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Meta-heuristic approaches for minimizing error in localization of wireless sensor networks

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ABSTRACT

Sensor node localization is considered as one of the most significant issues in wireless sensor networks (WSNs) and is classified as an unconstrained optimization problem that falls under NP-hard class of problems. Localization is stated as determination of physical co-ordinates of the sensor nodes that constitutes a WSN. In applications of sensor networks such as routing and target tracking, the data gathered by sensor nodes becomes meaningless without localization information. This work aims at determining the location of the sensor nodes with high precision. Initially this work is performed by localizing the sensor nodes using a range-free localization method namely, Mobile Anchor Positioning (MAP) which gives an approximate solution. To further minimize the location error, certain meta-heuristic approaches have been applied over the result given by MAP. Accordingly, Bat Optimization Algorithm with MAP (BOA-MAP), Modified Cuckoo Search with MAP (MCS-MAP) algorithm and Firefly Optimization Algorithm with MAP (FOA-MAP) have been proposed. Root mean square error (RMSE) is used as the evaluation metrics to compare the performance of the proposed approaches. The experimental results show that the proposed FOA-MAP approach minimizes the localization error and outperforms both MCS-MAP and BOA-MAP approaches.

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25 **1. Introduction**

Wireless sensor network is a kind of ad hoc network that consists 2604 of autonomous sensors with low cost, low energy sensing devices, 27 which are connected by wireless communication links. These sen-28 sor nodes are tiny in size and possess limited resources [1]. A sensor 29 network is similar to a general purpose mobile ad-hoc network 30 (MANET) in many aspects; they are distributed, self-organized and 31 multi-hopped but it lacks a fixed infrastructure. The main difference 32 [2] lies in the fact that the former has the following constraints: 33 lower cost, lesser bandwidth, smaller processing power, higher 34 redundancy and more power-constrained. 35

A fundamental problem in designing sensor network is localization [3] i.e. determining the location of sensors. Location information is used to detect and record events, or to route packets using geometric-aware routing. These sensors are usually deployed in large numbers over the region of interest for object monitoring

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http://dx.doi.org/10.1016/j.asoc.2015.05.053 1568-4946/© 2015 Published by Elsevier B.V. and target tracking applications. The densely deployed sensors are expected to know their spatial coordinates for efficient functioning of WSNs. Location awareness plays an important role in high-level WSN applications like locating an enemy tank in a battlefield, locating a survivor during a natural calamity and in certain low-level network applications like geographic routing and data centric storage.

It is important to note there is an uncertainty on the exact location of sensor nodes. One trivial solution is, equipping each sensor with a global positioning system (GPS) receiver that can provide the sensor with its exact location. As WSNs normally consist of a large number of sensors, the use of GPS is not a cost-effective solution and also makes the sensor node bulkier [4]. GPS has limited functionality as it works only in open fields and cannot function in underwater or indoor environments. Therefore, WSNs require some alternative means of localization.

This work is considered suitable for open fields and not for underwater or indoor environments. GPS information of the three anchors is used to calculate the estimates particularly suitable for open fields only and then localization error minimization is performed for the three proposed heuristic approaches. The speed of the mobile anchors is selected as 100 m/s in order to receive more number of beacon packets in a fixed time interval to have a significant increase in the percentage of localized nodes along

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with faster convergence. This is not a generalized procedure for all applications and is applicable only for military applications such as navigation, target tracking, search and rescue and in civilian applications such as disaster relief, time synchronization and surveillance operations. GPS will have limited functionality where line-of-sight (LOS) propagation does not exist. In particular, for indoor applications and under-water sensor networks, GPS will suffer from limited functionality.

Currently, the existing non-GPS based sensor localization algorithms [5] are classified as range-based or range-free methods. Range-based localization schemes rely on the use of absolute point-to-point distance or angle estimate between the nodes. They determine the position of unknown sensor nodes using locationaware nodes which are also called as anchors or beacons. The most preferred range-based localization techniques are received signal strength indicator (RSSI), time difference of arrival (TDoA), time of arrival (ToA), and angle of arrival (AoA). Range-based methods give fine-grained accuracy but the hardware used for such methods are expensive. In range-based mechanisms, the nodes obtain pair wise distances or angles [6] with the aid of extra hardware providing high localization accuracy. Hence, the uses of range-based methods are generally not preferred.

Range-free or proximity based localization schemes rely on the topological information (e.g., hop count and the connectivity information), rather than range information. Range-free localization schemes may be used with anchors or beacons. They do not require complex hardware and they are cost effective when compared to range-based schemes. Range-free methods use the content of messages from anchor nodes and other nodes to estimate the location of non-anchor sensor nodes. Centroid Algorithm and Distance Vector Hop (DV-Hop) Algorithm are examples for range-free algorithms. Range-free algorithms sometimes use mobile anchors for localization.

Localization problem can be mathematically stated as follows: consider a network formed by L = M + N sensor nodes, where M represents the anchor nodes and N represents the non-anchor nodes. 99 The anchor node is defined as a node that is aware of its own 100 location, either through GPS or manual recording and entering posi-101 tion during deployment [7]. Anchor node position is expressed as 102 $a_k \in \Re^n, k = 1, 2, \dots, M$ in *n*-dimensional coordinates. The non-anchor 103 104 node is defined as a node that is unaware of its own location. Non-anchor node position is expressed as $x_j \in \Re^n$, j = 1, 2, ..., N in 105 *n*-dimensional coordinates. The goal of a location system is to esti-106 mate coordinate vectors of all N non-anchor nodes. Generically, the 107 localization schemes operate in two phases: 108

Phase 1: Inter-node distances estimation based on hop connec-109 tion information or true physical distance calculation based on 110 the inter-node transmissions and measurements. 111

Phase 2: Transformation of calculated distances into geographic 112 coordinates of nodes forming the network. 113

The standard approach is to formulate localization problem as 114 an optimization task [8] with the nonlinear performance function 115 J_N as given by Eq. (1): 116

$$\min_{\tilde{X}} \left\{ J_N = \sum_{k=1}^M \sum_{j \in S_k} (\hat{d}_{kj} - \tilde{d}_{kj})^2 + \sum_{i=1}^N \sum_{j \in S_i} (\hat{d}_{ij} - \tilde{d}_{ij})^2 \right\}$$
(1)

where $\hat{d}_{kj} = ||a_k - \hat{x}_j||$, $\hat{d}_{ij} = ||\hat{x}_i - \hat{x}_j||$, a_k denotes the real position of the anchor-node k, \hat{x}_i and \hat{x}_j denote, respectively, the estimated 119 120 positions of nodes *i* and *j*, \hat{d}_{ij} and \hat{d}_{kj} are the estimated distances 121 between pairs of nodes calculated based on measurements, and 122

 S_i , S_k are sets of neighboring nodes defined by Eqs. (2) and (3) as follows:

$$S_k = \{(k,j): ||a_k - x_j|| \le r_k\}, \quad j = 1, 2, \dots, N$$
(2)

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$$S_i = \{(i, j) : ||x_i - x_j|| \le r_i\}, \quad j = 1, 2, \dots, N$$
(3)

where x_i and x_i denote real positions of nodes with unknown locations and r_i and r_k their corresponding transmission ranges. Various optimization techniques are used to solve the optimization problem as defined by the above Eq. (1). Hence, there is a need to choose an algorithm or technique that efficiently eliminates localization errors and optimizes the obtained locations such that it brings forth better accuracy in localization. Many researchers have suggested the use of heuristic methods and hence three meta-heuristic optimization techniques have been proposed in this work to minimize the error in localization.

