ORIGINAL RESEARCH PAPER
Pages: 359-398

A Survey of DV-Hop Localization Methods in Wireless Sensor Networks

Ghasem Farjamnia[1], Yusif Gasimov[2,3,4], Cavanshir Kazimov[5], Mehrdad hashemi[6]
[1,5,6] *Department of Applied Mathematics and Cybernetics, Baku State University, Baku, Azerbaijan*
[2]*Azerbaijan University, Baku, Azerbaijan*
[3]*Institute of Physics Problems, Baku State University, Baku, Azerbaijan*
[4]*Institute of Mathematics and Mechanics, ANAS, Baku, Azerbaijan*
Corresponding author: *ghasem.farjamnia@gmail.com*

DOI: 10.22070/jce.2021.14405.1186

Abstract- Wireless Sensor Networks (WSNs) are used to observe and monitor events in different environments. The successful operation of WSNs depends on locating the sensor nodes. The location of the nodes must be available to detect the occurrence of events and receive packets sent by nodes. Therefore, a key step in the design phase of WSNs is to determine localization algorithms. One of the known algorithms for locating unknown nodes is the DV-Hop algorithm. DV-Hop localization algorithm is a classic range free localization algorithm in WSNs. This algorithm operates based on distance and number of steps and uses beacon nodes to detect the location of unknown nodes. But positioning error is one of the main problems in DV-Hop. Researchers have used a variety of methods to correct positioning errors. In this paper, we divide the methods used to improve DV-Hop into four categories (meta-heuristic algorithms, RSSI, Distance Vector, and Weighted Centroid Localization (WCL)). Each method, based on its own performance has capabilities and features that help reduce DV-Hop error. This paper covers all DV-Hop literature in Elsevier, Springer, IEEE and other journals. Based on the performed studies on different methods in order to improve DV-Hop, we conclude that the distance vector method is more efficient. The improvement in DV-Hop using the Distance Vector compared to other methods is equal to 38%. The Distance Vector method includes more accurate localization information by varying the distance and number of steps.

***Index Terms*:** Wireless Sensor Networks, DV-Hop, Localization, Distance Vector

I. INTRODUCTION

With the advancement of MEMS (Micro Electromechanical System) electronic components, WSNs have indicated great increase more recently [1, 2]. They are commonly interconnected of large-area, resource-constrained sensor nodes that have the capability of propagation with each other and collaboratively collect simple sensing information from the physical globe. A sensor network is an

Manuscript received 23-Aug.-2020 and revised 2-Nov.-2020, *P- ISSN: 2322-4088*
Accepted on 11-December-2020 *E- ISSN: 2322-3936*

integration of sensing, processing, communication ability to watch and respond to occasions in an indicated environment. WSN is ordinarily made of tens to thousands of nodes that gather process and transfer information to a central location in cooperation [3]. WSNs technology includes cost reduction, reliability, scalability, flexibility, accuracy and ease of deployment that perform various operations in harsh environments [4]. The fast development of technology makes the sensors smaller and not expensive while billions of them are being deployed in various applications. Some of the potential applications domains are military, environment, healthcare and security [5, 6]. The layout of such a network is affected by many elements like fault production fees, Topology, hardware limitations, transmitting media and power consumption operating environment, network sensor. These elements are utilized as a guideline to design protocols and models for manufacturing effective sensor network [7, 8].

In the WSNs the location data of the nodes is very critical to the inspection mission [9, 10]. A WSN is integrated of a big number of very basic nodes deployed in sensor field in a dense manner. Consciousness of location is influential for WSN because in lots of applications (like Vehicle monitoring, visualization and environmental surveillance), location of sensor nodes is critical, and users should pay attention to the place in which events happen. Self-location can be defined that in accordance with some beacon nodes, sensor nodes estimate position information for oneself in accordance with a position model.

The positioning model can be sub-categorized into two categories based on the various information needed in the node location process: Range-based and Range-free [11, 12]. For the reason of power wastage and cost, individuals pay much more consideration to range-free models, like Centroid [13] DV-Hop (Distance Vector-hop) [14], CPE (Convex Position Estimation) [15], APIT (Approximate Point in Triangle) [16], and MDS-MAP [17, 18]. Nowadays, DV-Hop is one of the commonly-used and the most prevalent models. DV-Hop distributed localization model is a standard range free localization model in WSNs. Even though in comparison with easy to be used in terms of cost and resource restricted WSNs, DV-Hop is prone to low local function error as the other range free localization models. In DV-Hop the number of hops from an anonymous node and a beacon node is the approximate period and the average size of a single hop. The interval error calculated is primarily influenced by the distance of the WSN node and the network arrangement, thus the position error is not small, but high when the distance of the node is small in the network [19]. The main concept of DV-hop is: the anonymous node itself only transfers information with its near or neighbor nodes, the interval amid the anonymous node and the beacon node is shown by average hop interval and the shortest path amid two nodes, and at the next phase, it employs trilateral measurement to obtain the node location information. To gain higher positioning accuracy, each beacon node would most of time revise the hop interval and acquire the optimum average hop interval.

One of the positioning algorithms in WSNs is the DV-Hop that works based on the number of steps and distance. This algorithm has proven that it has problems in accurately determining the position of nodes in locating nodes. Therefore, in order to solve DV-Hop problems, various methods have been used to improve DV-Hop. In this paper, meta-heuristic algorithms, RSSI, Distance Vector, and Weighted Centroid Localization (WCL) methods to enhance and improve DV-Hop are reviewed. The main contributions of this paper are as follows:

Analysis of DV-Hop algorithm based on flowchart and its steps,

Reviews of different methods to improve DV-Hop in terms of benefits and goals,

Emphasis on future research on the DV-Hop algorithm,

This paper is organized as follow: In Section 2, we briefly introduce localization schemes. Section 3, we describe DV-Hop Protocol. In Section 4, we analyze and review the Improved DV-Hop methods. Section 5, covers analysis and discussion. In Section 6, we discuss and summarize the future research direction for the localization models.

II. LOCALIZATION SCHEMES

Localization Model is subcategorized into four parts is following:

GPS Based/GPS Free: GPS-based schemes have loads of costs and are potentially very pricey as GPS receivers have to be installed on any node. Localization accuracy is also so strong. Localization has now become a significant element of WSN. GPS is one of the renowned public location services. However, not low priced and enormous energy usage characteristics do not make it useful if every sensor node is outfitted with GPS receiver. In other terms, it is expected that in many approaches of localization only a small part of the sensor nodes is informed of their location details through GPS or manual configuration. GPS-free models never use GPS and determine the length around local network-dependent nodes and are not far more expensive relative to GPS-based models [20]. Some nodes have to be located thru GPS called beacon nodes or beacon nodes that speed up the process of localization [21]. All sensor nodes are incorporated with GPS in the GPS base system, this model ensures the true position among all nodes. But it's arduous to connect all the sensor nodes with GPS, the reason is that GPS communicates in line of sight and due to the impediments in the route if it requires plant density, the GPS won't work and the other excuse is that GPS increases network costs. To address this circumstance, another GPS-free scheme introduced that, rather than linking all the nodes to the GPS, only a few sensors are being incorporated into GPS that are often deemed to be the beacon node in free GPS, anonymous nodes that need to figure out where they are will use the beacon nodes to reach the position in the network [22].

Beacon Based/Beacon Free: In the beacon-based scheme, some of the nodes are so far aware of their position, as these nodes are superseded manually or are coupled with GPS [23]. Beacon nodes start a process of localization while the position of yet another unidentified node is determined. Accuracy in the beacon-based scheme is in respect to beacons' gigantic size or height. In certain terms, beacon free scheme employs neighboring interval knowledge to ascertain the location of anonymous nodes when no actual beacon node exists [23].

Centralized/Distributed: In centralized systems, all knowledge is linked to one key point or node, often referred to as "sink node or base station." Sink node determines node location and transmits data to trusted nodes. There is no increase in the cost of computing the clustered model and it does not take much energy compared to computing at the individual node. For distributed systems, sensors assess and approximate their individual places one by one, and communicate directly with beacon nodes. Distributed schemes have no clustering, and each node forecasts its own location [23]. In centralized scheme all nodes belong to the sink node, there is no need for other nodes to conduct any assessments as all communications are done across sink node allowing all calculations to the nodes. The advantage is that the more accuracy it provides [24]. All the nodes do the calculations in the distributed scheme and almost all of the nodes execute localization models and increases error [24].

Range Based/Range Free: Various kinds of methods are required to decide the interval or angle in the node center to identify the node location. Such estimates should be accurate as this knowledge is used to approximate the nodes’ position and the location model [25]. The range-based schemes allow estimating the true interval among both nodes whilst the range-free schemes entail only the information on connectivity around nodes [26]. The ranging options require information about interval (or angle) amid adjunct nodes to analyze the position. Vital techniques used throughout range-based localization are: I RSSI (Indication of received signal strength) [27](II) TOA (Time of Arrival) [28] (III) TDOA (Time Difference-of Arrival) [29] (IV) AOA (Angle of Arrival) [30].

Range-based approaches are much more accurate than range-free schemes, but require additional hardware. So, the overall cost in large-scale deployment becomes high. For range-free systems, certain small node numbers are set with GPS regarded as "anchors" or "beacons." Beacons relay their locality information to the network, and anonymous nodes approximate their locations as per beacon hop values [31, 32]. Localization based on range involves ultrasonic or infrared to approximate the physical separation amid each of the two sensor nodes so as to plan more reliable localization than free range localization. Whilst also trying to compare, range free localization models occasionally take geometric interval to replace the sensor nodes, for instance hop count interval. Range-based protocols include estimating position to one by one interval or angle, and Range-free protocols evaluate location by computing hop count and hop size.

Table I offers a description of various factors for the localization schemes. These factors have been selected as the main criteria in most papers and have been used to evaluate the localization algorithm [11].

Table I. Comparison of Localization Schemes by Different Factors

Factors	GPS Based	GPS Free	Beacon Based	Beacon Free	Centralized	Distributed	Range Free	Range Based
accuracy	High	Medium	Medium	Medium	Low	Medium	Medium	High
cost	High	Low	Low	Low	Low	Low	Low	High
energy consumption	High	Low	Medium	Medium	Medium	Low	High	Low
Computational cost	Medium	Low	Low	Medium	Low	Medium	Low	Low
Scalability	Medium	Medium	Low	Medium	Low	Low	High	Low
simplicity	Medium	High	Medium	High	High	Medium	High	Medium
communication power	High	Medium	Low	Medium	Low	Medium	Low	High
Data transmission power	High	Medium	Low	Low	Medium	High	Low	High
Sustainability	High	Medium	High	Medium	High	Medium	Medium	High
Reliability	Medium	High	Medium	High	Medium	High	Medium	High
flexibility	Medium	Medium	Low	Medium	Low	Medium	High	Low
Reinforceable	High	Medium	High	Medium	High	Medium	Medium	High
cooperation	High	Low	Medium	Medium	Medium	Low	High	Low
Connection maintenance	High	Medium	High	Medium	High	High	High	Medium

It is not suitable to localization of sensor nodes using GPS, since it uses lots of is energy and much more fee; it requires big size of hardware and has a line of sight problem. If GPS is deployed on every node, then it performs the node size and deployment fee [33]. In addition, GPS consumes high energy as it is not energy efficient and not appropriate for a network like WSN. In Centroid model, nodes can utilize the centroid of composition comes to scene from their proximate reference for positioning. The strategy related to the network connectivity; holistically, hence the strategy can only gain low-accuracy positioning. In addition, we need higher density of beacon nodes in this model [34].

The location is evaluated for the geometric position or placement of dependencies among the localized node and unbounded node. The position of the interval and angle between nodes is determined. There are lots of concepts utilized in localization like the following [35, 36]:

Lateration; happens at the time that interval amid nodes is calculated to foreshow location.

Angulation; happens at the time that angle amid nodes is calculated to foreshow location.

Trilateration; Location of node is calculated via interval measurement from three nodes. In this concept, what is calculated is the intersection of three circles that gives a single point that is a position of unbounded node.

Multilateration; In this definition the position calculation requires more than three nodes. The angle information is added to deduce location of the node in the angulation process. Two beacon nodes are formed by the triangle sides and a dumb node kind the vertices of a triangle, and the lines that join them. Once the positions of beacon nodes are recognized, it is also known the other part which is their interval, or one side of the triangle. The position of the dumb node can be determined as the third point of the triangle in the event that the two angles that the dumb node forms with the two beacon nodes are measured. This method is called triangulation for evaluating the position of a node.

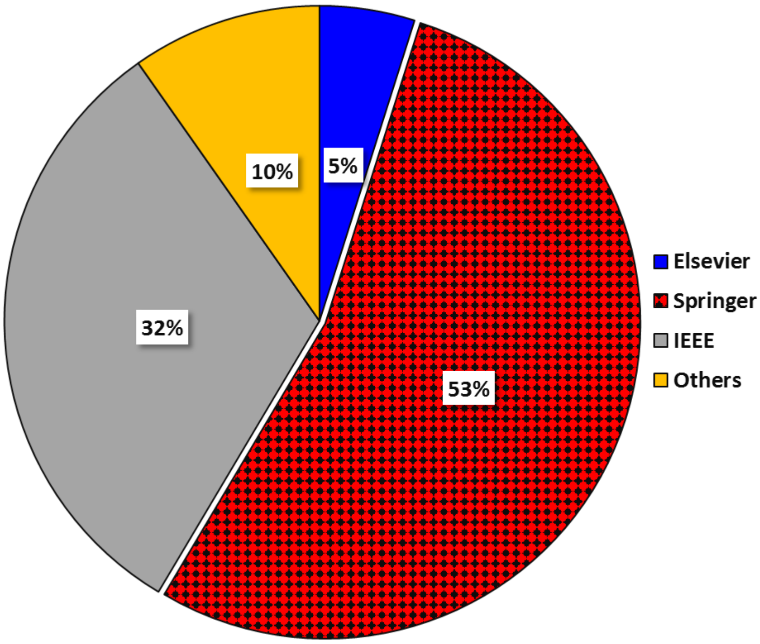

Fig. 1. Percentage of papers published by DV-Hop in various publications

III. DV-HOP PROTOCOL

DV-HOP is one of the conventional strong models, range-free models of localization. All advantages of range-free are provided by DV-Hop, but great problem-low positioning accuracy [37, 38]. Distance vector-hop model was at the first glance offered by $D.Niculescu$ and $B.Nath$ [37].

Various studies have been conducted since 2007 on DV-Hop to improve positioning. In Fig. (1) is shown the percentage of papers published by DV-Hop in various publications. According to Fig. (1), it is clear that the highest percentage of papers were published by Springer.

DV-Hop comprises three leaps as follows:

First Step: every beacon node transmits a message with location information and the initialized hop count value of 0 (x_i, y_i,0). When all neighboring nodes receive the message with hop count value from the nearby beacon nodes, a novel message with hop count value plus 1 (x_i, y_i,1) information is saved and broadcast to their neighbors. This cycle continues until messages are sent to all network nodes of the neighboring beacon nodes. Receiving node would still save the smallest hop count among many hop counts obtained from beacon nodes and ignore the message of a larger hop count from the same beacon node as well. In Fig. (2) is shown DV-Hop algorithm flowchart.

