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RESEARCH ARTICLE

A Novel Energy Efficient Cluster Based Routing in Wireless Sensor Network

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Abstract

Objective: Network lifetime of WSN can be extended through assigning nodes with higher energy levels as cluster heads. Cluster heads selection improves the packet transmission rate and conserves energy by reducing re-transmission. The proposed algorithm assigns nodes with high energy as clusters heads and finds optimal path which improves network coverage by avoiding dead nodes. **Methods:** To improve network lifetime and conserve node energy, a novel approach which involves optimum cluster head selection using Firefly algorithm (FF) and Glow Swarm Optimization (GSO) algorithm for routing in WSN (FFGSO) was developed. The cluster head selection is designed to be multi-objective function which meant for not only minimizing the energy consumption but also to minimize the distance and to improve coverage. **Findings:** The proposed model reduces energy consumption to about 16.21% which avoids dead nodes effectively and finds the shortest path to reach sink which eventually improves network coverage and improves the throughput by 9.52%. **Novelty:** To overcome the limitations of dead nodes and to improve the network lifetime, the proposed method introduces cluster head selection as a multi-objective function. To improve energy consumption, network lifetime and network coverage and to overcome the limitations of PSO-GSO, Leach and FF-PSO cluster head selection is designed as multi-objective function. The proposed method improves network stability and network lifetime through reducing energy consumption and finding the shortest path.

Keywords: Wireless Sensor Network; Cluster head selection; Firefly algorithm (FF); Glow Swarm Optimization (GSO); Energy efficient clustering

1 Introduction

WSNs are considered as dynamic ad-hoc networks which are resource constrained and are widely used to sense and collect information. Major challenge in Wireless Sensor Network (WSN) is efficient data transfer which largely depends on the energy resource where nodes with low energy or no energy affect the transmission of data. Nodes with no energy create voids in the network which increases the re-transmission rate and packet drops which consume more energy[1]. The performance of WSN depends on resource management which addresses scalability, reliability, stability and efficiency of the network[2]. Extending the network lifetime and management of resources is established through efficient network topology where the transmission and communication power of the sensors are kept at the maximum[3]. Energy conversation is the key component of resource management in WSN as low or no energy nodes affect the network performance and network stability. Clustering techniques are widely used to organize nodes in the network and manage effectively as clustering avoids dead nodes and improve transmission through nodes with higher energy. Clusters are formed based on the objective and application of the WSN such as energy conservation, path optimization, security and data transmission[4]. Though clustering technique offer many advantages, there are challenges in utilizing clustering technique as Cluster Head (CH) selection is not a single objective criterion to only reduce energy consumption[5]. It should be noted that the performance of a WSN is largely affected with transmission efficiency, routing path and packet delivery rate. Therefore, clustering technique that utilizes CH selection as a multi-objective function can extend the network lifetime and network performance[6].

To improve the network lifetime many clustering techniques are introduced which are heuristic and nature inspired. The network's lifetime can be extended through energy management and clustering techniques which are extensively employed to prolong node death, improve network performance and path optimization. Subha and Anandakumar[7] proposed an improved emperor penguin optimization algorithm for clustering nodes. The main objective of the proposed work is to conserve energy utilization using huddle boundary generation which optimizes the energy and distance while selecting the CHs. The proposed work achieved a throughput of 21.32% and residual energy of 18.74% and the method only considers single objective optimization. Reddy et al.,[8] proposed a hybrid method to reduce the distance between the CHs. Using multi-objective function, the cluster head selection is dealt by integrating Ant Colony Optimization (ACO) with Glow Swarm Optimization (GSO). The hybrid model has the ability to convergence at local optimum. The hybrid model showed higher performance than traditional GSO, ACO and PSO methods but the performance suffers when the iterations increase as the cost function did not converge in global optimum.

