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A DISTRIBUTED ADAPTIVE ALGORITHM FOR EFFICIENT LOCALIZATION OF SENSOR NODES IN AD HOC NETWORKS

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ABSTRACT

Node localization in a wireless ad hoc network of sensor nodes is essential for making informed decisions and maximizing the network's effectiveness and efficiency. Localization is often based on different measures with centralized distributed approaches. With empirical study, we found that the distributed approach to node localization is more robust than its centralized counterpart. Therefore, in this paper, we proposed an algorithm for sensor node localization in a distributed approach. Our algorithm, Distributed Optimized and Adaptive Node Localization (DOANL), exploits a collaborative method that can achieve efficient localization even in a smaller number of beacons. The foundation of our methodology is the Angle of Arrival (AOA) and Time of Arrival (TOA). Node and beacon deployment locations have an impact on the localization process as well. This work presents the Distributed Optimized and Adaptive Node Localization (DOANL) algorithm, which enhances localization accuracy in distributed wireless ad hoc networks by leveraging AOA and TOA with minimal beacons and minimizing error propagation, outperforming state-of-the-art. This paper also investigates this proposition by analyzing node deployment and network connectivity. We also found that error propagation across the network limits the accuracy of the proposed algorithm. To address this problem, we further optimized the DOANL algorithm by minimizing error propagation across the network. The suggested approach outperforms state-of-the-art ones in wireless ad hoc network localization, according to an empirical research conducted with an NS-3 simulation study.

Keywords – *Wireless Ad Hoc Network, Wireless Sensor Network, Node Localization, Distributed Adaptive Localization, Error Propagation.*

1. INTRODUCTION

Because it facilitates informed decision-making in routing and other network operations, node localization is an essential component of wireless ad hoc networks. Our research, focusing on the development of the Distributed Optimized and Adaptive Node Localization (DOANL) algorithm, has direct implications for the efficiency and effectiveness of these networks. Node localization can have two kinds of approaches such as centralized mechanisms and distributed mechanisms [1], [2], [3]. The centralized mechanisms depend on a centralized node, which must help other nodes find the locations, whereas the distributed approach helps other nodes discover their positions. Since node position is very important for making rooting and other decisions, finding the location in the network causes a certain overhead. There is a need to reduce the overhead in finding the location of nodes. In other words, node localization has to be done with minimal overhead in the network. Towards this end, the distributed approach is bound to be better than the existing approaches as formed in the literature. In this research, this hypothesis is investigated further with an empirical study. There are a number of distributed approaches for node localization, as illustrated in Figure 1.

