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Spatial Clustering Algorithm with Dynamic Multi Hop Routing for Wireless Sensor Networks

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ABSTRACT: Wireless Sensor Networks is a network in which each sensor node connects wirelessly and has capability of computations for data compaction, aggregation and communication but in limited way owing to the constrained power resource available with it. Available energy of network should be effectively and efficiently utilized so as to increase the network like time and throughput of the system. Standard algorithms have adopted clustering techniques so as to limit the energy expended for communication wherein only the cluster head takes on the responsibility of communicating the aggregated data of the whole cluster to the sink or base station. Many researchers have used spatial correlation based clustering but they have very rarely tried to integrate spatial correlation into routing techniques. Here in this paper we have integrated the spatial correlation in to routing technique to come out with a dynamic two hop or three hop structures for data communication to sink. Also we have refined the formation process of clusters or groups, taking the spatial correlation into account and cluster head election decided by a fitness-value (Fval) arrived at based on the real time node-reserve energy and estimated least communication energy required. Here, we analyze the effect of our refined approach on the throughput and network lifetime vis-à-vis the existing standard algorithms like Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm and its latest improved version known as Enhanced LEACH.

Keywords: Cluster, Spatial Correlation, Fitness Value, Two-Hop, Propagation Distance, Network-Lifetime.

Abbreviations: CH, cluster head; d, distance: DEEC, distributed energy efficient clustering; E, energy; Fval, fitness value; LEACH, Low Energy Adaptive Clustering Hierarchy; N, node; ND, node death;NDS, node's distance from sink; SEP, stable election protocol; OL, overlap; P_{loss}, propagation loss factor; R_s, range of sensing; ROL, region overlap; SC, solar chimney; SD, summative distance; V_{OL}, volume overlap; V_{comb}, volume of combined sensing region; W, weight;WSN, wireless sensor network.

I. INTRODUCTION

Spatially distributed sensor nodes when collectively and cooperatively performs physical and environmental monitoring without any human intervention forms a wireless sensor network. Since most tasks tended to by WSN are outside the scope of human interference and accessibility, the sensor nodes once deployed have to be on their own with no replacements available. Hence the most important parameter from design consideration is effective and efficient utility of available energy resource so as to achieve better network lifetime with increased throughput [1-3]. As a resolve to conserve energy most standard algorithms like LEACH and its variants [2,4-11] have incorporated a clustering technique [4, 10] using which the cluster members only forwards its sensed data to its cluster leader [1]. Cluster leader is supposed to collect, aggregate and communicate the aggregated data to sink or base station. Some algorithms also make provision for backup cluster leaders as seen in paper [6]. The cluster group formation and cluster leader selection should ensure proper load distribution across all nodes facilitating an improved network lifetime [2, 12]. Our approach also adheres to clustering process wherein clustering is done only once and employs a spatial correlation [13-23] assisted clustering. Also in our approach, cluster head selection employs an estimation check process to identify the best suitable cluster head during each round of data transfer based on the real time reserve energy of sensor node and least communication energy need.

Section-2 details the various related papers in this context. Correlation model and energy model is depicted in section 3 and 4 respectively. Proposed method and algorithm is explained at large in section 5 and 6 respectively. Section-7 is our results and findings at large while section-8 cover the final conclusion of our study.

II. RELATED WORK

LEACH was introduced by Heinzelman *et al.*, (2000) as a clustering protocol for WSNs which adopts a distributed algorithm towards cluster head and cluster formation than a centralized approach. The CH election is done using a probabilistic round robin manner without laying any emphasis on the nodal residual energy. Clusters or groups are formed as decided by non CH nodes to join any of the available CH nodes as its cluster member based on the least distance from self to the CH. The dynamic CH election and cluster formation during each round tries to ensure judicious load distribution in the network [24]. S.Singh et al. (2016) introduced energy efficient DEEC protocol wherein the authors have increased the network energy to achieve better network lifetime than that seen in standard DEEC protocol. But increasing the enegy resource of the network may not be a viable option at all times [17]. Kole et al. (2014) approached the clustering phase considering the node's distance from the sink while joining the CH. The distance based improved LEACH performs better than LEACH with regards to network lifetime and power consumption parameters [25]. Zhidong et al. (2018) have synthesized a new way of arriving at optimum groups or clusters with an approach involving balanced energy consumption between and within the clusters. Also they have used variance in set-up phase and included dormancy mechanism within each cluster to enhance energy utilization. They have also detailed a comparative analysis of their algorithm with regards to LEACH, SEP and DEEC algorithms. SEP can be considered to be an heterogeneous LEACH with normal and advanced type of nodes, wherein the advance nodes are slightly more energized which enhances the algorithm's stability [15]. Amer *et al.,* (2019) have worked upon the standard hierarchical protocol namely Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm and worked out a cluster head selection process which is based on combined distance of node to cluster head and the distance of that cluster head to the sink while determining the cluster to be associated with. The authors have shown improved performance over LEACH protocol in terms of extension of network lifetime and also minimizing power consumption [4, 5, 7].

III. PROPOSED CORRELATION MODEL

These Sensor nodes are characterized by their coverage area or sensing range. If a sensor node is very closely located to another sensor node, there may be overlaps in the region of coverage of these nodes. This scenario is depicted using a two dimensional representation in Fig. 1.

