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LOCALIZATION UPGRADING THROUGH DEUCE ADAPTATION WITH MUTABLE AMBIT PREMISED LOCALIZATION ALGORITHM IN WSN

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ABSTRACT

In modern era, significant obstacles have been encountered in case of earlier methods for attaining optimization for localization due to indiscriminately individualized developments in Wireless Sensor Network (WSN). In this connection, traditional optimization algorithms have lower computational effectiveness and they fail to converge towards the optimal global state, thereby, overlooking the ranging errors and localization geometry while negatively affecting precision and efficiency pertaining to localization in WSN. The current paper throws light on a new-fangled approach called Extemporaneity Bat Optimization Technique (EBOT) based on Deuce Adaptation, through two significant changes. Thus, a unique approach that improves the bat optimization method's exploratory while conjointly exploiting its characteristics. Further, EBOT adaptation 1 improves global search capabilities leading to better exploration, whereas EBOT adaptation 2 employs an enhanced local search method to promote exploitation. The proffered method also presents a Polarity Metamorphosis Strategy (PMS), which improves crossover and mutation operations thereby boosting the population heterogeneity as well as exploration capacities. Additionally, the strategy recognizes the importance of range errors and localization geometry in the context of positioning procedure. Again, the Mutable Ambit Premised Localization (MAPL) Algorithm is presented to élite primary nodes during triangulation based on an unpretentious assessment to enrich localization geometry. We The method enhances accuracy by considering localization geometry and range errors when estimating the final positioning with proficient adaptability.

Keywords: APIT, *BOA*, *CT, EBOT, FP-MPP-APIT, LE, MAPL, PMS, RMSE, WSN.*

1. INTRODUCTION

In current days, researchers are interested in studying Wireless Sensor Networks (WSNs) due to the rapid proliferation and upgradation in wireless technology [1-3]. The integration of optimization, flexibility, and changing contexts in the field of WSNs allows increasing emphasis of investigators in the field of localization and its betterment. In this research paper, we have proposed a novel approach named as Extemporaneity Bat Optimization Technique (EBOT) which involves a unique strategy that improves the global search capabilities. The novel approach includes EBOT adaptation 1 that enriches the global search capabilities leading to better exploration while another EBOT adaptation 2 that exploits an enhanced local search method to promote exploitation. Moreover, our proposed approach also incorporates the *Mutable Ambit Premised Localization (MAPL)* algorithm for enhancing localization strategies to élite the concerned *primary nodes* during triangulation based on an unpretentious assessment to improve the localization geometry. In this context, the Bat Optimization Algorithm (BOA)[3-7] is also used for solving optimization problems that is inspired by bat echolocation which is used haphazardly in real time in the context of *Extemporaneity Bat Optimization Technique (EBOT)*. With regard to WSN localization, this optimization method aids in dynamically modifying the localization parameters according to current network conditions. This approach's extemporaneity allows the algorithm to adjust to changes in sensor node placements, network topology, or ambient conditions, resulting in computations that are faster, more accurate, and

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require less energy. Similarly, Approximate Point in Triangulation Test (*APIT*) [8-12] is another approach that depends on the angle and relative positioning of data rather than exact distance measurements. Another sophisticated localization approach named as Fermat Point Mid Perpendicular Plane - Approximate Point in Triangulation Test (*FP-MPP-APIT*) [12-15] is a method that combines the ideas of the mid-perpendicular plane, which reduces positional ambiguity by utilizing geometric constraints, and the Fermat point, which minimizes the overall distance to many points. We have assessed the performance of our proposed algorithm EBOT against the existing approaches namely APIT, FP-MPP-APIT on the basis of following performance metrics: (i)Localization Time(LT) (ii)Localization Error (LE) (iii) Computational Time (CT) (iv) Root Mean Square Error (RMSE). In this context, *LE* describes the discrepancy between a node's estimated and actual positions. Similarly, the amount of time needed for a localization algorithm to calculate the approximate locations of sensor nodes inside the network is known as *CT.* Likewise, the average amount of the discrepancy between the estimated and actual node positions in localization is measured statistically using *RMSE.* The square root of the average of the squared discrepancies between the estimated and true positions is used to compute it. With regard to localization correctness.

In general, a ***WSN*** comprises of many interconnected sensors that monitor and communicate environmental data remotely. Here accurate localization is critical to *WSNs*' ability to comprehend sensor node positions and effectively interpret data. In many *WSN* applications, such as military surveillance and environmental monitoring, localization is essential. The purpose of this topic is to use adaptive strategies to improve the localization process. The lack of context in network data would diminish its usefulness in the absence of effective localization. Improving *WSN* localization directly raises the network's lifetime, accuracy, and energy usage. Because nodes and their operational environments such as mobile nodes and changing environments are constantly changing in *WSNs,* it is emerging as a crucial issue. The method can optimize resources and improve accuracy by focusing on regions of interest that are relevant at particular times by allowing the localization ambit to be modified. This adaptability ensures consistent, dependable positioning even in dynamic *WSN* circumstances by strengthening the localization process' resistance to change and thereby making it more flexible to changes in the actual environment.

Finding the locations of sensor nodes inside a *WSN* is known as localization. The central idea of the subject is *localization*. An improved localization procedure pinpoints each sensor's exact location, thereby enabling *WSNs* to follow and analyze data more efficiently. Better resource management, more effective routing, and higher-quality data collecting are all correlated with improved localization. More precise, real-time localization techniques are required as *WSNs* get more complicated in order to maintain network operation. PMS approach could be utilized in the context of WSNs and localization to modify the energy consumption, communication techniques, or signal strength according to the location or behavior of nodes. System characteristics further undergoes metamorphosis to guarantee that the network can continue to function properly in the face of change. By decreasing interference, enhancing signal quality, and optimizing resource usage, this flexibility may further improve the localization algorithm and enabling more accurate real-time location. By using the above technologies, we have improved the *LT, LE, CT and RMSE.*

In this context, the objective is to improve the localization such that the localization process remains energy efficient and robust in case dynamic surrounding for the sake of its adaptability so that the system can manage real-time changes while maximizing the performance and guaranteeing the proper effective localization process. This is also known as dual-mode adjustment. Every idea is essential to building a strong, cutting-edge WSN localization framework.

In *WSNs*, massive sensor nodes are placed at random or predetermined locations to collect and send information to different networks [1]. In this connection, WSNs are used in many industries, such as farming, actual time health surveillance, pollution in the air, humidity and temperature monitoring. Additionally, they are employed in the identification of landslides and fires in forests [2]. In addition, WSN is also used in many security-related applications, such as protecting private data from illegal access and various forms of attack in VANET and MANET [4], as well as in supervising computerized garbage [3]. Numerous problems affect WSNs, such as restricted nodes with sensor lifespans, navigation, localization, and node placement, and consumption of energy [5]. Expanding the network lifetime of WSNs is another problem, which concerns the amount of electricity the sensor networks consume. WSNs can have longer lifespans by using routing techniques based on clustering [6]. An additional issue that WSNs have is the ability to offer adequate connectivity with a limited number of nodal points that have sensors [7].

Localization is one of the primary problems faced by WSNs since the data acquired by the sensor nodes would be useless if the location from which they were obtained could not be determined [8]. Within WSNs, a large number of nodes are dispersed at random location in unexpected places. The localization problem seeks to determine the position of every sensor node within a WSN [9]. As a proxy for the localization problem, sensor nodes can be located by the global positioning system (GPS). Nevertheless, this approach is impractical since WSNs include a huge number of sensor nodes; every node would need a device that uses GPS, which would raise the level of complexity, expenditure, and electrical consumption of the entire network as a whole [10].

To address these problems, many researchers have created a variety of localization techniques. A small number of nodes for anchoring have been selected by the network so that all node sensors require GPS. All of these nodes act as anchors to assist in locating targeted nodes, which are the nodes that have yet to be identified [11]. The anchor node's position is one input that is used in the localization process, and measuring techniques are also used [12]. There are two sorts of localization strategies: range-free localization and range-based localization of information. In range-based localization, supplementary inputs such as Received Signal Strength (RSS) and Angle of Arrival (AOA) are also utilized. At the same time, connectivity of data is used as an extra input for range-free localization [13]. To achieve the localizing objective, studies are presently attempting to take use of node sensor interactions and connections [14]. Furthermore, localization techniques in WSNs are often classified into two main categories: range-based and range-free methods [15]. Conversely, range-free techniques leverage connectivity (e.g., hop counts) or pattern matching (e.g., fingerprinting), while range-based algorithms use estimated inter-node lengths or angles for localization. Depending on the range, technologies for localization and ranging include received signal strength indication, time difference of arrival, angle of arrival, and time of arrival. These methods are used to calculate and measure angles and distances. A positioning calculation technique such as Lateration [16] (the trilateration method or Multilateration), Min-max (bounding box) [17], or a method that uses probabilities (e.g., maximum likelihood) that utilizes the estimated distances to the nodes of reference as well as the geographical coordinates of the reference nodes can be used by an unknown node for determining its exact position.

