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A Clustering Approach in Wireless Sensor Network

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Abstract*— The IoT vision requires heterogeneous Wireless Sensor Networks (WSNs). WSNs use a virtual layer to collect information about the real area. WSNs are made up of wireless battery-powered systems which could heterogeneous characteristics with a variety of capabilities in terms of compute power, storage, & interaction.Wireless sensor network (WSN) nodes are devices with less energy, and the key goals of the WSN routing models are to lessen node energyuses& extended network lifetime. However, irrational considerations of node energy heterogeneity can result in an energy imbalance among nodes in Heterogeneous WSNs (HWSNs).This work proposes a new and dynamic Hybrid PSOSA-EBCS (Hybrid Particle Swarm Optimization Simulated Annealing-Entropy Based Clustering Scheme) method which reduces the rate of convergence from local entropy information of sensor nodes and uses this as criteria of better cluster formation and cluster head selection. Using a Hybrid Particle Swarm Optimization-Simulated Annealing technique, a specific fitness function was achieved through which cluster formation was optimized, and customized using the best fitness value of the nodes depending on the distance in Euclidean space between the sensor nodes. More specifically, we offer a novel hybrid methodology with a novel CH election strategy to balance node energy consumption & provide a more energy-efficient CH election beginning from any clustering factors. The simulation is run in MATLAB, and the results reveal that when compared to existing methods, this clustering technique improves the network lifespan on average.

***Keywords*— WSN, Residual energy (RE), CH selection, Energy-efficient (EE), Network Lifetime, PSOSA-EBCS**

I. INTRODUCTION

WSNs or wireless sensor networks are long accustomed to collectingdata derived from background& transmit it to one or more fusion centers over wireless signals. WSNs could be categorized as hierarchical or non-hierarchical depending on their network architecture. Sensors in hierarchical WSNs play a variety of roles since they are frequently split grouped together, some of them are chosen as group chiefs Within non-hierarchical WSNs, each sensor performs the same function, & network connectivity is frequently handledviaseveral wireless hopsinteractions.WSNs could be also classified as homogeneous [1], in which sensors share the same capability, such as a store, processing power, antennae, sensitivity, and so on, or heterogeneous [2,] in which sensors have varied capabilities. Due to the restricted energy facilities of sensors & complexity, if not impossibility, of recharging a battery of densely placed sensors, energy usesare a major bottleneck in WSNs. A sensor node's energy usage is divided into3 categories: interaction energy, compute energy [3], & sensing energy. Experimental calculates reveal that computing energy is insignificant in many applications when contrasted to interaction energy [4], [5]. Furthermore, the sensing energy of passive sensors like light sensors & acceleration sensors is very minimal. As a result, in exercise, sensor energy consumption is dominated by wireless transmission.

While WSNs offer a link among the physical & virtual worlds of data, the information gathered is useless unless it can be sent toaccess points and sensors & then toward base stations. In [6]&[7], links, as a critical requirement in WSNs, are extensively investigated using a binary interaction model. Because of restricted transmission power, each node in a binary interaction model could only interact with other nodes inside a fixed cost. Note that links are assured when nodes are connected via wire lines; but, due to the restricted accessible power in wireless transmission, this similar is not true with WSNs.

WSN contains a power unit, an analog-to-digital converter, computational process for processing unit, location discovery system, mobilizing unit & data communication transceiver. The sensing, processing,&interaction of desired information are 3key sources of energyused in the network. The maximum power of the transceiver unit is used on all three [8].Energy efficiency (EE) should be provided top priority & due to environmental variations, power depletion &the addition of possible nodes to the network nodes can be depleted batteries [9]. There have been considerable research and many techniques aimed at improving the network’s lifetime. As communique takes most of apower, energy use by aggregating data to be directed across channelsshould be minimized.