Second Step: This step determines a parameter called Hop-Size in this process beacon$i$, which is the mean of one hop's reach. This module is generally utilized to switch hop counts to physical interval, and is predicted by Eq. (1) [37]:

$$HopSize_i = \sum_{i\neq j}^{n} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \, / \sum_{i\neq j}^{n} h_{ij} \qquad (1)$$

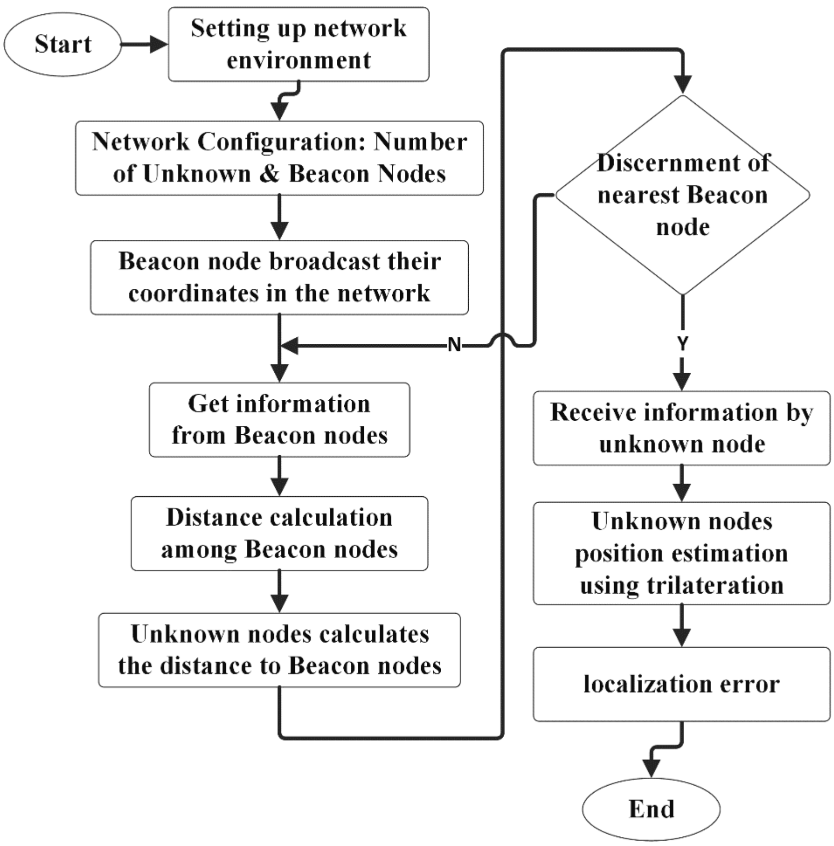

Fig. 2. DV-Hop algorithm flowchart [37]

In Eq. (1) (xi, yi) and (xj, yj) defines the positions of beacons i and j reciprocally, n is the quantity of beacons and hij is the minimum distance between beacon i and beacon j measured by hops. Then, each beacon announces the estimated $HopSize$ value. The anonymous nodes store only the $HopSize$ of the proximities beacon and broadcast it again.

Third step: In this phase, each anonymous sensor valuations its intervals to all beacons by multiplying its hop count to the beacon and the stored $HopSize$ as:

$$d_{ij} = HopSize_i \times h_{ij} \tag{2}$$

In Eq. (2) hij is the minimum hop count amid beacon i and anonymous node j. In this step, as for each anonymous node, its position is estimated utilizing *Trilateration* method and the measurement situations are the intervals to the first three contacted beacon nodes gained in the prior step. Now, formation of the system of equations is done by considering the positions of all beacons and their calculated intervals to the anonymous node as follows [37]:

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2}=d_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2}=d_2 \\ \cdots \\ \sqrt{(x-x_n)^2+(y-y_n)^2}=d_n \end{cases} \tag{3}$$

In Eq. (3) (x, y) is the computed position of anonymous node. Eq. (3) can be defined according to Eq. (4)

$$\begin{cases} x_1^2+x_n^2-2(x_1^2+x_n^2)x+y_1^2+y_n^2-2(y_1^2+y_n^2)y=d_1^2-d_n^2 \\ x_2^2+x_n^2-2(x_2^2+x_n^2)x+y_2^2+y_n^2-2(y_2^2+y_n^2)y=d_2^2-d_n^2 \\ \cdots \\ x_{n-1}^2+x_n^2-2(x_{n-1}^2+x_n^2)x+y_{n-1}^2+y_n^2-2(y_{n-1}^2+y_n^2)y=d_{n-1}^2-d_n^2 \end{cases} \tag{4}$$

Eq. (4) is modeled in the matrix template AX = b; where A, b and X are defined according to Eq. (5).

$$A=2\begin{bmatrix} (x_1-x_n) & (y_1-y_n) \\ (x_2-x_n) & (y_2-y_n) \\ \cdots & \cdots \\ (x_{n-1}-x_n) & (y_{n-1}-y_n) \end{bmatrix}, \quad X=\begin{bmatrix} x \\ y \end{bmatrix}, \quad b=\begin{bmatrix} x_1^2+x_n^2+y_1^2+y_n^2+d_n^2-d_1^2 \\ x_2^2+x_n^2+y_2^2+y_n^2+d_n^2-d_2^2 \\ \cdots \\ x_{n-1}^2+x_n^2+y_{n-1}^2+y_n^2+d_n^2-d_{n-1}^2 \end{bmatrix} \tag{5}$$

By estimating Eq. (5) with the lowest square method, the predicted location of anonymous nodes can be specified. The location coordinate of anonymous node *P* can be explored with help of Eq. (6). Where A^T shows the transpose of matrix *A*.

$$X=(A^TA)^{-1}A^Tb \tag{6}$$

IV. REVIEW OF IMPROVED DV-HOP

In consideration of distance vector, the DV-Hop is like the conventional routing schemes. The advantages of DV-Hop are being quick, feasible, good coverage and cost-effectiveness. This works fine in isotropic networks. An anonymous node in DV-Hop represents its lowest hop count from the beacon node, and therefore calculates interval from the beacon node by adding the least possible hop count and average hop interval. Additionally, the node uses a triangulation scheme or highest probability estimators to calculate its location. The big drawback of the DV-Hop is its low, but not strong positioning accuracy. Researchers have applied most of strategies to perform location accuracy of DV-Hop. In this part, improved DV-Hop is reviewed in terms of Meta-heuristic Algorithms, RSSI [39], Distance Vector, and Weighted Centroid Localization (WCL) [40]. Fig. (3) indicates the categorization of various models for enhancing DV-Hop.

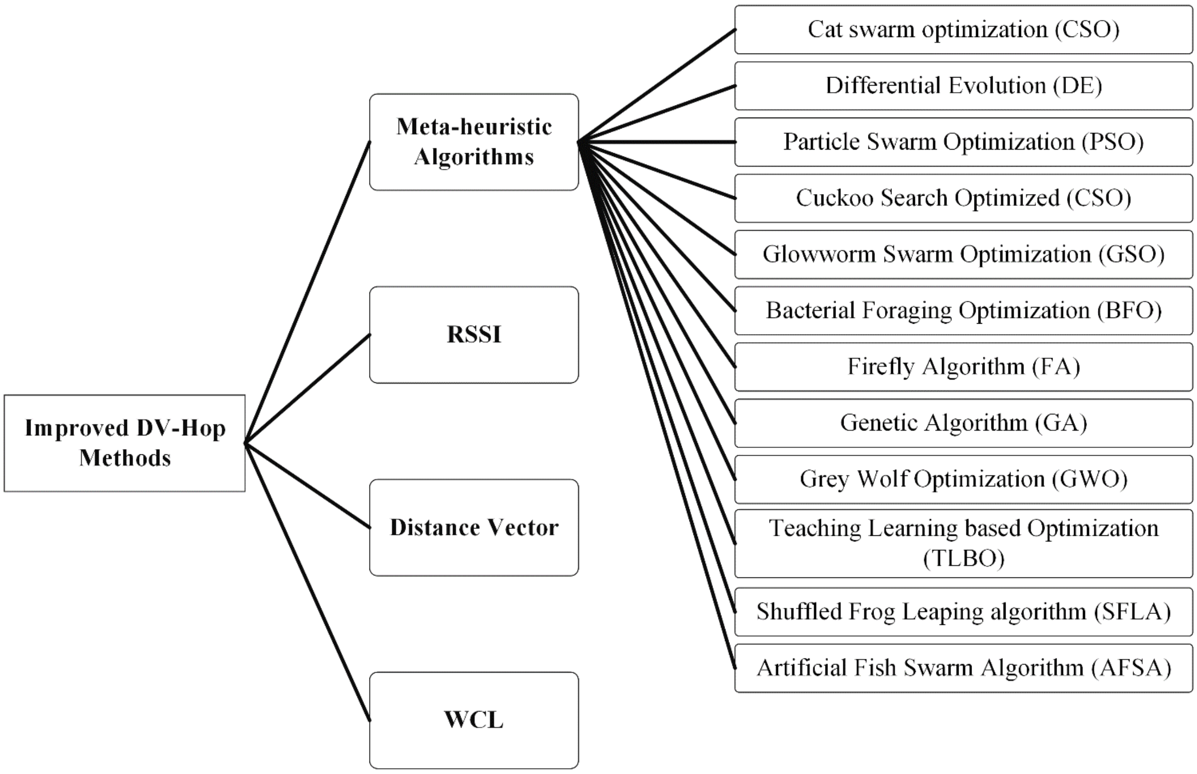

Fig. 3. Categorization of various models for enhancing DV-Hop

A. Improved DV-Hop based on Meta-heuristic Algorithms

A new algorithm called Parallel Compact Cat Swarm Optimization (PCCSO) has been introduced to improve DV-Hop [41]. PCCSO has the advantage of increasing local search capability and storing optimal location in the search space. The experimental results of PCCSO model on different functions showed that PCCSO had good convergence compared to PSO, CSO and CSO. Then, PCCSO is used for DV-Hop to effectively improve the localization accuracy of unknown nodes. PCCSO-based experimental results for number of different nodes showed that PCCSO-DV-Hop had less localization error than other DV-Hop-based optimization algorithms.

To successfully adopt the inadequacy of DV-Hop, a weighted Differential Evolution (DE) DV-Hop has been proposed in [42]. At first, so that to get higher accurate reckons of the mean of the hops and reduce the error impacts of subsequent node positioning, in the second stage of conventional DV-Hop, the model improves weighted correction on the average hop interval. Next, the model utilizes a DE, for the aim of making coordinates of anonymous nodes better. The proposed model reduces the mean positioning error, and after measurement the positioning precision is reached and the results with DV-Hop are distinguished. The model can also have higher positioning accuracy when the beacon node has less density and at the same time, model stability aspects have good specifications.

In [43], the Particle Swarm Optimization (PSO)-DV-Hop has been shown to resolve the inferior precision of the DV-Hop. Premised onto the DV-Hop, the model is applied to the weight of each beacon node, the mean interval is determined, the PSO is enhanced from two facets as these are the inertia weight and the active aspect to prevent the particles that are stuck in the partial alignment, and the position of the anonymous nodes is optimized instead. The simulation results demonstrate that under the same hardware circumstances, compared with the particle swarm based PSO-DV-Hop, the effect of the jump interval can be influentially reduced, node coverage increased, positioning accuracy and profundity of the positioning process performed and stronger usefulness.

The new PSO has been used by Singh and Sharma [44] for the DV-Hop. The results in simulation section indicate that the model changed is better located than the simple Hop localization and has a low error. As shown in the simulation part of this paper, the proposed method is highly effective and valid. They also examined the position of radio and beacon nodes in the error and variance of the location. The location calculation with the assistance of PSO was corrected in the used model. It is obvious that developed model boosts the accuracy and stability of localization model. But because of the use of PSO, there is a low rise in computation time.

Localization or placement of nodes in a WSN is fundamental to many position-conscious protocols. The classical global poisoning method used for local function of nodes is limited due to its high cost and indoor inability. As a result, numerous localization models have been used in recent years to develop localization accuracy and decrease utilization costs. One of the common localization techniques is to define localization as the least square localization (LSL) problem. The classical Gauss–Newton approach is weak during alignment of the LSL problem as partial minima can be obstructed. Unlike the DE, the position accuracy is increased as it demonstrates the optimum solution for the LSL problem worldwide. In addition, the DE speed convergence is not high since fixed values of the transverse factor are applied. In [45], an auto-adaptive single-bit-change factor (SA-MCDE) for LSL problems is used to perform a speed of convergence. The SA-MCDE combined the single-bit-change factor and the likelihood of convergence in each generation to better investigate and explore the optimum universal solution. It was improved position accuracy with high convergence of the SA-MCDE. The detailed simulation findings for the different localizing models show that more than 40% and almost 90% better location accuracy than classical techniques are provided in the SA-MCDE dependent setting.

A hybrid DV-Hop in accordance with hop-count quantization beacon and developed cuckoo search (HMCS-D) is utilized [46]. The first phase model uses the correction factor to rectify the quantity of hops that can decline the error resulting from the inaccurate recording of fewer hops; second, the sub-region of one hop area takes two sections, and the interval amid the anonymous nodes and the region's beacon nodes is projected by geometric method. Using this technique to measure the interval amid the anonymous node and the beacon node will achieve precision in positioning. When the anonymous node determines the average interval to the hop. Attempting to apply the CS that can efficiently adjust the phase size to boost search, the problem of localization is turned into a problem of universal and partial alignment. The obtained results showed that compared with the DV-Hop and CS-D models, the HMCS-D can achieve the positioning precision without increasing the hardware costs. Simulation analyses confirmed that the average positioning error of the HMCS-D decreases to 39.7 percent compared to the DV-Hop and 10.6 percent for CS. If it is proven that the HMCS-D performs the node location accuracy effectively, it therefore decreases the positioning error and does not affect the hardware cost.

A performed DV-Hop in terms of mixed chaos strategy (MGDV-Hop) is applied [47], in which the Glowworm Swarm Optimization (GSO) of hybrid chaotic strategy (MC-GSO) is in accordance with chaos mutation and chaotic inertia weight was employed. At the first step, GSO of hybrid chaotic model based on chaotic mutation and chaotic inertial weight updating (MC-GSO) is applied. The MC-GSO can be used to monitor each firefly's moving interval employing chaos mutation and chaotic inertial weight at the stage the firefly drops into the optimum locale. The empirical observations suggest higher convergence and better accuracy of MC-GSO, and prevent premature convergence. Next, it is advocated that MC-GSO replace the least square method when evaluating node coordinates to solve the problem that the DV-Hop accuracy is low. By introducing the error fitness function, the linear solution of coordinates is changed into a 2-dimensional heuristic optimization problem. The results and review of the simulation agree that the improved model (MGDV-Hop) lowers the average position error, improves the location coverage and lowers and maintains the energy system opposed to DV-Hop and the location model based on classical GSO (GSDV-Hop).

Bacterial Foraging Optimization (BFO) was proposed by Zhou et al. [48] to achieve the utility of local function error. They did an extensive research on simulations in different network contexts, the computation observations confirmed that when opposed with the basic DV-Hop, the proposed method gained considerably better positioning precision. The mean of error was substantially lower in both BFO-DVHOP and DV-Hop, as R (14 till 42) expanded. This endorses our belief that a sensor node will have more neighbors with a higher R value to support its localization. Similar to DV-Hop, BFO-DVHOP has reduced the mean error by up to 54 percent.