The above-mentioned comments indicate that the major obstacles must be overcome in order to improve wireless sensor node localization method. This research investigates techniques to improve the performance of range-based trilateration technique localization in order to enrich the service of WSN nodes in outdoor contexts that vary in both space and time. Thus, the study's suggestion may effectively decrease the node's localization error without increasing traffic on the network. As a result, using experiments, the paper examines how the localization geometries and extending inaccuracy affect the error in localization in 2D.

The main objective of our research is to develop a novel approach involving a unique strategy for improving the global search capabilities while conjointly incorporating *EBOT adaptation 1, EBOT adaptation 2, MAPL and PMS* for enhancing localization strategies to élite the concerned *primary nodes* during triangulation based on an unpretentious assessment to improve the localization geometry. The aim of the study is to optimize the Bat Optimization algorithm (BOT) for WSNs in order to decrease computation time and mean square error while enriching localization accuracy.

2. LITERATURE REVIEW

Many academicians have used various optimization techniques to tackle the problem of node localization in WSNs. In order to reduce averaged error in localization and locate nodes in WSNs, Particle Swarm Optimization (PSO) was first presented in [18]. To tackle the multifaceted localized predicament, two repetitive localized methods were proposed in [19]. PSO and the Microbial Forage Approach (BFA) techniques reduced the node power consumption in WSNs and reduced the amount of time required to establish target node positions. To lower the median error of nodes that originate with nodes that anchor, the optimization technique of bees is used in [20]. Two different situations were considered while determining the best location for the anchor nodes inside the installation region.

In the first strategy, every target network is surrounded by a maximum of three anchoring nodes, whereas in the subsequent technique, beacon networks are positioned in the centre of the surveillance area [21]. In order to place the nodes in the network's three deployment (3D) zones, stochastic PSO was presented in [22]. Compared to other PSO-based techniques, the target nodes have been positioned more precisely using the stochastic PSO algorithm. To increase the precision of localization and resolution rate, a hybrid bio-inspired optimization method based on PSO and BFO was used in paper [23]. In contrast to alternative computations, the PSO as well as BFO techniques resulted in lower node energy usage and more nodes for sensor localization.

In order to lower the deployment cost, a novel genetic optimization method was presented in [24] that makes use of an adequate number of anchor nodes to identify each target node in WSNs as introduced in [25]. The Cuckoo Search Optimization Algorithm (CSOA) aims to improve target node coordinate detection and achieve convergence with fewer iterations. The CSOA performs better than other optimization algorithms in determining the overall ideal results. To tackle the flip uncertainty problem in WSNs, the optimization technique known as gravitational search was modified in [26]. Apart from traditional optimization methods, a variety of meta-heuristic approaches have been investigated to improve the localized procedure because of their capacity to increase the accuracy of the initial localization method [27]. A genetic-based localization algorithm was developed that constrained the feasible population region at the moment the first population was formed in order to improve localization accuracy and convergence speed. In the functional area, the initial population is generated at random, and three anchor nodes are utilized as the centre to build three squares. The total working area of the unknown nodes is represented by the shadow area of the three-square connection. Particle swarm optimization is used [28] to refine the outcomes following the application of an improved localization method [29]. A great deal of the anchor- and range-based localization algorithms and approaches that have been proposed recently are based on trilateration [30-33].

Most range-based and range-free approaches, however, are well-researched while neglecting the impact of localization geometry on the localization error. The choice of reference nodes is critical to range-based localization, and trilateration-based localization in particular is dependent on it. The choice of reference nodes is crucial to the accuracy of localization and should not be overlooked. The nearest neighbour approach or random selection are common way to choose reference nodes without considering the localization geometry. By selecting the reference nodes based on localization geometry and distance measurement error, among other factors, localization error may be greatly reduced. Here *APIT* [33-36] is more resilient to inaccuracies in range measurements and appropriate for *WSN* situations with limited resources. For *WSNs* where minimizing computation and conserving energy is critical, *APIT's* efficiency in terms of communication overhead and energy is vital. By estimating the triangulation test point, the *APIT* method is applied to refine this localization. Moreover, *FMSL* is essential to ascertain the precise location of sensor nodes within a network. This process is known as localization. Frequency Modulation (FM) is used by FMSL to improve the signal robustness and tolerance level to outside noise. Security elements are also incorporated to guard against hostile assaults like spoofing and jamming. Moreover, *Modifiable Ambit Priority Localization (MAPL)* is another dynamic strategy that allows the region of interest (ambit) to be changed in response to requirements or conditions that change over time. Similarly, another approach called *Polarity Metamorphosis Strategy (PMS)* is used that alludes to the capability of dynamically altering specific system properties (such as signal polarity or data processing behaviour) in response to network or environmental variables.

3. PROBLEM STATEMENT AND PROPOSED APPROACH

3.1 Problem Statement

In recent years, a number of scholars have tackled the WSN localization problem using different optimization techniques. The utilization of optimization approaches for sensor node localization yields significant reductions in computation time and localization error. Nevertheless, by using useful evolutionary methods; computation time and localization error can still be reduced. In this context, localization has several shortcomings, such as scalability, accuracy, convergence time, and cost. On this basis, scalability or the ability to expand a WSN by adding nodes, is one of the most important factors in determining a network's success. Network latency is an additional issue in this connection. The primary goal of the researchers is to develop a precise and affordable localization optimization method, even if there is a trade-off between accuracy and WSN cost. The ratio of anchor to target nodes is another factor that affects WSN cost. WSN accuracy improves as the number of anchor nodes rises since the localization error falls as well. However, as GPS is used to estimate anchor node positions, this also leads to increased deployment costs for WSNs.

The length of time needed for convergence reflects how long the optimization approach takes for locating each target node in the *WSN*. Thus, finding the target nodes' exact location is the major purpose of the localization optimization procedure. The accuracy of the localization optimization technique is gauged by the average localization error. A lower average localization error indicates a more accurate optimization process. The differential evolution algorithm is used to find the best global solution that matches the estimated locations of unknown nodes. It requires a great deal of time and work, even if it increases the localization accuracy. Unfortunately, increasing localization precision often translates in decreasing energy efficiency due to increased computing and/or transmission expenses. Some techniques can be iterative that necessitates initial location estimates, or rely on historical network knowledge. The approach is sometimes tested with simulations that have possibly implausible setups or properties. On the other hand, the scalability of the algorithm is troublesome. Given the foregoing concerns, it is imperative that a novel approach be developed in the field of WSN competence by addressing the main challenges, namely computation time, mean localization error, number of localized nodes, potential error regarding average distance per hop, and distance estimation errors.

3.2 Proposed Extemporaneity Bat Optimization Technique (EBOT) Algorithm

In recent years, numerous researchers have utilized various optimization techniques to tackle the WSN localization challenges. These optimization methods are advantageous as they significantly reduce Computation Time and Localization Error. Despite this, there's still potential for further reduction in computation time and localization error through the use of practical evolutionary algorithms. Localization in WSNs faces several challenges, including accuracy, convergence time, cost, and scalability. Scalability, the ability to expand the WSN by adding nodes, is a key factor in determining its effectiveness. Another critical issue is the network cost for which researchers are still striving to develop an optimization technique that balances the cost and accuracy.

One factor influencing WSN cost is the ratio of anchor nodes to target nodes. Increasing the number of anchor nodes not only decreases the localization error and enhances accuracy, but also raises costs due to the use of GPS for anchor node positioning. In this context, the convergence time reflects how quickly the optimization method can confine each node in the WSN. The primary aim of the localization optimization algorithm is to accurately determine the positions of target nodes, with the average localization error thereby serving as a measure of accuracy. A lower average localization error indicates a more precise optimization process. The differential evolution algorithm is often employed to find the optimal global solution corresponding to the predicted locations of unknown nodes. While it enhances localization accuracy, it also demands significant time and energy. Enhancing localization accuracy typically leads to reduced energy efficiency due to higher computational and communication costs. Some methods may require initial location estimates which can be iterative, or rely on prior network knowledge. Additionally, simulations with potentially unrealistic setups or characteristics are sometimes used to test these methods, which can affect scalability. Therefore, there is a pressing need to develop a novel strategy in the field of *WSN* optimization.

This strategy should address the major challenges, including the mean localization error, computation time, distance estimation errors, and potential errors related to the average distance per hop to improve overall *WSN* performance.