Alabady et al.,[9] proposed an enhance routing protocol based on residual energy and distance (EECRED) to conserve energy, delay death of node, and extend network lifetime by selecting CHs based on residual energy and distance. The proposed method extends the network lifetime to 50%, 39.76%, 50%, and 83.64% compared with LEACH, LEACH-C, PC-LEACH, and EMRCR. However, the proposed method did not consider the energy consumption of CHs which are in longer distance during higher number of iterations. Rawat and Chauhan[10] proposed a clustering technique based on PSO using initial energy and residual energy for CH selection. The proposed method improved the network lifetime by 238%, 136%, 106%, and 71% when compared to the existing MDCH-PSO, MCHEOR, MOPSO, and HSA-PSO. The random global search lowers the convergence rate towards optimum solution when there are large numbers of nodes in the network.

Prithi and Sumathi[11] investigated the Particle Swarm Optimization–Grey Wolf Optimizer (PSO-GWO) algorithm to improve network lifetime through route optimization. The cluster head selection is based on MOD-LEACH algorithm and by learning the network dynamics using LD2FA theory, the paths are explored and optimum path is selected. The optimization of routes reduces the transmission counts as the dead nodes are not involved in path selection. The proposed model reduces energy by 13% and 15% than PSO and GA and 57% and 75% increase in network lifetime when compared with GA and LDC. As the paths are explored, updating the path table every time consumes additional energy which affects the network lifetime. Mehta and Saxena[12] studied hierarchical routing protocol with Fuzzy Multi-criteria Clustering and Bio-inspired Energy-efficient Routing (FMCB-ER) to extend the network lifetime. The cluster heads are selected using Fuzzy-AHP & TOPSIS and for optimization of routing Emperor Penguin Optimization method to minimize energy consumption and path selection. The proposed method reduces the energy consumption to 13% and increases the network lifetime to 8%. This work considers coverage as a parameter to reduce the transmission delays and packet loss. Due to random search and poor location update property of penguin search, achieving a balance between exploration and exploitation is tough in this method.

Alghamdi[13] proposed a hybrid algorithm for optimal cluster head selection using Dragonfly and Fire fly algorithms. The position of the Dragon flies is updated which increase the convergence rate of the proposed method. The proposed hybrid model achieved 74.98%, 23.45%, 31.05% and 45.06% better than the FF, GWO, WOA and DA algorithms. However, the energy convergence needs to be improved as the model achieved 50% of convergence only at 2000^{th} round better than GWO and WOA methods. Shahbaz et al.,[14] investigated the multi-path routing in terms of energy consumption, packet loss rate, and network lifetime using clustering method. The proposed method involves clustering phase using Firefly algorithm, path selection phase for route discovery phase using fuzzy logic. Energy consumption decreased by 14.06%, 45.4%, and 26.21% compared with EMEER, LEACH, and TEEN methods. The path selection and route discovery requires GPS which increase the cost of implementation to real world problems. Also, route discovery is initiated only when the path selection gets breaks which consume additional energy to initiate the CH selection. Pitchaimanickam and Murugaboopathi[15] proposed a hybrid method to select optimal clusters. The hybrid method involves Firefly algorithm and PSO, where the global candidate search

Firefly algorithm is improved using PSO search. The hybrid model reduces the energy consumption through optimal selection of CHs and also extends the network lifetime through increasing the number of alive nodes.

1.1 Motivation of the study

Many swarm intelligence algorithms are introduced to determine the optimal solution to reduce energy consumption and to increase the lifetime of the network[8,10,11]. The previous works suggested that an effective optimization technique is required to improve exploration and exploitation in the global and local space. Reduced energy utilization and improving network lifetime depends on the choice of clustering and routing method. PSO based clustering tend to suffer from premature convergence and require high parameter tuning such as optimal velocity which affect the convergence rate. The PSO exploration does not guarantee good results for high dimensional problems. In Leach the CHs are randomly chosen and the probability of a node to become a CH is high. Leach CHs are selected with high cluster members varying in each round and this property does not guarantee uniform energy consumption. Firefly algorithm has the ability to explore globally through attractiveness and also reach local solutions through light intensity which regroups the entire population and achieve high exploration rate. GSO is efficient in updating its decision range locally and have high convergence rate.

