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Spatial Correlation Based Clustering with Node Energy Based Multi-Hop Routing Scheme for Wireless Sensor Networks

Panchikattil Susheelkumar Sreedharan*, Dnyandeo Jageshwar Pete

Abstract: Major points of concern in implementing a wireless sensor network (WSN) are the network lifetime and energy utility within any delay tolerant network. Both these parameters define the success of the sensor network. The higher the expectancy of network Lifetime, the higher is the probability of acceptance of the network. Similarly, better the energy utilization in the network, better are the chances of success and implementation of the sensor network. Clustering is one such scheme adopted in WSN towards harnessing the best of above specified parameters for the network implemented. Most popular clustering techniques are the variants of LEACH protocol that facilitate cluster formation based on the proximity of an individual node to other nodes in the sensor network. These protocols are based on a single hop structure from the selected cluster heads in the network. This paper embarks on a multi-hop clustering algorithm that takes into consideration the spatial correlation between the nodes to form clusters and implements a highly energy efficient routing scheme which selects the multi-hop path in the network in a dynamic fashion.

Keywords: clustering; multi-hop; network lifetime; single-hop; spatial correlation

1 INTRODUCTION

Wireless Sensor Networks find its application in almost all fields of study like agriculture, environment monitoring, seismological study, defense and security and even extending into today's IoT [1]. It generally consists of high density sensor nodes that are spatially distributed in a given area of interest. Since these nodes are not easily humanly accessible, we have to be very particular about the energy utility in these nodes as its not possible to replace or recharge the batteries in them. Hence, many algorithms have adopted a clustering approach [2-11] with the cluster heads choosing a single hop data transfer mechanism to the sink. This mechanism is effective in case of small network area. But as the area of the sensor network grows in size, this particular mechanism can only support shorter network life time with reduced throughput. Standard algorithms like LEACH and its recent variants [4-15] are the examples of this particular approach. Here in this paper, we have proposed a cluster based multi-hop data transfer mechanism from the cluster head to the sink based on spatial correlation [16-23] between the scattered nodes. The routing path is arrived at dynamically based on the distance between the next possible hop satisfying a certain specified distance criterion and the minimum energy requirement to be satisfied by the next-hop cluster head. The performance of our proposed algorithm is compared with that of existing standard algorithm LEACH [24] and its recent variant Enhanced LEACH [7]. Therefore, here we have tried to implement an algorithm, which involves three phases .i.e. the clustering phase, cluster-head selection phase and the data transfer phase. The rest of the paper follows standard structure i.e. section II is dedicated to related work, section 3 & 4 covers the models used while section 5 details the methodology involved. Section 6 covers the algorithms implemented, section 7 details the findings and results and lastly, section 8 concludes the findings of the paper.

2 RELATED WORK

Reference [3] introduces the standard clustering algorithm LEACH wherein the authors R. Sinde et al. (2020) uses a randomized way of selecting cluster head and also supports the data fusion or aggregation within the cluster. Here the operation during each round of data transfer is divided into two phases namely the set-up phase and the data transfer phase. During the setup phase, the cluster head is selected along with the cluster formation. In addition, during the data transfer phase, the sensed data flows from the cluster member nodes to their respective cluster head and the cluster heads aggregates the received data from all its members and transfers the aggregated data to the sink in a single hop. However, here the drawback lies in the fact that the cluster head is chosen in a randomized way not taking into consideration the residual energy of the candidate nodes for cluster head function. In addition, the effective communication path between the cluster member nodes and the sink through the cluster head is not considered for cluster formation process. These drawbacks have been taken into account and addressed to some extent in the recent variations of LEACH algorithm to some extent. In [13], the authors D. Mahmood et al. (2013) have altered the selection of cluster head in such a way that the cluster head continues to be the head till it's energy falls below a required threshold level. In addition, as far as data communication is concerned, they have envisaged intra cluster communication, inter cluster communication and cluster-head to sink communication and accordingly they have chosen two levels of amplification. The choice of these levels can be made dynamic thereby not fixing the number of levels at two. In [15], Zhidong et al. (2018) have devised a new strategy to arrive at the best optimum number of clusters balancing the energy need between the clusters as well as within each cluster. In their proposed scheme, they have introduced the distance variance factor in the initial set-up phase, and effectively implemented the node dormancy to save energy. Again, as the network

area increases in size, the effectiveness of this algorithm also reduces since propagation of data involves two to three hops only. In [7], the authors Amer O. Abu Salem and Noor Shudifat (2019) have proposed an enhanced LEACH protocol, which takes into consideration the effective distance between the cluster members to the cluster head and from cluster head to the sink while implementing the cluster formation process. They have successfully shown that their scheme facilitates an extended network lifetime and reduced power usage in comparison to the standard protocol LEACH. But as the network area gets larger in size, even this protocol suffers due to higher levels of energy expended in transmitting the data to sinks which are very far located. Considering these shortcomings, our algorithms implements a multi hop mechanism for data propagation from the sensing nodes to the sink to have better energy efficiency and enhanced network lifetime.

