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Modified Fuzzy C Means and Ensemble based Framework for Min Cost Localization and Power Constraints in Three-Dimensional Ocean Sensor Networks

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Abstract

Background/Objectives: In this paper, the optimization problem is considered for Minimum Cost Localization Problem (MCLP) in 3D Ocean Sensor Network (OSN). The main aim of OSN is to localize all underwater sensors or the minimum travel distance of the ship which deploys and measures the anchors using the minimum number of anchor nodes. **Methods/ Statistical Analysis:** Minimum Cost Discrete multi-valued Particle Swarm Optimization (MCDPSO) and Hybrid Bee Linear Genetic Colony Algorithm (HBLGCA) are combined in this Hybrid Ensemble Framework Model (HEFM). Minimum travel distance of the ship which deploys and the anchors for OSNs are determined by the finalized minimum travel distance results. In Hybrid Ensemble Framework, a set of optimization algorithm using both trilateration and local sweep operations are presented to address the problem. The set of anchor node and its travelling order sequence are picked using both trilateration and local sweep operations based on a set of HEFM which is proposed by the hardness of 3D localization. **Findings:** Most of the existing localization algorithms only focus on checking the localizability of a network and/or distribution of nodes within a set of anchor nodes which are static in nature and measurement of distance to localize. The main aim of today's algorithm is to determine the min cost localization problem depending on a particular method that might not provide optimal results. To overcome all the above problem hybrid ensemble framework is formalized. Because of the complexity of the distributed approach, the current localization algorithms cause overhead and latency. Cluster based architecture for range-free localization is proposed in this paper to eradicate these problems in Wireless Sensor Network. The similar nodes are grouped using Modified Fuzzy C Means (MFCM) clustering. Some parameters such as quality of a link, energy and coverage are used to select the cluster-head. **Applications/Improvements:** These methods give better results for certain applications such as location-based routing due to localization problem and the results have been measured in terms of the energy, power and Quality of Service (QoS). The simulation results, show that the overhead, localization error, latency are reduced in proposed HEFM framework and the localization accuracy is increased.

Keywords: Hybrid Ensemble Framework Model, Localization, Modified Fuzzy C Means, Optimization, 3D OSN

1. Introduction

Due to the supply of such low energy value sensors, silicon chip and frequency electronic equipment for info transmission, there's a good and fast diffusion of Wireless Sensor Network (WSN). Wireless Sensor Networks that include thousands of minimum cost value of sensor nodes are employed in several promising applications

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like health police work, battle field surveillance and environmental observance. Localization is one amongst the foremost vital subjects as a result of the placement info is often helpful for coverage, deployment, routing, location service, target trailing and rescues[1]. Hence, location estimation may be a vital technical challenge for the researchers, and localization is one amongst the key techniques in WSN. Localization is one amongst the foremost difficult tasks in planning ocean detector networks[2,3] or general wireless detector networks[4] that aim to get the physical locations of every individual detector node. Location info is employed in several tasks of ocean detector networks like event police investigation, target/device trailing and coverage, environmental observance, tagging raw sensing knowledge and network deployment. In most of those ocean sensing applications, effort localization info is a vital a part of the sensing tasks. For instance, ocean survey knowledge no heritable by sensors are useless while not correct location info; target trailing desires the accuracy of location information and distance measure. Moreover, location info can even be utilized by bound networking protocols to boost the performance of ocean detector networks, like routing packets exploitation position-based routing[5] or dominant the constellation and coverage exploitation geometric strategies[6].

The usage of GPS is limited to surface nodes in light of the fact that the GPS sign does not engender through water. Even though for some physical sensor arrangement the ideas with GPS less positioning have been proposed, due to the properties of acoustic channel they must be modified. The acoustic channel has low data transmission, high engendering postponement and high bit lapse rate. Hence, restriction conventions need to work with least conceivable message trade. This is likewise directed by the restricted battery force of the sensor hubs and the trouble of reviving or supplanting batteries of the submerged hubs. In any case, it is all the more difficult to find hubs in submerged situations than in physical situations. Since the speed of acoustic sign can change with saltiness, weight and temperature, it is hard to get very exact extents between hubs submerged. Last, 3D organization of OSN obliges more stay hubs to find hubs in 3D sea space. All these make exact limitation in sea a testing errand. Lately, countless methods have been proposed for sea senor systems to limit submerged sensors by trading data with stay hubs. Some of them are talked about as takes after. In[7] propose a multi-stage restriction plan utilizing versatile guides. The signals intermittently climb and plummet in the water segment. When they reemerge, they get new GPS coordinates. At that point, they plunge to the level of the submerged sensors to promote these directions. Thusly, confined sensors get to be intermediary guides and engender their own directions and so forth. The objective is to restrict the hubs with the littlest number of signals utilizing intermediaries rather, yet accomplishing a sufficient exactness. The real advantage is the lessening in working expenses. Portability is a basic element in deciding execution. The execution (i.e., the rate of confined hubs amid a cycle, precision, postponement and correspondence expense) is tried in a recreation situation in light of a reasonable mobility model.

In[8] the main aim is large-scale USN's localization. They use double style and surface buoys of underwater nodes: Anchor nodes and normal sensing element nodes. Initially, anchor nodes are localized by the assistance of surface buoys and so the normal sensors are localized mistreatment these anchor nodes. Anchors are unfolded among sensors and realized higher large-scale 3D USN's localization. Even though this method has advantages; A main challenge is locating anchor nodes in an efficient way. In[9] the usage of mobile beacons is to enhance the coverage of localization in 3D space. Beacons dive and rise to perform as underwater GPS doesn't contemplate multi-stage localization. During this work, we have a tendency to complement the concept of DNR beacons with reiterative localization. In[10] a prediction-based localization system is projected to networks of mobile underwater sensing element. In[8] the same hierarchical USN was proposed. Here, anchor nodes are ready to predict their quality model and surface buoys are used to predict the accuracy via measurements. If the proposed system is correct enough, they are not update the broadcast messages. This suggests that if the nodes follow an exact quality pattern they are doing not receive surplus messages, saving from communication value. In[8,10] the surface buoys are used to localize the anchor nodes however the value or the rivalry which will be caused by this operation isn't mentioned. Their simulation results don't seem to be supported associate underwater physical layer or a MAC layer.

Whether having the guarantee of covering all sensors or not most of the authors try to localize sensors. They sometimes thought that there are enough anchor nodes to realize the goal. Recently, Huang et al.[11] proposed a downside replacement localization, known as Minimum Cost Localization Problem (MCLP), for 2D sensor networks in that all nodes are localized in a network mistreatment of minimum anchor nodes. Historically, Huang et al.[11] described a single-objective optimization problem to overcome MCLP problems. Therefore usage of single technique may not give optimum result. Because of quick convergence rate and straightforward implementation the Particle Swarm Optimization (PSO) algorithmic program is supported by several researchers. For instance, the log-barrier constraint function based PSO localization algorithm could accelerate the convergence speed and save energy[4], adaptation of crossover operator and the mutation operator of the PSO localization could avoid the premature convergence and the quantum mechanics based PSO localization algorithm could enhance the global convergence and achieve accuracy improvement.