Since nodes have to connect to complete a task, by continually sending duplicate data, they can use more of their energy. Many techniques to solve this problem have been produced. One of these approaches is called clustering. Many or many nodes are set into the cluster. A suitable CH (cluster head) is selected for every cluster based on some characteristics [10, 11]. CH is the head node where valuable data are gathered from cluster nodes' neighbours& transmitted towards Base Station (BS). Wireless networks may be defined as standardized or heterogeneous. Similar Sensor Nodes (SNs)with the same resources similar power, computational capacity & sensing range consist of homogenous networks. The design of effective protocols for homogeneous networks has been considerably examined. Wireless networks are, however, more heterogeneous [10, 12].

Energy-efficient clustering strategies have to be developed for heterogeneous sensor networks, as clustering systems are not working well on heterogeneous networks [10,12]. Clustering approaches must take into consideration such constraints as limited node energy capacity because a node's batteries cannot be replaced. The clustering procedure, therefore, needs to effectively balance energy inside the network to enhancethe total lifetime of asensor network.Sensors are small & thus havea very small capacity for processing, sensing, memory & communication. Any method of secure communication b/w sink & nodes is considered essential, and this is important in useslike military and healthcare [12]. Bandwidth can be preserved by clustering as It stopsneedless communication or exchange of data between cluster nodes [10].

Some of the issues are found with faithful CH selection, EE cluster formation & network management from the above clustering Protocols. The selection criteria for CH are indirectly linked to the probabilistic or probabilistic approach thresholds. By modifying the CH selection criteria, the most promising node may be selected to be CH, but internal overhead is decreased.Often node selected as CH is located near or adjacent, whichincreases network energy consumption and hence reduces network performance. The node with this position is therefore not adapted to CH's role. The nodes must be better externally and better connected to the nodes &mostly located in network properties. A better CH selection method thus improves network performance parameters.

II. LITERATURE REVIEW

In this paper [13], To abide by topological alterations in the network, a well-created method dependent on clustering is described, in which Secondary Cluster Head (SCH) is one division of the cluster head function &Primary Cluster Head (PCH). It also aims to choose sensors based on residual energy in order for them to work at their best. It makes use of multihop features & concentrates on improving cluster head choosing based on relative positioning, as well as intelligently controlling network topological alterations. The proposed performance of the protocol is evaluated by contrasting it to LEACH & TL-LEACH. Performance of the proposed procedure could be demonstrated in simulation outcomes, where it greatly increases network lifetime & is beneficial in terms of remaining energy improvement.

An energy-aware clustering/routing system dependent on the A* mechanism is described in this study [14]. MATLAB is used to analyze the method. In words of a no. of transmitting packets, the no. of dead nodes, & total network node energy, its performance is compared to that of a CBCCP & LEACH protocols. The outcomes reveal that the suggested algo outperforms the 2 methods that were contrasted.

The energy-capableConstructionAlgorithm for clustering with relay (EESCA-WR) is a grid-based data-collecting method developed in this research. Grids have numerous grid relays (GRs) and the grid leader (GL) in this method. A grid's number of GRs varies depending on a grid's geological. position in relation to a sink of destination (DS). As a result of this, we make sure that multi-hop short-distance data interactions result in a decrease in power usage. To considerably decrease the need for control messages in hybrid modes, the GLs are additionally rotated at the proper intervals. The suggested technique is distinct & superior for homogeneous & heterogeneous wireless sensor networks because it uses a threshold-based GL selection strategy, and a hybrid GL rotating policy, and a strategy of assigning faithful relayclusters in each grid. The suggested method's performance is evaluated by adjusting the length of anarea, the node density, grid size, and, & start energy. Experiments outcomes demonstratedby EESCA-WR are exceedingly flexible, energy-proficient, & could be utilized for big-scale WSNs with a small no. of control messages [15].