3 PROPOSED CORRELATION MODEL

Sensing range or coverage area of any sensor node is a typical characteristic, which influences its region of sensing. Wireless Sensor networks are network of sensor nodes that typically consists of multiple nodes, which are more closely located. Since these nodes are closely located to each other in many applications, we can derive a spatial correlation between these nodes dictated by the overlapping region of coverage or the sensing region.
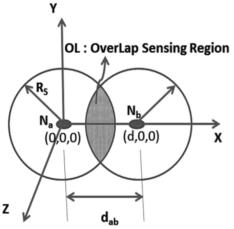

Figure 1 Over-lapped sensing region of sensor nodes [20]

Fig. 1 represents two nodes that are closely located to each other, separated by a distance d whose region of coverage is shown by the two circles with the nodes located at the Centre of each circle as depicted. We can observe that there is a region of overlap between the coverage areas of these two nodes that is highlighted by the shaded area. Now as the region of overlap increases the similarity in the data sensed by these nodes increases. Depending of the specific application requirement, we can have a trade-off between the data accuracy and the sensor nodes selected for communicating their sensed data instead of every node communicating their data to the sink. Hence, we try to make use of this spatial correlation between the sensor nodes in the

development of our algorithm wherein clustering or cluster formation also takes into account the spatial correlation between these nodes.

Fig. 1 represents a two dimensional model of the sensor node, its coverage area and the region of overlap between their coverage region [25]. In real time the regions correlate to a three dimensional structure wherein each region represents a specific volume. Here, we define spatial correlation between two sensor nodes by the amount of overlap in their coverage area. We can say that, in a homogeneous sensor network, spatial correlation exists if the distance of separation between the two sensor nodes is less than twice the sensing radii of each node, which is quite evident from the study of geometry of the figure represented above. Moreover, as the distance between these two nodes increases beyond twice the sensing radii of the nodes, we say that there is no spatial correlation between these two nodes. In addition, the two nodes are 100% spatially correlated if they are co-located i.e. the distance of separation between them becomes zero. Considering these facts, we can define the overlap coefficient of correlation [29] between any two nodes N_a and N_b as:

$$\sigma_{ab} = \frac{\text{Volume of Overlap - of - Sensing Regions of Nodes } N_a, N_b}{\text{Combined Volume - of - Sensing Regions of Nodes } N_a, N_b}$$

$$\sigma_{ab} = \frac{V_{OL}}{V_{Comb}} \qquad (1)$$

where V_{OL} and V_{Comb} is the volume of the overlapping region of sensing of the two nodes and combined volume of sensing regions of the two nodes considered respectively.
We also define the region of overlap (ROL) as:

$$(\%ROL)_{ab} = \sigma_{ab} \times 100 \qquad (2)$$

Using spherical geometry as given in [26], the numerator i.e. the dividend and denominator which is the divisor in Eq. (1) is expressed as:

$$V_{OL} = \frac{\pi}{12}(2SR - d_{ab})^2(d_{ab} - 4SR) \qquad (3)$$

$$V_{Comb} = \frac{8\pi \times SR^3}{3} - \frac{\pi}{12}(2SR - d_{ab})^2(d_{ab} + 4SR) \qquad (4)$$

Combining (1), (3) and (4), we express the overlap coefficient of correlation between the two nodes as:

$$\sigma_{ab} = \frac{(2SR - d_{ab})^2(d_{ab} + 4SR)}{32SR^3 - (2SR - d_{ab})^2(d_{ab} + 4SR)} \qquad (5)$$

where SR is assumed to be the uniform node sensing range, N_a, N_b are the two nodes considered at a distance d_{ab} from each other.
Thus, it can be expressed that $\sigma_{ab} = 0$ for any two nodes separated by a distance greater than twice the sensing range

of each node i.e. 2*SR*. Hence, we can sum-up the *SR* correlation coefficient between two nodes separated by a distance d as:

$$\sigma = \begin{cases} \dfrac{(2SR-d)^2(d+4SR)}{32SR^3-(2SR-d)^2(d+4SR)} & \text{if} \quad 0 \le d < 2SR \\ 0 & \text{if} \quad d \ge 2SR \end{cases} \quad (6)$$

Expression (6) represents the sensing region correlation model [20].

4 ENERGY MODEL

The standard reference energy model is taken from ref. [9] which gives a detailed analysis of two main types of energy associated with WSN namely the propagation energy which is the energy involved in the transmission of data from the sensor nodes to the sink and energy used for various electronics involved before transmission after reception of data in the nodes. The propagation distance decides whether the propagation energy is influenced by free space propagation model or multi-path propagation model. If the propagation distance is less than the crossover distance it is the free space propagation that defines the propagation energy and if the propagation distance is beyond the crossover distance, the propagation energy is defined by the multi space propagation model as given in ref. [9, 26, 27]. Using this model, the energy involved in the transmission of l-bit message is expressed as:

$$E_T = l \times E_{EX} + l \times p_1 \times d_T^{(n)} \quad (7)$$

where E_{EX} is the energy/bit involved in the electronics, $l \times p_1 \times d_T^{(n)}$ is the propagation-energy for l-bit message for covering a transmission distance d with a propagation loss exponent n.

Ref. [26] states for any transmission distance less than the crossover distance d_0, the free space model is applied and the expression for the transmission energy is given as:

$$E_{T1} = l \times E_{EX} + l \times \varepsilon_{fs} \times d_T^{(2)} \quad (8)$$

where $\varepsilon_{fs} = p_1$, i.e. the propagation loss for free space.

