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An Extended BBO based Energy Conservation Algorithm for Clustering and Routing in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks are constrained by limited battery lifetime. Therefore, extending the lifetime of the cluster heads is important for long run operation of wireless sensor network. In this article Extended Biogeography based optimization wireless clustering and routing algorithm (EBBO-CR) is proposed for extending the lifetime of a WSN. The proposed method minimizes the distance of a sensor node from its respective cluster head, distance of cluster head to the sink and number of hops required to transfer data from cluster head to sink using EBBO-CR. Energy efficient clustering and routing is done using a single fitness function. It is seen that EBBO-CR outperforms some of the famous algorithms like BBO, PSO, GLBCA, GA, LDC by a rate of 12, 45, 59, 63 and 66 % respectively.

Keywords: Gateway, Energy of gateway, Habitat, Habitat suitability index, crossover, migration.

1. INTRODUCTION

Wireless sensor networks have proved their utility in many areas such as deployment in battle fields, fighter jets, agriculture, weather forecasting and many more. A WSN scenario comprises many small size sensor nodes used to sense useful information [1] [13]. Each node is assigned to a cluster head or gateway. The battery operated gateways are similar to cluster heads and have similar functionalities [10]. Node sense useful information and transmit this information to the gateway. A gateway receives information from individual nodes, stores this information and sends it to the sink. This entire scenario forms a cluster in a wireless sensor network [12]. Clustering is important in WSN as it provides a hierarchal, organized and structured schema to collect useful information from various sources and transmit this information to sink through the gateway. Also, clustering reduces energy consumption in a WSN as all sensor nodes need not to communicate with the sink rather only gateway communicate with the sink as a representative of all sensor nodes contained in the cluster [9] [12]. In a clustered WSN scenario whole network is divided into gateways and sensor nodes out of which a gateway bears some extra responsibilities like: 1) Gateway is responsible for aggregating sensed data from its corresponding node. 2) Gateway is responsible for transmitting this sensed information to the sink [9]. One big problem with WSN is that it is operated by batteries and can operate as long as the battery is alive. Gateways in a WSN bear crucial responsibility. Since they are operated by battery, they are constrained by limited energy. Entire cluster goes down as soon as battery power of the gateway is consumed [12]. Figure 1 shows a hierarchal structure of WSN in which, if the battery of a gateway is consumed, the entire WSN may get disconnected

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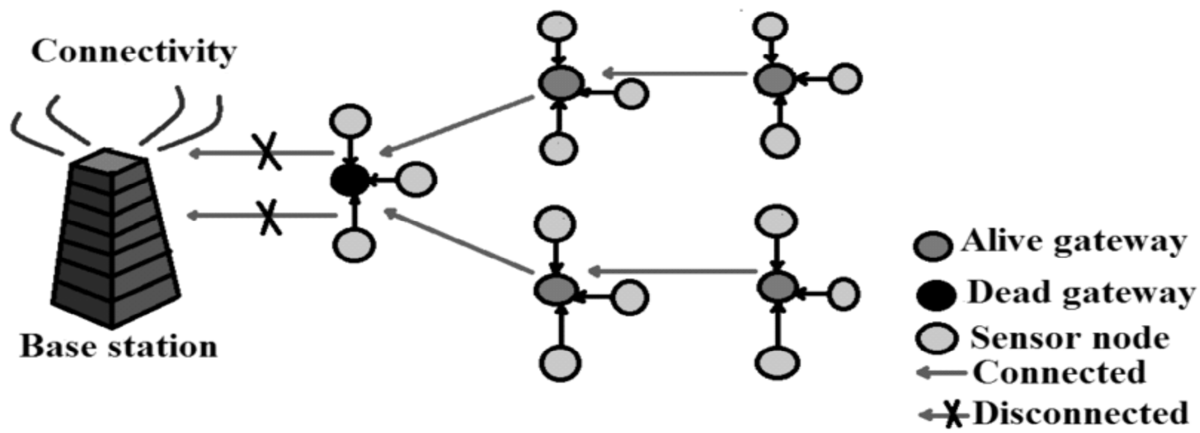

Figure 1: Hierarchal structure of WSN

Nature inspired artificial intelligence techniques have become popular in recent years and used frequently to solve and optimize many problems of wireless sensor networks. In the past energy efficient wireless clustering are being implemented by using some traditional artificial intelligence technique like Genetic Algorithm (WI et. Al., 2012) [9], particle swarm optimization [10]. This paper show that clustering and routing of a WSN scenario using EBBO [4] [6] gives better results than clustering using other artificial intelligence techniques implemented in the past.

Author's contributions

- EBBO-CR prolongs the lifetime of the gateway by optimizing the location of the gateway related to sink and sensor node.
- Improves network lifetime by non linear mapping of gateway identification. EBBO-CR minimizes the distance of a sensor node to the gateway, the distance of a gateway to the sink and also minimizes the number of hops taken by a gateway to forward data to the sink using a single fitness function.
- Extended BBO introduces the concept of evolution and extinction of species. New species keep evolving and poor species keep getting extinct.
- Ensures 100 % coverage of the whole area covered by the network.

The performance of the EBBO-CR is compared with BBO based wireless clustering (not present in literature) and some famous artificial intelligence based clustering techniques like, PSO based clustering [10], GA based clustering [9], GLBCA [11], LDC [2].