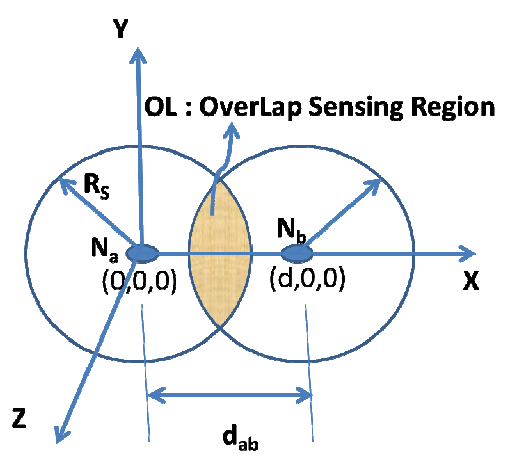

Fig. 1. Over-lapped sensing region of sensor nodes [20].

But in real sense, any coverage area of a sensor node can be represented by a spherical geometry with the node at the center and the sensing range as the radius of the sphere. to that of a sphere. Hence when there is an overlap between the coverage area of two nodes, the overall region of overlap can be visualized as a three dimensional structure that can be addressed as volume of overlap and the combined non repeating regions of coverage of the two sensor nodes can be addressed as combined volume. As the distance of separation between the any two nodes increases beyond twice the sensing radius of the nodes, there is no overlap in the region of coverage of the two nodes. But as the distance of separation between these nodes decreases below twice the sending radius of nodes, there is an overlap in the region of coverage of these sensor nodes. This correlation of overlap can increase between any two sensor nodes if the two nodes are brought near to each other and it can touch 100% if both the nodes are co-located. Hence we define an overlap correlation coefficient between nodes Na and Nb by the following expression:

$$\sigma_{ab} = \frac{Volume \quad of \quad overlap-of- \quad Sensin\, g\, Re\, gionsof \quad nodesN_a, \quad N_b}{Combined \quad Volume-of- \quad Sensin\, g\, Re\, gionsof \quad NodesN_a, N_b}$$

$$\sigma_{ab} = \frac{V_{OL}}{V_{Comb}} \tag{1}$$

Also we define $(\%ROL)_{ab} = \sigma_{ab} \times 100$ (2)

From the study of spherical geometry [26], the numerator and denominator in expression (1) can be expressed as:

$$V_{OL} = \frac{\Pi}{12}(2R_s - d_{ab})^2 (d_{ab} + 4R_s) \tag{3}$$

$$V_{Comb} = \frac{8\Pi R_s^{\,3}}{3} - \frac{\Pi}{12}(2R_s - d_{ab})^2 (d_{ab} + 4R_s) \tag{4}$$

Therefore using (3) and (4) in (1), we get the expression for overlap correlation coefficient between nodes Na and Nb as:

$$\sigma_{ab} = \frac{(2R_s - d_{ab})^2 (d_{ab} + 4R_s)}{32R_s^{\,3} - (2R_s - d_{ab})^2 (d_{ab} + 4R_s)} \tag{5}$$

where VOL represents the overlapping sensing region between two nodes expressed as volume of overlap, V_{Comb} represents the combined sensing regions of the two nodes under consideration (i.e Sensing region of node N_a + Sensing Region of Node N_b – Overlapped Sensing Region of N_a and N_b), $R_s$is the sensing range of all nodes under consideration, d_{ab} is the distance between nodes Na and Nb, Also (%ROL) represents percentage Regional OverLap between the sensing regions of Node N_a and N_b.

It is seen that as dab increases more than twice the sensing range Rs of the node, there is no overlap in terms of the sensing region of the two nodes Na and Nb. Therefore σ_{ab} = 0 in all such cases. Hence, we can express sensing region correlation coefficient of two sensor nodes N_a and N_b as:

$$\sigma_{ab} = \begin{cases} \dfrac{(2R_s - d_{ab})^2 (d_{ab} + 4R_s)}{32R_s{}^3 - (2R_s - d_{ab})^2 (d_{ab} + 4R_s)} & if \quad 0 \le d_{ab} < 2R_s \\ 0 & if \quad d_{ab} \ge 2R_s \end{cases} \tag{6}$$

The above expression (6) expresses the sensing region correlation coefficient model [20].

IV. ENERGY MODEL

The energy expended in this WSN system is made up of two main components. The first one is the energy of propagation or transmission energy and the second one is the energy expended in the various electronics of the system. Our energy model is based on the standard model detailed in paper [9]. We have adopted the standard energy model referred from paper [9]. The propagation energy is influenced by the distance of separation between the transmitter and receiver. If the distance of separation increases beyond the cross-over distance, the energy expended is influenced by the multipath factor otherwise it is influenced by free space equation [9, 27]. The energy involved in electronics of the system is used for pre-transmission processes like modulation, filtering, aggregation and others. Hence for transmitting a l-bit message, the combined energy needed can be given by:

$$E_{Trans} = 1E_{ELX} + 1*P_{loss}*d_{Trans}{}^{(n)}$$

Here in the above expression, E_{ELX} represents energy utilized for electronics per bit, $P_{loss}*d_{Trans}{}^{(n)}$represents the propagation energy used so as to cover the transmission distance per bit (here propagation loss dictates the value of P_{loss}, d_{Trans} is the distance between the transmitter and receiver and n represents the propagation loss exponent)

For $d_{Trans}< d_0$, 'P_{loss}' assumes values dictated by free-space equation. Hence the transmission energy [26], can be concluded as:

$$E_{Trans1} = 1E_{ELX} + 1\epsilon_{fspace}d_{Trans}{}^2 \tag{7}$$

where ϵ_{fspace} is the P_{loss} in free-space.
And for $d_{Trans}>d_0$, we have

$$E_{Trans2} = 1E_{ELX} + 1\epsilon_{mpath}d_{Trans}{}^4 \tag{8}$$

where 'P_{loss}' is specified by the multi-path transmission factor ϵ_{mpath}. Here cross-over distance d_0 is given by:

$$d_0 = \sqrt{\frac{\varepsilon_{fspace}}{\varepsilon_{mpath}}} \tag{9}$$

Where ϵ_{fspace} = 10 pico-Joules/bit/metre^2 and ϵ_{mpath} = 0.0013 pico-Joules/bit/metre^4 assuming a frequency of 914 k.Hz and a bit rate of 1Mbps [15].

