International Journal of Engineering & Technology, 7 (2.7) (2018) 494-501

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research Paper



Architectural analysis for lifetime maximization and energy efficiency in hybridized WSN model

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Abstract

It is well known that WSN is one of the leading techniques in granting pervasive computing for various applications regarding health sector and communication sector. However, the raising of issues in WSN is still a burden cause because of certain renowned terms like energy consumption and network lifetime extension. Clustering is a major contribution in any network and moreover Cluster Head selection is also a vital role since it is additively responsible in sending data to the base station, which means that Cluster Head directly makes its communication with base station. Day by day, the researches in cluster head selection get increased, but the requirements are not yet fulfilled. This paper proposes a energy efficient cluster head selection algorithm for maximizing the WSN lifetime. This paper develops a hybrid optimization process termed Group Search Ant Lion with Levy Flight (GAL-LF) for selecting the Cluster head in WSN. The proposed model is compared to the conventional models such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Group Search Optimization (GSO), Ant Lion Optimization (ALO) and Cuckoo Search (CS). The outcome of the simulation result shows the superiority of the proposed model by prolonging the lifetime of the network.

Keywords: *ALO; Cluster Head Selection; GAL-LF; Network lifetime; WSN*

1. Introduction

Wireless Sensor Network (WSN) is an all-time hot research topic, which steps its factual usage in many of the broad applications that range from industrial and military applications, especially in health sector and monitoring environmental strategies [3]. WSNs include a huge count of sensor nodes (SNs) that are arbitrarily deployed to sense and monitor both physical as well as environmental conditions [4]. Current enhancements in WSNs lead to various novel protocols that are particularly planned for sensor networks where energy awareness is a necessary concern. Mostly the attention, however, has been diverted for routing protocols as they might get varied based on the various application as well as network architecture.

Clustering is a method in which choosing of Cluster Head [7] [9] [10] is done for preserving the energy consumption in WSN [4]. The network is separated into various groups namely clusters, and this is the designing process of clustering technique. In each cluster there presents a leader namely cluster head. In any clusters, the head of the cluster is the only responsibility in collecting data from their member sensors. Data aggregation is performed by cluster head, and it eliminates the redundant data, which minimizes the energy depletion of the network. Conversely, cluster heads [6] [8] also consumes more energy due to extra overload for both receiving as well as data aggregation and also to transmit data to the sink [5]. Thus, the proper cluster head choosing plays a vital role for energy conservation and enhancement of WSNs lifetime. Moreover, cluster head selection is a optimization issue which is the NP-hard problem. Number of algorithms is there in cluster head selection, and some of them are Particle Swarm Optimization (PSO), Low Energy Adaptive Cluster Hierarchy (LEACH) algorithm and so on. Still, the problems raise in cluster head selection are high energy consumption, security, increasing of link distance, etc.

2. Literature Review

A. Related Works

In 2016, Gulnaz et al. [1] have developed a novel routing algorithm termed 'Sleep-awake Energy Efficient Distributed (SEED) clustering algorithm.' There made a separation in the network sensing field as the cluster head has direct contact with base station. Cluster head in high energy region has greater distance communication, and also it necessitates further energy cost when compared to cluster head in the low energy area. With the consideration of six criteria, they have examined the algorithm. Finally, the investigations were done for testing the developed approach. The investigational outcome has attained higher network lifetime along with the greatest throughput when compared to other existing algorithms.

In 2016, Shankar *et al.* [2] have proposed a hybrid model of 'Harmony Search Algorithm (HSA)' as well as 'Particle Swarm Optimization (PSO)' procedure for the efficient selection of cluster head. The model has attained global search with rapid convergence. With the developed hybrid model, the network lifetime has greatly enhanced, and the performance evaluation was done with

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the concern of some parameters like a number of alive nodes, throughput, count of dead nodes, energy. The output of the resultant hybrid model has exposed an improvement in the energy and the throughput by 83.89% and 29.00%, respectively, which was better than the PSO algorithm.

Mahajan *et al*. [3] have stated that in any clustering based approach, one of the major concepts is the choosing of proper cluster heads and also the development of balanced clusters as well. Initially, the cluster heads are chosen on the basis of weight metric, and later the formation of cluster carries out. This model aims at conserving sensor energy and load balancing. They have adopted a local clustering approach within the cluster for minimizing the evaluation rate and the cost of communication. Moreover, they have explored a novel approach for transmitting data. The proposed model has compared its performance with other conventional techniques like LEACH, WCA as well as IWCA. The developed model has shown the greatest enhancement with respect to lifetime as well as consumption of energy.