This study initially offers a low energy adaptive clustering hierarchy (HLEACH) model called on heterogeneous nodes. The sink node in the method first changes global data, like the ideal no. of clusters & average cluster radius, before broadcasting it. After receiving the broadcasting data, each CN determines its competition radius & then begins thatrivalry for CHs using the suggested rivalry laws. Finally, to improve the ultimate CHs distribution, the elected CHs are censored to task thatbest no. of clusters. Non-CH CNs & SNs synthetically evaluate Instances apart & link levels of CHs during the cluster creation stage, allowing the transfer of CNs between clusters & energy usesbetween CHs to be energy-proficiently managed. The results of the simulation show that the recommended strategy could not simply adequately balance the dispersion of CNs amongst clusters, assuring enough big network recognitionpossibility& network energy utilization for each cluster, but also equilibrium energy usage between CHs, thereby extending network lifetime[16].

The Coyote Optimisationdependent on a Fuzzy Logic (COFL) method is used in this research to present a new clustering technique for heterogeneous WSN. It combines fuzzy logic (FL) and the coyote optimisation algorithm (COA) scheme to reinforce &equilibrium aclustering technique to increase the lifespan of wireless networks while decreasing energy usage. A tentative collection of CHs is adopted to identified via FL-based clustering. The FL's outcome is included as a resolution in the COA's initial solutions. In addition, a novel fitness function was developed to reduce the overall Reduce inter-cluster distance between CHs nodes & base stations as well as the intra-cluster distance between each CH node & its cluster members. 3 distinct situations are used in a large simulation.The suggested COFL method is compared to well-known methods such as the Stable election protocol (SEP), low-energy adaptive clustering hierarchy model (LEACH), coyote optimisation algorithm (COA), grey wolf optimisation (GWO), and particle swarm optimisation (PSO) are all examples of standard models. The COFL technique outperforms previous methods in terms of alive node explication, energy use, throughput, and central propensity assessments for alive nodes and normalised energy. [17].

By explication interface energy consumption of clusters & abigvariation of energy levels in heterogeneous WSNs, this study suggests an (enhanced balanced energy efficiency network-integrated super-heterogeneous)-EBEENISH routing model. E-BEENISH is defined as weighted election possibilities of everybecoming a cluster head node (CH) depending on a remaining energy & distance between the sink & node. Furthermore, we investigate the influence of node heterogeneity on energy usage. We find that heterogeneity parameters recording energy imbalance illustrate the sensitivity of our stable election procedure in the network and that E-BEENISH gives the longest permanence field with a reasonable weight of energy & distance. Our simulation findings indicate that E-BEENISH could increase scheme lifetime by an order of magnitude contrasted to receive using existing clustering techniques thatare important for several software’s [18].

To improve node deployment, a heterogeneous 2-tier Lloyd method is suggested in this study. Furthermore, the study depicts sensor implantation when sensor & AP interaction ranges are constrained. Our suggested methods outperform current clustering strategies such as

Smallest Energy Routing, AccumulativeClustering, distributive Clustering, Particle Swarm improvement, Relay Node placing in Double-tiered Wireless Sensor Networks, & Enhanced Relay Node placing on average, according to simulation outcomes [19].

III. SYSTEM MODEL

The most important feature of a WSN is energy heterogeneity thatcomprises: computational heterogeneity, or energy heterogeneity. In this work, we analyze 3 energy levels heterogeneity normal, intermediate, and advanced types are three sensor nodes.the intermediate initial energy is between standard & progressive starting energy. If E0is the initial energy source for normal SNs, the initial energy of intermediate SNs is E_{int}= (1 + μ)$E_0$and of advanced SNs will beE_{adv}= (1 + α)E_0(SEP), The advanced or intermediate SNs have an energy weight factor of α and μ. Total initial energy will therefore be:

$$E_{Total} = \mathrm{n}E_0(1 + m\alpha + b\mu) \quad (2)$$

Here,n= total network no. of sensors
m= ratio of advanced SNs
b = ratio of intermediate SNs.