Though the effects of envisioned nodes happens continuously, because of ranging errors in some applications, localizations meet the gap distance constraint without meeting the geometric topology constraint. But in this PSO, discrete problems are only considered with binary valued solution elements. Modified Discrete Multi-Valued Particle Swarm Optimization (MDPSO) is proposed in this work, which doesn't depend on the single optimization problem. Combination of MCDPSO and HBLGCA procedure is proposed that is called as Hybrid Ensemble Framework Model (HEFM). The disadvantages of current localization algorithms are overhead, latency and so forth and the distributed approach is more complex. In order to overcome these issues, cluster based architecture for range-free localization in wireless sensor network is proposed in this paper. Grouping of the similar nodes are achieved by Modified Fuzzy C Means (MFCM) clustering. Then the optimization problem to 3D Ocean Sensor Networks is extended to form a Minimum Cost 3D Localization Problem (MC3DLP). Note that, manually configuring of an anchor node in ocean is very expensive and in underwater the working condition of GPS device is poor. In addition, a HEFM is introduced to handle localization errors caused by both ranging errors and flip ambiguity and to control errors induced in localization process. In addition, a new variation of MLCP is included and its optimization objective is the length of visited path for the ship. It is very difficult to implement in 3D OCN, because acoustic propagation in ocean varies with different salinity, pressure and temperature and larger ranging errors during the localization phase. The efficiency and effectiveness of all proposed methods are shown in the simulation results over random 3D Ocean Sensor Networks.

2. Related Work

Underwater localization techniques are classified as infrastructure-based vs. infrastructure-less. In infrastructure-based localization, reference nodes are deployed on surface buoys (localized via GPS) or at planned locations on the sea bottom. Supported the beaconing signals from the reference nodes, the gap to those reference nodes are often computed at every node victimization the propagation time. In general, there ought to exist a minimum of d+ one references to unambiguously localize a network in d-dimensional house. In[12], the authors propose a strictly distributed localization framework that employs a projection technique that transforms the 3D underwater positioning downside into its 2D counterpart.

In[13] the authors divide the localization method into 2 sub-processes: anchor node localization and standard node localization. They introduced a distributed localization theme that integrates 3D Euclidean distance estimation with an algorithmic location estimation methodology. In[9] the authors planned dive and-rise beacons that obtain their coordinates from GPS whereas floating higher than water, so dive into water. Whereas sinking and rising, they broadcast their positions. The necessity for synchronization amongst nodes with the higher than approaches is eradicated with AUV-aided localization via Omni directional. Remodel the 3D underwater positioning downside into its two-dimensional counterpart via a projection technique[14]. Then introduce a localization theme specifically designed for big scale acoustic underwater detector networks. The planned localization theme doesn't need time-synchronization within the network. This theme depends on Time-Differences of Arrival (TDoA) measured regionally at a detector to observe vary variations from the detector to a few anchors which will reciprocally hear one another. Time Differences of Arrival (TDoA) to live distances between nodes so use these distance estimations to reason positions of nodes. Usually, in range-based ways, precise ranges of anchor nodes are used, whose positions are proverbial beforehand or often measured by ocean surface buoys or vessels.

Range-free way's[15] don't use correct measurement techniques; instead, they use various ways like hop count or areas to find nodes with lower price. However, they sometimes offer coarse accuracy. The author tends to think about range-based localization ways wherever acoustic signals are used for estimating the gap between underwater sensors. Some comprehensive surveys on localization in ocean detector networks are often found. The Minimum Price Localization Problem (MCLP) is introduced for 2nd wireless detector networks by[11]. Given the set of sensors and distance measurements among them, it aims to seek out associate anchor set specified 1. The total network might be localized and 2. The full price of putting in these anchors is decreased. This is often a totally completely different downside from previous works on localization. The authors show that such a drag is incredibly difficult so gift a group of greedy algorithms through each trilateration and native sweep operations to deal with the matter. Recently, a genetic algorithmic rule for the MCLP is additionally planned by[16] of these studies tackle MCLP in 2nd cases; solve the matter beneath the one improvement ways wherever a minimum of 3 distance measurements are required to localize a detector node.

In recent times, some works have proven the effectiveness of multi objective improvement algorithms to unravel conflict multiple objectives. It's additional affordable to model the node localization as a multi objective improvement downside, which might be delineated as resolution in solving Pareto resolution, instead of merely being delineated as a single-objective problem. Supported this viewpoint, a multi objective model was adopted to unravel the node localization problem with fitness functions together with the localization accuracy and therefore the topological constraint and therefore the optimum resolution was achieved by the genetic algorithmic rule[17]. But, there are still some issues that aren't solved. 1. The estimation accuracy is stricken by the choice and mutation operators. 2. The convergence rate is slow. Multi objective particle swarm improvement has been proven with outperformance within the accuracy and therefore the convergence. A multi objective multileader PSO was wont to handle an additional objective by constraint handling methodology with advantage in terms of potency[18]. A bare-bones PSO was combined with the sensitivity-based agglomeration to unravel multi objective dependability redundancy allocation issues as a Pareto optimum solution with high effectiveness. The multi objective swarm improvement downside, chosen the worldwide best particle from a group of Pareto optimum solutions to unravel the convergence and therefore the diversity of solutions, was solved by combining PSO with charge system search[19].

Proposed a new scheme referred to as Discrete Quasi Monte Carlo Localization (DQMCL)[20] which employs the antithetic variance discount approach to enhance the localization accuracy. Maximum current Sequential Monte Carlo (SMC) and Adaptive Monte Carlo (AMC) localization method cannot be used in dynamic sensor community however DQMCL can work properly even without want of static sensor community with the assist of discrete energy manage approach for the whole sensor to improve the common localization accuracy. Additionally we examine a Quasi Monte Carlo technique for simulating a discrete time antithetic markov time steps to improve the life time of the sensor node. But, it always takes place that the effects of estimated nodes' localizations meet the space distance constraint without meeting the geometric topology constraint because of ranging mistakes in some real time applications. In some Monte Carlo based Localization algorithm like WMCL[26] achieve high sampling efficiency but only achieved minimum level of error rectification in range problem. Discrete event system based localization method[27] using local controllers for individual agents by using global supervision (controllable and uncontrolled events) but multiple numbers of states causes TOA problem.

