An Adaptive Genetic Co-relation Node Optimization Routing for Wireless Sensor Network

Nandoori Srikanth and Muktyala Siva Ganga Prasad

Abstract Wireless sensor network is designed with low energy, and limited data rates. In wireless sensor networks, the sensors are designed with limited energy rates and bandwidth rates. Maximizing the network lifetime is a key aspect in traditional Wireless communication to maximize the data rate in typical environments. The clustering is an effective topology control approach to organize efficient communication in traditional sensor network models. However, the hierarchical-based clustering approach consumes more energy rates for large-scale networks for data distribution and data gathering process, the selection of efficient cluster and cluster heads (CH) play an import role to achieve the goal. In this paper, we proposed an Adaptive Genetic Co-relation Node Optimization for selecting an optimal number of clusters with cluster heads based on the node status or fitness level. Using the tradition Genetic Algorithm, we achieved the Cluster head selection and the co-relation approach identifies the optimal clusters heads in a network for data distribution. Cluster head election is an important parameter, which leads to energy minimization, and it is implemented by Genetic Algorithm. Appropriate GAs operators such as reproduction, crossover and mutation are developed and tested.

Keywords WSN · GA · Adaptive genetic co-relation node optimization

1 Introduction

Wireless sensor network (WSN) is a self-organized network system with low amount of resources and constitutes of tiny sensors communicate to a remote base station [1]. Nowadays, WSNs are widely used as an effective communication interface medium to interact with physical world to exchange global information. In addition, WSN

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consist of spatially distributed autonomous sensors to cooperatively monitor physical or environmental conditions. Broadcasting across autonomous sensors produces more communication issues due to the lack of resources such as energy, bandwidth, and memory. The recent advances in the microelectromechanicalsystems (MEMS) Technology produced low-cost sensors, as a result, WSNs have paid more attention to different industrial applications [2].

For past few years, an intensive research was conducted to address the problems during data gathering and processing among group of sensors and to address the potential of collaboration among sensors. However, sensor nodes are constrained nodes and organizing large amount of communication services is a problem due to the lack of energy resources and bandwidth. However, the sensors are powered by low-cost irreplaceable batteries which makes for an interesting research to design a new energy-efficient protocol in an unattended hostile environment. Cluster-based protocols are one of the well-accepted protocols and organized the sensors effectively in the network [3]. In this clustering process, the network is divided into different zones, each zone represent as a cluster, each cluster consists of set of sensor nodes and cluster head (CH), the set of sensor nodes are represented as cluster member, the cluster members in each cluster exchange a data with cluster head (CH). The CH distributes the collected data to corresponding destination point. The overall data gathering and data distribution process needs more attention to improve the data distribution rate in typical environments. In order to organize an effective or efficient communication services, there were various cluster-based routing models were designed, i.e. LEACH [4], PEGASIS [5], TEEN [6], and APTEEN [7]. The main limitations of these protocols have identifying optimal clusters and optimal cluster heads (CH) for large scale network due to the exponential variation computational complexity. However the energy-efficient based and topology-based routing protocols address the node fitness issues, an inappropriate cluster and CH selection process increases communication overhead.

We introduce an Adaptive Genetic Co-relation Node Optimization for identifying an optimal cluster and optimal cluster head (CH). The adaptive energy rate allocation scheme identifies the optimal energy of each node, and the optimal nodes are assigned to genetic algorithm to identify the node co-relation. The genetic algorithm computes the node fitness and clustering fitness based on the node characteristics such as energy, distance to sink node, density, and fairness in different stages which is described in Sect. 4. The Genetic Co-relation Node Optimization Routing (GCNO) approach optimize the optimal routing based on the node fitness and fairness level in each cluster and corresponding cluster heads (CHs).

1.1 Contributions of the Paper

The following contribution were designed in this paper:

- We design a cluster-based wireless sensor network model by employing traditional adaptive energy rate allocation scheme.
- Discover an optimal clusters and cluster heads using Adaptive Genetic Co-relation Node Optimization scheme.
- Design a Genetic Co-relation Node Optimization Routing (GCNO) protocol for processing optimal routing.

The paper organizes the following sections, the Sect. 2 describes of related work, which describes the research gaps of various cluster-based routing protocols, Sect. 3 describes the network model and adaptive energy rate model. The Sect. 4 presents the genetic algorithm for optimization of clusters and cluster heads. Section 5 presents the Genetic Co-relation Node Optimization Routing protocol for route optimization. Section 6 presents the experimental student and result discussion (Fig. 1).

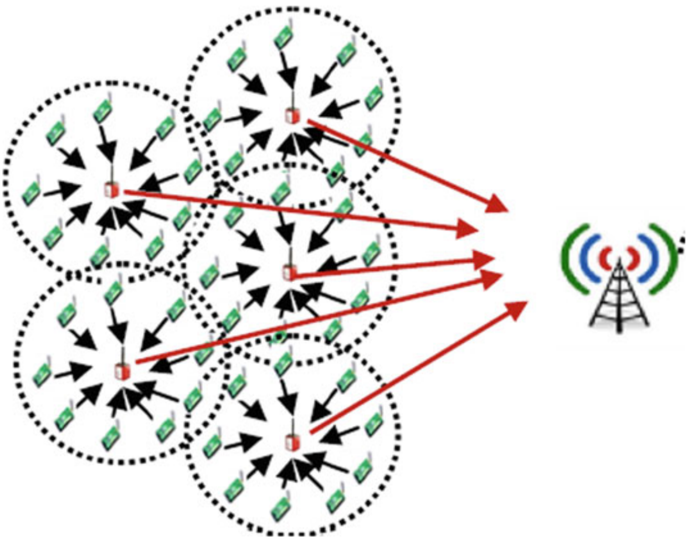

Fig. 1 Cluster-based WSN

2 Related Work

Author	Title	Research methodology	Research gap analysis
Sai Wang, Thu L. N. Nguyen, and Yoan Shin, Senior Member, IEEE (2018) [8]	Energy-Efficient Clustering Algorithm for Magnetic Induction-Based Underwater Wireless Sensor Networks	This paper presents the clustering techniques for MI-based UWSNs. The sensor nodes are configured with the Poisson distribution. To obtain a clustering rules by controlling the energy consumption, based upon the idea of the conventional HENPC (High energy node priority clustering) The proposed method is a dynamic protocol that is CH (cluster head) selection depends upon the remaining energy. From the side of saving energy, multi-hop data and nodes with high remaining energy preferred to be selected as CH(cluster head)s, can efficiently maintain the energy consumption for whole network	The clustering process is based on energy model, which is a tedious process, every time node energy state get varies which impacts on organizing clusters and increases network lifetime
Yi Zhou, Shubbhi Taneja, Chaowei Zhang, Xiao Qin, Senior Member, IEEE (2018) [9]	GreenDB: Energy-Efficient Prefetching and Caching in Database Clusters	This paper described about a parallel database system called Green DB, which is a energy-efficient system for clusters. The main feature of Green DB is a caching mechanism, which receives node or route information from passive nodes into active nodes. Green DB organizes an information table to maintain the nodes state information. This protocol designs a congestion-free route model to save energy and provides optimal route	Here the major limitation is, for construction of route data information by considering transnational database systems. This data saving process frequently needs to get update to maintain the node state. If any node state information wrong which impacts on overall network route

