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ONCTR: Optimum Number of Clusters and Transmission Range based Clustering in Wireless Sensor Networks

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Abstract
The field of Wireless Sensor Network (WSN) is striving for devising ways to minimize energy consumption. Clustering reduces energy consumption and increases scalability along with network lifetime. There is a need to identify appropriate number of clusters to balance traffic in network which is a challenging task for energy efficient WSN. Manually it is difficult to decide number of clusters. Finding optimum number of clusters to minimize energy consumption is the major issue in WSN. Existing algorithms find optimum number of clusters but not optimum transmission range. This paper contributes towards the aforesaid issue by proposing a novel method to find optimum number of clusters and a first attempt to find optimum transmission range. We report a new algorithm, where the number of clusters obtained from proposed method is compared with state-of-the-art methods. Extensive experiments are carried out and result comparison with state-of-the-art approaches demonstrate that our method shows significantly better performance. The analysis reveals that optimum number of clusters obtained by proposed method is less than state-of-the-art method. It is especially suitable for clustering in WSN.

Keywords: Optimal Clustering, Optimum Transmission Range, Self-organized Clustering

Introduction
In a sensor network, cost of communication between two nodes is much more than the cost of computation at each node where nodes are deployed randomly in a region. To provide a cost effective solution for minimizing communication overhead, nodes are grouped into various clusters. The challenges of energy efficient clustering are to find optimum number of nodes in a cluster, optimum number of clusters [1] and optimum position of CH [10][11].
In the design process of WSN, energy is the prime constraint. Optimum number of clusters is one of the ways to reduce energy consumption. However it has been observed that selecting random number of clusters gives non optimal results, increase in the number of clusters result into higher overall energy consumption and less number of clusters means more delay and more energy consumption. Hence there is need to address aforesaid issue. With this foothold, We are proposing a new method called as Optimal Clustering (OC). Here Self-organized (SO) Clustering is used [17].
The main contributions of this paper are summarized as follows:

1. We presented a Square Root Methodology to find optimum number of clusters from number of deployed sensor nodes.
2. We proposed OC method to find optimum number of clusters and optimum transmission range.
3. We conducted extensive experiment on WSN to obtain optimum number of clusters to verify our proposal and also perform empirical comparison with state-of-the-art algorithms.

The rest of the paper is organized as follows: related work gives overview of various methods for optimal clustering and finding optimal number of clusters in WSN. The Square Root Methodology (SRM) for optimum number of clusters is explained. Then the proposed Optimal Clustering algorithm is described. Experimental results are summarized along with analytical findings and future work.

Related Work
During the design of WSN, a lot of research has focused on several clustering approaches with some constraint based on energy efficiency and lifetime of network [2]. The extensive work is carried out to select number of clusters in clustering techniques. This can be classified as connectivity-based, centroid-based and spectral graph [18]. The paper proposes connectivity-based optimal clustering algorithm i.e. clusters are formed within the transmission range of sensor nodes.
In the past two decades, several researchers attempted to find optimum number of clusters in WSN. In LEACH, there are different numbers of clusters with different number of member nodes in various rounds. Hence energy consumption is also different in each round [3]. Hybrid Energy Efficient Distributed Clustering is based on iterative clustering process that uses the same approach to find optimum number of clusters as used in LEACH [4].
Gustafson-Kessel (GK) clustering algorithm forms clusters of equal area to achieve load balancing that uses fuzzy clustering to extend life of network [19]. Particle Swarm Optimization (PSO) algorithm for

clustering gives unique optimal number of clusters for multi-cluster structure for WSN [7]. In Multiple Parameter based Clustering (MPC), optimum number of clusters is obtained analytically using cross layer approach [8] [16].

