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Genetic Algorithm Based Optimized Adaptive Teen Routing for WSN

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***Abstract:** A sensor network with wireless communication channel and often termed as WSN comprises of a set of such as nodes with different computing power, and different energy levels. Clustering is an approach to increase the availability of the nodes in the network in terms of lifetime. But an efficient and an optimal to increase the remaining life period of the network is to use an efficient routing approach with hierarchical architecture where at different levels of clusters are formed. Efficient cluster formation in terms of energy and reliable routing are two widely analyzed challenges in WSN. Despite various clustering approaches developed by so many researchers still the design of optimal clustering strategy is remaining as an open challenge. This paper focuses on the design and evaluation of an energy-efficient hierarchical clustering approach of integrating an evolutionary algorithm and the Adaptive Threshold sensitive Energy Efficient routing protocol. Genetic Algorithm (GA) is used to optimize the energy exhaustion in the network.*

***Keywords:** hierarchical routing, Adaptive TEEN, evolutionary algorithm, and genetic algorithm*

I. INTRODUCTION

In WSN clustering with hierarchical topology is a way to lessen the energy spending within the cluster by aggregating and fusion of data. In cluster based routing hierarchical networks are created where the resources available in the network are efficiently used. By this approach the lifetime of the network is extended which in turn lessens the energy consumption in the network and makes the network scalable. The hierarchical routing has many merits as it arranges the nodes present in the network in a hierarchical pattern with an objective to optimize energy spend by the nodes. The data aggregation and fusion helps to achieve the objective by decreasing the number of messages transmitted from the sender to the Cluster Head (CH). Many variants of the hierarchical routing have been developed in the recent past and still many researchers are actively proposing a numerous number of approaches and methods to optimize the energy consumption in WSN.

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The adaptive clustering approach used widely in the WSN routing is initially proposed to reduce the energy spent during the transmission of data packets within the network [1]. In adaptive clustering approach the network comprises of a Base Station (BS), which receives the sensed data from the network nodes through the cluster heads. The Base Station doesn't have any energy constraints as it is connected to a power supply. So there is no need to optimize the routing between the Base Station to all the other nodes.

However the routing path from the nodes to the base station via the cluster heads needs to be optimized in terms of energy. Conventionally in hierarchical routing the cluster head receives the data from the internal nodes, aggregates and then forwards it to the Base Station. The cluster heads forms as a cluster with any one cluster head as its head. This pattern is iterated to form a multi-level clusters which can be structured hierarchically and the root not is termed as a Base Station. In this approach the nodes are required to send their data only to their cluster-head. The cluster head doesn't spend much energy on sending the data, but in turn spends energy in aggregating and forwarding the data to the next level in the hierarchy. This approach saves a great deal of energy.

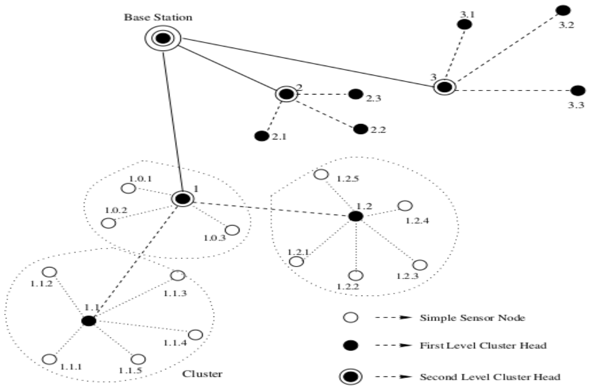

Fig. 1 Schematic view of Hierarchical Clustering in a WSN

In the lower levels of hierarchy the cluster head nodes transmit data over a larger distance and also they perform a large computations also. Hence the energy spent is larger in comparison with the cluster nodes in the network. To prevent the cluster heads dying out early due to this large energy spending, the cluster heads have to be selected among the other nodes after a time interval T termed as cluster period.

TEEN (Threshold sensitive Energy Efficient sensor Network) protocol is more suitable for reactive networks and to make it more robust and efficient; it is integrated with the evolutionary approach. The functioning of this protocol is also same as many other hierarchical routing protocols except that the transmission in the network is decided based on the two threshold values.

After a cluster period each cluster head broadcasts a hard and soft threshold value to their cluster members in addition to various other attributes. The hard threshold is an absolute value and if any of the cluster nodes sensed value is beyond this value, then the corresponding node must update the newly sensed value to its head node of the cluster. The Soft threshold is a difference between the consecutive values of the sensed parameter which in turn causes the node to switch its sender and transmit the attribute value to the cluster head.