A) RADIO ENERGY DISSIPATION MODEL

The binary processes that use a lot of energy in a wireless sensor network are receiving and sending messages. Due to the excessive amount of energy essential to extend signal amid distance & destination, energy used for transmitting a message is higher than the energy used to receive it. Here we use the same models, as several previous works (radio, data aggregation, and energy parameters). The consumed radio power is given by previous works to transmit the message l-bits at a distance d:

$$E_{Tx}(l,d) = \begin{cases} lE_{elec} + l_{\epsilon fs}d^2 \\ lE_{elec} + \ l_{\epsilon mp}d^4 \end{cases} \quad (2)$$

as well as the radio power consumed to transmit this message:

$$\mathrm{E_{Rx}}\ (\mathrm{l}) = \mathrm{lE_{elec}} \quad (3)$$

Where electronics energy consumption is E_{elec}& energy utilized by transfer amplifier for a distance more thand is ϵ_{mp}& for a distance small than d is ϵ_{fs}, energy utilized for integratedinformation is E_{DA}, & threshold distance is provided as:

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (4)$$

B) NETWORK MODEL

We find that in the R field size M, N SNs are random, so each of SNs has its unique ID. SNs are static. Any SN should know how its near neighbors interact and, if topology changes are regular, statically obtain them by Hello or periodically.

In some way's energy heterogeneity is inevitable among WSN nodes. The difference in energy between a sensor as well as its neighbors occurs as new sensors are introduced or the sensor nodes are revived, or if network settings are required for such applications, like diverse nodes with diverse sensor functions & therefore with diverse batteries.Inefficient usage of heterogeneous energy available among nodes would contribute to low performance and a short network life cycle. Despite some achievement in resolving this issue, the WSN continues to face the challenge of energy heterogeneity. We have a modified algorithm to disperse sensor energy properly and promise an expanded network lifetime.

IV. RESEARCH METHODOLOGY

A) *Hybrid Particle Swarm Optimization Simulated Annealing -Entropy-based Clustering Scheme (PSOSA-EBCS)*

In this part, we will talk about our suggestedPSOSA-EBCS. The key objectiveof this technique is to create anequally divided&self-organized clustering technique that enhances the network time and lowers the amount of energy used on the network as well.

For the accomplishment of this task, WPM (Weighted Product Model) accompanied byEWC(Entropy Weighted Coefficient)methods are appliedfor determining election decision problem dependingupon variouscriteria: residual energy (E(s_j)), no. of supported SNs ($N_{support}(s_j)$), distance to the base station (D(s_j)), & sum of adistance to all neighbor SNss_js (DN(s_j). It should define the following criteria:

- **Residual energy(E):**For each sensor node, Residual energy is the key feature, andthe lifetime of a network depends primarily on aresidual energy of SNs.
- **Distance to BS(D):**Distance to the base station must be assessed because a packet with more energy requirements to be transferred to BS.
- **Summation of distances to neighbor sensor nodes (DN):**Therefore, no. of long-distance packets among members & CHs will deplete battery power relatively quickly, given the support of the CH by its members.
- **No. of sensor nodes supported:** since the energy heterogeneity of sensor nodes is three levels, based on the initial energy consumed we may have three forms of CH., CH_0CH_{int},and CH_{adv} with initial energy E_0,E_{int}, &E_{adv}, correspondingly.The energy consumptionpercentage of every cluster head type would be c_0 = e_{CH}/E_0, c_{int} =e_{CH}/E_{int},&c_{adv} = $e_{CH}/E_{adv}$for CH_o, E_0, &E_{adv},correspondingly, whereasee_{CH} is specified by Eq. 11. It is clear that c_0>c_{int}>c_{adv}as E_{adv}>E_{int}>E_0,resulting in uneven energy

consumption among the CH_s.No. of SNs that can be enabled by each type of CHs is therefore expected to be calculated$c_0 \cong c_{int} \cong c_{adv}$. It will then determine the No. of SNs supported by each $N_{support}$.

$$N_{support} = \left\lfloor \frac{E_{Remaining}*(N-K)}{\frac{k}{3}(E_0 + E_{int} + E_{adv})} \right\rfloor \quad (5)$$

In the next subsection, we define the process for selecting CHs based on local sensor Node information (for example, remaining energy, distance to BS, & distance from local SNs.