The paper is divided into the following segments. The literature survey is presented in segment 2.The problem formulation is described in segment 3.An overview of Extended Biogeography based optimization is presented in segment 4. System model is presented in segment 5. EBBO-CR and the experimental results are presented in segments 6 and 7. The proposed work is concluded in segment 8.

2. LITERATURE SURVEY

Many researchers are working in this field for last few decades. In [7] LEACH is proposed. It is used in WSN as distributed cluster based routing algorithm and is effective in improving network performance. One problem with LEACH is cluster heads are selected without considering its primary parameters like residual energy which makes it inefficient in some cases [8]. In [11] HEED is proposed. HEED mainly focus on the residual energy of each sensor node. The main advantage of HEED over LEACH is that HEED distributes cluster heads in the field more effectively as compared to LEACH. HEED succeeds in achieving a prolonged network lifetime. In [15] a weight based clustering algorithm is proposed. They present a multi objective model. This model is used for efficient clustering such that it minimizes the intra cluster distance. Many approaches have been used in which artificial intelligence techniques are used to improve lifetime of a wireless cluster. In [9] a GA based load balancing, clustering algorithm is proposed. Mutation step of GA is used for load balancing. In [3] GA is used for routing of aggregated data between cluster head and sink. In this algorithm roulette wheel selection is used for selection of individuals and fitness of an individual is taken in terms of network lifetime. In [5] another routing algorithm is proposed in which attempt is made to reduce the communication distance between the sink and gateway using GA. One thing to be noted in both [3] and [5], focus is only on sending data from cluster head to the sink, there is no emphasis on energy consumption in data transfer between individual node to cluster head. All other work specified before except Kulia et. Al [10] did not use non linear programming for energy efficient clustering. NLP formation helps in extending the network lifetime. Kulia et. Al [10] used NLP for PSO based clustering considering the distance between a sensor node and the gateway. They did not consider distance of a gateway to the sink in clustering. In this paper, both the factors are considered and EBBO based clustering and routing is implemented to maximize NLP based objective function. When we consider the optimum location of a gateway relative to sensor node and the sink and number of hops taken by a gateway to reach the sink, the equation becomes NLP which will give a better solution. Also in EBBO HSI (fitness) of a habitat does not depend only upon migration instead it is the function of many combinations of gene values. In [5] and. [17] both Genetic Algorithms based routing algorithm focus upon minimizing the transmission distance, but it ended up increasing the number of hops which further results in more delay. Chiang S et. Al in MHRM [16] used the maximum distance for next hop selection, thus resulting in reducing the number of hops used in transmission, but this approach resulted in more energy dissipation due to increase in distance. Kulia et. Al. [10] tries to find a tradeoff between number of hops and transmission distance in such a way to find equilibrium between delay and transmission distance. Unlike all these three approaches the EBBO-CR uses a single fitness function for optimizing the energy level of a gateway. EBBO-CR achieves this objective by optimizing the distance of cluster head, both from sensor node and the sink, and then transmitting the data to the sink through shortest path.

3. PROBLEM FORMULATION

Gateways are operated by battery and they die as soon as their battery is consumed. Our goal is to extend network lifetime by maximizing the lifetime of a gateway.

Table 1

Acronyms	L_{net}	L_{gat}	E_{gat}	β	¥	(s_x, s_y)	(g_x, g_y)
Description	network lifetime	gateway lifetime	energy dissipated by the gateway	distance of i^{th} sensor node to j^{th} gateway	distance of j^{th} gateway to the sink	coordinates of the sensor node	coordinates of the gateway

Table 2

Acronyms	(b_x, b_y)	$V_{i,j}$	$U_{i,j}$	R_{comm}	A	A_i	S_k
Description	coordinates the gateway	decision of variable (clustering)	decision variable (routing)	communication range	deployment region	any subarea within A	number of sensor nodes present in A_i

Table 3

Acronyms	g_k	L_m	H_{gat}	η	G	N
Description	number of gateways present in A_i	minimum lifetime of the gateways	number of hops taken by a gateway to reach the sink	distance between 2 adjacent gateways	set of total gateways present in the network	set of natural numbers

Gateway lifetime varies inversely to number of sensor nodes assigned to each gateway. One way to counter this problem is to have more gateways in the network scenario which can share the load of network. But this approach also has a bottleneck, as the amount of gateways increase in the network; total network energy dissipation will also increase. Some of the terminology used in problem formulation is given in table 1, 2 and 3.

$$L_{net} \alpha L_{gat} \tag{1}$$

$$L_{gat} \frac{1}{\alpha} E_{gat} \tag{2}$$

Another important aspect is the route that a sensor node follows to reach the sink. Delay can be minimized by reducing the number of hops for data transmission.

$$delay \, \alpha \, H_{gat} \tag{3}$$

We have

$$\beta = \sqrt{(s_x - g_x)^2 + (s_y - g_y)^2} \quad 1 < i, j < N \tag{4}$$

$$¥ = \sqrt{(g_x - b_x)^2 + \left(g_y - b_y\right)^2} \quad 1 < i, j < N \tag{5}$$

Let $V_{i,j}$ be a decision variable which assigns every sensor node to its gateway and $U_{i,j}$ be a decision variable responsible for routing.

$$V_{i,j} = \begin{cases} 1 \; if \;\; node \; S_i \; is \; assigned \; to \; gateway \; g_j \, , \\ \qquad 1 < i < N, \;\; 1 < j < N \\ 0 \;\; otherwise \end{cases} \tag{6}$$

$$L_m = \min(L_i), \quad 1 < i < G \tag{7}$$

We can formulate the objective function as non linear programming.

