Efficient Sink Repositioning Technique using Hybrid Optimization Algorithm for Wireless Sensor Network

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Abstract- Wireless sensor network is a group of organized sensor nodes that are limited to their resources such as limited bandwidth, energy etc In a wireless sensor network (WSN), how to moderate the restricted power resources of sensors to broaden the network lifetime of the WSN as far as might be feasible while playing out the sensing and sensed data detailing errands, is the most basic issue in the network design. The data gathered from sensor nodes will be forwarded to the sink node to take proper actions. In order to avoid the failures, the sink nodes should be positioned in the better place for the resource optimization. In this paper, we propose an efficient sink repositioning technique (ESR).In the proposed method, first we will apply clustering for grouping the nodes that are adjacent to sink node. Clustering is done by an adaptive glowworm swarm optimization (AGSO) algorithm. The sink node can be designated as the cluster head initially. By making cluster, we are able to set the area of influence of sink which will help in repositioning of sink .For cluster head selection, we use threshold set algorithm (TS). We use sink positioning technique in which the position of the sink is to be selected among the position of existing sensors positions using Bactorial searchalgorithm (BS). For finding the nearest node to sink, the shortest path among all the nearest nodes should be considered. The node which has the shortest path is selected for position. The node which has the shortest path is selected for position.The proposed technique is implemented in the working platform of Network Simulator (NS-2) and the results will analyzed. Which shows number of sinks varies inversely with transmission range of nodes and network latency; this approach reaches to find the optimal position for all the sinks in order to optimize the lifetimeof the network and move according with intelligent sink positioning.

Keywords- WSN, sink repositioning, network lifetime, sink nodes, clustering, AGSO,BS,TS

I. INTRODUCTION

Wireless sensor network (WSN) architecture includes extensive number of sensor nodes that reports its estimations to sink or other access node that are circulated nearby[1, 2]. Generally, sensor nodes are conveyed in a geographical region for identifying some physical marvels like vibrations, earthquake and temperature [3]. Nature of the sensor utilized chooses the utilization of vitality in the detecting subsystem [4].The contact between base station or the entryway and a few remote sensors is accomplished in WSN through radio connections. Detected information at node level is assembled, packed and transmitted to the entry, either directly or by in-between nodes dependent on need. At last, the transmitted information is exhibited to the framework by entrance. The most essential issue to be considered in overseeing remote sensors is energy utilization. Substituting or recharging the batteries of sensors isn't such a simple work, so as to accomplish proficiency in vitality utilization for a more extended period[5] ;The energy must be protected. Energy is expended in sensor nodes by different methods, among that the correspondence element consumes up energy for a larger extent. The detected information can be transmitted specifically to the sink for smaller network, then again for large network information must be transmitted by multihop communication [6]i.e. information is transmitted through in-between sensor nodes. In above examined two cases, communication distance is a vital factor for energy utilization [7] .The topologies to be specific star, work, transport, tree and completely associated are the kinds of topologies in sensor networks. [8].

In wireless sensor networks (WSN), sinks are limited with plenteous assets and sensors that generate information are called as sources. The sources can pass on information to one or numerous sinks with the end goal of inspection and processing [9]. In WSN, sink reposition is favored by all applications that include constant traffic for even amidst different nodes [10], it can adjust the traffic stack and accordinglydecrease the overlook rate of continuous packets. To do , multiple sink deployment , sink repositioning and sink mobility is considered. Exact data of the area being observed is expected to offer a perfect arrangement by the sink organization strategy, yet this technique is certainly not a sensible frequently. To reposition the sink, it’s odd pattern of energy must be considered.

In uncertainty based WSN, sensor nodes doesn’t know the real time information on sink position is a major challenging one. In multi-hop communication approach, certain assessment strategy is required at each hop. The efficiency of its operation and effectiveness of WSN are determined by the node position.[11, 12] Use of nodes in the network relies free of metrics that believes a pattern of network operations or maintains the state of the network, which remains unaffected during the network lifetime [4, 13,14] .The nodes can be dispersed accordingly based on the requisite as either random or controlled.Sink relocation can be carried out in the following ways.[15]

- Multiple Sink Deployment: when utilizing the single sink, the reposition will be take additional time. The deploying multiple sinks may diminish the normal number of hop a message needs to go through and the information will dependably be sent to nearest sink. [16]
- Sink Mobility: if a sink moves quick enough to convey information with a fair postpone then it is called as mobile capacity and the WSN will take benefit of this mobile capacity. Subsequently with the mechanical developments, the mobile sink gets information from nodes and transports the information. Consequently for the decrease of energy utilization of nodes, this methodology exchanges data delivery latency.
- Deploying Multiple Mobile Sinks: For this situation, immediately and without causing buffer overflow, the numerous sinks are conveyed so the sensor information can be obtained.

This paper is organized as follows. Section II addresses the related work. Section III dealt with the problem identification. In section IV we have proposed our methodology in order to deal with the specified problem. In section V presents our system model and parameters. Simulation and evaluation results have been presented in section VII and finally section VIII concludes our paper. I

II. RELATED WORK

Liu et al (2014 summarized, a movement of fault detectors through which various centers can organize with one another in an end errand Fault detectors encode the investigation system to state changes. Each sensor can share in thefinding by venturing to every part of the identifier's present state to another state in perspective of neighborhood affirmations and after that passing the indicator to various centers. Having sufficient verifications, the blamelocator achieves the Accept state and yields a last discovering report. The paper assesses theexecution of our self-discovering instrument called TinyD2 on a 100-center point indoor proving ground and conduct field focuses on in the Green Orbs structure, which is an operational sensor framework with 330 centers outside [17].