In the existing work, EBCS was used that was applied on all the k number of sensor nodes (SNs) from S where S is a set of SNs& Cluster Heads (CHs) are elected afterward on k sensor nodes. But due to aninconsistent clustering scheme, the existing model leads to an inappropriate cluster formation. To solve this problem, a Hybrid Particle Swarm optimization(PSOSA) is used in this research where PSOSA is used for the clustering process where the clusters are formed based on best fitness value, and after clustering all CH nodesare elected in each cluster. The fitness function is evaluated based on the Euclidean distance of sensor nodes and nodes with less Euclidean distance will be kept in a cluster and the process will be continued until the appropriate clusters are formed.

A hybrid PSO algo with anSA operator is provided in this chapter. A basic description of a standard PSO method will be provided initially. Consider a D-dime searching space with a swarm of N particles searching for a best outcome within it. Every particle has its different velocity & position data. The velocity of a particle is denoted by $V_i^t = (V_{i1}^t, V_{i2}^t, \ldots, V_{iD}^t)$ and the position is denoted by $X_i^t = X_{i1}^t, X_{i2}^t, \ldots, X_{iD}^t$ in the ith iteration. The local optimal position P_i^t& global optimal position P_g^t denoted by $P_i^t = P_{i1}^t, P_{i2}^t, \ldots, P_{iD}^t$ and $P_i^t = P_{g1}^t, P_{g2}^t, \ldots, P_{gD}^t$. The particle moves according to the following equations at each stage.

$$V_i^{(t+1)} = \omega \times V_i^t + c_1 + r_1 \times (P_i^t - X_i^t) \times c_2 \times r_2 \times (P_g^t - X_g^t) \quad (6)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (7)$$

Where t describes the iteration number, & ω, c_1, c_2 are constants that affect the quality & velocity of a better outcome. The words r_1 & r_2 are random numbers that are equally dispersed on (0, 1), accordingly. If the maximum production or a specified value of health of p_g is reached, the iterations are ended criterion is identified.

The hybrid method's architecture PSO has distinct characteristics, like rapid convergence when combining local search (via self-knowledge) & global search (via neighboring knowledge) searches [21]. We focus on a particle's high search efficiency & simple algorithm design in the suggested hybrid method. As a local search method, SA completes particle attributesin probabilistic terms, successfully avoiding local optimum. A hybrid PSO & SA method protocol is suggested that takes benefit of these 2 methods, and its approach is described here:

Step 1 Initialize

Calculate the no. of particles & their starting locations & velocities.

Identify the variables, that include parameters of PSO renewal equations, like ω, c_1, c_2, & parameters of a simulated annealing operator, including initial temperature-T0, ultimate temperature-T_f, & reduction rate-α.

Establish the location & velocity info, i.e. when X_i^tand V_i^t are produced.

Calculate the rounds times I

Step 2 Standard PSO algorithm producea random no.r_1, r_2, the values of which are restricted in (0, 1).

For a particleX_i^t is createdviamodifying the particle's position & velocity equation during tterounds

Step 3 Implement the Simulated Annealing Operator

Identify rounds times L of simulated annealing. carry out local search operator to obtain$X_i^{t\prime}$ from X_i^t.

calculate the health of $X_i^{t\prime}$, i.e. $f(X_i^{t'})$.modify particle data after performinga simulated annealing operator.

If a global particle's health$f(P_g^t)$ is enhanced in theserounds, as wellmodifyP_g^t.

Step 4 Judge Interfere Operator

Maintain quality info. of actual particles, involvingP_i^t&P_g^t, & produce a random particle instead of their own participation in the round if the global bestresult recurrence is unaffected.

Step 5 Compare the terminate condition

If the outcomes propitiate, the endsituation, resultthatoptimaloutcomesassociated to P_g^tparticle, otherwise, skip to Step 2.