And for any transmission distance greater than the crossover distance d_0, the multi-path model is applied and the transmission energy is stated as:

$$E_{T2} = l \times E_{EX} + l \times \varepsilon_{mp} \times d_T^{(4)} \quad (9)$$

where $\varepsilon_{mp} = p_1$, i.e. the propagation loss in multi-path transmission. Here cross-over distance d_0 is given by:

$$d_0 = \sqrt{\dfrac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (10)$$

5 PROPOSED METHOD

Here we have selected a wireless sensor network area of 200 by 200 m^2 with a dense spread of sensor nodes in the given area. The total number of nodes are 1000 that are initially given a random spread across the network. The initial random locations of all these nodes are maintained the same throughout the simulation for varying parameters and algorithms under study in this paper. The sink is assumed to be centrally located and aware of all the GPS enabled node's location detail. The network is supposed to be a static homogeneous network that is the nodes are stationary in nature and uniformly energized at the beginning of implementation. All the nodes transmits their location detail to the sink and the sink implements the centralized clustering algorithm to form cluster groups based on the spatial correlation criterion chosen which is maintained throughout the network lifetime. The cluster information is relayed by sink to all the nodes which is now aware of its cluster details that is member ids and member locations. All the nodes keep a record of its neighboring nodes detail that are separated by a maximum specified distance (of 5*SR*) from itself which is the limitation placed for next hop node. Thus cluster formation phase is only implemented once in the lifetime of network. After the cluster formation phase, then we implement a cluster head election phase through a distributed algorithm implemented at the individual nodes in the network. This algorithm estimates a fitness function value for the node based on the leftover energy after the previous rounds of data transfer, its distance from sink and the sum of propagation distance from other member nodes to the candidate CH node within the cluster. Each node relays this value to its other cluster members and the node with largest valued fitness function is chosen as the cluster head for the cluster, thus presenting a dynamic CH selection process. The CHs then relay their election as CH to other member nodes as well as other CHs located nearby which are in the range of 5*SR* from itself. Initially all the CHs are by-default the main cluster heads. Few amongst these cluster heads that satisfy the defined minimum spatial correlation factor of 0.1 with their neighboring cluster head and whose fitness value is lower than neighbor cluster head are labeled as secondary cluster head. Now, here all the cluster members that satisfy a minimum spatial correlation factor of 0.1 with its cluster head are made to sleep, thereby avoiding any redundant data as defined in the application requirement based on the tradeoff chosen between data accuracy and number of active sensing nodes transmitting their sensed data i.e. energy conservation. All the members of associated secondary cluster are also checked for the satisfaction of minimum spatial correlation factor with the associated main cluster head too and are either made dormant or live depending on the conditions prevalent. Immediately after the segregation of the cluster heads as main or secondary cluster heads, each of the main cluster head finds the next hop node (which is also a designated main cluster head) to chart out the route forward towards the sink. These next hop nodes are selected only if they satisfy the minimum and maximum propagation distance fixed for being eligible which is between 2*SR* and 5*SR*. All these

intermediate routing nodes performs the role of a repeater for other main cluster head's relayed packets. In the absence of finding a suitable intermediate routing node, the cluster heads are programmed to directly send the message to the sink. Speaking of the data flow in the network, the secondary cluster heads will remove the redundant data received from its cluster members and forwards the aggregated data to the associated main cluster head for further transmission. The main cluster head also aggregates the data received from its cluster members and the associated secondary cluster heads and relays the aggregated data either to the sink directly or to the next hop cluster head node as estimated by the distributed algorithm running at the cluster head node itself. The sinks keeps a record of all the dead nodes or renders any node as dead if it does not receive any information from that node in the aggregated packet message relayed by its main cluster head in three consecutive rounds of data transfer. The sink is aware of the dead nodes and therefore has an estimate of the total number of packets to be received from the network. On receiving messages from all the active clusters or waiting for pre-specified buffer-time, it relays the start of next round to all nodes in the network. All the cluster heads on receiving the round-start message from the sink drops the data if any received by it and pending for further relay and starts initial phase of estimating the fitness function value for the next round under consideration, further followed up by the subsequent stages as defined in the implementing distributed algorithm at the node. The entire implementation is simulated using MATLAB@2016a wherein the cluster formation is carried out for various values of Spatial correlation factor ranging from 0.1 to 1 (one). Here we have chosen five values of spatial correlation factor i.e. 0.1, 0.2, 0.3, 0.5 and 0.7 for simulation purpose and studied the effect of the variation in spatial correlation coefficient on the network lifetime and throughput in our proposed approach along with the comparison of each results (specific values of correlation coefficient) with standard Algorithm namely LEACH and its recent variant called Enhanced LEACH.
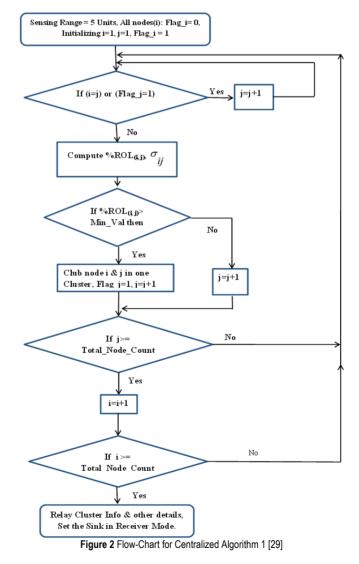
6 ALGORITHM

