this study are:

To showcase critical findings along with a preliminary framework to be used for additional research that would support the improvement of the localization algorithms used in AWSNs that vary based on the environment.

To come up with a new and effective localization method that can solve the problems of node localization in AWSNs.

Analyzing how the topologies of the environment influence the efficiency of the localization process by investigating errors that happen due to a change in the deployment field from regular to random and from 2D isotropic to anisotropic environments.

To study how the network layout and non-uniform communication affect the efficiency of the HCEDV-Hop algorithm by examining the influence of anisotropy and changes in the Degree of Irregularity (DOI) on localization accuracy in irregular deployment environments.

To demonstrate the ability of the HCEDV-Hop to enhance the accuracy and the time of the localization in scenarios that are irregular or have a complex deployment.

To assess the outputs of the simulation with reference to essential criteria of effectiveness, including mean square error (MSE), localization ratio, and running time of localization.

Novelty Statement:

Generally, multi-hop range-free localization methods manage their work properly in dense and evenly distributed networks. However, the design of the network has a very significant effect on the accuracy of these methods. In regular topologies, the geometric and hop distances match very well; however, in anisotropic networks, the existence of obstacles results in the distortion of paths and which causes mismatches that further lower the performance of the localization. Moreover, this performance drop is being deepened by the Degree of Irregularity (DOI), which is the more irregular node radiation, and thus, the simulations are more realistic. This paper proposes HCEDV-Hop, an improved DV-Hop routing algorithm for better disorderly DV-Hop wireless sensor network (AWSN) routing, which provides an improved DV-Hop solution to the problems mentioned above. The introduction of anisotropy-aware corrections for the AHD allows HCEDV-Hop to adapt more efficiently in the case of complex topologies such as C-shaped deployments. Its performance is verified through simulations and is compared with the standard DV-Hop protocol and RAL to show the accuracy improvements.

The remainder of the paper is organized as follows: Section II discusses the literature review, which gives the complete account of the past studies that have been done on WSN localization by regular and irregular shapes. Besides, it also briefly mentions the problems and limitations of the existing approaches and points out the gaps that the proposed model can cover. Section III explains the proposed design, C-shaped topologies, and different DOIs. Section IV describes the experimental conditions. Besides, it also describes the performance measures that have been used for different topologies and DOIs. Moreover, this part also features a comparison being made between the proposed model and the contemporary state-of-the-art models that show its superiority. Section V details the limitations of the author's work, elucidating the difficulties faced by the authors, and they also give suggestions about ways to improve the work. Finally, Section VI is the conclusion of the work, restating the main ideas, the part of the new model, and the possible projections of furthering the work.

Literature Review:

In recent years, the literature of WSN localization protocols has undergone significant development. The distributed-based or DV-HOP protocol is one of the most popular methods among several others. The DV-HOP technique first measures the distances to neighboring nodes and then estimates the location of the node. This method has been experimentally verified to yield accurate localization in isotropic WSNs. Nevertheless, it is not so effective in those fields that are anisotropic, where the direction changes the irregularities and distorts the distances that have been estimated.

The DV-hop algorithm finds and estimates distances to unknown neighboring nodes in a way that does not use traditional ranging methods. Essentially, each sensor node estimates its distance to the beacon node by using the average hop distance and the minimum hop count. Then, by multiplying the minimum hops by the average distance of each hop, the distance between the beacon node and the node itself can be computed. Finally, each node determines its location coordinates using various estimators, such as maximum likelihood estimation and triangulation. Actually, the three stages of the DV-hop algorithm are conceptually described below [27]:

Phase 1: Initially, all anchor nodes broadcast data packets with information in the format (ID; xi; yi; hop), where ID denotes the anchor node's identity. The neighbor node raises the hop value by one while storing the information sent by the anchor node. The source is no longer the recipient of this information. During the flooding communication stage, data from an anchor node may reach the same unknown node through multiple paths; however, the unknown node retains only the information corresponding to the minimum hop count.

Phase 2: Based on the minimum number of hops obtained by each anchor node in the network, the Average Hop Distance (AHD) per hop is calculated by the anchor node. The AHD is represented by Eq. **Error! Reference source not found.**)

$$AHD = \frac{\sum_{i=j} d_{i,j}}{\sum_{i=j} h_{i,j}} \quad (1)$$

Anchor node i sends the Hopsizei information to the network through multi-hop. An AHD is only recorded by the unknown node from the first received message. The relation between the unknown node and the anchor node is represented by Eq. (2).