V. PROPOSED METHOD

In this study, we have initially taken a random distribution of 100 sensor nodes, which are GPS enabled, spread in an area of 100*100 Sq.units. and maintained the same locations of all the nodes throughout, that is while simulating for LEACH, Enhanced LEACH and our proposed algorithm @MATLAB 2016. Here we have adopted a one-time centralized clustering mechanism wherein the sink or base station which is location aware of all the uniformly charged sensor nodes, runs a clustering algorithm based on the spatial correlation defined by the user. The same clusters are maintained throughout the lifetime of network. The sink or the base station is rich in resources with limitless energy. Hence the energy expended by the sink is not taken into consideration for analysis purpose. Once the cluster grouping is accomplished by the sink, the cluster details are relayed to the cluster members including the number of members in the cluster, member ID, location detail. Once the clusters are formed, the cluster head or leader is decided by a distributed algorithm [28] running on each node during the beginning of each round of data transfer. The algorithm determines a fitness value for each node to assume the role of cluster leadership. Each node after determining the fitness value relays it across the cluster members. The highest fitness valued node assumes the role of cluster head. The fitness value is influenced by the residual energy of node and the location of each node in the cluster from each other such that summation of distances of each member node from the assumed cluster head, if each member were to be the cluster head, should be the minimum distance of propagation collectively for that cluster, thus leading to a dynamic selection of cluster head during each round. Once the cluster heads are elected for each cluster they are then type cased as chief cluster head or subordinate cluster head or norml cluster head. This partitioning of CHs into chief and subordinate ones is carried out by the distributed algorithm again based on the estimated fitness value and the spatial correlation coefficient satisfying a minimum criterion of σ = 0.1. The chief cluster head receives the sensed data from its cluster members and also the aggregated data from associated subordinate cluster heads. The chief cluster head then aggregates the received data and transmits it to the sink or base station. Similarly, the associated subordinate CH aggregates the data received from its cluster members and transmits its aggregated data to its associated chief cluster leader, thereby effecting better energy utilization. The remaining cluster heads are the normal cluster heads which relays the aggregated data received from its cluster members to the sink directly. Here, we have further tried to harness energy saving by ensuring that any member node, if it shares 10% or more overlap in the coverage region with its associated cluster head or the chief cluster head as the case may be, then that node is restricted from relaying any data since it is assumed that the 10% overlap in their sensing regions or σ =0.1 would ensures almost similar readings sensed by its cluster head or chief cluster head owing to the spatial correlation existing between sensed data. Thus during each round of data transfer, in the beginning of operation the chief and subordinate cluster heads are identified and then implements the actual data transfer using either a two hop mechanism or three hop mechanism as decided by the distributed algorithm. In the simulation study, we have implemented different values of correlation coefficient for cluster formation and in effect try to analyze the effect on network lifetime and throughput achieved for each value of correlation coefficient. As a simulation case study, we have varied correlation coefficient from 0.1 to 0.7 through incremental steps of 0.1 and observed the influence on network lifetime and throughput.

VI. ALGORITHM

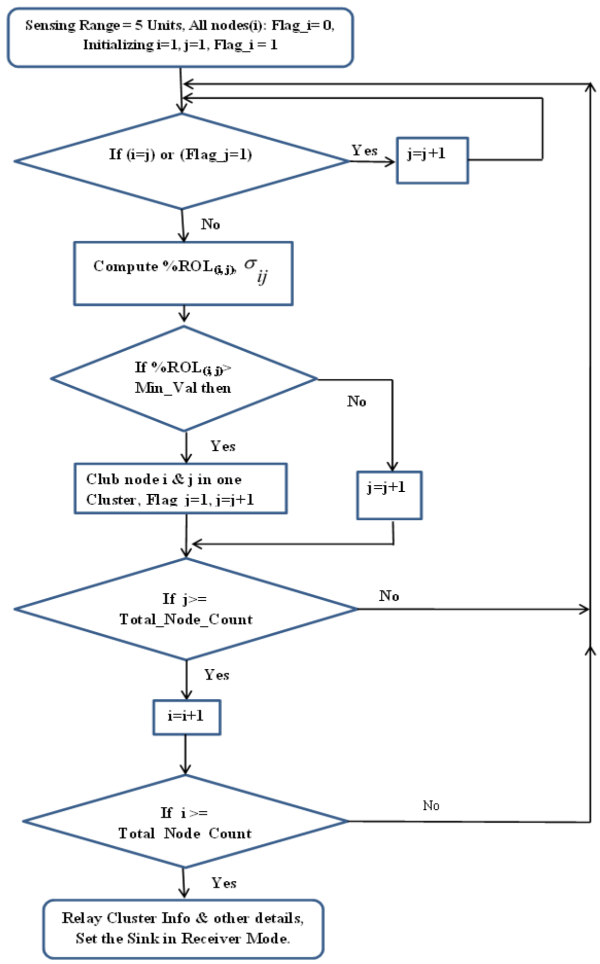

Fig. 2. Flow-Chart for Algorithm 1.