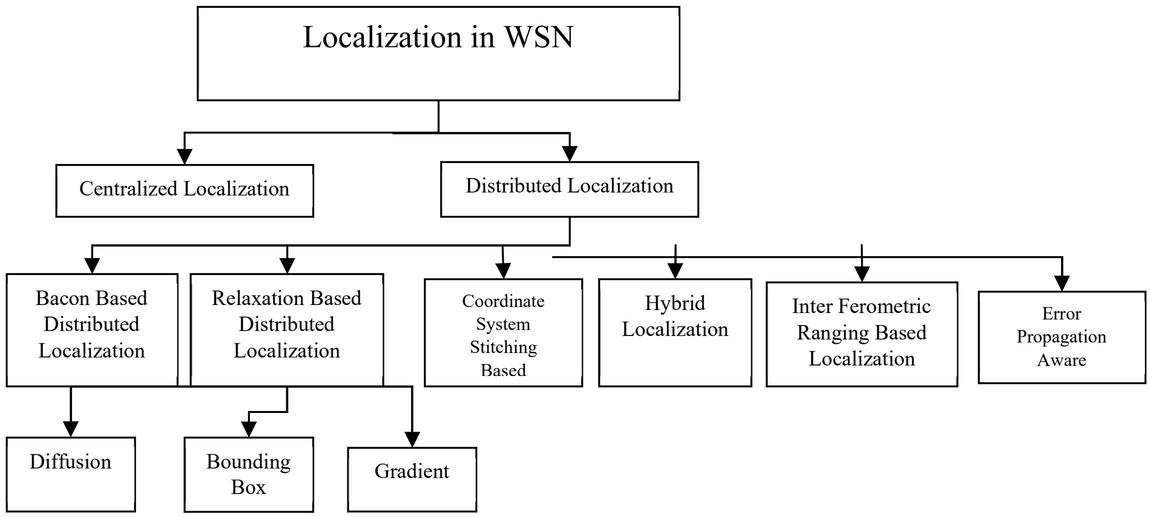

Figure 1: *Various node localization methods*

The distributed localization approaches differ from each other as their modus operandi is different. Among their methods are the relaxation-based method, the Bacon-based method, the hybrid localization method, the coordinate system-based method, and the error propagation method. Beacon-based techniques are used in this paper. For node localization in ad hoc networks, numerous methods are currently in use. Kim et al. [6] give an example of a bio-inspired wireless routing protocol that addresses issues like battery life and bandwidth constraints in mobile ad hoc networks. Sun et al. [8] introduce an improved nonlinear iterative localization algorithm for DVHop in wireless sensor networks, enhancing accuracy without increased computational burden. Balaji et al. [10] provide an energy-efficient wireless ad hoc network cluster optimization method that takes uncertainties into account. Sun et al. [13] create a localization technique for MI-based wireless sensor networks that takes the environment into account to increase accuracy in challenging settings.. The literature shows that there is a need to leverage performance in node localization procedures in a distributed approach that needs fewer beacons. This work introduces the Distributed Optimized and Adaptive Node Localization (DOANL) algorithm, which leverages a collaborative approach using Angle of Arrival (AOA) and Time of Arrival (TOA) for efficient node localization with minimal beacons, enhancing robustness in distributed wireless ad hoc networks. Additionally, it addresses error propagation through an optimized methodology, significantly improving localization accuracy compared to state-of-the-art approaches, as validated by NS-3 simulations. The following are the things we contributed to this paper. We have created a distributed approach for sensor node localization. The algorithm, known as Distributed Optimized and Adaptive Node Localization (DOANL), uses a collaborative approach to achieve efficient localization even with a smaller number of beacons. The Time of Arrival (TOA) and Angle of Arrival (AOA) are key components of our methodology. In order to achieve localization, node and beacon placement is essential. Our paper also delves into the analysis of node deployment and network connectivity in relation to this proposition. We found that the accuracy of the suggested algorithm is hampered by error propagation throughout the network. By reducing error propagation throughout the network, we improved the DOANL method to address this problem. Our methodology is more effective than the most advanced techniques for localizing sensor nodes in wireless ad hoc networks, according to an empirical investigation conducted with NS-3 simulation. The remainder of the document is arranged as follows: Section 2: Examines previous research on ad hoc network node localization techniques. Section 3: Describes the suggested distributed mechanism for node location in sensor ad hoc networks. Section 4: Outlines the findings from our observational research. Section 5: Provides recommendations for further research and concludes our work.

2. RELATED WORK

Many node localization approaches exist in the literature. Ansere et al. [1] present the adaptive beacon time synchronization method (ABTS),

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which improves accuracy, convergence speed, and energy efficiency for large-scale VANETs. Brennan et al. [2] talk about an industrial sensing ad hoc wireless sensor network. Results show adaptability to changes but at efficiency costs. Ballouk et al. [4] investigate Wireless Sensor Networks (WSNs), giving special attention to LEACH-based routing protocols that deal with data transmission, CH selection, and energy efficiency. Zhang et al. [5] provide a localization technique based on genetic algorithms and RSSI quantization that addresses irregular target appearances and optimizes network division. Kim et al. [6] give an example of a bio-inspired wireless routing protocol that addresses issues like battery life and bandwidth constraints in mobile ad hoc networks. Goyal et al. [7] introduce Enhanced Energy Proficient Clustering (EEPC) for optimized paths in dynamic Wireless Sensor Networks, improving energy efficiency and network lifetime. Sun et al. [8] introduce an improved nonlinear iterative localization algorithm for DVHop in wireless sensor networks, enhancing accuracy without increased computational burden. Hakala et al. [9] discuss the difficulties in RSSI-based outdoor localization in WSNs and suggest an adaptive technique to increase ranging precision. Balaji et al. [10] provide an energy-efficient wireless ad hoc network cluster optimization method that efficiently handles uncertainty and is based on fuzzy constraints. Turjman et al. [11] addressed IoT security by proposing a hybrid routing and monitoring system to improve safe data transfer in ad hoc sensor networks. Nandi et al. [12] emphasize fault tolerance and energy economy when putting forth a hierarchical data distribution protocol for wireless sensor networks operating in challenging conditions. Sun et al. [13]provide an environment-aware localization technique that enhances accuracy in challenging situations for MI-based wireless sensor networks. Verma et al. [14] intend to extend the lifespan of Wireless Sensor Networks (WSN) by selecting cluster heads using the Butterfly Optimization Algorithm (BOA). Ant Colony Optimization (ACO) optimizes route selection. The proposed methodology outperforms traditional methods in live nodes and network lifetime. Seddiki et al. [15] provide a trust management plan for WSNs with an emphasis on safe CH election and anti-malicious behavior monitoring. It demonstrates effective prevention and isolation of malicious nodes. Xie et al. [16] proposed LRAQS algorithm combines RAPS and QSSA for accurate anisotropic network localization. It improves distance estimation precision, outperforming other algorithms in various scenarios. Singh et al. [17] provide an Adaptive Flower Pollination Algorithm (AFPA) that outperforms existing algorithms in terms of convergence speed and accuracy for 3D wireless sensor network localization. The single anchor node (AN) concept is cost-effective but poses a risk if non-operational.