The proposed scheme is implemented using a combination of centralized algorithm run at the sink and a distributed algorithm run at each node. The centralized algorithm is taken from paper [28, 29] that facilitates the cluster formation at the sink side and then relaying the cluster information to the sensor nodes in the wireless sensor network area. The distributed algorithm accomplishes three tasks namely the cluster head selection and designating them as main cluster head or secondary cluster head followed by the next hop node estimation and finally the data transfer phase from the sensing node to the sink. The centralized cluster forming algorithm is shown in the flowchart in Fig. 2:

The cluster formation process is followed by the distributed algorithm that accomplishes the three tasks mentioned earlier namely the cluster head selection and designating them as main cluster head or secondary cluster head followed by the next hop node estimation and finally the data transfer phase. The distributed algorithm

implemented at the node level is depicted in the flow chart given in Fig. 3. The fitness-function (*ff*) value is expressed using the following expression [28, 29]:

$$ff = \left(\frac{W_a \times N_{\text{LOE}} + W_b \left(\frac{1}{SPD^2} \right)}{N_{\text{LOE}} + \left(\frac{1}{SPD^2} \right)} \right) \tag{11}$$

where *ff* represents fitness-function value for the node supporting its candidature for the role of CH, LOE represents its left-over energy (residual energy) after the previous round, W_a and W_b are the proportional weights expressed as:

$$W_a = \left(\frac{D_{\text{NS}}}{D_{\text{NS}} + SPD} \right), W_b = \left(\frac{SPD}{D_{\text{NS}} + SPD} \right) \tag{12}$$

Figure 2 Flow-Chart for Centralized Algorithm 1 [29]

Here D_{NS} represents distance between the node and sink, *SPD* represents sum of propagation distance. *SPD* is the total propagation distance encountered in a cluster owing to the

Flowchart boxes (Figure 3):

Each node receives their cluster details relayed by Sink. Sensing Range = 5 Units for all nodes

B

Compute fitness value (F_val) for the node

Relay the F_Val and check out for the F_val relayed by other cluster member

If all of the received Fval> own Fval

YES → Assume the role of Cluster member, Relay member details to the self anointed CH for the round

NO → Assume the role of cluster head for the round and relay the info to the cluster members along with location IDs, Fval

Check for becoming the Chief CH or subordinate CH or Normal CH

Is eligible for Chief CH or Sub-CH or Normal CH

Eligible For Sec-CH → Declare self as Sub-CH and also relay associated chief CH

Eligible For Main-CH → Declare self as Main CH and also relay associated Sec-CHs details

Eligible For N-CH → Declare self as Normal CH

Begin Data Operation for the current round (Start relaying sensed data to its CH

Relay TDMA Schedule for CMs and Receive the TDMA Schedule from its Main CH and align itself with system

Relay TDMA Schedule for CMs, Sec – CHs and Back Main CHs. Also estimate Next Hop node. Receive relayed msg from forward M-CH for its TDMA slot

Relay TDMA Schedule for CMs and Back Main CHs. Also estimate Next Hop node. Receive relayed msg from forward M-CH for its TDMA slot

Period1: Start receiving relayed data from its CMs

Period2: Relay the aggregated data to Main CH

Period1: Receive data during allotted TDMA slots from CMs
Period2: Receive from sec-CHs. Forward aggregated data from period 1&2 to Forward routing node in 1st period3
Period3: Forward all messages from Back CHs to Forward CHs in allotted TDMA Slot of period3

Period1: Receive data during allotted TDMA slots from CMs & Forward aggregated data from period1 to Forward-routing node in 1st period3 resp.
Period3: Forward all messages from Back CHs to Forward CHs in allotted TDMA Slot of period3

Wait for the End of Round declaration by Sink and on receiving EOR signal jump to step-B to start new round.
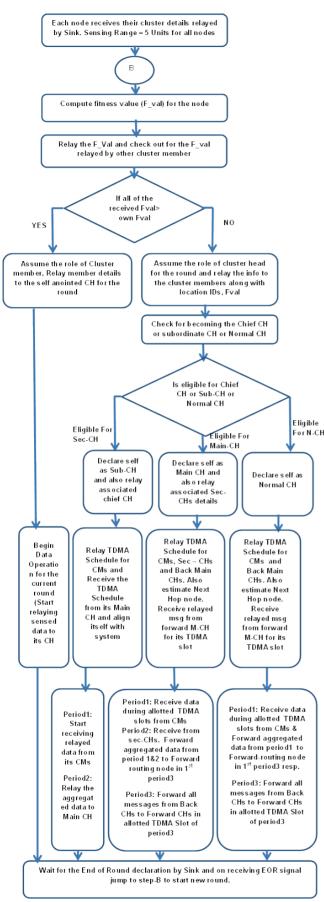
Figure 3 Flow-Chart for Algorithm 2