In our proposed scheme, we can divide the entire operation into three phases i.e. the one time clustering or grouping phase followed by the cluster head (chief cluster head and subordinate cluster head) selection phase followed by the data transfer or flow phase. The first phase involves the sink assisted centralized grouping of nodes into permanent clusters. The following flowchart represents the pseudo code implemented at the sink for sink controlled grouping algorithm:

The above flowchart details the process of grouping of sensor nodes into clusters at the sink. The spatial correlation coefficient is selected from the range given in Table 1 below during implementation of each instance of our proposed technique.

Table 1: Various instances of σ for simulation.

Simulation -Instance No/ Parameter	1	2	3	4	5	6	7
σ	0.7	0.6	0.5	0.4	0.3	0.2	0.1

The second phase of operation is the cluster head election phase and classifying each CH as chief CH or subordinate CH or a normal CH. The flowchart below represents the pseudo code implemented at each node (distributed algorithm) towards the second phase of operation for each round of data transfer. The fitness value calculated by each node determines whether the node will assume the role as cluster leader or as a cluster member. The fitness-value (Fval) is determined by the following expression:

$$F_{val} = \left(\frac{W1 \times NRE + W2\left(\frac{1}{SD^2}\right)}{NRE + \left(\frac{1}{SD^2}\right)} \right) \qquad (10)$$

Where Fval is the fitness-value of the node to be the CH, NRE is the node's residual energy, W1 and W2 are the proportional weights expressed as:

$W1 = \left(\frac{NDS}{NDS + SD}\right)$ and $W2 = \left(\frac{SD}{NDS + SD}\right)$, NDS is the node's distance from sink, SD is the summative distance. Here summative distance is the summation of distances of all remaining cluster members from self (node assuming to be the leader of cluster) in the cluster. W1 and W2 are the proportional weights used to influence the calculation of the fitness value such that the fitness value does not only depend on the residual energy of the node but it also takes into account the energy that would be expended by the member colleagues (if the node assumes the role of a cluster head) which is inversely proportional to the square of the distance from the assumed CH. The emphasis is also on minimum energy to be expended in intra cluster communication while selecting the cluster head with an aim to extend the network lifetime. In expression (10), the influence of residual energy is given a higher priority over summative distances which is evident from the expression itself. Thus once the cluster heads are elected and classified as chief CH or subordinate CH or normal CH, each CH schedules a time slot for each of its members to transfer data using TDMA scheduling [27]. Also the chief CH also provides scheduled time slot for all its associated subordinate CHs to transfer their aggregated data.

After the second phase of operation, the third phase is the data transfer operation from the cluster members to its cluster head which then forwards the aggregated data to chief CH or Sink directly. All the chief CHs after aggregating the data received from its cluster members and associated subordinate CHs, forwards it to sink.