Balico et al. [18] examine predicting localization in VANETs, comparing algorithms like dead reckoning, Kalman filter, particle filter, and machine learning. Vadivel et al. [19] provide a Multi-Adaptive Routing Protocol (MARP) in order to solve issues in IoT-based Cognitive Radio Mobile Ad-hoc Networks (CRMANET). NS3 simulations show that MARP, which is modeled after fish behavior, saves time and energy. Mandeep et al. [20] give a thorough explanation of the advantages, disadvantages, applications, and potential future developments of cluster-based routing protocols (CBRPs) for flying ad hoc networks (FANETs). Boukerche et al. [21] highlight the vital importance of connectivity and coverage difficulties in Wireless Sensor Networks (WSNs) and provide an overview of the most recent techniques that handle these problems. Çavdar et al. [22] explore localization in Vehicular Ad Hoc Networks (VANETs), emphasizing applications, techniques, and challenges. Future research could address security, privacy, mobility, protocol congestion, data transmission speed, authenticity, localization accuracy, and power consumption. Zaied et al. [23] present a game theory method based on reinforcement learning for distributed recovery of Coverage Holes in Wireless Sensor Networks (WSNs). Nodes adjust sensing range and reposition to sustain network coverage. Zhang et al. [24] improve the APTEEN routing protocol by utilizing a mix of fruit fly and genetic optimization methods to solve coverage and energy imbalance problems. The GA-APTEEN shows improved network lifetime and robustness. Lu et al. [25] explore mobile wireless sensor networks (MWSNs) focusing on lifetime maximization. Five evolutionary computing algorithms are compared, with GA and NFO showing superior performance in different scenarios. The study provides valuable insights for MWSN and WSN model optimization.

Jena et al. [26] the requirement for safe and effective routing techniques in mobile ad hoc

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networks (MANETs).It presents an adaptable routing protocol that is assessed by means of comprehensive simulations and dynamically configures in response to changing requirements and contextual characteristics. The suggested logic will be implemented in future work utilizing network function virtualization (NFV). Hu et al. [27] Define the self-adaptive multi-strategy artificial bee colony (SaMABC) algorithm for wireless sensor network coverage optimization. SaMABC outperforms other algorithms with up to higher coverage improvement. Ghonge et al. [28] The emergence of smart cities necessitates efficient ad hoc networks, where Software-Defined Networking (SDN) plays a crucial role. This book explores SDN applications, evaluations, and emerging technologies. Srilakshmi et al. [29] Mobile Ad Hoc Networks (MANETs) can benefit from improved energy-efficient and secure routing thanks to the Bacteria for Aging Optimization Algorithm (BFOA). Abdallah et al. [30] Energy savings, lower communication overhead, and improved performance are the main goals of geographic-based topology management algorithms for wireless ad hoc networks. In wireless sensor networks (WSNs), accurate localization of sensor nodes is crucial for effective data collection and network functionality. Traditional methods often rely on multiple anchor nodes or centralized systems, which can be resource-intensive and less adaptable to dynamic environments. Addressing these challenges, Kumar and Singh [35] introduced a coordinate-based auto-localization algorithm (CALA) that utilizes a single anchor node to determine the positions of mobile sensor nodes. This algorithm employs received signal strength indicator (RSSI) values, considering Rayleigh fading in the path loss model, to estimate distances between nodes. By moving the target node to two different locations and applying a parallel coordinate system, CALA effectively calculates the node's coordinates. Empirical evaluations demonstrated that CALA achieves an average localization accuracy of 90% in networks with 20 sensor nodes, marking a significant improvement over traditional methods. This approach offers a promising solution for resource-constrained WSNs, reducing the dependency on multiple anchor nodes and enhancing scalability and accuracy in node localization. From the literature, it was observed that there is a need for improving the state-of-the-art in distributed approach-based node localization that needs fewer bacon nodes.

3. PROPOSED METHODOLOGY

We propose a distributed approach for sensor node localization based on the characterization of radio frequency and ultrasonic ToA range technologies. Training characterization is crucial for finding the location of senses in the direction of localization. Ranging characterization includes analyzing received signal strength with the help of ultrasound or radio frequency.

3.1 Received Signal Strength

Utilizing the RF signal attenuation as a distance function is how the signal strength technique works. This connection may be used to create a mathematical propagation model. Extensive research on the propagation characteristics of radio frequency signals has demonstrated that radio signals can exhibit varying propagation qualities contingent upon environmental variations [18]. The radio signal is constantly disseminated with the same power in all directions surrounding the sensor node since it contains an omnidirectional antenna. As part of the radio design, the sensor nodes supply two RSSI (Received Signal Strength Indicators) resisters. RSSI registers are a common feature of many wireless network cards [23]. We performed a series of experiments using these registers to determine a suitable model for ranging. For example, the usable radio broadcast range at ground level at maximum transmit power level is about thirty meters; however, when the node is positioned at a height of 1.5 meters, the usable transmission range increases to about one hundred meters. These disparities meant that the best situation for creating a model was a perfect football field with every node at ground level. With the help of data from the RSSI register at various node separations and transmission power levels, we created a model for this setup.