Every cluster node senses its environment and when the sensed value reaches the hard threshold value, then immediately it has to switch on its transmitter and transmits the sensed data to the cluster head and it also maintains this value. After sensing a value higher than the hard threshold value and updating it to the cluster head during the same cluster period every node again sends the sensed data to the cluster head only when the change in the current sensed value and the previously sensed value is greater than the soft threshold value. Once a node transmits a value to the cluster head, then it is updated with the current value. The hard threshold limit prevents the frequent data transmission from cluster node to cluster head as it has to send the data only when the sensed range goes higher than the hard limit. Also the soft threshold also reduces the number of transmissions by preventing the transmission when there is only a small change in the current sensed value when compared to the previous value.

Depending upon the criticality of the sensed parameter the value of the soft threshold can be fixed. There is a trade-off between the accuracy of the sensed parameter and the energy consumption in the network. This tradeoff can be controlled by adjusting the soft threshold value. Generally in a network more energy is spent during the message transmission. Internally to avoid the collision among the cluster nodes either TDMA or CDMA based scheduling is implemented. When the application involves a time critical data, then CDMA based scheduling is preferred.

APTEEN (Adaptive Periodic Threshold-sensitive Energy Efficient Sensor Network) is one such variant of TEEN in which after deciding the CHs during the beginning of a cluster period the respective CH in a cluster broadcast the attribute and the thresholds as similar to the TEEN protocol. APTEEN follows TDMA based scheduling and it uses Count Time (CT) which fixes the maximum duration between two consecutive reports sent by a cluster node. The CT is a multiple of the length of the TDMA schedule [2].

II. RELATED WORKS

This section presents a detailed review of existing literatures in the area of cluster head selection using Genetic Algorithm and other approaches. In [3], clustering and routing in WSN is implemented using genetic algorithm based approach. Using a combination of energy remaining in the gateways and the distance between the nodes and the respective cluster head the clustering is implemented. The routing strategy is also based on the remaining energy in the gateway along with a trade-off between transmission distance and number of forwards. A novel Differential Evolution (DE) to increase the lifetime of the nodes available in the network by balancing the energy spend by the cluster heads and thereby minimizing the probability of death of the highly loaded CHs [4]. This approach achieves faster convergence by employing a local improvement phase of the conventional DE algorithm. In some of the literature the term gateway node is used interchangeably in the place of the cluster head node. Either gateway or CH will perform a same set of tasks rights from data aggregation and forwarding data packets to the BS.

An another routing protocol based on GA was proposed in [5] which reduces the consumption of energy in the network by reducing the distance a data is travelling within the network before it reaches the destination. Based on the current network state a routing schedule is generated by the genetic algorithm.

Multi agent based clustered network includes a four types of agent nodes, including regional-part of the base station, interface-common nodes between clusters, cluster and query-node which processes sensed attribute value. The regional agent lies nearby to the BS and is responsible for the computation based on genetic algorithm. The interface agent communicates with the clients to resolve their request. The cluster agents handle all agents available within the same cluster for query processing and efficiency in network. The query agents work within each sensor and it carries out acquisition, aggregation, processing, and transmission of the requested information. Multi objective based GA was used in efficient cluster head selection in [15].

The energy spending in the normal nodes and the gateway nodes are managed by the Particle Swarm Optimization based cluster [7]. A complete clustering solution is formed by implementing an optimal encoding technique before clustering. The fitness function focuses on the gateway node which consumes more energy while forwarding the packet nodes.

In another work a two stage approach was used for improving the selection of cluster head aiming at increasing the overall lifetime of the network [8]. After completion of a round the Base Station estimates the remaining energy of all the cluster heads and the mean energy of all other nodes in each cluster. If the residual energy available in the cluster head is less than the average energy of the respective cluster nodes, then the BS selects another node as cluster head and restructures the whole cluster.

By using GA an applicable density of cluster heads and the positions of the head nodes of the clusters are found and initially random generated nodes are considered as the cluster heads [9]. This approach also follows a two stage for creating and managing the cluster). In the steady phase all the cluster nodes communicate with their cluster heads by a TDMA - (Time Division Multiple Access) schedule. In [10] a GA based clustering algorithm to distribute the traffic evenly in the network by load balancing the load on gateway was proposed. The GA is modified by restricting the initial population generation in consideration of the connection between the nodes present in the cluster and their respective head nodes. Instead of selecting the mutation point randomly, it is generated in such a way to balance the load by varying the child's chromosomes. A multi objective GA was used in [11] at the top level and additionally a conventional GA is used to obtain optimal topology for transmitting data packets from cluster nodes to their respective CHs.