3. Modified Fuzzy C Means Clustering for OSN

In this paper, propose a cluster-based architecture for Minimum cost 3D localization problem in Ocean Sensor Networks (OSNs). The clusters are created using Modified Fuzzy C Means (MFCM) and the selection of cluster-head is based on the parameters such as quality of link, unused energy and maximum coverage. Each cluster is localized using a localization technique to overcome the Minimum cost 3D localization problem. Straight line scanning of the clusters is involved with deployed multiple sinks. Anchor and target nodes are node sequence that is obtained after performing the scanning process. The anchor nodes are used to find the position of the goal nodes. Hybrid Ensemble Framework Model (HEFM) is very helpful to choose placement of the target node. It includes a new variation of MLCP, which considers the distance of the visited path for the ship to achieve optimization goal. The location information of target nodes is maintained in the cluster head. Distance based MLCP technique is executed whenever any target node is not localized within the cluster under MLCP.

3.1 Similarity Measure Estimation

A time series function is formulated as the time-ordered data series at each sensor node. The three cases which are involved in similarity evaluation of the two time series are as follows:

The two sensor nodes N_i and N_j data values are same and assumed to be, if:

$mt_i = mt_j$, $D_{ij} < D_{th}$, $\delta_R < \delta_{min}$, and δ_R ABS(R_j–R_i)

Where mt_i and mt_j are the magnitudes of N_i and N_j values respectively, D_{ij} is the distance between N_i and N_j and D_{th} be the distance threshold , R_i and R_j are the rate of sending in N_i and N_j respectively and are given by :

$$R_i = \frac{NP_i}{T} \tag{1}$$

$$R_j = \frac{NP_j}{T} \tag{2}$$

Here NP is count of packets which are sent in a time period T. δR is the absolute difference of R_i and R_j and δ_{min} is the minimum threshold value for δR. This is used to represent two points in 3 dimensions. Coordinate of node i is (mt_i,D_i, and R_i) and Coordinate of node j is mt_i,D_i, and R_i. These coordinates and Euclidean distance are used to find Similarity Measure (SM) between the two nodes. The Euclidean distance between the nodes N_i and N_j is given by[21]:

$$SM_i = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2}, n = 3 \tag{3}$$

Here,

$$x_{i1} = mt_i, x_{i2} = D_i, x_{i3} = R_i \tag{4}$$

$$x_{j1} = mt_j, x_{i2} = D_j, x_{j3} = R_j \tag{5}$$

3.2 Estimation of Residual Energy

After one data communication the residual energy of each node (Ni)is found by[22]:

$$E_{res} = E_i - (E_{ix} + E_{rx}) \tag{6}$$

Where = node's initial energy and = transmission and reception data energy.

3.3 Estimation of Link Quality

Link quality indicator is an indicator which defines the characterization of strength and/or the received packet quality. It is proportional to Received Signal Strength (RSSI). It takes the value from 0 to 255:

$$LQ \propto RSSI \tag{7}$$

RSSI is defined as the ratio between received power and the reference power . As a general rule, r is equivalent to absolute value, say, 1Mw:

$$RSSI = 10.log\left(\frac{P_{rx}}{P_{ref}}\right)(dBm) \tag{8}$$

Increment in P_{rx} value, increases the RSSI value which also increases the quality of the link[23].

3.4 Estimation of Node Coverage

The node coverage (C_n) depends on the speed of corresponding node and degree of and is given by:

$$C_n=(\alpha * z_i)+(\beta * D_{ni}) \tag{9}$$

Where z_i is node's relative speed, D_{ni} is degree of node and α and β are constants. In the above Equation (9), z_i is based on the length between the nodes at time t and the D_{ni} is the direct wireless link among the nodes at time t.

3.5 Estimation of Distance

It is measured as the multiplication of transmission range and its hop counts among the sensor nodes[24]. It is given using:

$$D = \gamma * HC \tag{10}$$

Where γ range of transmission and HC is node's hop count.

4. Modified Fuzzy C Means Clustering

This algorithm groups the nodes into various clusters and includes the study of the data generation rate as well as the similarity between data series in the sink. The cluster-heads are chosen based on the unused energy, quality of link and coverage of node in each cluster. The separation of nodes N=(n_1,..n_k) into c cluster is done by the standard FCM objective function (see Figure 1) which is given as:

$$J = \sum_{i=1}^{c}\sum_{k=1}^{N}\mu_{ik}^{p}\left\|n_k - v_i\right\|^2 \tag{11}$$

Where $\{v_i\}_{i=1}^{c}$ the prototypes of the clusters and the array are $\left[\mu_{ik}^{p}\right]=U$ correspond to the partition matrix $U \in u$. The parameter is each fuzzy membership weighting exponent and determines the amount of clustering fuzziness. The minimization of FCM objective function is done if the nodes which are nearer to the centroid of its particular cluster head are assigned by high membership values and the nodes which are far away from the centroid of its cluster head are assigned by low membership values, modification is proposed to (11) by using a term that allows the influence of labeling of a cluster nodes to the labels in its immediate neighborhood nodes. The modified objective function is given by:

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{N}\mu_{ik}^{p}\left\|n_k - v_i\right\|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N}\mu_{ik}^{p}\left(\sum_{n_r \in N_k}\left\|n_k - v_i\right\|^2\right)^1 \quad (12)$$

Where N_k is the set of neighbors nodes of similarity function from Equation (1-10) and N_R is cardinality of the N_k. The parameter is controlled by the effect of the neighborhood node term.

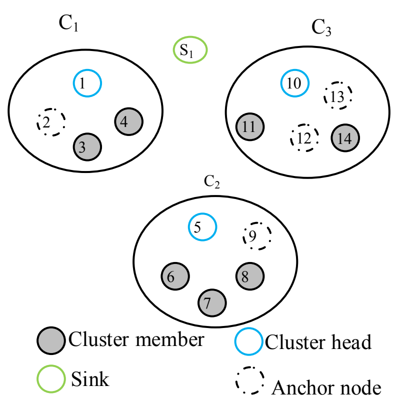


Figure 1. Cluster architecture.

This MFCM algorithm involves the similarity between data series in the sink as well as the study of the data generation rate. The MFCM clustering algorithm steps are as follows:

Algorithm 1: MFCM algorithm

- Each sensor node (N_i)transmits the data to the sink (S_i) with the specified data rate.
- S_i receives the data from each sensor node.
- Transmit data rate into the fuzzification value.
- S_i estimates the similarity measure SM (by (1-10)).
- Determine modified objective function J_m
- If $SM>SM_{th}$, where SM_{th} is the similarity threshold,

If $J_m< D$ then

Add these nodes in a cluster. Nodes within the cluster with E_{res}, LQ and C_n greater than threshold are chosen as cluster-head.

End if

- Stores the details of all the CHs and their data structures and broadcast cluster information packet (C_{IN}) to all the CHs.