$$d_{u,i} = AHD \times h_{u,i} \quad (2)$$

Phase 3: After estimating the distance to the anchor node, the unknown node's position is determined using maximum likelihood. Where d represents the distance between each anchor node and the unknown node, and (x_n, y_n) represents the location of the anchor M. The derivation of Equation **Error! Reference source not found.**) is:

$$CX_{un} = B \quad (3)$$

Were,

$$C = 2 \times \begin{bmatrix} x_n - x_1 & y_n - y_1 \\ x_n - x_2 & y_n - y_2 \\ \vdots & \vdots \\ x_{n-1} - x_n & y_{n-1} - y_n \end{bmatrix} \quad (4)$$

By means of least squares methods, the calculated coordinates can be given as below:

$$X = \left(C^T C\right)^{-1} C^T B \quad (5)$$

Although this method is very easy to generalize, it does have some limitations, including the fact that it must use curvilineal distance instead of distance in a straight line. The

Average Hop Distance (AHD) is consistently larger than the actual value due to the non-linear nature of communication paths. In WSNs, the nodes are randomly deployed in space, and the properties of this randomness ensure that AHD values are always larger than true values [35][36]. As such, the error rate is generally high. Therefore, it is essential to analyze the sources of error in DV-Hop to reduce inaccuracies and extend its applicability to a broader range of scenarios. Therefore, DV-Hop works poorly in extremely uneven or anisotropic topologies, which in turn restricts its ability to adjust in a complex environment of the real world.

Despite the shortcomings of DV-Hop, numerous researchers have proposed different variants. These adaptations aim to increase the accuracy of localization, create additional forms of robustness in difficult scenarios, and decrease the impact caused by varying network conditions. These alternative forms provide additional modalities and therefore more flexibility of localization within WSNs, rather than reverting to the limitations of DV-Hop by innovative techniques and algorithms.

In practical applications, range-free localization algorithms provide significant advantages in terms of cost and power efficiency, though this comes at the expense of reduced localization accuracy. If node positions are uniformly distributed, the range-free localization algorithm can solve the WSN localization problem and improve localization accuracy. The accuracy of localization is significantly reduced when node positions are not evenly distributed.

However, in AWSNs, where the nodes have directional radio ranges, the DV-HOP protocol may not work as well due to the mismatch between the directional distances and the isotropic distances used in the protocol. In light of this, several researchers have proposed modifications to the DV-HOP protocol to address this issue.

These modified protocols are designed to enhance localization accuracy in AWSNs and have demonstrated promising results in both simulations and practical implementations. Nevertheless, further advancements are still required to address existing limitations.

Anisotropy is represented via two stages, namely at the field level and at the node level. At the field level, anisotropy has been identified as the main factor of the fields' irregular shapes. Due to these irregular shapes, the distances are overestimated, thus the localization algorithms are indirectly affected [37]. The main reason for the overestimation of distances is the curved paths between nodes, as the shortest paths are not always straight lines due to the irregular shape. In the localization algorithms, these curved paths become the source of an error component, which leads to an increase in localization error [37].

Field irregularities and anisotropy have a major impact on node-to-node distance measurements and, consequently, localization algorithm performance [34]. To eliminate the impact of field factors on localization accuracy, the localization algorithms are tested in these regions.

Kouroshnezhad et al. [38] proposed a GPS-equipped drone as a mobile anchor for sensor-free localization. This drone must be used in conjunction with a range-based positioning algorithm that uses RSS measurements and range & range-difference measurements to locate sources [39]. These algorithms perform effectively in terms of accuracy and computation time; however, they are not well-suited for anisotropic networks due to their high cost.

S.J. Bhat et al stated another localization algorithm called Range Reduction Based Localization (RRBL) [34]. The localization accuracy is improved in this algorithm through the integration of properties from hop-based and centroid methods in a range of fields. Unknown nodes locate themselves by identifying nearby neighboring nodes within a specified threshold and reducing the potential range of their location. When insufficient neighbors are present, the least squares method is used for localization. In comparison to other hop-based and centroid-based localization techniques, the algorithm is tested under a variety of irregular and heterogeneous conditions. The RRBL outcomes show an enhancement in accuracy of 28% at a 10% reference node ratio and 26% at a 20% reference node ratio. Nevertheless, RRBL experiences a decline in performance in extremely sparse deployments and in situations where irregularities have significantly altered the hop- distance estimations. Moreover, the S.J.Bhat et al. S.J. Bhatti et al. presented a priority-based localization algorithm in [40] that uses AHD to rank certain reference nodes. The weighted centroid approach is then used to localize the nodes using high-priority reference nodes. According to the simulation results, the suggested algorithm's localization results outperform those of the current weighted centroid methods in anisotropic fields.