Khan *et al*. [4] have proposed a Fuzzy-TOPSIS approach, which was on the basis of multiple criteria decision making for selecting cluster head even more efficiently for maximizing the lifetime of WSN. They have considered various criteria such as residual energy; consumption rate of energy node; neighbour node counts; average distance among neighbouring nodes and distance from the sink. In order to minimize the consumption of energy, they have used a communication mechanism that was on the basis of intra-cluster and inter-cluster. They have also examined the effect of node density and various mobility strategy types for investigating the impact on the lifetime of WSN. For maximizing the distribution of load in WSN, they have proposed a knowable mobility along octagonal trajectory. The obtained results have enhanced the overall network lifetime and latency.

O.Deepa and J.Suguna [5] have proposed a Optimized QoS-based Clustering with Multipath Routing Protocol (OQoS-CMRP) for WSNs that have minimized the consumption of energy in sink coverage area via the application of Modified Particle Swarm Optimization (PSO)-based clustering algorithm. This forms the clusters for choosing the cluster heads in sink coverage area. They have used the Single Sink-All Destination algorithm for finding closer optimal multi-hop communication path. This was for the neighborhood nodes. In order to transfer data to sink, they have utilized Round-robin Paths Selection algorithm. As per QoS metrics, the proposed protocol has made its evaluation and also the comparison was made to some of the conventional protocols like EE-LEACH as well as EPSO-CEO. Finally, the output has shown the superiority of proposed work over other models.

B. Review

The detailed review on energy efficient CH selection in WSN is shown in with its respective features and challenges are given in Table I. On the contrary, HSA and PSO-based CH selection [2] attains faster convergence with improvement in residual energy and throughput. However, it suffers from the requirement of more number of iterations to get the optimum value, the problem of poor convergence in refined search stage, and sometimes it gets trapped in the local search area. In addition, [1] proposes the SEED clustering algorithm with higher network lifetime and throughput. However, the main issue of this technique is, it needs to select new random seeds every time to minimize the risk. Thus it is motivated to implement the energy efficient CH selection based on the effective optimization algorithm. CCWM [3] is applicable in number of sectors however, there requires more consumption of energy if there presents more clusters. Fuzzy-TOPSIS technique [4] is more robust in enhancing the network lifetime, still, the enhancement is needed in the dealing of vagueness in the developed model. Moreover, OQoS-CMRP [5] could attain better communication reliability; however, improvement is needed in the aspect of 'Security'. Thus, there require additional protocols to solve all the above mentioned drawbacks.

Table 1: Review on energy efficient CH selection in WSN

Author [Citation]	Adopted Methodology	Features	Challenges
Gulnaz *et al.* [1]	SEED clustering algorithm	❖ Higher network lifetime ❖ High throughput	❖ Require to select new random seeds every time to minimize the risk
Shankar *et al.* [2]	HSA and PSO	❖ Faster convergence ❖ Improvement in residual energy and throughput	❖ Needs to maximize the iteration to get the optimal value ❖ Slow convergence in refined search stage ❖ Get trapped in local search area
Mahajan *et al.* [3]	Cluster Chain Weight Metrics approach (CCWM)	❖ Applicable in various sector ❖ Enhances the energy efficiency	❖ More clusters result in more energy consumption ❖ Increase of link distance make worst performance
Khan *et al*. [4]	Fuzzy-TOPSIS technique	❖ More robust ❖ Enhances the network lifetime	❖ Not so Flexible ❖ Improvement is needed in dealing with vagueness in the Fuzzy TOPSIS
O.Deepa and J.Suguna [5]	OQoS-CMRP	❖ Attains better communication reliability ❖ Can maintain reasonable energy consumption	❖ Multimedia messaging application is impossible ❖ Enhancement is needed in the security of proposed model

3. Selection of cluster head in wireless sensor network

Let's take a WSN consideration that has N_{CS} number of clusters, where the cluster is termed as CS_i , where $i = 1,.....N_{CS}$. Here, NO_{ij} represents the node in cluster, where $i = 1,2,.....A$ and $j = 1,2,.....B$. The cluster head, CH_i is chosen from the presenting nodes in any cluster. Moreover, CH_i leads the other nodes in cluster. While selecting the cluster head, there needs the consideration of certain parameters like energy, packet delay and distance between nodes present in cluster. Only the cluster head has direct contact with base station B_s . Furthermore, the choosing of cluster head is not a simple task as it must consider some distinct WSN characteristics. Hence, it is more significant to propose an effective algorithm with parameter consideration, which absolutely enhances the performance of network

Objective model

WSN parameters like distance and energy are used for doing the selection of cluster head. Additionally, the proposed work considers QoS as the vital parameter for the effective performance of network. The network performance increases if there have high energy and QoS, and low distance. The objective model is determined in Eq. (1) and (2), where β denotes the constant value, 0.3. In Eq. (2), γ_1 γ_2 and γ_3 are specifying the

parameters of distance, energy and delay, respectively and $|| NO_r - B_s ||$ in Eq. (3) denotes the distance between the normal node and base station.