relay of messages from the cluster member to the candidate cluster head in the cluster for the round under consideration. W_a and W_b are dynamic proportional weights used to estimate the fitness function of the candidate node for cluster head election taking into consideration both the LOE of the node and the expendable energy in the cluster by the member nodes for intra-cluster communication (which should be minimum) proportionately. If SPD is maximum, that means more energy needs to be expended cumulatively by the cluster members and if SPD is minimum less energy needs to be expended cumulatively by the cluster members. Hence, ideally when SPD is lower, ff value should be higher and when SPD is higher, ff value should be lower which is satisfied by Eq. (10). Using the fitness function value, the distributed algorithm enables the selection of main cluster heads, secondary cluster heads and the further routing paths for the round under consideration. Each cluster head maintains a TDMA schedule for each of its cluster members for message transfers. The first period of each round is solely dedicated for cluster members to relay their data to their cluster heads. The second period is for secondary cluster heads to relay their data to the main cluster heads using a TDMA schedule dictated by its main cluster head. The third period is for the movement of aggregated data from the main cluster heads to their first forward routing node. A TDMA Schedule is also maintained by the forward (towards sink) main cluster head for all its neighboring back main cluster head (which are further away from the sink) that are in the range of 5SR. The third period is repeated till sink signals the end of round. Thus, using the defined TDMA schedules the data flow is simulated from the sensing nodes to the sink through various intermediary routing nodes. The sink receives the forwarded messages from various clusters and regularly checks for the reception of messages from all the active clusters. If the sink has received the aggregated data message from all the active clusters, it signals the end of round otherwise it waits for a specific period of time which is more than sufficient for the message from the farthest cluster to reach the sink before it signals the end of round to all the cluster members.

7 RESULT

In the simulation, we have enforced the above parameter values as specified in Tab. 1. We have implemented the simulation with varying degrees of correlation value chosen for clustering. Here the correlation value is varied between 0 and 100 percent and typically for our simulation we have selected a correlation value of 0.7, 0.5, 0.3, 0.2, and 0.1 (i.e. 70%, 50%, 30%, 20% and 10%) as the sample correlation values for which we have implemented our multi-hop routing algorithm. Under each correlation value, we have three instances of simulation with a minimum node energy parameter value set to each node at $10E_{min}$, $500E_{min}$, 1000Emin respectively to support multi-hop routing of data. Here E_{min} is taken as 0.0002 Joules and hence $10E_{min}$, $500E_{min}$ and $1000E_{min}$ which corresponds to a minimum nodal residual energy of 0.002 Joules, 0.1 Joules and 0.2 Joules respectively set for each node to participate in multi-hop

routing during each of the three instances of simulation respectively. The results for the various instances of simulations are represented below graphically. The results are expressed in terms of network energy utilization, throughput for the various algorithms under consideration and the network life-time reflected for all the algorithms under study. The network life-time is assumed to be the round of data transfer supported by the respective algorithm till the death of 70% of the sensing nodes present in the network. And the maximum throughput of the networks is taken as the total number of message packets arriving at the sink during the life-time of network. For the purpose of comparison in regards with the network energy consumption, we have taken the reference of LEACH and Enhanced-LEACH algorithm's network lifetime and it is observed that the network energy is depleted in case of LEACH and enhanced-LEACH before data transfer round number 1500. The simulation results encompasses the results for the standard algorithm LEACH, its advanced version Enhanced-LEACH and three instances of our proposed algorithm with varying values of correlation fixed for Spatial correlation based clustering.

Table 1 Parameters taken for simulation (@MATLAB 2016a)

No	Design Para-meters	Value/ Symbol
1	Total Sensor Nodes	1000
2	WSN Area	200×200 m^2
3	Initial energy of all sensor nodes	0.5 J
4	Sensing Range (SR) of Node:	5 m
5	Free-Space factor for propagation distance less than cross-over distance d_0 $(d < d_0)$	10 nJ/bit/m^2
6	Multi path factor for longer distance $(d > d_0)$	0.0013 pJ/bit/m^4
7	Energy required for reception & transmission of signals by Electronics involved	50 nJ/bit
8	Energy expended for data aggregation	5 nJ/bit
9	No of bits per message packet	4000 bits

The simulation for a correlation value of $\sigma = 0.7$ is depicted below with the three instances for the three minimum nodal energy parameter value set in our proposed algorithm. The graphical results of the three instances of simulation for our proposed algorithm with the set parameter values along with the simulation results for existing standard LEACH and Enhanced LEACH protocol is given below in Fig. 4(a), Fig. 4(b) and Fig. 4(c).

Fig. 4(a) represents the Network's energy utilization curve with respect to the rounds of data transfer rounds supported by the network for standard algorithms LEACH and Enhanced-LEACH in comparison to the three instances of our proposed algorithm with $\sigma = 0.7$.

Fig. 4(b) represents the Network's throughput curve with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with $\sigma = 0.7$ while Fig. 4(c) represents the comparative network lifetime with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with $\sigma = 0.7$.