Finding the least square t for every power level creates a model as in Eq. 1. A distance of r separates two nodes, and the RSSI register reading is P_{RSSI}. Parameters X and n are constants that may be derived as functions of distance r for any power level.

$$P_{RSSI} = \frac{X}{r^n} \qquad (1)$$

With signal strength ranging, an accurate distance estimate within a few meters may be obtained if all nodes are positioned on one plane. It's clear from this experiment that in all other cases, using radio signal power might be rather surprising. The

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other problem with the received signal strength technique is the low-cost, inaccurate radios in sensor nodes that do not have exact, well-calibrated components. This is why there are often considerable differences between nodes in the actual transmit power at the same transmit power level or in the actual RSSI measured for the same actual received signal intensity. It is common to observe differences of several dBs. These variations lack the precision necessary for fine-grained localization, even if they are appropriate for use in transmit power adaptation and RSSI measurements for link layer protocols. Standardizing the run-time RSSI readings to a common scale by calibrating each node against a reference node prior to deployment and storing gain factors in non-volatile storage are two possible solutions.

Additionally, we assess the time difference between two simultaneous radio and ultrasound signals at the receiver to determine the ToA range for the sensor nodes. About three meters, or eleven to twelve feet, is the ultrasonic range of the sensor nodes. We found this to be a practical range for multihop studies, although we also highlight that larger ranges may be achieved at higher power premiums and expenses. We apply linear regression, as in Eq. 2, to do the best line fit to calculate, with microcontroller time, the speed to sound. The estimated distance between two nodes, s and k, respectively, and the sound speed in timer ticks are represented by the variables d and k. S = 0.4485 and k = 21.485831 are the model parameters.

$$t = sd + k \qquad (2)$$

When there is a node spacing of less than three meters, this ranging system may deliver an accuracy of two millimeters. Ultrasound is subject to multipath effects, much as radiofrequency waves. Fortunately, it is simpler to find them. ToA measurement uses the first pulse to ensure it records the straight-line, or shortest path, reading. Using statistical methods like those in [30], Nodes that are not in a straight line of sight have their reflected pulses filtered out. We assessed the two range options and discovered that ToA using RF and ultrasonic is more dependable than received signal strength. ToA range, a considerably more trustworthy metric, just depends on the time difference, whereas received signal intensity is significantly influenced by fluctuations in the received signal's amplitude. We chose ToA as the primary ranging technique for the suggested strategy based on the results of our characterization. Ultrasonic signals can exhibit variability in their propagation parameters in response to environmental changes, much like that of radiofrequency signals. The proposed method dynamically assesses the signal propagation parameters whenever enough data is available to reduce these impacts. This guarantees that the proposed method can function in various conditions without needing previous calibration. When deploying a sensor network across a vast area, the properties of signal transmission may differ between different regions within the field. Improved location estimation accuracy is ensured by calculating the ultrasonic propagation characteristics in each node's vicinity. We are considering combining received signal strength and ToA approaches as potential options for our next study. In locations where network connectivity is inadequate for ToA localization, the received signal strength approach can be utilized to provide a proximity indicator because its effective range is equivalent to that of radio transmission. In the denser regions of the networks, the ultrasonic method will offer fine-grained localization. We want the boards to serve as the sensor nodes' location coprocessors in this setup.

3.2 Algorithm for Localization

Presenting our localization techniques, we have a ranging technique for determining the node separation. Based on an ad hoc network of nodes, the algorithms work with a minority of sensor nodes that have location awareness, which can be acquired manually or by GPS. Beacon nodes are those whose positions are known, whereas unknown nodes are those whose placements are unknown. Our objective is to fully distributedly predict the locations of as many unknown nodes as feasible. The suggested location-finding methods work in an iterative manner. Following the establishment of the sensor network, the beacon nodes broadcast their location to nearby neighbors. Unknown nearby nodes calculate their distance from one another and estimate their own positions using the broadcast beacon positions. An unknown node becomes a beacon once it has located itself and informs nearby unknown nodes of its approximate position, enabling them to locate themselves. This procedure continues until every unknown node that satisfies the multilateration criteria has a position estimate. This method is known as iterative multilateration, and its primary primitive is atomic multilateration. We describe atomic and iterative

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multilateration in detail in the next subsections. Moreover, we characterize cooperative multilateration as an improved primitive for iterative multilateration and offer some recommendations for additional improvements.

If an unknown node is within range of three beacons or more, it can estimate its position using the fundamental case of atomic multilateration. The node further calculates the ultrasonic propagation speed for its locale if three or more beacons are present. Equation 3 allows us to express the gap between the measured and expected Euclidean distance as the erroneously measured distance between an unknown node and its ith beacon. x_0 and y_0 are the expected coordinates for the unknown node 0, s is the anticipated ultrasound propagation time, and for i = 1, 2, 3,..., N, where N is the total number of beacons, ti0 is the time it takes for an ultrasound signal to propagate from beacon i to node 0.

$$f_i(x_0, y_0, s) = st_{i0} - \sqrt{(x_i - x_0)^2 + } (y_i - y_0)^2 \quad (3)$$

The minimal mean square estimate (MMSE) of a given setup of $f_i(x_0, y_0, s)$, If enough beacon nodes are available, calculations like Eq. 4 can be utilized to calculate the Maximum Likelihood of the node's position. The symbol α represents the weight allotted to each equation. We will assume for convenience that α = 1.