$$D_1 = \beta \times d^2 + (1-\beta)d^1 \; ; \; 0 < \beta < 1 \tag{1}$$

$$d^1 = \gamma_1 * d_i^{dist} + \gamma_2 * d_i^{energy} + \gamma_3 * d_i^{delay} \tag{2}$$

$$d^2 = \frac{1}{N_{CS}} \sum_{r=1}^{N_{CS}} ||NO_r - B_s || \tag{3}$$

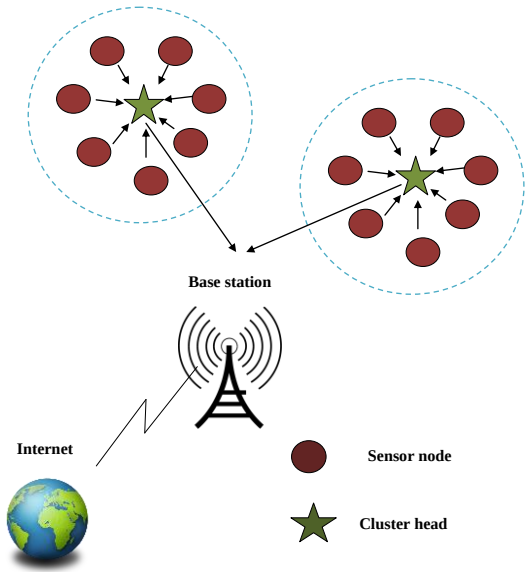


Fig. 1. Schematic diagram of cluster head selection in WSN

4. Optimal cluster head selection using hybrid optimization

A. Conventional GSO

In GSO [14], the population is denoted as 'group,' and the individuals in population are termed as 'member.' The visual scanning field is generalized to di dimensional space and that is considered by maximum $DI^{\max} \in \Re^1$ and minimum pursuit angle $\theta^{\max} \in \Re^1$. At t^{th} iteration, X_{PR} producer acts as specified below:

(i) Firstly, X_{PR} makes the scanning at zero degree and then, it laterally scans in scanning field via sampling three points (arbitrarily): point at zero degree X^{ZE} is determined in Eq. (4), Eq. (5) determines the point at right side hypercube X^{RI} and Eq. (6) gives the point at left side hypercube X^{LE}, where $n_1 \in \Re^1$ is the random number with mean 0 and Standard Deviation (SD) 1, $n_2 \in \Re^{r-1}$ is the dispersed random sequence in range (0,1), ψ denotes the head angle and UV signifies the unit vector.

$$X^{ZE} = X_{PR}^t + n_1 DI^{\max} UV_{PR}^t(\Psi^t) \tag{4}$$

$$X^{RI} = X_{PR}^t + n_1 DI^{\max} UV_{PR}^t(\psi^t + n_2\theta^{\max}/2) \tag{5}$$

$$X^{LE} = X_{PR}^t + n_1 DI^{\max} UV_{PR}^t(\psi^t - n_2\theta^{\max}/2) \tag{6}$$

(ii)Then the producer finds the best point with best resource (fitness). Moreover, if the best point has best fitness value than the current position, then the producer makes a fly towards that point. If the present position is superior than the fitness, then the producer turns its head to a new randomly selected angle, which is shown in Eq. (7), where $\alpha^{\max} \in \Re^1$ denotes the maximum turning angle.

$$\psi^{t+1} = \psi^t + n_2\alpha^{\max} \tag{7}$$

(iii) even though with the completion of i iterations, and if the producer cannot find the best location, then it turns its head towards zero degree, which is determined in Eq. (8), where $i \in \Re^1$ is a constant.

$$\psi^{l+i} = \psi^l \tag{8}$$

B. Conventional ALO

ALO [15] aids the 'hunting behavior' of antlions. The algorithm includes five major steps that are as follows: Ant's arbitrary walk, Building the trap, Ant's Entrapment, Prey catching, rebuilding the traps. Moreover, the main phases of antlions life cycle are 'larvae' and 'adult.'

Arbitrary walks of ant: The Ant's arbitrary walks are persisted according to Eq. (9), (10) and (11), where $cusum$ denotes the cumulative sum, iteration counts are determined by nu, $fu(s)$ denotes the stochastic function that is in Eq. (18), and st indicates the arbitrary walk steps.

$$AR(st) = \begin{bmatrix} 0, cusum(2\,fu(st_1)-1), cusum(2\,fu(st_2)-1), \ldots \\ \ldots\ldots, cusum(2\,fu(st_{nu})-1) \end{bmatrix} \tag{9}$$

$$fu(st) = \begin{cases} 1 & if \quad ran > 0.5 \\ 0 & if \quad ran \le 0.5 \end{cases} \tag{10}$$