In K-means, number of clusters is to be given as input but that is not optimum [5]. Elbow method is used to calculate number of clusters. It uses percentage of variance that is function of cluster number. Elbow and K-means method (EBK) uses Elbow method to find number of clusters and cluster formation is as per K-means. Authors have not clearly mentioned how cost of optimal quality solution is calculated. EBK produces quality clusters and overall process improves energy consumption and network lifetime. It gives only optimum number of clusters [6] [14]. Hence there is a need to have such an algorithm that gives optimal clustering with optimum number of clusters as well as optimum transmission range. First principal component generated using Principal Component Analysis (PCA) is initialized as a cluster centroid in K-means. This reduces time taken for clustering and increases accuracy of the process [9].

L-method works on the principle of 'knee of a curve' that means point of maximum curvature where x-axis represents number of clusters and y-axis represents evaluation metric. The evaluation metric is based on the clustering parameters such as distance, similarity, error and quality. Also L-method cannot work for one or two clusters [12]. Transmission range is one of the cluster quality parameter that is not evaluated against number of clusters. Fixed Optimal Clusters (FOC) algorithm analyzes an amount of optimal clusters based on the position of sink (far away or at the center of sensor field) and network model to extend lifetime of a network [13]. A fixed optimal cluster number is estimated along with CHs selection algorithm to utilize data correlation for aggregation [15]. Existing optimal clustering algorithm such as K-means, EBK and K-means PSO are compared as shown in the Table 1.

After comparison with algorithms mentioned in Table 1, we propose energy efficient Optimal Clustering which finds optimum number of clusters using OC method. Cluster Formation and CH Selection is dynamic and no need to recalculate position of CH. However it has been evident from the Table 1 that the issue of finding optimum number of clusters needs to be emphasized. Hence we have been considering this as a major parameter in our methodology and algorithm explained in subsequent sections.

Table 1. Comparison of Existing Clustering Algorithms

Algorithms	**K-means**	**Distributed K-means**	**Centralized K-means**	**EBK Algorithm**	**K-means PSO**
Optimum Number of Cluster calculation	No	No	No	Yes	No
Optimum number of cluster calculation method	Random Selection of Centroids	Random Selection of Centroids	Random Selection of Centroids	Elbow method	Static
Cluster Formation and CH Selection	Random	Distributed (Participation of each node in the process)	Controlled by Central Node	Dynamic	Random
Recalculate position of CH	Yes (Nearest Nodes to Centroid)	Yes (Nearest Nodes to Centroid)	Yes (Nearest Nodes to Centroid)	No	No
Energy Efficient	Less	Medium	Medium	Medium	Less

Square Root Methodology (SRM)

There are several clustering algorithms that need initial value 'C' to choose number of clusters. To improve performance of WSN, value of 'C' plays an important role. We have proposed the Square Root methodology to find optimum number of clusters which is described as follows:

Let (X_1, Y_1) and (X_2, Y_2) be the co-ordinates of two sensor nodes. Then the distance between two nodes is given by:

$$d = [(X_2 - X_1)^2 + (Y_2 - Y_1)^2]^{1/2}$$

i.e., $d^2 = [(X_2-X_1)^2 + (Y_2- Y_1)^2]$

Let, center of the sensor field is at origin of X-Y plane as shown in Fig. 1 (a). Hence,

$$d^2 = (X - 0)^2 + (Y - 0)^2 = (X^2 + Y^2) \quad \text{--------------(1)}$$

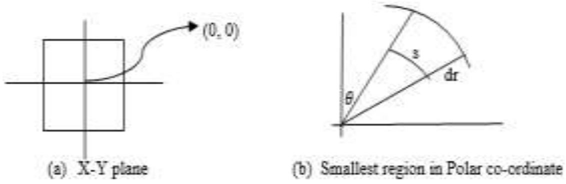

Figure 1. Calculation of area of sensor field

The distance between two sensor nodes i.e. distance from node to CH and CH to sink is denoted as d_{toCH} and d_{toSink}.
From equation (1), d^2_{toCH} or $d^2_{toSink} = (X^2 + Y^2)$
Average distance between all sensor nodes and cluster head over the region is calculated using double integrals as follows:

d_{toCH} or $d_{toSink} = \int_A \sqrt{X*X+Y*Y}\ \ 1/A * dA$ --- (2)