Here, our CH election process is defined. Depending on local sensor nodes, the selection of CHs must be taken. This kind of data is used as a criterion for adecision-making phase (like multi-criteria issues). To resolve this issue, we change the WPM to Multi-Criteria Decision Analytics Method (MCDA)[10].

1) WPM

In WPM, no. of ratios for every criterion, (c_i), are compared $(A_1, A_2, ..)$. Each ratio shall be raised to the relative weight equivalent (w) of the respective criterion. subsequent product(Ps) must be determined for n No. of parameters & n No. of alternatives for the two alternatives A_k and A_L using WPM;

$$P\left(\frac{A_k}{A_L}\right) = \prod_{j=1}^{m} \left(\frac{a_{K_j}}{a_{L_j}}\right) w_j \quad (8)$$

Now, K ≠ L; K; L = 1, 2, ..., n &a_{ij} is execution value of another optionA_i. If ratio $Ps\left(\frac{A_k}{A_L}\right) \geq 1$, Then alternative $A_k$it means that it is more valuable than other $A_k$uncertainty. The best substitute is one that is better than or at least equal to all others.

2) EWC

An entropy coefficient method for evaluating criterion weights is used.

- Calculate entropy in each criterion I = 1, the key steps for determining the weights of m criteria or n uncertainty are given as.

$$H_i = -\frac{1}{log_2 n}\sum_j^n p_{ij} log_2 p_{ij} \quad (9)$$

Here, $Ps_{ij}=\frac{c_i(s_j)}{\sum_j^m c_i(s_j)}j$ = 1, . . . n, $c_j(s_j)$ is performance value of alternative $s_j$and if p_{ij}= 0 then $p_{ij}log_2p_{ij}$= 0.

- Compute entropy coefficient weight (w_i) of every criterion i:

$$w_i = \frac{(1- H_i)}{m-\sum_i^m H_i} \quad (10)$$

Here, $0 \leq w_i \leq 1, \sum_{i=1}^m w_i = 1$

3) CH Election Decision

CH's election decision shall be taken by the following steps (Algorithm 1 includes the pseudo-code for this procedure):

- Measure each criterion's weight by using EWC.
- Using WPM, evaluate aproduction value Ps of every sensor node (s_j) by taking$m$ criteria as:

  $s_j.P = \left((s_j, c_j)\right)^{w_1}$ x $0(s_j, c_j)^{w_2}$ x . . . x $(s_j, c_j)^{w_i}$

  Here, w_1, w_2, . . . $w_i$are the weights for the criteria c_1, c_2, . . . ,$c_i$correspondingly.
- The CHs are selected for SNs with the largest Ps values.

Algorithm 1: EP (Election Procedure)

I/P: *St*= SNs set, k_{opt}=*optimal cluster*.
O/P:*K* number of SNs having the largest product values *Ps*.

Step 1. Form kopt clusters using PSO-SA
Step 2. For a=1 to kopt //nodes of cluster 1st
Step 3. St(j).c_i: define as criteria value of SN *j* for criterion *i* belong to cluster a.
Step 4. m_c: no. of criteria's
Step 5. n_a: no. of the alternative or SNs in *St*
Step 6. Execute *i*from 1 to *m* do
Step 7. Execute *j* from 1 to *n* do

$$Ps_{ij} = \frac{st(j).ci}{\sum_{u=1}^{n} \mathrm{St(u)}.c_i}$$

Step 8. End of step 4

$$Hi = -\frac{1}{\log_2 n}\sum_j^n Ps_{ij} log_2 Ps_{ij}$$

Step 9. End of step 5
Step 10. Execute *i from* 1 to *m* do

$$W_i = \frac{(1-H_i)}{\mathrm{m}-\sum_i^m H_i}$$

Step 11. End of step 8
Step 12. Execute j *from* 1 to *n* do

$$St(j).Ps = \prod_{i=1}^m (St(j).c_i)^{w_i}$$

Step 13. End of step 10
Step 14. Returns the optimal SN value from the St having the largest values of *Ps*.