Moreover, the regularization of arbitrary walk is done for making it within the search space, which is given in Eq. (11), where mi_j and ma_j denotes the minimum and maximum of arbitrary walk in j^{th} iteration and k_j^s and l_j^s indicates the minimum and maximum of j^{th} variable at s^{th} iteration respectively.

$$AR_j^{st} = \frac{(AR_j^{st} - mi_j) \times (l_j - k_j^s)}{l_j^s - mi_j} + q_j \tag{11}$$

Antlion's trap in Pit: The random walk of the ant is inclined in the antlions' trap, and the mathematical model is defined in Eq. (12) and (13), where k^s specifies the minimum variable at j^{th} iteration, l^s indicates the vector that includes maximum variable at j^{th} iteration, k_v^s and l_v^s specifies the minimum and maximum variables of whole variables for j^{th} ant, and $antlion_v^s$ refers to the position of chosen v antlion at s^{th} location.

$$v_j^s = antlion_v^s + k^s \tag{12}$$

$$l_j^s = antlion_v^s + l^s \quad (13)$$

Building the trap: Here, the hunting ability of antlion is modeled with the utilization of roulette wheel. This is how the ant lion gets picked under their fitness during optimization. The respective model provides best potential to the fitting antlion to catch the ants.

Descending ants towards antlion: The mathematical model of this step is defined as given in Eq. (14), where RA indicates the ratio, which is determined in Eq. (15), where I indicates the progressing iteration, the maximum iterations is defined as $I^{\max}$, and co specifies the defined constant, which is based on current iteration.

$$k^s = \frac{k^s}{RA} \& l^s = \frac{l^s}{RA} \quad (14)$$

$$RA = 10^c \frac{s}{I^{\max}} \quad (15)$$

Prey catching and pit rebuilding: If the ant reaches in the bottom of pit, then there comes an end for hunting, and it get stuck in the jaw of the antlion. After the completion of this phase, the antlion hit the trapped ant in the soil and slowly eats its body. Then the location update of antlion happens with newest one for enhancing the venture of grasping the new prey, which is determined in Eq. (16), where an_j^s indicates the position of j^{th} ant at s^{th} iteration.

$$antlion_v^s = an_j^s \;\; if \;\; FL\left(an_j^s\right) > FL\left(antlion_v^s\right) \quad (16)$$

Elitism: All ants should do a random walk around a distinct antlion via roulette wheel as well as elite as given in Eq. (17), where WA_{AR}^s indicates the arbitrary walk around the selected antlion through the roulette wheel at s^{th} iteration, WA_{EL}^s specifies the random walk around elite at s^{th} iteration.

$$an_j^s = \frac{WA_{AR}^s + WA_{EL}^s}{2} \quad (17)$$

C. Proposed hybrid model

When considering of existing GSO, it is observed that it suffers from certain issues like slow convergence along poor ability of exploration and exploitation. Moreover, the existing ALO algorithm also suffers from certain problems like greatest convergence time for uncertainty, changes in probability allotment**,** etc. To rectify all issues, this paper aims to develop a hybrid model that is explained as follows: the input to this algorithm is random solutions. The solution vector $SO_{EV} = \{CS_1, CS_2 ..... CS_{N_{CS}}\}$ implies a count of clusters. Each cluster $CS_i = \{NO_1, ... NU_n\}$ includes various nodes. Here, two operations are processed parallel with the solutions for choosing the proper cluster head. Best solution from the random solutions (i.e., 'cluster head') gets updated as per Eq. (4), (5), (6), (7) and (8), and the residual solutions are updated as per Eq. (17). The model outputs the best solution as HI^{best}. In the meantime, the input solutions are arbitrarily updated via Levy model, and the corresponding solution is termed as LE^{best}. Algorithm 1 gives the pseudo code of developed hybrid model.

Levy Flight [33]: The levy fight characteristics are reviewed from the flight behavior of various animals and insects. The levy flight characteristics show its ability by means of optimal search.

The average of both the HI^{best} and LE^{best} gives the optimal cluster head CH^{best}, which is determined in Eq. (18)

$$CH^{best} = \frac{HI^{best} + LE^{best}}{2} \quad (18)$$

ALGORITHM 1: GAL-LF algorithm for Cluster head Selection
Best solution Updating via GSO
Set $t := 0$
Population size initialization the PO_{sz} , position initialization X_i and head angle initialization, ψ_i
Fitness evaluation of initial members
While(if the stop criteria not satisfied)
For(each member i in group)
Choose the producer: X_{PR}
Do Producing:
Evaluate the fitness of the present member
End for
Set $t = t + 1$
End while
Residue solution updation using ALO
Population initialization of antlions and ants
Fitness evaluation of antlions and ants
The best antlions are positioned and supposed as the elite
While (stop criterion not satisfied)
For all ants
Antlion that uses roulette wheel is selected
update k and l using Eq. (14) and (15)
Production of random walk and normalization via Eq. (9) and (11)
Ant position update the by Eq. (17)
End of
Fitness value evaluation
Antlion is replaced with its succeeding, and if antlion becomes fitter with Eq. (16)
Elite update, if antlion outfit more apt than the elite
End while
Return elite
Returns the best solution HI^{best}
Random solutions update via Levy Flight
Return the best solution LE^{best}
Identify the Optimal Cluster head CH^{best} using Eq. (18)