5. Graph Model Representation for Minimum Cost 3D Localization Problem

Each cluster nodes in the 3D OSN will be taken as a graph and represented by G = (V,E), where V is underwater sensing element nodes which is simply taken as the set of nodes and E is linking between sensing element nodes within the sensing range which is taken as a set of links. Here, consider all the sensor nodes are static, so the movement caused by subsurface current is avoided. In addition assume that all sensors are having similar sensing ranges. At initial stage of the localization positions of anchor nodes which are considered as subset of sensor nodes $B \subset V$ are required to be identified (i.e., deployed and measured by a ship visit). GPS devices will be inactive under the water. So the sensor nodes will be used to find their position throughout the localization process by calculating the distance of the link E and the anchor node's position B in underwater. Because of the variation in the performance of shallow sensing element nodes among a ship's sensation those will be captured, the underwater sensing element nodes distributed in numerous depths. Thus, the group of shallow sensor nodes are described as $V' \subset V$ as shown in Figure 2 and it will be assumed as anchor nodes. Note that if all shallow sensors become anchors, some underwater sensor nodes may not be localized. So, after all shallow sensors are set as anchors localized sensors only will be considered in V. The Minimum Cost Localization Problems (MCLPs) in a 3D OSN aims to localize all underwater nodes and reduces the cost which includes equipment, deployment and measurement cost for anchor nodes. The following 3D MCLP problems are considered by measuring anchor node cost per unit as in[15].

5.1 Definition 1: Minimum Cost Localization Problem 1 (MCLP-1)

In a 3D Ocean Sensor Network 'G', find a subset B of shallow sensor nodes that will be anchor nodes should be found using following steps. 1. The localization of given graph is done by all sensor nodes in V and the measurement of distance between all links and anchor node's position are done; and 2. The anchor nodes |B| count is minimized. The cost per anchor node includes the deployment cost and measurement cost for all anchors and it depends on the travelling route length P of the route the ship (shown in Figure (2)). The definition of the MCLP problem follows:

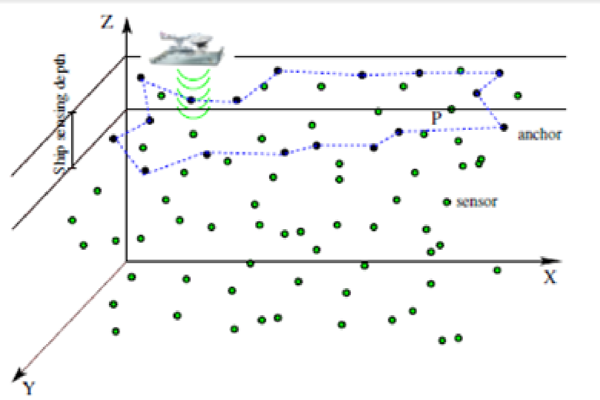


Figure 2. Illustration of localization scenario in ocean sensor networks: black nodes are selected anchors from the shallow sensors, while other green nodes are localized via 3D localization method. P represents the travelling path of the ship to visit all anchors.

5.2 Definition 2: Minimum Cost Localization Problem 2 (MCLP-2)

A 3D Ocean Sensor Network G is given, how anodes of subset B of shallow sensor become anchor nodes can be found using the following steps 1. Localization of all sensor nodes in V is done using the graph, the link distance and all anchor node's position and 2. Minimization of the total route length |P| taken by the ship to visit all anchors is done. Every shallow sensors are selected as anchors in worst case assumption (i.e., B = V 0) and all sensors in V will be localized. It is known that both MCLPs always have a possible solution. The 2D MCLP[8] is a special case of MCLP-1. MCLP-1 and 2D MCLP is NP-hard because the optimal solution of such problems is complex in nature. In MCLP-2, finding the minimum length route to visit all anchors alone without considering the localization part is the well-known Travel Salesman Problem (TSP), which is NP-hard. Hence, MCLP-2 is also NP-hard. During this period the energy of each iteration time is calculated and stored in to its respective time slot of present, past and future time periods.

6. Proposed Hybrid Ensemble Framework Model (HEFM) Methodology

Hybrid Ensemble Framework Model (HEFM) is introduced in this section to solve MCLP problems by finding the anchor set. Because of the usage of simple color coding in proposed HEFM, every sensor node v is marked with different colors. v's color and status is denoted by s(v). Different colors of the nodes such as white, black and green nodes represent different situation such as the node which is not localized yet, the selected anchor node which is used to get the ship's position by connecting the ship and the node and non-anchor node whose position will be found by using localization respectively. All sensor nodes are represented as a white node at first. The main aim of Hybrid Ensemble Framework Model (HEFM) is to get the positions of all nodes through the minimum travelling distance of the smallest group of anchors (black color nodes) or the anchor groups (nodes in either black or green). The fundamental concept is, all sensor nodes will be represented as white color initially and with its rank r(v) = 0 (Line 1-2). Here, r(v) is the node rank of a node v indicates number of neighbors which are localized (nodes with black or green color) . If the number of the sensor nodes is large then the identification of the node rank r(v) becomes difficult. If a sensor node is having less than four black marked neighbors (Line 3-5), that node cannot be localized by others. Based on the above problem, all these nodes are represented as shallow sensor nodes. In first step (Line 6-13) if the algorithm picks one white sensor node which can be localized more, in next step colors it as black. The benefit of marking a node v black is defined as the number of newly marked green nodes g(v) when v is marked as black. The above said procedure continues until there is no white node and the selected anchor nodes by the algorithm are all black nodes. In algorithm 2, a function MARK in which localization is done as repeated process based on the underline localization method (trilateration) will be called, whenever it sees a node with black or green.

6.1 Algorithm 2: Hybrid Ensemble Framework Model (HEFM) with MFCM

For each cluster $C_n \in C$.
Represented as graph $G = (V,E)$.
For each $v \in V$ do.

$s(v)$ = white and r(v) = 0.
Find the degree or the rank value of the node from HEFM ()// call the optimization method.
If the degree of the node is less than or equal to the threshold $d_{th}(r)$=3 then.
Mark (v,black).
While $\exists v$ whose s(v) = white do.
Backup current status of all nodes.
Mark (v,green) = g(v) and restore all status of nodes.
Let v_{max} is the white node with the maximum g(v).
Mark (v_{max}, black).
Return all Backup black nodes as the anchor nodes.

In algorithm 3 the mark function is represented as a multilateration (iterative trilateration). If a node is in color of black or green, its all rank status of the white neighbors will be increased by one. A node can be marked as green too, if its white neighbor's rank reaches 4. Within a local neighborhood the consistency of possible positions of nodes is checked, based on this checking the localization has been improved by using sweep operations and localizing more nodes if possible. If two neighboring nodes which has rank 3 (i.e., the possible each positions are limited to two locations), the positions of bogus will be eliminated by the distance between these two nodes. Note that whenever a unique match cannot be found, local sweep cannot realize two nodes. The sweeps are limited within two-hop or three-hop ranges to reduce the overhead.