Energy dissipated at the cluster head is given as follows:

$E[d^2_{toCH}] = \iint d^2 * \text{density} * dx\, dy$ --------------- (3)

From equation (2) equation (3) is rewritten as follows:

$E[d^2_{toCH}] = \iint (X^2 + Y^2) * \rho * (X, Y)\, dx\, dy$

$E[d^2_{toCH}] = \iint (X^2+Y^2) * \rho * (X, Y)\, dA$ ------(4)

where, area of region is dA = dx*dy
Computing double integrals in rectangular co-ordinates is same as in polar co-ordinates.
Area of smallest rectangular region ≅ Area of smallest region on circle
Hence, dA = dx dy = r*dr*dθ
Area of smallest region on circle = a*dr = r*dθ*dr = r*dr*dθ
i.e. as shown in Fig. 1 (b), a = r*dθ
Equation of a region, $r^2 = X^2 + Y^2$
ρ = sensor nodes density i.e. number of sensor nodes over the sensing area = 1 / A
The coverage area of a sensor node is considered to be a circle. Hence area of coverage $A = \pi r^2$ and therefore,
$r = \sqrt{A/\pi}$ where 'r' is the radius of coverage. Here, θ varies from '0' to '2π' and r varies from '0' to 'r' that means $\sqrt{A/\pi}$.
Hence, equation (4) becomes as follows:

$E[d^2_{toCH}] = \int_0^{2\pi} \int_0^{\sqrt{A/\pi}} r^2\, (1/A)\, r\, dr\, d\theta$ -------- (5)

Assume, M x N is an area of a region in which 'S' number of sensor nodes are deployed. Now equation (5) becomes as follows:

$E[d^2_{toCH}] = \int_0^{2\pi} \int_0^{\sqrt{M*N/\pi}} 1/(M*N)\, r^3\, dr\, d\theta$ ------ (6)

Let C is the total number of clusters hence area of single cluster is M*N/ C, then equation (6) becomes:

$E[d^2_{toCH}] = C/(M*N) \int_0^{2\pi} \int_0^{\sqrt{M*N/C*\pi}} r^3 dr\, d\theta$

$E[d^2_{toCH}] = C/(M*N) \int_0^{2\pi} \{[r^4/4]\, |\sqrt{M*N/C*\pi}\}\, d\theta$

$E[d^2_{toCH}] = C/(M*N) \int_0^{2\pi} \{\{[(M*N/C*\pi)^{(1/2*4)}]/4\}-0\}\, d\theta$

$E[d^2_{toCH}] = C/(M*N) \int_0^{2\pi} [(M*N)^2/4C^2*\pi*\pi]\, d\theta$

$E[d^2_{toCH}] = M*N/4C*\pi*\pi \int_0^{2\pi} d\theta$

$E[d^2_{toCH}] = M*N/4C*\pi*\pi\, [2\pi - 0]$

$E[d^2_{toCH}] = M*N/2\pi C$ ------------------------ (7)

Sink is located at the center of M x N sensing area and the energy dissipated to the sink is as follows:

$E[d^2_{toSink}] = \int_0^{2\pi} \int_0^{\sqrt{M*N/\pi}} (X^2 + Y^2)*\rho*(X,Y)\, dxdy$

$E[d^2_{toSink}] = \int_0^{2\pi} \int_0^{\sqrt{M*N/\pi}} 1/(M*N) * r^3 * dr\, d\theta$

$E[d^2_{toSink}] = 2\pi\, (1/M*N)*\{ r^4/4\, |\sqrt{M*N/\pi}\, \}$

$E[d^2_{toSink}] = 2\pi\, (1/M*N) * [(M*N)^2 / 4\pi^2]$

$E[d^2_{toSink}] = (M*N) / 2*\pi$ ------------------- (8)

Initially, total number of hops is calculated to find total energy dissipated in the network.