Shahzad et al. [41] introduced DV-HopMax, a modified version of the DV-Hop algorithm that applies to both isotropic and anisotropic wireless sensor networks (WSNs), which also features a control parameter that can be used to lower errors in distance estimation. Essentially, the method makes use of the closest reference nodes to calculate the position of the target node. Nevertheless, its success is very much dependent on the value of the MaxHop parameter, i.e., the performance is quite sensitive to the setting of the MaxHop value. The latter sensitivity is what restricts the level of robustness that the algorithm may have, as well as the extent to which it can be flexible, largely because there is a need for pre-setting the optimal parameter values in such networks. In addition, there is the issue of static parameter settings, which the algorithm is quite dependent on that resulting in the algorithm being less scalable when dealing with large and heterogeneous deployments, hence the possibility of using adaptive or self-tuning mechanisms for enhancing its reliability.

Introducing multi-objective optimization can increase problem complexity and computational overhead. To overcome the limitation of DV-MaxHop, Improved DV-MaxHop [42] was introduced. In improved DV-Maxhop, we take a corrections approach that modifies the AHD of each link between the anchor and unknown nodes, thereby refining the distances. Such a method would still be less environmentally friendly and less practical for AWSN on a large scale due to the increased computational demand.

Asaaf et al. [31] presented a novel anchor choice method for AWSNs that significantly improves the distance measurement accuracy, which then gives the overall localization accuracy to be better. Their method, while exhibiting high precision as compared to typical range-free algorithms, particularly in scenarios of an irregular non-specular radiation, still implicates a large computational overhead. The additional processing requirement may result in more considerable energy usage, which is a major disadvantage in energy-limited sensor nodes. Besides, the algorithm's reliance on very accurate anchor selection makes it less flexible in highly dynamic or large WSN deployments. Therefore, the next research work should concentrate on how to maintain accuracy while increasing computational efficiency so as to be able to use the method in real-world situations.

Considering this, various variants of the DV-HOP protocol have been proposed in the literature, including directional virtual coordinates, directional distances, and weighted virtual coordinates, to improve localization accuracy in AWSNs. These variants have shown promising results in simulation and implementation studies, but there is still a need for further improvement in this area. Most of the techniques mentioned above cannot completely solve the problem of irregularity in direction and still need some adjustment depending on the specific context, which lessens their ability to be used in different situations.

In cases like these, the conversion of hop-based predictions into distance measurements that are accurate becomes a challenge, and as a result, there are overestimations due to the indirect nature of the paths that lie between the anchors and unknown nodes. The presence of more obstacles and gaps leads to these errors in distance estimation, which contributes to a drop in localization accuracy [31][40]. While many studies on WSN localization have focused on different aspects, we have found that most of the research work in the area of WSN localization has overlooked the issue of wireless channel characteristics

[41][42]. This gap highlights the need for algorithms that specifically consider the properties of wireless channels to provide a more accurate and adaptive localization in anisotropic environments.

Methodology:

Although these developments have greatly advanced knowledge and expertise in WSN localization, it becomes clear that substantial improvements in accuracy are still needed for AWSNs. To tackle the problems noted earlier, this paper presents a new range-free localization method specifically for addressing the above issues in AWSNs, to greatly enhance the accuracy of sensor node localization.

HCEDV-Hop Algorithm:

The HCEDV-Hop algorithm, as shown in Table 1, improves WSN localization efficiency. We also identified that if a correction step occurs in the localization, it further improves the algorithm's accuracy in AWSNs, as shown in Figure 1. Consequently, in the analysis of our HCDV-Hop method, we incorporated real wireless parameters intended to be more reasonable in evaluating this method to ensure the practicality of the proposed method in practical applications.

The HCEDV-Hop localization technique [43] proposed by M. Fawad et. al, is a modified distance vector algorithm that uses C-shaped terrain characteristics to facilitate improved localization accuracy. The use of C-shaped terrain is meant to develop solutions that better represent the conditions characteristic of the real world. Valleys and coastlines in nature often demonstrate C-shaped boundaries, and as a result, scientists and engineers take a specific interest in how WSNs behave, including adaptations in those particular environments. Importantly, the HCEDV-Hop algorithm has set a boundary on the distance of broadcasting t hops during the last two phases. Consequently, any packet originating from an anchor beyond t hops will be discarded. Restricting broadcasting to *the* hops not only reduces power consumption but also enhances localization accuracy in scenarios with uneven sensor node distributions.

AWSN C-Shape Topology:

Various applications of WSNs demand the placement of nodes across various domains [44][45]. To illustrate, in smart city applications, sensor nodes must be placed inside various Business and Industrial units, each having various sizes and shapes. In applications such as military surveillance, disaster relief, or forest fire detection, the deployment areas often feature rugged terrain with hills, valleys, and water bodies. Under such conditions, WSN coverage zones tend to form irregular shapes. However, in current research, the localization algorithms have been limited to the boundaries of regularly 2D shaped [43][46][42][47][48]. To simulate a forest fire monitoring scenario, a mountainous terrain was chosen as the deployment area, with sensor nodes positioned as illustrated in Figure 2.