With the motivation by the aforementioned, the present work proposes a novel energy efficient clustering and routing method to improve the network lifetime and reduce energy consumption. The development of the proposed work considers the opportunity of overcoming the limitations of poor balance between exploration and exploitation, premature convergence, high parameter tuning, uneven energy consumption and long distance path to sink. The present work also provides a literature survey of several clustering and optimization methods used to improve network lifetime. The proposed approach is capable of bringing down energy consumption, minimizing distance and reducing transmission delay which improves the network lifetime and coverage. The proposed clustering method with adjusted step size routing achieved low energy consumption, high throughput and extends network coverage when compared with PSO-GSO, Leach and FF-PSO methods.

1.2 Major contribution of the paper

This work developed a clustering and routing method to reduce energy consumption and improve network lifetime using Firefly algorithm and Glow Swarm Optimization algorithm. The optimal cluster head is selected through clustering of network nodes using Firefly algorithm. The clustering algorithm selects the optimal CH using different parameters such as energy, distance to its neighbors and attractiveness. The proposed method finds the optimal route to the destination through GSO technique. Using the fitness function of Glow Worms (GW), a routing mechanism is derived between CHs using distance, signal strength, number of nodes and residual energy. To improve the coverage rate in the transmission, the proposed method introduces step size constraint which also balances the hop count to the destination. The adjusted step wise routing using GSO algorithm selects the optimal path which reduces energy consumption; minimize distance to sink and reduce transmission delays which improves the overall network coverage and stability of WSN. The simulation results show that the proposed method achieved higher performance over PSO-GSO, Leach and FF-PSO methods.

2 Methodology

A WSN consists of large number of stationary nodes N_n(transmitter) distributed randomly and a base station (receiver) separated by distance d. Each sensor node is equipped with battery which supplies energy (E) to perform tasks such as sensing, aggregation and transmission. Nodes can communicate each other if the nodes are in the transmission range. Every node in the network has a uniform energy level and the transmission power is determined by the distance d between the communicating nodes. The base station Bs can directly communicate with all sensors in the network. A node can act as a sensor node (data collection) and as a transmitter. To reduce the distance and conserve energy over transmission, clustering based routing methods are introduced. Clustering selects cluster head (CH) with maximum energy to send the data to the Bs. A node to be selected as CH should satisfy objectives such as energy, distance and transmission delay such that the energy level of the nodes is conserved to extend the network lifetime. Also, the nodes with higher energy levels are considered for the CH selection than nodes with less energy level. The total energy required to transmit message is given by,

$$E_t\left(K:d\right) = \begin{cases} E_e * K + E_{fs} * K * d^2,\ if d < d_0 \\ E_e * K + E_{pw} * K * d^2,\ if d \geq d_0 \end{cases} \quad (1)$$

Where E_t(K:d) is the total energy expenditure to transfer K bits over distance d, $E_e$is the electronic consumption, E_{fs}, E_{pw}*are the* electronic consumption for different channel models, d_0 is the threshold distance which is calculated by

