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Investigating Optimization Techniques for Cluster Head Election in WSN

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ABSTRACT
Wireless sensor network (WSN) is a briskly augmenting high-tech platform with remarkable and neoteric applications. Many new protocols specifically designed for the requirement of energy awareness are provided as per consequence of newfangled advances in WSN. In Actu, optimization of the network operation is vital to prolong network's lifetime. For energy-efficiency in WSNs, one of the most accepted solutions is to cluster the networks. The regular nodes sensing the field and sending their data to the cluster-head, and then, transmitting to the base station is a process usually followed in a typical clustered WSN. Furthermore, cluster formation done inaptly, can make some CHs burdened with high number of sensor nodes. This overwork may lead to abrupt death of the CHs thereby deteriorating the overall performance of the WSN. Network Lifetime can be increased by preventing faster death of the highly loaded CHs. Three evolutionary algorithms namely Flower Pollination Algorithm (FPA), Harmony Search Algorithm (HSA) and Particle Swarm Optimization (PSO) with appropriate fitness functions are compared with the intrinsic properties of clustering in mind. The main idea is the embodiment of criteria of compactness (i.e. cohesion) and separation error in the fitness function to direct the search into promising solutions. The property of heterogeneity of nodes, in terms of their energy; in hierarchically clustered wireless sensor networks has also been involved. Simulation over 20 random heterogeneous WSNs shows that our FPA always prolongs the network lifetime, sustain more energy in comparison to the results obtained using the PSO and HSA protocols.

Keywords
Flower Pollination Algorithm (FPA), Harmony Search Algorithm (HSA), Particle Swarm Optimization (PSO), Cohesion, Separation, Fitness Function.

1. INTRODUCTION
The development of wireless sensor networks (WSNs) is triggered by the major advances in wireless communication technology. A WSN comprises a large number of pint-sized, low power and economical sensor nodes, which are arbitrarily or manually deployed over an abandoned target area. Sensing, Computing, and Wireless communication capability along with a power unit are the components equipped with every sensor node. The role of an event detector and the data router is played by all sensor nodes. These sensor nodes periodically collect local information of the targets, process the data and finally send it to a remote base station (called sink). Wireless sensor networks have been pervasive in potential applications in diverse areas including disaster warning systems, health care system, battlefield surveillance system, environment monitoring system, intruder detection, and so on.

1.1 Motivation
Mostly energy of a sensor node is consumed in transmitting and receiving packets. In WSNs, the key power provider of a sensor node is battery. However, in most application plots, it is generally difficult to reach the locus of sensor nodes. Due to large number of sensor nodes, substitution of batteries is nearly impossible. However, the battery energy is definite in a sensor node and a sensor node depleting its battery may result in making sensing area uncovered. Consequently, the most critical issue for the long run operation of WSNs is consumption of energy by the sensor nodes is. New and efficient power saving algorithms must be developed in order to increase energy efficiency and extend the network lifetime. Clustering is the most effective technique for economy of the sensor nodes in terms of energy.

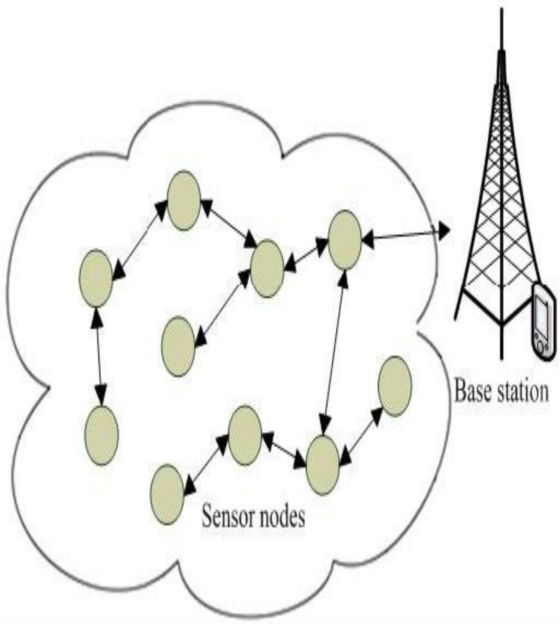

Fig 1 Shows an Infrastructure of Wireless Sensor Networks. Power saving is one of the most important features for the sensor nodes to extend their lifetime in wireless sensor networks

Necessity of a routing protocol is there when packets cannot be sent from source node directly to its destination node but the assistance of intermediate nodes is taken to forward these packets on its behalf. According to the criteria of network structure selected, routing protocols for WSNs can be categorized into many out of which hierarchical network routing is mostly used. Partitioning of the network into clusters to achieve energy-efficiency and scalability symbolizes hierarchical network routing. One of the prominent hierarchical network routing protocols is low-energy adaptive clustering hierarchy (LEACH), which has been widely accepted for its energy efficiency and simplicity [1].

In the clustering environment, transmission of data accumulated by the nodes to BS through cluster heads (CHs) takes place. Due to communication of data over shorter distances in such an environment, the energy expended in the network is liable to be significantly lower compared to direct communication of every sensor to BS. Most of the clustering algorithms are heuristic in nature, and their main aim is to produce the clusters minimum in number and trans-mission distance to be the least. These algorithms also differentiate themselves by the manner in which the CHs are elected. The LEACH algorithm [11] and its other variants make use of stochastic self-election, where a probability p is carried by each sensor node to be a CH in each round. It assures that every node will happen to be a CH only once in 1/p rounds. This regular change of energy-intensive CH function aims to deal with the power procedure for extended network life.