The research introduces *EBOT* based on Deuce Adaptation. This involves refining the exploration and exploitation capabilities of the bat optimization algorithm to enhance the performance of *WSNs*. *EBOT* adaptation 1 introduces a superior global search method to improve the algorithm's exploration feature. Meanwhile, *EBOT* adaptation 2 employs a better local search technique to enhance the exploitation feature. Importantly, these adaptations do not require additional devices, thus maintaining the cost-effectiveness of *WSNs*. Furthermore, both adaptations converge faster and require less computation time compared to existing algorithms. The research also employs a basic differential evolution process where three different individuals are selected randomly for individual updating, crossover, and mutation. While this method is straightforward, it reduces algorithm efficiency by updating individuals without utilizing the data of the best individuals identified by the

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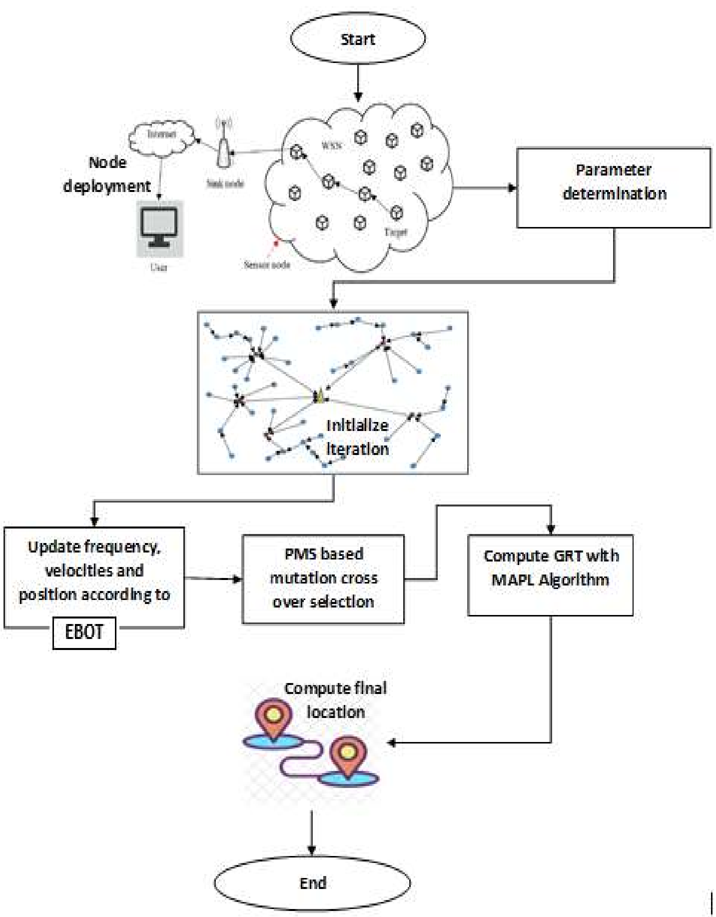
search process. When heuristic knowledge of the global optimum individual is integrated, it results in individual convergence and reduced population diversity. To counter this, the study introduces a novel *Polarity Metamorphosis Strategy* (*PMS*) that enhances the mutation and crossover operations, thereby, improving the population heterogeneity and the algorithm's overall exploration capability.

Figure 1: Proposed architecture

Moreover, the research emphasizes the



importance of considering localization geometry and ranging errors during the localization process. By selecting primary nodes during triangulation through a simple evaluation method known as the Mutable Ambit Premised Localization (MAPL) Algorithm, the study aims to optimize localization geometry. Additionally, it accounts for the combined effects of range errors and localization geometry when estimating the final position. The proposed method's low cost and scalability make it suitable for implementation in WSN nodes. In our proposed approach, sufficient number of sensor nodes were located using the original bat optimization technique. The bat optimization approach consumes an inferior nasty localization error and computation time than other methods. However, because it does not localize every target node in the network, its success rate is lower. The search region cannot be thoroughly explored by *EBOT* in all directions. Therefore, the bat optimization procedure must be modified to astound these problems and cut down on computation time and mean localization error further. Two adaptations of the bat algorithm for optimization are put forth in this study. Adaptation of the bat optimization method is shown to improve the exploration and exploitation capabilities of the bat algorithm, hence, enabling greater effectiveness of WSNs. With *EBOT adaptation 1*. Moreover, an updated global search method is introduced that improves the exploration function of the bat optimization algorithm. Afterwards, with *EBOT adaptation 2,* an upgraded local search technique is used to enhance the exploitation feature of *EBOT*.

3.2.1 EBOT Adaptation 1

It is challenging to find the ideal solution globally while the bat optimization method is stuck at the local optimum option. Thus, it is imperative to steer the current response toward the overall best solution. In the suggested EBOT Adaptation 1, the enhanced global search approach is employed to boost EBOT's global search capabilities. The basic idea behind the enhanced global search strategy is to use various techniques and to explore a wider area of the search area in order to locate the global optimum solution.

In the search area, a random deployment of O targeted node and N anchor nodes results in an estimated population size of Q, indicating the presence of Q possible solutions. Two frequencies are created in the suggested EBOT adaptation 1 for updating bats speed. Both of these frequencies are designated as $G_j(1)$ and $G_j(2)$ for i-th node of sensors. Equations 1 and 2 are used to get the values of these frequency ranges:

$$G_j(1) = G_{\min} + \left(G_{\max} - G_{\min}\right)\varepsilon \tag{1}$$

$$G_j(2) = G_{\min} + (G_{\max} - G_{\min})\phi \tag{2}$$

$G_j(1)$ and $G_j(2)$ have values that are dependent on $\varepsilon, \phi, G_{\min}, G_{\max}$. The random numbers ε *and* ϕ have ranges between 0 and 1. Then, the following equations are used to update the bats' position as well as acceleration:

$$W_j^U = W_j^{U-1} + \left(Y^c - Y_j^U\right) \times G_j(1) + \left(Y^x - Y_j^U\right) \times G_j(2) \qquad (3)$$

Wherein Y_j^U denotes the ith bat's current solution at moment U, and Y^c and Y^x stand for the most effective and weakest responses, respectively. The first bat optimization process creates fresh solutions centred on the best ideals, eventually trapping EBOT in the local optimum position. The bats in the original bat algorithm merely moved in the direction of the best answer; they did not investigate the entire area. The goal of the suggested *EBOT* Adaptation 1 is to discovered the global best value by expanding the search space for bats. In the suggested *EBOT* adaptation 1, the bats would seek the entire space, covering the ideal response to the worst possible answer, in order to identify the overall best option. In the event that the optimization problem involves minimization, Y^c and Y^x values are established.

$$Y^c = \min(f(Y)) \qquad (4)$$

$$Y^x = \max(f(Y)) \qquad (5)$$

Wherein the optimization problem's objective function is denoted by $f(Y)$. After the first iteration, the values of the worst and best solutions are determined once more after updating the positions of each bat and computing the objective function for each bat. The bats' velocities are efficient consuming these finest and nastiest values in the following repetition, and so forth.

3.2.2 EBOT Adaptation 2

Compared to previous techniques to explain the node localization problem, the suggested *EBOT* adaptation 1 contained all the target nodes in the WSN and had the minimum mean localization error. Compared to existing methods, the suggested *EBOT* adaptation 1 converges more quickly and requires less time to localize all nodes. But when updating bat velocity, there's a propensity to include the worse solution. Furthermore, *EBOT* Adaptation 2 is recommended as a solution to this issue and to additionally decrease the mean error in localization while curtaining the corresponding computational time. In the proposed *EBOT* Adaptation 2, an enhanced local search approach is employed to enhance *EBOT's* local search features. The primary rationale behind the enhanced local approach is to create new bat solutions by utilizing the best existing local solution and accessible data. The bat velocity was updated using the worst and current best solutions found by the enhanced local method. The suggested EBOT adaptation 2 does not include the poorest answer; instead, it searches a narrow region that is closer to the best solution found to date. The following equation is used in the planned EBOT adaptation 2 to alter bat velocity:

$$W_j^U = W_j^{U-1} + \left(Y^c - Y_j^U\right) \times G_j(1) - \left(Y^x - Y_j^U\right) \times G_j(2) \qquad (6)$$

The initial term $\left(Y^c - Y_j^U\right) \times G_j(1)$ in this formula indicates that the outcome is moving in the direction of the optimum solution, implying that the newly produced solutions is getting closer to the optimal value. The subsequent term $\left(Y^x - Y_j^U\right) \times G_j(2)$ indicates that the worst value is being avoided by the solution. Equations 1 and 2 are used to calculate the values of $G_j(1)$ and $G_j(2)$. The optimized local search approach does not cover the full searching area; instead, it focuses on the narrow window surrounding the optimal result. Eq. 9 is used to update the bat locations after every bat's motion has been changed. At every iteration, the suggested *EBOT* Adaptation 2 always goes closer to the local best answer and attempts to proceed farther towards the most undesirable option. The node localization problem has four main problems: mean localized erroneous time required for computation, the amount of localized nodes, and speed of convergence. The population's heterogeneity as well as the technique's overall exploring capability improvisation are essential for *WSN* node localization that has been discussed in following section.