$$F(x_0, y_0, s) = \sum_{i=1}^{N} \alpha^2 f(i)^2 \quad (4)$$

A system with an overdetermined solution for the position of the unknown node 0 can be created if a node contains three or more beacons, using a set of three equations of type (3). In the event that four or more beacons are present, the ultrasonic propagation speed (s) can also be calculated. Once $f_i(x_0, y_0, s)$ is equal to Eq. 3. by squaring and rearranging the component pieces, the resulting system of equations can be linearized to generate equation 5.

$$-x_i^2 - y_i^2 = (x_0^2 + y_0^2) + x_0(-2x_i) + y_0(-2y_i) - s^2 t_{i0}^2 \quad (5)$$

We may remove the $(x_0^2 + y_0^2)$terms for each of the k such equations by deducting the kth formula found in the remaining ones.

$$-x_i^2 - y_i^2 + x_k^2 + y_k^2 = 2x_o(x_k - x_i) + 2y_o(y_k - y_i) + s^2(t_{ik}^2 - t_{i0}^2) \quad (6)$$

You can use the matrix solution for MMSE [25] to solve this system of equations, which has the form y = bX. It is provided by $b = (X^T X)^{-1} X^T$y , where

$$X = \begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) & {t_{k0}}^2 - {t_{k1}}^2 \\ 2(x_k - x_2) & 2(y_k - y_2) & {t_{k0}}^2 - {t_{k2}}^2 \\ \vdots & \vdots & \vdots \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) & {t_{k0}}^2 - {t_{k(k-1)}}^2 \end{bmatrix}$$

$$y = \begin{bmatrix} -x_1^2 - y_1^2 + x_k^2 + y_k^2 \\ -x_2^2 - y_2^2 + x_k^2 + y_k^2 \\ \vdots \\ x_{k-1}^2 - y_{k-1}^2 + x_k^2 + y_k^2 \end{bmatrix}$$

and

$$b = \begin{bmatrix} x_0 \\ y_0 \\ S^2 \end{bmatrix}$$

We specify the following criteria for atomic multilateration based on this solution.

3.3 Collaborative Approach

It is highly likely that certain nodes in an ad-hoc deployment with a dispersed beacon distribution will not satisfy the atomic multilateration requirements. Atomic multilateration, for example, cannot be used to determine the position of an unknown node if it never has three surrounding beacon nodes. When a node attempts to forecast its position by taking into account the consumption of location data over multiple hops, this is referred to as collaborative multilateration. Assume sufficient data is provided to generate an overdetermined system of equations with a distinct set of solutions. If so, a node can estimate its position and the position of one or more additional unknown nodes by solving a series of simultaneous quadratic equations. The following is the formal definition of collaborative multilateration: You may think of ad-hoc networks as connected undirected graphs. G =(N, E) has a set E with at least n-1 edges and |N|= n nodes. A set B denotes the beacon nodes, and a set U denotes the unknown nodes, where U ⊆ G. Finding a remedy is our goal.

$x_u, y_u \ \forall_u \subseteq U$ by minimizing

$$f(x_u, y_u) = D_{iu} - \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2} \quad (7)$$

for each pair of participating nodes, i,u, such that u ⊆ U and i ⊆ B. Regarding: x_i, y_i each node pair i,u is a participating pair and is known if i ⊆ B. The following is a definition of participating nodes and participating pairs. Here are two important definitions. If a node has three or more participating neighbors and is either a beacon or an unknown, it is considered a participating node. A participating node pair is an identifiable pair of linked nodes in which all unknowns participate.

According to this formulation, the collaborative multilateration nodes constitute a subgraph of G, for which every edge E connecting two participating nodes may be expressed as an equation in the form of a 7. Every node considered has to be included for a unique solution. In instances when certain network regions exhibit low beacon density and unsatisfied atomic multilateration requirements, collaborative multilateration can help iterative multilateration. When there is a low beacon percentage, collaborative multilateration can be useful. Two network sizes of 200 and 300 nodes are taken into account in this scenario, together with a sensor field of 100 by 100 and a sensing range of 10. The correlation between network density and localization is further supported by this result. When comparing a network with 200 nodes and the same beacon ratio, fewer node locations could be calculated for the 300 node network. Higher levels of connectedness are the cause of this.

3.4 Optimization

Two more refinements might further increase the precision of the predicted positions in the multilateration methods covered in this section. First, weighted multilateration can be used to minimize error propagation. According to this technique, during a multilateration, beacons with greater confidence in their position are given a larger weight than beacons with less confidence. One can additionally compute and use as a weight in later multilaterations the degree of confidence in the expected position of a newly-bearing node. Additionally, the cumulative error can be decreased by using collaborative multilateration across a larger scope. We want to continue working on this problem and will write a report on the solution approach and additional assessment of these optimizations in the future.