5. Evaluation of parameters

The mathematical model of three parameters is determined below:

Energy: The used energy in WSN is specified in Eq. (19), where $EN(NO_i)$ and $EN(CH_j)$ specifies the energy of i^{th} normal node and energy of j^{th} cluster head, respectively.

$$d^{energy} = \frac{d^{energy}(b)}{d^{energy}(a)} \quad (19)$$

$$d^{energy}(b) = \sum_{j=1}^{B} uEN(j) \quad (20)$$

$$uEN(j) = \sum_{\substack{i=1 \\ i \in j}}^{A} \left(1 - EN(NO_i) * EN(CH_j)\right); \quad 1 \le j < B \quad (21)$$

$$d^{energy}(u) = B * \underset{i=1}{\overset{A}{Max}}\left(EN(NO_i)\right) * \underset{j=1}{\overset{B}{Max}}\left(EN(CH_j)\right) \quad (22)$$

Distance: Eq. (23) gives the mathematical model of distance, where $d^{dist}(b)$ denotes the distance between normal node and cluster head and between the cluster head and base station of the network, which is defined as shown in Eq. (24) and $d^{dist}(a)$ specifies the distance between two normal nodes, which is shown in Eq. (25). The value of $d^{dist}(b)$ should be in [0,1] range.

$$d^{dist} = \frac{d^{dist}(b)}{d^{dist}(a)} \quad (23)$$

$$d^{dist}(b) = \sum_{i=1}^{A}\sum_{j=1}^{B} \left\| NO_i - CH_j \right\| + \left\| CH_j - B_s \right\| \quad (24)$$

$$d^{dist}(a) = \sum_{i=1}^{A}\sum_{j=1}^{B} \left\| NO_i - NO_j \right\| \quad (25)$$

Delay: Node's data transmission delay is determined in Eq. (26), where the delay value in Eq. (26) should be among the range [0, 1]. If the count of nodes in a cluster minimizes, then the minimization of delay occurs. In Eq. (26), WSN cluster head is determined by numerator value, and the total number of nodes is specified by the denominator value.

$$d^{delay} = \frac{\underset{j=1}{\overset{B}{Max}}\left(CH_j\right)}{A} \quad (26)$$

6. Simulation results

A. Simulation setup

The proposed GAL-LF of cluster head selection in WSN is implemented in MATLAB 2015a. The simulation procedure of the proposed CH selection comprise parameters such as distance, delay, and energy of WSN devices. Here the nodes were distributed within the WSN network of the area $100m \times 100m$ with base station at center. The initial energy E^{In} of the network has value 0.5, the energy of free space model E^{fr} has $10\,pJ/bit/m^2$. Further, the energy of power amplifier E^{power} is set as $0.0013\,pJ/bit/m^2$, the transmitter energy E^{tr} is set as $50nJ/bit/m^2$, and the data aggregation energy E^{Da} was set as $5nJ/bit/signal$. The proposed CH selection model implies Sensors that varied from 100, 125, and 150 and the clusters that varied from 10, 15 and 20, respectively. The analysis was carried out for 2000 rounds by comparing it with other conventional GA [11], PSO [12], ABC [13], GSO [14], ALO [15] and CS [16] based cluster head selection models.

B. Alive nodes

In this paper proposed model is compared to other conventional methods by analyzing the number of alive nodes over number of rounds, which is illustrated in Fig 2, Fig 3 and Fig 4. Here, the analysis is done by varying the sensors present and clusters in network, which is already described in simulation setup. Fig 2 shows the graphical representation of alive node analysis with 100 sensor nodes and all varied clusters. Fig 3 is the resultant graph of alive node analysis for 125 sensor nodes and all cluster variation [17-27]. Similarly, Fig 4 shows the graphical illustration of alive node analysis for 150 sensor nodes and all cluster variations. All the Figures (Fig 2, 3 and 4) show the analysis in terms of number of nodes alive versus number of rounds. As the number of rounds increases the number of alive nodes gets minimized. It is clearly evident from Fig 2 (a), initially the alive node count is 100 and as the number of rounds increases the alive node count decreases and however, the proposed GAL-LF at 2000 round holds 30 alive nodes, whereas the remaining methods suffers from poor performance with less alive nodes (10 for ABC, 12 alive nodes for GA, 17 alive nodes for PSO and so on). Similar performance is observed from the remaining Fig 3 and 4.