A novel DV-Hop of WSNs based on Firefly Algorithm (FADV-Hop) is utilized [49]. The novel Localization applies the fitness function to show the sum of the error of the anonymous node and the n normal node. By theoretical reasoning and simulation, the findings indicate that the FADV-Hop decreases the location error and performed the Localization precision. The mean location error of DV-Hop is 7.6639, and the mean location error of FADV-Hop is 4.63.

A new local function model in WSN based on beacon nodes to perform the accuracy in location estimation has been utilized [50]. At first, system model of WSN node localization is made based on the WSN environment. Next, conventional WSN node localization models such as DV-HOP, GA, and PSO are researched. Localization model of WSN is applied by utilizing dynamic mathematics modeling. And the finding of simulation that is contrasted with the conventional model demonstrated that proposed model outperformed in accuracy and coverage of WSN. The simulation findings indicate that the performance of the proposed location model is higher than the traditional localization models. At the time which the proportion of beacon nodes is raised to about 45%, the localization error is originally stable, but localization accuracy of proposed model is improved in higher degree.

To minimize the local function error of the DV-Hop due to the estimated estimate of the average hop sizes per beacon, the Gray Wolf Optimization (GWO) is used to calculate the average hop size [51]. In terms of GWO, two models are used. The first modifies DV-Hop's second phase by having a standardized mean hop scale. At first, the second model uses GWO and the next weighted approach is used to achieve a better interpretation of average hop sizes and to research each beacon's function. The first one employs GWO (GWO-DV-Hop) to determine a good measure of average interval per hop, and the next one, a weighted GWO (Weighted GWO-DV-Hop), considers average interval per hop while measured using GWO for each beacon node, and then, each node uses a weighted approach to obtain weighted average interval per hop. Findings from the simulation indicate that two models are gaining greater value than previous DV-Hop. By using GWO in the second stage of DV-Hop, the localization error is decreased when approximately 10%.

A state-of-the-art DV-Hop was used by using the PSO [52]. However, PSO has other derivatives such as slow convergence, late-evolutionary precision. An updated adaptive PSO (MPSO) is used because of these issues. MPSO changes the weight and speed parameters of each particle self-adjusting and separates the particles. Such figures will explain both partial and universal search capabilities. In simulation tests, the DV-Hop is probably higher than the common DV-Hop, based on the adaptive PSO adjusted for the localization coverage rate. With the performance of beacon nodes, the average local function error of DV-Hop, PDV-Hop and MPDV-Hop is decreased slowly, and the average local function error of MPDV-Hop is significantly lower than that of DV-Hop and PDV-Hop that means the performed model gains lower error.

A performed DV-Hop based on path matching and PSO has been used [53]. Total of nodes are inconstantly expanded in a square network structure. In the scheme one, with the raising of beacon rate, the range error is decreased both for DV-Hop PSO and the DV-Hop. However, in comparison with the DV-Hop, PMDV-Hop (Path Matching DV-Hop) can be decreased around 35% range error. With the performance of beacon percentage, the localization error is decreased all for their model, the DV-Hop. However, PMDV-Hop can be decreased around 35% local function error in comparison with the DV-Hop, around 18% when it compares with IDV-Hop1, around 26% as it compares with IDV-Hop2, and around 39% when it compares with QDV-Hop.

A new highly accurate local function based on DV-Hop and DE called DECHDV-Hop for WSN has been utilized [54]. In DECHDV-Hop, a novel parameter CH is defined. CH (continuous hop-count abbreviation) has been converted from the isolated value to sustained values that are more appropriate for hop-counting. DE is applied to locate anonymous nodes by formulating the position estimation process as an alignment problem to further reduce the localization error. The proposed DECHDV-Hop achieves greater precision in the local function without the need for additional hardware. The thorough research is carried out in four different situations of simulation on the network. The findings indicate that DECHDV-Hop significantly performed to DV-Hop, GADV-Hop and PSODV-Hop in all conditions. In particular, DECHDV-Hop has definite merits in C-shaped network topologies situations. For C-shaped network topologies situations, DECHDV-Hop can decrease local function error about 70% when it compares with DV-Hop.

A performed interval vector hop (IDV-Hop) that applies teaching learning-based optimization (TLBO) has been used to accurately locate nodes [55]. Hop sizes of the beacon nodes in the applied model are changed by trying to add correction factor. The definition of collinearity is introduced for the reduction of position errors triggered by collinear beacon nodes. To achieve better coverage of the location, target nodes have been upgraded to assistant beacon nodes in such a sense that those target nodes are modified to associate beacon nodes located in the first round of localization. The position of target nodes has been developed as an alignment problem and an effective parameter free alignment technique viz to achieve higher efficiency in localization precision. TLBO was made use of. Computation researchers noted that the proposed model is generally 47.30% and 22% more profitable than DV-Hop, Genetic Algorithm-based DV-Hop (GADV-Hop) and IDV-Hop using PSO models according to the order and gaining greater positioning coverage with rapid convergence.

A PSO-based Enhanced Localization (PSODV-Hop) for WSNs was formulated [56]. The scheme proposed curtails communication amid nodes, that dramatically reduces the node's energy usage. It has also managed to increase the precision of the local function without any extra hardware charges. Different tests were carried out in simulated environments to verify the utility of their modified model (PSODV-Hop) with original DV-Hop and enhanced DV-Hop version for WSNs.

Based on connectivity and GA, a new series of free localization model in WSNs has been suggested [57]. GA has been used in this method to find the best possible way to real position of anonymous node. The experimental simulations demonstrated that the positioning accuracy of primary DV-hop has been certainly enhanced by the new method. Totally, in compare to the anonymous node, placing the node on the approximate position has the minimum connectivity difference, so the best precise approximate position can be observed by minimizing the connectivity difference. Actually, although based on information connectivity only the best positions are chosen in each process that a group of possible candidate positions is made. We find the nearest position to the anonymous node after the other GAs operators are used. Based on GA (MSL), the simulation results of the Multi-Step-Localization demonstrated that the precision of location is increased considerably. This is owing to the new approach of the MSL model that provides more flexibility by considering the issue of localization as an ensemble of linked sections that have a significant effect on the precision of localization.

Many applications in WSN need to figure out exactly where the sensor nodes are located. Due to the reduced precision of the Range-free models, $Mehrabi\ et\ al.$ [58] suggested the enhanced DV-Hop based on the Shuffled Frog Leaping algorithm (SFLA). In the second stage of the primary DV-Hop and hybrid GA-PSO, they used SFLA to enhance its precision in the final stage of the primary DV-Hop. In this study, we use SFLA in the second stage of DV-Hop to enhance Hop-Size error. Greater accuracy, easy implementation, computing proficiency, quick convergence are the benefits of SFLA. Also, in order to find a solution to the greater error of least square method, the hybrid GA-PSO is engaged in the last stage of DV-Hop. Further, population-based representation of solving problem in GA and PSO make it possible to use PSO to optimize the best individuals of the GA that can lower convergence time prominently. The performance of DV-Hop is developed by the hybrid GA-PSO that has the ability to reduce the error amid the real and approximate coordinates. Simulation findings indicate that their suggested model localization error was considerably smaller than the primary DV-Hop, enhanced SFLA and PSO-based DV-Hop, and enhanced GA-based DV-Hop. The price of enhancing accuracy is rising the time of calculation.

The Bacterial Foraging Optimization (BFO) is presented to develop the DV-HOP, with the purpose of increasing the inside positioning precision and reduce the positioning error in WSNs. In computing the common interval per-hop, the standard DV-HOP is not very precise and it highly impacts on the positioning precision. Therefore, a new BFO-DV-Hop is suggested [59]. The average interval per-hop is computed by the standard DV-Hop based on the Euclidean interval and the minimum quantity of hops directly and the spread of the variable network typology by chance that results in the low precision in common hop interval approximation. The common interval per-hop is computed by the BFO with the use of the minimum hops of nodes and the position data of beacon nodes in BFO-DV-HOP. Simulation conclusion demonstrated that in compare to standard models, 30% beacon nodes can capably decrease the positioning error and 10% can get a better efficiency.

For WSNs is planned an evolutionary algorithm called Oriented Cuckoo Search (OCS) [60], with the combination of two various types of random distributions the quest for worldwide research is dominated. For further research, ten various random distributions are engaged and compared with CEC2013 test suits. Numerical findings indicate the highest performance obtained by combining the hybrid distribution with Levy distribution and Cauchy distribution. In addition, OCS is also integrated into the method of DV-Hop with this hybrid distribution to develop the precision efficiency. Simulation findings showed that, compared to three other DV-Hop models, their changes obtained better accuracy efficiency [61]. An enhanced GA was suggested to decrease the local function error outcome of DV-Hop. Simulation findings indicate that, compared to other models, the enhanced model increased the precision of the location.

Based on composite PSO, a smart location model is suggested for DV-Hop [62] to enhance the precision of node location in WSNs. After the stage of maximum probability technique, the problem of unsure place is converted into a multi-dimensional alignment problem. Furthermore, appropriate location precision is achieved in NP problems with the benefit of composite PSO. The outcomes of the study proved that, compared to traditional methods, their suggested model is great in reducing position error, enhancing precision and reliability. DV-Hop location is the most frequently used model for node location in WSNs. But, in determining the position of anonymous nodes, it does not take into consideration the effect of the average interval per hop, leading in decreased positioning precision. A fresh AFSADV-Hop (Artificial Fish Swarm DV-Hop) based on AFSA was suggested to answer this problem [63]. Since AFSA has a quicker rate of convergence and can deal with the problem of nonlinear function alignment, it is used to tackle the average range alignment per hop, this reduces the position error due to the average range per hop, so that it is nearer to the real value. The simulation findings indicated that the enhanced model can enhance the precision and reliability of the model efficiently without increasing the price of the hardware. AFSADV-Hop's has been increased location precision an about 19.5% ~27% compared with the DV-Hop.

An enhanced DV-Hop is suggested based on extremely confused and simple PSO [64] to fix the problem of low localization precision of the conventional DV-Hop, Results of the simulation revealed that the precision of the location is much greater than that of the DV-Hop and that of the integrated DV-Hop based on conventional PSO. And the fresh model is converging quicker than the optimized conventional PSO-based DV-Hop. When the proportion of the beacon node is low, the impact is more apparent. It is obvious that the greater the location precision, the more beacon nodes engaged in localization. The location error of DV-Hop reduces from 93% to 57% due to the simulation in a fairly small ratio of beacon nodes, When the amount of beacon nodes rises from 4 to 10; DV-Hop based on conventional PSO optimized converges gently with fewer beacon nodes and the location error ranges from 75% to 49%; Based on The PSO-optimized, DV-Hop has a quicker convergence velocity and greater location precision when the amount of beacons is very low. The error of localization reduces from 59% to 30%.

An altered location model for DV-Hop has been suggested to enhance the bad location output of the DV-Hop [65]. First, on the boundary territory of the observing areas, some beacon nodes are spread. Second, the average one-hop range of beacon nodes is altered. In addition, the average one-hop interval used by each anonymous node to calculate its own location is altered by measuring N from beacon nodes with an average one-hop range. At last, the PSO was used to accurate the position assumed by the 2D hyperbolic location model. It can be seen that their suggested model clearly increases the accuracy and reliability of the location. But with regard to PSO, it has very little rise in the computing time.

Table II summarizes the improved DV-Hop papers based on the meta-heuristic algorithm derived from objectives and disadvantages.

Table II. Summary of Improved DV-Hop based on meta-heuristic algorithms derived from Objectives and Disadvantages

Refs	Used Method	Objective	Description	Disadvantages	Year	Publisher
[41]	Parallel Compact Cat Swarm Optimization (PCCSO)	decrease average positioning error	correcting the position estimation with PCCSO	increase in run time	2021	Springer
[42]	Differential Evolution (DE)	To reduce the hop interval error	The DE is used to optimize the positioning result of the anonymous node	increase node power consumption and increase the time	2019	IEEE
[43]	Particle Swarm Optimization (PSO)	(1) increase accuracy (2) higher search efficiency and better stability	Reduce hop interval effect, increase node coverage, boost positioning accuracy and the positioning process robustness.	increase in computation time	2019	Springer
[44]	PSO	decrease local function error and increase accuracy	correcting the position estimation with PSO	increase in computation time	2019	Springer
[45]	DE	increase accuracy	SA-MCDE based localization model with rapid precision, convergence, positioning and low cost of service	increase in computation time	2019	Springer
[46]	Cuckoo Search Algorithm (CSA)	decrease average positioning error	Proposed model effectively improved the node local function error, reduce the positioning error and without affecting the hardware cost	increase in run time	2019	Springer
[47]	glowworm swarm optimization (GSO)	Reduce the average position error, boost localization and balance the power consumption	high accuracy and avoids the premature convergence	increase in run time	2019	other
[48]	Bacterial Foraging Optimization (BFO)	improving the localization accuracy	Proposed method attained outstandingly higher positioning accuracy than the basic DV-Hop	increase in computation time	2019	Springer
[49]	Firefly Algorithm (FA)	To reduce the hop interval error	FADV-Hop reduced the location error and improves the Localization accuracy	increase in computation time	2019	Springer
[50]	PSO and Genetic Algorithm (GA)	improving the accuracy and coverage of WSN	The obtained results showed that the performance of the proposed location model is better than the common localization models.	increase in run time	2018	Other
[51]	Grey Wolf Optimization (GWO)	The localization error is decreased by almost 10 percentage by using GWO	The assessments proved the priority of developed model over DV-Hop in terms of local function error	increase in computation time and run time	2018	Springer
[52]	Developed adaptive PSO (MPSO)	average local function error is lower	Average position error is less than DV-Hop and PSO-based DV-Hop	Increasing the number of repetitions	2018	Springer
[53]	PSO	Good results on both interval prediction precision and average position precision of node	aiming to improve the prediction precision of beacon–node interval	increase in computation time	2018	Springer
[54]	DE	reducing local function error	The position estimation method is developed in conjunction with weighted square errors of the	increase in computation time	2018	Elsevier

			calculated period as a minimizing alignment issue			
[55]	Teaching Learning based Optimization (TLBO)	achieved high positioning coverage with fast convergence	The key benefit of the present research is improved local function precision, a positioning coverage and rapid convergence in an area where resources are minimal	Increasing the number of repetitions	2017	Springer
[56]	PSO	decreasing the energy utilization of the node	Determine the value of minimum hop from all nodes to every beacon node	Increasing the number of repetitions	2017	Springer
[57]	GA	best accuracy	Predicted Euclidian interval amid the anonymous node and each beacon. The physical position of anonymous node will be predicted progressively based GA alignment	Increasing the number of repetitions	2017	Springer
[58]	Shuffled Frog Leaping algorithm (SFLA)	Easier deployment, better solutions, application efficiency and faster convergence	proposed method has decreased the local function error efficiently without additional hardware	increase in computation time	2016	Springer
[59]	BFO	reducing positioning error	BFODV-HOP and assessment results showed that it can be reduced the positioning error and improved positioning accuracy apparently	Increasing the number of repetitions	2016	IEEE
[60]	oriented CSA	average localization error is lower	In OCS, the partial search adaptability is guided by the best position, as well as the universal search capability is affected by different random distributions	Increasing the number of repetitions	2016	Elsevier
[61]	GA	Increasing localization accuracy	developed GADV-Hop restrained the feasible region of initial population and develops the quality of initial population	Increasing the number of repetitions	2015	Springer
[62]	PSO	reducing communication consumption	proposed method has decreased the localization error	Increasing time complexity	2015	IEEE
[63]	Artificial Fish Swarm Algorithm (AFSA)	reducing average interval per hop	reducing the amount of energy system	Increasing time complexity	2015	Other
[64]	PSO	Increasing localization accuracy	Hybrid of DV-Hop and extremum disturbed and simple PSO	Increasing the number of repetitions	2014	Springer
[65]	PSO	Increasing localization accuracy	PSO is used to correct the position expected by the 2D hyperbolic model, bringing the outcome similar to the real location	Increasing the number of repetitions	2012	Other

Table III summarizes the improved DV-Hop papers based on meta-heuristic algorithm derived from the analysis and results.