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Author	Title	Research methodology	Research gap analysis
Amjed Mahamood (Feb 2017) [10]	ELDC: An Artificial Neural Network-based Energy-Efficient and Robust Routing Scheme for Pollution Monitoring in WSNs	Amjed et al. proposed a group based protocol based on the dynamic cluster process. The evaluation of dynamic cluster formation based on the network condition improves the node selection and route rote selection. To minimize the energy consumption of the network this mechanism takes the consideration of EEUC (energy-efficient unequal clustering). This process assigns border group ahead to distribute the group data to the other group users	The dynamic cluster formation consumes more energy for organizing group-based communication
Sudeep Tanvar, Sudanshu Thyagi (2018) [11]	LA-MHR: Learning Automata Based Multi-level Heterogeneous Routing for Opportunistic Shared Spectrum Access to Enhance Lifetime of WS	The LA-based multihop heterogeneous routing improves the sensing node stability by validating the sensing field. The cluster head selection process evaluated based on the spectrum data and based on the SLA. The BS allocates a spectrum to the selected CH. The spectrum allocation rate estimated based on the distance of Base Station to the CH distance rate	The major limitation here is a multi-level process which takes more travelling cost
Xi Tao and Wei Song, Senior Member, IEEE (2018) [12]	Location-Dependent Task Allocation for Mobile Crowd sensing with Clustering Effect	This paper discovers resource allocation problem from two different features. The first process focuses on data distribution and designs a genetic algorithm (GA) to maximize data distribution quality. Then, the next process considers the profit of nodes into account and proposes a detective algorithm (DA) to improve the profit	Major problem is resource allocation due to the lack of node cooperative communication problem

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Author	Title	Research methodology	Research gap analysis
Tung-Wei Kuo, Kate Ching-Ju Lin, and Ming-Jer Tsai [13]	On the Construction of Data Aggregation Tree with Minimum Energy Cost in Wireless Sensor Networks: NP-Completeness and Approximation Algorithms	This paper presents the problem of data aggregation problem. This problem was overcome with relay node NP-complete. Using NP-complete formation the approximate route formation will be estimated and process the data aggregation	This paper resolves the data aggregation construction process by using NP-Completeness. But this process needs more computation resources and requires more energy
Mohammed Mohsen Mohammed Nasr, Abdeldime Mohamed Salih and Lian-Feng Shen (2016) [14]	Analytical Exploration of Energy SavingsforParked Vehicles to Enhance VANET Connectivity	This paper focuses on energy-saving process of VANET model by considering the relay node energy state and by discovering the optimal energy harvested relay nodes. In this process, first, the relay nodes and forwarder nodes are elected based on the energy and distance rate values and identifies the current load of relay nodes it distributes the resources and workload	If more number of vehicle increase more number of relay and forward nodes required
Andrei Horvat MaLevente, Fuksz Petrică C. Pop and Daniela Dănciulescu (2015) [15]	A Novel Hybrid Algorithm for Solving the Clustered Vehicle Routing Problem	This paper designs a hybrid route optimization method based on the genetic algorithm to resolve the clustering and routing process problem. The protocol determines an NP-hard combinatorial optimization problem that generalizes the classical vehicle routing problem (VRP) and generalized vehicle routing problem (GVRP)	The hybrid novel approach overcomes the routing problem but failure to achieve network lifetime

3 Network Modelling

We considered a set of sensor nodes with different states such as handoff state and forwarding state. All the sensor nodes are distributed through the network and can initiate communicate any arbitrary directions with the minimum energy rate of λ_{E_i} and handoff rate λ_{o_i}. The initial sensing, transmission and receiving rate defined as $\left\{\lambda_{E_s}, \lambda_{E_{tx}}, \lambda_{E_{rx}}\right\}$. Initial communication service rate defined as μ_i. The network is divided into a set of clusters $\{C_i\}$, each cluster organizes the set of sensor nodes with initial communication rates. The following equation organizes set of clusters for set of nodes and with their corresponding communication states.

$$C_i = \frac{\left| n \log_{10} N \right|}{\mu} \tag{1}$$

where C_i represents a set of clusters in a network, n is set of nodes and N is a total network area

Each node state in each cluster varied with respective of energy rates and communication rates, we adopt Hidden Markov model (HMM) to analyse each sensor state by estimating each node energy rate λ_{E_n} and communication propagation rate μ_{n_i}. In this HMM mode, each sensor node states is represented as $s_i = \{n_s,\ n_{tx},\ n_{cs},\ n_{idle}\}$, the node state will transfer from one state to another statue in cluster state and following model represents the transition model to determine and analyse the sensor node state level.

The following definitions are determined to analyse the sensor node state.

Definition 1: Busy state To determine the node busy state $P(n_b)$, we estimate the node busy state probability by considering average difference rate of node communication arrival rate λ_o and handoff rate λ_H.

Definition 2: Transmission state The transmission state of sensor node $p(n_{tx})$ derived based on the estimation of current node communication range rate μ and average distance rate μ_d.

Definition 3: Handoff state The sensor node handoff state probability determines the probability node current energy rate λ_{E_n} and communication distance rate μ_d of current sensor node.

The symmetric equation for node state $\{s_i\}$ is derived as

$$\sum_{i=0}^{s} P(s_i) = \frac{\lambda_O + \lambda_H}{i\mu} P(i-1), \quad 0 \le i \le S. \tag{2}$$

The average rate of all nodes states must be equal to one:

$$\sum_{i=0}^{S} P(s_i) = 1. \tag{3}$$

The communication blocking probability B_O when all S sensor nodes are busy, which it can be derived as

$$B_O = P(S) = \frac{\frac{(\lambda_O + \lambda_H)^S}{S!\mu^S}}{\sum_{i=0}^{S} \frac{(\lambda_O + \lambda_H)^i}{i!\mu^i}} \tag{4}$$

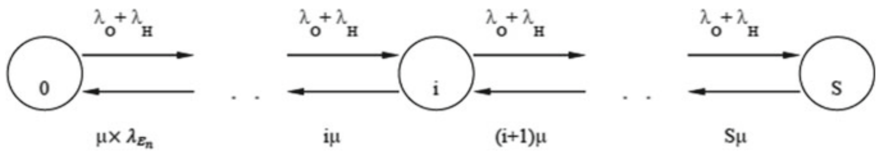


Fig. 2 Node state transition model

The node balance state equations derived as

$$\begin{cases} i\mu P(i) = (\lambda_O + \lambda_H)P(i-1), 0 \le i \le S_C \\ i\mu P(i) = \lambda_H P(i-1), \mathrm{S}_C \le i \le S \end{cases}. \tag{5}$$