Table 1. Comparison of previous works

Year	Authors	Algorithm	Objective	Clustering method	Optimization	Outcome
2022	Subha R, Anandakumar	Improved Emperor Penguin Optimization Algorithm-based Clustering Protocol (IEPOACP)	reduce energy consumption, increase network life time	Improved Emperor Penguin Optimization Algorithm		reduces energy by 18.74%, throughput improves to 21.32%
2021	D. Laxma Reddy, Puttamadappa C, H.N. Suresh	ACI-GSO	distance, delay, and energy	Hybrid optimization algorithm	Glowworm Swarm Optimization (GSO)	Energy reduced to 4.37%, 2.26%, and 2.42% better than GSO, ACO, and PSO
2021	Salah Abdulghani Alabady and Sukaina Shukur Alhajji	enhance energy conservation based on residual energy and distance (EECRED)	prolong network lifetime, reduce energy consumption, delay death nodes		EMRCR	improved network lifetime to 83.64% than LEACH-C 39.76%
2021	Piyush Rawat and Siddhartha Chauhan	a particle swarm optimization-based energy efficient clustering protocol (PSO-EEC)	enhance the network lifetime and performance	PSO		improved network lifetime by 238%, 136%, 106%, and 71% as compared to the existing MDCH-PSO, MCHEOR, MOPSO, and HSA-PSO
2021	S. Prithi1 and S. Sumathi	hybrid Particle Swarm Optimization–Grey Wolf Optimizer (PSO–GWO)	reduce energy consumption, increase network life time	MOD-LEACH	PSO-GWO	energy is reduced by 13% and 15% than PSO and GA and an increase of 15% utilization of energy than LDC. 57% and 75%increase in network lifetime when compared with GA and LDC
2020	Deepak Mehta and Sharad Saxena	Fuzzy Multi-criteria Clustering and Bio-inspired Energy-efficient Routing (FMCB-ER)	less energy consumption & increase network life time	Fuzzy-AHP and TOPSIS	Emperor Penguin Optimization (EPO)	reduces the energy consumption to 13% and increases the network lifetime up to 8%
2020	Turki Ali Alghamdi	hybrid Dragonfly Alorithm and Firefly algorithm (FPU-DA)	alive node analysis, normalized network energy, delay analysis	Dragonfly Algorithm	Firefly algorithm	45.95%,18.92%, 24.32% and 24.32% better than the FF,GWO,WOA and DA algorithms for alive nodes, 50% better than the GWO and WOA algorithms
2020	Amir Nader Shahbaz, Hamid Barati, Ali Barati		reduce energy consumption, increase network life time	Firefly	Fuzzy systems	energy consumption decreased by 14.06%, 45.4%, and 26.21% compared with EMEER, LEACH, and TEEN
2019	Pitchaimanickam, B., Murugaboopathi,	Hybrid approach of Firefly Algorithm with Particle Swarm Optimization (HFAPSO)	less energy consumption & increase network life time	LEACH-C	HFAPSO	reduced energy consumption and improve network lifetime

$d_0 = \sqrt{\frac{E_{fs}}{E_{pw}}}$ and the total energy required to receive K bits is given by,

$$E_t\left(K:d\right) = E_e * K \tag{2}$$

The total energy consumption for integrating T data packets of K bits is given by $E_i\left(K:d\right) = T*K*E_t$ and E_t is the energy consumption for 1 bit data.

2.1 Cluster head selection using Firefly Algorithm

Firefly algorithm is inspired from luminescence activity of firefly which aims to solve the optimization of a given fitness function through finding the best position. The firefly algorithm [16] is based on swarm intelligence where fireflies are attracted to each other's brightness. The flies with low brightness are attracted towards brighter flies and the attraction becomes less for flies with larger distance. Hence, the brightness of the solution is defined by the objective function where the brightness falls with increase in objective function and the brightness increases with decrease in objective function. The brightness b of a firefly at a given point p can be expressed as b(p) α f(p) where f(p) is the objective function of a solution and b(p) is the attractiveness of a solution.

$$b(p) = \begin{cases} \dfrac{1}{f(p)},\; iff(p) > 0 \\ 1+f(p),\; otherwise \end{cases} \tag{3}$$

The attractiveness of a solution decreases for larger distance and is given by Equation (4) and b(r) represents the brightness for a given distance r and b_0 is the brightness of the solution. The absorption of brightness is given by γ.