3.2.3 Polarity Metamorphosis Strategy (PMS)

In the *DV-Hop* localization procedure, the error is large since the distance among an unidentified node and the anchor node is a rough indication. The median distance per hop is determined by the innovative localization algorithm using the impartial approximation standard, and the regular distance per hop obtained by this method has an estimation error of zero. The mistake does, however, follow the Gaussian distribution. The mean square error is a more realistic estimate of the sub-error than using merely the adaptation or deviations, based to the measurement estimation theory, which also states that that is the cost function. As a result, this investigation's average distance per hop computation formula is enhanced.

A. The Flooding Procedure

Among the classic routing algorithms, flooding is extremely straightforward and dependable. Unfortunately, it wastes a lot of network possessions and creates a lot of connectivity expenditures, which renders routing and link resources ineffective. This paper's *DV-Hop* algorithm's first and second steps' routing algorithms are based on flooding, which also includes the original *DV-Hop* method.

B. Method for Determining the Average Distance per Hop

Letting the resultant value of Expression (7) be zero in accordance with the conventional way on the impartial approximation standard to determine the average distance of per-hop $Hopsize_j$.

$$g_1 = \frac{1}{n-1}\sum_{j\neq k}^{n}\left(e_{j,k} - Hopsize_j . i_{j,k}\right) \quad (7)$$

Now the regular detachment per hop is determined using the least median square error requirement.

$$g_2 = \frac{1}{n-1}\sum_{j\neq k}^{n}\left(e_{j,k} - HopSize'_j . i_{j,k}\right)^2 \quad (8)$$

Depending on the minimal mean square error criterion and assuming a given $\frac{\partial g_2}{\partial HopSize'_j} = 0$, the predicted median distance per hop can be calculated as follows:

$$HopSize'_j = \frac{\sum_{j\neq k}^{n} i_{j,k} e_{j,k}}{\sum_{j\neq k}^{n} i_{j,k}^2} \quad (9)$$

Equation (10) can be able to be used to compute the average distance of each hop.

$$HopSize'' = \frac{\sum_{j=1}^{n} HopSize'_j}{n} \quad (10)$$

Every anchor node computes $HopSize''$ and then uses regulated flooding to transmit the mean distance per hop $HopSize''$ throughout the system. Equation (11) is used by unidentified node v to compute its detachment from anchor node j once it obtains data gathered from the other node.

$$e'_{v,j} = HopSize'' \times i_{v,j} \quad (11)$$

C. Enhancement of the Differential Evolution(DE) Method

Three distinct individuals are selected at random to execute the mutation and crossover, along with individual update processes in the fundamental differential evolution algorithm. Although this method is very straightforward, it reduces algorithm efficiency since it updates individuals blindly without using the data of the ideal persons found through the algorithm's research. As a result, the fundamental differential evolution algorithm in the enhanced algorithm incorporates the interpersonal aspect of PSO. The upgraded individual can get the optimum separate heuristic data and accelerate the algorithm's convergence speed by learning from the optimal individual $Y_h = (y_{h1}, y_{h2}, \ldots, y_{ho})$ in the overall population. Entities are inclined to congregate to the global optimal person with the technique's operation upon including the global optimal personal's heuristic knowledge. This results in individualized converging and a decrease in population adaptation. The next set of improvements includes increasing the number of mutations and crossing operations in order to enhance both the population's variety and the method's universal exploring power.

D. Crossover

The objective individual (y_j^u) and the mutated individual (w_j^{u+1}) are crossed in the basic differential evolution process to produce the study distinct (v_j^{u+1}). In order to have the present individuals y_j^u learn from the ideal individual y_{best}^u of the group, the communal knowledge component of the particle swarm optimization procedure is added to the revised method. The outcomes are then combined against the mutation vector w_j^{u+1}. The procedure's optimization performance is increased by employing the heuristic info approved by the collection best value. Here is how the crossover operation is done:

$$v_{j,k}^{u+1} = \begin{cases} w_{j,k}^{u+1}, & if \quad s_k \le DS \quad or \quad k = socs\_j \\ y_{j,k}^u + rand[0,1] \times d \times \left(y_{best}^u - y_{j,k}^u\right), & otherwise \end{cases} \quad (12)$$

The symbol $d = 2, y_{j,k}^u + rand\,[0,1] \times d \times \left(y_{best}^u - y_{j,k}^u\right)$, denotes that an individual y_j^u gains knowledge about the population's individual y_{best}^u.

E. Decision making

Minimal probabilities adaptations at random on the adaptation vector are used in the enhanced differential genetic evolution technique to improve both the population's variety and the capacity for global search. The way the alteration works as follows:

$$w_j^{u+1} = \begin{cases} y_k^{(M)} + rand[0,1] \times (y_k^V - y_k^M), & if \quad rand[0,1] \le Q_s \\ y_{s1}^u + G \times (y_{s2}^u - y_{s3}^u), & otherwise \end{cases} \quad (13)$$

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Q_r Stands for the likelihood of variability at random. The fundamental difference evolution method adopts the mutation operation mode when the value of the accidental amount rand [0, 1] is greater than the random mutation probability Q_r ; if not, randomized mutations is carried out.

F. Algorithm pseudo code

In this paper, an improved mutation and crossover operation based on DE, named Polarity Metamorphosis Strategy, is proposed. Algorithm 1 shows the related pseudo-code.

Algorithm 1

```
1.  Initialization of the parameters (overall node count O, anchoring node proportion q, interaction range S)
2.  Input: criticism settings of the proposed algorithm
3.  The nodes for network installation that create a virtual network architecture
4.  Estimate the value of hop count i_{j,k} depends upon the shortest path algorithm
5.  for l=1 to O
6.          for i=1 to O
7.              for j=1 to O
8.  If shortpath(j,l)+shortpath(l,k)<shortpath(j,k)
9.  Shortpath(j,k)=shortpath(j,l)+shortpath(l,k);
10.                 End
11.             End
12.         End
13. End
14. Estimate  HopSize" (average distance per hop) ;
15. Estimate  unidentified spaces;
16. for l=1 to OQ
17. Initialize: produce OQ individuals which comprise of a dual range of attributes;
18. Estimate and assess every individual y_j ;
19. u=1;
20. while u < u_max do
21.   for j=1 o OQ
22.     Mutation vector w_j^u is produced
23.     for k=1 o E
24.         Depends upon the crossover, Experimental vector w_j^u has been obtained;
25.     end
26.     Experimental vector v_j^u has been chosen
27.     If f(v_j^u) < f(y_j^u) then
28.         y_j^{u+1} = v_j^u ;
29.     else
30.         y_j^{u+1} = y_j^u ;
31.      End
32.    End
33.      u=u+1;
34.   end
35.    The position of the unidentified link is the ideal person;
36. end
```

The technique works as follows: lines 1–13 correspond to the Polarity Metamorphosis Strategy, which initializes network settings and generates a replicated system topology while using the fastest possible process to extract the hop-count value amongst nodes. The data regarding a hop-count number amongst nodes is obtained, and Equation (10) is used to get the average distance per hop. Next, line 15 determines the approximated distances between unidentified and anchor nodes. In the third stage, which corresponds to lines 16–36, the maximum amount of repetitions is set, and the parameters of the DE algorithm are initialized in order to estimate the location of unknown nodes. Line 22's target individual selection equation is mutated, and lines 23–25 employ Equation (13) for the cross-operation to test individuals. In lines 27–31, the subsequent cohort of persons for the target and exploratory individuals are chosen using the greedy criterion; after the iteration, the ideal individual in the group is the predicted place of the unknown node.

3.2.4 Mutable Ambit Premised Localization(MAPL) Algorithm

The localization geometry and ranging errors exhibit variability across the entire network, contingent upon the set of orientation nodes utilized for localization. Contingent on the reference set used, this invariably results in different localization mistakes for a given node. We present a MAPL algorithm that seeks to determine the most effective combinations among reference nodes at a particular moment by considering the results of simulations.

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For each arrangement of three nodes of reference (trilateration) that satisfies the requirements, the suggested algorithm calculates an unknown node's location estimate and chooses n possibilities according to a criterion to be utilized during the ultimate position compute. The goal of adapting the best nodes for reference and position estimates at a given moment is to minimize localization error while maintaining the algorithm's maximum scalability and cost-effectiveness. Combinations of more than three reference nodes may be subjected to the *MAPL* method, potentially lowering adaptation mistakes. Nevertheless, in that scenario, a more significant processing cost would be associated with lateration and Geometry of Reference Triangle(GRT) value computation. A more thorough explanation of the algorithm is provided below.