The average rate of the overall state is

$$\sum_{i=0}^{S} \boldsymbol{P(i) = 1}. \tag{6}$$

The blocking probability $P(B_o)$ for organizing communication is derived as (when a set of senor nodes S_c are busy state):

$$P(B_o) = \sum_{i=S_C}^{S} P(i). \tag{7}$$

The blocking probability $P(B_H)$ for a handoff communication is when a set of S sensor nodes busy in a cluster S_c (Fig. 2)

$$P(B_H) = P(S) = \frac{(\lambda_O + \lambda_H)^{S_C} \lambda_H^{S-S_C}}{S!\mu^S} P(0). \tag{8}$$

3.1 Adaptive Energy Rate Allocation

Wireless nodes have low data error rates. Sensed data is compressed and available at required data rates. By maintaining the fixed data rate, error will be low and leads to require that physical layer sensor node information be made available at the MAC layer. The proposed method is to solve data rate fluctuation, which makes the use of state information of sensor nodes. This makes to determine transmission data rate. By using sensor node estimation power indication P_r, can be calculated as

$$p_r = \frac{\mathrm{P_t} \times \mathrm{G_t} \times \mathrm{G_r} \times \mathrm{H_t} \times \mathrm{H_r} \times \lambda^2}{(4 \times \pi \times \mathrm{d})^2 \times \mathrm{L}} \tag{9}$$

Signal power at transmitting node is represented with $\mathrm{P}_{\mathbf{t}}$, and signal power at receiving node is represented with $\mathrm{P}_{\mathbf{r}}$. The free space propagation model is represented with Eq. (2). Transmitter gain is represented with G_t and receiver gain is represented with G_r, H_t and H_r are height of the transmitter and receiver, is wavelength, d is distance between the transmitter and receiver and L is system loss. The transmission data rate is mapped by the received signal strength. This data rate matching is done by threshold-based technique. Receiver sends data to transmitter in a determined bit rate. By receiving the data rate of transmitter, the receiver adjusts the data rate accordingly at the physical layer. Other neighbour nodes that hear the packet will update the information in their network allocation vector (NAV) and hold their transmission until current transmission gets completed.

To minimize the energy consumption, an energy allocation scheme is designed. Resource allocation, joint power control, scheduling schemes over the time window T can be expressed as

$$Minimize \sum_{m=1}^{M}\sum_{t=1}^{T} p_t^m \tag{10}$$

$$\text{subject to} \sum_{m=1}^{M} p_t^m \le P_{max} \forall t \tag{11}$$

$$\sum_{t=1}^{T} b_m^t \log_2\left(1 + \frac{h_t^m p_t^m}{N_o b_t^m}\right) = W^m \forall m \tag{12}$$

$$\sum_{m=1}^{M} b_t^m \le B \forall t \tag{13}$$

The objective function of problem (P1) expresses the total power consumption assigned to all users across all time intervals. Constraints (9) guarantee that the power allocated to all users at each time interval is below the ceiling value *Pmax*. Constraints (12) guarantee that the information message will be delivered to each user within the predefined time horizon of T seconds and (13) limits the power assigned per user at each time slot to the system power. Inequalities (14) define the continues variables of the problem. Note that in problem (P1) the non-linearities are found in the constraints of the problem. It is easy to show that this problem can be transformed into a nominal convex non-linear optimization problem by linearizing the constraints as follows:

$$Minimize \sum_{m=1}^{M}\sum_{t=1}^{T} \frac{N_o b_t^m}{h_t^m}\left(2^{\frac{r_t^m}{b_t^m}} - 1\right) \tag{13}$$

$$subject\ to \sum_{m=1}^{M} r_t^m \le R_t \forall t \tag{14}$$

$$\sum_{t=1}^{T} r_t^m = W^m \forall m \tag{15}$$

$$r_t^m \geq 0 \tag{16}$$

$$b_t^m \geq 0 \, \forall t, m \tag{17}$$

This gives the optimum energy rate allocation in order to achieve minimum power consumption within the message delivery delays.

For a given aggregate data requirement, $\sum_{m=1}^{M} W^m = W$, with delay flexibility T, the optimal rate allocation to minimize the downlink power consumption can be expressed as follows:

This gives the optimum energy rate allocation in order to achieve minimum power consumption within the message delivery delays. For a given aggregate data requirement, $\sum_{m=1}^{M} W^m = W$, with delay flexibility T, the optimal rate allocation to minimize the downlink power consumption can be expressed as follows:

$$\mathbf{f}(\mathrm{r_t}) = Minimize \sum_{t=1}^{T} \frac{N_o b_t^m}{h_t^m} \left(2^{\frac{r_t^m}{b_t^m}} \right) \tag{18}$$

$$\sum_{t=1}^{T} r_t^m = W \tag{19}$$

$\boldsymbol{h_t}$ is the average sensor node gain of the moving terminals and r_t is the total rate allocated at time t to satisfy all requests. Equation (19) is monotonically increasing and convex function in r. Problem (P3) is an optimization problem over the simplex (20). Using the Karush–Kuhn–Tucker (KKT) optimality conditions, we show that this system of equations can be solved analytically for $\mathrm{r_t}$. For a local minimum $\mathrm{r_t}$ in the system of Eqs. (19) and (20), there exists a scalar λ_ such that

$$\mathrm{r_t^*} \in \arg\ \min\{\mathrm{f(r_t)} - \lambda^* \left(\sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{r_t} - \mathrm{W} \right) \tag{20}$$

The first-order necessary condition is $\frac{\partial f(r_t^*)}{\partial r_t} = \lambda^*$ while $\sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{r_t^m} = \mathrm{W}$ Eq. (16) and λ^* is unconstraint. For these conditions, the following holds:

$$\sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{B} \log_2 \frac{\lambda^* \mathrm{h_t}}{\mathrm{N_o} \ln 2} = \mathrm{W} \tag{21}$$

Solving for λ^* and substituting back in $\frac{\partial f(r_t^*)}{\partial r_t} = \lambda^*$, r_t^* can be derived as

$$r_t^* = \frac{\mathrm{W}}{\mathrm{T}} + \mathrm{B}\log_2 \frac{\mathrm{h_t}}{\sqrt[\mathrm{T}]{\mathrm{h_1 h_2 \ldots .. h_T}}} \tag{22}$$

4 Adaptive Genetic Corelation Node Optimization

In this research, we categorize a GA to optimize the cluster head assignment for Wireless Sensor Network by categorizing into two different steps. First, the initial population is considered as a set of cluster members. Second, a chromosome represents a set of cluster members C_i assigned to a base station B. Each chromosome represent as a kXk matrix, each row represents a set of cluster members assigned to a base station B. The chromosome of the (i, j)th element is set to 1 if he particular cluster members $\{C_i\}$ allocates to the particular base station B_i, if the cluster members are unused it set as 0. The number of 1^s in each row is M and number of 0^s is $M - N$. We setup the used and unused cluster members to the base station to maximize the energy and optimize the energy rate by allowing the cluster member borrowing optimization .