Because of soaring energy consumption and data processing necessities due to overload on CH; classical algorithms such as LEACH etc. have been stopped being brought into play. Therefore, contemporary researchers have started using biologically inspired optimization techniques for evolving cluster-based hierarchical routing protocols in WSN [2].

The major objective of these bio-inspired clustered routing protocols is formation of clusters in sensor networks in a dynamic manner in order to reduce the consumption of energy resources of the network, which in turn, prolong network lifetime. On the other hand, making a careful examination of their outcomes, individual can observe that one frequent off-putting result emerges. Although these Bio-inspired routing protocols make network survive longer, but they lessen the stability phase of the network (the time interval before the death of the first node) which is central for many operations where the reliability regarding feed-back from network is needed. This negative aspect, perhaps arises due to a single common parameter (transmission distance) that mainly characterizes the indispensable component of any bio-mimic algorithm; the fitness function.

Therefore, our motivation lies in the fact that there are many applications present that would profit greatly from productively maintaining the lifetime and stability of the WSN. This paper demonstrates that revisiting the definition of the fitness function to include the impact of two clustering aspects, viz. cohesion and separation error.

1.2 Our Contribution

In this paper, comparison of the three algorithms for WSNs namely FPA, HSA, PSO has been done. The key purpose is to find out the algorithm helpful in elongating the network life time of the WSN by paying heed to the energy spending of the common sensor nodes and the CHs. By the network life time, we mean the time interval from the deployment of the WSN until the death of the first CH. The death of the first CH can be deferred through balancing the energy consumption of the CHs which is implemented by the rate of energy consumption and residual energy. We perform extensive simulation of the three algorithms. The experimental results reveal the effectiveness of the three algorithms in terms of network life and energy consumption [3].Our main contributions in this paper can be summarized as follows:

Simulations of FPA, HSA, PSO to demonstrate that which algorithm is superior to others in terms of network life, number of dead sensor nodes, energy consumption of the network.

The rest of this paper is organized as follows. Section 2 briefly reviews some heuristic and meta-heuristic hierarchical routing protocols in WSN. Section 3 describes radio energy and other WSN communication models used. Section 4 defines some metrics used for performance measures. Section 5 presents simulation results, and finally Section 6 concludes this paper with possible future directions.

2. LITERATURE REVIEW

2.1 Heuristic Approaches

Generally, a network is broken down into clusters which are non- overlapping by clustering algorithms and each cluster contains one leader known as CH. Non-CH nodes pass on their sensed data to CHs which aggregates this sensed data as these signals can be adequately linked because of the spatial proximity of the nodes, and transmits to BS. Optimality in clustering is due to the sound division of energy consumption over all sensors and the total energy consumption being at minimum. Creation of clusters takes place in LEACH [1] by means of a distributed algorithm, where independent decisions are taken by nodes without any central in-charge. At the outset, decision to become a CH is carried out by node with a probability q and it is then broadcasted. Each non-CH node adjudges its cluster by preferring the CH for which least communication energy is needed to be reached. The task of being a CH is rotated at regular intervals among the nodes of the cluster in order to balance the load. The rotation is accomplished by letting each sensor node, s, to opt for a random number T between 0 and 1. A node becomes an apt choice to be a CH for the current rotation round if the number is less than the following threshold [15]:

$$T(S) = \begin{cases} \dfrac{q}{1 - qX\left(r \bmod \dfrac{1}{q}\right)} & if S \in G \\ 0 & otherwise \end{cases} \quad (1)$$

Where q = the desired percentage of CH nodes in the sensor population,

r= the present round number, and

G = the set of nodes that have not been CHs in the last 1/p rounds.

2.2 Metaheuristic Approaches

Most of the metaheuristic based clustering algorithms that have been reported for WSNs dealt with CH selection only. Recently, a GA-based load balanced clustering algorithm put forward by (Kuila et al.[4]) for WSNs in which the formation of clusters takes place in such a manner that there is minimization of the maximum load of each gateway .However, the direct communication of CHs with the BS which may not be practical for large area networks is demerit of this algorithm. There is no consideration regarding residual energy of the sensor nodes and gateways in cluster formation which may direct to inequity in energy consumption of the sensor nodes in this algorithm. PSO and ant colony optimization (ACO) are applied in WSNs for other optimization problems also and they can be found in [5]-[7].

However, the overhead of data routing in phase of cluster formation is not considered in any of the above algorithms. Even, nature inspired approach with focus on cluster formation has not been used with any of the above algorithms except Kuila [8].While LEACH-like strategies suppose homogeneous WSNs, hierarchical routing in heterogeneous sensor networks where an appropriate percentage of the sensor population is set with more energy than the remaining of the normal sensors in the same network. Heterogeneity is generated by these advanced nodes in terms of node energy .According to Kuila [3], assume E_0 as initial energy of every normal sensor node. Then each advanced node's energy is$E_0(1+\alpha)$. According to [15], if the fraction of advanced nodes is m and the additional energy factor between advanced and normal nodes is α then:

$$q_{nrm} = \frac{q}{1+\alpha X m} \quad (2)$$

$$q_{adv} = \frac{q}{1+\alpha X m} X(1+\alpha) \quad (3)$$

The threshold for normal sensors, T (S_{nrm}), and the threshold for advanced nodes T(S_{adv})as follows [15]:

$$T(S_{nrm}) = \begin{cases} \dfrac{q_{nrm}}{1-q_{nrm}X(r \bmod \frac{1}{q_{nrm}})} & if S_{nrm} \in Q' \\ 0 & otherwise \end{cases} \quad (4)$$

$$T(S_{adv}) = \begin{cases} \dfrac{q_{adv}}{1-q_{adv}X(r \bmod \frac{1}{q_{adv}})} & if S_{adv} \in Q'' \\ 0 & otherwise \end{cases} \quad (5)$$