Table 1. Algorithm: HCEDV-Hop Localization (HCEDV-Hop)

Step	Description
Input	Total nodes N, Anchor nodes M, Coordinates (Xi, Yi), Communication range R, Deployment area 500 × 500 m²
Output	Estimated positions Xn of unknown nodes
Initialization	Set Packet = 0. Select anchors for localization. Initialize hop counts.
Hop Count Calculation	For each node pair (i,j): Increment Packet If distance(i,j) ≤ R → hop = 1 Else hop = hop + 1 Update hop table: hij = hji

BAG Message Broadcast	Each anchor sends a BAG message (N_ID, Coordinates, Hop) Receiving nodes update H_Table with (N_ID, Coordinates, Hop) If the node has ≥ 3 anchors → apply multilateration for the initial estimate
Distance Estimation (RSSI or AHD)	For each unknown node: If hop = 1 → Estimate distance using RSSI: d = A - 10n log10(RSSI) Else → Compute Average Hop Distance (AHD): AHD = (Σ dij) / (Σ hopij)
Refined AHD Calculation	Under threshold t, compute refined AHD: AHD_ref = ((R - AHD) × HC) / R
Error-Corrected Distance	Estimate corrected distance: di = hop × AHD_ref
Position Estimation (Least Squares)	For each unknown node u, estimate coordinates: (xu, yu) = argmin Σ (sqrt ((xu - Xi) ² + (yu - Yi) ²) - di) ²
Threshold Correction	Apply threshold-based refinement to reduce error and energy consumption.
Output	Final estimated positions of unknown nodes.

A 2D C-shaped field is illustrated in Figure 3 to demonstrate node deployment over flat regions with DOI values of 0.2 and 0.5. Due to the anisotropic application and fields' intrinsic irregularities, variable distance measurements between nodes have an impact on the accuracy of localization techniques [31][34][42]. Assessing these techniques in these challenging scenarios enables understanding and mitigating the effect of the factors that adversely affect localization accuracy.

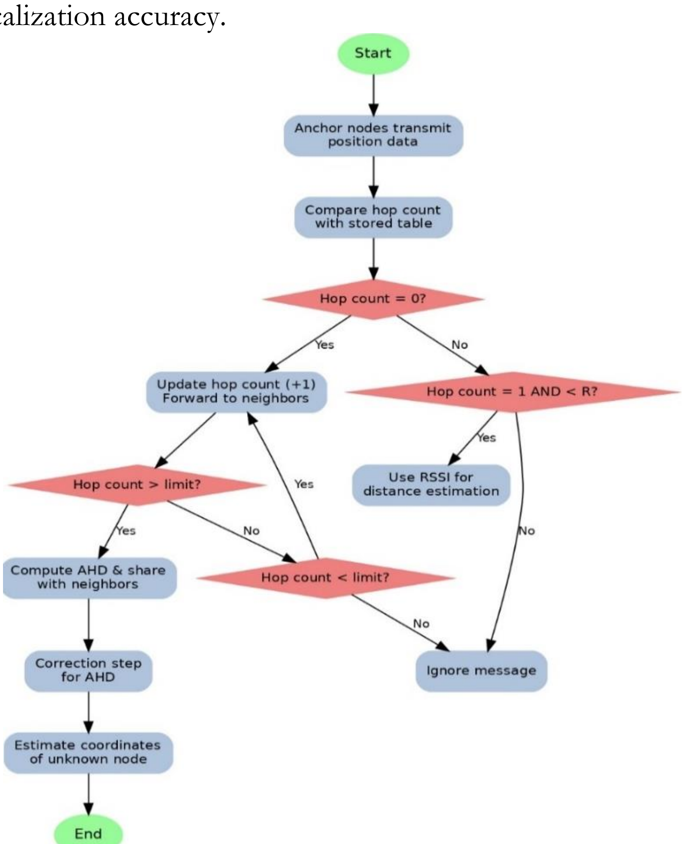

Figure 1. HCEDV-Hop Algorithm [1]

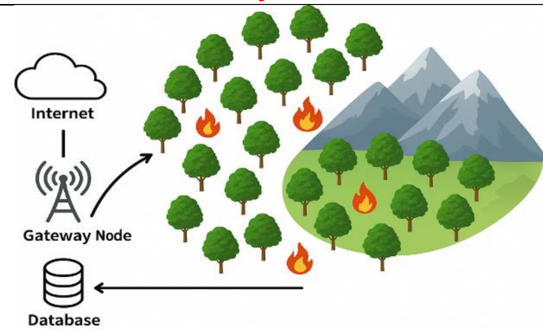

Figure 2. AWSN in C-shape Scenario

Experimental Setup:

To evaluate the performance of the HCEDV-Hop algorithm, we implemented the approach proposed by M. Fawad et al. [42] within an Anisotropic Wireless Sensor Network (AWSN). A C-shaped deployment scenario was designed to simulate irregular network conditions, and specific configurations were applied to assess the algorithm's effectiveness under these settings.