Maximize

$$Z = \frac{L}{\beta} + \frac{L}{¥} \tag{8}$$

$$1 < i < N$$

For routing we have

$$U_{i,j} = \begin{cases} 1 \; if \; next \; hop \; of \; g_i \; is \;\; g_j \, , \\ \qquad 1 < i < N, \;\; 1 < j < N \\ \quad 0 \;\; otherwise \end{cases} \tag{9}$$

Maximize

$$X = \frac{1}{¥} + \frac{1}{H_{gat}} \tag{10}$$

$$1 < i < N$$

Combining above equations (8 and 10) we can have a single objective function for both clustering and routing.

Maximize

$$P = \frac{L}{\beta} + \frac{L}{¥} + \frac{1}{H_{gat}} \tag{11}$$

Subject to constraint

$$\sum_{j=1}^{N}\left(\sum_{i=1}^{N} V_{i,j} > 1\right) = G, \qquad 1 < i,j < N \tag{12}$$

$$\sum_{j=1}^{N} V_{i,j} = 1, \qquad 1 < i,j < N \tag{13}$$

$$\beta\, V_{i,j} \leq R_{comm},\ 1 < i,j < N \tag{14}$$

$$V_{i,j} \in \{0,1\} \ \ 1 < i,j < N \tag{15}$$

$$\sum_{j=1}^{N} U_{i,j} = 1, \qquad 1 < i,j < N \tag{16}$$

$$U_{i,j} \leq R_{comm} \quad 1 < i,j < N \tag{17}$$

To ensure efficient deployment following constraints must hold.

$$¥ A_i \in A, S_k > 1 \tag{18}$$

$$¥ A_i \in A, g_k > 1 \tag{19}$$

In EBBO-CR, objective function 11 is maximized using EBBO. EBBO-CR ensures 100 percent deployment and also maximizes the network lifetime.

4. A BRIEF OVERVIEW OF EXTENDED BBO.

This section presents extended BBO model [4] [6]. HSI of a habitat does not depend only on immigration and emigration instead it is a function of varying characteristics of a habitat as shown in equation 19.

$$HSI_i = func_i(SIV) \tag{20}$$

Let the set of SIVs ranges from m_1 to m_t.

HSI of a habitat is given by following equation.

$$HSI_i = w_1\, m_1^{\theta 1} + w_2\, m_2^{\theta 2} + \ldots\ldots w_t m_t^{\theta t} = \sum_{j=1}^{t} w_j\, m_j^{\theta j} \tag{21}$$

During HSI calculation, bad SIVs of a habitat are removed. Let the weight allotted to each sensor node be w. Weight is assigned to each sensor node based on β, ¥ and H_{gat}. Adding this new factor w in the HSI calculation will help us reject far located sensor nodes during cluster formation.

Initially universal habitat contains all the candidate solutions which are equal to the number of species. Define an ideal habitat with ideal SIVs. Candidate solution is compared with the Ideal habitat. Ideal HSI (HSI_{ideal}) value and threshold HSI (HSI_{th}) value are calculated [6]. HSI_{th} is one third of HSI_{ideal} Also calculate HSI of the candidate solution (HSI_i) based on its SIVs and compare its HSI with HSI_{th}. The candidate solution can only be made ideal solution if its HSI is greater than HSI_{th}. If HSI of the candidate solution is greater than HSI_{th}, calculate the effort required to transform that solution into an ideal solution using the following equation.

$$Effort = \sum_i (HSI_{ideal} - HSI_i) * w, \quad 1 < i < n \tag{22}$$

Above effort is calculated only for those candidate solutions whose HSI is greater than HSI_{th}. Now for these habitats, Calculate the selectivity factor. Selectivity factor determines the selectivity of a particular habitat to be chosen as the best habitat. Selectivity factor is calculated as given in the following equation.

5. SYSTEM MODEL

In our algorithm, we have considered equal energy for all the sensor nodes. The path loss exponent is taken as 2. Free space and multipath fading channels are used as given in equation 24. E_{tr} is the energy consumed in transmission of a m-bit message. E_{el} is the energy dissipation rate for operating electronics in the model. K_{diss} is the dissipation constant. E_{amp} is the amplifier for transmission. E_{rec} is the receiving energy.

$$E_{tr} = E_{el} * K_{diss} + E_{amp} * K_{diss} * d^2$$
$$if\ d < d_0 \tag{24}$$

$$E_{tr} = E_{el} * K_{diss} + E_{amp} * K_{diss} * d^4$$
$$if\ d \geq d_0 \tag{25}$$
$$E_{rec} = E_{el} * K_{diss}$$

Apart from above factors another factor data aggregation energy (E_{DA}) is used as energy dissipated in aggregation of sensed data whose value is taken as 5 nj/bit/message.

6. PROPOSED ALGORITHM

Let S_N sensor nodes are distributed arbitrarily. Let N_{CH} be the number of gateways present in the scenario Every sensor node is assigned a degree of importance vector (Deg_{imp}) having size equal to N_{CH}.