The detailed process is described as follows. The evaluation function $F(c, g)$, for low energy rate a chromosome c at cluster member g is

$$\boldsymbol{F}(\boldsymbol{c}, \boldsymbol{g}) = \begin{cases} \emptyset(\boldsymbol{c}, \boldsymbol{g}), \textit{if } \Phi(\boldsymbol{c}, \boldsymbol{g}) \geq (1- \in).\Phi_{\boldsymbol{cn}} \\ 0 \end{cases} \tag{23}$$

$\emptyset(\boldsymbol{c}, \boldsymbol{g})$ is the aggregate energy of low energy handlers of chromosome c at generation g as

$$\emptyset(\boldsymbol{c}, \boldsymbol{g}) = \sum_{\boldsymbol{i}} \sum_{\boldsymbol{j} \in \boldsymbol{C}_i(\boldsymbol{c},\boldsymbol{g})} \sum_{\boldsymbol{n} \in \mathcal{L}_i(\boldsymbol{c},\boldsymbol{g})} \boldsymbol{R}_{\boldsymbol{i},\boldsymbol{n}}^{\boldsymbol{j}} \tag{24}$$

$C_i(c, g)$ and $\mathcal{L}_i(c, g)$ are set of chosen cluster members at base station B_i, a set of low energy operators under base station of chromosome c at generation g. $\Phi(c, g)$ is the corresponding energy for all users computed as

$$\boldsymbol{\Phi}(\boldsymbol{c}, \boldsymbol{g}) = \sum_{\boldsymbol{i}} \sum_{\boldsymbol{j} \in \boldsymbol{C}_i(\boldsymbol{c},\boldsymbol{g})} \sum_{\boldsymbol{n} \in \boldsymbol{\upsilon}_i} \boldsymbol{R}_{\boldsymbol{i},\boldsymbol{n}}^{\boldsymbol{j}} \tag{25}$$

$\boldsymbol{\upsilon_i}$ denotes the set of all users at base station B_i, $\boldsymbol{\Phi_{cn}}$ is the aggregate energy of all users using the cluster member sets determined by the adaptive rate allocation scheme in Sect. 4

Initial Population Generation

In this section, we consider a set of cluster member allocation which were determined by the conventional scheme $\boldsymbol{\Phi}_{\boldsymbol{cn}}$, choose a random base station to generate a chromosome for used and unused cluster members. The used cluster members are randomly selected and replaced with unused cluster members. A chromosome is generated for each cluster member at each chosen cluster head, some used cluster members are randomly elected and substituted with unexploited cluster members. If the aggregate energy rate of the low energy sensor nodes is less than the conventional scheme function $\boldsymbol{F}(\boldsymbol{c}, \boldsymbol{g})$, then this chromosome is discard, and this process is repeated until a optimal chromosome is found. When such a chromosome is discovered, then another base station is randomly elected, and the entire process is reorganized until to form the initial population.

Initial population Formation

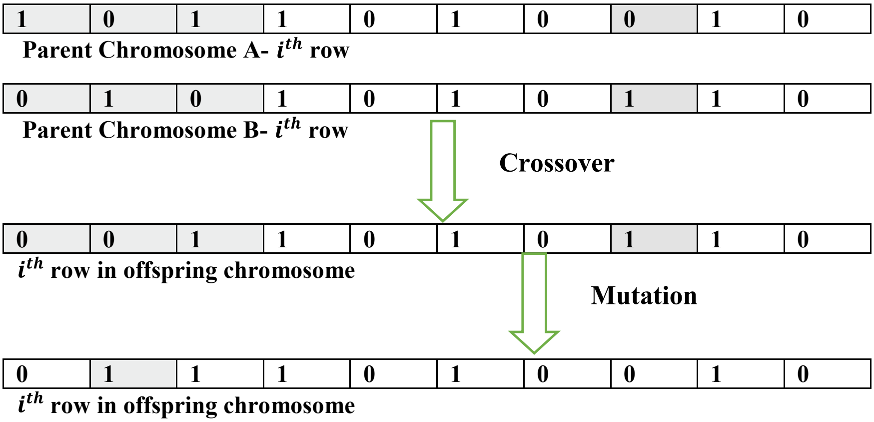
Step 1: Consider a cluster C_i with k number of calls, the cluster member frequency for the $k-1$ calls is assigned by $f_{i*k} = (k-1) \times \alpha + 1$, where α is the minimum frequency rate for maximum demand i^{th} cluster, and is assigned by $\alpha = \left[\frac{\beta}{m_i^*}\right]$ where β is a total number of lower bound o required frequencies in the network and $\alpha > c_i^*$

Step 2: Let discovery the next largest number of calls for the cluster C_{i-1}

(a) Estimate a number of available frequencies in the subgroup whose size is α
(b) Randomly choose a frequency from the frequency block which it was represented in step (a)
(c) Assign a frequency to the randomly chosen subgroup.

Assign a frequency to the chosen subgroup for the next call, with a regular time interval with previous assigned frequencies. The assignment should satisfy the co-cluster member constraint or adjacent cluster member constraint.

Step 3: Repeat the assigning process to the remaining subgroups. Let consider the base station chromosomes information, which was estimated in chromosome generation section, based on the generated chromosome data, if the two chromosome elements have the same value, this value is assigned to the corresponding element position of the offspring chromosome. The outstanding elements of the offspring are occupied with the randomly chosen values based on this condition If $if(P_r) > P_X$ where P_r is randomly generated probability and P_X is a crossover probability, then generate a random crossover point and assign energy rate.



The above figure represents the crossover and mutation process, and based on the above figure, the total number of cluster members assigned to the base station $B = 10$ and total number of cluster members used are $Ch = 5$. Based on the figure, both parent chromosome (A and B) elements are same, where the remaining elements in offspring chromosome are filled with randomly generated elements of both parent chromosomes, where the elements 2 and 3 of parent chromosome A are copied to the offspring, as are elements 1 and 8 of parent chromosome B.

Once the crossover process evaluated the results, the mutation process initiate with the mutation probability $P(mu)$ at each row of the offspring chromosome. Randomly selected elements 1's are replaced with randomly selected elements 0's. A randomly chosen row of the corresponding offspring is replaced with the randomly generated row containing M 1's. This indicates that the cluster member set of a randomly chosen basestation is fully re-generated.

5 Genetic Corelation Node Optimization Routing

In GCNO routing algorithm, a node broadcast a route RREQ packet to discover the next corresponding node based on node intimacy and energy value features

$$R_{ij}(req) = \tau_{ij}^{\alpha} n_{ij}^{\beta}$$

Based on the below network graph, each node contains with their own node intimacy rate trails, the GCNO routing protocol broadcast GCNO RREQ packet by considering initial intimacy rate trails rate to discover shortest path-based node corelation weightage value. The initial route discovery starts from node A and it reaches destination node G (Fig. 3).