Wang et al (2014) proposed system utilizes information identified with the lasting battery vitality of sensor hubs to adaptively alter the transmission scope of sensor hubs and the relocation plan for the sink. Some hypothetical and numerical dissect are given to demonstrate that the EASR technique can expand the system lifetime of the WSN essentially. Sink migration is an effective system lifetime expansion strategy, which abstains from devouring excessively battery vitality for an explicit gathering of sensor nodes[18]

Zou et al, (2015) proposed an investigation that includes the examining of wireless sensor networks when eavesdropping attackers are present. These systems comprise of various sink hubs and in addition sink hub. A sensor that contains most astounding mystery level is incorporated into the sensor organizes through the ideal sensor booking technique. This is utilized for the insurance of remote transmission from the listening in assaults. This hub with most elevated mystery level sends the data to the sink. For giving round-robin planning some shut shape articulations are executed by the likelihood of event of a block event. [19].

Zhu et al, (2015) projected a Tree Cluster-Based Data-Gathering Algorithm (TCBDGA). This is utilized for the WSNs and with the mobile sink. A tree development technique is utilized for this. The tree comprises of different tree hubs. Sub-rendezvous points (SRPs) are some extraordinary hubs that are chosen. The bases of determinations are the traffic stack and the jumps that are included to the root hubs. Correlations are made with different systems and the outcomes demonstrate that the TCBDGA can adjust the complete load of the network. Through this technique theenergy utilization is additionally decreased. The primary issue that is the hotspot issue is totally drained. This strategy additionally gets the opportunity to expand the lifetime of the network [20].

Zhou, et.al, (2015) proposed the planning mobile sinks energy effectively, while dragging out the network lifetime, is a dare. To cure this issue, they proposed a 3 phase energy-balanced heuristic. Specifically, the system area is immediately isolated into framework cells with the equivalent geological size. These bunches are balanced by (de)allocating network cells contained in these groups, while considering the vitality utilization of sink development. Along these lines, the vitality to be expended in each bunch is around adjusted considering the vitality utilization of the two information assembling and sinks development. Exploratory assessment exhibits that this technique can create optimal grid cell division inside a restricted time of cycles, and draw out the network lifetime[21].

Pant et al (2017) proposed technique sorted in two different ways, sink transmission and reposition. Sink transmission activity performed by checking the received signal strength utilizing of heterogeneous lower vitality utilization. Opposite side the errand of sink movement performed by matrix based detecting (earlier for development hub). Simulation results demonstrate that their proposed AST-EASR boosted the system of network lifetime of WSN as contrast with regular methodologies like, vitality mindful sink migration (EASR) and one-advance moving scheme. .[22]

Jong et al (2017) proposed QHBM algorithm had been structured and evaluated for calculating sink repositioning in WSN. The QHBM impersonates the queen honey bee relocation in nature where sink moves to better places where

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the nodes have highest remaining energy noteworthy outstanding vitality. Sink choice is guided by scouts (CH hubs). The sink utilizes the likelihood of every segment to assess goal. In the wake of getting an alarm, sink moves towards chosen post in a cardinal course. We found that QHBM can expand arrange lifetime about 22.22% more than static sink. Moreover, the proposed calculation likewise outperformed the current sink repositioning calculations in term of a lifetime. QHBM can accomplish the lifetime extension of WSN about 17.02 and 10.61% more noteworthy than arbitrary and meet sink repositioning techniques, separately. QHBM can outperform EASR in lifetime development for about 7.74%. In addition, QHBM can outperform the EASR, meet and irregular stroll in term of packets deliver to sink and holding up time.[23]

Pushpalatha et al (2018) presented the novel technique specifically life time and unwavering quality concerned ideal sink repositioning. Saving the energy use of sensor hubs and enhancing the system lifetime with the concern to optimal clustering result is the significant goal of this examination work. In this proposedstudy work, Energy and Distance aware Clustering Technique is initiated to group the in between sensor/mobile nodes that are closer to both sink hub and the sensor hub which are prepared to exchange the information. Here Weight K-implies calculation is adjusted to group the hubs. To guarantee the effective transmission of information without node failure, optimal cluster head choice is performed by utilizing the cat swarm optimization algorithm with the goal of additionally remaining vitality and accessible data transfer capacity. This finds the most appropriate position for the sink hub [24]

Kumar et al (2018) intended an advance Location Aware Routing for Controlled Mobile Sinks (LARCMS), which will helps in limiting announcing delay, upgrading system of network lifetime, dealing with sink position refreshes and giving uniform vitality utilization. The proposed method utilizes two versatile sinks in predefined direction for information gathering and gives better outcomes contrasted with existing strategies. The execution of LARCMS is assessed by contrasting and comparable portable sink directing conventions through broad reproductions in MATLAB[25]