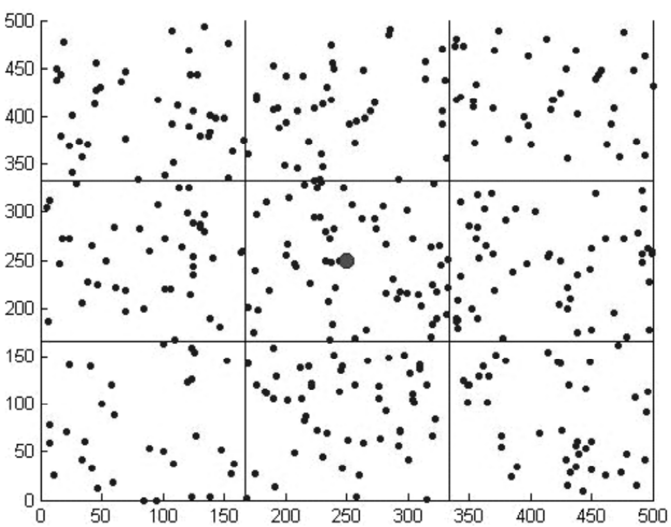

Figure 2: Sensor nodes placed at random locations with a sink

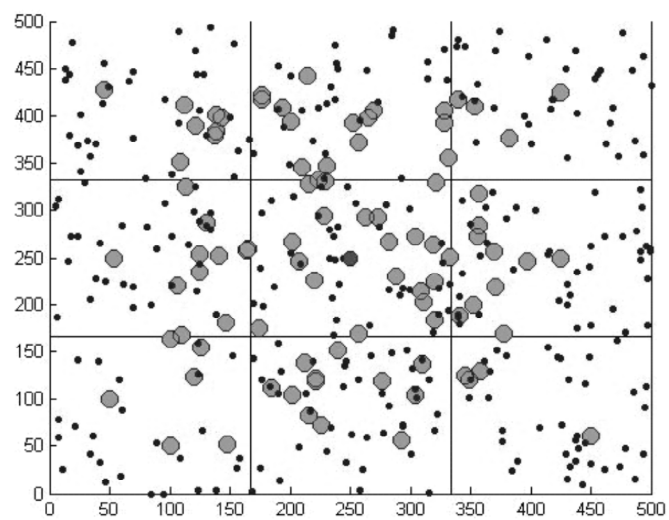

Figure 3: Clustering of sensor nodes

Here, Entries in this vector contain the weight assigned on the basis of á as given in equation 26.

For each S_i, Assign Deg_{imp} to S_i. Equation 26 shows that α depend on the distance of S_i from all gateways, distance of gateway to the sink and the number of hops taken by g_i to reach the sink using dijkasta's algorithm for the shortest route.

$$\alpha = \frac{1}{\beta} + \frac{1}{\text{¥}} + \frac{1}{H_{gat}} \tag{26}$$

Hence, using the above formula, each S_i is given a weight from 1 to 5 for each gateway based on á and accordingly 5 shows the highest weight and 1 shows the lowest weight. Now from each importance vector choose the best SIV to form a feature/ideal habitat. Based on the SIVs present in the feature habitat, Calculate HSI_{ideal}.

$$HSI_{ideal} = \frac{1}{\Sigma\, SIV_{ideal}\ of\ all\ importance\ vector} \tag{27}$$

Let us assume HSI_{th} is one third of ideal HSI.

$$HSI_{th} = \frac{HSI_{ideal}}{3} \tag{28}$$

Now random clustering is performed which will produce a population of candidate solutions. Calculate the HSI of the candidate solution (HSI_{can}) by choosing the weights of the gateways from sensor node's importance vector and using this weight for HSI calculation.

$$HSI_{can} = \frac{1}{\Sigma\, SIVs\ prsent\ in\ the\ candidate\ soulution\ vector} \tag{29}$$

Compare the HSI_{can} to HSI_{th}. Chose only those candidate solutions where $HSI_{can} > HSI_{th}$. This will give us only good solutions For the selected candidate solutions, Calculate the effort required to convert those solutions into ideal solutions according to equation 22, based on effort, calculate selectivity factor of each solution according to equation 23. The solution having the highest selectivity factor is the optimum solution.