Radio Irregularity Model (RIM):

A node's communication range is influenced by the transmission power of the sensor as well as the communication environment. Although sensor nodes emit signals with reasonable power, there are attenuating factors in the environment, such as trees, buildings, people, mountains, etc. This means that radio signals are always being continuously modified due to the gradual change in direction. The node's radiation continued to change due to the anisotropy of natural networks. In this paper, we employed the well-known DOI model to analyze the effects of irregularity. Using the DOI model adds realism to the simulation, and it can also more closely model the real world. The RIM describes the specific behavior of the radio signal using real data collection from real sensor devices [49]. The RIM model has a metric called DOI, which correlates to the maximum percentage change in path loss for each degree of anisotropic change in the radio propagation direction [49][50][51]. Communication irregularity alters the radio propagation pattern, causing it to exhibit non-linear behavior [52]. The RIM model is expressed mathematically as in **Eq.**Error! Reference source not found.**):**

$$R(\text{Signal}) = T(p) - DOI\ (\text{loss}) + F \quad (8)$$

$$DOI\ (l) = \text{loss} \times K^{*}\theta \quad (9)$$

Were,

$$K_i = 1 + \gamma * DOI,\ \gamma \in [-1,1] \quad (10)$$

In **equation** Error! Reference source not found.**)**, the data variable γ shows a random number resulting from the Weibull distribution defined in [51]. The communication boundaries exhibit a fully circular shape when DOI = 0. When it comes to the node I's communication range at DOI=0, this can be CRi. A DOI of zero means there is no irregularity, indicating the event or phenomenon to which these data belong is fully regular and stable. When the DOI is 0.2, it reflects a moderate level of irregularity. This means we are inferring that the patterns or data are not extremely irregular but have some sort of fluctuating or random nature. A DOI value of 0.5 indicates a high degree of irregularity, resulting in unpredictable pr opagation patterns. The communications range continually becomes unstable. Figure 3 shows a node's communications range at different DOIs.

Simulation Design and Network Model:

We tested the efficiency of the proposed method using an Intel® Core™ i5 CPU @ 2.0 GHz with 8 GB RAM. We applied localization accuracy as the performance measurement. We used MATLAB 2020a [53] simulators to evaluate the performance of the proposed algorithm by localization accuracy. The experiment was conducted with AWSN deployed on a 500 * 500 area, a total of 500 sensor nodes were used, 50 of which were deployed as anchors. The deployment includes both regular and random distribution in the field, as illustrated in Figure 4.

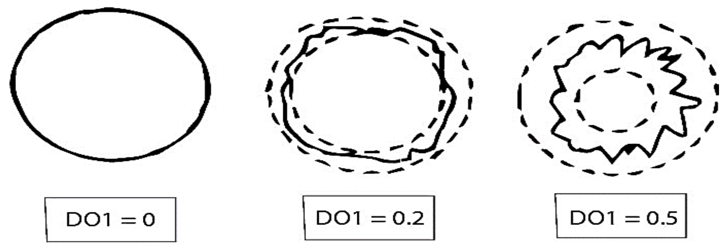

Figure 3. Impact of DOI Variations

Regular Deployment:

In regular deployment, sensor nodes are deployed systematically over a 500*500 area, as seen in Figure 4a. Thus, there is a uniform distribution of nodes, and an equal distance between the adjacent nodes.

Random Deployment:

In random deployment, on the other hand, the sensor nodes are positioned randomly across the 500 * 500 area as shown in Figure 4b. This node distribution exhibited a high DOI, making it representative of real-world scenarios. A communication range of 100 m was adopted for both regular and random deployments.