The total number of hops for clustered network = number of hops (inter-cluster + intra-cluster)

$E\{Hops\} = E_{Total} = E_{CH} + E_{non\text{-}CH}$ ----------------- (9)

E_{Total} is the total energy dissipated in the sensing area to transmit 'b' number of bits.

E_{CH} = Energy required for {transmitter + data aggregation + receiver + amplifier}

$E_{CH} = (S/C–1)*b*E_{elec} + S/C*b*E_{aggr} + b*E_{elec} + b*\mathcal{E}_{amp}*d^2_{toSink}$ ----------------(10)

Where, 'b' is the number of bits transmitted, E_{elec} is radio dissipation energy constant for Transmitter and Receiver (per bit energy consumption),

$\mathcal{E}_{amp}$ is per bit amplified transmitting energy over the region, E_{aggr} is per bit energy required for aggregation.

$E_{non\text{-}CH}$ = Energy required for {receiver + amplifier}

$E_{non\text{-}CH} = b* E_{elec} + b* \mathcal{E}_{amp} * d^2_{toCH}$ --------------(11)

$E_{cluster} = E_{CH} + \{S/C – 1\}\, E_{non\text{-}CH}$

$E_{cluster} \approx E_{CH} + \{S/C\}\, E_{non\text{-}CH}$

Substitute the values from equation (10) and (11) into the equation (9).

$E_{Total} = b*\{(S/C-1)* E_{elec}+ S/C* E_{aggr}+ E_{elec}+ \mathcal{E}_{amp}*d^2_{toSink}\} + S/C \{ E_{elec} + \mathcal{E}_{amp}* d^2_{toCH}\}$ $E_{Total} = b * \{2S * E_{elec} + S * E_{aggr} + \mathcal{E}_{amp} * [C * d^2_{toSink} + S * d^2_{toCH}] \}$ -------------------- (12)

Number of optimum clusters C_{opt} can be obtained taking derivative of equation (12) w.r.t. total number of clusters C and equating it to zero.

$\delta E_{Total} / \delta C = 0$

Substitute values for d^2_{toCH} as well as d^2_{toSink} in equation (12) from equation (7) and (8)

$$d^2_{toSink} + \frac{-S*M*N}{2\pi*C*C}\Big|_{C = Copt} = 0$$

$$C_{opt} = \sqrt{S * M * N/2\pi}/ d_{toSink}$$

$$C_{opt} =\sqrt{s/2\pi} *\sqrt{M * N} *\sqrt{2\pi}/\sqrt{M * N}$$

$$C_{opt} \cong \sqrt{S}$$

Thus, the optimum number of clusters is based on the number of sensors in the entire network. **Optimum Clustering**

This section describes Optimal Clustering phases and OC model.

Optimal Clustering Model

Optimum Number of Clusters (ONC) model is described as follows:

ONC = {SN, NC, TR}

SN = Set of all nodes present in the network **=** {n1, n2, n3, ….}

NC = Number of clusters = {nc1, nc2, nc3, …}

T**R** **=**Transmission Range

Phases of Optimal Clustering (OC)

Optimal Clustering consists of five different phases which are described as follows:

Phase 1: Calculation of Optimum Number of Clusters

Sensor nodes are grouped in a non-overlapping clusters using SO clustering by varying transmission range. It gives number of clusters for a specific range. Graphs are plotted by taking transmission range at x-axis and the number of clusters at y-axis. Two lines are drawn aligned to x-axis and y-axis which will cover maximum points on graph. First line is defined by two distinct points (x1, y1) and (x2,y2) and second line by (x3, y3) and (x4, y4).The intersection of two lines is (x, y) which satisfies equations of two lines and is given by equation (13) and (14):

(x-x1)(y2-y1)=(y-y1)(x2-x1) ………… (13)

(x-x3) (y4-y3) = (y-y3) (x4-x3) ………… (14)

The value of the x is the optimum transmission range for optimum number of clusters given by y.