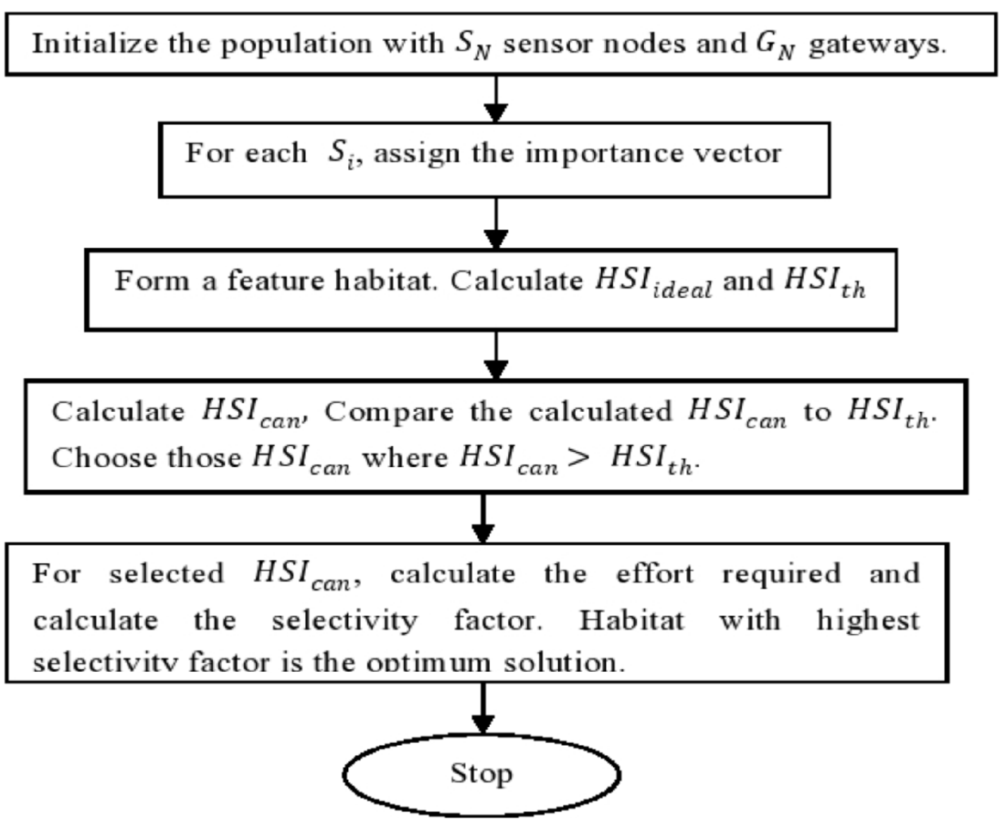

Figure 4: Flowchart of EBBO-CR algorithm

Random distribution of nodes is shown in figure 2 and cluster formation is shown in figure 3. A flowchart of EBBO-CR algorithm is shown in figure 4.

7. RESULTS

Extensive simulations of *EBBO-CR* are performed using Matlab based on the parameters specified in table 3. Results show that EBBO outperforms the performance of BBO [14] based clustering, PSO [10], GA based clustering [9], GLBCA [11], LDC [2] and EBBO-clustering further improves the performance of BBO. Initial energy of the sensor nodes is taken as 2J and initial energy of a gateway is taken as 10 J. Parameters of the existing algorithm [10] are kept the same while comparing our algorithm with existing work. Simulation parameters used are given in table 4.

Table 4
Parameters used

Parameter	*Value*
A (meters)	500 * 500
S_N	200 – 500
G_N	60 – 90
Sink location (meters)	(500, 250), (250, 250)
Transmission distance	150 m
Initial energy of node	2 J
Packet size	4000 bit
d_0	87 m

For comparison, we implemented clustering based on PSO [10] and BBO based clustering, which is not implemented in the literature. For the sake of simulation consider two network scenario WSN 1 and WSN 2. For WSN 1 the sink is placed at coordinates (500, 250). For WSN 2 sink is placed at coordinates (250,250)

Case 1 - Comparison of the EBBO-CR algorithm with existing algorithms for WSN 1. Compare the performance of EBBO-CR with some existing algorithms such as BBO, PSO, GLBCA, GA, LDC [10] for 60 and 90 gateways as shown in figure 5 and 6. As visible from the figure, network lifetime of sensor nodes has increased by implementing EBBO-CR. This is because EBBO-CR considers the weight assigned to a sensor node as combination of β and ¥ which is why it finds the optimum location of the gateways with respect to sensor node and sink in such a way that both the above distances are minimized and minimum energy is dissipated for any transfer of information from sensor node to the sink through gateway.

Case 1- Comparison for WSN 1.