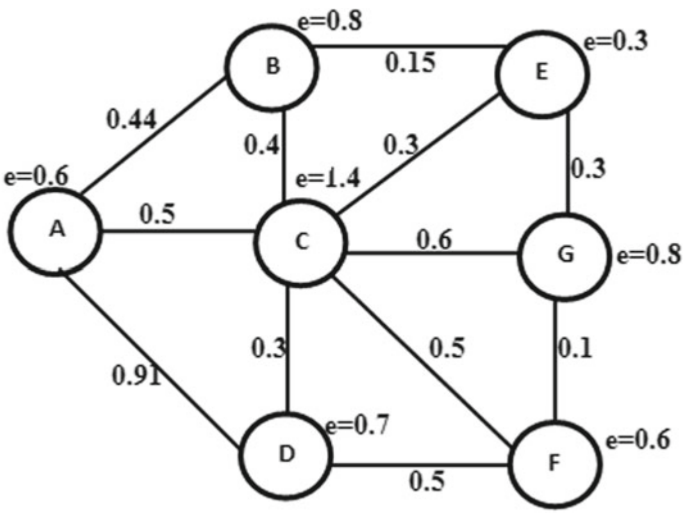


Fig. 3 Network graph

The graph can be represented in the form of matrix

$$\begin{bmatrix} & A & B & C & D & E & F & G \\ A & 0 & 0.44 & 0.5 & 0.41 & \infty & \infty & \infty \\ B & \infty & 0 & 0.3 & \infty & 0.15 & \infty & \infty \\ C & \infty & 0.4 & 0 & 0.3 & 0.3 & 0.5 & 0.6 \\ D & \infty & \infty & 0.3 & 0 & \infty & 0.6 & \infty \\ E & \infty & 0.15 & 0.3 & \infty & 0 & \infty & 0.3 \\ F & \infty & \infty & 0.5 & 0.5 & \infty & 0 & 0.1 \\ G & \infty & \infty & 0.6 & \infty & 0.3 & 0.1 & 0 \end{bmatrix}$$

Theorem 1 Considered $\{\alpha, \beta, \rho\} = \{10, 2, 1\}$.

A:

$$B(s, e) \quad \varphi_{ab} = \frac{B_e}{B_e + C_e + D_e} \quad P_{ab} = s^{\alpha}(\varphi_{ab})$$

$$: \ C(s, e) \quad \varphi_{ac} = \frac{C_e}{B_e + C_e + D_e} \quad P_{ac} = s^{\alpha}(\varphi_{ac})$$

$$: \ D(s, e) \quad \varphi_{ad} = \frac{D_e}{B_e + C_e + D_e} \quad P_{ac} = s^{\alpha}(\varphi_{ad})$$

B:

$$C(s,e) \quad \varphi_{ac} = \frac{C_e}{C_e + E_e} \quad P_{bc} = s^{\alpha}(\varphi_{bc})$$

$$: \; E(s,e) \quad \varphi_{ac} = \frac{E_e}{C_e + E_e} \quad P_{be} = s^{\alpha}(\varphi_{be})$$

C:

$$B(s,e) \quad \varphi_{cb} = \frac{B_e}{B_e + E_e + G_e + F_e + D_e} \quad P_{cb} = s^{\alpha}(\varphi_{cb})$$

$$: \; E(s,e) \quad \varphi_{ce} = \frac{E_e}{B_e + E_e + G_e + F_e + D_e} \quad P_{ce} = s^{\alpha}(\varphi_{ce})$$

$$: \; G(s,e) \quad \varphi_{cg} = \frac{G_e}{B_e + E_e + G_e + F_e + D_e} \quad P_{cg} = s^{\alpha}\left(\varphi_{cg}\right)$$

$$: \; F(s,e) \quad \varphi_{cf} = \frac{F_e}{B_e + E_e + G_e + F_e + D_e} \quad P_{cf} = s^{\alpha}\left(\varphi_{cf}\right)$$

$$: \; D(s,e) \quad \varphi_{cd} = \frac{B_e}{B_e + E_e + G_e + F_e + D_e} \quad P_{cd} = s^{\alpha}(\varphi_{cd})$$

D:

$$C(s,e) \quad \varphi_{dc} = \frac{C_e}{C_e + F_e} \quad P_{dc} = s^{\alpha}(\varphi_{dc})$$

$$: \; F(s,e) \quad \varphi_{df} = \frac{F_e}{C_e + F_e} \quad P_{df} = s^{\alpha}\left(\varphi_{df}\right)$$

E:

$$B(s,e) \quad \varphi_{eb} = \frac{B_e}{B_e + C_e + G_e} \quad P_{eb} = s^{\alpha}(\varphi_{eb})$$

$$: \; C(s,e) \quad \varphi_{ec} = \frac{C_e}{B_e + C_e + G_e} \quad P_{ec} = s^{\alpha}(\varphi_{ec})$$

$$: \; G(s,e) \quad \varphi_{eg} = \frac{G_e}{B_e + C_e + G_e} \quad P_{eg} = s^{\alpha}\left(\varphi_{eg}\right)$$

F:

$$D(s,e) \quad \varphi_{fd} = \frac{D_e}{D_e + C_e + G_e} \quad P_{fd} = s^{\alpha}\left(\varphi_{fd}\right)$$

$$: \ C(s, e) \quad \varphi_{fc} = \frac{C_e}{D_e + C_e + G_e} \quad P_{fc} = s^{\alpha}\left(\varphi_{fc}\right)$$

$$: \ G(s, e) \quad \varphi_{fg} = \frac{G_e}{D_e + C_e + G_e} \quad P_{fg} = s^{\alpha}\left(\varphi_{fg}\right)$$

Case 1: let assume **{α, β, ρ} = {5, 3, 5}.**
Table 1 represents the visited and unvisited nodes and functional values, each packet bounded with bit vector [0, 0, 0, 0, 0, 0, 0] to represent visited and unvisited information. According to Table 2, node A elects node C over node B, due to the higher intimacy and energy rate function value of AC. Then the bit vector of C value set as 1 will be considered as higher energy rate node, rather than other nodes. From node C, to next hop node B, based on the higher intimacy and energy value function, and set a bit vector as 1 and CB is considered because it has higher energy rate compared to CD. From node B, the to next node E, based on the route discovery rate function, and set a bit vector as 1 and BE is considered because it has higher intimacy and energy value compared to other nodes. From node E to the route discovery process discover the destination G and finds the destination G and elects the optimal path EG and set E and G bit vector value as 1. Finally, the source node A reaches to the destination node through optimal path of $A \rightarrow C \rightarrow B \rightarrow E - G$.

5.1 RREP Fault Diagnosis Routing Vector at Destination

Based on the Case 1, three consecutive bits are used to discover the optimal routing path, based on the previous case; the node A begins the route discovery process with a set of bit vectors in route vector. Based on the final routing vector set [011010100000000000000] bits, the first three bits 001 be examined as node C, next three bits 011 considered as node B, and next three bits 010 considered as node E and next three bits 100 as destination node G. Finally, the discovered optimal path is A-C-B-E-G.