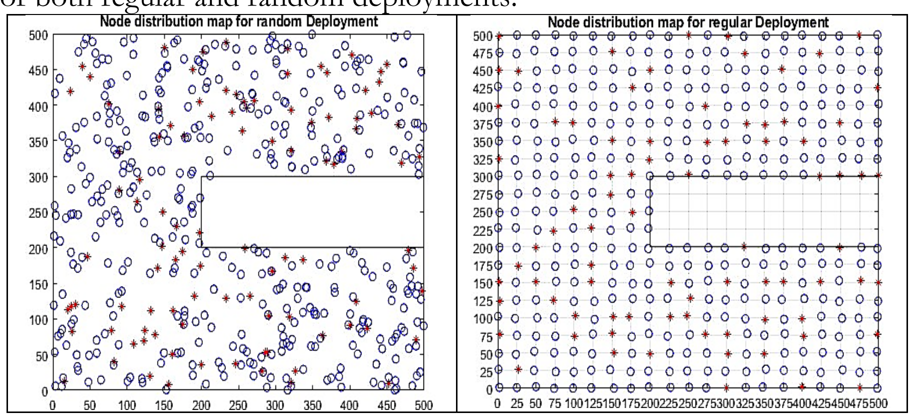

Figure 4. a) Randomly WSN Deployment and b) Regular WSN Deployment

It is easy to evaluate the performance of both regular and random deployment using the setup with 50 iterations. Regular deployment has a controlled environment, and random deploys in an uncontrolled manner. The simulation configuration is shown in

Table **2**.

Table 2. Parameters of AWSN

Simulation Parameters	Value
AWSN field (m^2)	500*500
Total Nodes	100-500
Anchors	50 – 100
Threshold(hops)	3 – 7
Radius (m)	100
DOI	0.2 & 0.5
Operating system	Window 10
Simulator	Matlab 2020a
Packet size	1024 bytes
Communication Range	100

Performance Analysis:

In evaluating the proposed approach for AWSNs, both localization accuracy and cost parameters were considered. First of all, the simulations are implemented to perform a comparative analysis between the new algorithm and the most significant existing algorithms for localization, such as DV-Hop [27] and RAL [29]. The comparison is done considering the same network settings to ensure the fairness of the results. The efficacy of the HCEDV-Hop was considered based on the following metrics:

Accuracy:

Localization error is defined as the difference between the computed locations versus the actual locations, and is used as a measure of accuracy, which can be assessed by changing parameters like average localization error, node density, etc. The evaluation of the accuracy is done under the following:

Average Localization Error Analysis (ALE):

The ALE [10][54] represents accumulated localization errors over unknown nodes. The ALE, used as the evaluation criterion, is computed as presented by Eq. **Error! Reference source not found.**).

$$ALE = \frac{\sum_{i=1}^{n}\sqrt{(x_i - x)^2 + (y_i - y)^2}}{n \times R} \quad (11)$$

In equation **Error! Reference source not found.**), the numerator shows the Euclidean distance [55] between the estimated (x,y) and actual (xi,yi) locations, which corresponds to the ALE calculation. Where R indicates the radius and n denotes the total nodes.

To investigate the impact of anisotropy, location results in an anisotropic field are compared to those from regular deployment and random deployment. Many different localization algorithms are used involving 2D fields. From Table 3**Error! Reference source not found.**, all methods encountered higher errors in isotropic fields, with DOI = 0.5.

Table 3. ALE of AWSN

Proposed Algorithm with different DOI	Max	Avg.	Min	Std. Dev
HCEDV-Hop with Uniform topology having DOI =0.2	1.335537	0.89813	0.48900	0.126464
HCEDV-Hop with Uniform topology having DOI=0.5	1.426774	0.94135	0.60968	0.157711
DV-Hop with Random topology having DOI =0.2	Nil	1.27	Nil	Nil
RAL with Random topology having DOI =0.2	Nil	1.00	Nil	Nil
HCEDV-Hop with Random topology having DOI =0.2	1.386214	0.92159	0.59657	0.101157
DV-Hop with Random topology having DOI =0.5	Nil	1.40	Nil	Nil
RAL with Random topology having DOI =0.5	Nil	1.15	Nil	Nil
HCEDV-Hop with Random topology having DOI =0.5	1.489655	1.031969	0.82601	0.114893

The performance comparison of the proposed HCEDV-Hop algorithm with DV-Hop and RAL under different DOI values, as shown in Fig. 12, clearly indicates that it had the best accuracy of localization. In the case of the uniform topology, HCEDV-Hop reached the lowest average localization error of 0.8981 at DOI = 0.2, and slightly increased to 0.9414 at DOI = 0.5 while still stable. In the random topology, HCEDV-Hop was always ahead of DV-Hop and RAL, with average errors of 0.9216 at DOI = 0.2 and 1.0320 at DOI = 0.5. The standard deviation values were also smaller, indicating more stable and reliable results. At DOI

= 0.2, HCEDV-Hop achieved 27.43% lower ALE than DV-Hop and 7.84% lower than RAL. At DOI = 0.5, it remained better by 26.29% and 10.27% respectively. The improvement was evident with AHD and threshold correction, which reduced estimation variation. The performance decreased when DOI increased from 0.2 to 0.5 due to stronger path-loss and link asymmetry, which elevated AHD and worsened multi-lateration, increasing ALE. In regular deployment, the average error rose by 4.8% (0.94135 vs. 0.89813) and the maximum by 14.3% (1.526774 vs. 1.335537). The effect was more severe in random deployment at DOI = 0.5, explained by cumulative irregularities in node placement and communication variability. Based on the outcomes, the superior performance was achieved in regular deployment at DOI = 0.2. Regular grids ensured uniform spacing and anchor geometry, making per-hop distance consistent, reducing boundary effects, and improving localization accuracy. Figure 5 showed that regular deployment had a lower ALE than random deployment.