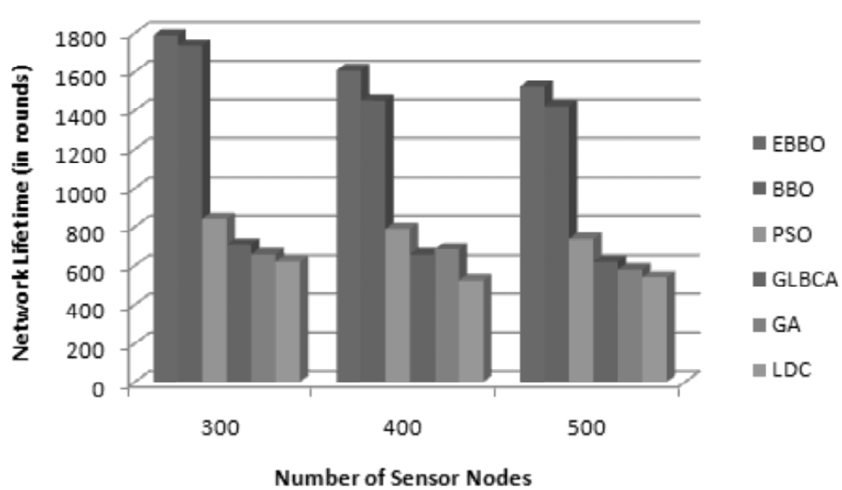

Figure 5: WSN lifespan when number of gateways are 60

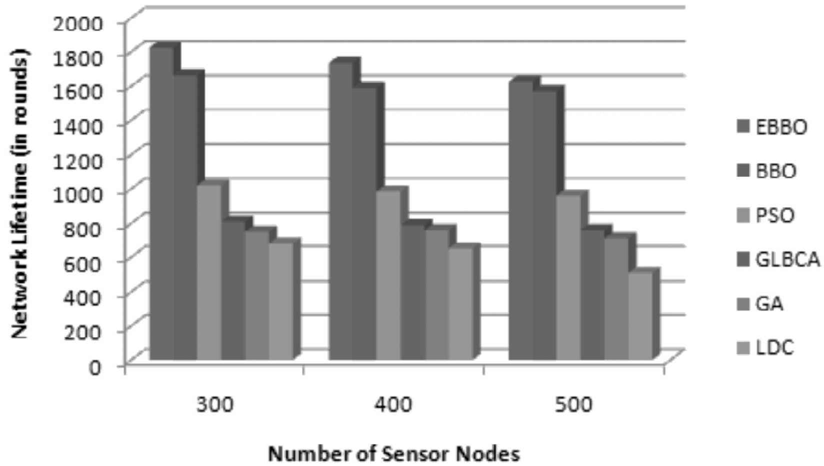

Figure 6: WSN lifespan when number of gateways are 90

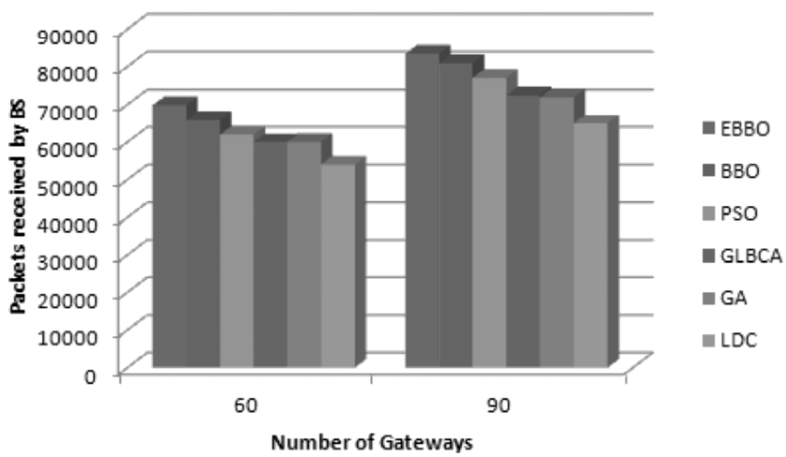

Figure 7: Total packets transmitted to the base station for WSN 1

Also, our deployment area is divided into many square shaped subareas, while finding the optimum location of the gateway; each subarea is assigned a minimum number of gateway and sensor nodes to maintain efficient coverage. EBBO-CR is compared in terms of number of packets transmitted as shown in figure 7.

Case 2 – Comparison of EBBO-CR algorithm with existing algorithms for WSN 2

Similar comparisons as above are performed for WSN 2 scenario. The performance of EBBO-CR is shown in figure 8, 9 and 10. Figure 11 shows the scalability of EBBO-CR. It shows that as increase, network lifetime will also increase.

Case 2- Comparison for WSN 2

An active node in a network is the one which have non zero energy and have at least one gateway in its range to which it can send its information. If a sensor node has non zero energy, but does not have any gateway in its range to transmit data, it is also considered inactive. Simulations are performed for S_N = 600 and G_N = 60 as shown in figure 12 and 13 for WSN 1 and WSN 2. EBBO-CR performs better than previous works in number of inactive nodes. This is due to the reason that our fitness function minimizes the distance between a sensor node and a gateway which improves the lifetime of a normal sensor node. Our fitness function also extends the lifetime of the gateways in the network, which helps in less number of inactive nodes.