At the end of everyiteration$r$ & based on a receivedpersondata (id, $E_{Prediction}$, $E_{Residual}$,$N_{Support}$), CH performs Algorithm 1 in order to take 3 cases are clusterheads:

a) The number of SNs to be designated as cluster heads (φ) is empty, so that for the next round no CMs or CHs current may be CH as the energy required for CH $e_{CH}$is greater than energy estimate $E_{prediction}$. In this case, existing cluster heads will notify their CMs directly regarding sending their data to the base station. Here it is, by avoiding clusters, we prevent inaccuracy & unpredictable behavior. The positive aspect is, however, that if data are being sent directly to the BS with the remaining energy of SN.

b) If φ comprises just one CH then for the next round CH will continue to work as CH.

c) If ć includes several CH ($|\varphi|$> 1), the election procedure must be carried out in the CH process with the set ̈φ (EP (φ; for decision-making purposes.

Algorithm 2: PSOSA-EBCS (At base station)

Step 1. define as present round no.
Step 2. St: SNs set.
Step 3. k_{opt}: optimized cluster heads
Step 4. check whether p=1then
1) The base station is execute using *EP (St,* k_{opt}*)*
2) The base station broadcasts BE_{CH} messages to the *K* number of SNs having the largest product values *Ps*.
Step 5. Finally, wait until data received

Algorithm 3: PSOSAEBCS (At CH)

Step 1. G_{CM} (ch) defines as a list of Cluster Members for Cluster Head.
Step 2. ψ: considers the number of SNs to nominating the cluster heads.
Step 3. p: define as present round no.
Step 4. St: SNs set.
Step 5. check whether BECH message is acknowledged then
1) Advertising the CH via broadcasting $CH_{Announce}$ message
2) Waits for $JOIN_{Request}$message from neighboring SNs
Step 6. Check whether JOINRequest message is acknowledged fromthe sj then add SN sj to the GCm (sj)
Step 7. TDMA slot has been transmitted to CMs.
Step 8. Data transmitting stage
1) Check whetherdata has received to $G_{CM}(s_i)$ members then do**a**fusion of data on the data & forward this toward the base station
2) Compute $E_{prediction}$ (s_i, r + 1) &$N_{support}(s_i)$
3) Check whethere_{CH}<$E_{prediction}$ (s_i, r + 1) **then a**dded ch to the ψ
Step 9.**for** all SN $cm_i \in G_{CM}$ (s_i) **do**
1) Check whethere_{CH}<$E_{prediction}$ (cm_i, r + 1) **then** added cm_i to the ψ
2) Check whether| ψ| = 0 **then** CH notifies G_{CM} (s_i) to transmit directly to the Base node.
3) Renounce their roles as a CH & forward direct to the Base node otherwise
4) Check whether | ψ | = 1 &$s_i \in \psi$**then**$s_i$agrees to endure working process as a **CH** or els**e** Check whether| ψ | > 1 **then** s_i is executed using EP (ψ,1)
5) $s_i$broadcasts BE_{CH} message to the succeeding CH member node.
6) End

The CH-SN has several alternatives if the cardinality is larger than one. The first method is to keep operating as CH-SN & 2nd alternative is to use one of these CMs for CH.

Cluster head implements EP election process, taking into consideration members including $N_{support}$, criteria, *E*, *D* or *DN*, then measures or compares product value of every member node also then takes up SN with greatest product value, P as next cluster head (Algorithm 3, step 34);

Every cluster head sends BE_{CH}message to selected CHs. selected CHs proclaim their prelude, by CSMA. advertisesmall message $CH_{Announce}$ includes ID of cluster head. Formerly, the step of cluster construction is implemented (Algo. 4).

Cluster Formation Step: Every non-cluster head node chooses a cluster head that utilizes the lowest cost of communication depending upon the signal intensity of ad transmits & received JOIN Request message to CH selection, to make sure concise information is sent to BS. The CHs createa TDMA plan or transmission plan that transfers their data to each CM. This prevents collisions among data messages & allows radio mechanisms of CMs to be disabled during transmission only. The last step in the setup process is the development and transmission of TDMA routines.