C. Normalized energy

This section explains the performance analysis in terms of normalized energy by comparing the proposed work over conventional methods. Fig 5 reviews the graphical representation of normalized energy analysis with 100 sensor nodes and all clusters. The resultant graph in Fig 6 is for the normalized energy analysis for 125 sensor nodes and all cluster variation. Similarly, Fig 7 reviews the graphical illustration of normalized energy analysis for 150 sensor nodes and all cluster variations. Here, From Fig 5, (a), it is proven that as the number of rounds increases, the energy level decreases, but the proposed method shows its better performance over other methods in terms of higher energy level even in the final round 2000. The same results are observed from all the graphs shown in Fig 6 and 7.

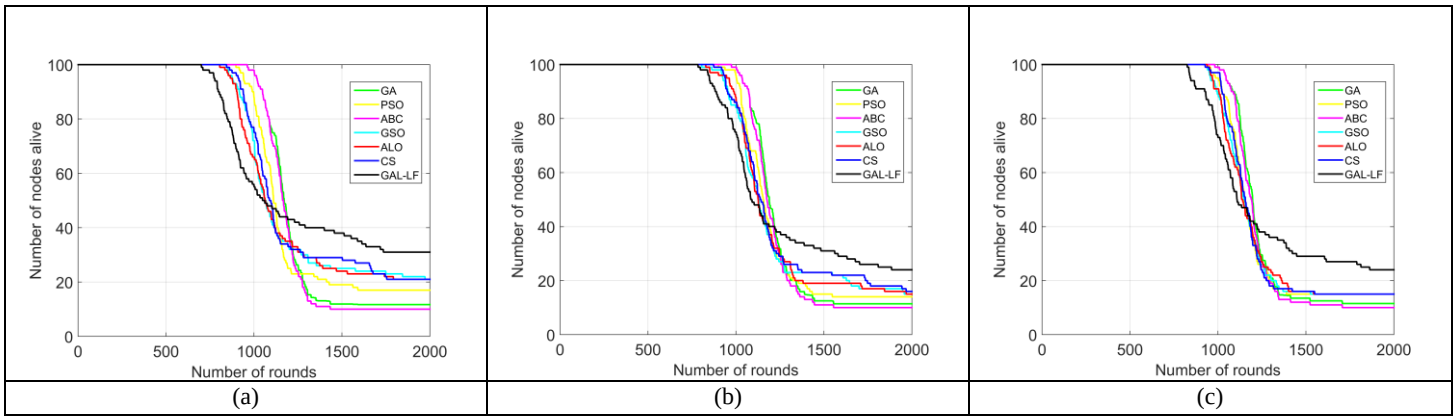


Fig. 2. Alive node analysis by comparing proposed model with conventional methods (a)Sensor node 100 and cluster 10 (b) Sensor node 100 and cluster 15 (c) Sensor node 100 and cluster 20

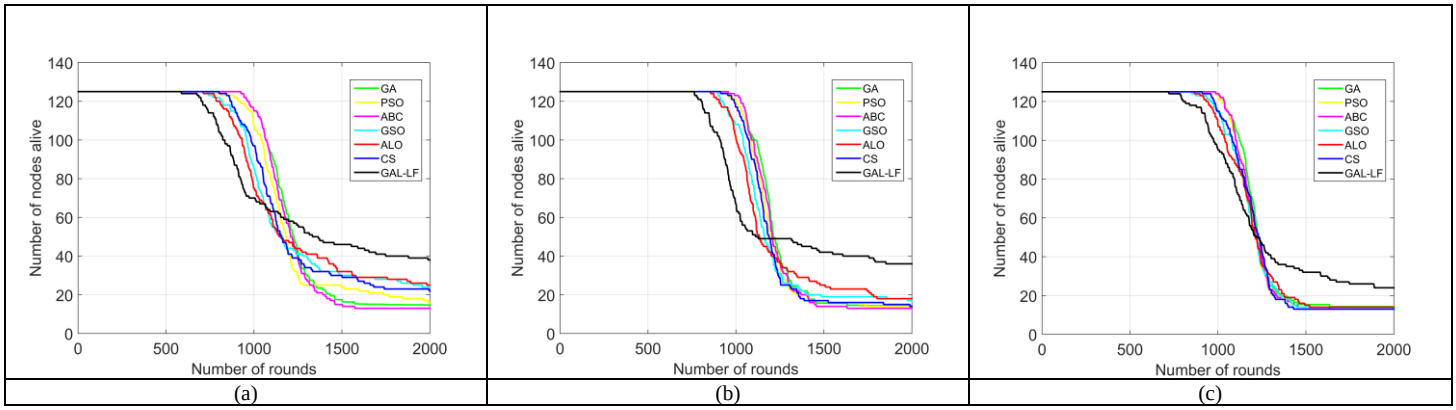


Fig. 3. Alive node analysis by comparing proposed model with conventional methods (a)Sensor node 125and cluster 10 (b) Sensor node 125 and cluster 15 (c) Sensor node 125 and cluster 20