3.5 Placement of Node and Beacon

The positioning of the beacons and network connectivity are key factors in the location-finding algorithm's performance. In this section, we do a brief probabilistic analysis to ascertain how a field's uniform node placement might meet the connection requirements. Next, we will conduct a statistical analysis based on these findings to determine the proportion of beacons needed. Assuming that sensor nodes are uniformly distributed throughout the sensor field, the probability that each node in the network has a degree of three or higher is the primary metric of significance for node deployment analysis. In a network of N nodes arranged in a square field on side L, the probability P(d) of a node with degree d is given by the binomial distribution in Eq.8, and the likelihood P_R being in transmission range.

$$P(d) = P_R^d . (1 - P_R)^{N-d-1} . \binom{N-1}{d} \quad (8)$$

$$P_R = \frac{\pi R^2}{L^2} \quad (9)$$

The binomial distribution explained earlier converges to a Poisson distribution as N approaches infinity. One can ascertain the likelihood of a node possessing degree three or higher by considering that λ = N. P_R, which gives us Eq. 10.

$$P(d) = \frac{\lambda^d}{d!} . e^{-\lambda} \quad (10)$$

$$P(d \geq n) = 1 - \sum_{i=0}^{n-1} P(i) \quad (11)$$

Furthermore, it is possible to determine the number of nodes needed per unit area in terms of λ. The likelihood of a node having a degree larger than three or four for various values of λ, additionally to the range R = 10 and size L = 100 of the eld. Eq. 11 provides these odds for us.

3.6 Proposed Algorithm

We proposed a distributed algorithm for sensor node localization. Our algorithm, Distributed Optimized and Adaptive Node Localization (DOANL), exploits a collaborative method that can achieve efficient localization even in a smaller number of beacons. The foundation of our methodology is the Angle of Arrival (AOA) and Time of Arrival (TOA). The localization process is also influenced by node and beacon deployment locations.

Algorithm: Distributed Optimized and Adaptive Node Localization (DOANL)
Input: Number of nodes N, number of beacons B

1. Begin
2. For each node n in N

3. estimatedDistance←DistanceFromNeighbors(N)
4. estimateBeaconLocations←FindNeighborBeaconLocations(B)
5. locationOfNode←FindLocation(estimatedDistance, estimateBeaconLocations, n)
6. add n to B
7. End For
8. For each beacon node b in B
9. propagate location to neighbors
10. End For
11. End

Algorithm 1: Distributed Optimized and Adaptive Node Localization (DOANL)

Algorithm 1 is designed for locating nodes within a network. Two inputs are needed by the algorithm: the total number of nodes (N) and the number of beacon nodes (B) that have positions known. The process is iterative, focusing on each node individually. It involves the following steps: Estimating Distance from Neighbors: For each node, the algorithm calculates its estimated distance from its neighboring nodes. Beacon Location Estimation: Using nearby beacon nodes as reference points, which are nodes with known positions, the algorithm then calculates the locations of these nodes. Finding the Current Node: The algorithm uses the estimated distances and beacon locations to find the current node. Updating Beacon Nodes: By adding the node to the group of beacon nodes, the localized region of the network is expanded. After iterating through all nodes and updating their locations, the algorithm enters a second loop focused on beacon nodes. Each beacon node propagates its location to its neighbors, enhancing the network's localization accuracy.

The DOANL algorithm operates on a distributed approach, allowing nodes to calculate their positions based on local information without requiring a centralized control system. This method is adaptive because it updates the set of beacon nodes as more node locations are determined, potentially improving the localization process over time. The algorithm's optimization aspect likely refers to its efficiency in calculating node locations with the available data, although specific optimization techniques are not detailed in the provided text. In summary, the DOANL algorithm is a distributed, optimized, and adaptive method for localizing nodes within a network by estimating distances to neighbors, determining beacon locations, calculating node positions, and updating the network with new beacon nodes. The algorithm's iterative process ensures that each node's location is estimated and that the network's localization capabilities are progressively enhanced as more nodes are localized.

4. EXPERIMENTAL RESULTS

The suggested distributed adaptive algorithm for the effective localization of sensor nodes in ad hoc networks is presented experimentally in this part. The results of the proposed algorithm in a distributed environment are compared with those of its centralized counterpart. Both distributed and centralized methods can be used to estimate the location of sensor nodes in an ad hoc network. The centralized technique uses a central base station to determine and gather each node's position. With respect to the distributed approach, each node can find its own location. The empirical study shows that distributed approaches are better than centralized approaches for many reasons. Sensor node location estimation in the centralized technique requires additional communication costs. A further issue with this method is called time synchronization. The third problem with the centralized approaches is the placement of the central nodes, which will impact the estimation of the location of nodes. The system's resilience declines with centralized techniques since the nodes won't be able to get the location data if the routes to the central node are disrupted. This brings up yet another issue.

Table 1: Traffic Analysis With Centralized And Decentralized Approaches Considering 10% Beacons

Network Size	Bytes Transmitted (thousands)	
	Distributed	Centralized
100	0	50
200	40	90
300	40	300
400	50	300
500	60	400
600	60	450
700	110	650

As presented in Table 1, the traffic requirements of centralized and distributed approaches for node localization in ad hoc networks are provided against network size. The observations are with 10% beacons.