Localization in wireless sensor networks is considered as intrinsically an unconstrained optimization problem [9]. The proposed meta-heuristic optimization approaches namely, Bat Optimization Algorithm, Modified Cuckoo Search algorithm and Firefly Optimization Algorithm have been applied over the initial location estimation using Mobile Anchor Positioning (MAP). The MAP is a range-free approach, where the anchor nodes broadcast their location while moving and the obtained localization result is optimized by means of the optimization strategies as stated above.

The remainder of this paper is organized as follows: Section 2 categorizes the related research and reviews the relevant literature. Section 2.1 enumerates the pros and cons of some existing rangebased localization approaches. Section 2.2 highlights the pros and cons of some existing range-free localization approaches. Section 2.3 highlights the pros and cons of some existing hybrid localization approaches. Section 2.4 discusses the pros and cons of some existing mobile anchor based localization approaches. Section 2.5 discusses the pros and cons of some existing evolutionary based localization approaches. Section 3 elaborates on proposed metaheuristic approaches for localization. Section 3.1 illustrates the range-free localization approach namely, Mobile Anchor Positioning (MAP). Section 3.2 depicts the flowchart for localization steps used in Bat Optimization Algorithm with MAP (BOA-MAP). Section 3.3 portrays the flowchart for localization steps followed in Modified Cuckoo Search with MAP (MCS-MAP) Algorithm. Section 3.4 lists the localization steps for Firefly Optimization Algorithm with Mobile Anchor Positioning (FOA-MAP) and its flowchart. Section 4 details on the experimental results, simulation settings in NS-2, RMSE table and graph for comparing performance of the three proposed meta-heuristic approaches. Section 5 discusses the concluding remarks and the scope for future research.

2. Literature review

Localization techniques in the literature are categorized as range-based localization techniques, range-free localization techniques, hybrid localization techniques, mobile anchor based localization techniques and evolutionary based localization techniaues.

2.1. Reviews on range-based localization techniques

Range-based localization techniques rely on the availability of distance (or) angle information between the nodes to determine the unknown sensor node's position. Sensor nodes are equipped with extra hardware, which is capable of estimating distance (or) angle by means of techniques such as received signal strength indicator (RSSI), time of arrival (ToA), time difference of arrival (TDoA), (or) the angle of arrival (AoA). The typical geometrical approaches widely used for location estimation are Tri-lateration

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and Multi-lateration. Inspite of requiring extra hardware, the
 range-based localization techniques have the advantage of fine
 resolution. In addition, the localization precision of range-based
 approach is higher than that of the range-free approach.

Mayuresh Patil et al. [10] had proposed a distributed localization 187 scheme based on received signal strength indicator (RSSI) by the 188 three masters. The actual location was calculated from the received 180 signal strength (RSS), which gives the distance information. The 100 distance from three masters is determined and the sensor node 191 can compute its location by using circular triangulation concept. 192 The relationship that is used to calculate the distance, from the RSS 193 value, is as stated in Eq. (4): 194

$$_{95} \quad \frac{P_r}{P_t} = \frac{A_{er}A_{et}}{r^2\lambda^2} \tag{4}$$

where P_r and P_t denote the received power and transmitted power 196 in Watts respectively. A_{er} and A_{et} are the effective apertures of the 197 antenna transmitter and receiver in m^2 respectively; r denotes the 198 distance in meters and λ denotes the wavelength in meters. The 199 simulation was performed by considering a sensor network hav-200 ing sensor nodes placed in a square region of size 100 units \times 100 201 202 units area and with 100 and 1000 nodes. The simulation using one master method based on RSSI was performed. At first the rela-203 tive distances computed comes to the master (beacon node) and 204 then the beacon calculates the location of the nodes and trans-205 mits the entire information back to the nodes. Though one master 206 method was accurate, it requires high power beacon and a lot of 207 power wastage occurs while transmitting the relative distances 208 to the master. The two master methods for localization uses two 209 high power beacons and unknown sensor node detects the signal 210 strength from these two beacons, calculates its location using circu-211 lar triangulation. Disadvantages of two master method is it requires 212 two high power beacons and also ambiguity arises while calculating 213 the unique location using two beacon nodes and localization has to 214 be done frequently wasting the power. The three master methods 215 uses three beacons and the advantage in this localization method 216 is that the beacon power required will be the same as any other 217 ordinary node and any node in the network can work as a beacon. 218 The other advantage is that the communication overhead required 219 is reduced and during localization, the anchors or beacons back-220 off by a random time interval. This reduces collisions and hence 221 retransmissions. This also reduces the power consumption and the 222 localization time of the network. Based on the simulation results, 223 with regard to the localization error and power consumption, the 224 225 authors have verified that the three master approach performs relatively much better than two-master and one master approaches. 226 Unlike ToA and TDoA, the RSS algorithm works not on signal delay 227 but on signal strength analysis. 228

Xiao et al. [11] had proposed TDoA for localizing the sensor 229 nodes. TDoA algorithm operates by considering a transmitter P that 230 sends a message, then analyzing the received signal correlation 231 (delay) in more than two receivers it becomes possible to com-232 pute the distances between the point P (whose position is to be 233 computed) and each receiver (whose positions are known). TDoA 234 requires time difference of arrival of the signal from the unknown 235 node to the two different beacon or anchor nodes but do not require 236 the propagation time. Hence, the time synchronization between 237 anchor nodes and unknown nodes is reduced. 238

Peng and Sichitiu [12] had proposed a probabilistic localization 239 scheme using angle of arrival (AoA) which is susceptible to mea-240 surement noise and other problems if the unknown sensor nodes 241 are unable to hear directly from a sufficient number of beacons. 242 Probabilistic localization scheme is such that instead of maintaining 243 a single hypothesis on the configuration, it maintains a probability 244 245 distribution over the space of all possible hypotheses. The authors 246 termed this localization as probabilistic since the measurement;

noise is modeled probabilistically and the algorithm utilizes the model to localize the unknowns. The position information of the beacons and the AoA information at each unknown are flooded within a limited number of hops. The position of each sensor node is determined using a probability density function of the twodimensional coordinate random variable (X,Y) in a collaborative and distributive manner. By using both the position of the beacons and the AoA measurements, each unknown sensor node determines it position. The simulation results convey that even with inaccurate AoA measurements and a small number of beacons, the proposed approach achieves both very good accuracy (i.e. difference between the real position of nodes and calculated position by the localization algorithm) as well as precision (i.e. the uncertainty in the position estimate) compared to the results with simulation results of ad hoc positioning system (APS) + angle of arrival (AoA) based localization. The proposed approach also achieves much better coverage than the existing APS + AoA scheme.

Chaczko et al. [13] has suggested time of arrival (ToA) for localizing the sensor nodes. ToA algorithm principally operates by considering the signal delay. If a sensor P with unknown position (x, y) sends a signal s(t), then the received signals are generally computed using the relationship as shown in Eq. (5):

$$y_j[t] = k \cdot s(t - t_j) \tag{5}$$

where j = 1, 2, 3 refers to receivers located in the known positions (x_j, y_j) . Assuming that perfect synchronization distances exist between the transmitter P and the receivers, then computation of $y_j[t]$ becomes much easier. Similar to the TDoA technique, this time of arrival technique only differs by means of using the absolute time of arrival at a certain base station rather than the measured time difference between departing from one and arriving at the other station. The distance can be directly calculated from the time of arrival as signals travel with a known velocity. As with TDoA, synchronization of the network base station with the locating reference stations is important. The demerit of this approach is that ToA definitely needs strict time synchronization of the whole network, which is hard to achieve in practice.