Similarly, we have implemented the simulation for varying values of correlation and the graphical results for the same are presented below. For correlation value of $\sigma = 0.5$, we have the following results.
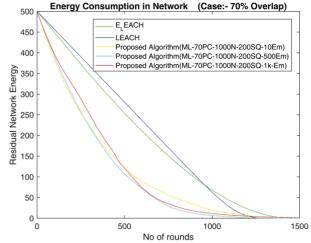

Figure 4(a) Network Energy Utilization for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.7$)
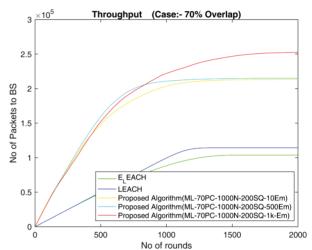

Figure 4(b) Network's Throughput curve for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.7$)
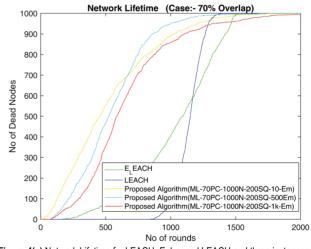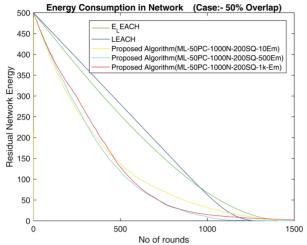

Figure 4(c) Network Lifetime for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.7$)

Fig. 5(a) represents the Network's energy utilization curve with respect to the rounds of data transfer rounds supported by the network for standard algorithms LEACH

and Enhanced-LEACH in comparison to the three instances of our proposed algorithm with $\sigma = 0.5$.

Figure 5(a) Network Energy Utilization for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.5$)
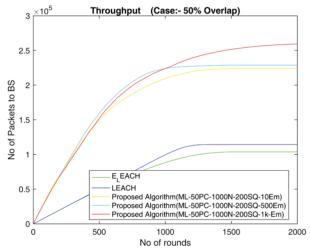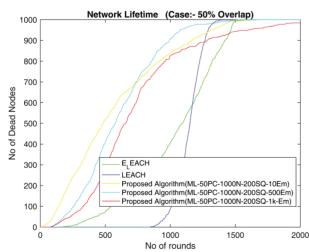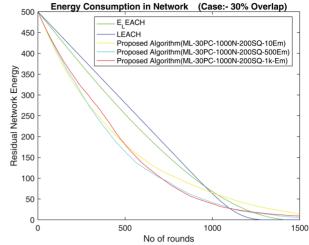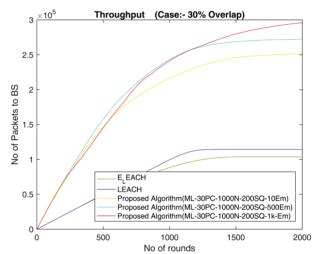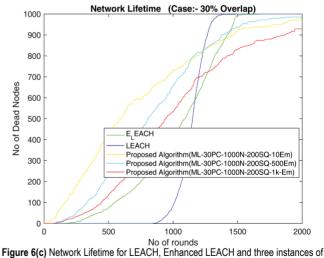

Figure 5(b) Network's Throughput curve for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.5$)

Figure 5(c) Network Lifetime for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.5$)

Figure 6(a) Network Energy Utilization for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.3$)

Figure 6(b) Network's Throughput curve for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.3$)

Figure 6(c) Network Lifetime for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.3$)

Fig. 5(b) represents the Network's throughput curve with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm

with σ = 0.5 while Fig. 5(c) represents the comparative network lifetime with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with σ = 0.5.

For correlation value of σ = 0.3, we have the following results:

Fig. 6(a) represents the Network's energy utilization curve with respect to the rounds of data transfer rounds supported by the network for standard algorithms LEACH and Enhanced-LEACH in comparison to the three instances of our proposed algorithm with σ = 0.3.

Fig. 6(b) represents the Network's throughput curve with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with σ = 0.3 while Fig. 6(c) represents the comparative network lifetime with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with σ = 0.3.
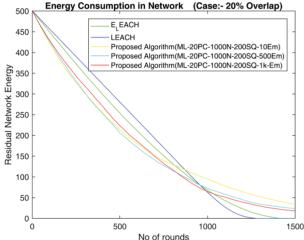

Figure 7(a) Network Energy Utilization for LEACH, Enhanced LEACH and three instances of our proposed Algorithm (σ = 0.2)
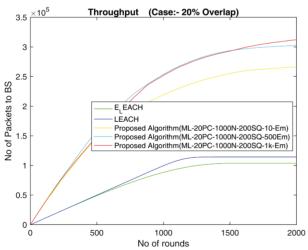

Figure 7(b) Network's Throughput curve for LEACH, Enhanced LEACH and three instances of our proposed Algorithm (σ = 0.2)

For correlation value of σ = 0.2, we have the following results:

Fig. 7(a) represents the Network's energy utilization

curve with respect to the rounds of data transfer rounds supported by the network for standard algorithms LEACH and Enhanced-LEACH in comparison to the three instances of our proposed algorithm with σ = 0.2.

Fig. 7(b) represents the Network's throughput curve with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with σ = 0.2 while Fig. 7(c) represents the comparative network lifetime with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with σ = 0.2.
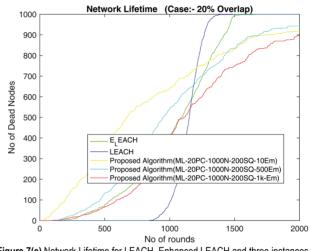

Figure 7(c) Network Lifetime for LEACH, Enhanced LEACH and three instances of our proposed Algorithm (σ = 0.2)

For correlation value of σ = 0.1, we have the following results:

Fig. 8(a) represents the Network's energy utilization curve with respect to the rounds of data transfer rounds supported by the network for standard algorithms LEACH and Enhanced-LEACH in comparison to the three instances of our proposed algorithm with σ = 0.1.
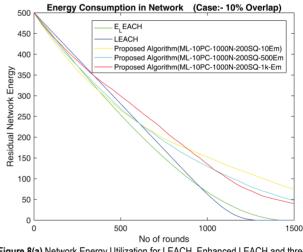

Figure 8(a) Network Energy Utilization for LEACH, Enhanced LEACH and three instances of our proposed Algorithm (σ = 0.1)

Fig. 8(b) represents the Network's throughput curve with respect to the rounds of data transfer supported for all the

existing protocols and instances of our proposed algorithm with $\sigma = 0.1$ while Fig. 8(c) represents the comparative network lifetime with respect to the rounds of data transfer supported for all the existing protocols and instances of our proposed algorithm with $\sigma = 0.1$.
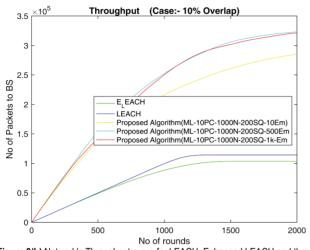

Figure 8(b) Network's Throughput curve for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.1$)

The above graphical results are represented in tabular form in Tab. 2 and Tab. 3. Tab. 2 represents the output values corresponding to the results obtained during the simulation of existing algorithms standard LEACH and Enhanced-LEACH. Tab. 3 on the other hand represents the various output values of the various instances during the simulation of our proposed algorithm with $\sigma = 0.7, 0.5, 0.3, 0.2$ and 0.1.
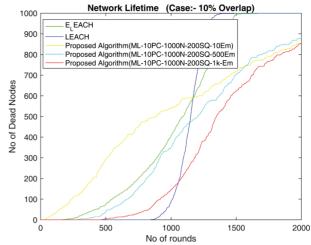

Figure 8(c) Network Lifetime for LEACH, Enhanced LEACH and three instances of our proposed Algorithm ($\sigma = 0.1$)

Table 2 Parameters observed during simulation of LEACH, ENHANCED LEACH algorithms

Parameters/ Algorithms	1000-Sensor Nodes in 200×200 m²	
	LEACH	E-LEACH
Clusters formed Roundwise between:	1 to 128	1 to 134
1st Node Death (ND) Round	845	160
10% ND Round	1011	546
20% ND Round	1065	750
50% ND Round	1152	1091
70% ND Round (LifeTime)	1198	1252
Throughput	112795	100009
Balance Network Energy after 1500 rounds	0	0

Table 3 σ and corresponding results for 1000 Nodes spread in a WSN Area of 200×200 m²

σ	0.7			0.5			0.3			0.2			0.1		
E_{min} Set for Forwarding Agent	E_{min} = 0.002 J	E_{min} = 0.1 J	E_{min} = 0.2 J	E_{min} = 0.002 J	E_{min} = 0.1 J	E_{min} = 0.2 J	E_{min} = 0.002 J	E_{min} = 0.1 J	E_{min} = 0.2 J	E_{min} = 0.002 J	E_{min} = 0.1 J	E_{min} = 0.2 J	E_{min} = 0.002 J	E_{min} = 0.1 J	E_{min} = 0.2 J
No of Clusters present	953	953	953	847	847	847	634	634	634	522	522	522	374	374	374
1st ND Round	9	68	74	9	74	74	21	64	74	27	93	93	23	175	465
10% ND Round	126	212	293	139	256	331	161	332	445	197	466	590	237	659	917
20% ND Round	205	311	399	217	354	439	269	466	596	321	627	798	404	810	1077
50% ND Round	457	524	582	484	576	656	595	803	941	671	948	1113	885	1205	1348
70% ND Round	674	670	740	750	737	816	952	1050	1205	1130	1241	1395	1454	1493	1621
Throughput (K)	175.48	191.02	194.92	187.30	202.94	207.06	211.74	248.28	260.44	231.42	278.97	287.72	257.82	305.42	308.29
Balance Energy	0 J	0 J	1.04 J	0 J	0 J	2.79 J	13.1 J	5.36 J	9.24 J	33.4 J	23.7 J	18.1 J	74.5 J	47.1 J	40.5 J
	Balance Energy in the network after 1500 rounds of data transfer in each of the algorithms considered														

The step-wise analysis of the above results is given below:

Here we have taken the life-time of networks as the time or the round till the number of active sensor nodes in the network falls below 30% of the actual nodes present at the beginning. In other words, it is the time or round till which the number of dead nodes touches or surpasses 70% of the total number of nodes present in the network.

7.1 Observation-1

From Tab. 2, it is clear that standard LEACH protocol supports 1198 rounds of data transfer with a throughput of

1,12,795 packets while Enhanced-LEACH supports 1252 rounds of data transfer with a throughput of 1,00,009. Thus we observe that Enhanced-LEACH gives a better network lifetime in comparison to Standard LEACH protocol but its throughput is reduced in comparison to Enhanced-LEACH protocol.