A. Choosing Reference Amalgamation

Initially, based on the RSSI values, an unknown node creates a reference set of the o best reference nodes, or $T_{REF} = \{j | RSSI_j \in \max_o RSSI\}$, where j is the index of the reference node. The work attempting to prevent the reference section that are far away or have a poor link by eliminating the referencing networks with poor RSSIs. For shorter routes, distance predictions should generally be more accurate. Next, the node creates each potential arrangement of three nodes for T_{REF}, so that $D(o,3) = k$ combinations $D_1, ... D_k$. For instance, the total quantity of permutations $D(5,3) = 10$ if $o = 5$. The number of combinations rises rapidly when more than five reference nodes are used; the total quantity of l- combinations of o nodes is $\binom{o}{l} = \frac{o!}{l!(o-l)!}$. The amount of 3-node permutations would be $D(4,3) = 4$ *or* $D(3,3) = 1$, which would likely result in a performance degradation if there are fewer than five reference nodes accessible. Therefore, a minimum of five reference nodes are required for full operation. A minimum of three reference nodes are needed for trilateration.

B. Estimating Triangles Reference

Based on their geometry, the node determines whether reference triangles are suitable for localization or not. Every network calculates the GRT value for each combination of D_j as follows: $GRT = \frac{e_{\max}}{e_{\min} + e_{ne}}$, where $e_{\max}, e_{\min},$ *and* e_{ne} are the reference triangle D_j's maximum, minimum, and median edge lengths, correspondingly. The work established the criteria that follow for the ratio of the edges that needed to be met in order to eliminate any poorly constructed rectangles:

$$GRT_j < GRT_{th} \tag{14}$$

Wherein the supplied threshold value for GRT is GRT_{th}, and the *GRT* value for combination D_j is GRT_j. It is possible to tighten or relax the condition by adjusting the threshold value, GRT_{th}. This scenario eliminates reference node combinations that are almost collinear or poorly constructed, as these could negatively impact localization accuracy. The algorithm's crucial step is the removal of roughly collinear reference triangles. While faulty triangles can yield significant localization errors smoothly with comparatively minor detachment errors, decent triangles can tolerate more enormous detachment mistakes and still harvest decent localization accuracy. All feasible pairings of the n adjacent nodes, which are used for reference might not be appropriate for information localization. The initial positioning estimations will be generated for all combinations in a very unfavorable geometry scenario $GRT \geq GRT_{th}$. In normal circumstances, the unidentified node should lie among the reference nodes' convex hulls. Perhaps the node itself is within or outside the convex hull, which may only be speculated upon based on location estimates, which are likely imprecise. In addition, the appropriateness of the reference nodes cannot be described by convexity alone. According to the circumstances, a node without the convex hull could have a Healthier Localization geometry Horizontal Dilution of Precision(HDOP) than one inside. Furthermore, it may be deceptive to compute HDOP using the location estimates alone. Nonetheless, we decided to use the precise outline of the reference triangles that we are aware of in order to assess the appropriateness of the referenced nodes in the network. Additionally, GRT might be utilized to eliminate inefficient permutations before computing any regions, which saves additional energy.

C. Estimating its initial form position

The node will apply the reference node positions as well as the distance estimates in trilateration to determine its original location estimate. If the provisional declaration above is valid for the specific reference triangle D_j. The node's algorithm calculates a preliminary position calculation, $\hat{y}_j, \hat{z}_j$ for each arrangement of reference nodes D_j that satisfies the requirement.

D. Estimating the ultimate position in computation

The work initially calculates the distinction among the traveling distance assessment $\hat{e}_j$ to the referencing node j (e.g., based on RSSI) and the detachment e'_j to the references node j is estimated primarily on the precise location assessment in order to determine the error of every position estimate $\hat{y}$. A distinction Δe_j, is calculated as follows:

$$\Delta e_j = \hat{e}_j - \sqrt{(\hat{y} - y_j)^2 + (\hat{z} - z_j)^2} \qquad (15)$$

Where, the position of the reference node j is located at (y_j, z_j) and the geographical coordinates of the position approximation are $(\hat{y}, \hat{z})$.

The research utilizes the average of the absolute distance differences, $\Delta\bar{e}$ as a criterion to try and identify the best location predictions (which are less accurate). In particular, the following formula is used to calculate $\Delta\bar{e}$ for all combinations of authorized nodes of reference and unknown nodes:

$$\Delta\bar{e} = \frac{1}{o}\sum_{j=1}^{o}\left|\hat{e}_j - \sqrt{(\hat{y} - y_j)^2 + (\hat{z} - z_j)^2}\right| \qquad (16)$$

Where the total number of referencing connections is o = 3, the assumption that a smaller value $\Delta\bar{e}$ often translates into a less extensive localization mistake is the basis for the requirement. This is quite similar to the concept of minimal squares prediction in the practice of localization, which minimizes the sum of the quadratic residuals or the disparities amongst the distance and location estimations.

Thus, on average localization error or Mean Absolute Error (MAE) rises with average $\Delta\bar{e}$. When poor geometries and increased range error combine to create the average $\Delta\bar{e}$ increases, the localization error MAE increases. As a result, it is justified as a valid estimation for localization errors. Following that, by aggregating the n preliminary placement assessments among the pairings that have the least, the final position estimation, $(\hat{y}, \hat{z})$ is calculated. $\Delta\bar{e}$ is described in this manner:

$$(\hat{y}, \hat{z}) = \left(\frac{1}{n}\sum_{j}\hat{y}_j, \frac{1}{n}\sum_{j}\hat{z}_j\right)\Bigg|_{j \in \min_o \Delta\bar{e}} \qquad (17)$$

Wherein $(\hat{y}_j, \hat{z}_j)$ the matching location is estimated and j is the precedent reference collection directory. The work employ aggregating instead of simply determining the position approximation with the least $\Delta\bar{e}$ in order to increase resilience.

3.3 Significance of Proposed *EBOT* Approach in the Context of State of Art in Literature

This research is notable for resolving the shortcomings of earlier threads of work in literature. The current paper involves a new-fangled approach called Extemporaneity Bat Optimization Technique (EBOT) based on Deuce Adaptation, through two significant alterations. It includes a unique approach that improves the bat optimization method's exploratory strategy while conjointly exploiting its characteristics. Moreover, EBOT adaptation 1 improves global search capabilities leading to better exploration, while EBOT adaptation 2 makes use of an enhanced local search method to promote exploitation. The proposed strategy too presents the Polarity Metamorphosis Strategy (PMS) that improves crossover and mutation operations while boosting the population heterogeneity and exploration capacities. Additionally, the strategy recognizes the importance of range errors and localization geometry in the context of positioning procedure. Again, the Mutable Ambit Premised Localization (MAPL) Algorithm is presented to élite primary nodes during triangulation based on an unpretentious assessment to enrich localization geometry. The accuracy of localization provided by the traditional Bat Optimization Technique (BOT) and related algorithms, such as FMSL, is limited in dynamic and resource-constrained WSN situations because they frequently converge at local optima. Furthermore, in order to reach acceptable accuracy, earlier algorithms needed longer computation times and a larger node density. On the other hand, even with fewer anchor nodes, the suggested EBOT modifications effectively lower localization errors and calculation times. This is a major advancement toward increasing the effectiveness, scalability, and applicability of WSN localization for real-time deployments. EBOT adaptations 1 and 2 provide improved node localization even in the presence of changing network and environmental variables by superseding the global and local search algorithms. This has significant ramifications for real-world WSN systems, where real-time processing, precision, and energy efficiency are essential components.

4. RESULT AND DISCUSSION

The suggested work has been evaluated through MATLAB-implemented simulation on a desktop PC equipped with a 8 GB RAM, single Intel(R) Core

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(TM) and Windows 7 operating system. The two-dimensional coordinate plane is mainly taken into account in this inquiry. The experimental area measures 100 × 100 m^2 and all data are averaged after being run 100 times separately.