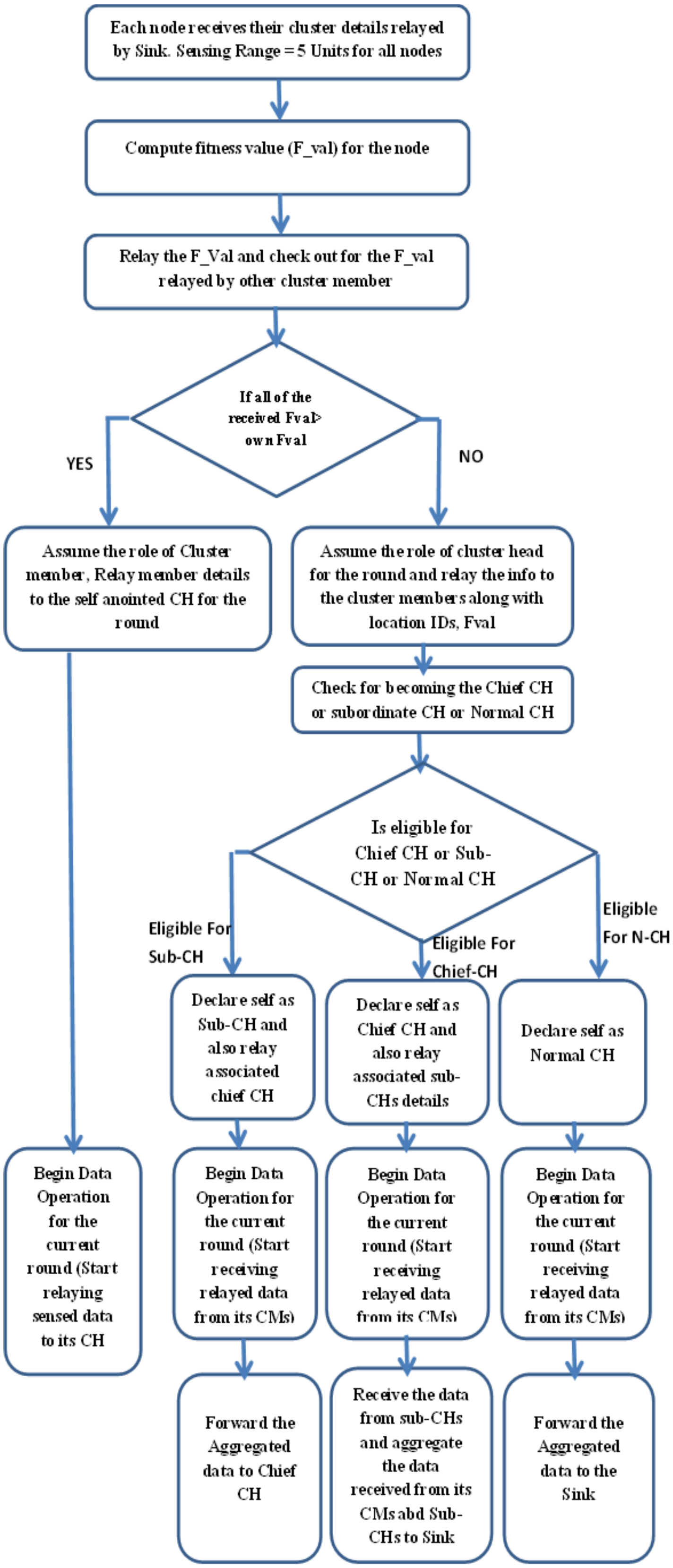

Fig. 3. Flow-Chart for Algorithm 2.

VII. RESULTS

Table 2: Parameters taken for simulation (@MATLAB 2016a).

S.No.	Design Para-meters	Value/ Symbol
1.	Total Sensor Nodes	100
2.	WSN Area	100*100
3.	Initial energy of all sensor nodes	0.5 J
4.	Each node's Sensing Range(R_S):	5
5.	Distance between node N_a&N_b	d_{ab}
6.	Spatial Correlation Coefficient	σ
7.	Free Space factor for shorter distance ($d<d_0$)	10 nJ/bit/m^2
8.	Multi path factor for longer distance ($d>d_0$)	0.0013 pJ/bit/m_4
9.	Energy expended in the Electronics to transmit or receive the signal	50nJ/bit
10.	Energy expended for data aggregation	5 nJ/bit
11.	Message Length	4000 bits

The above design parameters have been adopted in the simulation of our proposed algorithm. The simulations are implemented for our proposed algorithm with various values of σ as given in table 1. In our simulation, we have ensured the initial location of 100 sensor nodes spread randomly in an area of 100*100 sq.units is kept the same for all the instances of σ chosen. Below are the graphical results for all the instances chosen for simulation:

Simulation Instance 1: for σ = 0.7 or %ROL = 70%

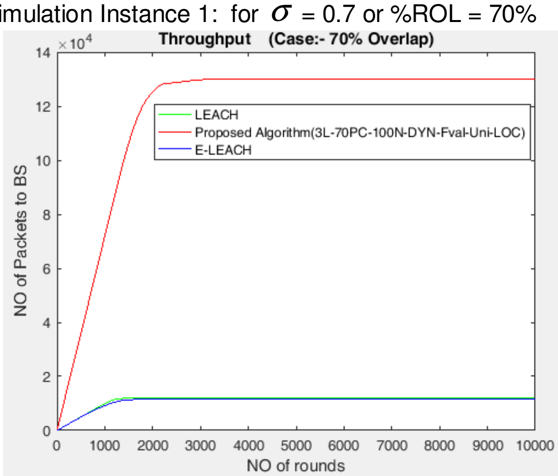

Fig. 4 (a) Throughput (σ = 0.7)

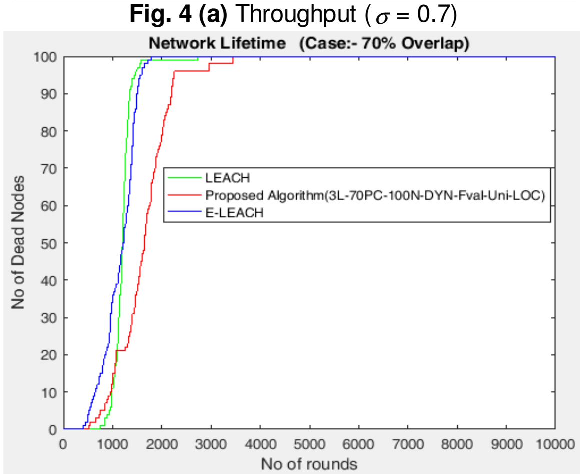

Fig. 4 (b) Network Lifetime (σ = 0.7)

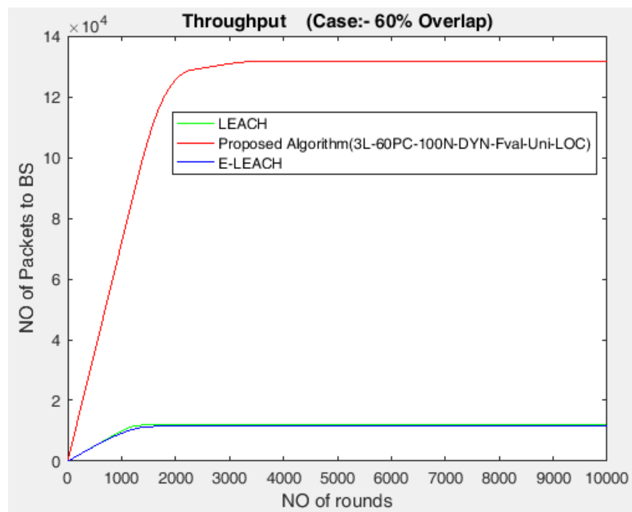

Fig. 5(a) Throughput (σ = 0.6)