Where r=present round,

Q'is the set of normal nodes not been CHs within the last $1/q_{nrm}$rounds, T(S_{nrm}) is the threshold applied to a population of n X (1-m) normal no-des, This provides assurance about each normal sensor node to become a CH exactly once every 1/q x (1 + αX m) rounds and the average number of cluster heads that are normal nodes per round to be equal to n X (1-m) X q_{nrm}, Q'' = set of advanced nodes that have not become CHs within the last $1/q_{adv}$ rounds (S_{adv}) =threshold applied to a population of n X m advanced nodes. This guarantees that each advanced node will become a CH exactly once every ((1)/ (q) x ((1 + αx m))/ (1+α)))) rounds.

Evolutionary Algorithms (EAs) are one of the most employed metaheuristics. EAs stimulated by the power of natural evolution, have been widely used as exploration and optimization tools in different problem domains. The general EA framework begin with an initial population of solutions and get accustomed to various sorts of selection and variation operators so as to frequently produce new solutions. The likelihood of selection of an individual depends on its being better. For analyzing the quality of an individual computation in relation to its fitness is done. The issue critical to a successful EA performance is the preference of a good fitness function. It builds the foundation for selection, and thus assists the progress of improvements. A function that select and give responsibility of quality measure to individual solutions: Fitness function (i.e. Transmission distance, or in short, distance).This is the chief aspect used to minimize network energy consumption. Hence, to be more precise judging the soundness of the clustering solutions provided by the routing protocol algorithm, we have to reconsider the distance function to present two clustering purposes: cluster's cohesion or scatter (intra-distance) and cluster separation (inter-distance). Intra-distance can be quantified by:

$$Compactness = \sum_{i=1}^{CH_s} \sum_{\forall n \in C_i} d(n, CH_i) \quad (6)$$

wherein illustration of number of cluster heads is done by CHs. The i^{th} cluster distinguished with cluster-head CH_i is C_i, along with any cluster member node, n, which not cluster head but relevant to the cluster C_i that measure up the nominal distance inter se non cluster head node, n and CH_i. Furthermore, similar to [15] the computation of inter-distance as the minimum Euclidean distance amid any pair of cluster heads is given by:

$$d_{min} = \min_{\forall C_i C_j C_i \neq C_j} \{d(CH_i, CH_j)\} \quad (7)$$

Subsequently, the objective (i.e. fitness) function is to concurrently minimize f1 = Compactness/d_{min} and f2=number of CHs. Accordingly, the fitness function is represented as:

$$Fitness = w \times f1 + (1-w) X f2 \quad (8)$$

where w is a pre-defined weight (set in the experiments to 0.5)

At the commencement of each round, the dual-phase clustering process consisting of the cluster setup and steady state phases is used. In the direction of guiding the CH election, a population of individuals that evolves toward keeping an optimal number of clusters is taken. An absolute-length list with range equivalent to the total number of nodes in the WSN is used to characterize each individual. The cluster head and cluster member nodes are designated with values 1 and 0 respectively, while dead nodes are expressed as −1. Random initialization of each individual of the population with 1s and 0s according to the probability q in (1) of the preferred percentage of CH nodes, as in [15]:

$$I_{ij} = \begin{cases} 1 \;\; if\; E(node_j) > 0\; and\; random_j \leq q \\ 0\; if\; E(node_j) > 0\; and\; random_j \geq q \\ -1 \qquad\qquad \text{otherwise} \end{cases} \quad (9)$$

∀i∈ {1,.. ,n} and ∀ j ∈ {1, . . .,N}where n is the number of individual solutions and N is the number of sensor nodes in the network.

Similarly, Flower Pollination Algorithm (FPA) is a fresh bio-inspired optimization algorithm that stand for the real life practices of the flower pollination[9].In FPA, an objective function is used which is to be minimized or maximized(e.g., *min or* max f(x), x=(x_1, x_2, x_3, …., x_d)).

A population of *(n)* flowers/pollen gametes with random solutions is taken at initial stage. *The best solution g_k*in the initial population is found. A switch *probability p* ∈[0, 1].Here (rand < p) means that during simulation, a global search (cross-pollination) is applied by one part of the algorithm and the other part will perform local search (self-pollination). In the case (rand < p) and p = 0.8 for instance, means that 80% of the simulation, the algorithm will do local search, and 20% will do global search. Inversely, with (rand > p) we will get 80% of global search and 20% of local search. *The stopping criterion (either a fixed number of generations/ iterations or accuracy) is* defined. Until maximum iterations is reached, for all n flowers in the population, global and local pollination is performed according to specified criteria in which if any random number ,*rand* generated is less than switch probability, a d-dimensional step vector L which complies with Levy's distribution is drawn .In addition ,

If rand >p,j and k among all solutions is randomly chosen from a uniform distribution in [0, 1]and a local pollination is done via:

$$x_i^{t+1} = x_i^t + E(x_i^t - x_k^t) \quad (11)$$

New Solutions are evaluated. If new ones are better, they get updated in the population. Again, the current best solution $g_k$is found. The best solution achieved at the end is given as output.