The work proposed in [12] discusses about a cluster head weight selection method termed as Cluster Chain Weight Metrics approach (CCWM). This approach takes a network service parameters and enhances the overall performance of the network. This approach both conserves the energy and attempts to distribute the load evenly in the network. In [13] a multi cluster head based protocol is proposed which considers the ratio between the overall energy consumption and the sum of distances between the cluster nodes in order to maintain the average energy spent among the nodes even.

A modified synchronous and heuristic firefly algorithm was proposed in [14] to select optimal cluster heads.

The performance of the heuristic algorithm was compared with LEACH and observed to be better.

III. RADIO MODEL

More active research is going on in the field of low-energy consuming radios having different characteristics that will influence the advantage of different protocols over the others. This work assumes a simple radio model where the radio spends $E_{elec} = 50\frac{nJ}{bit}$ For the functioning of transceiver circuit and $e_{amp} = 100\frac{pJ}{bit}/m^2$For the amplifier in the transmission circuit. Energy loss caused due to transmission in the channel is considered as $r^2$and for sending a $k-bit$ message over distance d the energy spend by this radio model is calculated as follows;

$$E_{Tx}(k,d) = E_{Tx-elec}(k) + E_{Tx-amp}(k,d) \quad \text{Eq. 1}$$

$$E_{Tx}(k,d) = Elec * k + e_{amp} * k * d^2$$

And to receive the same $k-bit$message the radio model spends

$$E_{Rx}(k) = E_{Rx-elec}(k)$$

$$E_{Rx}(k) = E_{elec} * k \quad \text{Eq. 2}$$

By this model it is also assumed that the radio channel is symmetric in a way of energy spend, by transmitting the data from a source its like the nodes transmitting from A to destination B is same as in the aspect ration of energy spend, to transmit a message from node B to A for a given signal to noise ratio.

IV. PROPOSED METHODOLODY

The proposed routing protocol is integrated with a TEEN routing algorithm and genetic algorithm to decide the CH based on different parameters which are explained in this section. The performance of any GA based optimization technique is decided by the selection of Fitness Function. The objective is to minimize the energy consumption in the network and thereby increase the lifetime of the network. Some of the GA based approaches have not considered the residual energy of nodes in the cluster in the fitness function and the energy spend by the cluster head next to the BS in the hierarchy for transmitting the packets to the BS. The fitness function is refined to ensure that the reliability of data is assured. The proposed protocol is threshold sensitive and is based on genetic algorithm. For efficient cluster head selection the factors considered are transmission distance, average minimum distance, energy left per node, cluster head transmission energy, cluster head count, and cluster distance. These factors constitute the fitness function.

Transmission Distance (TD): The distance between the source node and the node where the data packets aggregated. To achieve the final objective of reduced energy consumption this distance measure has to be reduced and it is represented as in Eq. 3

$$TD = \sum_{i=1}^{CHs} \sum_{\forall n \in Cl_i} dis(mn, CH_i) \quad \text{Eq. 3}$$

Average Minimum Distance (AMD): The AMD is measured by calculating the average Euclidean distance between the cluster heads in the network. The AMD must be maximized such that the distance between the cluster heads is large. The AMD is calculated as represented in Eq. 4 below where nc represents the number of cluster head.

$$AMD = \sum_{\forall Cl_i, Cl_j, Cl_i \neq Cl_j} dis(CH_i, CH_j)/nc \quad \text{Eq. 4}$$

Energy Left per node (EL): It is the residual energy in all the individual nodes present in the network. When this measure is maximized, then the energy is uniformly spend in the network and thus the early dying of node is prevented. In Eq.4 the total residual energy in a node is represented where ED_i represents the energy spend by a node i.

$$EL = \sum_{i=1}^{n} (E_{oi} - ED_i) \quad \text{Eq. 5}$$

Transmission Energy Dissipated (T ED): It is the total energy spent in the network to transmit a data from the source node to the BS. The energy spent to transmit, receive and aggregate the data is summed to estimate TED.

$$TED = \sum_{i=1}^{mn} ETX_i + \sum_{j=1}^{nc} (ERX_j + EDA_j) \quad \text{Eq. 6}$$

ETX_i represents the energy consumed at the network to transmit the data packet from the member node to its respective cluster head. ERX_j denotes the total energy spent by the cluster head in aggregating the data packets.