Data Transmission Phase: Usually, in its time range, every CM only sends its data to CH involved (Algorithm 4, Step 8-11). Though, the data message in our EBCS proposed includes CM ID, residual energy, $N_{support}$&$E_{prediction}$data, implying that local CM information can be used to identify cluster head rotation in the following rounds.

Whileentire data of CH is usual, such signal processing functions like data aggregation are executed. The aggregated results are then transmitted to the base station. At end of this stage, each CH typically decides whether to proceed as CH or to leave the role of piggybacked CM information (Algorithm 3, Steps 17-38).

Algorithm 4 PSOSA-EBCS (None CH sensor node side)

Step 1. Check whether $CH_{Announce}$ msg acknowledged s_j **then**
1) send $JOIN_{Request}$ to s_j that requires minimum communication cost,
2) wait until the TDMA slot message has been scheduled.

Step 2. Check whether TDMA slot message has acknowledged **then** wait up to their time slot

Step 3. Check whether **the** time slot is true **then**
1) Compute $E_{Prediction}$ & $N_{support}$
2) Transmission of collected data towards CH node along with (id, $E_{prediction}$, $E_{residual}$, $N_{support}$)

Step 4. Check whetherdirect to BS message received **then** forwarded collected data directly the BS.

C. EBCS (Entropy-Based Clustering Scheme) Analysis

The cluster head collects, aggregates, and transmits data from its CMs to BS. Data is aggregated. The energy consumed by a cluster head, therefore, increases energy consumed by CM. In EBCS, SNs $CH_{Announce}$with a higher production value of SN with highest residual energy, highest no. of neighbors, & near to base station will more reasonable to be selected as cluster head. Besides, each non-CM that receives $CH_{Announce}$ accepts CH that needs minimum cost of communication depending upon distance b/w it & cluster head candidates. It would balance network load while cluster head rotation in the following rounds.

Lemma 1: Proposed entropy-based clustering scheme has O(N) interchanged messages as overhead, here N is no. of SNs.
Proof: If k is anaverage no. of cluster heads per iteration. We will have these overhead messages in every round:

- for transmitting k messages $CH_{Announce}$by all cluster heads.
- N to K messages for $JOIN_{Request}$t via non-CMs.
- k messages for transmitting TDMA agendaviaentire cluster heads.
- N to k messages to transmit data to cluster heads via CMs.
- k messages to transmit information to the node via cluster heads.
- Lastly, in aworst-case, k messages for cluster head alternation (this would take place here every cluster head defines to stay as cluster head or choose one of these members to be following cluster head). So, EBCS above would be $O(N)$ as $k << N$.

V. SIMULATION RESULTS

MATLAB is used to simulate our algorithm. In our simulations, 100 sensors will be randomly deployed, in 100 to 100 regions, 150 to 150 regions, 200 to 200 regions, 250 to 250 nations, 300 to 300 regions, 350 to 350 square meters in a 2-dimensional plane with BS focused. As described in Section III, the radio model or energy parameters are applied.

I. CONCLUSION

The heterogeneous network typically difficult to deal with heterogeneous data transmission service quality requirements. Subsequently, we are using heterogeneous nodes to complete the transmission of data for these different types in this study. In this work, we have introduceda new concept of EBCS followed by a genetic algorithm that aims to produce better clusters of sensor nodes improving the network lifetime by reducing dead node rounds which also results in reduced residual energy. The outcomes are compared to the existing study approach, and it is discovered that latest version of EBCS utilizing Hybrid PSOASA is more capable, precise, & speedy in words of network lifetime, & management of a CN allocation between clusters, & energy consumption between CHs. Eventually, the appropriate number of CNs & SNs to deploy and their initial energy to improve energy usage competence, likea ratio of network lifetime to implementation price, are theoretically derived.

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