Table III. Summary of Improved DV-Hop based on meta-heuristic algorithm derived from Goals and Analysis

Refs	Goals	simulator	Assessed factors	Area	Number of Nodes
[41]	PCCSO for node localization in WSNs	MATLAB R2017b	1) appraisement of the qualification of beacons on Positioning Error 2) appraisement of the qualification of beacons on Positioning Coverage	150*150	150
[42]	Weighted DV-Hop Localization for WSNs based on DE	MATLAB	1) Analysis Based on the measurement of Beacon Nodes 2) appraisement of domain Radius on Average Positioning Error	100*100	100
[43]	Research on the DV-Hop Location Model Based on the PSO for the Automatic Driving Vehicle	MATLAB R2014b	1) The appraisement of the maximum of network nodes on the average positioning error 2) appraisement of beacon nodes on average positioning error 3) The appraisement of the domain radius on the average positioning error	100*100	200
[44]	Performance Evaluation of Improved Localization for WSNs	MATLAB 2015a	1) qualification of No. of Beacon Nodes on indigenization Results 2) qualification of Radio Range on indigenization Results	100*100	100
[45]	DE for node localization in WSNs	MATLAB	1) local function error for different number of anonymous nodes 2) local function error for different number of beacon nodes 3) Convergence speed comparisons among different alignment techniques	100*100	100
[46]	Hop-Count Quantization Ranging and Hybrid CSA for DV-HOP in WSNs	MATLAB 2014	1) qualification of Different Beacon Node on Positioning Accuracy 2) appraisement of domain radius on Positioning Accuracy 3) the effect on the decreasing error of the maximum of nodes	200*200	180
[47]	DV-Hop Node Location Model Based on GSO in WSNs	MATLAB 2015a	1) appraisement of domain radius on Mean Positioning Error 2) appraisement of the qualification of beacons on Positioning Error 3) appraisement of the qualification of beacons on Positioning Coverage 4) Node Energy system	100*100	100
[48]	DV-Hop based on BFO	NS2	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100	100
[49]	A New DV-Hop Location of WSNs Based on FA	MATLAB	1) appraisement of the No. of Beacons on Positioning Error	100*100	100
[50]	Dynamic Mathematics Modeling and Node Localization	NS2	1) The interval amid anonymous node and beacon node is calculated by the minimum hop	150*150	400
[51]	DV-Hop for Randomly Deployed 2D and 3D WSNs	MATLAB	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100 300*300	200 to 450
[52]	DV-Hop Node Localization Based on Improved PSO	MATLAB	1) appraisement of the measurement of Beacons on Positioning Error 2) Domain Range	100*100	100
[53]	Developed DV-Hop by PSO	MATLAB	1) local function error in a square network versus the beacon node ratio 2) Range error in a square network versus number of nodes 3) local function error in a square network versus qualification of nodes 4) Range error in a square network versus radius	100*100	200
[54]	A Top Accurate Localization with DV-Hop and DE for WSN	MATLAB 2014a	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100	100
[55]	Improved DV-Hop localization using TLBO	MATLAB 8.1	1) qualification of variation in domain range 2) Effect of node density 3) Effect of radio irregularity	100*100	50 to 400
[56]	A PSO Based Improved local function error for WSNs	MATLAB 2015a	1) appraisement of Beacon Nodes on indigenization Error, Error Variance and Accuracy 2) appraisement of maximum of Sensors on local function Error, Error Variance and Accuracy	100*100	100

			3) appraisement of Radius on local function Error, Error Variance and Accuracy		
[57]	A New Range Free Localization Based on GA	MATLAB	1) Declarations Results via measurement of sensor nodes 2) Assessments Results via Radio Ranges of Sensor Nodes 3) Assessments Results via measurement of Beacon	50*50	20
[58]	Developed DV-Hop based on intelligent models	MATLAB	1) The appraisement of the qualification of beacon nodes on the positioning accuracy 2) The appraisement of domain range on the positioning accuracy 3) The appraisement of qualification of sensor nodes on the local function error	100*100	100
[59]	Developed DV-HOP Based on BFO	MATLAB R2014a	1) Positioning Accuracy Analysis 2) Relationship amid beacon and positioning error 3) Relationship amid the position error and the total number of nodes	100*100	100
[60]	A novel oriented cuckoo CSA to improve DV-Hop	MATLAB 2011	1) appraisement for domain radius 2) Average position error vs. domain radius 3) appraisement for number of different nodes 4) Average error in location vs. measurement of nodes 5) Average error in location vs. measurement of beacons	100*100	100
[61]	Developed localization model based on GA in WSNs	MATLAB 7.11.0	1) Number of beacon nodes 2) domain Radius	100*100	100
[62]	Developed DV-HOP based on composite PSO	MATLAB	1) appraisement of the ratio of Beacon Node on the average location error 2) appraisement of maximum of nodes on the mean positioning error	100*100	100
[63]	An Improved DV-Hop Based on AFSA	MATLAB7 .0	1) domain radius(m) 2) Number of nodes 3) Number of beacon nodes	100*100	100
[64]	Improving localization in WSNs Based on Improved PSO	MATLAB7 .0	1) measurement of beacon nodes involved in local function error 2) Error offset amid original and estimated location of anonymous node	300*300	100
[65]	Improved DV-Hop in WSNs based on interval	MATLAB2 009a	1) Error finding with different measurement of beacon nodes 2 Error finding with different measurement of beacon nodes 3) Error finding with different measurement of nodes 4) Error finding variance with different measurement of nodes	100*100	100

B. Improved DV-Hop based on RSSI

The RSSI is used as the approach for calculating interval. To approximate the interval amid adjacent nodes, the RSSI is based on the signal strength indicator obtained [66]. In open space, the RSSI rating is inversely proportional to the transmitter-receiver square interval [67]. With the rise in range, the radio signals reduce. Reflection, diffraction and dispersion may affect the propagation of the radio signals. Such effects can influence the precision of the measurement, particularly in indoor settings. Thus, this approach is more appropriate for outdoor apps than for indoor apps. The benefit of this approach is that no extra hardware is required because the RSSI approach function is available in most wireless devices. Local energy system is not greatly affected. A node uses RSSI measurements in an RSSI-based range model to approximate its ranges from the beacons using a recognized model of signal propagation [67]. Even though attenuation of the signal is often linked to the particular setting, the signal propagation model, the most suitable model for the present setting, is crucial for the precision of the range. Now, the shadowing model is commonly used for modeling the loss of wireless signal propagation [24] that is as follows:

$$Pr(d) = Pr(d_0) - 10nlog10(d/d_0) + X\sigma \quad (7)$$

Where d and d_0 indicate the actual range and the reference range, alternately; where $Pr(d)$ and $Pr(d_0)$ indicate the signal power obtained in dBm at the actual range and the reference range; n is the path loss index, Xσ is gauss random distribution function while the mean is 0. For most of the indoor applications, $d_0 = 1$ meter and $Pr(d_0)$ is calculated by free space path loss formula. The noise $X\sigma$ is generated from sources that are changeable in time and fixed in time. We suppose that $X\sigma$ is a spread random Gaussian variable with zero mean and variance σ^2 to properly model the random impacts of shadowing. Environmental variables and surrounding structure specify the path loss exponent *n*. It is simple to see that the range of error is essentially brought about by the impact of physical environment. Therefore, the improved shadowing model is utilized as pursues:

$$RSSI(d) = A - 10nlgd \quad (8)$$

In Eq. (8) $RSSI\ (d)$ is the sign power obtained at range$d$ and *A* is the receiver's sign power obtained from a one-meter transmitter. Particular hardware and environment parameters *A* and *n* are strongly linked in Eq. (8), in the recent indoor environment, if $A\ and\ n$ are precise, the RSSI-based range is great. A group of online or offline RSSI measurements amid the beacons calculate the parameters of the signal distribution model [67] in the majority of RSSI-based range models. Obviously, online RSSI measurements require calculation and communication. Although, this is not the case in a functional setting where it is highly hard to determine the signal propagation model at any specific time and space, the parameters of the approximate model may not correctly represent the actual radio channel of an indoor setting.

A new RSSI-based solution is proposed to estimate the distance between unknown nodes and the beacon [68]. The main purpose of this model is to reduce errors and detect accurate position. A hybrid DV-Hop ($Cheikhrouhou\ et\ al.$) [69] was suggested using RSSI for wide-scale WSNs, Conventional range based localization models use triangulation to approximate only those wireless nodes inside a one-hop interval from the beacon nodes. On the other side, multi-hop localization models strive to locate the wireless nodes that may be physically residing away from beacon nodes at various hops. DV-Hop experiences decreased precision because it just uses the arrangement of the network (i.e. couple of hops to beacons) instead of the intervals among pairs of nodes. They suggested an improved DV-Hop in this study, which also utilizes the RSSI values combined with one-hop surroundings connections. In addition, they used localized nodes by supporting them to become extra beacon nodes. Their simulations indicated that the suggested model considerably outperforms the initial DV-Hop and two of its newly released variants, i.e. RSSI Auxiliary Ranging and the Selective 3-Beacon DV-hop. All the more accurately, the suggested model increases location precision by nearly 95%, 90%, and 70%, compared to the fundamental DV-Hop, Selective 3-Beacon, and RSSI DV-Hop models, separately, in certain situations.

Two enhanced DV-Hop were proposed with the following titles: Equal Sub-Area-Based DV-Hop (ESAB-DV-Hop) and Equal Sub-Area-Based DV-Hop with RSSI (ESAB-DV-Hop with RSSI). The results showed that the error of the two models is less than DV-Hop [70]. The two models suggested are gotten from the DV-hop approach. The first relies on splitting the network area into sub-areas and setting the nodes with anonymous places to estimate their beacon nodes position in the same sub-area and the second relies on splitting the network area into sub-areas and each node with an anonymous place estimates the interval amid itself and other nodes using hop check amount if they are not adjacent beacon nodes and RSSI if they are adjacent beacon nodes. Simulation findings revealed that the location precision of the Equal Sub-Area-Based DV-Hop (ESAB-DV-Hop) is 13.5% is superior to the standard model and 12% is superior to the new model that helps solve the same issue when the overall quantity of nodes is 100, the connectivity range is 20 m and the proportion of beacons is 10%. The Equal Sub-Area-Based DV-Hop with RSSI (ESAB-DV-Hop with RSSI) approach is 17.5% is superior to the standard model and 16 is superior to a new model that helps solve the same issue when the overall quantity of nodes is 100, the connectivity range is 20 m and the proportion of beacons is 10%.

An enhanced DV-Hop was suggested in conjunction with RSSI Ranging Technology [71]. The enhanced DV-Hop is used a bunch technique to decrease the overhead communication and the likelihood of group conflict in the main stage phase of DV-Hop; The acquired Signal Strength Indicator (RSSI) range approach is used to substitute the range measurement of one hop away from the beacon node in the DV-Hop; then approximate node positions with quasi-Newton alignment method rather than the Least square process.

Based on RSSI Auxiliary Ranging, an enhanced DV-Hop has been suggested [72]. An enhanced DV-Hop twice-refinement localization model based on an auxiliary range of obtained signal strength indicator (RSSI) and anonymous node error correction is suggested using its own centroid. In order to get the interval amid neighboring nodes for auxiliary positioning, the enhanced model used RSSI range technology, as well as used the centroid coordinates of the anonymous nodes to correct their own original positioning outcomes, and after that reposition the anonymous nodes using the coordinates that have been checked. Simulation findings indicated that compared to the conventional DV-Hop and several new improved DV-Hop in the same experimental setting, without extra hardware expenditure, this study's enhanced DV-Hop just requires nodes with an RSSI indicator function and provides a little overhead computing and communication, considerably diminished the node localization error and enhanced the localization precision.

A RSSI-based feedback system was proposed for DV-Hop and RFDV-Hop [73]. It can be divided into two stages. First, RSSI is used to substitute the hops of DV-Hop in order to approximate the original position of the anonymous node. The interval distinction between the real location on the beacons is often used as a correction element, as is the approximate spot calculated by the DV-Hop. When measuring distances between anonymous node and beacons, as well as the change component, the exact location of the anonymous node was calculated. The simulations demonstrate that RFDV-Hop can easily the overall position and optimize the localization.

An enhanced DV-Hop is suggested to fix the issue of bad localization precision of the DV-Hop [74]. The suggested idea for changing the hop-count amid nodes is based on the RSSI approach. This article discusses the notion of fundamental node signal strength that will be used to alter hop count. The hop coefficient and hop-size coefficient are arranged to alter separately the hop count and hop size of anonymous nodes. Furthermore, to restrict the transmission interval of network data packets, the packet life cycle is placed forward. The simulation outcome indicated better localization precision of the suggested idea can considerably decrease the prediction error of hop count and hop size amid nodes.

Using the current enhanced model, the anonymous node location is located based on RSSI [75]. This erases the combined error and enhanced the precision of the location. Beacon nodes distribute their location and hop parameters adjusted zero to adjacent nodes. After the packet has been gotten, the quantity of hops is calculated by the adjacent node with obtaining signal strength analysis RSSI values to setting threshold Simulation tests indicated that the enhanced model's location error was superior to the DV-Hop, which decreased by 15% or more. The best choice is that the positioning error reduces to 15%, meeting the requirement for precision of the location of the sensor network.

Based on RSSI, enhanced DV-Hop has been suggested [76]. First, the RSSI value is applied to accurate the interval amid anonymous nodes and source nodes within a single hop range. Second, to further decrease the interval error amid anonymous nodes and source nodes, a certain quantity of correction value is added to the initial hop. Simulation outcome indicated that this article's enhanced model achieves a rise of 9.4% -13.7% compared to the classic DV-Hop; when node connection radius is 30m. This article's enhanced model achieves a rise of 10.4% -14.3% compared to the classic DV-Hop; when node connection radius is 40m. This article's enhanced model achieves a rise of 12.1%-17.7% compared to the classic DV-Hop, when node connection radius is 50m and the source nodes ration is modified slowly, Outcome of simulation indicated that enhanced model increases accuracy of localization. Range-free localization model was suggested using the interval ratio based on the WSN DV-HOP [77]. By changing the overall hop length of the network, an enhanced SDDV-HOP (Shortest Intervals DV-HOP) is suggested. They used the approximate interval from the RSSI-distance model as the loads of the edges. The simulation findings revealed that the localization precision can be significantly enhanced by the SDDV-HOP compared to the DV-Hop.