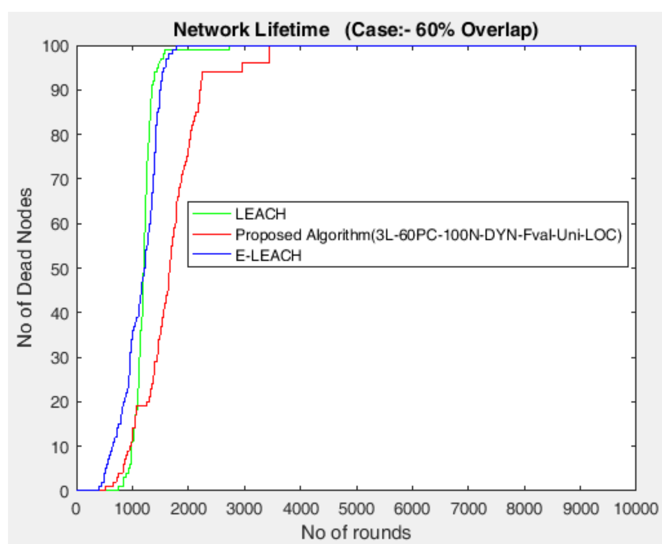

Fig. 5 (b) Network Lifetime (σ = 0.6).

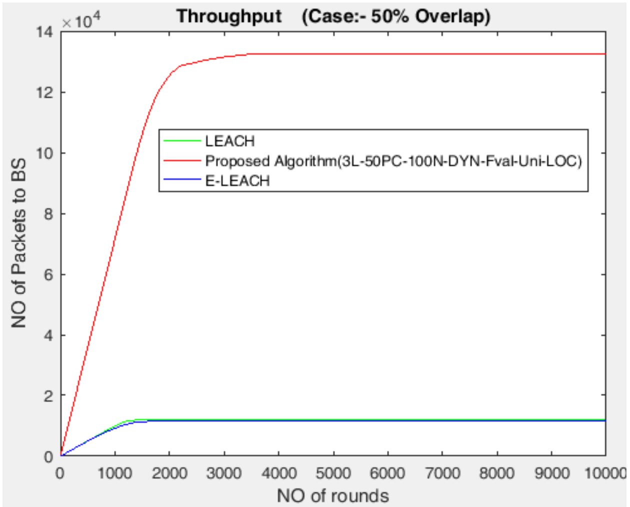

Fig. 6(a) Throughput (σ = 0.5).

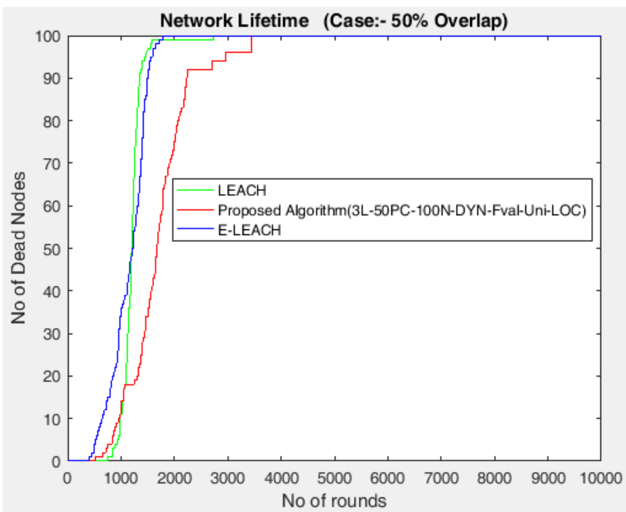

Fig. 6(b) Network Lifetime (σ = 0.5).

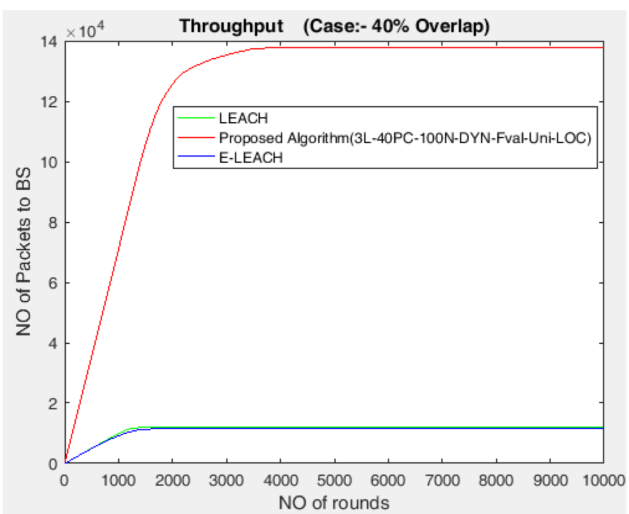

Fig. 7(a) Throughput (σ = 0.4)

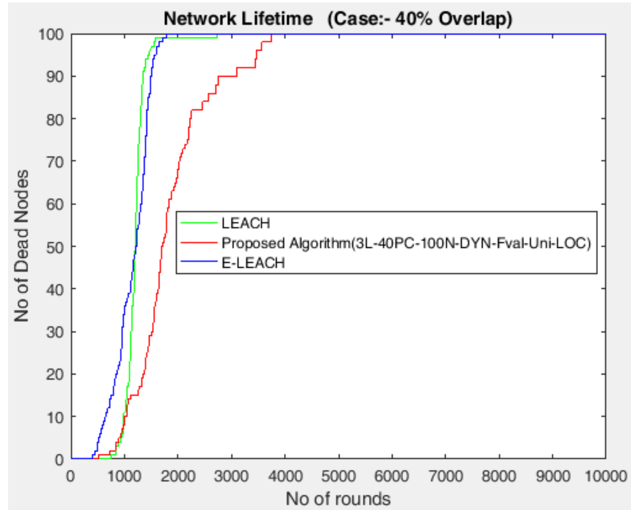

Fig. 7(b) Network Lifetime (σ = 0.4).