Mustapha et al. [14] has proposed a new localization algorithm, high accuracy localization based on angle to landmark (HA-A2L). Landmark is the term used to indicate the positioned nodes. This new protocol allows nodes to exchange information pertinent to localization process and a localization algorithm that uses estimation of distances and incoming angles to locate the non-positioned nodes in sensor networks. The AoA technique used here is obtained by means of an antenna array. Triangulation technique can be adopted in order to compute the distance between the nodes, provided the angles of arrival between the neighboring nodes are known. After the distance computation, either trilateration (or) multilateration techniques are used to calculate the positions of nodes. Thus, the localization algorithm followed by the authors improves the coverage and produces highly accurate location positions compared to many other existing methods. The demerit observed is that after distance computation if trilateral localization is used, then it not only produces large location errors but also easily tends to an abnormal phenomenon. Also distance computation is possible only if the angles of arrival between the neighboring nodes are known.

Kuruoglu et al. [15] have proposed the three dimensional adapted multi-lateration (3D-AML) technique for handling the distance measurement errors in three-dimensional environments. 3D-AML is an extension of 2D-AML, which follows the concept of intersecting spheres in 3D and the geometric properties to calculate the location of a sensor node, which is exactly similar to the concept of intersecting circles in 2D environments. 3D-AML performance is compared with the conventional multi-lateration technique of GPS. The simulation results proved that the 3D-AML method has lower 247

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localization error than the conventional multi-lateration technique 312 of GPS for noisy measurements, when the Modeling of ranging 313 errors is done with Gaussian distribution having zero mean and 314 varying standard deviations. Generally, ranging errors affect the 315 accuracy of estimated positions but this 3D-AML is robust against 316 ranging errors, provides lightweight and accurate localization. This 317 robust localization scheme is useful if the distance measurements 318 to anchors can be retrieved using any of the conventional ranging 310 methods and can be modified to support Mobile WSN. In addition, 320 the AML is advantageous for iterative localization, since the local-321 ized nodes become reference nodes and employed in the process 322 of localization. 323

Shaoping et al. [16] has proposed the Iterative multilateral local-324 ization algorithm based on Time rounds (IMLBTR). The triangular 325 placement scheme can reduce error accumulations by reducing 326 the number of iterations. But trilateral localization not only pro-327 duces large location errors but also easily lend to an abnormal 328 phenomena. One such algorithm suggested as an alternative is 329 the Iterative multilateral algorithm based on Time rounds. In this 330 IMLBTR method, an unknown node estimates its location and it 331 becomes a beacon node and broadcasts its location to neighboring 332 333 nodes, by which those nodes estimate their position. This algorithm introduces time round scheme, localizes round after round, and 334 it limits the minimum number of neighboring beacon nodes that 335 localization requires in different time rounds. In first round, local-336 ization based on anchors, all unknown nodes, whose neighboring 337 nodes have three or more anchors, are localized. In subsequent 338 rounds, the calculated sensor nodes also becomes anchor nodes 339 and gets added to anchor nodes list and proceed computing the 340 positions of remaining nodes. This process continues until all the 341 nodes position in the region of interest was found. 342

Some common limitations that can be observed from these
 range-based approaches are the following:

- Assuming that perfect synchronization distances exist between the transmitter P and the receivers, which need not be the case always in reality.
- 2. The cost encountered will be more if one of the conventional
 ranging methods (which involve hardware) is used while retriev ing the distance measurements to anchors.
- 3. The approaches increase the computation time for localizationof the sensor nodes.
- 4. There may be a greater chance of positional error of nodes getting propagated from one round to the other as the localization process is iterative.

356 2.2. Reviews on range-free localization techniques

The range-free (or) proximity based localization techniques 357 does not depend on distance (or) angle information but they 358 depend on the topology and connectivity information to determine 359 the unknown sensor node's position. In range-free localization 360 schemes, the position of the sensor node is determined based on 361 information transmitted by nearby anchor nodes (or) neighboring 362 nodes, based on hop (or) triangulation basis. Range-free localization 363 techniques are cheaper when compared to range-based techniques. 364 Some of the typical range-free approaches are approximate point-365 in-triangulation test (APIT), centroid scheme, distance vector (DV) 366 hop scheme and amorphous scheme. 367

Chong Liu and Kui Wu [17] have performed the performance evaluation especially on two novel Range-free localization techniques namely APIT and ring overlapping based on comparison of received signal strength indicator (ROCRSSI). This performance evaluation was to alleviate effectively the APIT's inherent "undetermined node" problem and for achieving higher estimation accuracy with lower communication overhead. This work investigates the system configurations, which directly influence the performance of APIT and ROCRSSI, including anchor deployment strategies, which is seldom addressed by most of the existing works. The simulation results are appealing since under the same system configuration, ROCRSSI outperforms APIT in terms of both estimation accuracy and energy efficiency.

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Deng et al. [18] has proposed centroid localization algorithm, in which the anchor or beacon nodes broadcast their positions and each sensor node will calculate its position as a center of the connected anchor nodes. Centroid localization algorithm is simple and economical but it depends on a number of anchor nodes. This is because for the purpose of good localization, all the sensor nodes must be connected to the anchor node. It is observed that the centroid localization algorithm may cause large error and the localization precision will drop because of the set of asymmetrical reference anchor nodes distributed around the unknown node.

Ji Zeng and Hongxu [19] have proposed an improved APIT algorithm for location estimation in WSN. In this APIT range-free localization algorithm, the location estimation was performed by means of isolating the environment into triangular regions between the anchor nodes. Based on the presence of each sensor node inside or outside of those triangles, the possible likely area has been narrowed down in which the node can reside and then compute the centroid of polygons. The basic concept of APIT algorithm is that the unknown node first hears the information of all the nearby anchors. Then all triangles are formed by connecting every three anchors, which are selected from these anchors in the ergodic. Now test the node whether it is within each triangle or not. Finally, the center of gravity (COG) of the intersection of all of the overlap triangles is calculated in which the node resides to determine its estimated position. The improved APIT algorithm that is proposed in this work performs best when compared to the original APIT algorithm, based on the metrics such as high node packet loss rate and node density. The main drawback in APIT approach is that the sensor nodes must be connected to a number of anchor nodes.

Kenneth et al. [20] have suggested a classical protocol for centralized localization method called as semi-definite programming (SDP) for sensor network node localization with the use of incomplete and noisy distance measurements between the nodes as well as anchor position information. They have performed this work for the proposed SDP and Edge-based SDP schemes especially in the presence of uncertainties namely-anchor position uncertainty, propagation speed uncertainty and combining both these uncertainties. The Computational time and Mean square error (MSE) were compared to the proposed SDP and Edge-based SDP. The results conveyed that proposed SDP could give very accurate node localization than standard SDP, only when the anchor positions are of errors. The limitation observed is that the results of simulation inferred that Edge-based SDP scheme is much more computationally efficient than the proposed SDP scheme, provided the MSE values are higher.

Gao and Lei [21] have suggested that traditional DV-Hop algorithm can be applied in three steps. In the first step, all anchor nodes broadcast a beacon message to all the other nodes. The format of the beacon message is $\{id, x_i, y_i, Hop count\}$ and then it flooded through the whole network. The initial value of Hop Count is zero. In the second step, the anchor nodes get minimum hop count value to the other anchor nodes according to the result in the first step. In the third step, the unknown node can calculate their location based on least square method. DV-Hop algorithm is a range free algorithm which employs a classical distance vector exchange so that all nodes in the network get the distances, in hops to the anchors. Then the average hop distance was calculated and should be applied to the sensor nodes for localization. Since the sensor and anchor nodes are placed uniformly in the entire area, DV-Hop method works well in the case of isotropic networks. It

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can be observed from the DV-Hop scheme that since the nodes are
not uniformly distributed, the relationship between hop counts
and geographic distances are weak, which results in large errors
while considering anisotropic networks.