6.2 Algorithm 3: Multilateration and Local Sweep with HEFM

For each cluster $C_n \in C$.
Represented as graph $G = (V,E)$.
For each $u \in U$ do.
s(u) = color and r(v) = 0.
For each v of u's white neighbor do $r(v)$++.
For each v of u's white neighbor with degree of the node r(v) from HEFM () is greater than or equal to 4 do.
MARK(v, green).
If two white neighbors of u (say v and w) both have ranks same returned from HEFM () and are neighbor to each other then.
MARK (v, green) and MARK (w, green).
If the degree of the three nodes u, v, w is less than or equal to the threshold $d_{th}(r)$=3 then.
MARK v, w as green.
MCLP-2 is solved by replacing white node with the maximum g(v in algorithm 2 as g(v) = total number of newly added green nodes/ distance from v to the last selected black node.

6.3 Hybrid Ensemble Frame Work Model

In this section, the HEFM implementation of the EFM concept is proposed, with the flow charts and pseudo codes. In HEFM, an information system is represented as a couple (C;G) where C = (C_1,..C_k) and G are finite, non-empty sets of clusters from MFCM and represented as graph with edges u, v, respectively. Graph edges can be represented as either qualitative (discrete-valued) or quantitative (real-valued). Here, the representation of graph nodes is as the binary string b of length M belongs to the rank value of the node, b_i=1if $G_i \in$ B, b_i=0 otherwise. An HFSE can therefore be represented by a set of such binary strings, E={b_1,..,b_K }={r(v),…$r(v)_k$), where K is the size of the ensemble, in this work the ensemble's size be the 30 nodes, graph nodes is totally divided into 6 set of the nodes. The finally selected nodes of the graph by the HEFM are the outcome elements of E, will be denoted as hereafter. Ensemble construction will be obtained by employing Minimum Cost Discrete multi-valued Particle Swarm Optimization (MCDPSO) and Hybrid Bee Linear Genetic Colony Algorithm (HBLGCA). The ensemble diversity can be naturally obtained from the differences in opinions reached by the evaluators themselves. Random Generator (PRG) is used to randomize the ensemble construction process, as illustrated in Figure 3, so that the available FS algorithms are randomly selected when forming the ensemble. This randomized approach may be:

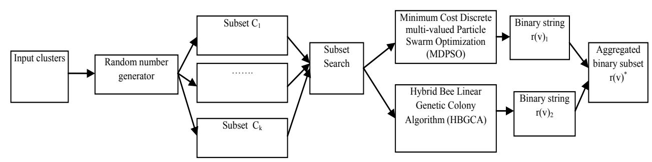


Figure 3. Flow chart for mixture of algorithms.

6.3.1 *Minimum Cost based Discrete Multi-Valued Particle Swarm Optimization (MDPSO)*

Localization problem and Minimum Cost Location Problem (MCLP) has a major difficult task is discrete optimization in modern research investigation under OSN. The optimization in OSN is defined as problems where solution will be only one discrete value such as either 0 or 1. If all rank values of the nodes solution elements are either 0 or 1, that optimization is called as binary optimization which is the basic form of optimization. Some general form of optimization has problems that have solution elements with n different unordered values, where n could be any integer greater than 1. The general case problems are solved by Particle Swarm Optimization (PSO). Particle Swarm Optimization (PSO) is an optimization technique developed by James Kennedy and Russell Eberhart[25,28]. PSO derives a set of potential problem solutions as a swarm of particles which is moving about in a virtual search space. In this work each node is assigned by a particle and rank value of nodes is considered as their fitness. PSO is an algorithm which is considering the concept of the movement of flocking birds and their interactions with their neighbors in the group. Initially randomized position (np_i) and (possibly) randomized velocity (pv_{ij}) is assigned in the n-dimensional search space in every nodes of cluster in the swarm, where $np_{i,j}$ represents the location of node index i in the j-th dimension of the rank values search space. The optimization of candidate node rank value solutions is obtained by flying the particles based on the fitness rank value of node, which is attracted to node positions in the search space to get better results. The best rank value position of its highest rank value ($np*_{i,j}$) is remembered by each node in the cluster (particle). Every node particle will be a neighborhood of other nodes particles so it is considered as a member. This neighborhood of node is considered as a subset of the particles (local rank value neighborhood) or all the particles (global rank value neighborhood). The results of local node rank value are the standard method is to set neighbors in a pre-defined rank fitness value in the search space. Binary values can also be applied. Binary value is solved by using the modified algorithm is given by:

$$pv_{i,j} = pv_{i,j} = pw.rand().(np*_{i,j} - np_{i,j}) + nw.rand().(np*_{i,j} - np_{i,j}) \tag{13}$$

$$np_{ij} = 1 \text{ } if \text{ } (rand\ (v_{i,j}) < r\ (v_{i,j}))\ , 0 \text{ } otherwise \tag{14}$$

From the above algorithm it is clear that no inertia coefficient is used here and the velocity of each node is updated in the same way as in standard PSO. A new node value is assigned to a particle by assigning the velocity term to the range and setting the node element randomly to probability of taking given by $r\ (v_{i,j})$. In this algorithm the main variation is the velocity term is limited to $|\ v_{i,j}\ | < V_{max}$, where V_{max} is integer value typically close to 6.0. The discrete-valued problems are optimised by the discrete-value modification in PSO (henceforth referred to as DPSO[25]) in a perfect way but it has some discrete problems with binary valued solution elements. In DPSO, the velocity term contains values which are the probabilities of solution elements and the particle contains the solution elements. But in MCDPSO algorithm, the nodes particles themselves contain the probabilities of solution elements and assuming values. In MCDPSO each particle's node rank value is represented from being 2-dimensional to 3-dimensional: $np_{i,j,k}$ is the probability of node position i, element j assuming value k be either 0 or 1. A node rank value is considered as fitness, at each evaluation time the solution elements are generated probabilistically for making stochastic evaluation. At the time of fitness evaluation a node position (particle i) and the real-rand valued terms $np_{i,j,0} ..., np_{i,j,n}$ must be transformed to generate a value from 0 to n for solution element and use the weighted sum as the probability:

$$np'_{i,j} = \sum_{k=0}^{n} rv(np_{i,j,k}) \tag{15}$$

$$P(rv_j = k) = \frac{rv(np_{i,j,k})}{np_{i,j}} \tag{16}$$

Here $np_{i,j}$ refers normalizing node rank value coefficient for node particle i and element j. By using this MCDPSO, the particle generates any minimum cost localization problem solution with varying probabilities depending on its terms. An adjustment is applied to node particle terms after each modification of the particle values. This adjustment is given by:

$$np'_{i,j,k} = np_{i,j,k} - cn(i,j) \tag{17}$$

For all k, where is the probability indicator of particle i, element j assuming value k, with chosen such that:

$$\sum_{k=0}^{n} rv(np_{i,j,k}) = 1 \tag{18}$$

MCDPSO technique differs from standard PSO, inertia coefficient w linearly decreases from 1.2 at the start of the algorithm to 0.6 at the end. Ring topology is used for the swarm and assigned the nearest particle on each side to be a neighbor, pw and nw are both set to 2.0.