III. PROBLEM METHODOLOGY AND SYSTEM MODEL

A. Problem methodology

Yasotha et al. [21] an approach for static sinks repositioning and finding the optimal multi sink location. In that mobile sinks are moved arbitrarily and sinks are moved independently in various clusters. The gathered data will be sending to the goal through sink node/base station. Sink node energy depletes speedier contrast with different nodes introduce in the network since sink node will go about as a gateway to different nodes. The static nodes for gathering pressing data's and mobile sink for colleting un-critical data's in the system region. This approach depends on two fields are multiple sinks positioning and the one of a kind sink relocation. This approach has the preferred standpoint while moving the sinks to their optimal positions for the whole system. In the high traffic are the optimal arrangement will be utilized as a part of powerful way. Moving the sinks towards the overwhelming traffic permits acquiring a power sparing gave that a dependability of these territories exists. Repositioning of the static sink will be actualized in routing stage to keep away from the packet loss. Finding the optimal arrangement will upgrade the energy proficiency of the nodes and it in a roundabout way expands the system lifetime.

In existing research work, some problems are there. In the existing relevantwork, the plan presented in the paper isn't reasonable for fast mobile nodes since its considering the base geographical distance between nodes for clustering, the plan of in the paper can't perform well when the network is too little and too vast, the strategy isn't appropriate for expansive scale network due to it might be confront issue of computational overhead if number of nodes are so extensive. We analyze from the existing papers for sink repositioning technique using different algorithms to improve the lifetime and energy efficient

B. System model

We use the WSN environments, it is reasonable to assume that sensor nodes have a fixed and relatively short transmission range. A clustered structure organizes the sensor nodes into clusters, each governed by sink. The nodes in each cluster are involved in message exchanges with their respective sink.

Fig.1: System model of proposed efficient sink repositioning technique (ESR)

IV. Proposed efficient sink repositioning technique

A. Cluster formationusing adaptive glowworm swarm optimization

Cluster analysis isone of thesignificantmethods in exploratory data analysis, neural computing, machine learning, pattern recognitionand other engineering area. The clustering aims at identifying and extracting significant groups in underlying data. Glowworm swarm optimization (GSO) is a new swarm intelligence (SI) algorithm, was proposed in [26]. Currently, they have not researchedallied to the clustering analysis based on the Adaptive GSO algorithm. In this paper, we will propose new clustering based adaptive GSO algorithm in WSN

The glowworm swarm optimization (GSO) is a swarm intelligence (SI) optimization algorithm developed based on the behavior of glowworms. The behavior pattern of glowworms which is used for this algorithm is the apparent capability of the glowworms to change the intensity of the luciferin emission and thus appear to glow at different intensities. The GSO algorithm makes the agents glow at intensities approximately proportional to the function value being optimized. It is assumed that glowworms of brighter intensities attract glowworms that have lower intensity. The second significant part of the algorithm incorporates a dynamic decision range by which the effect of distant glowworms are discounted when a glowworm has sufficient number of neighbors or the range goes beyond the range of perception of the glowworms.

The working function of the GSO algorithm is the transaction between the given 3 mechanisms which are:

1.Fitness broadcast: Glowworm consist of emission of light pigment called luciferin, the highest value of luciferin calculates the fitness value of glowworm. This allows the glowworm to glow at certain rate which is directly proportional to the optimized function value. There is no reduction in the luciferin level, if it is sensed by the neighbor due to distance.

2.Positive Axis: In a search space of multiple glowworms, each glowworm moves to the neighbor whose glow is brighter then itself. The probabilistic mechanism has been used to select the best from them.

3. Adaptive neighborhood: To identify neighbors, glowworm uses adaptive neighborhood range.

The exposition of the algorithm is presented for maximization problems. However, the algorithm can be easily modified and used to find multiple minima of multimodal functions. AGSO starts by placing a population of m glowworms randomly in the search space so that they are well dispersed. Initially, all theglowworms contain an equal quantity of luciferin l_0. Each cycle of the algorithm consists of a luciferin update phase, a movement phase, and a neighborhood range update phase (Fig. 2).

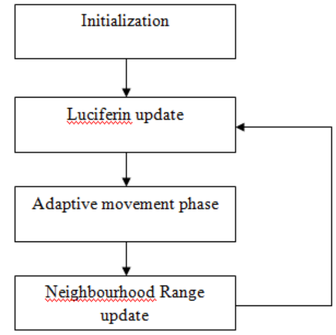

Fig.2: The phases of AGSO algorithm

Luciferin update phase: The luciferin update depends on the function value at the glowworm position. During the luciferin-update phase, each glowworm adds, to its previous luciferin level, a luciferin quantity proportional to the fitness of its current location in the objective function space. Also, a fraction of the luciferin value is subtracted to simulate the decay in luciferin with time. The luciferin update rule is given by:

$$l_k(t+1) = (1-\rho)l_k(t) + \gamma D(x_k(t+1)) \quad (1)$$

Where, $l_k(t)$ represents the luciferinlevel associated with glowworm k at time t, ρ is the luciferin decay constant (0 < ρ < 1), γ is the luciferin enhancement constant and $D(x_k(t))$ represents the value of the objective function at glowworm n's location at time t.