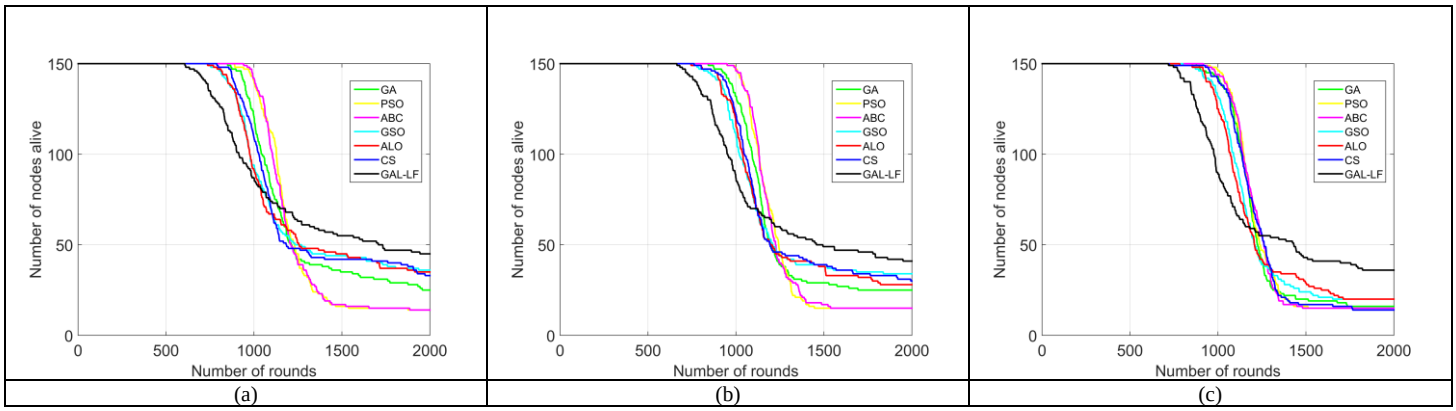


Fig. 4. Alive node analysis by comparing proposed model with conventional methods (a)Sensor node 150 and cluster 10 (b) Sensor node 150 and cluster 15 (c) Sensor node 150 and cluster 20

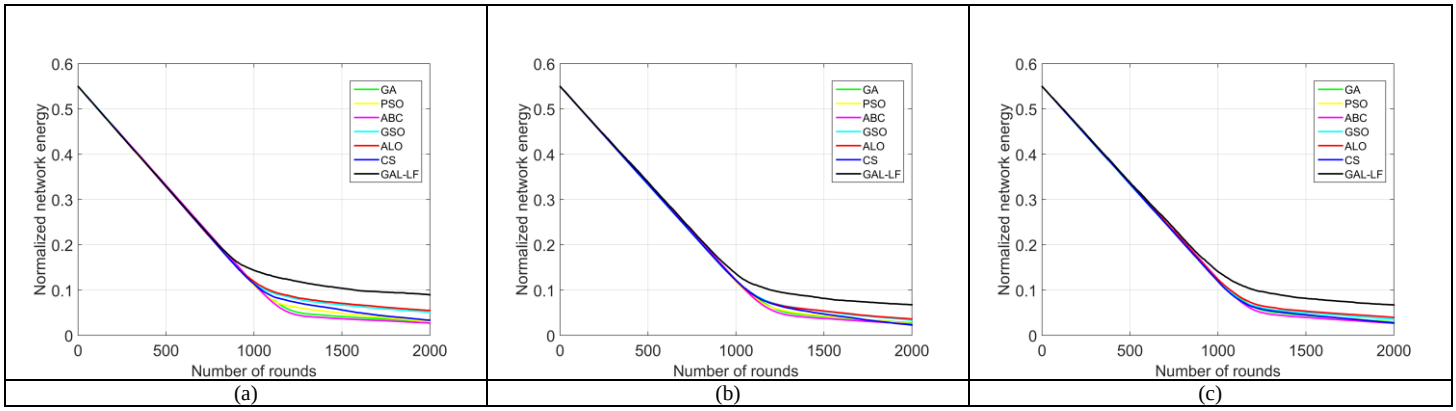


Fig. 5. Normalized energy analysis by comparing proposed model with conventional methods (a)Sensor node 100 and cluster 10 (b) Sensor node 100 and cluster 15 (c) Sensor node 100 and cluster 20