Case 2: let assume **{α, β, ρ} = {5, 2, 3}.**
In order to evaluate the corelation process at destination, an GCNO RREP routing vector is considered. In this expertise, the route vector initiates the route bit vector at destination and process the higher intimacy and energy rate function, to elect the optimal nodes. According toTable 2, the destination node G chooses C node over E, C because of its higher rate and establish a path of $C \leftarrow G$ over GE and GB. Now, the node C elects next higher energy node as B over D and establish a path of $B \leftarrow C \leftarrow G$. Finally from node B, identifies the target source node, and establish the optimal and corelation RREP as $A \leftarrow B \leftarrow C \leftarrow G$. Based on this trusted path, the bit vector gets changed.

Table 1 GCNO RREQ route

Non-interacted	Interacted	Current node	A	B	C	D	E	F	G	Bit vector
B,C,D,E,F,G	A		∞	∞	∞	∞	∞	∞	∞	[0,0,0,0,0,0,0]
B,D,E,F,G	A	A		0.00352866326	0.0049152	0.0000768	∞	∞	∞	[1,0,0,0,0,0,0]
B,D,E,F,G	A,C	C		0.004608	∞	0.0000704	0.00003072	0.0000608	0.00256	[1,0,1,0,0,0,0]
D,E,F,G	A,C,B	B		∞	∞	0.0000928	0.0002151296	0.00008	0.0008019	[1,1,1,0,0,0,0]
D,F,G	A,C,B,E	E		∞	∞	0.0001056	∞	0.0000028	0.0009234	[1,1,1,0,1,0,0]
D,F	A,C,B,E,G	G								[1,1,1,0,1,0,1]

Table 2 GCNO RREP

Non-interacted	Interacted	Current node	A	B	C	D	E	F	G	Bit vector
A,B,C,D,E,F,G			∞	∞	∞	∞	∞	∞	∞	[0,0,0,0,0,0,0]
B,C,D,E,F,A	G	G	∞	0.00055	0.0057344	∞	0.0002916	∞	0	[0,0,0,0,0,0,1]
B,D,A,F,E	G,C	C	0.002969	0.00386	∞	0.0001056	∞	∞	∞	[0,0,1,0,0,0,1]
E,D,F,A	G,C,B	B	0.003528			0.00009912	0.000234	0.0000864		[0,1,1,0,0,0,1]
C,F,D	G,C,B,A	A								[1,1,1,0,0,0,1]

6 Experimental Study

In this section, we analyse the performance of the proposed GCNO scheme. We simulated WSN with a set of sensor nodes and each mobile is represented as a sensor device, which captures a data and transfer data towards destination. We compared the performance of Genetic Corelation Node Optimization (GCNO) on these parameters packet delivery ratio (PDR), Average throughput, Average delay, energy consumption and network overhead. We compare the performance of GCNO with particle swarm optimization based energy-efficient cluster head Selection algorithm [16]. The proposed system is simulated with the network simulator-2 (NS-2) [17] with the simulation parameters of Table 1.

No. of nodes	300, 400, 500 and 600
Area size	1000 × 1000
Mac	802.11
Routing protocol	GCNO
Transmision range	250 m
Simulation time	20 s
Traffic source	CBR
Packet size	512
Receiving power	0.395
Sending power	0.660
Idle power	0.035
Initial energy	10.0–50 J
Data rate	2 Mbps

6.1 Simulation Results

In this experimental model, we simulate the WSN model with the variation of number of nodes and energy levels. In this simulation we consider the network area size as 1000 m × 1000 m, for 300–600 sensor nodes, with the initial energy rate of 10 J–50 J with different number of clusters and cluster heads. Initially the nodes were dynamically placed and scattered in random locations. We compute the total number of clusters and total number of optimal cluster heads using Genetic Corelation Node Optimization scheme. We evaluated the proposed Genetic Corelation Node Optimization performance by conducing multiple simulations by varying number of clusters and cluster heads for group of nodes. First, we deploy the Genetic Corelation Node Optimization scheme to validate the performance to measure the energy consumption rate, throughput rate, delay rate and packet delivery ratio. Initially we consider 300 sensor nodes with the energy rate between 10 and 50 J. The following results define the comparison of GCNO and PSO-ECHS.

6.1.1 Based on Number of Nodes

In this scenario, we consider different network size, we varied number of sensor nodes from 300 to 600 nodes, we have considered minimum energy rate as 10 J, we vary the number of cluster and cluster head to analyse the performance of GCNO and PSO-ECHS schemes. Based on the simulation experiments, we evaluated the performance of both schemes under different clustering environment.

Figure 4 shows the packet delivery ratio of GCNO and PSO-ECHS techniques for different number of nodes scenario. We can conclude that the packet delivery ratio of our proposed GCNO approach has 8.1% of higher than PSO-ECHS approach.

Figure 5 shows the average overhead of GCNO and PSO-ECHS techniques for different number of nodes scenario. Based on the simulation results the average overhead rate of PSO-ECHS increased with number of clusters for more number of nodes compare to proposed GCNO approach.

Figure 6 shows the energy consumption of GCNO and PSO-ECHS techniques for different number of nodes scenario. According to the results, the energy consumption of our proposed GCNO approach has lesser energy consumption compare to PSO-ECHS approach.