Movement phase: During the movement phase, each glowworm decides, using a probabilistic mechanism, to move toward a neighbor that has a luciferin value higher than its own. That is, glowworms are attracted to neighbors that glow brighter. For instance, there are four glowworms (m, n, o and p) that have relatively higherluciferin level than glowworm q. Since q is located in the sensor-overlap region of o and p, it has only two possible directions of movement. For each glowworm k, the probability of moving toward a neighbor l is given by:

$$P_{kl}(t) = \frac{l_l(t) - l_k(t)}{\sum_{K\in N_k(t)} l_m(t) - l_k(t)} \quad (2)$$

Where $l \in N_k(t)$, $N_k(t) = \{k : d_{kl}(t) < r_d^k(t); l_k(t) < l_k(t) < l_i(t)\}$ is set of neighbors of glowworm k at time t, $d_{kl}(t)$ represents the Euclidean distance between glowworms k and l at time t, and $r_d^k(t)$ represents the variable neighborhood range associated with glowworm k at time t. Let glowworm k select a glowworm $l \in N_k(t)$ with $p_{k,l}(t)$ given by equation 4.2. Then, the discrete-time model of the glowworm movements can be stated as:

$$x_k(t+1) = x_k(t) + s\left(\frac{x_l(t) - x_k(t)}{\left\| x_l(t) - x_l(t) \right\|}\right) \quad (3)$$

Where, $x_k(t) \in R^M$ is the location of glowworm k, at time t, in the m-dimensional real space R^M, $\| \, . \, \|$ represents the Euclidean norm operator, and s (>0) is the step size.

Adaptive movement phase: In basic GSO algorithm foundation, introduce leader mechanisms. Before each generation of the algorithm, set the best glowworm's position as the leader in the current generation. After each generation, all glowworms are moved to the location of the leader, so that the glowworm swarm has high ability of searching global optimization, and improving the algorithm's ability in high dimensional space optimization. Improved algorithm updates the location as the following formula:

$$x_k(t) = x_k(t) + rand \; *(x_{leader}(t) - x_k(t)) \quad (4)$$

Where, $x_{leader}(t)$ is the position of the t^{th} leader, $x_k(t)$ is the position of the glowworm

Neighborhood range update phase: Each agent k is associated with a neighborhood whose radial range is dynamic in nature ($0 < r_d^k \leq r_s$). For instance, a chosen neighborhood range rd would work relatively better on objective functions where the minimum inter-peak distance is more than r_d rather than on those where it is less than r_d . Therefore, GSO uses an adaptive neighborhood range in order to detect the presence of multiple peaks in a multimodal function landscape.

Let r_0 be the initial neighborhood range of each glowworm (i.e.) ($r_d^k(0) = r_0 \forall i$). To adaptively update the neighborhood range of each glowworm, the following rule is applied:

$$r_d^k(t+1) = \min\{r_s, \max\{0, r_d^K(t) + \beta(n_t - |N_K(t)|)\}\} \quad (5)$$

Where, β is a constant parameter and n_t is a parameter used to control the number of neighbors.A full parameters analysis is found in Krishnan and Ghose(2008b)[26], show that the choice of these parameters has some influence on the performance of the algorithm. Thus, only n and r_s need to be selected. These parameters value brings more convenience to people to apply the GSO algorithm. Let the parameter value be taken as ρ = 0.4, λ = 0.6, β = 0.08, n_t = 0.03, l_0 = 5.The working formation of cluster formation is summarized in algorithm 1.

Algorithm 1: Adaptive GSO Algorithm

Set number of dimensions=y
Set number of glowworms=z
Let s be the step size
Let $x_k(t)$ be the location of glowworm k at time *t*
deploy_ agents_ randomly;
for k =1 to n do $l_k(0) = l_0$
$r_d^k(0) = r_0$
Set maximum iteration number = $(iter\_\max)$;
{
for each glow worm k do: % Luciferin - update phase
$l_k(t+1) = (1-\rho) l_k(t) + \gamma D(x_k(t+1))$; Eq(4.1)
for each glow worm k do: % Movement phase
{
$N_k(t) = \{k : d_{kl}(t) < r_d^k(t); l_k(t) < l_k(t) < l_i(t)\}$;
for each glowworm $l \in N_k(t)$ do:

$$P_{kl}(t) = \frac{l_l(t) - l_k(t)}{\sum_{K \in N_k(t)} l_m(t) - l_k(t)} \quad ; \% \text{ Eq 4.2}$$

$l = select\_glowworm(\vec{p})$;

$$x_k(t+1) = x_k(t) + s\left(\frac{x_l(t) - x_k(t)}{\left\| x_l(t) - x_l(t) \right\|}\right) \; ; \% \text{ Eq 4.3}$$

$x_k(t) = x_k(t) + rand \; *(x_{leader}(t) - x_k(t))$ % Adaptive Movement phase Eq 4.4

$$r_d^k(t+1) = \min\{r_s, \max\{0, r_d^K(t) + \beta(n_t - |N_K(t)|)\}\}$$

; Eq 4.5

}

$t \leftarrow t+1;$

}

B. Cluster selection using threshold set algorithm

The selection of a cluster head[27, 28], each sensor node generates a random number between 0 and 1. If the number is less than the threshold value T (e), the sensor node selects itself as a cluster head for current round; the threshold value selection Equation (4.6) is presented as follows:

$$T(e) = \begin{cases} \left[\dfrac{p(ch)}{1p(ch)\left[r \bmod \left(\frac{1}{p(ch)} \right)\right]} \right] & if \;\; e \in G \\ 0 & Otherwise \end{cases}$$

(6)

In Equation (4.6), p(ch) is the prearranged percentage of cluster heads (e.g., p(ch) = 0.1), r is the current round of iteration and G is th become cluster heads.