6.3.2 Hybrid Bee Linear Genetic Colony Algorithm (HBLGCA)

In this paper a hybrid HBLGCA is proposed by combing ABC and GA procedure to achieve Minimum Cost Location Problem (MCLP) in modern research investigation under OSN. HBLGCA method is basically a hybrid of ABC and GA to the three basic operators of Bee colony for achieving the optimal solution to solve MCLP.

6.3.3 Linear crossover Genetic Algorithm (LGA)

The updation of MCLP solution is done by Linear crossover Genetic Algorithm (LGA) in which employed bees and onlooker and scout bees are applied before each successful updation respectively. Because of the updation a modification occurs on the position (solution) in the memory which is used to find a new degree node value path chain and also test the degree rank value of nectar amount r(v) (fitness value) of the new solution. In general reproduction, crossover and mutation are the three main process in GA. Reproduction inherits best nodes from previous generation. Nodes with high degree of node rank value r(v) from a cluster is having higher chances to solve MCLP through a fitness-based selection rule. In the crossover phase, two artificial employee bees (nodes) are randomly selected from the present population and based on the selected crossing site they exchange their node bits. Crossing sites are chosen by a random node number. We consider only linear operation of cross over because cross over performs well in this work. In this proposed work the bits each node bits are represented as the real number which belongs to the node number and distance value of nodes from cluster head to cluster member with k number of parameters.

6.4 Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) algorithm is an algorithm which uses intelligent behavior of honey bee foraging used for optimization. It uses the concept of inspecting the real bee's behavior in finding nectar amounts and sharing the information of food sources to the other bees in the hive. In this work each bee and their fitness value is considered as nodes in the graph G = (u,v) and rank value of node which is hop count distance between source to destination node respectively. Efficient division of labor and self-organization is performed to maximize the higher rank value stored in the hive by specialized bees. The Artificial Bee Colony has following three agents:

- **Employed Bee:** Information of all nodes in the graph location and the quality are gathered by Employed bees (nodes) after visiting the optimal MCLP food source. Based on the rank value of node employed bees are investigating MCLP search locally and exploiting the neighboring MCLP locations for each nodes and search the best MCLP food's location in the surrounding nodes of the present value.
- **Onlooker Bee:** Onlooker bees are bees which find the best node position based on the rank value and are waiting on the dance area. The best node position is selected based on the basis information of nodes and their rank value that is provided by employed bees. The global optimal node position to MCLP is discovered through the global search and random search which are performed by onlooker bees and in OSN.
- **Scout Bee:** Random search is done by scout bees to get optimal solution for MCLP in OSN. The node area's rank value which was uncovered by employed bees is discovered by scout bees and these bees and their operation of search are completely random in nature. Scout bees are trapping the local minima and avoid optimal solution search process in MCLP. The above three processes are basic operation of ABC. Initially the ABC algorithm starts with population assumption. Initial population is generated from number of nodes in the graph with the size equals to the size of population or total number of graph nodes. Each node rank value solution is denoted by nb_{ij} which is the position of food source, where i represents a particular solution (*i*=1,2,… ..,*NF*) and each solution is a D-dimensional vector of a particular solution (*j*=1,2,….,*D*) Employed bees starts their work of searching only after initialization of population from the random nodes of the graph. The optimal nodes in the food source are found by employed bees using node rank value. If the new optimal solution converges better than the previous one, old rank value of node is replaced the new one. The rank value is calculated based on the rank fitness value of each node. If the employed bees completes the calculation of optimal solution of all nodes, calculation of a optimal node position is done by onlooker bee based on the probability value P_i explained in the following equation (19):

$$P_i = \frac{f_i}{\sum_{i=1}^{NF} f_n} \tag{19}$$

Where f_i is the fitness or rank value of the solution i, here f_i is set to 3 and NF is population size. The new candidate solution is generated from the previous solution of artificial bee using the following equation:

$$V_{ij} = nb_{ij} + \varnothing_{ij} (nb_{ij} - nb_{kj}) \quad (20)$$

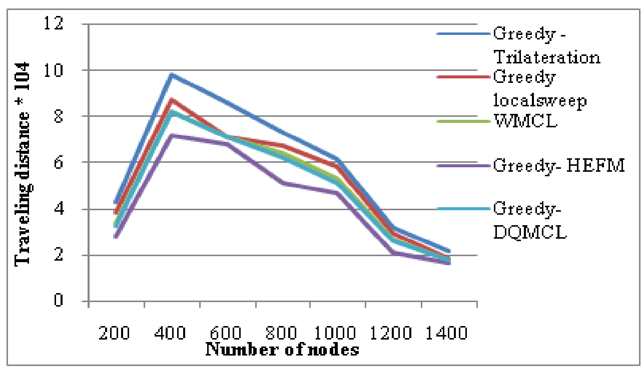
Where j is a dimension index (j = 1,2,….,D), k is particular individual's index (k = 1,2,3…..,NF) and i is particular solution's index (i = 1,2,…..,NF). K should not equal to x and k is selected randomly. $\varnothing_{ij} \in$ is a random number. If the new optimal solution found by onlooker bees converges better than the previous one, old rank value of node is replaced the new one and new rank value of node replaces the old one based on the rank fitness value of each node. If not, the old node rank value is retained. If there is no improvement in node rank value solution up to predetermined number of cycles then the current node rank value is rejected and replaced by onlooker bee and new node rank value of scout bees respectively.

6.5 Hybrid Bee Linear Genetic Colony Algorithm (HBLGCA) for Minimum Cost Location Problem (MCLP)

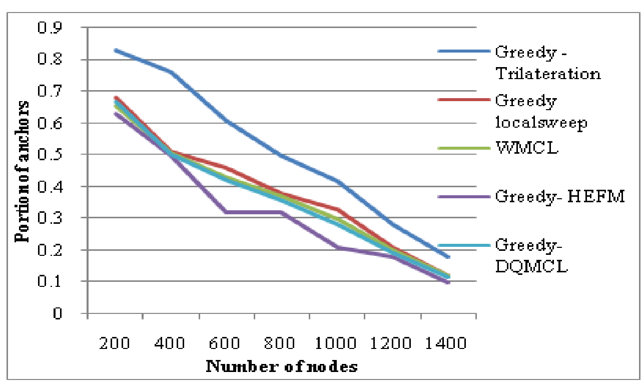
In the HBLGCA[29,30], an initial population is set randomly by selecting random node from graph and starting values are selected from the search space than the individual sequence vector associated with each node. In this work each bee and their fitness value is considered as nodes in the graph G = (u,v) and rank value of each node respectively. The node rank value is hop count distance between sources to destination node. Sequence vector is a member of the ABC in each population. Then the rank value of the each node is determined and considered as fitness value of each individual. The next step is individuals are visited by employed bees of Bee colony. To avoid local max problem, linear crossover operation is applied to employee bee nodes in the graph. In this phase after generation of new node's solutions the candidate sequence on the basis of candidate solution is produced. Then the fitness of individual is computed and if the new node rank value of each node position is better than the existing node position then it replaces the older node position and the probability for each nodes are calculated in the graph. After that crossover phase, two artificial employee bees (nodes) from present population are randomly selected and they do cross over based on the crossing site determined by another random node number. If the fitness (rank) value of the new nodes position converges better than old node position fitness value, old node position is replaced with new node. After that the onlooker bee phase is applied to calculate the new node position vector, a new sequence vector and the cost of this offspring. The fitness value of the each individual is calculated using the sequence and its cost from the cost matrix.