Table IV summarizes the improved DV-Hop papers based on RSSI derived from the objectives and disadvantages.

Table IV. Summary of RSSI-Based Improved DV-Hop papers derived from Objectives and Disadvantages

Refs	Goals	Objective	Description	Disadvantages	Year	Publisher
[68]	Improving Positioning Based on RSSI	reducing the localization error	distance between the unknown node and beacon node based on the “RSSI-Distance”	There is a distance limit.	2020	Springer
[69]	A Hybrid DV-Hop Using RSSI for Localization in Large-Scale WSNs	decreasing local function error	Developed DV-Hop hat also uses the RSSI values associated with links amid one-hop neighbors	Interference in packets	2018	Other
[70]	Developed DV-Hop Localization Model	decreasing the error of the position of anonymous nodes	Generated results show that the local function error of the Equal Sub-Area-Based DV-Hop (ESAB-DV-Hop) method is lower than the DV-Hop	more calculations	2017	Springer
[71]	Developed DV-Hop Combined with RSSI Ranging model	reducing the local function error	Developed DV-Hop can be significantly reduced the local function error without increasing computing complexity	Increasing the size of the routing table	2016	Springer
[72]	Developed DV-Hop based on RSSI auxiliary ranging	reducing the local function error	The Developed model uses RSSI ranging technology to get the interval amid adjacent nodes for auxiliary positioning	it is not suitable for large scale	2016	IEEE
[73]	Research on Developed DV-Hop Based on RSSI and Feedback model	reducing the localization error	RFDV-Hop can use the RSSI and the feedback of location bias to decrease the local function error	connectivity to the network demand is high	2015	Springer
[74]	Developed DV-Hop based on RSSI for WSN	decreasing local function error	proposed model has better local function and can be reduced the appraisement error of hop count and hop size amid nodes significantly	it is not appropriate for broad	2015	IEEE
[75]	Developed DV-Hop positioning model based on hop interval correction	decreasing local function error	Analysis showed that the positioning error of improved model is better than DV-Hop that reduced by 15%.	the density of the beacon nodes is very large	2014	IEEE
[76]	Developed DV-Hop Based on RSSI Value and Hop Correction	decreasing local function error	RSSI value is used to correct the interval amid anonymous node and reference nodes in the range of single hop	more calculations	2013	Springer
[77]	Developed DV-HOP Based on the Ratio of Intervals	reducing the localization error	The analysis results showed that SDDV-Hop could improve the local function error greatly compared with DV-HOP	the density of the beacon nodes is high	2013	Springer
[78]	Developed DV-HOP positioning model based on one-hop subdivision and average hopping interval modification	reducing the local function error	The established DV-Hop can reduce position errors dramatically without increasing device complication	communication overhead	2012	Other
[79]	DV-Hop Localization Model	High positioning accuracy	RSSI value has been applied to reduce the error of measurement	the density of the beacon nodes is high	2010	IEEE

Table (V) summarizes the improved DV-Hop papers based on RSSI derived from the analysis and results.

Table V. Summary of Improved RSSI-Based DV-Hop papers derived from Goals and Analysis

Refs	Goals	simulator	Assessed factors	Area	Number of Nodes
[68]	Developed DV-Hop	MATLAB 2015b	1) measurement of nodes 2) Number of beacon nodes	100*100	100
[69]	A Hybrid DV-Hop Using RSSI for Localization in Large-Scale WSNs	MATLAB	1) local function Error vs. Transmission Range 2) local function Error vs. Beacon Population 3) local function Error vs. Node Density	100*100	100
[70]	Developed DV-Hop	NS2	1) local function Error vs. beacon nodes 2) local function Error vs. measurement of nodes	100*100	100 to 200
[71]	Developed DV-Hop Combined with RSSI Ranging model	MATLAB7 .0	The measurement of data packets	100*100	200
[72]	Developed DV-Hop based on RSSI auxiliary ranging	MATLAB	1) domain radius(m) 2) qualification of nodes 3) measurement of beacon nodes	100*100	100
[73]	Research on Developed DV-Hop Based on RSSI and Feedback model	MATLAB 2010B	1) measurement of nodes 2) Number of beacon nodes	100*100	100
[74]	Developed DV-Hop based on RSSI for WSN	MATLAB	1) The capability of beacon nodes on the position function 2) The capability of nodes amount on the position function 3)The impact of communication radius on position function	100*100	200
[75]	Developed DV-Hop positioning model based on hop interval correction	MATLAB R2012a	1) The Ration of Beacon Node 2) Node domain Radius(m)	1000* 1000	300
[76]	Developed DV-Hop Based on RSSI Value and Hop Correction	MATLAB	1) Node domain Radius(m)	100*100	100
[77]	Developed DV-HOP Based on the Ratio of Intervals	MATLAB	1) local function Error vs. beacon nodes 2) local function Error vs. number of nodes	100*100	100
[78]	Developed DV-HOP based on one-hop subdivision and average hopping interval modification	MATLAB	1) The Ration of Beacon Node 2) Node domain Radius(m)	100*100	100
[79]	Expanded DV-Hop to reduce the error	NS2	1) local function error 2) measurement of beacons	100*100	300

An enhanced RADV-HOP (RSSI and overall hopping distance changing DV-HOP) is suggested [78]. Using RSSI, the RADV-HOP subdivides one hop into several levels, and changes the overall hopping interval used in the DV-Hop of location. Simulation findings indicate that the RADV-Hop only requires a node connection chip with RSSI indicator feature in the same network situation compared to DV-HOP, provides a small amount of overhead computing and communication and does not require additional overhead hardware; when each hop is split into three levels, the standardized location error is reduced by 65%. The RADV-HOP can reduce the standardized location error by 45%, compared to other enhanced DV-HOP, at the price of a small computational complexity and the same overhead connection. Location of nodes is one of WSN's main technologies. Considering the hardware and price factors, the DV-Hop is highly used. The primary location error of DV-Hop is the interval amid anonymous nodes and beacon nodes. The measurement error, which is

Table VI. Summary of Improved DV-Hop based on Distance derived from Goals and Analysis

Refs	Goals	Objective	simulator	Assessed factors	Area	Number of Nodes
[80]	optimized formulation to calculate the average hop-size of anchor nodes	minimize the localization error in the estimated distance between anchor and unknown node	MATLAB 2017a	1) Number of nodes 2) Number of beacon nodes	100*100	100 to 200
[81]	Developed DV-Hop Based on Minimum Hops Correction and Reevaluate Hop Distance	reducing the node positioning error	MATLAB	1) Position function error when improving the average hop distance 2) Position function error when improving the minimum hop count 3) Position function error when improving the average hop distance and the minimum hop count at the same time	100*100	200
[82]	Performance Evaluation of DV-HOP in WSNs	reducing localization error	MATLAB	1) local function Error Vs measurement of nodes for different values of Beacons 2) local function Error versus Beacon Node Ratio for Different Values of Communication Range 3) local function Error versus domain Range	100*100	50 to 300
[83]	Developed local function based on IMDV-hop for extensive WSNs	Accuracy and energy system performance has improved	NS2	1) local function error as a function of beacon ratio 2) local function delay for node density as a function of beacon ratio 3) local function energy for node density as a function of beacon ratio	100*100	100
[84]	Developed DV-HOP Based on High-Precision in WSN	reducing localization error	MATLAB	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100	100
[85]	An Improved DV-Hop based on Average Hop and Node Distance Optimization	lower error rate than the DV-Hop	MATLAB	1) Number of nodes 2) Number of beacon nodes	100*100	100
[86]	Developed DV-Hop with Jaccard Coefficient Based on Optimization of Distance Correction	high positioning accuracy	MATLAB R2014a	1) Average Positioning Error Under Different Domain Radius 2) Positioning Errors at Different Beacon Node Densities	100*100	150
[87]	An Energy-Efficient DV-Hop	decreasing network communications	MATLAB	1) The qualification of beacon densities on localization errors 2) The qualification of beacon densities on localizable sensor rates 3) The impact of node densities on localization errors	40*40	200 to 400
[88]	Beacon node Selection and Global Optimized Solution for DV-Hop in WSNs	better accuracy than DV-Hop	MATLAB	1) ratio of beacon nodes	100*100	100
[89]	Developed DV-Hop Based on Average Hop Distance and Estimated Coordinates	Increasing localization accuracy and reduce the positioning error	MATLAB	1) ratio of beacon nodes 2) Position error with communication radius changing	100*100	100
[90]	Developed centroid DV hop	more superior in terms of positioning error	MATLAB	1) Comparison by varying domain radius	300*300	100

				2) Comparison by varying total number of nodes		
[91]	DV-Hop for WSNs to reduce the error	better localization accuracy by minimizing the error	MATLAB 2008b	1) Maximum nodes number versus localization error 2) Percentage of beacon nodes versus localization error	200*200	400
[92]	Developed DV-Hop based on Modified Hop-Size	minimum localization error	MATLAB	Average localization error	300*300	2000
[93]	Developed DV-Hop Distributed Active Multi-Hop Local function	Increasing localization accuracy	OMNET ++	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	1000* 1000	50 to 100
[94]	Reinforcement of DV-hop in hybrid optical WSNs	improving the localization accuracy	MATLAB	1) Communication radius(m) 2) Number of nodes 3) Number of beacon nodes 4) Relative local function Error	100*100 50*200 400*400 10*40	30 to 200
[95]	Improvements of DV-Hop localization for WSNs	Low localization error	MATLAB	1) ratio of beacon nodes 2) Position error with communication radius	100*100	100
[96]	Power fruitful range-free localization for WSNs	better localization performance	MATLAB 2008b	1) Maximum nodes number versus localization error 2) Percentage of beacon nodes versus localization error	100*100	100
[97]	Developed DV-Hop Through Anchor Position Re-estimation	better performances in local function precision	MATLAB	1) measurement of Beacon Nodes 2) Maximum nodes number 3) Communication radius(m)	100*100	100 to 400
[98]	DV-hop-MSO based on local function in WSNs	decreasing local function error	MATLAB	1) appraisement of Beacon Nodes Density on the Positioning Error 2) The Effect of Network Connectivity on the Positioning Error 3) The Impact of Total Number of Nodes on Positioning Error	100*100	300
[99]	Improvement on Localization Error and Adaptability in DV-Hop	better local function performance	MATLAB	1) domain radius(m) 2) measurement of beacon nodes	200*200	100
[100]	Developed DV-hop Based on Iterative Computation for WSNs	better local function accuracy	MATLAB	1) local function error with multiple beacon nodes 2) local function error with different radio range of sensor nodes	100*100	100
[101]	Developed model Based on DV-Hop for WSNs	decreasing local function error	MATLAB	1) The relationship amid the number of beacons and localization error 2) The relationship amid the number of nodes and the localization error 3) The relationship amid communication and the localization error	100*100	200
[102]	Developed Local function for WSNs Based on DV-Hop	decreasing local function error	NS3	1) domain radius(m) 2) measurement of beacon nodes	100*100	50 to 300
[103]	Developed Local function model Based on DV-Hop for WSNs	decreasing local function error	MATLAB	1) domain radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100	200
[104]	Developed DV-Hop local function error for precise positioning	improve localization accuracy without increasing hardware cost	NS2	1) ratio of beacon nodes to anonymous nodes	100*100	250
[105]	Developed DV-	location accuracy is	NS2	1) domain radius(m)	100*100	100

	HOP Based on Beacon Nodes at Borderland of WSNs	high		2) measurement of nodes 3) measurement of beacon nodes		
[106]	Research of Developed DV-Hop in Coal Mine Monitoring Application for WSNs	enhancing positioning accuracy	NS2	1) local function Coverage Rate (The Proportion of Localization Nodes) 2) The measurement of Package Sending	100*100	200
[107]	Developed DV-Hop local function	decreasing local function error	NS2	Error location with multiple beacon nodes	200*200	200
[108]	RMADV-Hop: An Improved DV-Hop local function	high positioning accuracy	OMNET ++	1) domain radius(m) 2) measurement of beacon nodes	800*500	200
[109]	An Improved local function error on DV-Hop for WSNs	enhancing positioning accuracy	MATLAB	1) measurement of beacon nodes 2) local function Error vs Sensor Nodes	100*100	200
[110]	Developed DV-Hop with altered distance error for WSNs	reducing cumulative distance error	NS2	1) domain radius(m) 2) measurement of beacon nodes	100*100	100
[111]	An advanced DV-hop for Irregularly Shaped Sensor Networks	Reducing localization error and computational complexity	NS2	1) domain radius(m) 2) measurement of beacon nodes	100*100	300

the distance amid unspecified nodes and beacon nodes, was reduced by estimating the overall hop-length and RSSI value in [79], Simulation Findings indicated that this model of location is efficient, which increases the precision of location.

C. Improved DV-Hop based on Distance Vector

In this strategy, with the assistance of location data and the hop count obtained from beacon nodes, anonymous nodes estimate their location data. Beacon nodes are provided with GPS tools and sporadically reports a beacon consists of identity, location data, and hop threshold [112]. All anonymous nodes within the neighborhood beacon nodes check for hop threshold. If the anonymous nodes hop amount is lower than the hop threshold, improving the hop count by 1 will send further beacon. Else the beacon will be dismissed. Sending the message in this way helps to keep up minimum hop count with each beacon node within the network.

Table VI summarizes the improved DV-Hop papers based on distance derived from analysis and results.