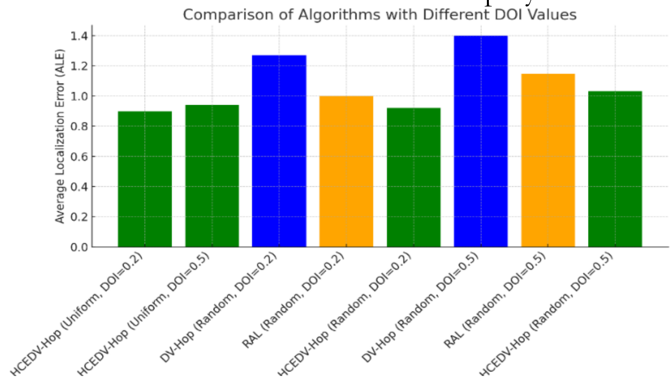

Figure 5. ALE for AWSN Topologies

Impact of Varying Node Density:

Furthermore, we assessed the impact of varying node density on localization performance under DOI settings of 0.2 and 0.5, which serve as benchmarks for evaluating the algorithm.

Experiments extracted from the simulation space allow us to vary the total node count from 100 to 500, whilst the anchor field is held steady at 50. Figure 6 illustrates the ALE for various nodes.

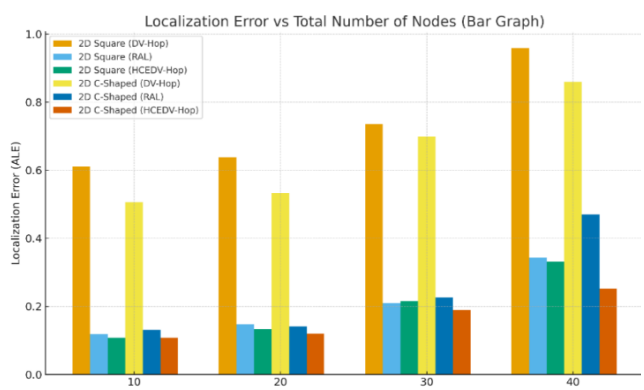

Figure 6. Node distribution under random and regular deployment

Table **4** presents a thorough breakdown of localization errors seen in various node density situations. This provides a clearer understanding of the influence of node density on localization performance.

Table 4. Localization Error vs Total Number of Nodes

Ref. Node Ratio	2D Square (DV-Hop)	2D Square (RAL)	2D Square (HCEDV-Hop)	2D C-Shaped (DV-Hop)	2D C-Shaped (RAL)	2D C-Shaped (HCEDV-Hop)

10%	0.610	0.118	0.108	0.506	0.131	0.108
20%	0.638	0.147	0.134	0.532	0.141	0.120
30%	0.736	0.21	0.215	0.699	0.226	0.190
40%	0.959	0.343	0.332	0.859	0.47	0.252

The ALE in the C-shaped regular topology increases from 82.78% at 100 nodes to 118.14% at 500 nodes when the DOI is set to 0.2.

Under the same conditions, increasing the DOI to 0.5 further amplifies the error, rising from 84.63% with 100 nodes to 128.10% with 500 nodes. When the DOI was 0.2, the ALE for the C-shaped random topology increased from 86.64% at 100 nodes to 155.02% at 500 nodes. Likewise, the error increased from 87.91% at 100 nodes to 171.98% at 500 nodes when the DOI is raised to 0.5.

Run time Cost of Localization:

The runtime cost of localization is defined by the time required to complete the localization process. The size and scalability of the network influenced the duration of the process. In this study, the runtime for localizing a single node using the DV-Hop, RAL, and HCEDV-Hop algorithms was compared in both 2D square and C-shaped fields.