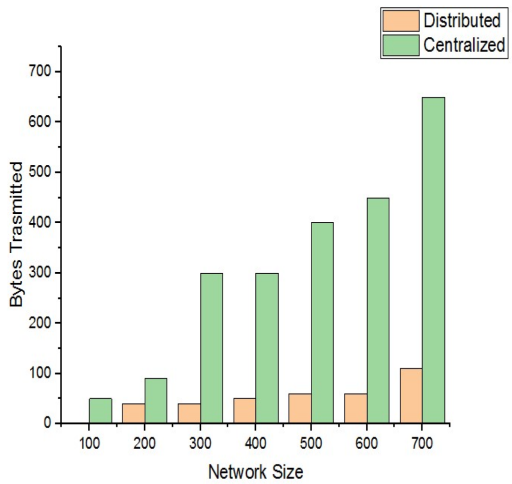

Figure 2: Traffic Analysis In Centralized And Distributed Implementations When 10% Beacons Are Used

As shown in Figure 2, the x-axis denotes different network sizes in increments of 100, starting from 100 to 700. The y-axis indicates the number of bytes transmitted, with values from 0 to 700 x 1000. For smaller networks (100, 200), the bytes transmitted are relatively low but gradually increase with network size. By the time the network size reaches 700, the bytes transmitted in the centralized network are significantly higher (around 700x1000). Even for the largest network size (700), the bytes transmitted in the distributed network are much lower than in the centralized network, reflecting better performance. The findings show that, as networks get larger, there is a discernible difference in the amount of data that is transferred between centralized and distributed networks. Centralized networks tend to transmit more bytes than distributed networks, and this disparity becomes more pronounced with larger network sizes. This suggests centralized networks might be less efficient for data transmission for larger networks than distributed networks. These observations are when 10% beacons are used.

Table 2: Traffic Analysis With Centralized And Decentralized Approaches Considering 20% Beacons

Network Size	**Bytes Transmitted (thousands)**	
	Distributed	**Centralized**
100	0	30
200	30	90
300	30	180
400	30	300
500	60	580
600	80	650
700	90	880

Table 2 shows that traffic requirements for centralized and distributed approaches to node localization in ad hoc networks are provided based on network size, with observations made using 20% beacons.

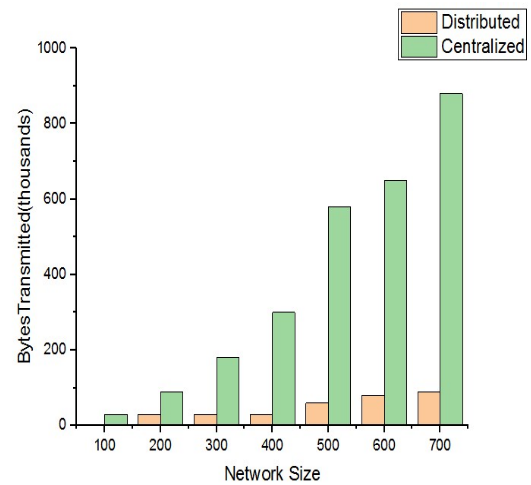

Figure 3: Traffic Analysis In Centralized And Distributed Implementations When 20% Of Beacons Are Used

The network size, which ranges from 100 to 700 nodes, is represented by the x-axis in Figure 3. The number of bytes of data transmitted by each node is shown on the y-axis. The Distributed configuration consistently results in fewer bytes transmitted per node compared to the Centralized configuration across all network sizes. A larger communication overhead is indicated by the significant increase in data delivered in the Centralized arrangement as the network capacity grows. The Distributed configuration shows a relatively stable amount of data transmission, making it more scalable and efficient for larger networks. These observations are when 20% of beacons are used.

Table 3: Energy Consumed By A Node For Localization Using 10% Beacons

Network Size	**Energy required per node (J)**	
	Distributed	**Centralized**
100	0	0.4
200	0.3	0.9
300	0.3	2.8
400	0.4	2.8
500	0.4	3.4
600	0.3	4
700	1	5.5

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As presented in Table 3, the energy consumption required by a node during the localization process is distributed in a centralized fashion based on the number of nodes. These observations are made with 10% beacons.

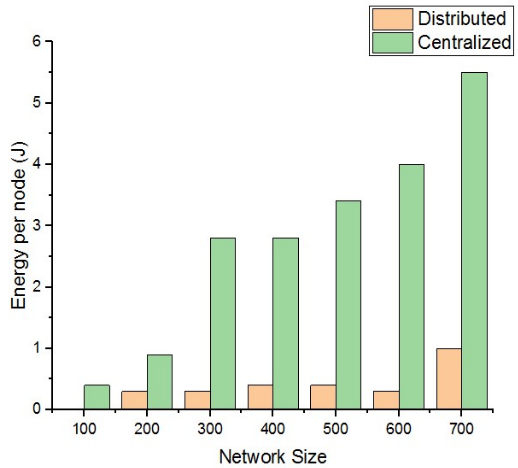

Figure 4: Energy Consumption Per Node In Centralized And Distributed Implementations When 10% Beacons Are Used

As seen in Figure 4, the network size is represented by the x-axis, which ranges from 100 to 700 nodes. The energy used by each node is shown on the y-axis as joules (J). The Distributed configuration consistently consumes less energy per node than the Centralized configuration across all network sizes. The Centralized arrangement shows a considerable increase in energy usage with increasing network size, suggesting lower efficiency at bigger sizes. The distributed configuration shows relatively stable energy consumption, making it more scalable and efficient for larger networks. These observations are using 10% beacons.