Phase 2: Cluster Head Selection

Phase 1 gives optimum number of clusters and optimum transmission range. CH selection in OC is one on the basis of highest residual energy and non-zero number of neighbors otherwise node will be a cluster member.

Phase 3: Cluster Formation using optimum number of clusters and optimum range

The cluster formation is based on node distance. If node is in the optimum transmission range of a CH then it becomes member of a cluster.

Phase 4: Data Transmission

After formation of clusters, the member nodes sends data to their respective CHs. Data aggregation is carried out at each CH. Then all CHs send data to either CH or to Sink.

- Intra cluster
- Inter cluster (Only CH to CH)
- Finally to Sink

Phase 5: Re-clustering

After data transmission, the energy level of CH goes down as it consumes more energy and thus it cannot be continued as a cluster head. Hence, re-clustering takes place when residual energy of any CH goes below threshold value. Sensor node with highest residual energy is selected as CH.

Experiments The sensor network is setup where all sensor nodes are stationary, homogeneous and can compute the approximate distance to other sensors. Sink is located at the center of sensor field and is static. NS-2 simulator is adopted to analyze optimal clustering algorithm. Table 2 shows the parameters used in setting up the wireless sensor network. The number of sensor nodes are considered as 50, 60, 70, 80, 90, 100, 110 and 120. Transmission range is varied from 200m to 500m with the interval of 50m.

Analysis Optimal Clustering algorithm is run for various numbers of nodes and transmission ranges. Values for number of clusters are obtained using SO clustering and the graph is plotted for transmission ranges v/s number of clusters as shown in Figure 2. The knee point is determined and shown with a ring in Figures 2(a) to 2(h). For example, 50 sensor nodes are deployed and transmission range is varied. At each transmission range, number of clusters is obtained. Graph is plotted and lines are drawn such that it passes through maximum points on the graph. Point of intersection of these lines gives optimum number of clusters and optimum transmission range. For 50 nodes, the optimum transmission range obtained is 250 m and optimum number of clusters obtained is7, as shown in Figure 2a. For 60 nodes, the optimum transmission range obtained is 200 m and optimum number of clusters obtained is 7, as shown in Figure 2b. The same procedure is carried out for different number of nodes, and values are obtained.

Table 2. Sensor Node Configuration Parameters

Parameter	Value
Network Area	3400m x 1800m
Channel Type	Wireless
Number of Nodes	50, 60,………120
Initial Energy	1000Joules
Threshold Energy	100Joules
Transmission Range	200m, 250m,……..500m
Transmitting and Receiving Power	1Watt
Simulation Period	100 Seconds