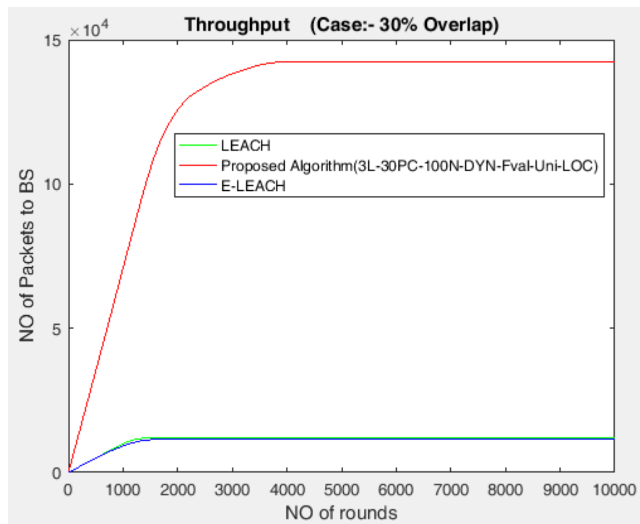

Fig. 8(a) Throughput (σ = 0.3).

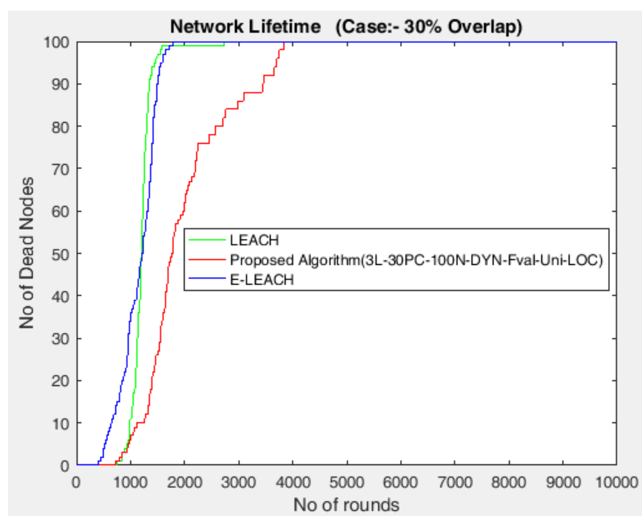

Fig. 8(b) Network Lifetime (σ = 0.3).

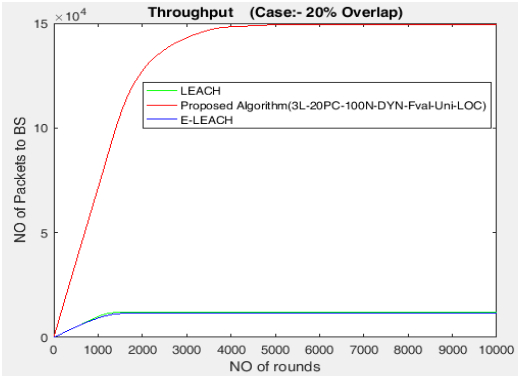

Fig. 9(a) Throughput (σ = 0.2).

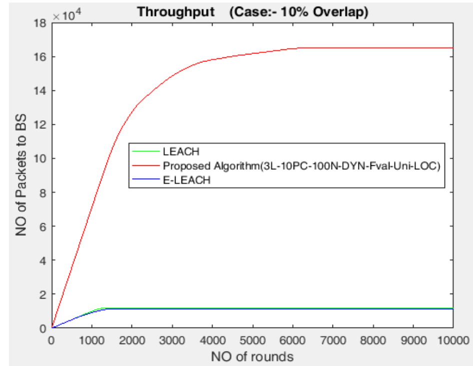

Fig. 10(a) Throughput (σ = 0.1).

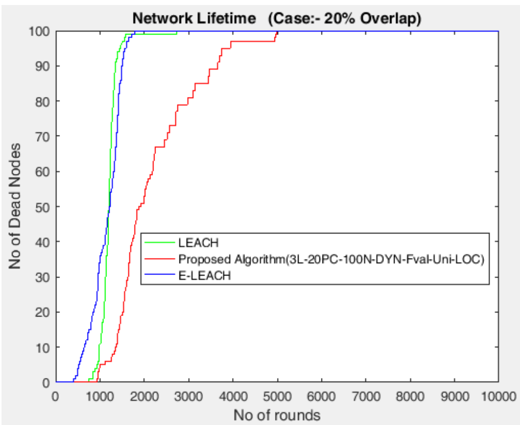

Fig. 9(b) Network Lifetime (σ = 0.2).

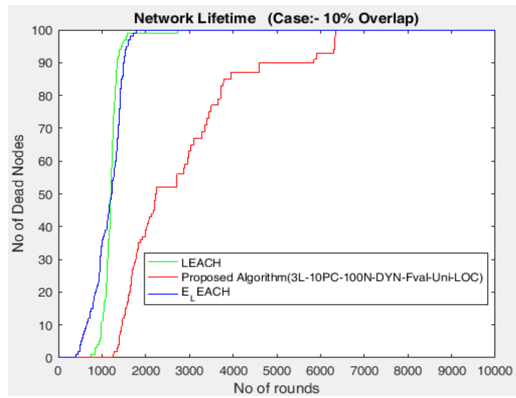

Fig. 10(b) Network Lifetime (σ = 0.1).