D. Improved DV-Hop based on Weighted Centroid

WCL means an improvement of centroid localization approach. Arranges of anonymous node stays at the centroid of the polygon developed by beacon nodes in this approach [127]. It is allowed that an anonymous node estimates its location (x, y) from the locations of beacon nodes as below:

$$(x, y) = \left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right) \tag{9}$$

Table VII. Summary of Improved DV-Hop based on Weighted Centroid derived from Goals and Analysis

Refs	Goals	Objective	simulator	Assessed factors	Area	Number of Nodes
[113]	DV-HOP Based Hybrid Range-Free Localization Methods for WSNs	high localization accuracy	MATLAB	1) measurement of beacon nodes vs. local function error 2) communication range vs. local function error 3) Increasing number of nodes vs. local function error	500*500	1500
[114]	A New Distance Vector-Hop Localization Based on Half-Measure Weighted Centroid	reducing the localization's average error	MATLAB	1) Communication radius(m) 2) measurement of nodes 3) measurement of beacon nodes	100*100	100
[115]	Developed Location Model Based on DV-Hop for Indoor Internet of Things	improving the information localization and perception accuracy	MATLAB	measurement of beacon nodes	100*100	100
[116]	Developed DV-Hop Using Locally Weighted Linear Regression in Anisotropic WSNs	Increasing localization accuracy	MATLAB R2013b	1) measurement of Beacon Nodes Density on the Positioning Error 2) measurement of maximum of Nodes on Positioning Error	1000*1000	200
[117]	DV-Hop Localization Model Based on Minimum Mean Square Error in Internet of Things	increased significantly in the positioning accuracy	MATLAB	1) Comparison of the Number of Different Beacon Nodes 2) Comparison of different domain radius positioning effects 3) Comparison of the Total Positioning Effect of various Nodes	100*100	100 to 200
[118]	An Improved DV-Hop via Inverse Distance Weighting Method in WSNs	high positioning accuracy and no increasing complexity and cost	MATLAB R2015b	1) The position error with domain radius(m)	100*100	200
[119]	A weighted centroid localization model for randomly deployed WSNs	Low localization error and low power consumption	MATLAB	1) outcome on local function error ratio by varying the beacon ratio 2) outcome on local function error ratio when varying domain radius 3) outcome on local function error when varying total number of nodes 4) outcome on average energy system	500*500	500
[120]	Weighted DV-Hop Positioning in WSNs	Low localization error and low power consumption	MATLAB	1) domain radius(m) 2) Maximum sensors number 3) Maximum beacons number	100*100	100
[121]	Developed Hop Size prediction for DV-hop in WSNs	superiority in localization accuracy	MATLAB R2012b	1) Maximum Nodes Number 2) Ratio of Beacon to Maximum Node Number 3) domain Radius	100*100	100
[122]	Developed DV-Hop Model Based on the Node Deployment in WSNs	Increasing localization accuracy	MATLAB	1) Maximum Nodes Number 2) Ratio of Beacon Nodes to Maximum Nodes Number	100*100	100
[123]	A patient Tracking and Positioning system based on improved DV-Hop	High positioning accuracy	NS2	1) Ratio of Beacon Nodes to Maximum Nodes Number	100*100	100

[124]	An improvement of DV-Hop model for WSNs	improving the positioning accuracy	MATLAB	1) The outcome of the beacon node on the local function error 2) the outcome on positioning error of the maximum of nodes 3) The outcome of threshold M on the positioning error	100*100	100
[125]	An Advanced DV-Hop for WSNs	Increasing localization accuracy	MATLAB 2008b	1) measurement on Maximum Nodes 2) Ratio of beacon nodes to maximum nodes number 3) radius of sensor node	100*100	100
[126]	DV-Hop Based on Centroid in WSNs	Increasing localization accuracy	NS2	1) measurement on maximum nodes 2) Ratio of Beacon to maximum nodes number	100*100	100 to 200

Furthermore, the distance amid unidentified node and beacon node is regarded as weight and this ratio is increased by coordinates of beacon nodes and then divided by the amount of weights in order to obtain the location data. Let $W(i)$ is the weight ratio that is estimated amid k beacon nodes using these weight values as below:

$$(x, y) = \left(\frac{\sum_{i=1}^{k} W(i) \times x_i}{\sum_{i=1}^{k} W(i)}, \frac{\sum_{i=1}^{k} W(i) \times y_i}{\sum_{i=1}^{k} W(i)}\right) \tag{10}$$

Table VII summarizes improved DV-Hop papers based on weighted centroid derived from analysis and results.

V. DISCUSSION

Using the average per-hop distance item and the hops the location model for DV-Hop estimates the distance. Considerably, DV-Hop's accuracy is calculated by estimating the average per-hop distance. All nodes in the dense networks must be distributed uniformly to create DV-Hop's average per-hop distance in a sensible prediction range, but it is very hard to accomplish the even propagation of nodes in the actual setting, so DV-Hop's location error rises.

The localization model for DV-Hop has several requirements for beacon node density. The error of location is much lower and the beacon node density is higher. When the density reaches a certain proportion, the propagation of beacon nodes is more even, the location error will be lower. Enhancing beacon node density implies a rise in beacon node numbers. Since a beacon node's cost is one hundred

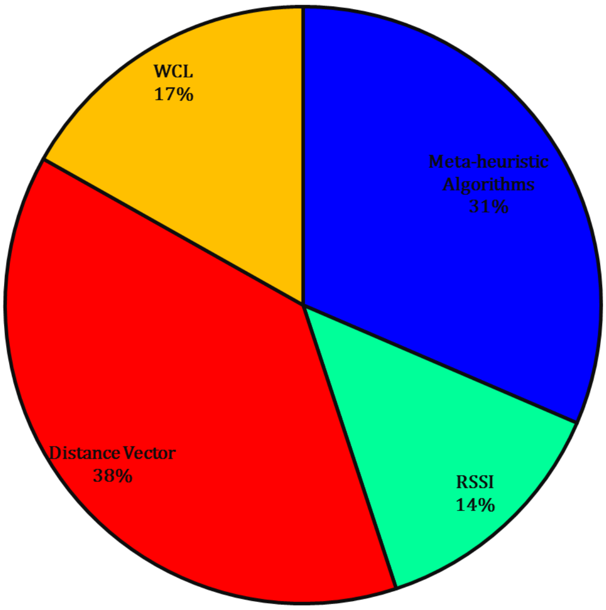

Fig. 4. Percentage of models used to enhance DV-Hop.

times higher than a normal node, enhancing node density significantly improves network expenses. But if propagation is very hard as well, the beacon nodes can be set artificially.

There is also some dependency on the value of hops in the DV-Hop localization. Two nodes can be linked within their connection radius based on connectivity, i.e. the distance amid two nodes within one hop can be far or close. So, if the distance hops values of two such nodes are registered as one, some location errors will lead.

Based on node connectivity, the location model for DV-Hop calculates the distance. Therefore, it is possible to solve the problem that the range-based location cannot find the anonymous nodes when the anonymous nodes do not interact directly with beacon nodes. Connectivity-based technology, though has two significant issues. First, it is possible that the positioning error quickly collect and spread, therefore localization efficiency can be impacted. Second, environmental barriers can influence network connectivity, ultimately resulting in a low position precision [128].

Fig. (4) indicates the proportion of DV-Hop efficiency of meta-heuristic algorithms, RSSI, Distance Vector, and WCL. It can be seen from Fig. (4) that the proportion of Distance Vector is greater than in meta-heuristic algorithms, RSSI, and WCL.

RSSI is a type of technology used to regulate the attenuation of the signal. RSSI is used as an assistant positioning approach in the DV-Hop to restrict the quantity of hops and the overall jump distance. The RSSI is used to enhance the approach of distance estimate and to create feedback channels amid anonymous nodes and beacons that integrate precise location. The location error channels can be dramatically decreased by these feedbacks and support the capacity for distinct network design to self-stabilize. In Localization Accuracy, Node Density, Beacon Density,

Table VIII. Comparison of Proposed Models derived from Meta-heuristic Algorithms for Improved DV-Hop

Refs	Localization error	Node density	beacon density	Positioning Error	Transmission Range	Energy consumption	Computational Time	Run Time
[41]	Low	Normal	Medium	Medium	Small	Low	Medium	Medium
[42]	High	Normal	Medium	Low	Medium	Low	High	Medium
[43]	High	Medium	Low	Low	Small	Medium	Medium	Low
[44]	Medium	Normal	Low	Low	Small	Low	Medium	Low
[45]	Medium	Normal	High	Low	Medium	Low	Medium	Medium
[46]	Medium	Normal	Low	Medium	Small	Low	Medium	Low
[47]	High	Normal	Low	Low	Small	Low	High	Medium
[48]	High	Normal	Low	Medium	Small	Medium	High	High
[49]	Medium	Normal	Medium	Low	Small	Low	High	High
[50]	High	Normal	Medium	Low	Medium	Low	High	High
[51]	High	Medium	Medium	Low	Small	Medium	High	Medium
[52]	High	Normal	Low	Low	Small	Low	High	High
[53]	High	Normal	Medium	Medium	Small	Low	High	Low
[54]	High	Normal	Low	Low	Small	Medium	High	Medium
[55]	Medium	Normal	High	Medium	Small	Low	Medium	Low
[56]	High	Normal	High	Low	Small	Low	Medium	Medium
[57]	High	Normal	Low	Low	Small	Medium	Medium	Low
[58]	High	Medium	Low	Low	Small	Medium	Medium	Medium
[59]	High	Normal	Medium	Low	Small	Medium	High	Medium
[60]	Medium	Normal	Low	Medium	Small	Low	High	High
[61]	High	Normal	Low	Low	Small	Low	High	Low
[62]	High	Normal	Low	Low	Small	Medium	High	Medium
[63]	Medium	Medium	Medium	Medium	Large	Medium	Medium	Low
[64]	High	Normal	Low	Low	Small	Medium	Medium	High
[65]	High	Medium	Medium	Medium	Medium	High	High	Medium

Positioning Error, Transmission Range, Energy Consumption, Computational Time, and Run Time, we have described localization models as seen in Tables VIII to XI.

Table VIII shows a comparison of the proposed models derived from meta-heuristic algorithms for Improved DV-Hop based on various factors.

Table IX shows a comparison of the proposed models derived from RSSI in order to Improved DV-Hop based on various factors. Table X shows a comparison of the proposed models derived from Distance Vector in order to Improved DV-Hop based on various factors.

Table IX. Comparison of the Proposed Models derived from RSSI for Improved DV-Hop

Refs	Localization error	Node density	beacon density	Positioning Error	Transmission Range	Energy consumption	Computational Time	Run Time
[68]	Medium	Normal	Medium	Medium	Medium	Low	High	Medium
[69]	High	High	Medium	Low	Small	Medium	Medium	Medium
[70]	Medium	Normal	High	Low	Medium	Low	High	High
[71]	High	Normal	High	Medium	Medium	Medium	Medium	High
[72]	Medium	Normal	Medium	Medium	Medium	Low	High	Medium
[73]	Medium	Normal	High	Low	Small	Medium	Medium	High
[74]	High	High	Medium	Medium	Small	Low	Medium	Medium
[75]	High	Normal	High	Low	Small	Low	Medium	High
[76]	High	Medium	Medium	Low	Medium	Low	High	High
[77]	High	Normal	Medium	Low	Small	Medium	Medium	Medium
[78]	High	Normal	High	Low	Small	Medium	Medium	Medium
[79]	Medium	Normal	High	Low	Small	Low	Medium	High

Table X. Comparison of Proposed Models derived from Distance Vector for Improved DV-Hop

Refs	Localization error	Node density	beacon density	Positioning Error	Transmission Range	Energy consumption	Computational Time	Run Time
[80]	Medium	Normal	Low	Medium	Medium	Low	Medium	Low
[81]	High	Normal	Low	Low	Small	Low	High	High
[82]	Medium	High	Low	Low	Medium	Low	Medium	High
[83]	High	Normal	Low	Medium	Small	Low	Medium	High
[84]	Medium	Normal	Medium	Low	Small	Medium	Medium	High
[85]	Medium	Normal	Medium	Low	Small	Medium	Medium	High
[86]	Medium	High	Low	Low	Medium	Low	Medium	High
[87]	High	Normal	Low	Medium	Medium	Low	Medium	High
[88]	High	Normal	Low	Medium	Medium	Low	Medium	Medium
[89]	Medium	Normal	Low	Medium	Medium	Low	High	Medium
[90]	High	High	Low	Low	Small	Low	High	Medium
[91]	High	Normal	Low	Low	Small	Low	High	High
[92]	Medium	Normal	Medium	Low	Small	Low	High	Medium
[93]	Medium	Normal	Medium	Low	Medium	Low	Medium	High
[94]	High	High	Medium	Low	Medium	Low	High	High
[95]	High	High	Medium	Low	Small	Low	High	Medium
[96]	Medium	Normal	Low	Low	Small	Low	High	Medium
[97]	High	Normal	Low	Medium	Small	Low	High	Medium
[98]	Medium	High	Medium	Medium	Medium	Low	High	Medium
[99]	High	Normal	Low	Medium	Medium	Medium	Medium	Medium
[100]	Medium	Normal	Low	Low	Medium	Medium	High	Medium
[101]	High	High	Low	Low	Medium	Medium	High	High
[102]	Medium	Normal	Medium	Low	Medium	Low	Medium	Medium
[103]	Medium	Normal	Medium	Low	Small	Low	Medium	High
[104]	Medium	Normal	Medium	Low	Medium	Low	High	Medium
[105]	High	High	Medium	Medium	Small	Low	High	Medium
[106]	Medium	Normal	Medium	Medium	Medium	Low	Medium	High
[107]	High	Normal	Low	Medium	Small	Medium	Medium	Medium
[108]	Medium	Normal	Low	Low	Medium	Medium	Medium	Medium
[109]	High	Normal	Low	Medium	Medium	Medium	Medium	Medium
[110]	Medium	Normal	Low	Low	Small	Low	High	High
[111]	High	High	High	Low	Medium	Low	High	High

Table XI shows a comparison of the proposed models derived from WCL for Improved DV-Hop based on various factors.

Table XI. Comparison of the Proposed Models derived from WCL for Improved DV-Hop

Refs	Localization error	Node density	beacon density	Positioning Error	Transmission Range	Energy consumption	Computational Time	Run Time
[113]	High	High	High	Low	Small	Low	High	Medium
[114]	High	Normal	Low	Low	Small	Low	Medium	Medium
[115]	High	Normal	Low	Low	Small	Medium	High	High
[116]	High	High	Medium	Medium	Medium	Low	High	Medium
[117]	High	Normal	Low	Medium	Medium	Medium	Medium	Medium
[118]	High	Normal	Low	Low	Medium	Medium	High	Medium
[119]	High	High	Low	Low	Small	Medium	High	High
[120]	High	Normal	Medium	Low	Medium	Low	Medium	Medium
[121]	Medium	Normal	Medium	Low	Small	Low	Medium	High
[122]	Medium	Normal	Medium	Low	Medium	Low	High	High
[123]	High	High	Medium	Medium	Small	Medium	High	Medium
[124]	High	Normal	Medium	Low	Medium	Low	Medium	High
[125]	High	Normal	Low	Medium	Small	Low	High	Medium
[126]	High	High	Low	Medium	Small	Medium	Medium	Medium

VI. Conclusion and Future Works

Using the recognized locations of beacon nodes, location in a WSN is the method of discovering location by a location anonymous node**.** Based on the protocol for distance vector routing the localization model for DV-Hop is a distributed model for range-free localization. The primary concept is to determine the distances amid beacon nodes and anonymous nodes by increasing the average hop distance of beacon nodes in WSNs by the hop count. The intention and purpose of this study was to raise awareness among experts of different methods for the recognition of WSNs Localization models. In this paper, we review the four primary techniques of enhancing DV-Hop. The most commonly used approaches were meta-heuristic algorithms, RSSI, distance vector, and WCL for location. Analyzes showed that distance vector models play a major role in improving DV-Hop. Other environments, such as underwater, underground, body, mobile and multimedia, can be used for some open problems for future localization research.

References

[1] C. Singhal and V. Patil, "HCR-WSN: Hybrid MIMO cognitive radio system for wireless sensor network," *Computer Communications*, vol. 169, no. 1, pp. 11-25, March 2021.

[2] G. Farjamnia, Y. Gasimov, and C. kazimov, "An Improved DV-Hop for Detecting Wormhole Attacks in Wireless Sensor Networks," J*ournal of Communication Engineering,* vol. 9, no. 1, pp. 29-52, Feb. 2020.

[3] G. Farjamnia, Y. Gasimov, and C. Kazimov, "Review of the Techniques Against the Wormhole Attacks on Wireless Sensor Networks," *Wireless Personal Communications,* vol. 105, No. 4, pp. 1561-1584, April 2019.

[4] V. Kanwar and A. Kumar, "DV-Hop localization methods for displaced sensor nodes in wireless sensor network using PSO," *Wireless Networks,* vol. 27, No. 1, pp. 91-102, Jan. 2021.

[5] P. Dewal, G.S. Narula, V. Jain, and A. Baliyan, "Security Attacks in Wireless Sensor Networks: A Survey," i*n Cyber Securit*y, Singapore: Springer Singapore, June 2018.