Another algorithm based on the musical process in which a perfect condition of harmony is found is HSA (Harmony Search Algorithm)[13]. HSA seeks a perfect state of harmony which is further estimated on the basis of aesthetic estimation, as the best state (i.e., global optimum) decided by objective function is searched by its optimization process. *Steps pursued in HSA [11]:*

- Initialize the optimization problem and algorithm parameters.
- Initialize the harmony memory (HM).
- Improvise a new harmony from the HM.
- Update the HM.
- Go to step 3 until termination criterion is reached.

In this algorithm worst fit and worst location are found in initial population. New Harmonics are generated either by choosing a random harmonic (based on HMCR) or by adjusting pitch randomly of existing harmonic (based on PAR) or by generating new harmonics via randomization. Improvisation in initial Population, which is Harmony Memory here, is done by comparing the values in New Harmony with worst fit ones. In this way, best solution is reached upon updating HM until maximum iterations.

Influenced by the social behavior of a flock of migrating birds trying to reach an unknown destination [12], an algorithm named as PSO came into existence. In PSO, each solution is imagined as a 'bird' in the flock and is referred to as a 'particle'. A particle is analogous to a chromosome (population member) in Gas .In comparison to GAs, in the generative procedure followed in the PSO, new birds are not created from parent ones. Alternatively, the birds in the population only change their social behavior and accordingly their movement towards a destination.

PSO consists of following steps *[10]:*

- Generate a random population of N solutions or particles
- Repeat
- For each particle, calculate fitness
- Initialize the value of the weight factor(w) for that iteration
- For each particle, set pbest as the best position of that particle.
- Set gbest as the best fitness of all particles.
- For each particle, calculate particle velocity (V).

Global pollination is carried out via:

$$x_i^{t+1} = x_i^t + L(x_i^t - g_k) \quad (10)$$

- Update particle position (X)
- Continue until terminating condition

In each time interval (cycle), the position of the best particle (gbest) is calculated as the best fitness of all particles. Accordingly, each particle updates its velocity $V_i$to get closer to the best particle gbest, as follows:

$$V_i^{k+1} = w.V_i^k + c1.rand_1.(pbest_i^k - x_i^k) + c2.rand_2.(gbest_i^k - xik \quad (12)$$

Where w is the weight factor for that iteration

Also, c1 and c2 are two positive constants named learning factors; $rand_1$ and $rand_2$are two random functions in the range [0, 1]. As such, using the new velocity V_i, the particle's updated position becomes:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (13)$$

Table 1: Initial Parameters of three algorithms PSO, FPA, and HSA

Criteria	PSO	FPO	HSA
Parameters	The population size (number of particles), number of generations and the weight factor w	Standard gamma, local random walk, switch probability	HMS harmony memory size, H M(Harmony Matrix) ,HMCR,PAR

3. NETWORK COMMUNICATION MODEL

To estimate power utilization of a LEACH protocol, a simple radio model is presented in [11].In this model, a radio consumes E_{elec}=50nJ/bit to run the transmitter or receiver circuitry. Depending on the transmission distance, both free space e_{fs} and the multi-path fading channel e_{mp} models are used for transmitter amplifier [14].The radios have power control and are capable of expending the minimum required energy to reach the intended recipients.

The radios can be turned off to avoid receiving unintended transmissions. To transmit a l-bit message for a distance d between the sender and the receiver, the radio expends the following amount of energy [15]:

$$E_{Tx}(l,d) = \begin{cases} l\,X\,E_{elec} + l\,X\,\varepsilon_{fs}d^2\,, if\ d \le d_0 \\ l\,X\,E_{elec} + l\,X\,\varepsilon_{mp}d^4, if\ d > d_0 \end{cases} \quad (14)$$

Where the smaller distance is defined as

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (15)$$

The optimal number of constructed clusters is given by:

$$k_{opt} = \sqrt{\frac{n}{2\pi}}\frac{2}{0.765} \quad (16)$$

Where n is number of nodes; The optimal probability of a node to become a cluster head,p_{opt}, can be computed as follows:

$$p_{opt} = \frac{k_{opt}}{n} \quad (17)$$

4. PERFORMANCE MEASURES

The measures that we used are to compare the performance of algorithms:

Stability Period: The time period ranging from the commencement of network operation until the demise of the first sensor node is defined as "Stability period". It is also referred as "stable region."

Instability Period: This is the time gap from the loss of the first node until the demise of the last sensor node. It is also known as "unstable region."

Network lifetime: The time extent from the inauguration of operation (of the sensor network) until the expiration of the last alive node is called "lifetime of network".

Number of cluster heads per round: This immediate measure reflects the number of nodes which would send aggregated information received from their cluster members straightforwardly to the sink.

Number of alive (total, advanced and normal) nodes per round: This direct measure indicates the overall number of nodes and that of each type whether normal or advanced that has not yet expended all of its energy.

Evidently, the reliability of the clustering process of the sensor network depends on the span the stable region and the unstable region. On the other hand, there is a tradeoff between reliability and the lifetime of the system.

5. SIMULATION RESULTS

In this section, we examine the performance of our FPA against the well known heuristic protocol HSA and the PSO in terms of the span of the stability period, network lifetime, and the residual energy in the network while heterogeneity in the clustered wireless sensor networks is present.