Table 3: σ and corresponding results for 100 Nodes spread in a WSN Area of 100*100 Sq. Units.

σ	0.7	0.6	0.5	0.4	0.3	0.2	0.1
No of Clusters present	98	96	95	90	86	81	72
1st Node Death (ND) Round	527	527	527	527	716	932	1250
10th ND Round	946	946	946	1001	1123	1347	1452
20th ND Round	1065	1250	1302	1347	1392	1518	1635
50th ND Round	1642	1675	1682	1701	1772	1883	2229
75th ND Round (Network-LifeTime)	1919	1973	1998	2170	2237	2707	3443
Throughput [No. of Packets sent to Sink in its Lifetime (75% ND)]	123630	124932	125308	128957	130579	140134	154173

Table 4: Parameters observed during simulation of LEACH, E-LEACH algorithms.

Parameters/Algorithms	100-Sensor Nodes in 100*100 Sq. Meters	
	LEACH	**E-LEACH**
Clusters formed Roundwise between:	1 to 22	1 to 21
1st Node Death (ND) Round	757	396
10% ND Round	989	644
20% ND Round	1090	844
50% ND Round	1199	1203
75% ND Round (LifeTime)	1269	1398
Throughput [No. of Packets sent to Sink in its Lifetime (75% ND)]	11680	11201

The simulation of our proposed scheme involves multiples instances wherein we are varying the spatial correlation coefficient from 0.7 to 0.1. The effect of this variation on the throughput and network lifetime is noted for analysis purpose.

Also these results are compared with the simulated results for the standard LEACH protocol and Enhanced LEACH protocol. On analyzing the simulated results presented in graphical Fig. 4-10 and tabular forms given in tables 3 & 4, we arrive at the following inferences:

We observe a convergence pattern as far as the network life time is concerned for our proposed algorithm as we decrease the spatial correlation coefficient value σ from 0.7 to 0.1. The first node death is reflected in round number 527 and it remains the same for decreasing value of σ from σ = 0.7 to σ = 0.4. And also the 10th node death is reflected in round number 946 for the decreasing value of σ from σ = 0.7 to σ = 0.5. Hence the influence of the choosing of σ is reflected from σ = 0.4 to σ = 0.1 in the simulation results. Also from the data presented in tables 3 & 4, we can say that our proposed algorithm shows improved results over enhanced LEACH algorithm in all instances considered in our proposed algorithm. And while comparing our proposed algorithm with standard LEACH protocol, our algorithm improves over LEACH after the death of 10% of nodes for the instances ranging from σ = 0.7 to σ =0.5 and for σ = 0.4 to σ = 0.2 we see further improvement in the network life time even for node deaths less than 10. And finally for σ = 0.1 we see improved network lifetime even starting from the first node death when you compare with standard LEACH algorithm. Thus we see a convergence towards improved network lifetime for instances of our proposed algorithm with σ = 0.7 to σ =0.1.

Further we can say that for a network life time defined as the time till the death of 75% of nodes, we observe that Enhance LEACH shows improved results over standard LEACH algorithm as seen in Table 4 which is evident from paper [7] it supports 1398 rounds of data transfer during the lifetime of network while standard LEACH supports 1269 rounds of data transfer during the lifetime. In comparison to both, standard LEACH and Enhanced LEACH, as seen from table 3 and Table 4 all the instances of our proposed algorithm shows improved results by a large margin. To estimate we can say that our instances with σ = 0.7 to σ = 0.5 gives almost 37% to 42% increase in network lifetime over the network lifetime of Enhanced LEACH. While instances with σ = 0.4 to 0.2 gives an increase of 55% to 93% over the network Lifetime of Enhanced LEACH. Lastly, the instance of σ = 0.1 gives an increase of 146% over the network lifetime of Enhanced LEACH algorithm.

Throughput in the context of our study has been defined as the total number of packets of data sent to the sink by the cluster heads during the lifetime of network. Throughput, in the case of LEACH and Enhanced LEACH is almost the same which is reflected in the graphs given in Fig. 4 to figure-10. But throughput for instances with σ = 0.7 to σ = 0.1 in our proposed algorithm gives approximately 10 to 13 times the throughput achieved in LEACH and Enhanced LEACH [7].

Thus we advocate the use of a spatial correlation between nodes in the clustering process, so as to achieve optimum cluster size and in-effect optimum network lifetime and throughput which is dictated by the tradeoff between the quality of spatially correlated data and correlation coefficient (instances with varying σ) chosen for implementation of our proposed algorithm.

VIII. CONCLUSION

From the detailed results and inferences drawn in the earlier section, we conclude that our proposed algorithm outreaches both standard LEACH and Enhanced LEACH in terms of network lifetime and throughput with the best performance being reflected in instances of implementation with lower values of σ ranging from σ = 0.4 to σ = 0.1 for our proposed algorithm. Hence we can conclude that our proposed spatial clustering with dynamic multi-hop extends the lifetime of the wireless sensor network by harnessing the spatial correlation existing between nodes in fostering a clustering mechanism that works towards the criterion of minimizing the energy expended during each round of data transfer and at the same time supporting an even distribution of load among the cluster members. Also the phenomenon of selectively making the correlated nodes to switch off their transmissions that satisfy the pre-defined correlation criterion with their CH or Chief CH further helps in extending the network lifetime this

IX. FUTURE SCOPE

From a future scope point of view, we can try to further develop or grow this dynamic three hop path towards the sink into multiple hops which would support larger sized (area) WSN.

Conflict of Interest. There is no conflict of interest.

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