[6] V. Kanwar and A. Kumar, "DV-Hop-based range-free localization algorithm for wireless sensor network using runner-root optimization," *The Journal of Supercomputing*, vol. 77, No. 3, pp. 3044-3061, July 2021.

[7] V. Choudhary and S. Taruna, "A Distributed Key Management Protocol for Wireless Sensor Network," *in Advanced Informatics for Computing Research*, Singapore: Springer Singapore, Nov. 2019.

[8] S. Lalar, S. Bhushan, and Surender, "Performance Analysis of Clone Node Attack in Wireless Sensor Network," *in Proceedings of 2nd International Conference on Communication, Computing and Networking*, Singapore: Springer Singapore, Dec. 2019.

[9] D. Giri, S. Borah, and R. Pradhan, "Approaches and Measures to Detect Wormhole Attack in Wireless Sensor Networks: A Survey," *in Advances in Communication, Devices and Networking, Singapore:* Springer Singapore, May 2018.

[10] Q.-w. Chai, S.-C. Chu, J.-S. Pan, P. Hu, and W.-m. Zheng, "A parallel WOA with two communication strategies applied in DV-Hop localization method," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, No. 1, pp. 50, Feb. 2020.

[11] G. Han, H. Xu, T.Q. Duong, J. Jiang, and T. Hara, "Localization algorithms of Wireless Sensor Networks: a survey," *Telecommunication Systems,* vol. 52, No. 4, pp. 2419-2436, April 2013.

[12] V. Vivekanandan and V.W.S. Wong, "Concentric Anchor Beacon Localization Algorithm for Wireless Sensor Networks," *IEEE Transactions on Vehicular Technology*, vol. 56, No. 5, pp. 2733-2744, Sep. 2007.

[13] N. Bulusu, J. Heidemann, and D. Estrin, “GPS-less low-cost outdoor localization for very small devices,” *IEEE Personal Communications*, vol. 7, No. 5, pp. 28-34, Oct. 2000.

[14] H. Shoufeng, Z. Xiaojia, and L. Xinxin, “A novel DV-Hop localization algorithm for asymmetry distributed wireless sensor networks,” *in 2010 3rd International Conference on Computer Science and Information Technology*, May 2010.

[15] L. Doherty, K.S.J. pister, and L.E. Ghaoui, “Convex position estimation in wireless sensor networks,” *in Proceedings IEEE INFOCOM 2001. Conference on Computer Communications. Twentieth Annual Joint Conference of the IEEE Computer and Communications Society (Cat. No.01CH37213)*, April 2001.

[16] T. He, C. Huang, B.M. Blum, J.A. Stankovic, and T. Abdelzaher, "Range-free localization schemes for large scale sensor networks," *in Proceedings of the 9th annual international conference on Mobile computing and networking.* Dec. 2003, Association for Computing Machinery: San Diego, CA, USA. p. 81–95.

[17] S. Yi and W. Ruml, “Improved MDS-based localization,” *in IEEE INFOCOM* 2004, March 2004.

[18] Y. Shang, W. Ruml, Y. Zhang, and M.P.J. Fromherz, Localization from mere connectivity, *in Proceedings of the 4th ACM international symposium on Mobile ad hoc networking & computing.* March 2003, Association for Computing Machinery: Annapolis, Maryland, USA. p. 201–212.

[19] A. Ouyang, Y. Lu, Y. Liu, M. Wu, and X. Peng, “An Improved Adaptive Genetic Algorithm based on DV-Hop for Locating Nodes in Wireless Sensor Networks,” *Neurocomputing*, vol. 458, No. 1, pp. 500-510, Jan. 2021.

[20] J. Lee, W. Chung, and E. Kim, “A new range-free localization method using quadratic programming,” *Computer Communications*, vol. 34, No. 8, pp. 998-1010, June 2011.

[21] S. Sivasakthiselvan and V. Nagarajan, “A new localization technique for node positioning in wireless sensor networks,” *Cluster Computing*, vol. 22, No. 2, pp. 4027-4034, March 2019.

[22] M. Bal, L. Min, S. Weiming, and H. Ghenniwa, “Localization in cooperative Wireless Sensor Networks: A review,” *in 2009 13th International Conference on Computer Supported Cooperative Work in Design*, April 2009.

[23] A. Ghebleh, M. Abbaspour, and S. Homayounnejad, “A Centralized Approach for Secure Location Verification in Wireless Sensor Networks,” *in Sensor Systems and Software*, Berlin, Heidelberg: Springer Berlin Heidelberg, Oct. 2011.

[24] C. Poellabauer, Range-Free Localization Techniques, in The Art of Wireless Sensor Networks: Volume 1: Fundamentals, H.M. Ammari, Editor. Oct. 2014, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 353-384.

[25] M. Hamdani, U. Qamar, W.H. Butt, F. Khalique, and S. Rehman, “A Comparison of Modern Localization Techniques in Wireless Sensor Networks (WSNs),” *in Proceedings of the Future Technologies Conference (FTC) 2018*, Cham: Springer International Publishing, Oct. 2019.

[26] X. Shen, Z. Wang, P. Jiang, R. Lin, and Y. Sun, “Connectivity and RSSI Based Localization Scheme for Wireless Sensor Networks,” in Advances in Intelligent Computing, Berlin, Heidelberg: Springer Berlin Heidelberg, Oct. 2005.

[27] T. Chen, L. Sun, Z. Wang, Y. Wang, Z. Zhao, and P. Zhao, “An enhanced nonlinear iterative localization algorithm for DV_Hop with uniform calculation criterion,” *Ad Hoc Networks*, vol. 111, No. 1, pp. 102327, Feb. 2021.

[28] X. Yang, J. Ma, and Y. Lu, “Research on Localization Scheme of Wireless Sensor Networks Based on TDOA,” *in Computational Intelligence and Intelligent Systems*, Singapore: Springer Singapore, Nov. 2018.

[29] T.-X. Cong, E.-C. Kim, and I. Koo, “RSS Based Localization Scheme Using Angle-Referred Calibration in Wireless Sensor Networks,” *in Advanced Intelligent Computing Theories and Applications. With Aspects of Theoretical and Methodological Issues*, Berlin, Heidelberg: Springer Berlin Heidelberg, Dec. 2008.

[30] F. Liu, X. Cheng, D. Hua, and D. Chen, “TPSS: A Time-Based Positioning Scheme for Sensor Networks with Short Range Beacons,” *in Networking and Mobile Computing*, Berlin, Heidelberg: Springer Berlin Heidelberg, Dec. 2005.

[31] S. Halder and A. Ghosal, “A survey on mobile anchor assisted localization techniques in wireless sensor networks,” *Wireless Networks*, vol. 22, No. 7, pp. 2317-2336, Oct. 2016.

[32] S. Parulpreet, K. Arun, K. Anil, and K. Mamta, Computational Intelligence Techniques for Localization in Static and Dynamic Wireless Sensor Networks—A Review, *in Computational Intelligence in Sensor Networks,* B.B. Mishra, et al., Editors. May 2019, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 25-54.

[33] M. Nabil, R.A. Ramadan, H. ElShenawy, and A. ElHennawy, "A Comparative Study of Localization Algorithms in WSNs," *in Advanced Machine Learning Technologies and Applications,* Berlin, Heidelberg: Springer Berlin Heidelberg, Nov. 2012.

[34] Y. Zeng, J. Cao, J. Hong, S. Zhang, and L. Xie, "Secure localization and location verification in wireless sensor networks: a survey," T*he Journal of Supercomputing*, vol. 64, No. 3, pp. 685-701, June 2013.

[35] W. Wang, H. Shi, P. Huang, F. Wu, D. Fang, X. Chen, and Y. Xiao, "A Self-Localization Scheme with Grid-Based Anchor Selection in Wireless Sensor Networks," *in Advances in Wireless Sensor Networks*, Berlin, Heidelberg: Springer Berlin Heidelberg, Dec. 2015.

[36] S. Pandey and S. Varma, "A Range Based Localization System in Multihop Wireless Sensor Networks: A Distributed Cooperative Approach," *Wireless Personal Communications*, vol. 86, No. 2, pp. 615-634, Jan 2016.

[37] D. Niculescu and N. Badri, "Ad hoc positioning system (APS) using AOA," *in IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No.03CH37428),* March 2003.

[38] D. Niculescu and B. Nath, "Ad hoc positioning system (APS)," *in GLOBECOM'01. IEEE Global Telecommunications Conference (Cat. No.01CH37270),* Nov. 2001.

[39] T. Chen, L. Sun, Z. Wang, Y. Wang, Z. Zhao, and P. Zhao, "An enhanced nonlinear iterative localization algorithm for DV_Hop with uniform calculation criterion," *Ad Hoc Networks*, vol. 111, No., pp. 102327, May 2021.

[40] C. Müller, D.I. Alves, B.F. Uchôa-Filho, R. Machado, L.L. de Oliveira, and J.B.S. Martins, "Improved solution for node location multilateration algorithms in wireless sensor networks," *Electronics Letters*, vol. 52, No. 13, pp. 1179-1181, June 2016.

[41] J. Li, M. Gao, J.-S. Pan, and S.-C. Chu, "A parallel compact cat swarm optimization and its application in DV-Hop node localization for wireless sensor network," *Wireless Networks*, vol. No., pp. Feb 2021.

[42] Y. Huang and L. Zhang, "Weighted DV-Hop Localization Algorithm for Wireless Sensor Network based on Differential Evolution Algorithm," *in 2019 IEEE 2nd International Conference on Information and Computer Technologies (ICICT),* Nov. 2019.

[43] P. Huang, X. Xiang, and B. Huang, "Research on the DV-Hop Location Algorithm Based on the Particle Swarm Optimization for the Automatic Driving Vehicle," *in Advancements in Smart City and Intelligent Building*, Singapore: Springer Singapore, April 2019.

[44] S.P. Singh and S.C. Sharma, "Performance Evaluation of Improved Localization Algorithm for Wireless Sensor Networks," *in Smart Innovations in Communication and Computational Sciences,* Singapore: Springer Singapore, Dec 2019.

[45] V. Annepu and A. Rajesh, "Implementation of self adaptive mutation factor and cross-over probability based differential evolution algorithm for node localization in wireless sensor networks," *Evolutionary Intelligence*, vol. 12, No. 3, pp. 469-478, March 2019.

[46] X. Yu and M. Hu, "Hop-Count Quantization Ranging and Hybrid Cuckoo Search Optimized for DV-HOP in WSNs," *Wireless Personal Communications,* vol. 108, No. 4, pp. 2031-2046, Oct. 2019.

[47] L. Song, L. Zhao, and J. Ye, "DV-Hop Node Location Algorithm Based on GSO in Wireless Sensor Networks," *Journal of Sensors,* vol. 2019, No., pp. 2986954, Feb. 2019.

[48] C. Zhou, Y. Yang, and Y. Wang, "DV-Hop localization algorithm based on bacterial foraging optimization for wireless multimedia sensor networks," *Multimedia Tools and Applications*, vol. 78, No. 4, pp. 4299-4309, Feb. 2019.

[49] J. Lu and D. Zhao, "A New DV-Hop Location of Wireless Sensor Networks Based on Firefly Algorithm," *in International Conference on Applications and Techniques in Cyber Security and Intelligence ATCI 2018*, Cham: Springer International Publishing, Nov. 2019.

[50] X. Liu and C. Liu, "Wireless Sensor Network Dynamic Mathematics Modeling and Node Localization," *Wireless Communications and Mobile Computing,* vol. 2018, No., pp. 1082398, May 2018.

[51] A. Kaur, P. Kumar, and G.P. Gupta, "Nature Inspired Algorithm-Based Improved Variants of DV-Hop Algorithm for Randomly Deployed 2D and 3D Wireless Sensor Networks," *Wireless Personal Communications,* vol. 101, No. 1, pp. 567-582, July 2018.

[52] F. Zhou and S. Chen, "DV-Hop Node Localization Algorithm Based on Improved Particle Swarm Optimization," *in Communications, Signal Processing, and Systems,* Singapore: Springer Singapore, Oct. 2018.

[53] Q. Shi, Q. Xu, and J. Zhang, "An Improved DV-Hop Scheme Based on Path Matching and Particle Swarm Optimization Algorithm," *Wireless Personal Communications,* vol. 104, No. 4, pp. 1301-1320, Feb 2019.

[54] L. Cui, C. Xu, G. Li, Z. Ming, Y. Feng, and N. Lu, "A high accurate localization algorithm with DV-Hop and differential evolution for wireless sensor network," *Applied Soft Computing*, vol. 68, No., pp. 39-52, July 2018.

[55] G. Sharma and A. Kumar, "Improved DV-Hop localization algorithm using teaching learning based optimization for wireless sensor networks," *Telecommunication Systems*, vol. 67, No. 2, pp. 163-178, Feb. 2018.

[56] S.P. Singh and S.C. Sharma, "A PSO Based Improved Localization Algorithm for Wireless Sensor Network," *Wireless Personal Communications*, vol. 98, No. 1, pp. 487-503, Jan. 2018.

[57] T. Najeh, H. Sassi, and N. Liouane, "A Novel Range Free Localization Algorithm in Wireless Sensor Networks Based on Connectivity and Genetic Algorithms," *International Journal of Wireless Information Networks*, vol. 25, No. 1, pp. 88-97, March2018.

[58] M. Mehrabi, H. Taheri, and P. Taghdiri, "An improved DV-Hop localization algorithm based on evolutionary algorithms," *Telecommunication Systems,* vol. 64, No. 4, pp. 639-647, April 2017.

[59] H. Huang, H. Chen, S. Cheng, and F. Li, "An improved DV-HOP algorithm for indoor positioning based on Bacterial Foraging Optimization," *in 2016 8th International Conference on Wireless Communications & Signal Processing (WCSP),* Dec. 2016.

[60] Z. Cui, B. Sun, G. Wang, Y. Xue, and J. Chen, "A novel oriented cuckoo search algorithm to improve DV-Hop performance for cyber–physical systems," *Journal of Parallel and Distributed Computing,* vol. 103, No., pp. 42-52, May 2017.

[61] B. Peng and L. Li, "An improved localization algorithm based on genetic algorithm in wireless sensor networks," *Cognitive Neurodynamics,* vol. 9, No. 2, pp. 249-256, Jan. 2015.

[62] C. Chuan, G. Zhiqiang, L. Lixia, and W. Qiwu, "AN improved DV-Hop location algorithm based on composite Particle Swarm Optimization," *in Third International Conference on Cyberspace Technology (CCT 2015),* Oct. 2015.

[63] K.R. Xiaoying Yang, "An Improved DV-Hop Algorithm Based on Artificial Fish Swarm Algorithm," C*hemical Engineering Transaction*s, vol. 46, No. 1, pp. 223-228, Dec. 2015.

[64] Q.-g. Zhang and M. Cheng, "A Node Localization Algorithm for Wireless Sensor Network Based on Improved Particle Swarm Optimization," *in Mechatronics and Automatic Control Systems,* Cham: Springer International Publishing, Dec. 2014.

[65] X. Chen and B. Zhang, "Improved DV-Hop Node Localization Algorithm in Wireless Sensor Networks," *International Journal of Distributed Sensor Networks*, vol. 8, No. 8, pp. 213980, Aug. 2012.