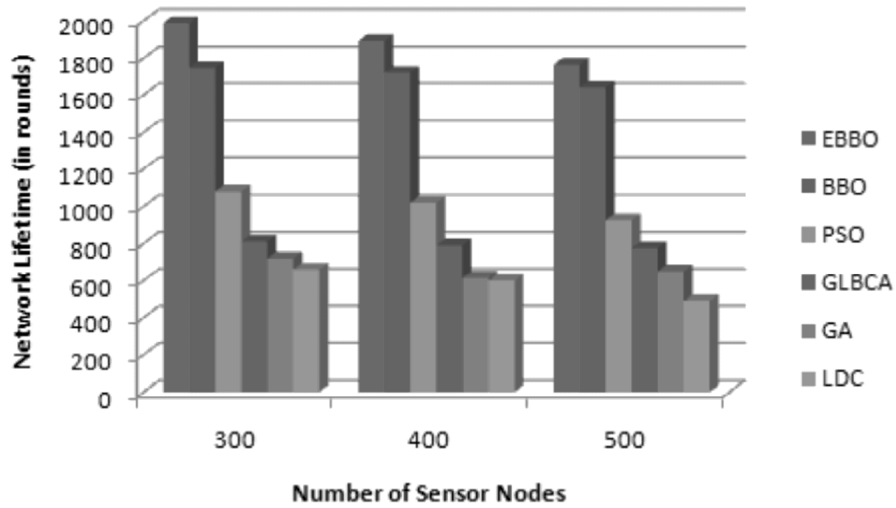

Figure 8: WSN lifespan when number of gateways are 60

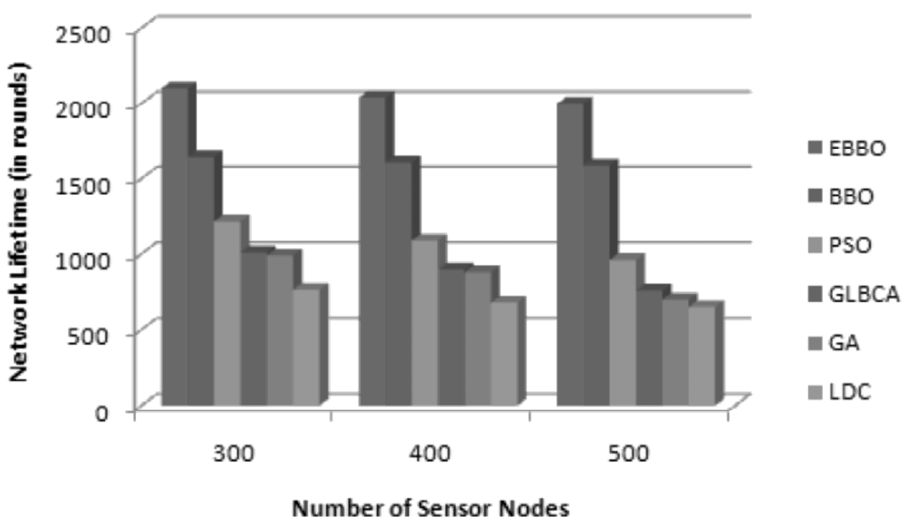

Figure 9: WSN lifespan when number of gateways are 90

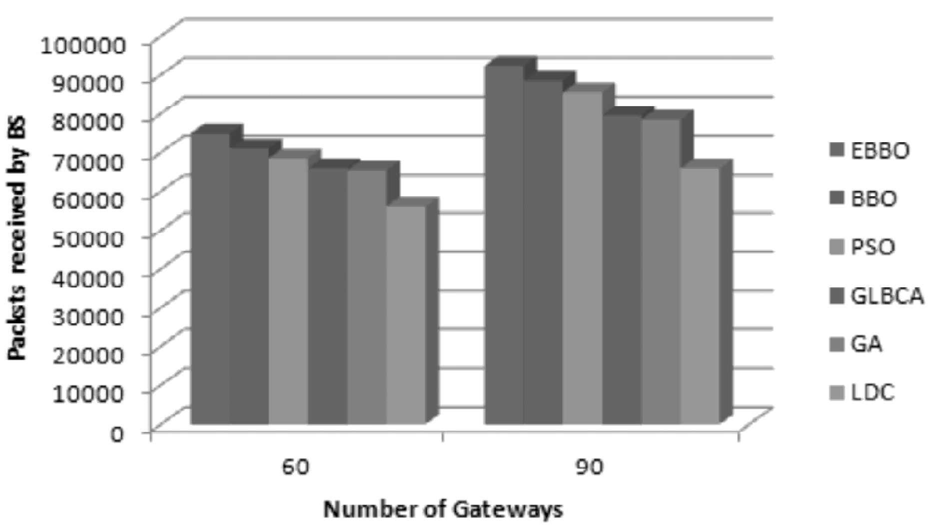

Figure 10: Total packets transmitted to the base station for WSN 2.

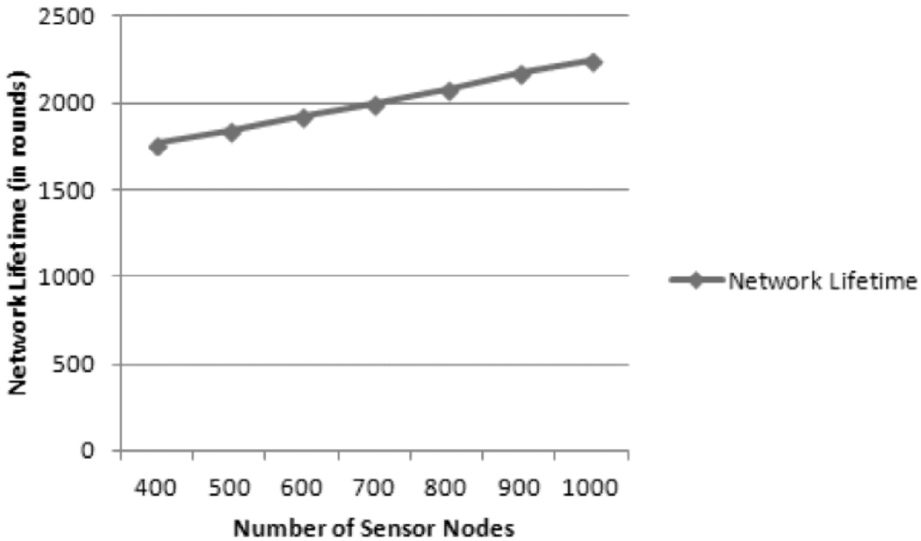

Figure 11: WSN lifespan increase with increase in

Figure 14 shows the comparison in terms of number of hops covered for $S_N = 600$ and $G_N = 60$ with sink coordinates (500, 250). In this case MHRM performs better than GAR and PSO. This is because MHRM increased the distance to minimize the number of hops. EBBO-CR minimizes the number of hops with minimization of transmission distance. Thus improving the network lifetime as well as reducing the delay by minimizing the number of hops.

8. CONCLUSION

An energy efficient network is achieved using a new nature inspired approach, EBBO. EBBO-CR maximizes the NLP formulated based on gateway lifetime, the distance between a sensor node and a gateway, distance between a gateway and the sink and number of hops taken by a node to reach the sink. Optimum placement of the gateways, related to sensor node and the sink and minimum number of hop count promises long lifetime for the WSN. Also the proposed algorithm, prolongs the network lifetime significantly by the rate of 12, 45, 59, 63 and 66 % as compared to BBO, PSO, GLBCA, GA and LDC respectively.