Threshold Equation for Cluster Head Selection 1: The approach increasing the network lifetime is the inclusion of the remaining energy level available in each node. It can be achieved by modifying the threshold. In this way, each node has different threshold in comparison with a random number. Therefore, high energy level nodes have greater probability to be elected as cluster heads than low energy level ones.

From Equation (4.6), the modified threshold value $T(e)_1$ can be obtained by using number of sensor nodes and cluster head nodes present in the network is as follows in Equation (7):

$$T(e)_1 = \begin{cases} \left[\dfrac{e}{D - e\left[r \bmod \left(\frac{N}{e} \right)\right]} \right] & if \;\; e \in G \\ 0 & otherwise \end{cases} \qquad (7)$$

Where N as the total number of sensor nodes in the network, c as the number of cluster head nodes for each round, r as the number of the current round, and G is the set of nodes that have not been selected as cluster heads in the last N/e rounds. The nodes shall transmit broadcast information after being selected as cluster heads. Each non-cluster head node determines to which cluster it belongs by choosing the cluster head that requires minimum communication energy. After this, it must inform the cluster head node that it will be a member of the cluster. Each node transmits a join-request message (Join-REQ) back to the chosen cluster head using a non-persistent CSMA MAC protocol

Threshold Equation for Cluster Head Selection 2: An additional method of finding the threshold based selection of cluster heads among the sensor nodes [29]is formulated in the followings. In this network E_0 as the initial energy of each node, it is clear now that when multiple cluster heads are randomly selected within a small area, a big extra energy loss occurs. The amount of lost energy is approximately proportional to the number of cluster heads in the area. Of course, there is a precondition on this conclusion, that is, cluster heads are 208 very closely located and the distance between them becomes negligible. Thus the new threshold is made to have reasonable numbers of cluster heads are consuming minimum energy and the network lifetime is also ultimately increased by the Equation (4.8). Where, s is the number of nodes that are excluded from the cluster head selection due to the location reason, with an initial value of 0. When s increases, $T(e)_2$ increases as well, which will ensure sufficient number of cluster heads will be generated.

$$T(e)_2 = \left[\frac{p(ch)}{1 - p(ch)\left[r \bmod \left(\frac{1}{p(ch)} \right)\right] - (p(ch)\, x\, s)} \right] if \;\; e \in G$$

(8)

The optimal number of cluster-heads[30] can be achieved based on analyzing the network energy consumption. First, the total energy consumption for data communication can be reduced to minimum in each round. Second, it is necessary to make sure the network energy can be distributed to each sensor node, thus effectively extending the network lifetime[31]. To simplify the algorithm, here are some assumptions in this paper. Each cluster has the equal number of sensor nodes, and a total of N nodes are deployed in a field of size A × A. If the WSN consists of c clusters, N/e nodes can be achieved in each cluster, including one cluster-head and (N/e)-1 non-cluster head sensor nodes. The WSNs is covered by a circular area. Therefore, the energy consumption of one cluster-head in a frame can be calculated using Equation 9.

$$E_{ch} = LE(N/e - 1) + LE_{df}\left(\frac{N}{e}\right) + \frac{L}{\eta}\left(E + \varepsilon_{amp} d_{bs}^4\right)$$

Algorithm 2: Threshold set clustering algorithm

Procedure *QT_clust_radius (G, D)*

If $(|G| \leq 1)$ *then output G, else do* % *Base case*
For each $i \in G$
Set flag= TRUE; set A_i *= {i}* % A_i *is cluster started by i*
While ((flag) and ($A_i \neq G$ *))*
For each $j \in (G - A_i)$
If distance (i , j)>d/2)
Then set flag = FALSE
Else set $A_i = A_i \cup \{j\}$ % *Add j to cluster* A_i
Identify set $C \in \{ A_1, A_2, ... A_{|g|} \}$ *with maximum cardinality*
Output C
Call
QT_Clust_radius (G-C,D)

In Equation (9), where L is the length of data packet, d_{bs} is the distance from cluster-head to the base station, EDA as the energy consumption of data fusion for each signal and η as the data fusion ratings.

Finally, the optimal number of cluster heads (e_{opt}) can be calculated as follows

$$e_{opt} = \sqrt{\frac{N}{2\pi}} \sqrt{\frac{\varepsilon_{amp}}{E + \varepsilon_{amp} d_{bs}^4}} \sqrt{\eta M^2}$$

Threshold set clustering algorithm: Threshold clustering algorithm uses the Heyer Quality Threshold Clustering (QTC)

C. Sink Repositioning Technique using Bactorial Search Algorithm

In sink repositioning technique,the sensors are randomly deployed within the geographic extent of the whole network. A single static sink and multiple mobile sinks are deployed in the network. The static sink is deployed at the center of the network .Depending upon the traffic in the network the nodes will sink. The node will move towards most nearest hop to form a new location. This will reduce the energy consumption and increase the overall performance [32]. The important parameters for the sink relocation are:

G: Gateway present in the cluster

G_1: Group of sensors located less distance D from G

G_R: Group of sensors that are one hop away on the active route

G_{R1}: Group of sensors in GR which are also in G_1, i.e. $G_{R1} = G_1 \cap G_R$

G_1^{new} : Group of sensors less than distance D away from the gateway at the new place

G_R^{new} : Group of sensors those are one hop away on new route at the new place

G_{R2}: Group of sensors in G_R new which are also in G_1^{new}, i.e.