4.1 Evaluation metrics

We have assessed the performance of our proposed approach while comparing it with two existing approaches on the basis of the following performance metrices.

i. **LE:** As discussed earlier, by measuring the discrepancy amongst the intended nodes' predicted the errors associated with target nodes' are added and their average gets calculated. The precision of the optimization techniques employed for localization is indicated by the average localization error. LE indicates the precision of the localization technique and is commonly expressed as the euclidean distance between these two places. A more accurate estimation of the node's position is indicated by a smaller localization error. For the applications that depend on precise location data, minimizing localization error is essential.

ii. **CT:** The total amount of time the optimization method needs to complete all calculations involved in the localization of every target node in a WSN is known as the time required for computation T(s). The tic toc function is used to calculate the calculation time T(s). CT comprises of the amount of time needed for position computation, distance estimate, and signal processing. In real-time applications in particular, faster calculation times are preferred since they guarantee prompt updates of node positions without undue delay.

iii. **RMSE:** RMSE offers a thorough perspective that takes into account both minor and major inaccuracies. Better localization algorithm performance is shown by a lower RMSE.

$$RMSE = \sqrt{\frac{1}{O_M}\sum_{j=1}^{O}\sqrt{\left(Y_j - y_j\right)^2 + \left(Z_j - z_j\right)^2}} \tag{18}$$

4.2 Performance Assessment

The performance analysis of the proposed work has been demonstrated from Figure 2 to Figure 5. Hence the performance evaluation is based on MSE, RMSE, computational time, and localization error. Figure 2 emphasizes the proposed work performances in terms of MSE which shows the way of increase of total amount of anchors and improvement of localization precision. There is an ideal number of anchoring for combining accuracy and utilization of resources, even if adding more count leads to higher accuracy up to a point where the improvement rate starts to decline.

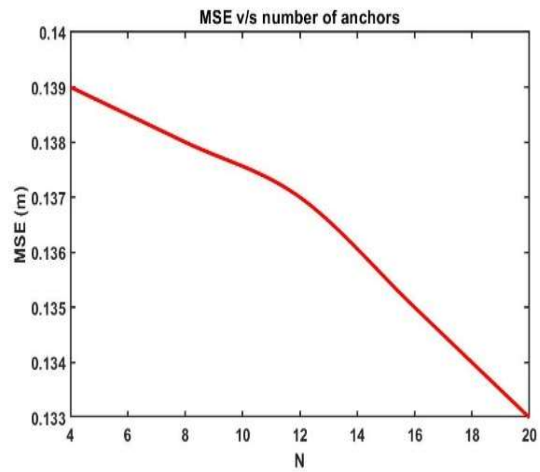

Figure 2: Proposed analysis based on MSE

The significance of anchor quantity in mitigating localization error is shown in Figure 3. Improved accuracy in localization is achieved by adding more anchors, but the rate of improvement diminishes with additional anchors, suggesting a possible sweet spot for distributing resources concerning precision.

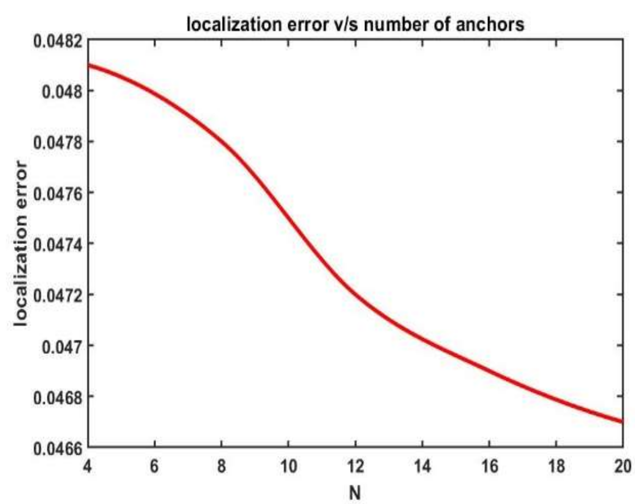

Figure 3: Proposed analysis based on localization error

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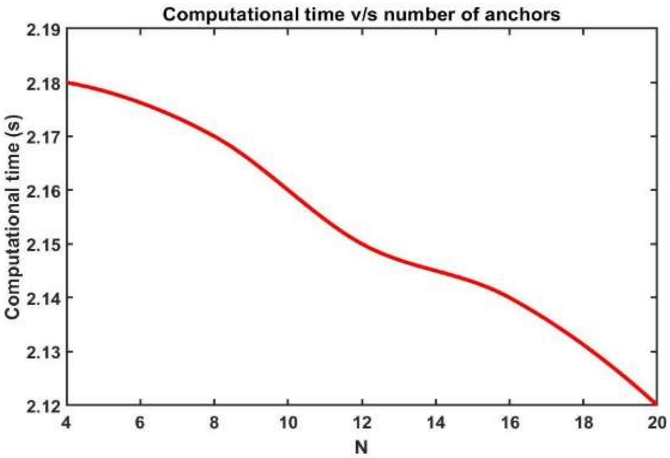

Figure 4:computation time of the proposed work

Figure 4 shows how a greater number of anchors might reduce the time for computation, which could improve the efficiency of the localization or positioned method. Analogously to the earlier graphs, the decrease in calculation time exhibits decreasing outcomes, indicating the ideal number of anchors to strike a balance between computational effectiveness and precision.

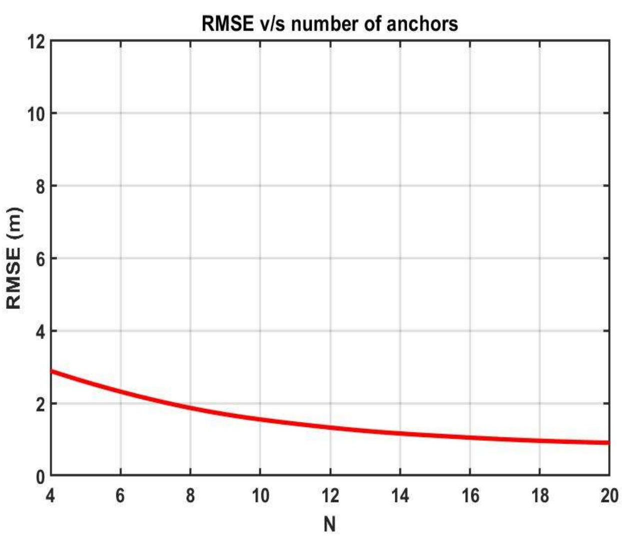

Figure 5: RMSE of the proposed work

In Figure 5 RMSE of the proposed work has been illustrated. It describes how the number of anchor nodes increases with decreasing the RMSE value. Hence it shows the proficiency of the proposed work in a proficient manner.

Table 1 Localization error

Anchor node	EBOT	FP_MPP_APIT	APIT
4	2.88331	3.132997	9.53871
8	1.862817	2.607026	6.632681
12	1.322399	2.183025	5.040205
16	1.046243	1.836802	3.543095
20	0.904523	1.623802	3.358337

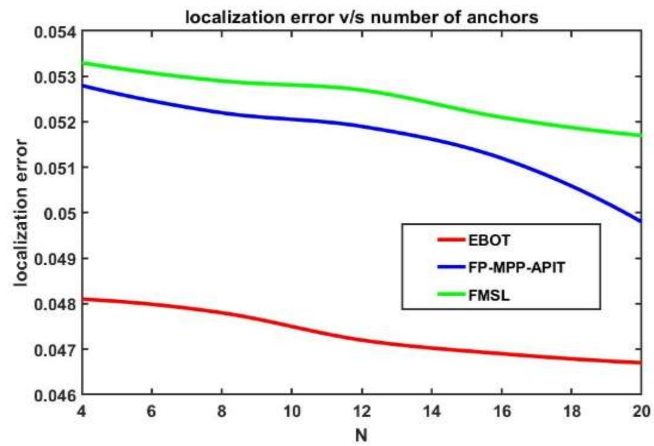

Figure 6: localization error v/s number of anchors

The curves in Figure 6 and Table 1 show that the average localization error of the aforementioned strategies gradually decrease with an increase in anchor nodes. This is a pretty logical statement since the more major nodes that anchor, the more information they supply, which improves the localization accuracy of the unknown nodes. In particular, the localization error of the FMSL technique is smaller than that of the FP-MPP-APIT strategy when the same number of anchor nodes are utilized. This situation is mostly caused by the recommended method's usage of the philosophical Fermat point and mid-perpendicular planar modelling to decrease the expected range of unknown node placements.