The Amorphous algorithm is similar to DV-hop algorithm, but it assumes to know the network density in advance. It uses offline hop-distance computations, improving the location estimates through a neighbor-information exchange. It is to be noted that APIT, Centroid, DV-Hop and Amorphous schemes are all distributed algorithms and they are characterized by simple computation, reduced traffic and better scalability.

Lee et al. [22] have proposed a new robust range-free local-452 ization algorithm called optimal proximity distance map using 453 quadratic programming (OPDMQP). Unlike other algorithms focus-454 ing on isotropic networks, the proposed algorithm works well not 455 only in isotropic networks but also in anisotropic networks. Mathe-456 matical modeling is performed to establish a relationship between 457 proximity within the sensor nodes and geographical distances in 458 a wireless sensor network. OPDMQP algorithm defines a set of 459 constraints on the given network topology and formulates the 460 localization problem into a quadratic programming (QP) problem. 461 462 The proposed OPDMQP resolves the problem of proximity distance map (PDM) by embedding the constraints of WSNs into the local-463 ization problem. The proposed method was demonstrated to be 464 superior in two types of anisotropic networks namely C-shaped 465 topology and X-shaped topology. The proposed OPDMQP method 466 outperforms other methods in terms of localization error and hence 467 results in reliable localization estimates 468

469 Some common limitations observed from these range-free470 approaches are the following:

471 1. The observation is that, these approaches are not robust to
 472 the interference of environment noise and only provide coarse 473 grained accuracy.

4742. The approaches take more computational time for finding the475 positions of sensor nodes.

476 2.3. Reviews on hybrid localization techniques

Hybrid localization techniques can combine simple geometry of
triangles and stochastic optimization algorithms (or) it can be two
geometrical approaches combined (or) it can be two stochastic optimization algorithms for estimating the position of non-positioned
nodes in a WSN.

Minghui and Yilong [23] have proposed an algorithm for accu-482 rate narrowband angle of arrival (AoA) estimation in unknown 483 noise fields and harsh WSN scenarios. A maximum likelihood (ML) 484 criterion was derived w.r.to AoA and unknown noise parame-485 ters, since noise covariance is modeled as a linear combination 486 of known weighting matrices. They have proposed particle swarm 487 optimization (PSO) for tackling the cost function in ML criteria in an 488 efficient manner. The simulation results demonstrated that espe-489 cially in unfavorable scenarios, PSO-ML significantly outperforms 490 other popular techniques and produces superior bearing estimates. 491 The demerit observed is that the performance of PSO-ML criterion 492 was not tested in favorable scenarios of WSN. 493

Zhang et al. [24] proposed a Genetic Simulated Annealing algo-494 rithm based Localization (GSAAL) algorithm for wireless sensor 495 network (WSN). The proposed algorithm adopts two new genetic 496 operators namely, single-vertex-neighborhood mutation and the 497 descend-based arithmetic crossover. Genetic Algorithm is good at 498 global search but is poor at local search. The advantage of using 499 simulated annealing (SA) algorithm is it attempts to avoid being 500 trapped in a local optimum by sometimes allowing the temporal 501 502 acceptance of inferior solutions. During searching for the optimal 503 solution, SAA not only accepts optimal solutions, but also accepts the degraded solutions at a certain degree. SA is good at local search. The merit of this algorithm observed from results of simulation is that it can achieve higher accurate position estimation and can improve the calculation efficiency greatly than the semi-definite programming with gradient search localization (SDPL).

2.4. Reviews on mobile anchor based localization techniques

Ssu et al. [25] presented a range-free algorithm, which uses the following conjecture. A perpendicular bisector of a chord passes through the center of the circle. When there are two chords of the same circle, their perpendicular bisectors will intersect at the center of the circle. A mobile anchor moves around the sensing field broadcasting beacons. Each sensor node chooses two pairs of beacons and constructs two chords. The sensor node assumes itself as the center of a circle and determines its location by finding the intersection point of the perpendicular bisectors of the constructed chords. With this scheme, no extra hardware or data communication is required for the sensor nodes and also obstacles in the sensing field can be tolerated. Simulation results predict that this scheme performs better than other range-free schemes.

Zhen Hu et al. [26] proposed a radio-frequency (RF) based mobile anchor centroid localization method (MACL) for WSNs. In this method, a mobile anchor node moves in the sensing field and broadcast its current location periodically. Simulations and tests from an indoor deployment using the Cricket location system were used to investigate the localization accuracy of MACL. From the results of RF based MACL, it provides less computational complexity with low communication overhead, low cost, and flexible accuracy. The demerit observed in this scheme is that the authors use simulation and tests only from an indoor deployment to investigate the localization accuracy and can provide flexible accuracy but not high accuracy.

Zhang Baoli et al. [27] proposed a range-free algorithm, which works as follows. The trajectories of the mobile anchor are in such a way that it moves in a straight line. As it moves, it periodically broadcasts its location to the sensor nodes. A sensor node selects four beacons among all collected beacons. The first group (two beacons) is the location of the mobile anchor node when it first enters the communication range of the sensor node. The second group is the location of the mobile anchor node when it second enters the communication range of the sensor node. After these positions and the communication range are obtained, four circles are constructed with the chosen four points as centers. Four-intersection points s_1 , s_2 , s_3 , s_4 of the circles are calculated. Then using the centroid formula on these four intersection points, the position of the sensor node is calculated. The limitation that can be observed is that the node positions can be determined accurately only if the beacon operates along straight-line traverse routes which need not always be realized in practice.

Hung Wu et al. [28] proposed a distributed localization approach known as the rectangle overlapping approach (ROA), which uses a moving beacon equipped with a GPS and a directional antenna. The positions can be determined using simple operations according to the current state of the moving beacon, including the rotation angle and position. Simulation results show that this scheme is very efficient and the node positions can be determined accurately.

Karim et al. [29] proposed a range-free energy efficient localization technique using mobile anchor (RELMA) especially for large scale WSNs to improve both accuracy and energy efficiency by minimizing the number of anchor nodes used. The RELMA_Method 1 as well as RELMA_Method 2 has used the sensing range for each pair of nodes to communicate instead of the communication range to reduce the power consumptions of the nodes. The performance of RELMA_Method 1 and RELMA_Method 2 are compared only with the existing neighboring-information-based

localization system (NBLS). Simulation results demonstrate the fact that RELMA_Method 1 and RELMA_Method 2 outperform NBLS 569 in terms of localization accuracy as well as energy efficiency. The 570 demerit observed is that for computing the node positions, the 571 authors have used only the sensing range for each pair of nodes 572 to communicate instead of the communication range which need 573 not always be the case when it is realized in practice. 574

Huan-Qing et al. [30] proposed a weighted centroid localiza-575 tion method using three mobile beacons. These beacons preserve a 576 special formation while traversing the network deployment area, 577 and broadcast their positions periodically. The location unaware 578 sensor nodes that are to be localized, estimate the distances to these three beacons and use weighted centroid localization method 580 to find its position. Through simulation results, this method was found superior to weighted centroid localization method with a 582 single mobile beacon as well as to trilateration. It is observed that for estimating the node positions, the authors have used distances to three beacons and also weighted centroid localization method which increases the computation time during localization process.