7. Simulations Results

To be able to examine the effectiveness of proposed techniques, widespread simulations are carried out on random generated 3-D OSNs. In all simulations, a hundred ~1050 sensor nodes are randomly deployed in $(2000m)^3$ cubic area. The sensing range of each node is set to be 300m, i.e., if the space among nodes is much less than or same to 300m, recollect that there is a distance calculation between them. The sensing range of the ship is ready as 900m. A sure number of sensor nodes' coordinates are generated inside the cubic area. Then using all of the shallow nodes as anchors and trilateration, all sensor nodes



(a)



(b)

Figure 4. Performances of different methods for MCLP1. (a) Number of anchors. (b) Portion of anchors.

which can't be localized will be deleted. Only remember all sensor nodes which are localizable while all shallow sensor nodes are set as anchors. For every set of simulations, the simulations are executed for one hundred instances (i.e. over a hundred random networks) and report the average results.

In MCLP-1, the intention is to lessen the quantity of anchors. Figure 4(a) suggests the absolute quantity of anchors selected by using all algorithms. It is observed that the less anchor nodes decided on gives higher outcomes. Among all the techniques, the random approach calls for the maximum wide variety of anchors. HEFM attains the higher overall performance, because it can be localize extra nodes at every step. All of the greedy algorithms will converge after the sensor nodes turn out to be denser. Lastly, the entire number of anchors to begin with increases with the node quantity and then drops down sharply about 400. Figure 4(b) indicates the percentage of anchors to the whole wide variety of shallow sensor nodes. Genuinely, the percentage of anchors drops while the variety of sensors increases. While the sensor community is sparse, maximum of shallow sensors must be anchors. Whilst the sensor community may be very dense, simplest very small percent of nodes desires to be anchors. This indicates that proposed HEFM can attain higher performances for huge-scale 3D sensor networks.

In MCLP-2, the purpose is to lessen the travelling distance of the ship because of high value of traveling inside the sea. Figure 5(a) suggests the traveling distance of each algorithm primarily based on the visiting series of the greedy algorithms. Though the random technique has a longer travelling distance whilst as compared with other greedy methods. Furthermore, greedy-local sweep has identical performances as greedy-Trilateration. It means that the anchor numbers plays vital function inside the randomly deployed network. This may be because of the same distance amongst sensor nodes in a uniformly random deployment. Feed the positions of all selected anchors in a genetic TSP set of rules and use the output path because the direction of the ship. Figure 5(b) indicates the outcomes. Furthermore, the distinction between the alternative grasping strategies grows to be smaller and HEFM nevertheless yields the excellent bring about time period of travelling distance.

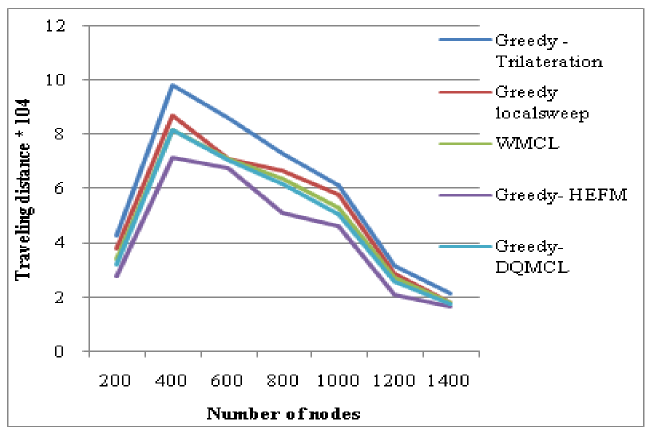
Then the performances of different proposed algorithms are studied. In this, set = 0:5 for certain simulation. In this case, the anchor selection approach will play a complex role in reducing the total number of anchor nodes. In Figure 6(a), Greedy-Local Sweep and Greedy-HEFM can provide the best result. Also, same experiments like MCLP-1, at first when sensor network is thin; most of the shallow nodes have to be anchors. Slowly, as sensor network become denser, only small portion of shallow nodes are required to be anchors. This confirms that the confidence threshold plays more vital part in controlling localization errors as shown in Figure 6(b).

Some of the other metrics are mainly evaluate the performance according to the following metrics:

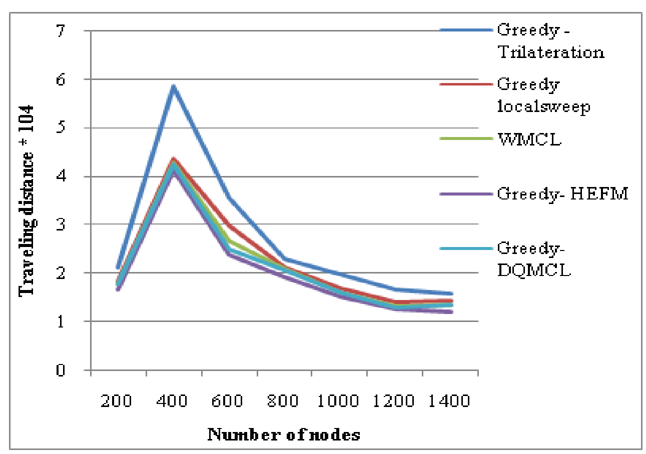
Average Energy Consumption is defined as the average energy consumed via the nodes during the receiving and sending the packets.

Packet Delivery Ratio is described as the number of data packets successfully received through the total number of packets sent.