$$b\left(r\right) = \frac{b_0}{1+\gamma r^2} \tag{4}$$

The Gaussian form of absorption of brightness can be derived as

$$b\left(r\right) = b_0 e^{-\gamma r^2} \tag{5}$$

Also, the distance as the main factor that determines the attractiveness of a solution and the distance vary for better solution. The varying distance r_{xy} for two solutions p_x and p_y is given by Equation (6). β_0 represents the attractiveness of a solution at r=0 (zero distance).

$$\beta\left(r\right) = \beta_0 e^{-\gamma r^2} \tag{6}$$

The distance between two fireflies can be calculated using the Euclidian distance, where d is the problem parameter. The parameter settings for a given problems d takes β_0 =1 and α € [0, 1], the variation of attraction corresponding to speed of convergence γ is from 0.01 to 100.

$$r_{ij} = \left\|x_i - x_j\right\| = \sqrt{\sum^d{}_{n=1}\left(x_{i,n} - x_{jn}\right)^2} \tag{7}$$

Pseudo code for Firefly algorithm

```
Initialize the population of solutions x_i (i=1,2,3,…n)
Brightness b_i at point p_i is f(p)
Define absorption of brightness γ
Define iteration numbers Itn
While Term < Itn do
  For i =1 to n, do
    For j = 1 to i do
      if b_j< b_i, then
        Move solution b_j towards b_i,
  Evaluate new solution and replace with best solution, update brightness γ
      End if
    End for j
  End for i
  Rank firefly and find the current best
End while
```

2.2 Routing with Glowworm swarm optimization (GSO)

GSO was developed by Krishnanand and Ghose[17] inspired from swarm behavior of Glowworm. Glowworm exhibit luminescence property called luciferin and worms with high luciferin are attracted by the worms with less luciferin. A glow worm usually moves from its local space towards brighter worms and has low luciferin. A glow worm with higher luciferin attracts its neighbors and each glowworm has its own decision space and the decision space is used to make decisions whether to move to another decision space or to stay. Attracting with high luciferins or moving to neighbors helps GW to make firm groups at different positions in the space. Using the group positions, the objective position of finding optimal solutions is derived using the GW position and the level of luciferin levels. The initialization of GW and its movement is marked by three phases namely, luciferin update, movement and neighborhood range update. Each GW (W_i) in the space exhibits different levels of luciferin L_i that needs to be updated. The objective function f for a particular position P_i at particular time T_i is given by f (P_i * T_i) and the luciferin update is given in equation 8, where α corresponds to luciferin decay $0 < \alpha < 1$ and β symbolizes luciferin enhancement.

$$L_i(T_i) = (1-\alpha)\, L_i\,(T_i - 1) + \beta\, f\,(P_i * T_i) \tag{8}$$

The probability of a GW moving from towards its neighbor should satisfy two conditions, i.e. a GW should fall within the decision space and the luciferin level should be higher. The probability of a GW moving (Pm) at T_i is given by the equation 9.

$$Pm\; Ti = \frac{Wx\; Ti - w_y Ti}{\sum_{N_{Ti}} Wx\; Ti - w_y Ti} \tag{9}$$

The position of GW (W_i) is updated using new updated position (P_j) for a particular amount of steps (st) using Equation (10).

$$PositionWi(Ti) + st * \left(\frac{PW_x\; Ti - Pw_y\; Ti}{\|PW_x\; Ti - Pw_y\; Ti\|}\right) \tag{10}$$

The decision range dr for localization is adjusted through Equation (11), where N^x is a parameter to adjust neighbors, δ is the constant parameters and Ne is the control parameter to control the number of neighbors.

$$(dri(Ti+1) = min\,(Pm, max\,(0, dri\,(Ti) + \delta(Ne - (N^x\,(Ti)|)\}\} \tag{11}$$