Liao et al. [31] proposed an algorithm (mobile anchor posi-587 tioning) in which each sensor node receives beacons (messages 588 589 containing location information) in its receiving range from the moving anchor as the anchor moves around the sensing field. 590 Among the received beacons, the sensor node selects the farthest 591 two beacons. The node constructs two circles with each chosen bea-592 con as center. The radius of the circle is the communication range 593 of the sensor node. It determines the intersection points of the two 594 circles. Out of the two points, one is chosen to be the location of 595 the sensor node based on a decision strategy. Demerit noticed in 506 this approach is that the un-localized nodes compute their loca-597 tions due to beacon packets broadcasted from mobile anchors and 598 also from stationary localized nodes leading to limitation in com-599 munication cost and also provide only coarse-positioned location 600 accuracy. 601

Some common limitations that are observed from these mobile 602 anchor based approaches are the following: 603

- 1. In these approaches their accuracy will not be very high i.e. only 604 coarse-positioned accuracy is achieved unlike the fine-grained 605 accuracy in range-based localization. 606
- 607 2. In these approaches, it is observed that after the first round localization is performed, the un-localized sensor nodes can compute 608 their locations with the help of localized stationary sensor nodes, 609 which leads to limitation in communication cost not only due to 610 beacon packets broadcasted from mobile anchors but also by the 611 packets broadcasted by stationary localized sensor nodes. 612

2.5. Reviews on evolutionary based localization techniques 613

Gopakumar and Jacob [32] proposed the swarm intelligence based approach for localization of the sensor nodes for this nonlinear optimization problem. The objective function chosen is the mean squared range error of all neighboring anchor nodes. The PSO algorithm provides better convergence than simulated annealing and ensures solution without trapped into local optima.

Yu zeng et al. [33] proposed a novel WSN node localization 620 algorithm based on an improved simulated annealing algo-621 rithm. Simulation results demonstrate the fact that this algorithm 622 achieves superior performance when compared to traditional 623 simulated annealing algorithm and the positioning accuracy has 624 increased nearly doubled. In addition, the algorithm is very simple 625 and the computational loads are very small, therefore it is suitable 626 for node location of wireless sensor network. 627

Wenwen and Wuneng [34] proposed the genetic algorithm 628 629 for localization of the sensor nodes and constructed the solution space, coded the solutions, formulated the fitness function and used 630

appropriate selection mechanism to choose the parents for the next generation. The reproduction operation on the individuals is performed and the solution is obtained with high accuracy. The above genetic algorithm approach gives good localization accuracy. The demerit observed in this method is that, the solution space is very huge and the algorithm has to search a large number of solutions in each of the iterations or the number of iterations will be large. When the area of the sensing field increases, the computation involved also increases.

Jia Huan and Wang [35] proposed a new localization method with mobile anchor node and genetic algorithm. It combines weighted centroid method with genetic algorithm. Initially, the mobile anchor node, which is equipped with GPS, was allowed to traverse around the entire sensing area. The unknown sensor nodes can obtain useful information for localization through mobile anchor node. Then, the initial coordinates of unknown sensor nodes are calculated by the weighted centroid method. Now, the initial position coordinates of the unknown sensor nodes are converged toward the actual coordinates. As the genetic algorithm is iterative - looped, the localization accuracy is improved to some extent. The merit observed in this proposed localization algorithm when compared to genetic algorithm proposed by Wenwen et al. [34] is that this algorithm need not search for a large number of solutions in each of the iterations and also the solution space is relatively smaller. The demerit noticed in proposed weighted centroid combined with genetic algorithm is that it provided only coarsepositioned location accuracy.

Lei et al. [36] proposed a Mobile Anchor Assisted Localization Algorithm based on PSO (MAAL_PSO) pertaining to adverse or dangerous application environments. The region of interest (ROI) is divided into grids and the mobile anchor deploys virtual anchors on the vertex of each grid. Based on this deployment, the node localization is converted into non-linear constrained optimization problem solved by PSO with the help of mobile anchor. After a few iterations, performance evaluations demonstrate that this algorithm improves localization accuracy. It is also robust to the interference of environment noise. The demerit observed from this proposed method is grid (uniform) deployment of sensor nodes used in the ROI is not applicable as the sensor nodes are generally noticed to be randomly deployed for real-time environments.

Han Bao et al. [37] proposed a PSO based localization algorithm (PLA) for WSNs with one or more mobile anchors. PLA does not require the mobile anchors to move along an optimized or a pre-determined path. This property makes mobile data sinks with localization capability to serve for data gathering and network management applications. Simulation results demonstrate that PLA can achieve superior performance in various scenarios i.e. in wide range of conditions when compared to centroid localization method and also to a Mobile Anchor Assisted Localization Algorithm based on particle swarm optimization proposed by Lei et al. [36].

Some common limitations that can be observed from these evolutionary based approaches used for localization are the following:

- 1. The observation is that, these evolutionary based approaches considered are not robust to the interference of environment noise.
- 2. These approaches are suitable for node location of wireless sensor network only when the computational loads are very small.
- 3. In these approaches, each mobile anchor broadcasts beacons periodically, and the sensor nodes can locate themselves only upon the receipt of multiple beacon messages, which in turn increases the computational time during localization process and also provides only coarse-positioned location accuracy.

Based on the literature review done, it is identified that the range-free localization schemes, does not involve the usage of

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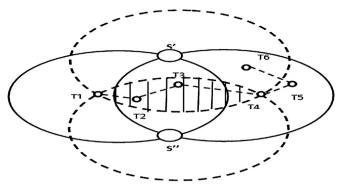
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any hardware and hence the cost is reduced when compared to 605 range-based localization schemes. It is necessary to propose suit-696 able evolutionary approaches for localization to be combined with 697 mobile anchor positioning (MAP) method, a range-free localiza-698 tion scheme in order to minimize the localization error further. 600 Though the percentage of localized nodes in MAP method is high 700 indicating that it is appropriate for localization purpose, but it does 701 not guarantee fine-grained accuracy in localization and therefore 702 evolutionary algorithms are needed to be applied over the results 703 of MAP for minimizing localization error largely. In order to avoid 704 being trapped into local minima as well as to provide faster con-705 vergence, it is essential to apply certain meta-heuristic techniques 706 over the results of MAP method in order to minimize the localiza-707 tion error far better than the existing approaches specified in the 708 literature. 709

Many design optimization problems are highly non-linear, 710 which can typically have multiple modal optima and so it is chal-711 lenging to solve such multi-modal problems. In order to understand 712 this issue, traditionally considered global optimization algorithms 713 are applied but could not produce good results. The latest trends 714 are to apply new meta-heuristic algorithms [38]. A meta-heuristic 715 716 algorithm is also a heuristic algorithm, but considered as a more powerful one, since it is a mechanism that avoids being trapped in 717 a local minimum. Moreover, the meta-heuristic is able to employ 718 heuristics methods by guiding them over the search space in 719 order to exploit its best capabilities to achieve better solutions. In 720 many instances, a heuristic method provides a result that is "good 721 enough". Heuristic algorithms use the trial-and-error, learning and 722 adaptation to solve problems. We cannot expect them to find the 723 best solution all the time, but expect them to find good enough 724 solutions or even the optimal solution most of the time, and in 725 a reasonably and practically short time [39]. The heuristic meth-726 ods are used for their speed, while the other methods can be very 727 expensive when considering computing resources. Thus a heuristic 728 method can balance the quality of the result with the time spent 729 on computation. It is possible that the heuristic method fails on 730 certain instances (it cannot find any result), but these situations 731 are extremely rare. Meta-heuristic is a framework that gives direc-732 tions on how to solve a set of problems. Modern meta-heuristic 733 algorithms are almost guaranteed to work well for a wide range 734 735 of tough optimization problems. The successful meta-heuristic techniques [40] are inspired by nature as they have been devel-736 oped based on some abstraction of nature. Certain meta-heuristic 737 approaches proposed in this paper with Mobile Anchor Positioning 738 (MAP) method are Bat Optimization Algorithm with MAP (BOA-739 MAP), Modified Cuckoo Search with MAP (MCS-MAP) algorithm 740 and Firefly Optimization Algorithm with MAP (FOA-MAP). The loca-741 tion of nodes is initially estimated using MAP. Then the proposed 742 meta-heuristic approaches are applied over the results obtained 743 by MAP. The observation is that, when FOA is applied over the 744 results of MAP, it estimates the location of the sensor nodes provid-745 ing very high accuracy better than MCS-MAP as well as BOA-MAP 746 approaches. 747