$G_{R2} = G_1^{new} \cap G_R^{new}$

P_i: Packet traffic calculated as the number of packets per frame

PT: Group containing packet traffic of each sensor.

PT^{new}: Group consisting of packet traffic of each sensor

E (Tri): Energy consumed by a node in transmission of a packet to the next hop

The parameters like G_1^{new}, G_R^{new}, G_{R2} and P_T^{new} are calculated by locating the sink node at new location. The re-routing can cause high packet loss which is due to the energy depletion or failure of a relay node or is triggered by a change in data sources that requires setting a new topology [33].

The important parameters for sensor networks are average delay per packet, data transmission rate and throughput. All the parameters are designed based on the network operating over time period and are typically network-wide in scope. If the transmission energy is positive then sinking of the node is easy. If the total transmission energy has to exceed the threshold value then overhead will occur. The movement the gateway and the network level is based on the constant δ. The condition for relocation is given by: (10)

$$\sum_{\forall i \in G_R} E(TRi) \times Pi - \sum_{\forall j \in G_R^{new}} E(TRi) \times Pj > \delta$$

(11)

- Calculation of Links Weight

The energy consumed for the communication is defined by the distance between the nodes i and j. Since the required energy is proportional to distance squared, the wait will show the same behavior. The lowest is the destination node energy and the highest is the link weight. The link weight is defined as follows:

$$W(i,j) = CF_0 \times dist(i,j)^{\exp CFO} + CF_1 \frac{1}{energy(j)}$$

(12)

where,

• W(i, j) is the weight of a link between nodes i and j

• dist(i, j) is the energy consumed by the communication between nodes i and j

• energy(j) is the remaining energy in node j

• CF_0, CF_1, and expCF0 are coefficients for equation balancing

When a packet arrives to a sink by implementing, only the transmission energy consumption has been considered. The routing protocol is divided in several periods. The major periods are data transferring phases and routing phases.

a. Bacteria Foraging Algorithm

It was introduced by the Kevin M.Passino[34, 35]. This algorithm is used to solve control and distributed optimization problems in the network. It is generally based on the Foraging theory. Foraging theory assumes that animals search and find the nutrients in a way that maximize the energy i.e, E per unit time T. The four different steps in the algorithm are Chemotaxis, Swarming, Reproduction and Elimiation and dispersal. The key idea of BFOA is mimicking chemotactic movement of virtual bacteria in the problem search space.

S : overall bacteria present in the population
p : search space dimension
N_c : chemotactic steps
N_s : swimming length
N_{ed} : number of elimination-dispersal events
P_{ed} : Elimination-dispersal probability
N_{re} : reproduction steps present
C(i): The size of the step taken in the random direction specified by the tumble.

- Chemotaxis

This step is used to simulate the movement of an E.coli cell by using the process swimming and tumbling via flagella. In two different ways the E.coli bacterium can move. The bacteria can move in the same direction otherwise it can alter the direction between two modes of operation for the entire lifetime.

- Swarming

An interesting group behavior of E.coli and S. Typhimurium, are intricate and stable spatio-temporal patterns (swarms). The two behaviors are formed in semisolid nutrient medium.

- Reproduction

When asexually split into two bacteria the least healthy bacteria eventually die when each of the healthier bacteria (which yielding lower value of the objective function), which are then located in the same place. This will give the swarm size constant.

- Eliminational-Dispersal

Due to various reasons sudden changes in the local environment of the bacterium population may occur. The changes like regions are killed or a group is dispersed into a new part of the environment. Elimination and dispersal events can be used to destroy chemotactic progress, but they also have the effect of assisting in chemotaxis, since dispersal may place the bacteria near good food sources.Sink repositioning technique using bactorial search algorithm is summarized in algorithm 3 as given below.

Algorithm 3: Bactorial Search algorithm

Step 1	Initialization
	Initialize the parameters S, N_c , N_s , N_{re}, N_{ed}, P_{ed} and the C (i) [i = 1, 2……S]
Step 2	Calculate l = l+1, this indicate the Elimination-Dispersal loop
Step 3	Calculate k = k+1 this indicate the Reproduction loop
Step 4	Chemo taxis loop: j= j+1
	Calculate Compute cost J(i, j, k, l) = J(i, j, k, l)+J_{cc}(θ^i (j,k,l),P(j,k,l)), save the cost for the comparison process.
	Calculate the Move let by $\theta^i(j+1,k,1)=\theta^i(j,k,1)+C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$
Step 5	If j <Nc the calculate the value of J(i, j, k, l)
Step 6	Reproduction - calculate $J^i_{health}=\sum_{j=1}^{N_c+1}(i,j,k,l)$
Step 7	If k <N_{re} then find the Elimination-Dispersal loop
Step 8	In the evaluation, if i=1, 2,…..,S and each having a probability P_{ed}, remove and disperse bacterium. Eliminate a bacterium and disperse one to a random location by optimization process. If l <N_c go to step 1

Return Sink repositioning

V. RESULT AND DISCUSSION

This section contains result and discussion about the metrics like Packet deliver ratio, delay, drop, energy consumption could be analyzed to show the performance. The proposed methodology is implemented in the working platform of NS-2 and results will be investigated with the existing techniques as far as different standard assessment measurements to demonstrate the system effectiveness.