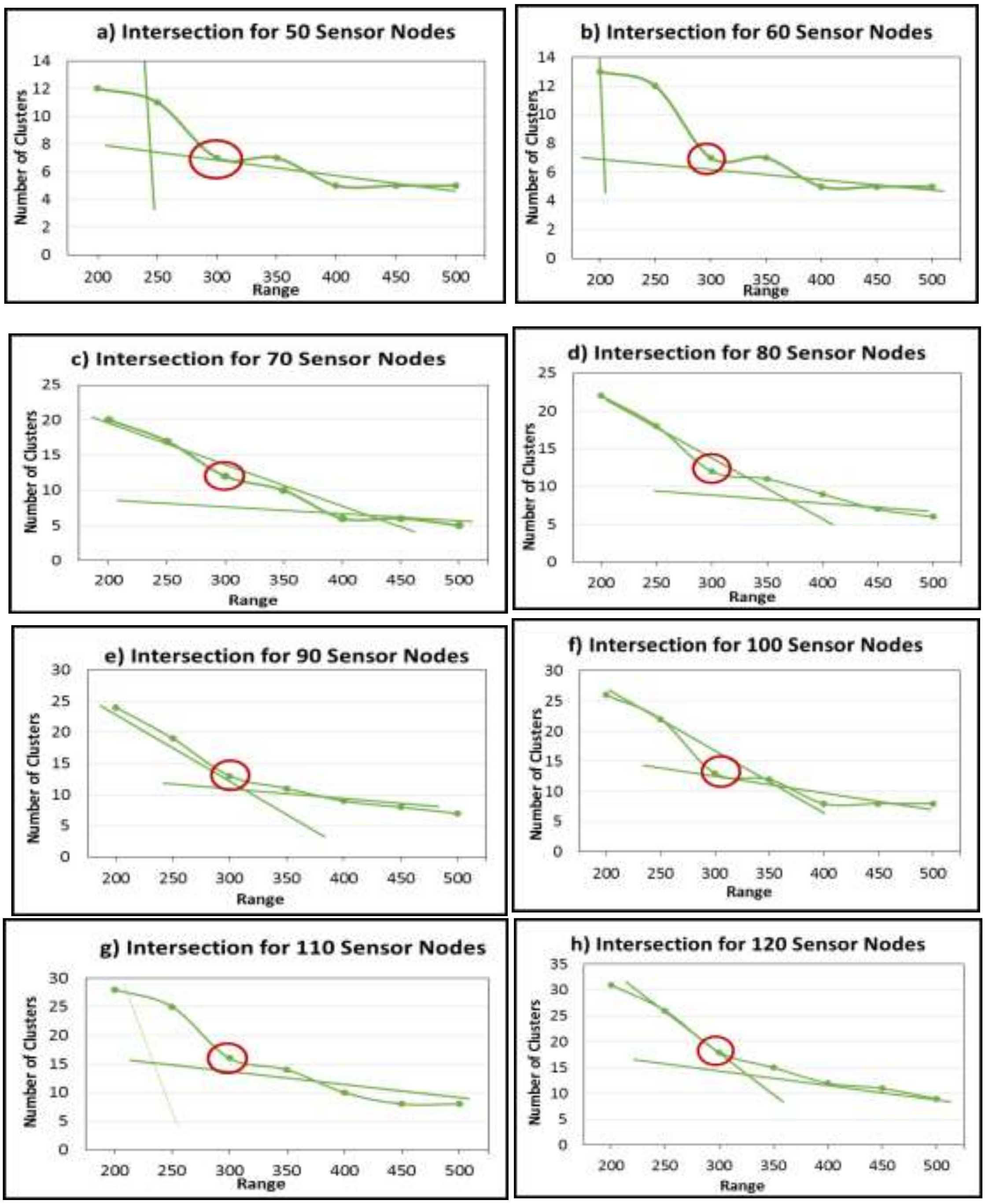

Figure 2. Calculation of ONC and Optimal Transmission range

Table 3. Number of Clusters Obtained by Self-organized Clustering

Y-axis	Number of Clusters							
Range (X-axis)	Number of nodes 50	Number of nodes 60	Number of nodes 70	Number of nodes 80	Number of nodes 90	Number of nodes 100	Number of nodes 110	Number of nodes 120
200	12	13	20	22	24	26	28	31
250	11	12	17	18	19	22	25	26
300	7	7	12	12	12	13	16	18
350	7	7	10	11	11	12	14	15
400	5	5	6	9	9	8	10	12
450	5	5	6	7	8	8	8	11
500	5	5	5	6	7	8	8	9

Table 3, gives number of clusters obtained by Self-organized Clustering. The lines are drawn on the curve aligned to x-axis and y-axis passing through maximum points on the curve. The x and y coordinate of the intersection of this two lines is the optimum range and optimum number of clusters obtained for OC method respectively as shown in Figure 2(a) to 2 (h). Table 4 gives Comparison of Number of Clusters and Range for k-means and OC Method. Table 5 gives Comparison of Number of Clusters and Range for Elbow and OC Method.