3. Proposed meta-heuristic approaches for localization 748

The localization strategy used in this work can be visual-749 ized to work in two phases. In the first phase, a range-free 750 algorithm namely Mobile Anchor Positioning (MAP) is used for 751 determining the location of the unknown sensor nodes. Since a 752 range-free algorithm, which offers coarse-grained accuracy is used, 753 the obtained location will be just an estimate. In the second phase 754 (post optimization phase), Bat Optimization Algorithm with MAP 755 756 (BOA-MAP), Modified Cuckoo Search with MAP (MCS-MAP) algo-757 rithm and Firefly Optimization Algorithm with MAP (FOA-MAP) are



O S' and S'' indicate the possible locations of the sensor node

Beacon packets

Shaded area from T1 to T4 represents the shadow region

Fig. 1. Node seeking information from neighbor sensors.

applied over the results of MAP in order to enhance the localization accuracy further.

3.1. Mobile Anchor Positioning (MAP)

The simulation environment is set-up as follows: the sensor nodes are randomly deployed in the sensing field. The assumption made during simulation is that the Mobile anchors, which are location aware nodes move throughout the sensing field according to the positional data specified in a movement file, which is given as input to the network simulator (NS-2). As they move around the sensing field, they periodically broadcast messages containing their current location at fixed time interval to all the nodes, which are at a hearing distance from it. Such messages are known as beacons. The mobile anchors traverse around the field with a specific speed and their directions are set to change for every 10s. All the nodes in the communication range of the mobile anchor will receive the beacons. A sensor node will collect all the beacons in its range and store it as a list. Communication range of the sensor node and the mobile anchor node are assumed as same. Once enough beacons are received and if a sensor node does not receive a beacon, which is at a distance greater than the already received ones, the localization will begin at that particular node.

Assumption made in the simulator is that same transmission range is used for all the sensor nodes as well as mobile anchor nodes and each mobile anchor broadcasts a beacon packet per second. This is followed because the comparison will be valid with the three proposed heuristic approaches and with MAP only in the same transmission range. No specific mobility model is considered when designing these approaches and experiments. Instead of using random way point mobility model, the mobile anchor nodes in the proposed approaches have been given a predefined (regulated) movement based on a movement file which is fed as input to NS-2 simulator and not random movement.

Assume that the sensor node has received and stored four beacons (locations of the mobile anchor) in its list $\{T_1, T_2, T_3, \text{ and } T_4\}$ as shown in Fig. 1. From the list, two beacons, which are farthest from each other, are chosen (T_1, T_4) . These points are known as Beacon points. These two points are marked as the end of the sensor node's communication range since the sensor node has not received a beacon farther from this point. Hence T_1 and T_4 (Beacon points) represent either two positions of the same mobile anchor or positions of two different mobile anchors when they were at the end of the sensor node's communication range.

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With these two Beacon points as centers and the communication range of a sensor node as radius, two circles are constructed. Each circle represents the communication range of the mobile anchor, 802 which has sent the beacon. The sensor node has to fall inside this 803 communication range, as it has received the beacon. Since the sen-804 sor node has received packets either from both anchors or from the 805 two positions of the same anchor, the node has to fall inside of both 806 circles. Hence, it can be concluded that circles will intersect each 807 other. 808

The intersection points of both circles are determined (S_1, S_2) 809 which are the possible locations of the sensor node. The reason is as 810 follows: The two farthest points (Beacon points) are the end points 811 of a sensor node's communication range. The sensor node lies on 812 the circumference of the other circle since it is the same with the 813 other mobile anchor position. Therefore, the sensor node lies on 814 the circumference of both circles. The points which are satisfying 815 the above condition are known as intersection points. By means 816 of Mobile Anchor Positioning, the location of the sensor node has 817 been approximated to two locations. 818

3.1.1. Identifying the sensor locations using MAP with Mobile 819 820 Anchor (MAP-M)

The visitor list is searched after identifying the two possible 821 positions i.e. the intersection points. If a node could hear around 822 its range, there is a possibility of a beacon point which can be sit-823 uated at a distance r from one of the two possible locations. Thus, 824 there is a point in the list, whose distance from one possible loca-82.5 tion is less than r, and the distance from other possible location 826 is greater than r, then the first possible location is chosen as the 827 location of the sensor node. 828

It is assumed that the communication range of a mobile anchor is 829 R. The MAP-M maintains the visitors list after receiving the beacon 830 packets from the mobile anchor. The information from the visitor 831 list is used to approximate the location of the sensor node. Let the 832 visitor list of a sensor node S consists of various location informa-833 834 tion represented as $\{T_1, T_2, \dots, T_n\}$. The beacon points are the two extreme points i.e., T_1 and T_n . Beacon points are called as extreme 835 points because the mobile anchor nodes broadcast beacons peri-836 odically during every time interval, which is received by unknown 837 sensor nodes that fall inside the communication range of mobile 838 839 anchor. When the mobile anchors continue broadcasting beacon packets, after a particular time interval, there will be an idle period 840 for mobile anchors which clearly indicates that the respective bea-841 con points serve as the two extreme points. Two circles with radius 842 R and center T_1 and T_n are constructed and their intersection points 843 of them are found to be S' and S". 844

If there is any Ti $(2 \le i \le n-1)$, such that the distance between Ti 845 and S' is less than R and that between Ti and S'' is greater than R, we 846 can conclude the location of the sensor node as S'. It is because of the 847 fact that the sensor node should lie inside the communication range 848 of mobile anchor to receive the beacon packets. Consequently, the 849 distance between the sensor node S and beacon packet Ti should be 850 less than R. There is an area named as the shadow region, as shown 851 in Fig. 1. If all the Beacon points lie inside this region, it will not 852 be possible to determine the location of the sensor as the shadow 853 region comes under the range of both the intersection points. This 854 could be explained by drawing two circles with S' and S'' as center 855 and the shadow region is the intersection of the two circles. In order 856 to estimate the location of the sensor node, there is a need that at 857 least one of the beacon packets in the visitor list must lie outside 858 the shadow region, as shown in Fig. 1. 859

Therefore, it is not possible to determine the location of the 860 sensor node S using the available beacon packets. Thus the node 861 is made to wait until it gets further beacon packets. If no further 862 863 beacons are obtained, a single position of sensor node S cannot be 864 obtained. The node will have two positions S' and S''. To overcome

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this problem, the method of Mobile Anchor Positioning-Mobile Anchor & Neighbor (MAP-M&N) is being adopted.

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3.1.2. Forming additional anchors and identifying the sensor locations using MAP with Mobile Anchor & Neighbor (MAP-M&N)

The location estimation done for sensors using MAP-M method gives positions for few sensors and for the others, it gives two positions. It is the responsibility of MAP-M&N method to produce outputs with a single position for each sensor. It is possible for the sensor nodes that have already determined their location to assist other nodes in determining their locations. As soon as the location is identified, the localized nodes start acting like anchors. They embed their calculated location inside the packet and then broadcast the beacons. Nodes, which are at its hearing range and waiting for additional beacons to finalize their location, can make use of these beacons. However, if the sensor node has determined its location, it simply discards the beacon packet. As a consequence, by using MAP-M&N method, the cost of movement of the mobile anchor can be reduced.