Table 4: Energy Consumed By A Node For Localization Using 20% Beacons

Network Size	Energy per node (J)	
	Distributed	Centralized
100	0	0.3
200	0.3	0.8
300	0.3	1.4
400	0.4	2.8
500	0.5	5
600	0.8	5.6
700	0.9	7.5

As presented in Table 4, the energy consumption required by a node during the localization process is distributed in a centralized fashion based on the number of nodes. These observations are made with 20% beacons.

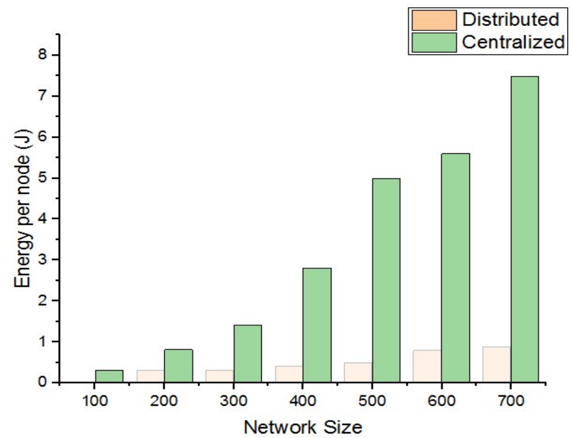

Figure 5: Energy Consumption Per Node In Centralized And Distributed Implementations When 20% Beacons Are Used

Figure 5 illustrates this with the network's size represented by the X-axis rising from 100 to 700. The Y-axis represents the energy consumption per node in joules (J). The energy consumption per node in a distributed system is relatively low and gradually increases as the network size increases. The energy consumption per node in a centralized system is significantly higher and increases more rapidly with the network size. For smaller network sizes (100 to 300 nodes), both systems' energy consumption per node is relatively low, but the centralized system still consumes more energy than the distributed system. As the network size grows (400 to 700 nodes), the energy consumption difference between the distributed and centralized systems becomes more pronounced. The centralized system's energy consumption grows exponentially compared to the distributed system's relatively linear growth. The distributed system is more energy-efficient per node than the centralized system, particularly as the network size increases. This makes distributed systems more scalable and cost-effective for energy consumption for larger networks.

5. DISCUSSION

A distributed technique is proposed in this paper to achieve sensor node localization in ad hoc networks. The proposed technique can achieve localization with very few beacon nodes. The network gains location awareness with the proposed methodology during deployment. With the proposed methodology, the nodes in the network can dynamically find their own location. Towards this end, a two-phase approach is employed. This method incorporates the estimating process with ranging techniques. Through the act of ranging, every node is able to determine how far away its neighbors are. During the estimation stage, ranging information is used by every node whose location is known. Each node may find its own location based on the known location and the locations of beacon nodes. Following its self-discovery, a note turns into a beacon node, assisting other nodes in the network in locating themselves. A comparison is made between the centralized technique and the dispersed strategy that is suggested. Our study revealed that the proposed distributed approach has provisions to improve the network's performance, while the centralized approach causes more overhead on the network. The proposed methodology has certain limitations, as discussed in Section 5.1.

5.1 Limitations of The Study

There is a need to improve accuracy for bigger networks with the proposed methodology. The proposed methodology must be extended to reduce error propagation and improve accuracy in node localization. Another possibility is that 3D localisation can be incorporated to improve the methodology further.

5. CONCLUSION FOR FUTURE WORK

We have developed an algorithm for localizing sensor nodes in a distributed manner. Our algorithm, Distributed Optimized and Adaptive Node Localization (DOANL), uses a collaborative approach to achieve efficient localization even with fewer beacons. Time of Arrival (TOA) and Angle of Arrival are key components of our technique (AOA). The localization process is also influenced by the positions of nodes and beacons. Our research analyzed node deployment and network connectivity to investigate this proposition. This work presents the Distributed Optimized and Adaptive Node Localization (DOANL) algorithm, which enhances localization accuracy in distributed wireless ad hoc networks by leveraging AOA and TOA with minimal beacons and minimizing error propagation, outperforming state-of-the-art. We discovered that error propagation across the network affects the algorithm's accuracy. We optimized the DOANL algorithm to tackle this issue by minimizing error propagation. An empirical study using NS-3 simulation revealed that our algorithm can localize sensor nodes in wireless ad hoc networks more effectively than existing methods. We intend to implement 3D localization of sensor nodes under their visualization in a distributed environment in the future.

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