5.1 Simulation Settings

The different optimization techniques are implemented in MATLAB. The simulations are carried out on 20 dissimilar heterogeneous sensor networks, each being a collection of 100 sensor nodes deployed randomly in a space of 100 m × 100 m sensor field .This is the implication of selection of the horizontal and vertical coordinates of each sensor randomly between zero and the utmost value of the dimension. Advanced nodes' percentage is set to 10% of the total nodes for 10 networks and 20% for the rest of 10 networks. BS is positioned at the center (50, 50) of the sensor field. For being just in comparison, the characteristics of the networks and communication models used for the optimization techniques' simulations are made identical. The initial energy of a normal node is set to E_0 = 0.5 J, ε_{fs} = 10 pJ/bit/m^2, ε_{mp} = 0.0013 pJ/bit/m^4, and E_{DA} = 5 nJ/bit/report. Average results of the 10 simulations are provided both qualitatively and quantitatively. The population size is set to be 20.

5.2 Evaluations

In order to study the performance of the optimization techniques in several network test instances and to study their behavior, Figures 2 and 3 statistically qualify them after averaging results over the generated WSNs with 10% and 20% of node heterogeneity, respectively.

The figures depict the number of nodes alive versus protocol rounds.

Additionally, to give a detailed approach into the performance

of these protocols, quantitative results are also incorporated thereby summing up the network lifetimes (Tables 2 and 3), history of dead nodes (Tables 4 and 5), the energy left in the network while protocol rounds proceed (Tables 6 and 7), and first node's death (FND), half node's death (HND), last node's death (LND) (Tables 8 and 9).Note that in each table, the best performance values are given in bold.

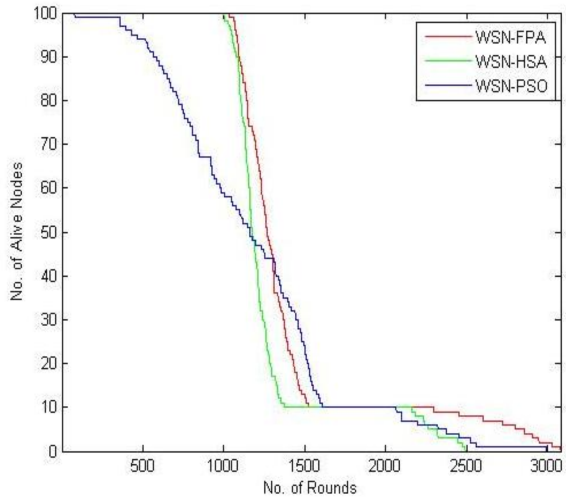

Fig 2: Total number of alive nodes in the network versus rounds. Average results over 10 networks with 10% node heterogeneity shows that nodes alive of FPA and HSA are greater in number than PSO

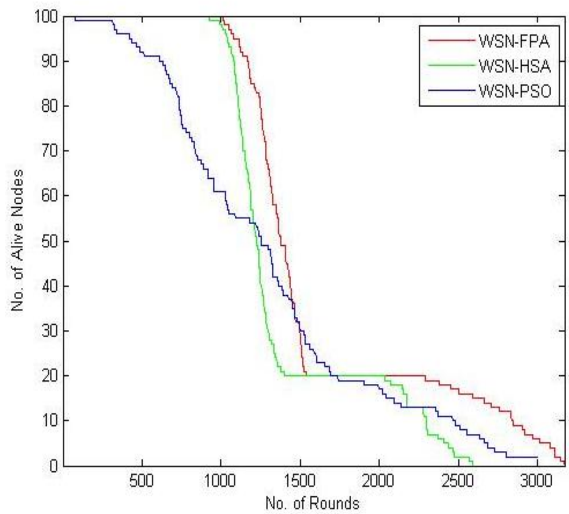

Fig 3: Total number of alive nodes in the network versus rounds. Average results over 10 networks with 20% node heterogeneity shows that nodes alive of FPA and HSA are greater in number than PSO

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The results in Tables 2 and 3 trace the average round number in which a known proportion of nodes die for the compared protocols. Outcomes in the tables evidently demonstrate the positive impact of the FPA and HSA over PSO for decreasing number of dead nodes while the protocol rounds proceeds.PSO keeps the last 10% nodes (as in Fig. 1) and the last 20% nodes (as in Fig. 2) alive for longer number of rounds.

This reveals that PSO preserves some energy in the last 10% or 20% alive nodes (usually advanced nodes) after the death of all normal nodes but it does this after 50 % of nodes of the network are dead. This observation can be quantitatively presented in Tables 4 and 5 for the two groups of WSNs.

Table 2: Round history of dead nodes over simulation of 10 WSNs (with 10% advanced nodes)

%Dead Nodes	FPA	HSA	PSO
10	**1092**	1074	568
20	**1138**	1101	718
30	**1196**	1134	840
40	**1233**	1157	978
50	**1265**	1174.5	1160
60	**1307**	1209	1321
70	1365	1239	**1444**
80	1433	1281	**1514**
90	1521	1375	**1607**
100	**3079**	2490	2988

Table 3: Round history of dead nodes over simulation of 10 WSNs (with 20% advanced nodes).