Table 4. Number of Clusters and Range for k-means and OC Method

Number of Sensor Nodes	k-means		OC Method	
	Number of clusters	Transmission Range	Optimum number of clusters	Optimum Range
50	11	250	7	250
60	13	200	7	200
70	6	450	8	425
80	10	350	7	366
90	12	350	10	337
100	9	400	13	383
110	25	250	14	250
120	15	350	14	337

Table 5. Number of Clusters and Range for Elbow and OC Method

Number of Sensor Nodes	Elbow Method		OC Method	
	Number of clusters	Transmission Range	Optimum number of clusters	Optimum Range
50	11	250	7	250
60	13	200	7	200
70	6	450	8	425
80	9	350	7	366
90	11	350	10	337
100	8	400	13	383
110	25	250	14	250
120	15	350	14	337

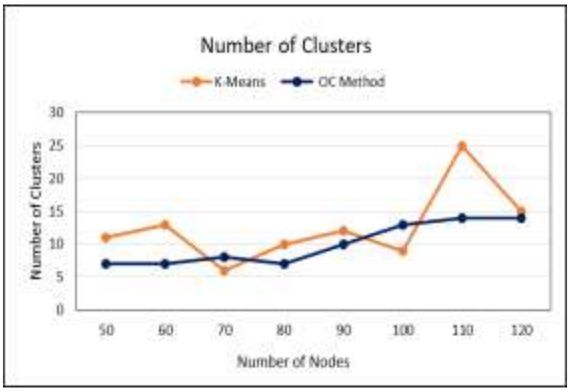

Figure 3. Comparison of Number of Clusters for k-means and OC Method

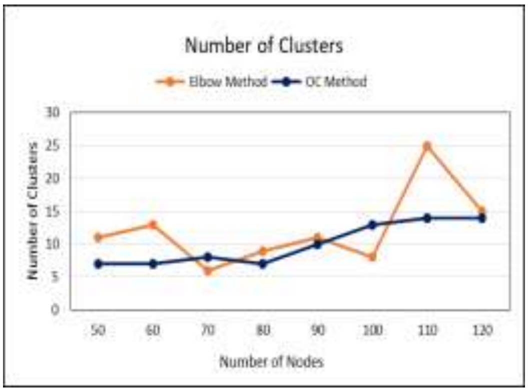

Figure 4. Comparison of Number of Clusters for Elbow and OC Method

Graph of optimum number of clusters obtained from k-means and OC method is plotted as shown in Figure 3. Graph of optimum number of clusters obtained from Elbow method and OC method is plotted as shown in Figure 4. X-axis represents number of nodes and Y-axis represents number of clusters. It shows that the OC method gives optimum number of clusters as compared to k-means and Elbow method. Square Root Method gives only Optimum number of clusters (which is approximately equal to square root of total number of sensor nodes) and not Optimum transmission range. For example, for 50 nodes, 7 clusters are obtained so on and for 120, we get 11 clusters.

Results for Average Energy Consumption and Network Lifetime

K-means and Elbow method are implemented as in [5] [6]. Table 5 gives values of Average Energy Consumption for K-Means, Elbow and OC Method. Fig. 5 and Fig. 7 show comparison of Average Energy Consumption and Network Lifetime for K-Means and OC Method respectively. Table 6 gives values of Network Lifetime for K-Means, Elbow and OC Method respectively.

Fig. 6 and Fig. 8 show comparison of Average Energy Consumption and Network Lifetime for Elbow and OC Method respectively. OC Method gives optimum number of clusters and hence results for energy and network lifetime are better as compared to K-Means and Elbow method.

Table 6. Average Energy Consumption and Network Lifetime

	Output of OC		**Output of k-means**		**Output of Elbow**	
Number of Nodes	**Average Energy Consumption (Joule)**	**Network Lifetime (second)**	**Average Energy Consumption (Joule)**	**Network Lifetime (second)**	**Average Energy Consumption (Joule)**	**Network Lifetime (second)**
120	17.99	3612.83	26.07	3004.58	18.38	3534.80
110	11.21	6331.21	23.55	5381.53	11.21	6331.21
100	21.02	2806.80	26.98	2343.30	22.85	2756.83
90	15.87	3464.56	24.87	2811.90	17.23	3308.12
80	19.39	3144.46	27.24	2920.98	22.50	3436.44
70	23.02	2735.87	27.83	2217.99	24.90	2609.41
60	5.97	6526.90	17.85	5547.86	5.975	6526.90
50	8.85	4405.63	20.49	3744.79	8.85	4405.64