[66] Z. Wang and J. Chong, "Research on Improved DV-HOP Localization Algorithm Based on RSSI," *in 2020 International Conference on Computer Network, Electronic and Automation (ICCNEA)*, Sep. 2020.

[67] T. Chen, L. Sun, Z. Wang, Y. Wang, Z. Zhao, and P. Zhao, "An enhanced nonlinear iterative localization algorithm for DV_Hop with uniform calculation criterion," *Ad Hoc Networks,* vol. 111, No., pp. 102327, 2021.

[68] X. Ding and S. Dong, "Improving Positioning Algorithm Based on RSSI," *Wireless Personal Communications,* vol. 110, No. 4, pp. 1947-1961, Oct. 2020.

[69] G.M.B. Omar Cheikhrouhou, and Roobaea Alroobaea, "A Hybrid DV-Hop Algorithm Using RSSI for Localization in Large-Scale Wireless Sensor Networks," *Sensors*, vol. 18, No. 1, pp. 1-14, Nov. 2018.

[70] E. Mohamed, H. Zakaria, and M.B. Abdelhalim, "An Improved DV-Hop Localization Algorithm," *in Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2016,* Cham: Springer International Publishing, June 2017.

[71] H. Shi and L. Peng, "An Improved DV-Hop Node Localization Algorithm Combined with RSSI Ranging Technology," *in Proceedings of the 5th International Conference on Electrical Engineering and Automatic Control,* Berlin, Heidelberg: Springer Berlin Heidelberg, April2016.

[72] H. Xie, W. Li, S. Li, and B. Xu, "An improved DV-Hop localization algorithm based on RSSI auxiliary ranging," *in 2016 35th Chinese Control Conference (CCC),* Sep. 2016.

[73] F. Liu and G.-z. Feng, "Research on Improved DV-Hop Localization Algorithm Based on RSSI and Feedback Mechanism," *in Advances in Wireless Sensor Networks,* Berlin, Heidelberg: Springer Berlin Heidelberg, Sep. 2015.

[74] X. Yang, M. Liu, and D. Deng, "An improved DV-Hop algorithm based on RSSI for WSN," *in 2015 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, Sep. 2015.

[75] Y. Wang and K. Qian, "An improved DV-HOP positioning algorithm based on Hop distance correction," *in 2014 11th International Computer Conference on Wavelet Actiev Media Technology and Information Processing(ICCWAMTIP)*, Dec. 2014.

[76] Z. Guo, L. Min, H. Li, and W. Wu, "Improved DV-Hop Localization Algorithm Based on RSSI Value and Hop Correction," *in Advances in Wireless Sensor Networks,* Berlin, Heidelberg: Springer Berlin Heidelberg, Oct. 2013.

[77] Y. Hu, Z. Shan, and H. Yu, "Research on Improved DV-HOP Localization Algorithm Based on the Ratio of Distances," *in Internet of Things*, Berlin, Heidelberg: Springer Berlin Heidelberg, May 2012.

[78] X.Y. A. Zhang, H. Hu, X. Ding, "Improved DV-HOP positioning algorithm based on one-hop subdivision and average hopping distance modification," *Chinese Journal of Scientific Instrument,* vol. 33, No. 11, pp. 2552-2559, Dec. 2012.

[79] Z. Jungang, W. Chengdong, C. Hao, and X. Yang, "An improved DV-Hop localization algorithm," *in 2010 IEEE International Conference on Progress in Informatics and Computing,* May 2010.

[80] S. Messous, H. Liouane, and N. Liouane, "Improvement of DV-Hop localization algorithm for randomly deployed wireless sensor networks," *Telecommunication Systems,* vol. 73, No. 1, pp. 75-86, July 2020.

[81] W. Fang, H. Xu, and G. Yang, "Improved DV-Hop Algorithm Based on Minimum Hops Correction and Reevaluate Hop Distance," *in 2019 5th International Conference on Information Management (ICIM),* March 2019.

[82] V. Gupta and B. Singh, "Performance Evaluation of DV-HOP Localization Algorithm in Wireless Sensor Networks," *in Soft Computing: Theories and Applications,* Singapore: Springer Singapore, Sep. 2018.

[83] J. Zhu, C. Lv, and Z. Tao, "An improved localization scheme based on IMDV-hop for large-scale wireless mobile sensor aquaculture networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2018, No. 1, pp. 174, July 2018.

[84] P. Gou, F. Li, X. Han, and X. Jia, "An Improved DV-HOP Localization Algorithm Based on High-Precision in WSN," *in 2018 International Conference on Robots & Intelligent System (ICRIS)*, May 2018.

[85] F. Zeng, W. Li, and X. Guo, "An Improved DV-Hop Localization Algorithm Based on Average Hop and Node Distance Optimization," *in 2018 2nd IEEE Advanced Information Management,Communicates,Electronic and Automation Control Conference (IMCEC)*, June 2018.

[86] W. Fang, G. Yang, and Z. Hu, "An Improved DV-Hop Algorithm with Jaccard Coefficient Based on Optimization of Distance Correction," *in Bio-inspired Computing: Theories and Applications,* Singapore: Springer Singapore, Feb. 2018.

[87] M. Liu, B. Huang, Q. Miao, and B. Jia, “An Energy-Efficient DV-Hop Localization Algorithm,” *in Algorithms and Architectures for Parallel Processing,* Cham: Springer International Publishing, June 2018.

[88] L. Gui, X. Zhang, Q. Ding, F. Shu, and A. Wei, “Reference Anchor Selection and Global Optimized Solution for DV-Hop Localization in Wireless Sensor Networks,” *Wireless Personal Communications,* vol. 96, No. 4, pp. 5995-6005, Oct. 2017.

[89] W. Gao, Y. Sun, W. Li, and W. Wang, “An improved DV-Hop algorithm based on average hop distance and estimated coordinates,” *in 2017 29th Chinese Control And Decision Conference (CCDC),* Nov. 2017.

[90] H. Agarwal, A. Dwivedi, and A. Kaur, “An improved centroid DV hop based algorithm,” *in 2017 Recent Developments in Control, Automation & Power Engineering (RDCAPE)*, May 2017.

[91] S.K.D.K. Lobiyal, “Novel DV-Hop localization algorithm for wireless sensor networks,” *Telecommunication Systems,* vol. 64, No. 3, pp. 509-524, June 2017.

[92] M. Salama and M. Kandil, “An Improved DV-hop Localization Algorithm Based on Modified Hop-Size,” *in 2016 World Symposium on Computer Applications & Research (WSCAR),* March 2016.

[93] W. Kun, T. Yuzhen, Z. Zhen, and S. Yinhua, “An Improved DV-Hop Distributed Active Multihop Localization Algorithm,” *in 2016 International Computer Symposium (ICS),* July 2016.

[94] X. Li, L. Yan, W. Pan, and B. Luo, “Optimization of DV-hop localization algorithm in hybrid optical wireless sensor networks,” *Journal of Heuristics*, vol. 21, No. 2, pp. 177-195, April 2015.

[95] S.T.I. Mezei, “Improvements of DV-Hop localization algorithm for wireless sensor networks,” *Telecommunication Systems*, vol. 61, No. 1, pp. 93-106, Jan. 2016.

[96] S. Kumar and D.K. Lobiyal, “Power efficient range-free localization algorithm for wireless sensor networks,” *Wireless Networks,* vol. 20, No. 4, pp. 681-694, May 2014.

[97] S. Gayan and D. Dias, “Improved DV-Hop algorithm through anchor position re-estimation,” *in 2014 IEEE Asia Pacific Conference on Wireless and Mobile*, Oct. 2014.

[98] X. Lv, X. Sun, X. Zhou, and G. Xu, “DV-hop-MSO Based Localization Algorithm in Wireless Sensor Networks,” *in Advances in Wireless Sensor Networks*, Berlin, Heidelberg: Springer Berlin Heidelberg, Sep. 2014.

[99] Y. Zhou, B. Gao, T. Xing, X. Chen, and D. Fang, “Improvement on Localization Error and Adaptability in DV-Hop Algorithm,” *in Advances in Wireless Sensor Networks,* Berlin, Heidelberg: Springer Berlin Heidelberg, July 2013.

[100] X. Jun and T. Wei Wei, “An improved DV-hop algorithm based on iterative computation for wireless sensor network localization,” *in 2013 IEEE International Workshop on Electromagnetics, Applications and Student Innovation Competition*, Aug. 2013.

[101] S. Bing and X.W. Jie, “An Improved Algorithm Based on Dv-Hop Localization for Wireless Sensor Network,” *in Proceedings of the International Conference on Information Engineering and Applications (IEA)* 2012, London: Springer London, July 2013.

[102] L. Jicheng, W. Wenxiu, and S. Yintong, “An improving localization algorithm for wireless sensor networks based on DV-Hop,” *in Proceedings of 2012 International Conference on Measurement, Information and Control,* April 2012.

[103] S.A. Long Chen, Sunshin An, “an Improved Localization Algorithm Based on DV-Hop for Wireless Sensor Network,” *IT Convergence and Services,* vol. 1, No. 1, pp. 333-341, Nov. 2012.

[104] W. Yu and H. Li, “An improved DV-Hop localization method in Wireless Sensor Networks,” *in 2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE),* May 2012.

[105] X. Tao, G. Zou, Y. Yi, and W. Ping, “An Improved DV-HOP Localization Algorithm Based on Beacon Nodes at Borderland of Wireless Sensor Networks,” *in Future Wireless Networks and Information Systems*, Berlin, Heidelberg: Springer Berlin Heidelberg, Aug. 2012.

[106] G. Xiang-ping, H. Rong-lin, and Yangsong, "Research of improved DV-Hop algorithm in coal mine monitoring application for WSNs," *in 2011 IEEE 3rd International Conference on Communication Software and Networks*, June 2011.

[107] W. Yunqi, T. Wo, P. Yuanquan, and L. Ying, "A new improved DV-Hop localization algorithm," *in IET International Conference on Communication Technology and Application (ICCTA 2011*), July 2011.

[108] T. Yi, Z. Fang, and R. Li, "RMADV-Hop: An Improved DV-Hop Localization Algorithm," *in 2010 Seventh International Conference on Information Technology: New Generations*, Dec. 2010.

[109] L.A. Brito, Y. Liu, and Y. Garcia, "An improved error localization on DV-Hop scheme for wireless sensors networks," *in 2010 3rd International Conference on Advanced Computer Theory and Engineering(ICACTE)*, Dec. 2010.

[110] X. Yi, Y. Liu, L. Deng, and Y. He, "An Improved DV-Hop Positioning Algorithm with Modified Distance Error for Wireless Sensor Network," *in 2009 Second International Symposium on Knowledge Acquisition and Modeling,* Nov. 2009.

[111] Y. Niu, S. Zhang, X. Xu, H. Huo, and S. Gao, "An Enhanced DV-hop Localization Algorithm for Irregularly Shaped Sensor Networks," *in Mobile Ad-Hoc and Sensor Networks,* Berlin, Heidelberg: Springer Berlin Heidelberg, Oct. 2007.

[112] P. Li, L. Sun, Q. Fang, J. Xie, W. Yang, and K. Ma, "An Study of Indoor Localization Algorithm Based on Imperfect Signal Coverage in Wireless Networks," *in Advances in Swarm Intelligence,* Berlin, Heidelberg: Springer Berlin Heidelberg, Dec. 2013.

[113] A. Dwivedi and P.R. Vamsi, "DV-HOP Based Hybrid Range-Free Localization Methods for Wireless Sensor Networks," *in Futuristic Trends in Network and Communication Technologies,* Singapore: Springer Singapore, Dec. 2019.

[114] L. Jian Yin, "A New Distance Vector-Hop Localization Algorithm Based on Half-Measure Weighted Centroid," *Mobile Information Systems,* vol. 2019, No. 1, pp. 9892512, Jan. 2019.

[115] Q. Cai, "Improved Location Algorithm Based on DV-Hop for Indoor Internet of Things," *in Computational Intelligence and Intelligent Systems,* Singapore: Springer Singapore, Aug. 2018.

[116] W. Zhao, S. Su, and F. Shao, "Improved DV-Hop Algorithm Using Locally Weighted Linear Regression in Anisotropic Wireless Sensor Networks," *Wireless Personal Communications,* Vol. 98, No. 4, pp. 3335-3353, Feb. 2018.

[117] G. Li, S. Zhao, J. Wu, C. Li, and Y. Liu, "DV-Hop Localization Algorithm Based on Minimum Mean Square Error in Internet of Things," *Procedia Computer Science,* vol. 147, No. 1, pp. 458-462, Jan. 2019.

[118] W. Wang, X. Cao, M. Qian, and L. Ai, "An Improved DV-Hop Localization Algorithm via Inverse Distance Weighting Method in Wireless Sensor Networks," *in Industrial IoT Technologies and Applications,* Cham: Springer International Publishing, Dec. 2017.

[119] A. Kaur, P. Kumar, and G.P. Gupta, "A weighted centroid localization algorithm for randomly deployed wireless sensor networks," *Journal of King Saud University - Computer and Information Sciences,* vol. 31, No. 1, pp. 82-91, Jan. 2019.

[120] J. Mass-Sanchez, E. Ruiz-Ibarra, J. Cortez-González, A. Espinoza-Ruiz, and L.A. Castro, "Weighted Hyperbolic DV-Hop Positioning Node Localization Algorithm in WSNs," *Wireless Personal Communications,* vol. 96, No. 4, pp. 5011-5033, Oct. 2017.

[121] X. Zhipeng, L. Chunwen, and L. Huanyu, "An improved hop size estimation for DV-hop localization algorithm in wireless sensor networks," *in The 27th Chinese Control and Decision Conference (2015 CCDC),* May 2015.

[122] N.G. J. Zhang, and J. Li, "An Improved DV-Hop Localization Algorithm Based on the Node Deployment in Wireless Sensor Networks," *International Journal of Smart Home,* vol. 9, No. 10, pp. 197-204, May 2015.

[123] B. Qi, H. Miao, X. Yuan, and X. Xiao, "A patient tracking and positioning system based on improved DV-Hop algorithm," *in 2015 International Conference on Information and Communication Technology Convergence (ICTC)*, Oct. 2015.

[124] Y. Hu and X. Li, "An improvement of DV-Hop localization algorithm for wireless sensor networks," *Telecommunication Systems,* vol. 53, No. 1, pp. 13-18, May 2013.

[125] S. Kumar and D.K. Lobiyal, "An Advanced DV-Hop Localization Algorithm for Wireless Sensor Networks," *Wireless Personal Communications,* vol. 71, No. 2, pp. 1365-1385, July 2013.

[126] D. Zhang, F. Liu, L. Wang, and Y. Xing, "DV-Hop localization algorithms based on centroid in wireless sensor networks," *in 2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet),* Aug. 2012.

[127] J. Chen, W. Zhang, Z. Liu, R. Wang, and S. Zhang, "CWDV-Hop: A Hybrid Localization Algorithm With Distance-Weight DV-Hop and CSO for Wireless Sensor Networks," *IEEE Access,* vol. 9, No. 1, pp. 380-399, Dec. 2021.

[128] S.J. Bhat and K.V. Santhosh, "A Method for Fault Tolerant Localization of Heterogeneous Wireless Sensor Networks," *IEEE Access,* vol. 9, No. 1, pp. 37054-37063, March 2021.