%Dead Nodes	FPA	HSA	PSO
10	**1165**	1078	614
20	**1246**	1110	734
30	**1280**	1138	834
40	**1323**	1186	1026.5
50	**1375**	1225	1251
60	**1437**	1250	1365
70	1495	1294	**1498**
80	1538	1401	**1694**
90	**2835**	2295	2462
100	**3170**	2590	2999

Table 4: Round history of advanced and normal dead nodes for a total of 3079 rounds

%Rounds	FPA		HSA		PSO	
	AN	NN	AN	NN	AN	NN
10	0	0	0	0	0	1
20	0	0	0	0	0	12
30	0	0	0	0	0	35
40	0	38	0	68	0	54
50	0	90	0	90	0	84
60	0	90	0	90	0	90
70	0	90	0	90	3	90
80	2	90	8	90	7	90
90	4	90	*	*	9	90
100	10	90		-	10	90

Table 5: Round history of advanced and normal dead nodes for a total of 3170 rounds

%Rounds	FPA		HSA		PSO	
	AN	NN	AN	NN	AN	NN
10	0	0	0	0	0	2
20	0	0	0	0	0	11
30	0	0	0	1	0	36
40	0	26	0	64	0	51
50	0	80	0	80	0	74
60	0	80	0	80	1	80
70	0	80	7	80	7	80
80	4	80	18	80	12	80
90	11	80	*		18	80
100	20	80		-	18*	80

Table 6: Average remaining energy over protocol rounds for a total of 2988 rounds (with 10% advanced nodes).

%Rounds	FPA	HSA	PSO
10	**42.1789**	41.9570	40.6074
20	**29.3757**	28.9108	26.8052

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30	**16.6179**	15.8454	15.9126
40	6.0571	5.3871	**8.3370**
50	**3.7643**	3.4241	3.6915
60	**2.3854**	2.0354	2.2083
70	**1.1359**	0.6534	0.9049
80	**0.4627**	0.0127	0.2033
90	**0.0743**	-	0.0518
100	**0.0001**	-	-

Table 7: Average remaining energy over protocol rounds for a total of 2988 rounds (with 20% advanced nodes).

%Rounds	FPA	HSA	PSO
10	**46.7906**	46.5469	45.2957
20	**33.6030**	33.0935	31.2734
30	**20.4087**	19.6639	20.3332
40	10.1743	9.2743	**12.4187**
50	6.9180	6.1785	**7.2952**
60	**4.6512**	3.4509	4.4012
70	**2.4726**	0.9717	2.2476
80	**0.9212**	0.0335	0.7212
90	**0.3595**	-	0.1595
100	**0.0045**	-	-

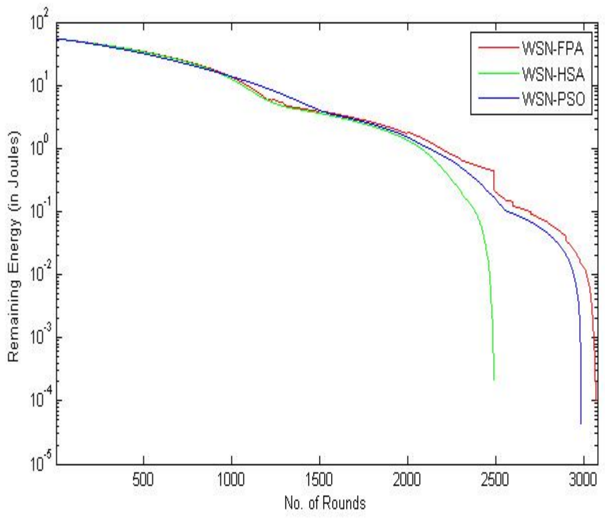

Fig 4: Remaining energy vs number of rounds in a network with 10% heterogeneity. FPA has max average remaining energy

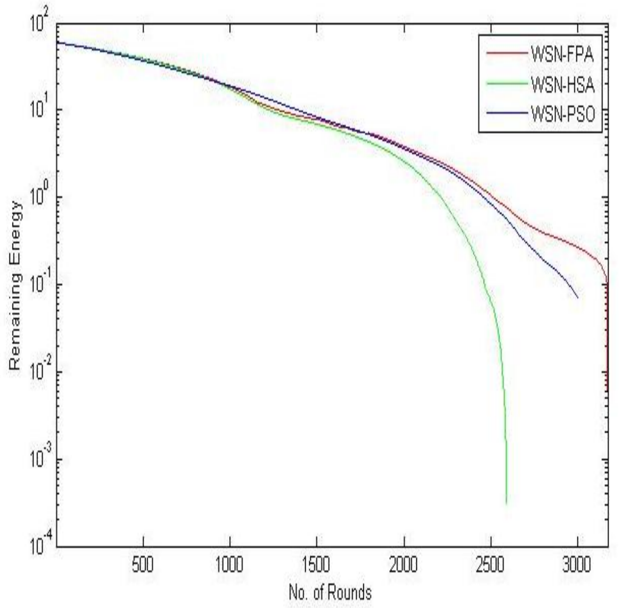

Fig 5: Remaining energy vs number of rounds in a network with 20% heterogeneity. FPA has max average remaining energy