2.3 Proposed Firefly-Glowworm Swarm Optimization (FFGSO)

The effective routing of data through depends on the number of hop counts between CHs and the sink. For optimal path, when the distance to the sink i.e., the hop count is minimal the transmission delays are avoided. Also if the hop count is too minimal the rate of coverage becomes weak and to improve the coverage rate and to balance the hop count, the steps required to reach sink is formulated using the Equation (12), where A is the arbitrary number for a normal distribution, e is the constant, xi (st) is the number of steps required, Itn is the number of iterations and xb is position of the glowworm at n^{th} round. With adjusted step size of proposed GSO routing removes redundancy in traditional GSO and also improves the coverage rate.

$$st = A(st).(len(e - \frac{st}{Itn}))\; \|xi(st) - xb(st)\| \tag{12}$$

Using the fitness function of GW, a routing mechanism is derived between CHs using distance, signal strength, number of nodes and residual energy. During each round the energy is depleted after transmission and might cause transmission failure, to avoid this, the fitness function for high transmission is given by the equation, where e constitutes the residual energy, d is the distance between the CHs, Cn is the number of nodes present in the cluster and Sst is the signal strength.

$$F(t) = e + d + Cn + Sst \tag{13}$$

For effective transmission, finding nodes that have poor or zero energy is vital. Finding the zero energy nodes Eo is given in Equation (14) where e_{req} is the required energy level of a node to participate in transmission and Eo is the dead node.

$$P(Eo) = [|e_1 > e_{req})|,\; |e_2 > e_{req})| \ldots |e_n > e_{req})|] \tag{14}$$

The fitness function for finding zero energy nodes is given by f(Eo) and the fitness value is calculated and the routing is achieved using the fitness function in Equation (13) if the fitness value is 1.

$$f(Eo)f(Eo) = \begin{cases} inf & P_{Eo} == 0 \\ f & P_{Eo} == 1 \end{cases} \tag{15}$$

3 Result and discussion

The proposed cluster head selection strategy of FFGSO is evaluated on NS2. The simulation parameters were given in Table 2 and the experiments were conducted with varying rounds of 50 and 100. The performance of the network is interpreted through alive nodes, dead nodes, energy consumption and throughput vs number of rounds. The transmission range was kept at 150 m, initial node energy was 5J, packet size of 4000 bits with message size of 200 bits. The performance of the proposed approach is compared with other methods such as FF-PSO, Leach and PSO-GSO. The GSO routing parameters are given in Table 3.

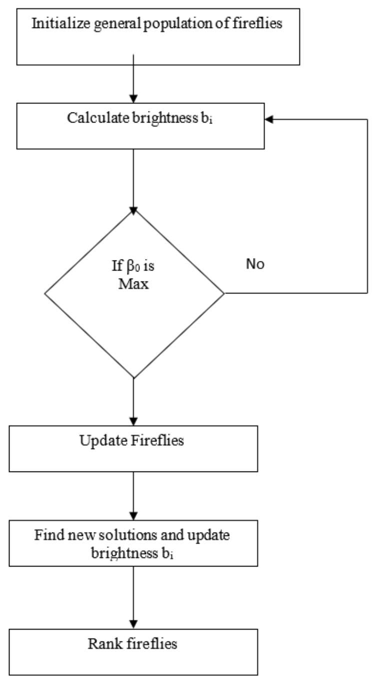

Fig 1. Cluster head selection using Firefly algorithm

Table 2. Simulation Parameters

Parameter	Value
Area (X,Y)	250 * 250 m^2
SN range	250 * 250 m^2
Transmission range	150 m
Node energy	5 J
Packet size	4000 bits
Message size	200 bits
Number of iterations	100
Number of nodes	100

Table 3. GSO Parameters

GSO Parameter	Value
No of nodes	100
Sensing field	250 * 250
Communication radius	15
Sensing Radius	8
Initial luciferins	12