Figure 7 shows the delay occurred for all the four schemes such as greedy-local sweep as Greedy-Trilateration,

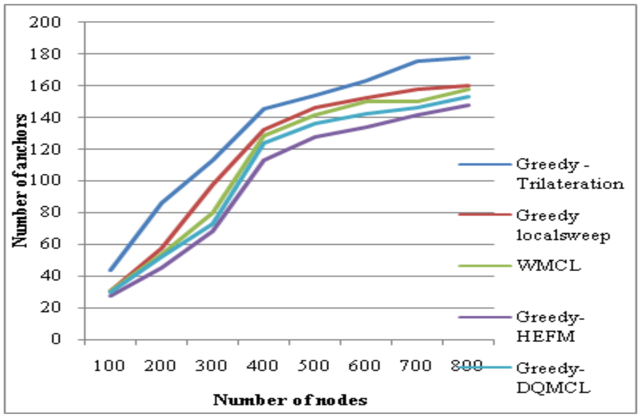


(a)

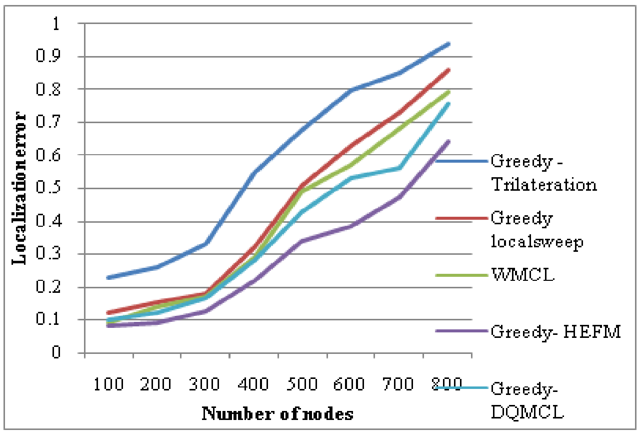


(b)

Figure 5. Performances of different methods for MCLP2. (a) Travel distance before TSP. (b) Travel distance before TSP.



(a)



(b)

Figure 6. Performances of different methods with = 0:5.(a) Number of anchors. (b) Number of anchors.

Greedy-DQMCL and Greedy-HEFM, when the transmission range is increased. The increase in transmission range results in the increase of delay for all four schemes, since more nodes have to be localized. From the Figure 7, can see that the delay of Greedy-HEFM is 2% less than Greedy-DQMCL, 5% less than Greedy-Trilateration and 10% less than greedy-local sweep, 4% less than WMCL since Greedy-HEFM uses the clustered architecture for performing MCLP localization.

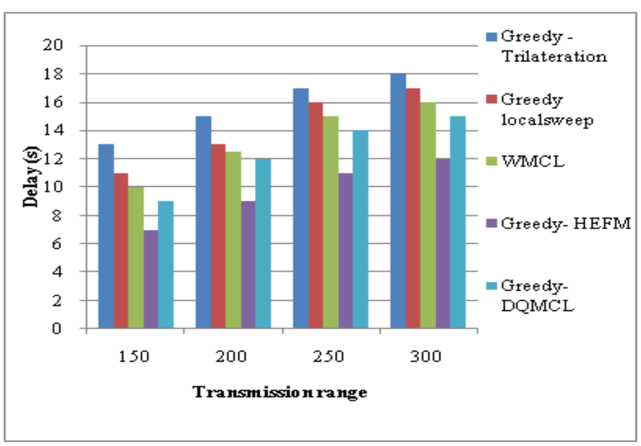


Figure 7. Transmission range versus delay.

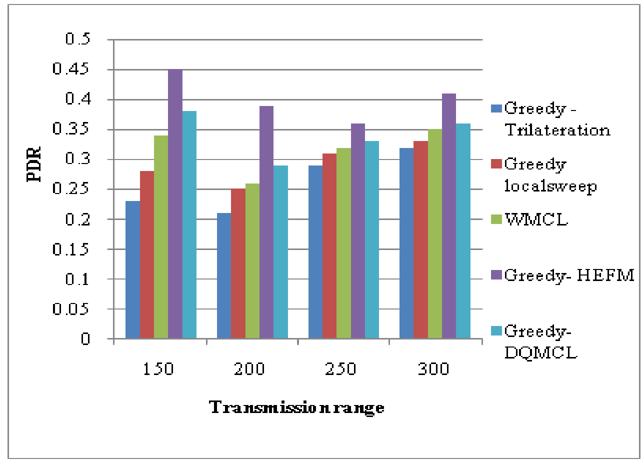


Figure 8. Range versus delivery ratio.

Figure 8 shows the packet delivery ratio of all the four schemes such as greedy-local sweep, Greedy-Trilateration, Greedy-DQMCL and Greedy-HEFM, when the transmission range is increased. It can be seen that the delivery ratio of Greedy-HEFM is 8% higher than Greedy-DQMCL, 12% greater than WMCL, 14% higher than Greedy-Trilateration and 23% higher than greedy-local sweep. This is due to the fact that Greedy-HEFM has the features of cluster-based power efficient scheduling for efficient delivery of data.

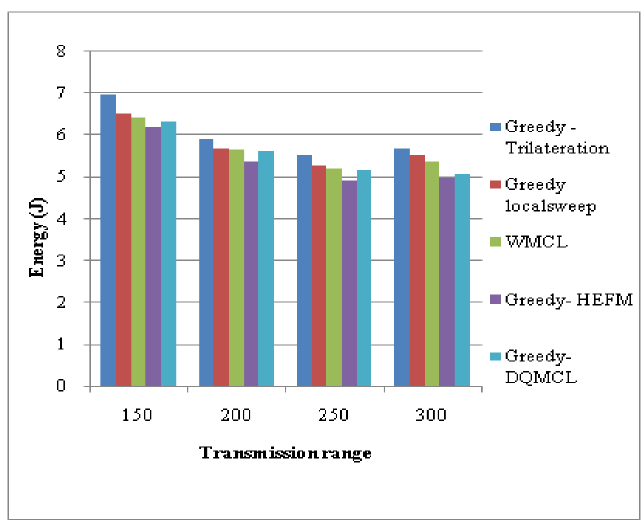


Figure 9. Range versus energy consumption.

Figure 9 shows the average energy consumption occurred for all the four schemes such as greedy-local sweep as Greedy-Trilateration, Greedy-DQMCL and Greedy-HEFM, when the transmission range is increased. The increase in transmission range results in the slight decreases of energy consumption for all four schemes, since more nodes have to be localized. From the Figure 9, it can see that the energy consumption of Greedy-HEFM is 1% less than greedy-DQMCL, 0.89% less than Greedy-Trilateration and 0.62% less than greedy-local sweep, since Greedy-HEFM uses the clustered architecture for performing MCLP localization to reduce the transmission power.

8. Conclusion and Future Work

The localization issue of wireless sensor nodes has been more difficult to solve, when taking into consideration the realities of real world surroundings. In this paper, a cluster-based structural design is proposed for Minimum cost 3D localization problem in Ocean Sensor Networks (OSNs). This technique forms the clusters using Modified Fuzzy C Means (MFCM) and the selection of cluster head depending on the parameters like link quality, residual energy and coverage. The design is presented, implementation and evaluation on localization system for OSN, called Hybrid Ensemble Framework Model (HEFM). The proposed Hybrid Ensemble Framework Model (HEFM) localization solution does not require any additional hardware for the sensor nodes, other than what already exists. The minimum cost localization problem is improved to 3D OSN to predict the optimal anchor set to localize all sensor nodes in the network. Two versions of MC3DLP are introduced to decrease the number of anchors, at the same time as optimizing the traveling distance of a sea surface vessel to see all selected anchors. As future work, like to discover the self-calibration and self-tuning of the HEFM scheme. The accuracy of the system can be improved further if the distribution of the event, rather than a single MCLP, is reported.

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