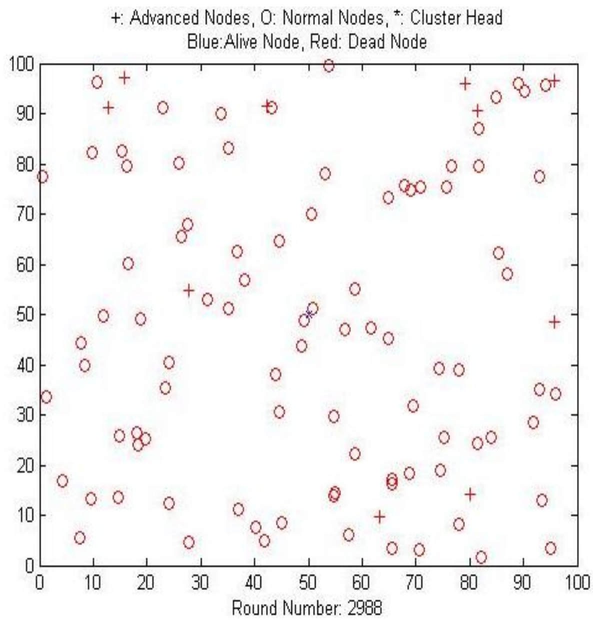

Fig 6: Network with 10% heterogeneity with PSO implemented dies at 2988 round

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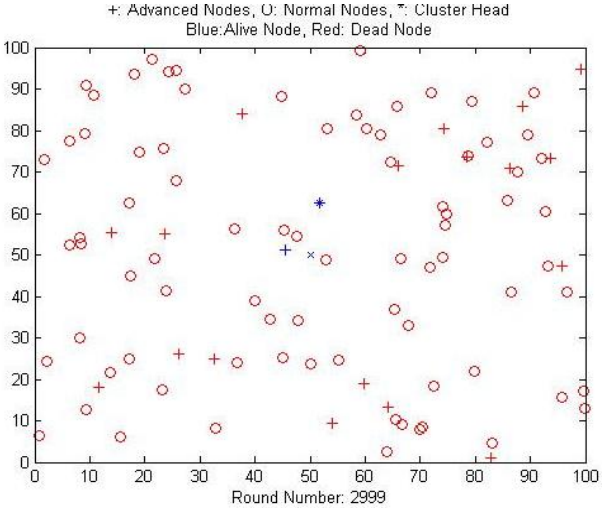