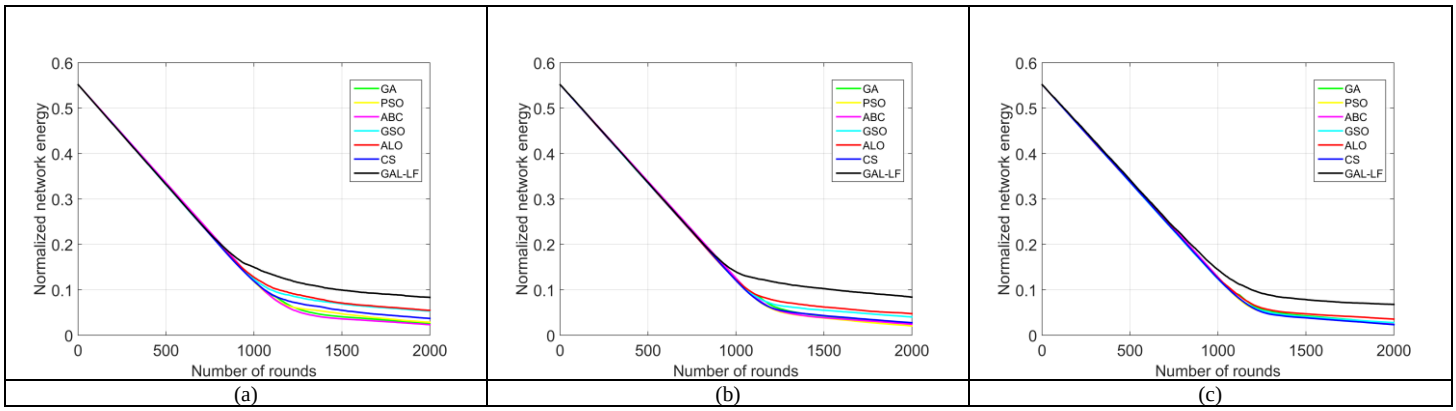


Fig. 6. Normalized energy analysis by comparing proposed model with conventional methods (a)Sensor node 125and cluster 10 (b) Sensor node 125 and cluster 15 (c) Sensor node 125 and cluster 20

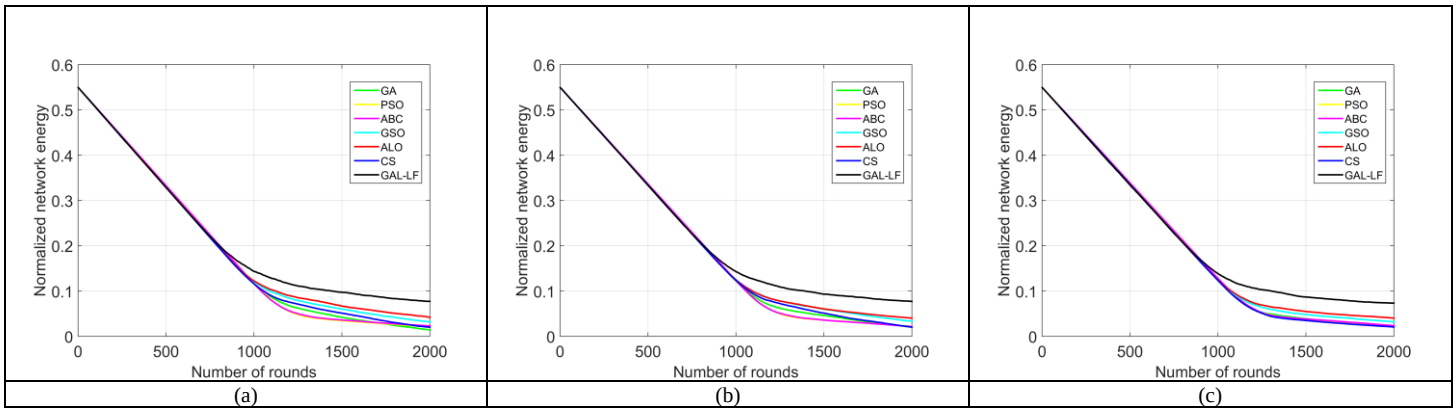


Fig. 7. Normalized energy analysis by comparing proposed model with conventional methods (a)Sensor node 150 and cluster 10 (b) Sensor node 150 and cluster 15 (c) Sensor node 150 and cluster 20

7. Conclusion

This paper has proposed a GAL-LF algorithm for evolving energy aware cluster head selection in WSN network. The simulation of the proposed work was done with the consideration of energy, distance, and delay of the sensor nodes in WSN network. After the simulation work, the performance analysis took place by considering normalized energy and alive nodes of the selected cluster head. The performance of the developed model was compared with conventional GA, PSO, ABC, GSO, ALO and CS-based cluster head selection models, and has proven the superiority.

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