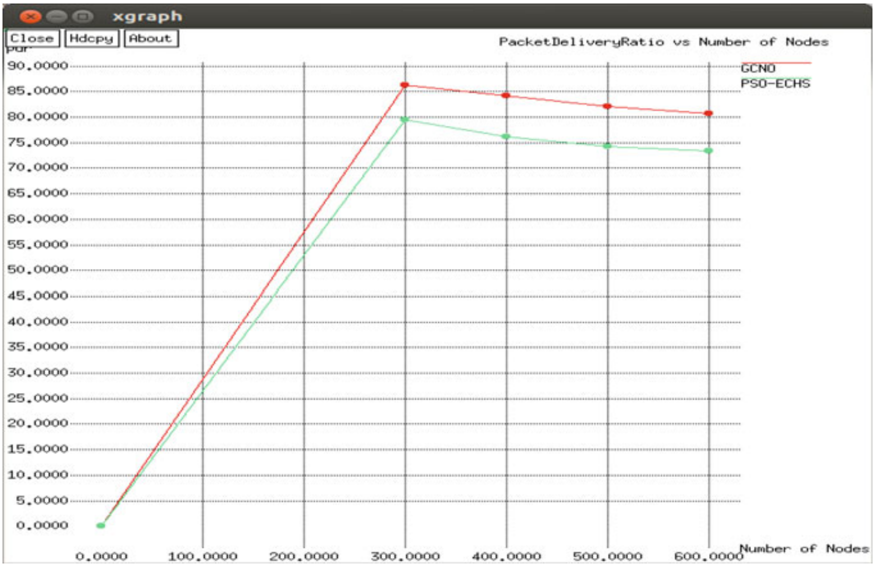


Fig. 4 Number of nodes versus packet delivery ratio

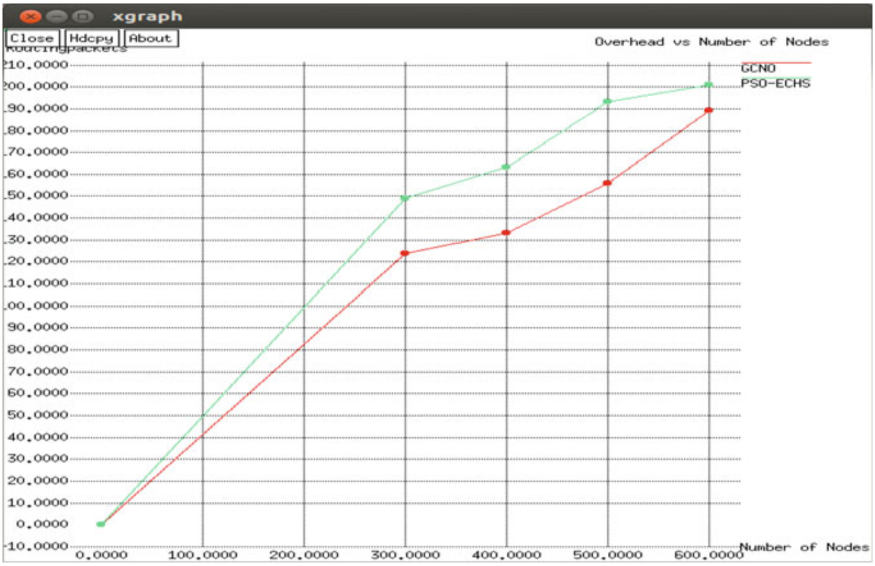


Fig. 5 Number of nodes versus overhead

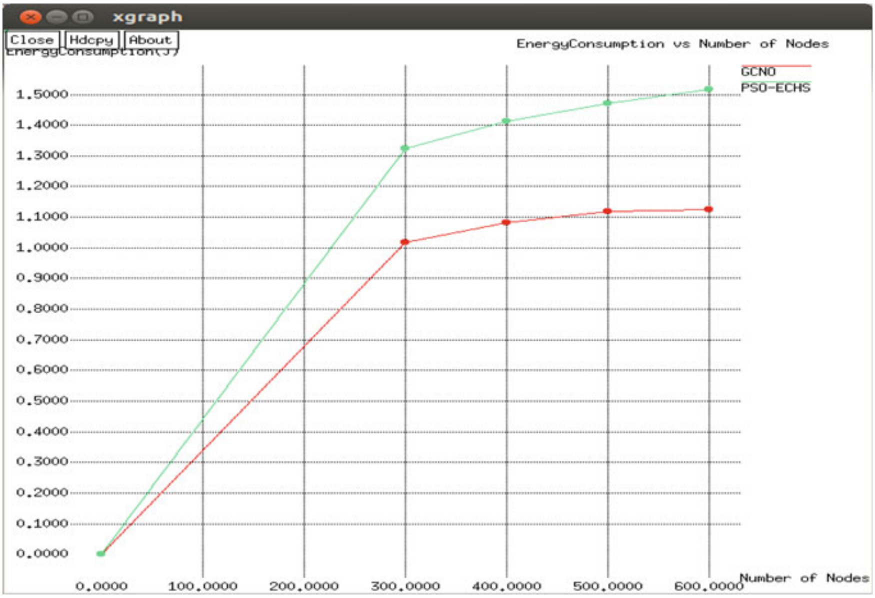


Fig. 6 Number of nodes versus energy consumption

Figure 7 shows the end-to-end delay of GCNO and PSO-ECHS techniques for different number of nodes scenario. The delay rate was increased while number of nodes increased in both schemes while comparing to GCNO the PSO-ECHS have higher delay for number of nodes.

6.1.2 Based on Energy Rates

In our second experiment, we vary the energy rate as 10, 20, 30, 40 and 50.

Figure 8 shows the packet delivery ratio of GCNO and PSO-ECHS techniques for different energy rates. We can conclude that the packet delivery ratio of our proposed GCNO approach have better packet delivery ratio compare to PSO-ECHS approach, it shows the various of 8.7% variation on both scenarios.

Figure 9 shows the average overhead of GCNO and PSO-ECHS techniques for different energy rates. Based on the results, we can observe that the overhead of our proposed GCNO approach has 7.6% of lesser than PSO-ECHS approach.

Figure 10 shows the energy consumption of GCNO and PSO-ECHS techniques for different energy rates. We can conclude that the energy consumption of our proposed GCNO approach has 10.4% of less than PSO-ECHS approach.

Figure 11 shows the end-to-end delay of GCNO and PSO-ECHS techniques for different energy rates. We can conclude that the delay in our proposed GCNO approach has 11% of less than PSO-ECHS approach.