Fig 7: Network with 20% heterogeneity with PSO implemented dies at 2999 round

Table 8: Average of FND, HND and LND in 10 simulations with 10% heterogeneity

	FPA	HSA	PSO
FND	**1034**	1001	80
HND	**1265**	1174.5	1160
LND	**3079**	2491	2988

Table 9: Average of FND, HND and LND in 10 simulations with 20% heterogeneity

	FPA	**HSA**	**PSO**
FND	**1015**	925	80
HND	**1375**	1225	1251
LND	**3170**	2590	2999

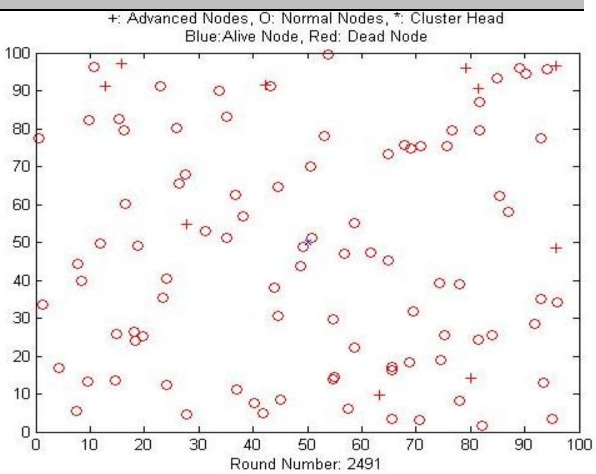

Fig 8: Network with 10% heterogeneity with HSA implemented dies at 2491 round

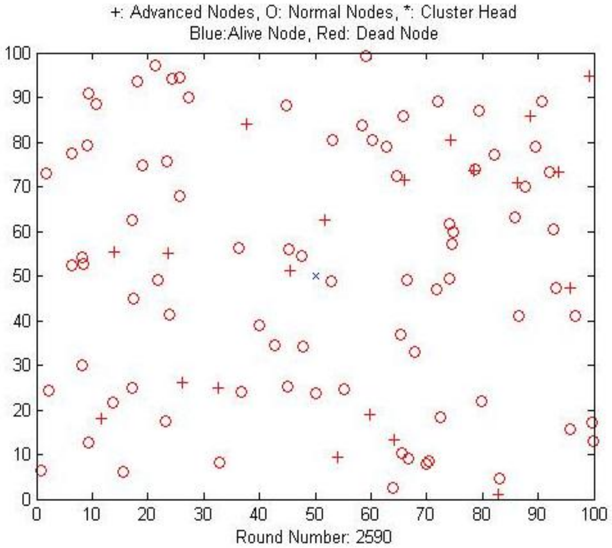

Fig 9: Network with 20% heterogeneity with HSA implemented dies at 2590 round

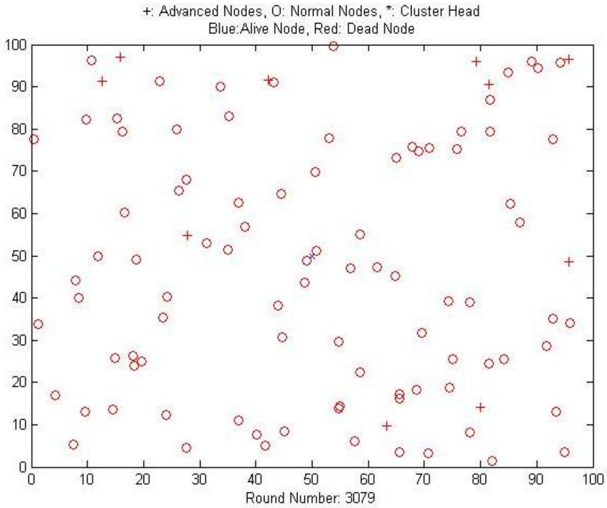

Fig 10: Network with 10% heterogeneity with FPA implemented dies at 3079 round

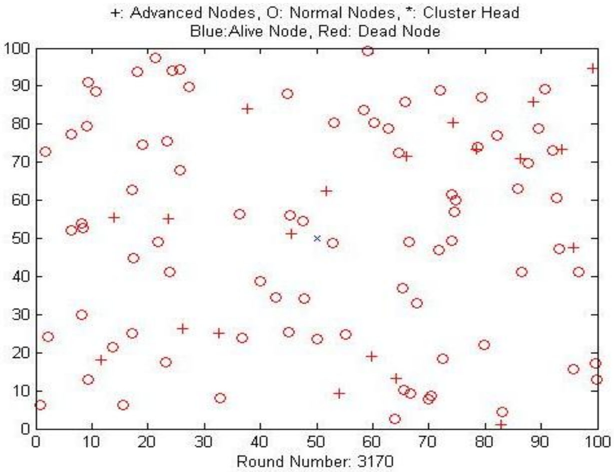

Fig 11: Network with 20% heterogeneity with FPA implemented dies at 3170 round

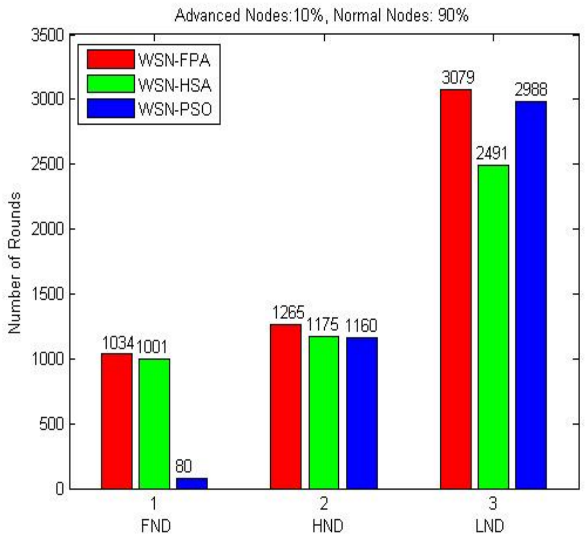

Fig 12: Bar Graph of a network with 10% heterogeneity

FPA performs better than HSA as HSA's 18 advanced nodes die ,PSO's 12 advanced nodes die when 80% rounds are over while FPA's 4 advanced nodes die with 20 % heterogeneity in network.

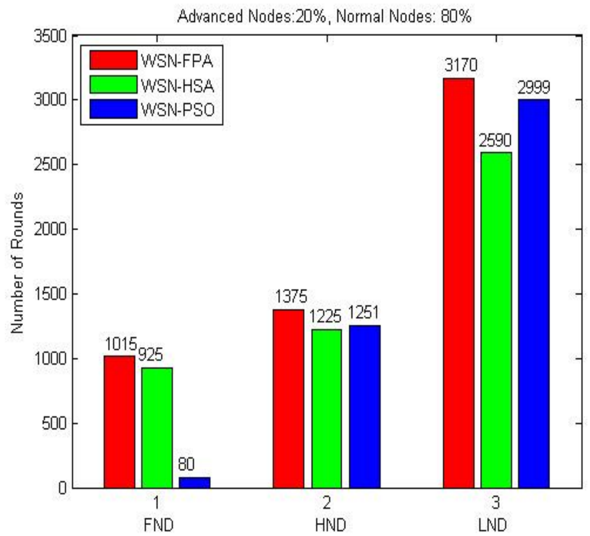

Fig 13: Bar Graph of a network with 20% heterogeneity

Additional remark can be drawn from Figures 2 and 3 that if we intend to find the efficient algorithm then ignore PSO whose 50 % nodes die very early with which half of its sensing is lost.

Tables 4 and 5 gives the number of advanced and normal nodes found dead at a given rounds percentage while the protocols proceed for a total of 3079 rounds (Table 4) or 3170 rounds (Table 5).

In the tables, * means that the remaining nodes were dead before the corresponding rounds percentage, while – means that the whole WSN is dead.

Tables 6 and 7 depicts that FPA has more remaining energy than HSA, thereby proving FPA to be more efficient than HSA. Tables 8 and 9 prove that for FND, HND, LND FPA proves to be best.

Figures 4 and 5 are interpreting results regarding average remaining energy corresponding to rounds of all algorithms. Figures 6, 7, 8, 9, 10, 11 tell at which round network dies in PSO, HSA and FPA respectively. Figures 12 **and** 13 depict the bar graph of networks for PSO, HSA and FPA with 10% and 20% heterogeneity thereby proving FPA better for FND, HND, LND than HSA and PSO.

6. CONCLUSION

Selection of a routing protocol for a wireless sensor network depends on various factors like network lifetime, and stability period. Three evolutionary algorithms with appropriate fitness functions are compared with the intrinsic properties of clustering in mind. The main idea is the incorporation of compactness (i.e. cohesion) and separation error criteria in the fitness function to direct the search into promising solutions. Against PSO and HSA, the overall results reveal that the FPA achieves longer network lifetime, more average remaining energy

Future research directions can be inspired from the reported results. First, the competition of FPA and HSA with PSO for prolonging stability period until FND may give birth to another fitness variant that can be more adaptive with the extra nodes heterogeneity. Another direction may assume the impact of varying BS location at the corner rather than at the centre of the sensor field.

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