3.1.3. MAP-M&N algorithm procedure

The steps involved in finding the location of the sensors in the field using MAP-M&N algorithm are as listed below:

- 1. Deploy 100 sensor nodes randomly in the 1000 m \times 1000 m area of the sensing field in the simulation environment and deploy 3 location aware nodes (anchor nodes) i.e. sensor nodes fit with GPS
- 2. The Mobile Anchor nodes move throughout the sensing field according to the positional data specified in the movement file which is given as input to the NS-2 simulator. They periodically broadcast their location packets, which are known as beacon packets, while on the move through the sensing field.
- 3. Every sensor node maintains a visitor list containing beacon packets based on the information obtained from anchors. Visitor list corresponds to the list of anchor node's coordinates stored every time in the unknown sensor nodes for determining its position.
- 4. The sensor nodes can identify the farthest beacon packets and choose those beacon packets as beacon points.
- 5. With those two beacon points as the centers and the communication range of a sensor node as radius, two circles are constructed and the intersection points are found.
- 6. Sensor nodes try to identify its position out of the two intersection points. Here, at least one of the beacon points in the visitor list must lie outside the shadow region or based on the beacon points obtained from the neighboring nodes.
- 7. The approximate location for each of the sensor nodes is estimated using MAP-M&N method.

3.2. Bat Optimization Algorithm with Mobile Anchor Positioning (BOA-MAP)

Bat algorithm is based on the echolocation features of microbats. The algorithm follows frequency-tuning technique to increase the diversity of solutions in the population, while at the same, it uses the automatic zooming to try to balance exploration and exploitation during the search process by mimicking the variations of pulse emission rates and loudness of bats when searching for prey. As a result, it proves to be very efficient with a typical quick start. The Bat algorithm [41] was developed with the following three idealized rules:

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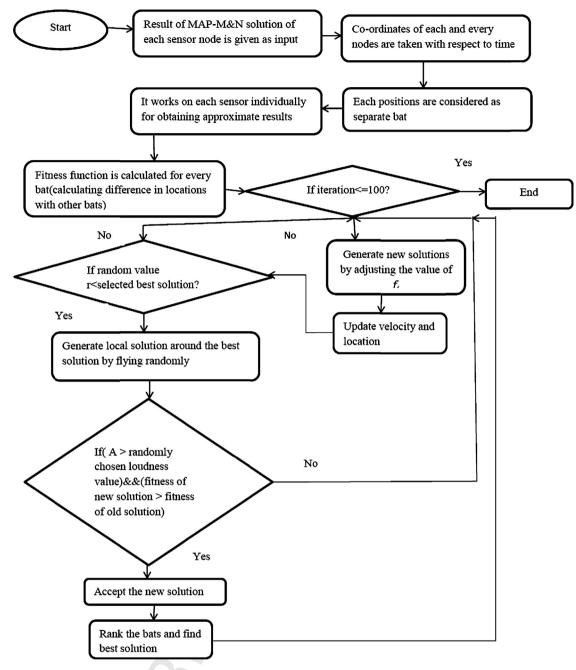


Fig. 2. Localization flowchart for BAT Optimization Algorithm with MAP (BOA-MAP).

- 922 1. All bats use echolocation to sense distance, and they also 'know'
 923 the difference between food/prey and background barriers in
 924 some magical way.
- 2. Bats fly randomly with velocity v_i at position x_i with a frequency f_{min} , varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and rate of pulse emission $\in [0,1]$, depending on the proximity of their target.
- 930 3. Although the loudness can vary in many ways, we assume that 931 the loudness varies from a large (positive) A_0 to a minimum 932 constant value A_{min} .

3.3. Modified Cuckoo Search with Mobile Anchor Positioning (MCS-MAP) Algorithm

The proposed evolutionary strategy applied along with the results of MAP-M&N as input is the Modified Cuckoo Search (MCS) [42] optimization algorithm, which is one such evolutionary algorithm inspired by the lifestyle of the cuckoo bird.

Each cuckoo lay eggs [43] at random positions inside the chosen area around it with a radius as stated by,

$$r = \left[\frac{\text{number of eggs per cuckoo}}{\text{sum}}\right] * [\text{radius Coeff} * (varHi - varLo)]$$
(6)

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The localization steps followed in WSN using Bat Optimization
 Algorithm (BOA) is as depicted in the flowchart shown in Fig. 2.

MCS algorithm makes two variations while comparing with Cuckoo Search Optimization algorithm. The first variation

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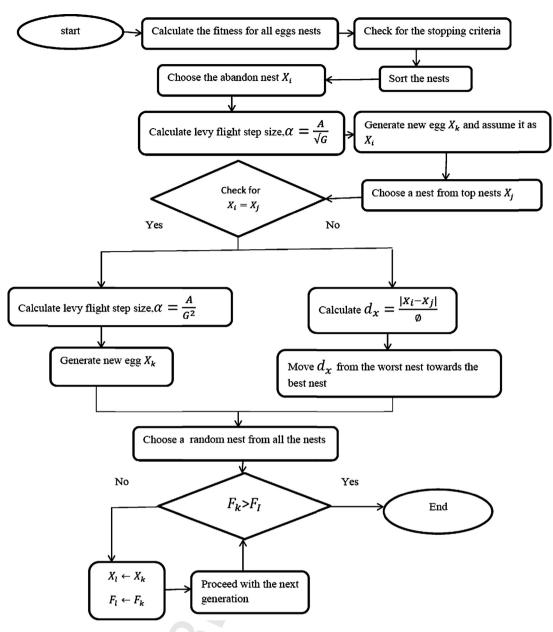


Fig. 3. Flowchart for localization steps in Modified Cuckoo Search with MAP (MCS-MAP).

encourages more localized searching and the second variation
brings about the replacement of eggs with lesser profit. Modified
Cuckoo Search (MCS) meta-heuristic is applied for unconstrained
optimization problems. Mature cuckoo's lay egg in other bird's
nests, the eggs hatch and grow if they are not identified by the host
birds and destroyed. The ultimate aim is to find the best habitats
leading to the global maximum of objective functions.

The steps in finding the location of the sensors in the field using MCS-MAP algorithm as depicted in the flowchart shown in Fig. 3.

3.4. Firefly Optimization Algorithm with Mobile Anchor
 Positioning (FOA-MAP)

Firefly meta-heuristic algorithm is powerful in local search. The
 algorithm follows the peculiar characteristics of the fireflies. Some
 of the flashing characteristics of the fireflies [44] were idealized
 with the following three rules:

- 1. All fireflies are unisex, so that one firefly is attracted to other fireflies regardless of their sex.
- 2. Attractiveness is proportional to their brightness and thus for any two flashing fireflies, the less bright one will move toward the brighter one. Attractiveness is proportional to their brightness and they both decrease as their distance increases. If there are no brighter fireflies than a particular firefly, it will move randomly in the space.
- 3. The brightness of a firefly is somehow related with the analytical form of the cost function. The brightness of a firefly is determined by the landscape of the objective function, which is to be optimized.