Table 5. Run Time Analysis of Localization Algorithms

Ref. Node Ratio	2D Square (DV-Hop)	2D Square (RAL)	2D Square (HCEDV-Hop)	2D C-Shaped (DV-Hop)	2D C-Shaped (RAL)	2D C-Shaped (HCEDV-Hop)
10%	0.610	0.118	0.108	0.506	0.131	0.108
20%	0.638	0.147	0.134	0.532	0.141	0.120
30%	0.736	0.21	0.215	0.699	0.226	0.190
40%	0.959	0.343	0.332	0.859	0.47	0.252

Runtime analysis, as represented in

Table **5**, indicates that DV-Hop is most expensive in terms of computational cost, and it runs this way under both 2D Square and 2D C-shaped topologies. On the other hand, RAL and HCEDV-Hop show limited runs having significantly lower computational costs. As can be seen in 2D Square topology, DV-Hop moves from 0.610 at 10% reference nodes to 0.959 at 40%, thus RAL, and HCEDV-Hop adjust accordingly, but within limited ranges, RAL from 0.118 to 0.343 and HCEDV-Hop from 0.108 to 0.332, respectively. Just to compare, RAL can cut off runtime from DV-Hop by approximately 80–65%, where HCEDV can even step it down further by about 82–66% across different ratios. In the 2D C-shaped topology, we can also observe a similar trend, where the performance of algorithms is as follows: DV-Hop (0.506 to 0.859), RAL (0.131 to 0.470), and HCEDV-Hop (0.108 to 0.252). Thus, RAL can lower runtime by about 74–45%, whereas the proposed HCEDV is the closest to the optimum, reducing runtime by approximately 79–71% compared with DV-Hop. These findings show that RAL can considerably lower runtimes; however, the highest and most stable values of HCEDV always remain below, thus making it the most computationally efficient algorithm out of the three. When comparing the results overall, they provide evidence that HCEDV-Hop presents a significant compromise between computational efficiency across both isotropic and anisotropic 2D deployments, which makes it more suitable for real-time and large-scale WSN localization, especially with improvements of over 65% as depicted in Figure 7.

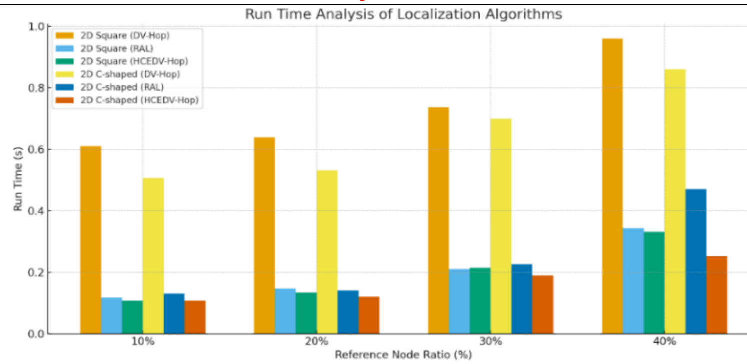

Figure 7. Run Time Analysis

Discussion and Analysis:

In this section, we take a close look at the key findings and what they mean. Results showed that the ALE increased with the number of nodes. In the HCEDV-Hop simulation configuration, the anchor count was fixed at 50 while the total nodes was increased from 100 to 500, thus the anchor ratio went down from 50% to 10%. This decrease in anchor density aggravated geometric dilution, as there were fewer well-placed references for each unknown node and, in addition, a higher dependency on multi-hop communication in the C-shaped topology, which consequently led to the rise of the AHD error and the cumulative hop inflation. Besides that, regular deployments with similar DOI values always had lower localization error than random deployments. The network size and the level of blockage were also two of the most important factors that influenced the localization accuracy in C-shaped topologies. The results extend the understanding of the performance of different localization algorithms in random and regular deployment and indicate their application in a wide range of scenarios. Besides that, HCEDV-Hop attained over 65% of runtime improvement against DV-Hop in both isotropic (square) and anisotropic (C-shaped) 2D fields, with the square field showing slightly lower execution times due to its regular and uniform topology.

Limitations of the Current Work:

Although the HCEDV-Hop showed significant gains in localization accuracy and energy efficiency in both unobstructed and obstacle-rich scenarios, the simulations were primarily conducted on idealized conditions, which is one of the work's limitations. Depending on the context in which they are used, various metrics besides energy consumption and accuracy, such as bandwidth utilization, scalability, or localization latency, may be as important.

Conclusion:

We proposed a resource-efficient localization technique that utilizes hop distance measuring for a static AWSN configured in a C-shaped. The proposed solution targets poor estimation by adding an error-correcting step to the distance measurement. Ultimately, the system becomes reliable and accurate in the C-shape topology. The proposed model monitored and controlled the broadcasting to run within predefined thresholds with obstacles. Our method outperforms and gets the desired results in the C-shaped topology compared to other benchmarks.

Regularly deploying a DOI of 0.2 lowers the maximum error and enhances localization performance. Nonetheless, the average and maximum errors are higher with a DOI of 0.5. In isotropic and anisotropic 2D fields, HCEDV-Hop improves runtime by more than 65%; execution times are marginally slower in the square field.

WSNs are typically deployed in dynamic scenarios with different levels of interference and impediments in the real world. Further research is required to assess whether the algorithms are suitable for real-world use in a range of contexts, specifically complex and dynamic ones.

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