Table 2 RMSE comparative analysis

Anchor node	EBOT	FP_MPP_APIT	APIT
4	0.0481	0.0528	0.0533
8	0.0478	0.0522	0.0529
12	0.0472	0.0519	0.0527
16	0.0469	0.0512	0.0521
20	0.0467	0.0498	0.0517

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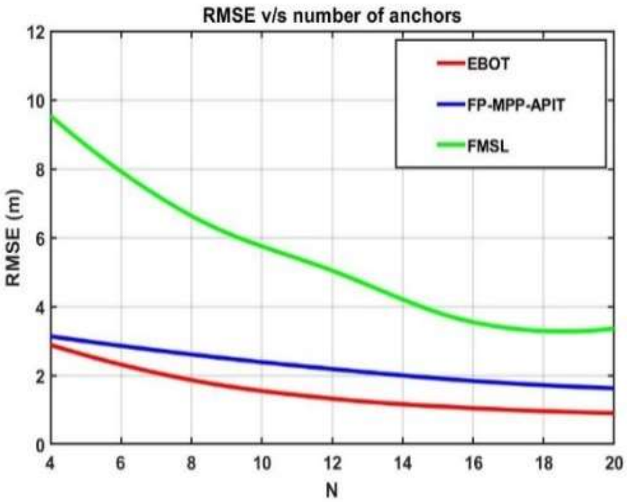

Figure 7: RMSE v/s number of anchors

When comparing EBOT to FP-MPP-APIT and FMSL, Figure 7 and Table 2 show that EBOT performs better in localization accuracy. Between 4 and 20 anchors (N), EBOT maintains the lowest RMSE. This suggests that, compared to the other approaches, EBOT yields more precise localization results. As the number of anchors increases, the RMSE for EBOT drops, suggesting that EBOT efficiently uses more anchoring to enhance localization accuracy. EBOT performs better than the other approaches even when there are fewer anchors (N=4), and the performance gets better still when there are more anchors. Compared to other techniques like FP-MPP-APIT and FMSL, EBOT offers notable advantages in terms of accuracy and reliability, demonstrating its effectiveness as a localization approach. Because of its dependable operation, it is the best option for applications that need exact placement.

Table 3 MSE V/s Number of nodes

Anchor node	EBOT	FP_MPP_APIT	APIT
4	0.139	0.151	0.159
8	0.138	0.15	0.157
12	0.137	0.148	0.156
16	0.135	0.145	0.155
20	0.133	0.141	0.153

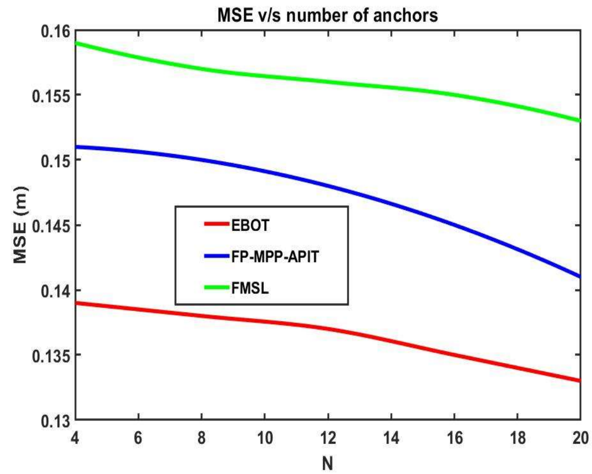

Figure 8: MSE V/s Number of nodes

The MSE for the EBOT technique grows with the number of anchors (N) between 4 and 20, from roughly 0.14 meters to about 0.135 meters, which is illustrated in Figure 8 and Table 3. As the number of anchors rises, the MSE progressively falls. This suggests that adding additional anchors increases the accuracy of the EBOT approach. Among all evaluated values of N, EBOT has the lowest MSE of the three methods (FP-MPP-APIT, FMSL, and EBOT), indicating that it offers the best consistent localization. The most dependable technique for lowering error in this situation is the EBOT approach, which benefits from an increase in anchor count in terms of diminishing the MSE.

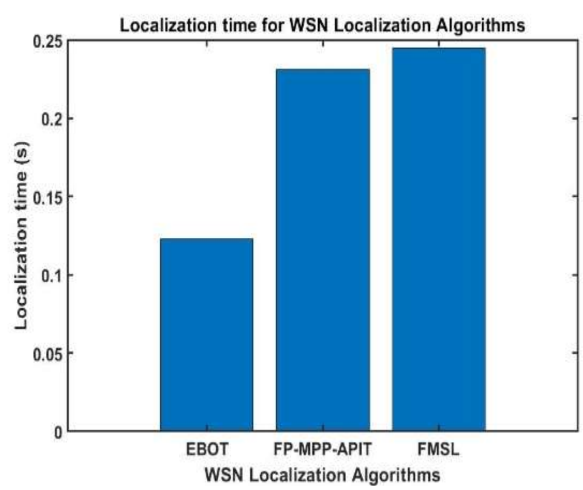

Figure 9: localization time

The localization times (in seconds) with three distinct Wireless Sensor Network (WSN) localization techniques are contrasted in Figure 9. At about 0.1 seconds, the EBOT method has the fastest localization requirement. Compared to EBOT, the FP-MPP-APIT algorithm takes around 0.21 seconds longer to localize. Out of the three, the FMSL method takes the longest to localize, roughly 0.22 seconds, slightly longer than FP-MPP-APIT. In summary, the EBOT method demonstrates its efficacy and efficiency in WSN localization tasks by achieving the shortest localization time and providing the lowest MSE, as previously described.

Table 4 Computational time

Anchor node	EBOT	FP_MPP_APIT	APIT
4	2.18	2.27	2.31
8	2.17	2.24	2.29
12	2.15	2.23	2.27
16	2.14	2.19	2.25
20	2.12	2.17	2.24

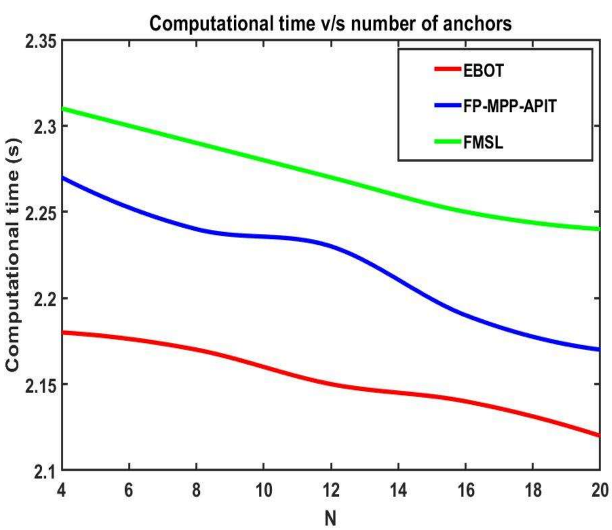

Figure 10: Comparative analysis Computation time

The connection among the computing time (in seconds) and the number of anchors (N) is depicted in Figure 10 and Table 4. Because of the three approaches, EBOT consistently has the lowest computational time. As the number of anchors increases, the computing time drops off a little bit, from roughly 2.17 seconds at N=4 to roughly 2.13 seconds at N=20. FP-MPP-APIT computes more slowly than EBOT. With more anchors, the computational time likewise gets shorter. At N=4, it is roughly 2.27 a few moments, and at N=20, it is about 2.18 seconds.

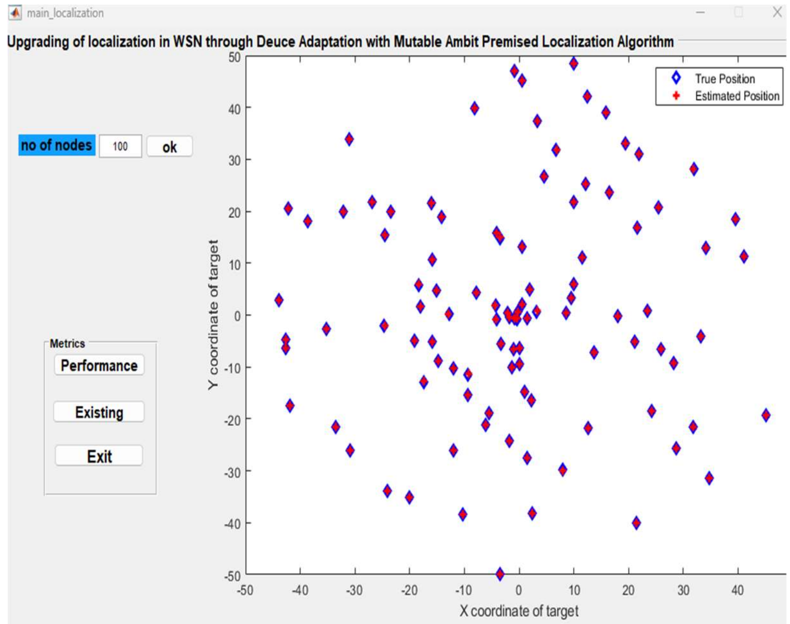

Figure 11: Localization of the nodes

The Figure 11 shows the outcomes of a localization method employing the Deuce Adaptation with a Mutable Ambit Premised Localization method in a WSN. The nodes' real locations within the WSN are represented by their "True Position". The approximate positions for the localization algorithm estimated are defined by Estimated Position. A scattering diagram showing the locations of the networks throughout a 100x100 region is included in the visualization. The input value "no of nodes = 100" indicates 100 nodes. There is an estimated position (Red Cross) for every genuine position (blue diamond). The fact that the blue diamonds, or genuine orientations, and the red traverses, or approximated orientations, are nearly identical and it suggests that the localization method does an excellent work of determining the nodes' accurate positions. The prediction's inaccuracy is shown by the tiny variations between the red crosses and blue diamonds. The illustration shows that a slight variation from the actual coordinates of nodes in a WSN may be achieved when accurately predicting their positions using the Deuce Adaptation with Mutable Ambit Premised Localization Procedure.