The steps in finding the location of the sensors using FOA-MAP Algorithm are as follows:

1. The results of MAP-M&N algorithm, giving the approximate solution of the location of each sensor at each specified time 979

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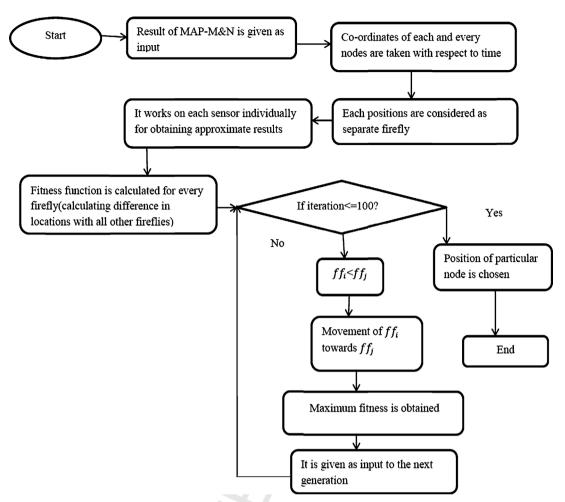


Fig. 4. Flowchart for localization steps in Firefly Optimization Algorithm with Mobile Anchor Positioning (FOA-MAP).

instance is given as the input to the post optimization algorithm
 namely, Firefly Optimization Algorithm (FOA).

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- 2. Let each node's (x,y) co-ordinate at different instances of time be $(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)$ where *n* denotes the number of sensor nodes. Each of these positions is considered as a separate firefly. Hence, producing as much of fireflies in the approximate positions found at regular intervals.
- 3. The firefly algorithm works on each of the sensor individually
 for obtaining an approximately accurate location of it. Each
 firefly represents the approximate position of that particular
 sensor.
 - 4. In each generation, the fitness is calculated for every firefly. Fitness is determined by calculating the difference in location with all the other fireflies.
 - In every generation, each of the fireflies is considered at a time and being compared to all the other fireflies for their fitness.
- 6. Let the considered firefly be ff_i . If the fitness ff_i is less than that of the firefly being compared to (ff_j) , then ff_i moves toward that firefly ff_i .
- 7. Movement of ff_i toward ff_j varies according to the formula as listed in Eqs. (7) and (8):

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_i - x_j) + \alpha \varepsilon_j$$
(7)

where r_{ij} gives the Cartesian distance between ff_i and ff_j which is defined as,

$$_{4} r_{ij} = ||f_{i} - f_{j}|| (8)$$

- 8. Each of the fireflies undergoes this process and finally the firefly with maximum fitness is chosen and carried over to the next generation.
- 9. This position is given as the input to the next generation, fireflies are produced randomly and the process is continued until the termination criterion is being met.
 - (a) Termination criteria = maximum iterations or profit value.
 - (b) Maximum iteration = arbitrarily chosen as 100.
 - (c) Profit value = minimum difference in values (10 cm) obtained in the current and the previous rounds.
- 10. Thus firefly with maximum fitness in the last generation is chosen as the position for that particular node.

The flowchart in Fig. 4 below portrays the localization steps followed using Firefly Optimization Algorithm with MAP (FOA-MAP).

4. Experimental results

In order to compare the performance of three proposed approaches namely, BOA-MAP, MCS-MAP and FOA-MAP in minimizing the localization error is analyzed by simultaneously running in the NS-2 simulator. The simulation settings mentioned in Table 1 have been maintained for all these experiments.

Ad hoc on-demand distance vector (AODV) routing protocol is used especially for broadcasting messages (Hello Packets) during localization and it does not concentrate on routing process in this work. Proposed localization algorithms sits on the application layer since after performing location estimation of the sensor nodes,

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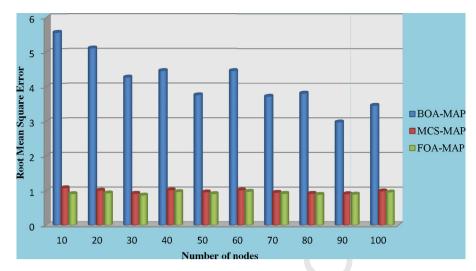


Fig. 5. Graph for comparing RMSE in BOA-MAP, MCS-MAP and FOA-MAP approaches.

Table 1

Simulation settings.

Parameter description	Value	
Area of the sensing field	$1000m\times1000m$	
Number of sensor nodes	100	
Number of mobile anchors	3	
Speed of mobile anchors	100 m/s	
Time interval between successive anchors	1 s	
Execution time	500 s	
Transmission range	250 m	
Routing protocol	AODV	
MAC protocol	IEEE 802.11	
Number of generations	10-100	

Table 2

RMSE calculation for BOA-MAP, MCS-MAP and FOA-MAP approaches

No. of nodes	RMSE value obtained for BOA-MAP	RMSE value obtained for MCS-MAP	RMSE value obtained for FOA-MAP
10	5.57	1.08	0.91
20	5.11	1.01	0.93
30	4.27	0.92	0.87
40	4.46	1.02	0.97
50	3.76	0.96	0.91
60	4.46	1.02	0.98
70	3.72	0.95	0.92
80	3.81	0.92	0.89
90	2.98	0.91	0.90
100	3.46	0.99	0.96

it is suitable for applications such as environmental monitoring,weather forecasting, target tracking, etc.

The localization accuracy has been measured based on the mini mization in positional error. Root mean square error (RMSE), which
 is calculated using the formula given in Eq. (9):

1035 RMSE =
$$\sqrt{\frac{\sum_{i=1}^{n} [x_{act(i)} - x_{obt(i)}]^2 + [y_{act(i)} - y_{obt(i)}]^2}{N}}$$
 (9)

where $x_{act(i)}$, $y_{act(i)}$ represent the actual values of x and y coordinates of the sensor nodes, $x_{obt(i)}$, $y_{obt(i)}$ represent the obtained values of x and y coordinates of the sensor nodes and N represents the total number of localized sensor nodes. Table 2 shows the simulation results only after performing ten trials and by taking average of those values, the results have been generalized from that perspective. From Table 2, it can be observed that the RMSE value drastically reduces while applying FOA-MAP approach when compared to applying BOA-MAP and MCS-MAP approaches. This observation is graphically represented in Fig. 5, where *x*-axis represents the number of nodes and *y*-axis corresponds to RMSE value of the sensors. The observation is that there is an increase in RMSE value for the proposed approaches corresponding to 60 nodes when compared to 50 and 70 nodes scenario because the sensor nodes are randomly deployed and every time when the simulator is run for a new trial, the nodes are placed randomly at new positions and localization is performed on them. This can be inferred from Table 2.

5. Conclusions and scope for future research

In this paper certain meta-heuristic approaches, specifically, Bat Optimization, Modified Cuckoo Search and Firefly Optimization have been used to estimate localization information of the nodes in a WSN. The initial solution for these approaches has been taken from the standard range-free localization mechanism namely Mobile Anchor Positioning (MAP) method, which does not involve the usage of any hardware. As MAP method does not give finegrained accuracy in localization, meta-heuristic approaches are applied on the results of MAP. The FOA-MAP algorithm applied over MAP has significantly reduced the localization error. From the simulation results obtained using NS-2, by using the proposed FOA-MAP approach, there was a drastic reduction in the localization error. With regard to 100 nodes scenario on an average, Firefly Optimization Algorithm with Mobile anchor positioning (FOA-MAP) has reduced the RMSE based localization error by 8.08% when compared to MCS-MAP algorithm. FOA-MAP approach seems to bring down the RMSE based localization error by 72.25% when compared to BOA-MAP algorithm.

Thus, it can be concluded that FOA-MAP meta-heuristic optimization approach is better than using MCS-MAP and BOA-MAP optimization algorithms. In addition, hybridization of optimization such as Genetic Algorithm combined with Firefly can also be applied to further reduce the localization error. The localization error of the new hybrid Firefly algorithm could be compared with the standard Firefly algorithm (FOA-MAP) in order to validate its performance.

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