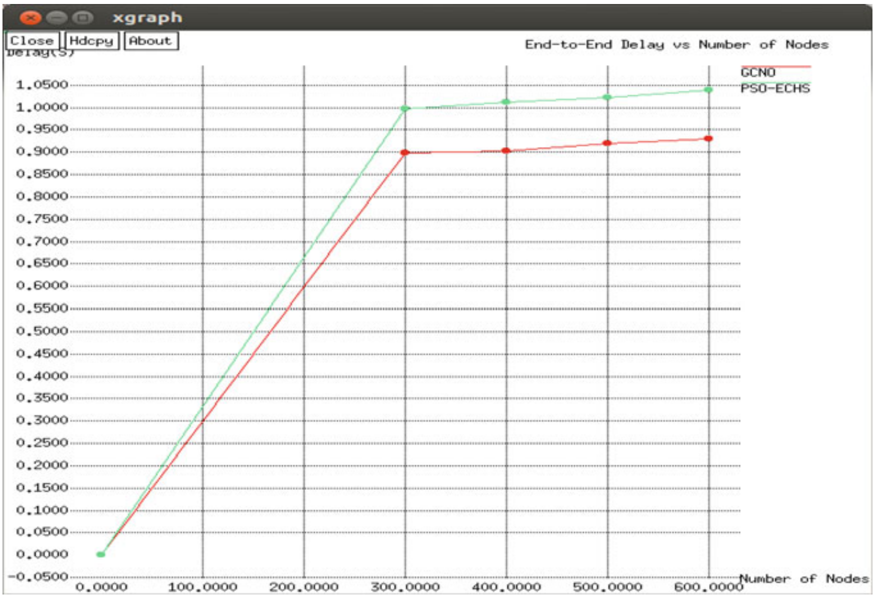


Fig. 7 Number of nodes versus end-to-end delay

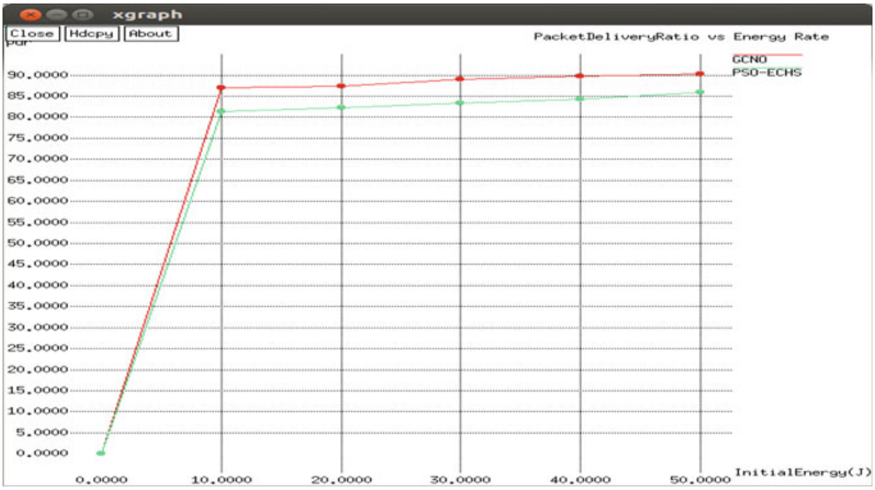


Fig. 8 Energy rate versus packet delivery ratio

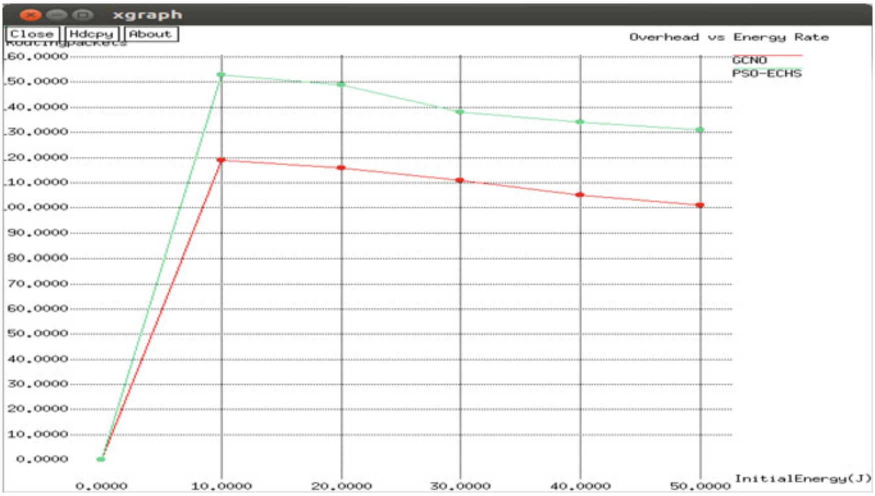


Fig. 9 Energy rate versus overhead

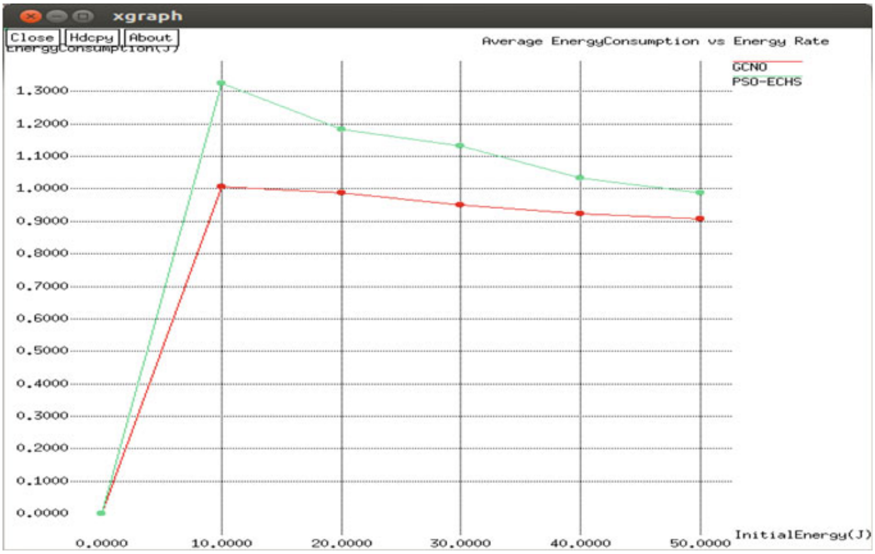


Fig. 10 Energy rate versus energy consumption

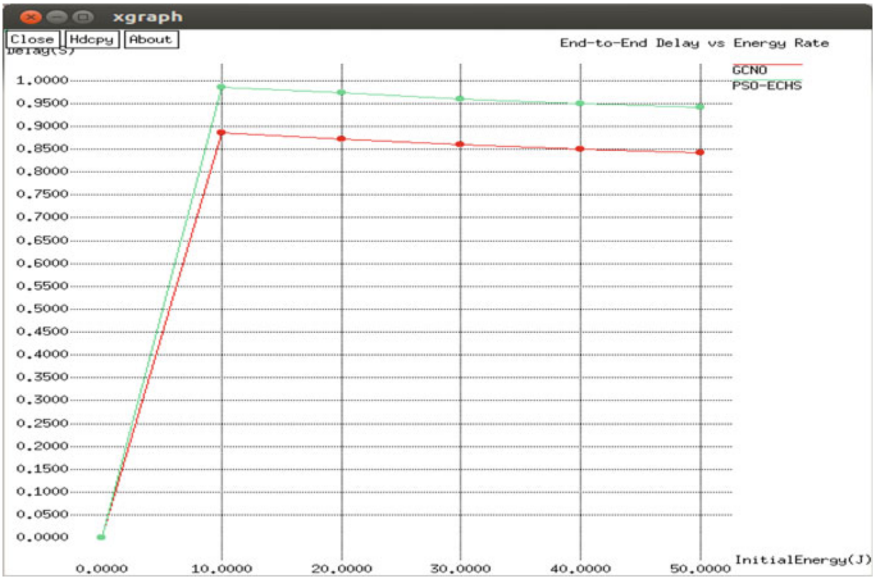


Fig. 11 Energy rate versus delay (S)

7 Conclusion

In this paper, we propose an adaptive Genetic Corelation Node Optimization Routing (GCNO) for Wireless Sensor Network (WSN). The adaptive energy rate allocation scheme minimizes the error rate and allocates the optimized clusters based on the node state. In order to identify the node fitness status, the adaptive Genetic Corelation Node Optimization scheme finds the appropriate cluster set to sort out the cluster head selection problem from a set of used and unused cluster members to maximize the data handling performance. The Genetic Algorithm approach was employed to determine the efficient energy for high energy efficient and radio access network model, and based on the simulation results, the energy is saved up to 11.91%, with increase of sensor nodes. This is achieved by designing a traditional cluster-based wireless network model by adopting traditional adaptive GA node optimization routing scheme. The proposed scheme is compared with various traditional schemes in different aspects like Energy consumption, Packet delivery ratio, Lifetime, etc.

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