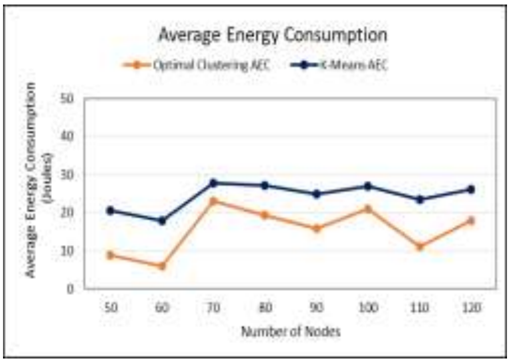

Figure 5. Comparison of Average Energy Consumption for k-means and OC Method

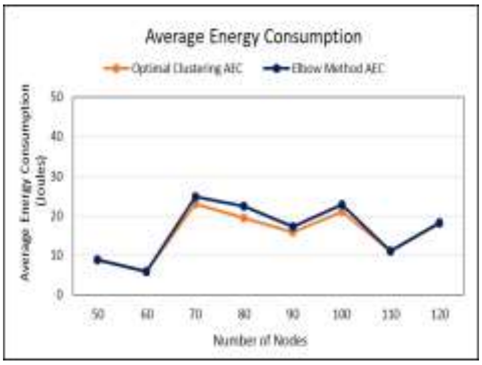

Figure 6. Comparison of Average Energy Consumption for Elbow and OC Method

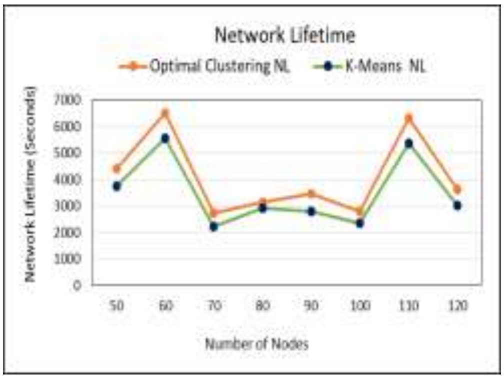

Figure 7. Comparison of Network Lifetime for k-means and OC Method

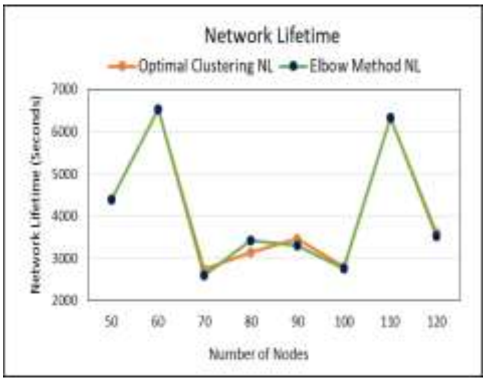

Figure 8. Comparison of Network Lifetime for Elbow and OC Method

Conclusion and Future Work

An Optimal Clustering algorithm uses Self-Organized Clustering based on the attributes like node degree, distance and residual energy. Number of clusters for k-means and Elbow method are obtained and compared with OC method. OC method gives Optimum number of clusters and Optimum transmission ranges. Optimum number of clusters obtained from Square Root Method is approximately equal to square root of total number of sensor nodes. k-means gives random number of clusters which is not optimum and there is need to recalculate position of CH which is not required in OC method. OC performs better in terms of energy and network lifetime. Average Energy Consumption in OC is reduced by 1.23% as compared to k-means and 0.31% as compared to Elbow Method. Similarly, Network lifetime is increased by 18.93% as compared to k-means and 4.62% as compared to Elbow Method.

In future, mobile nodes and sink can be introduced in the sensor network to have more energy efficient WSN.

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