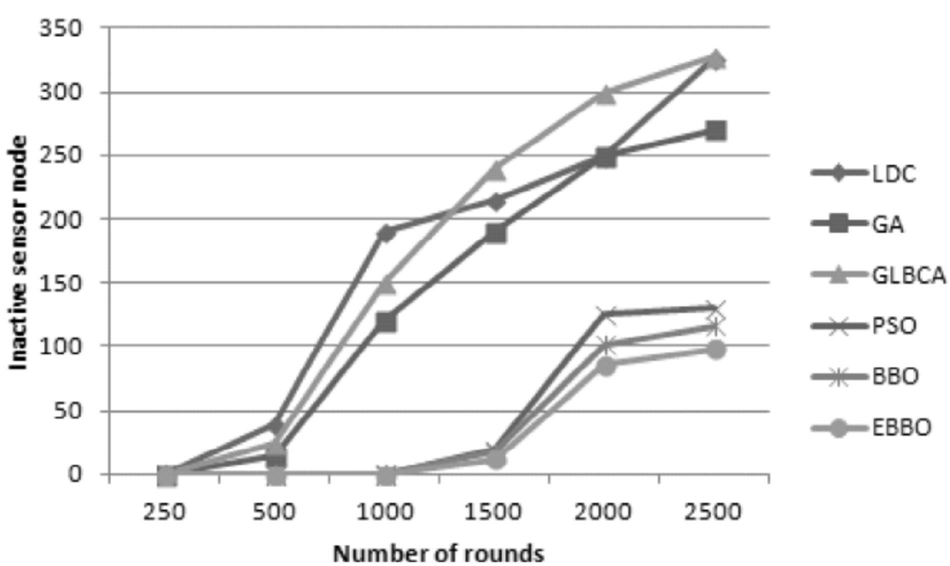

Figure 12: Total number of inactive sensor nodes for WSN 1

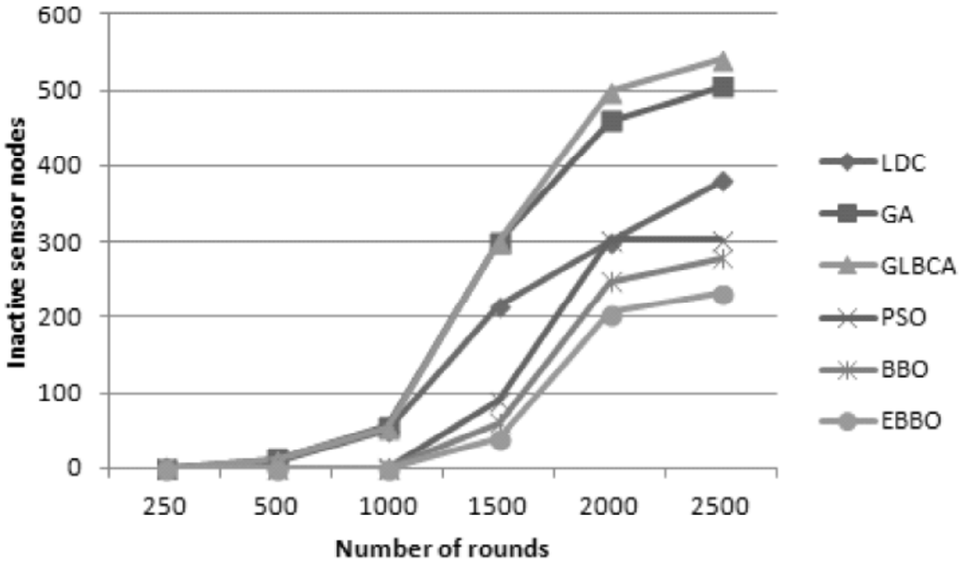

Figure 13: Total number of inactive sensor nodes for WSN 2

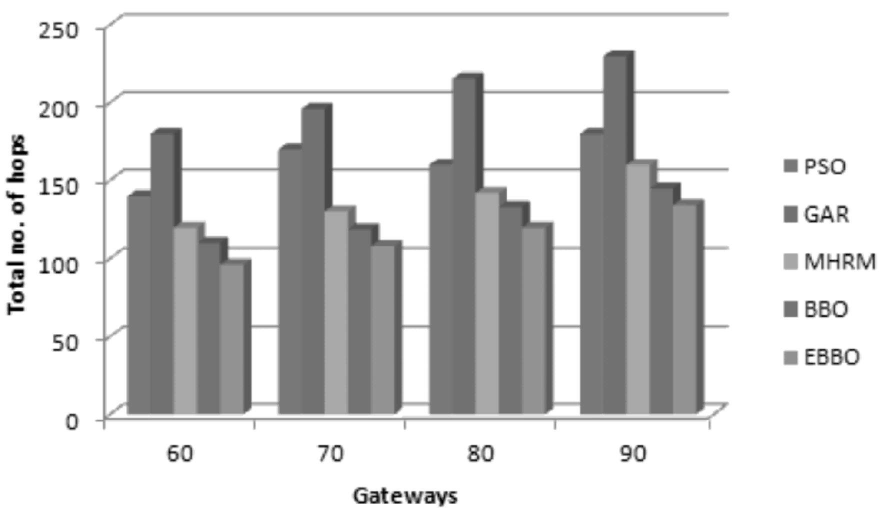

Figure 14: Total number hops covered for different number of gateways

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