In this paper, we proposed a cluster based optimal sink repositioning technique for wireless sensor network. We compared the proposed cluster based optimal; sink repositioning (COSR) method and existing method Multipath routing Multiple sink nodes (MRMS). Here, we show result compared proposed and existing method.

A. Evaluation Metrics

The performance of the system is measured on standard statistical measures including Packet deliver ratio, delay, drop, energy consumption are exploited here.

Packet Delivery Ratio (PDR)
This network performance metric is defined as the ratio between the number of data packets successfully delivered to the destination and the number of packets transmitted by the source.

$$PDR = \frac{P_{\text{Received}} * 100}{\sum_{i=1}^{n} P_{Generated\ i}}$$

Where,

P_{Received} represents the total number of packets received by the sink node,

$P_{Generated}$ is the total number of packets generated by the source nodes

n represents the number of sensor nodes

Delay
Delay is the difference between information reception time of an actor node and information transmission time of sensor nodes.

$$d = t - r$$

Where,
t be the transmission time of a packet
r be the reception time of that packet

Packet Drop
It is the number of packets not received in the destination is the packet drop rate.

$$D_p = S_p - R_p$$

Where,
D_p Dropped packets
S_p Number of Send Packets
R_p Number of Received Packets

Energy Consumption
Calculate Energy consumption of each node to transmit and receive packet based on distance from sink node by using energy consumption formula

$$E_{packet} = E_{transmit} + E_{receiver} + E_{idle} + E_{sleep}$$

B. Performance Analysis

The performance assessment ofan efficient sink repositioning technique (ESR) for wireless sensor network can be analyzed and compared the Multipath routing Multiple sink nodes (MRMS) existing method. . We showed the proposed method with existingmethod comparison using different parametric of varying node and time. Weperform the metrics are Packet deliver ratio, delay, drop, energy consumption with varying node and time. Here, we showed the comparisonfigure in different metric with varying node and time.

The varying node with metrics such as Packet deliver ratio, delay, drop, energy consumption comparison figure as given below.

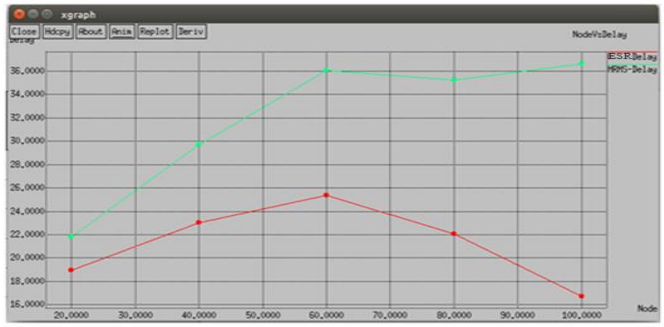

Fig.3: Node Vs Delay

From the fig 3, the proposed and existing method as far as delay. While looking at it presented that the proposed method has lee delay when compared to the existing method (MRMS). In the fig 3 result showed the proposed ESR method is has a less delay with varying node.

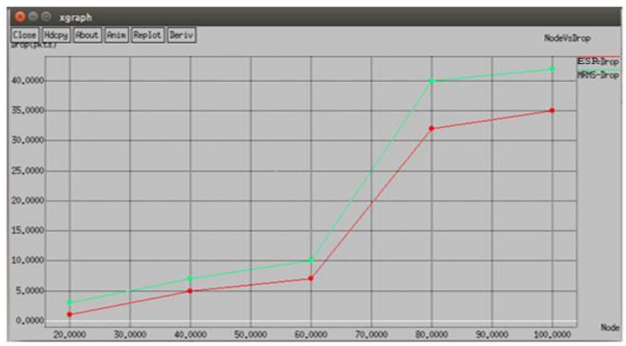

Fig.4: Node Vs Delivery ratio

The fig 4 shows the proposed and existing method comparison chart for delivery ratio with varying node. While compared the existing method (MRMS), the proposed method is high delivery ratio. The proposed ESRmethod has a high ratio with varying node.

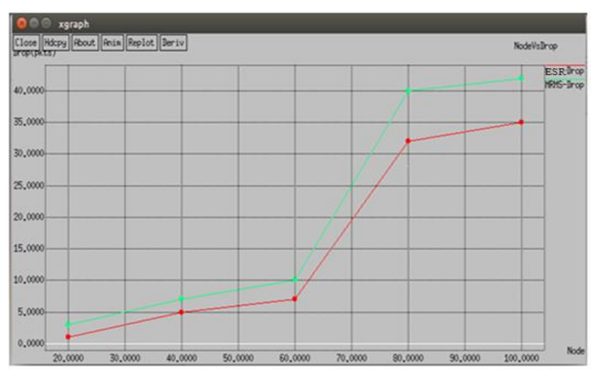

Fig.5: Node Vs Drop

The fig 5 showed the proposed and existing method in term of dropping. The comparison graph result showed the proposed method has a less drop while comparing the existing method (MRMS). The proposed ESR method has fewer drops with varying node.