The proposed FFGSO algorithm is simulated using the parameter setting given in Table 1. The simulation is performed for alive nodes, dead nodes, energy and throughput. The performance of the proposed FFGSO is compared with FF-PSO, Leach and PSO-GSO. Figure 2 and Figure 3 shows the number of alive nodes and dead nodes with progressive number of rounds. The number of alive nodes increases with the increase in number of rounds for the proposed method, at 50^{th} round the number of alive node for the proposed FFGSO, PSO-GSO, Leach and FF-PSO is 76 (23%), 56 (445%), 55 (45%) and 66 (34%) which is greater than Reddy et al.,[8]. The number of alive nodes sustained at 100^{th} round for FFGSO, PSO-GSO, Leach and FF-PSO is 33, 19, 21 and 26. Also, at the 50^{th} round the number of dead nodes for the proposed method is 28 while PSO-GSO, Leach and FF-PSO have 35, 38 and 32 dead nodes. At 100^{th} round leach and FF-PSO have 95 and 97 dead nodes while FFGSO and PSO-GSO have 80 and 81 dead nodes. At the end of 100^{th} round, proposed method have 20 alive nodes while other methods have less than 20 alive nodes showcasing that the proposed method FFGSO prolongs the network lifetime than PSO-GSO, FF-PSO and LEACH from Pitchaimanickam and Murugaboopathi[15]. The proposed method reduces dead node to about 20% over other. The CH aggregates the data and forwards it to sink and at each round, the energy in nodes gets depleted quickly and dies soon whereas CH are selected based on the residual energy at each round of transmission extending the network lifetime. The presence of alive nodes increases the packet transmission rate of FFGSO as the proposed technique carefully avoids the dead nodes in the network which eliminate the energy waste on exploration and CH selection.