4.3 Proposed EBOT versus Prior Research work

It is evident from the analysis of the data that the EBOT greatly enhances the major WSN localization assessment metrics as follows:

- **Localization Error**: In every anchor node scenario, EBOT adaptations achieve fewer localization errors and consistently beat FP-MPP-APIT and APIT. As the number of anchors rises, the localization error decreases, indicating that EBOT efficiently makes use of additional anchor nodes to improve accuracy (Fig. 6, Table 1)
- **RMSE and MSE**: The suggested approach exhibits a sharp decline in RMSE and MSE with the addition of more anchor nodes, indicating that EBOT effectively reduces mistakes in comparison to rival techniques (Figs. 7, 8, Tables 2, 3). This indicates the resilience of the suggested local and global search methods.
- **Computation Time**: For real-time WSN applications, the EBOT adaptations require much less computational time (Fig. 10, Table 4) in comparison to FMSL and FP-MPP-APIT. Hence, EBOT is demonstrated to have the shortest computation time, making it the more effective option for large-scale networks.

All of these enhancements show that the suggested EBOT modifications are better than the earlier algorithms. They are more appropriate for real-time, scalable WSN deployments since they not only improve localization accuracy but also use less resources. This work suggests fresh directions for future research on the application of WSN localization algorithms in more complicated contexts, such as three-dimensional areas. Further, researchers should examine the application of EBOT adaptations in more complicated situations, especially three-dimensional localization, and explore its potential for mobile WSNs, building on the achievements of the current study. This expansion would provide additional proof of the suggested algorithm's stability and scalability in a variety of changing network scenarios.

4.4 Research Contribution with respect to Current Study

The suggested study significantly advances the field of WSN localization by introducing two adaptations of the Extemporaneity Bat Optimization Technique (EBOT). In resource-constrained WSN situations, EBOT adaptations 1 and 2 outperform conventional techniques like FP-MPP-APIT, APIT in terms of localization accuracy, computing time, and efficiency. Although previous methods resulted in poor node localization, they were constrained by convergence to local optima and frequently suffered from excessive calculation durations, even though they improved WSN localization. Through improved global and local search algorithms, the EBOT adaptations 1 and 2 provide a more efficient solution by improving the search and exploitation capabilities. Even with fewer anchor nodes, these advancements enable faster convergence and improved accuracy. As the results justify that both EBOT modifications outperform state-of-the-art techniques in terms of Mean-Square Error (MSE) and Root-Mean-Square Error (RMSE) with faster convergence times, hence, less computation time, and more accurate localization can be achieved in case of the proposed approach.

5. CONCLUSION AND FUTURE DIRECTION

For several purposes, WSNs require precise geographical information from which the data was obtained. Consequently, every sensor node location determines WSN effectiveness. Compared to current methods, the initially developed BOT had a lower mean error in localization and a faster time for computation. Nevertheless, the localization effectiveness is limited to the local ideal value and is not 100%. This research proposes two EBOT adjustments to overcome these issues with previous efforts. To enhance the search and exploitation capabilities of the proposed EBOT adaptations 1 and 2, we have implemented global and local search algorithms to identify optimal solutions more effectively. The effectiveness of these EBOT adaptations is compared to other optimization techniques. The performance of the proposed EBOT is evaluated alongside other methods such as the FP-MPP-APIT method and APIT under various conditions involving anchor and target nodes. The results justified that, compared to existing algorithms, the proposed EBOT achieve lower mean localization errors while localizing more target nodes and have faster convergence speeds. These benefits and the overall effectiveness of the adaptations are supported by assessments and analysis, which demonstrate an improvement in the average distance per hop of anchor nodes. Future research should explore the application of this technique for node localization in more complex three-dimensional spaces. These objectives have been successfully attained, as evidenced through several assessment metrics such as mean square error (MSE), root-mean-square error (RMSE), localization error, and computation time. The experimental findings show that the suggested EBOT perform better than the state-of-the-art techniques like FP-MPP-APIT and APIT. The best overall performance is achieved by EBOT, which achieves lowest localization errors at 0.04, minimal RMSE at 0.90, lowest computational time at 2.12, lowest MSE at 0.133 which asserts the effectiveness of the proposed EBOT approach.

Although the suggested techniques exhibit significant advancements, there are still potential risks to their validity. Furthermore, the trials were carried out in controlled settings, which can be different from real-world settings with more dynamic elements. Subsequent investigations ought to concentrate on expanding this research to more intricate situations and verifying its efficacy in varied settings.

Despite the encouraging results, there are a few possible risks to the validity that need to be taken into account as follows:

i. Hardware and Software Constraints: A desktop computer with an Intel Core CPU and 8 GB of RAM was used to run the simulation. When tested on other hardware or in more resource-intensive environments, the results may differ. Utilizing MATLAB within a certain operating system (Windows 7) could potentially impact the consistency of the outcomes across various software configurations.

ii. Two-Dimensional Test Environment: The study's two-dimensional focus makes real-world circumstances easier to understand because WSNs are frequently employed in three-dimensional contexts.

iii. Fixed Experimental Area: The test took place in an area measuring 100 by 100 square meters. The accuracy of localization and computing efficiency of the EBOT modifications may be impacted by fluctuations in bigger or more irregularly shaped deployment areas.

iv. Anchor Node Assumptions: To increase the accuracy of localization, the analysis makes the assumption that there are more anchor nodes. Nevertheless, in practical implementations, the quantity and dispersion of anchor nodes are frequently restricted or irregular, potentially diminishing the efficacy of the suggested methodology.

v. Limited Algorithm Comparisons: While FP-MPP-APIT and FMSL were compared with the EBOT adaptations, further comparisons with other cutting-edge localization methods may offer a more thorough assessment of the suggested algorithms' efficacy.

The suggested EBOT adaptations might be strengthened and made more appropriate for a larger variety of practical uses by resolving these issues and following these new lines of inquiry. Subsequent investigations ought to concentrate on resolving these constraints and broadening the scope of the suggested methodology by incorporating three-dimensional space implementation while handling dynamic environments with enhanced global optimization for large scale networks.

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AUTHOR CONTRIBUTION

These contributions show how earlier studies on computing efficiency, error reduction, and localization strategies impacted and informed the assessment of EBOT adaptations in the current study.

- **Sucheta Panda** used MATLAB to do a comprehensive simulation analysis and created the fundamental evaluation measures, like RMSE and MSE, for evaluating the performance of the suggested EBOT method. Her research highlighted the significance of anchor quantity in localization and identified a key threshold at which adding more anchors optimizes accuracy without needlessly increasing processing power. Her contributions were critical in attaining mean localization errors that were lower and convergence speeds that were faster than those of previous methods, demonstrating the usefulness of their research in practical wireless sensor network applications.
- **Sushree Bibhuprada B. Priyadarshini** developed the computational time metrics for the EBOT and other comparing approaches, which made a substantial contribution to the performance evaluation. The findings of their investigation highlight the significance of striking a balance between accuracy and resource consumption, since the suggested EBOT changes not only decrease localization mistakes but also enhance computing efficiency.

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- **Prabhat Sahu** helped in the literature survey part while framing some of the theoretical foundations of the localization procedure.

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Table 5 Comparison Of Existing Approach With Proposed Approach

Features	**Earlier Techniques (Original Bat Optimization and Additional Algorithms)**	**Suggested Method (EBOT Modifications 1 and 2)**
Mean localization error	Less than the majority of current algorithms, although still constrained by local optima	Much reduced localization mistakes with comparison to current techniques.
Computation Time	Quicker than a lot of conventional methods.	Quicker computation time.
Effectiveness of localization	Confined to the optimum value in the area; not entirely successful	More target nodes can be found more successfully, and global optimization is improved.
Investigative Proficiencies	Typical skills for searching and exploiting	Improved local and global search algorithms to identify solutions more successfully
Speed of Convergence	Not designed for quick convergence, but moderate	Faster convergence after fewer repetitions, both adaptations exhibit quick convergence.
Comparing with Alternative Methods	When compared to EBOT, FP-MPP-APIT and APIT typically perform worse.	The localization accuracy and speed of EBOT Adaptations 1 & 2 surpass these techniques.
Optimization of Anchor Node	A slight improvement in the placement of the anchor nodes	An increase in anchor nodes' average distance travelled per hop improves localization accuracy.
Utilizations in Complicated Situations	Most useful in 2D environments, less useful in 3D ones	The goal of future work is to apply this to more intricate three-dimensional settings.