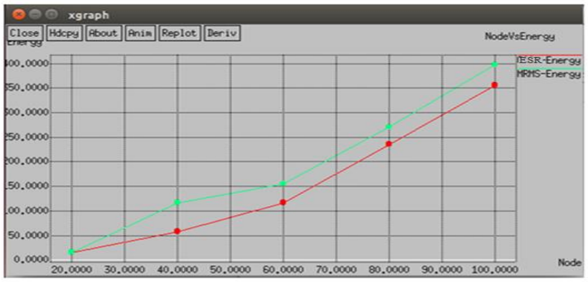

Fig.6: Node Vs Energy

The fig 6 explained comparison graph for energy consumption in varying node. In the graph, we analyzed the proposed method has a less energy while comparing the existing method (MRMS). The proposed COSR method has less energy with varying node.
The varying time with metrics such as Packet deliver ratio, delay, drop, energy consumption comparison figure as given below.

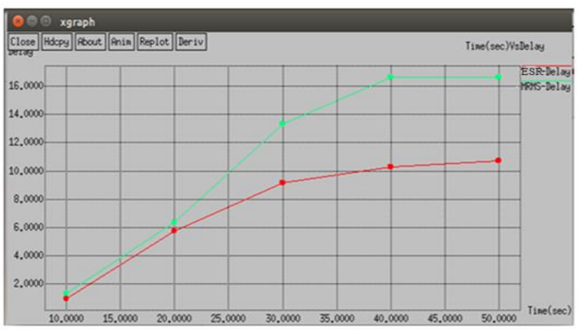

Fig.7: Time Vs Delay

From the fig7, the proposed and existing method in term delay. While looking at it presented that the proposed method has lee delay when compared to the existing method (MRMS). In the fig7 result showed the proposed ESR method is has a less delay with varying time.

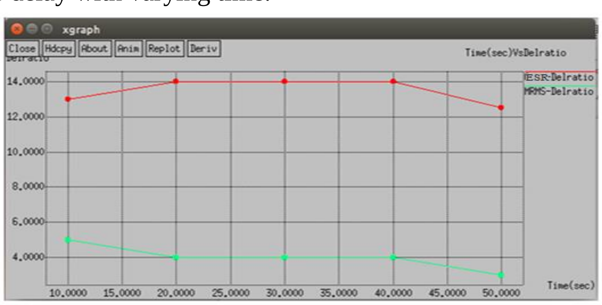

Fig.8: Time Vs Delivery Ratio

The fig 8 shows the proposed and existing method comparison chart for delivery ratio with varying time. While compared the existing method (MRMS), the proposed method is high delivery ratio. The proposed ESR method has a high ratio with varying time.

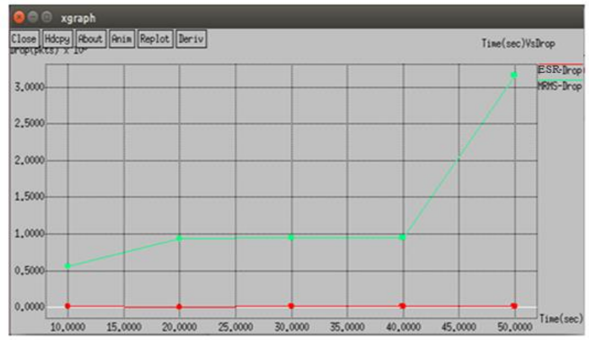

Fig.9: Time Vs Drop

The fig 9 showed the proposed and existing method as far as dropping. The comparison graph result showed the proposed method has a less drop while comparing the existing method (MRMS). The proposed ESR method has fewer drops with varying time.
The fig10 explained comparison graph for energy consumption with varying time. In the graph, we analyzed the proposed method has a less energy while comparing the existing method (MRMS). The proposed ESR method has less energy with varying time.

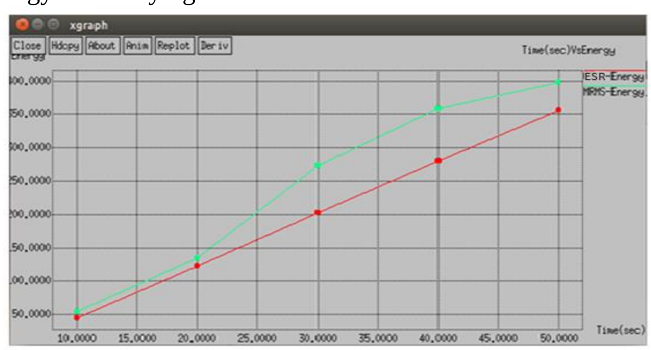

Fig.10: Time Vs Energy

Thus the proposed ESR method gives better result compared existing method. It has been clearly measured with the performance metrics such as delivery ratio, energy consumption, delay and drop. From the above all figure, we analyzed improve performance of proposed method (ESR) such as high delivery ratio, less delay, fewer drops and less energy while comparing the existing method (MRMS). The result show the proposed ESR method is improved the performance metrics with varying node and time.

VI. CONCLUSION

Efficient sink repositioning (ESR) technique using a hybrid optimization algorithmfor wireless sensor network has been successfully proposed.ESR showed the improved performance compared to existing system with varying node and time. This method have been evaluated using simulation and compared with MRMS existing method, it showed the enhanced result such as less energy, few losses, high delivery ratio and less delay.Therefore, it is quicker and also more accurate to detect the node with higher energy and to select the cluster head. Some advantageous of this methods are increased lifetime of networks, improvement in network's reliability and decrease in data transference delay.

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