7.2 Observation-2

From Tab. 3, it is observed that for $\sigma = 0.7$ and $\sigma = 0.5$, our algorithm is not at all competitive with either LEACH or Standard LEACH is concerned as far as network-lifetime is concerned. But as you decrease the value of σ to 0.2 and 0.1, we observe that when we increase the minimum residual energy required for all the sensor nodes to participate in the data routing process as a forwarding agent, there is a measurable improvement in the network lifetime which is better than that observed with standard LEACH and Enhanced LEACH. For the simulation of our proposed algorithm with $\sigma = 0.2$ and the minimum node residual energy of 0.1 J, the network lifetime observed is 1241 almost equal to that observed in LEACH with 1252 rounds of data transfer. But when minimum node residual energy (E_{min}) is fixed at 0.2 J, the network lifetime in our proposed algorithm increases drastically to 1395 rounds of data transfer.

Similarly the simulation of our algorithm with $\sigma = 0.1$ with various values of minimum residual energy set for each node to be allowed to participate in the data routing process shows much better network lifetime than that observed with LEACH and Enhanced LEACH simulation. The network lifetime for our proposed algorithm with $\sigma = 0.1$ and a minimum data-routing-participating residual energy for nodes set at 0.002 J, 0.1 J and 0.2 J is at 1454, 1493 and 1621 respectively which reflects a drastic improvement over the measurements seen in LEACH and Enhanced LEACH.

7.3 Observation-3

As far as throughput measurements are concerned, it is reflected from Tab. 2 and Tab. 3 that throughput in our proposed algorithm increases from 1,75,487 packets to a maximum of 3,08,290 packets for correlation value of $\sigma = 0.7$ to $\sigma = 0.1$ which are comparatively much higher values than that observed with the simulation of LEACH and Enhanced LEACH each with a throughput value of 1,12,795 and 1,00,009 respectively.

7.4 Observation-4

As far as the energy utility parameter is concerned, it is seen from the graphs in Fig. 4(a) and Fig. 5(a) that for $\sigma = 0.7$ and $\sigma = 0.5$, energy consumption in LEACH and Enhanced LEACH is better than all the instances of proposed Algorithm. It is observed that the energy in the network is exhausted before round number 750 in all instances of simulation using our proposed algorithm with $\sigma = 0.7$ and $\sigma = 0.5$ which is approximately half the Network-Lifetime observed in LEACH and Enhanced LEACH.

But as the value of σ is further decreased, we observe a

gradual improvement in Network Lifetime using our proposed algorithm over LEACH and Enhanced LEACH. It is observed that for $\sigma = 0.3$, 0.2 and 0.1 even after round number 1500, which is taken as a reference, there is network energy balance in the network and the amount of network energy balance in the network increases as the value of σ decreases from 0.3 to 0.1, thereby increasing the network-lifetime.

For $\sigma = 0.2$ and $\sigma = 0.1$, we observe the best performance for our proposed algorithm with reference to the performance of LEACH and Enhanced LEACH, wherein even after 1500 rounds of data transfer, there is a network energy balance ranging from 18 J to 74 J respectively for the various instances considered for σ. This improvement in network energy consumption is reflected in the enhanced lifetime of the network using our proposed algorithm having $\sigma = 0.1$ with a network lifetime of 1454 rounds, 1493 rounds, 1621 rounds for the three instances of our algorithm defined by $E_{min} = 0.002$, 0.1 and 0.2 respectively which is much higher than the network lifetime seen in LEACH and Enhanced LEACH. Similarly for $\sigma = 0.2$, the improvement in network energy consumption is seen from the observed data represented in Tab. 2 and Tab. 3. In this case of our proposed algorithm we arrive at a network lifetime of 1130 rounds, 1241 rounds, 1395 rounds associated with the three instances of our algorithm defined by $E_{min} = 0.002$, 0.1 and 0.2 respectively. Thus the observed lifetime in this case with $E_{min} = 0.2$ shows drastic improvement over LEACH and Enhanced LEACH.

8 CONCLUSION

From the above findings presented in section 7, we come to the following conclusions:

For $\sigma = 0.7$ and 0.5, the results achieved are inferior to standard LEACH and Enhanced LEACH algorithms as far as network lifetime is concerned. But throughput is better using our proposed algorithm which is greater than LEACH and Enhanced LEACH by about 1.2 to 1.4 times.

But as we decrease the value of σ to 0.3, we see throughput increases from 1.8 to 2.3 times the throughput observed using LEACH and Enhanced LEACH. But the network Lifetime lags behind LEACH and Enhanced LEACH very narrowly.

Further as we decrease the value of σ to 0.2, we can conclude from the findings and results that the throughput is enhanced to around 2.05 to 2.5 times the throughput observed in LEACH and Enhanced LEACH. As far as the network lifetime is concerned, the lifetime is almost comparable to that achieved in Enhanced LEACH in case of second instance ($E_{min} = 0.1$ J) of our Proposed Algorithm. Similarly for the third instance ($E_{min} = 0.2$ J) of our proposed algorithm, the network lifetime surpasses the lifetime as seen with Enhanced LEACH by around 150 rounds.

Lastly when the value of σ is decreased to 0.1, from the findings and results of the previous section we can conclude that the throughput using our proposed algorithm is enhanced to around 2.28 to 2.73 times the throughput available with LEACH and Enhanced LEACH. And as far as the network

lifetime is concerned, our proposed algorithm gives a better network lifetime which shows a rise of around 200 to 350 additional rounds of data transfer in comparison to standard algorithms LEACH and Enhanced LEACH which converges to better energy utilization in our proposed algorithm.

Notice

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