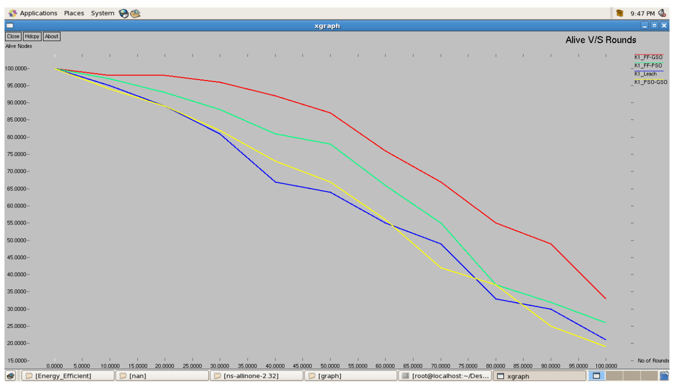

Fig 2. Alive nodes vs No of rounds

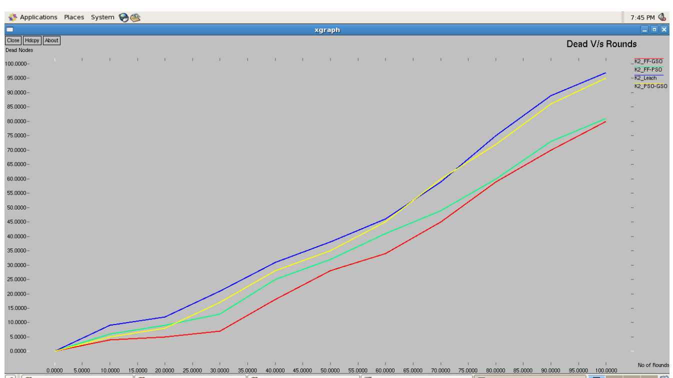

Fig 3. Dead nodes vs No of rounds

Figure 4 shows the energy consumption rate for FFGSO is less compared to PSO-GSO, leach and FF-PSO. Thus, the proposed algorithm demonstrated the superiority of consuming less energy over PSO-GSO, leach and FF-PSO and the energy residuals after 100^{th} round is 16.21% for FFGSO, 15.21% for PSO-GSO, 15.21% for leach and 1.18% for FF-PSO surpasses Shahbaz et al.,[14] EMEER method and Mehta and Saxena[12] FMCB-ER. The energy consumption is reduced as a result of CH selection through clustering which is higher than the Reddy et al.,[8] ACI-GSO method & Prithi and Sumathi[11] PSO-GWO method. The CH enable the shortest path to reach the sink by reducing the distance to sink and avoids dead nodes which reduces the energy consumption for each round. The experiment results show that the proposed FFGSO reduces energy consumption through efficient routing over shortest path and increase the number of alive nodes and decrease number of dead nodes which eventually improve the network stability. Once the network stability improves, the transmission of data packet also increases which improve the network throughput (Figure 5). The throughput for FFGSO at 50^{th} round is 90, 87 for PSO-GSO, 74 for Leach and 81 for FF-PSO and at 100^{th} round the throughput improves to 99, 95, 92 and 94 which eventually improve the throughput by 9.52% for the proposed model compared to Mehta and Saxena [12] FMCB-ER method. Based on the simulation results, the proposed FFGSO clustering technique demonstrated higher performance with energy efficient routing.

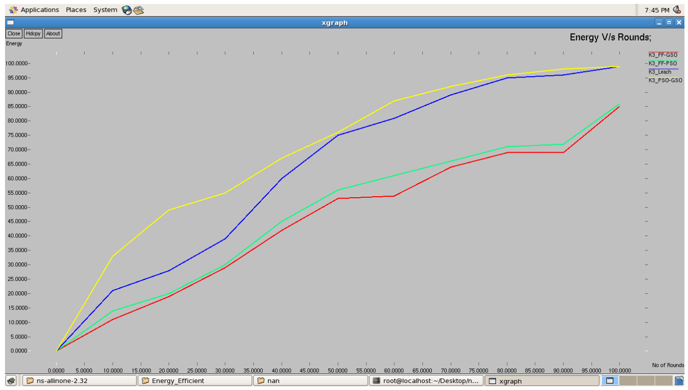

Fig 4. Energy vs No of rounds

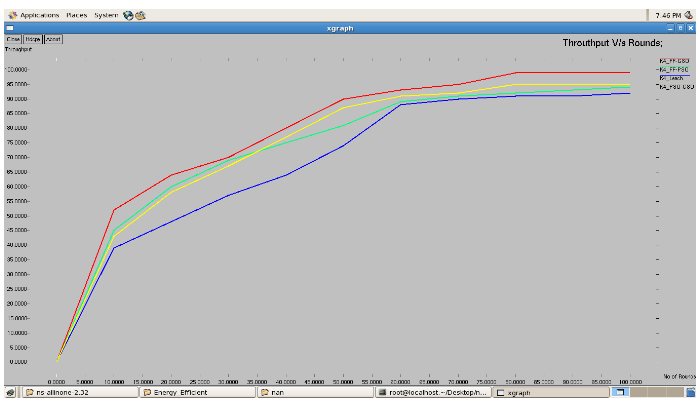

Fig 5. Throughput vs No of rounds

4 Conclusion

The proposed FFGSO technique use FF for cluster head selection and modified GSO for routing. The FF algorithm clusters the network nodes with respect to residual energy, distance and transmission range. These parameters are used to derive multi-objective function using FFGSO algorithm to find optimum cluster head and optimum paths to the CHs that route to sink. With adjusted step size of modified GSO routing removes redundancy in traditional GSO and improved the coverage rate minimizing the energy and maximizing the network lifetime to about 9.52%. The performance of the proposed FFGSO technique is compared with PSO-GSO, Leach and FF-PSO for alive nodes, dead nodes, energy consumption and throughput with number of rounds. The simulation results show that the proposed method achieved higher performance over PSO-GSO, Leach and FF-PSO method. Energy residuals after 100^{th} round remained 16.21% for FFGSO, 15.21% for PSO-GSO, 15.21% for leach and 1.18% for FF-PSO. In the future, data aggregation, stability and security of the proposed model will be studied and state-of-art geographic routing techniques will be compared with the present model.

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