Cluster Distance (CD): It is the addition of all the distances between the member nodes and their respective head nodes, and the distance between the cluster head and the BS. A cluster comprising of k member nodes the inter-cluster distance CD is expressed as in Eq. 7 where in d_{ih} is the distance from the node i to the cluster head h. d_{hs} is the distance between the cluster head and the base station.

$$CD = \sum_{i=1}^{k} d_{ih} + d_{hs} \quad \text{Eq. 7}$$

Cluster Distance - Standard Deviation (SD): In a spatially distributed sensor nodes the variation in the cluster distances will be small. The cluster distances will not be same when the sensor nodes are not uniformly distributed. In the case of randomly deployed sensor nodes the variance in the cluster distance remains in an acceptable range. The cluster distance with a standard deviation ⍰ is represented as in Eq. 8.

$$SD = \sqrt{\sum_{i=1}^{h} (\mu - d_{clusteri})^2} \quad \text{Eq. 8}$$

The fitness function is a combination of the above mentioned parameters and it is represented as in Eq. 9

$$FF = \sum_i (w_i \times f_i), \forall f_i \in \{TD, AMD, EL, TED, CD, SD\} \quad \text{Eq. 9}$$

For the initial iteration of the genetic algorithm the weights are assigned with equal value and the after each iteration the value is evaluated to find the best fit chromosome and their weights are updated as follows

$$\Delta f_i = f_i - f_{i-1}$$
$$w_i = w_{i-1} + c_i \Delta f_i$$
$$c_i = \frac{1}{1+e^{-f_i}} \quad \text{Eq. 10}$$

During the initial generation the GA forms the clusters using all the nodes in the network and as generation proceeds only alive nodes will be used to create clusters. After receiving all the required information to construct the cluster the base station using the population generated by the genetic algorithm creates the new cluster. The sensor nodes are configured as per the new cluster information provided by the BS. This is repeated after every cluster period.

V. SIMULATION AND RESULTS

The simulation environment consists of 200 nodes (N), spatially distributed over an area of 100 × 100 m^2 denoted as M, and the distance between the BS and the network is 200m. The simulation of the proposed approach is implemented in MATLAB tool and analyzed the impact of the energy efficiency on the network. The various simulation parameters are mentioned in the Table 1. The probability that a node can be a cluster head is 0.05. The flow chart in Fig. 2 presents the phases and the execution of the various processes during the simulation of the proposed protocol. The simulation starts with an initial setup phase in which the network is created with a pre-defined number of nodes. Each node is randomly assigned with an x and y location and an initial energy of 2J. The setup phase is continued by the election phase where in the network nodes is divided into individual clusters and each cluster is managed by a cluster head selected during the election phase. During the transfer phase with each cluster node transmits the data to the cluster head, which in turn aggregates and forwards the data to the base station. After each transmission the event is logged in a file with the details, including the total amount of energy consumed during the transmission, lists of dead and live nodes, and if the number of live nodes falls below the minimum pre-defined value then the simulation is stopped.

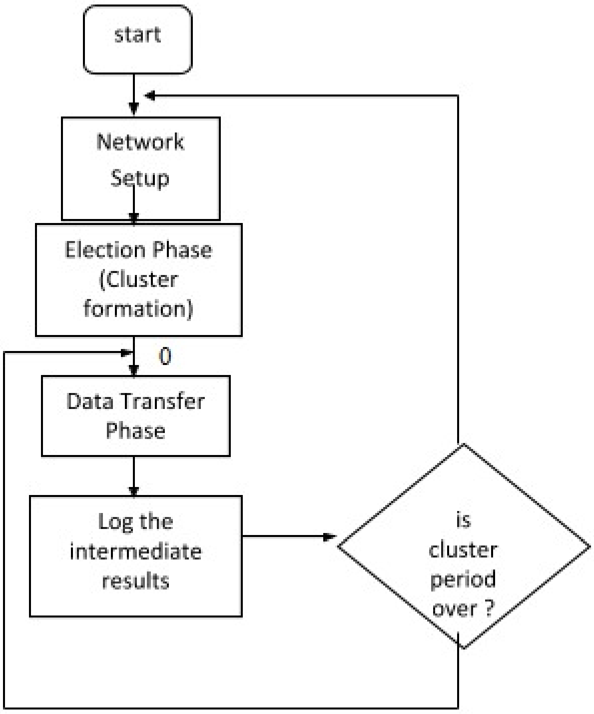

Fig. 2 Flow chart of the proposed clustered routing

The efficiency of the GA mainly relies on the fitness function and in the proposed approach the weights of the fitness function are updated using a reinforcement learning as given in Eq. 10. But the overall performance of the algorithm heavily depends on the randomly chosen initial weights. The weights should be chosen such that the overall network lifetime is increased. The fitness function chooses an optimal solution for most of the generation as there is a little variation in the best and average fitness value during generation.

Table 1. Simulation Parameters

Transmission and receiving energy	50 nJ/bit
Initial energy in node	2 J
Energy required to aggregate data	5 nJ/bit/message
Size of packet	2000 bits
% of Cluster Head	5%
# of nodes	200
Network area	100m x 100m
Location of BS	50m x -100m

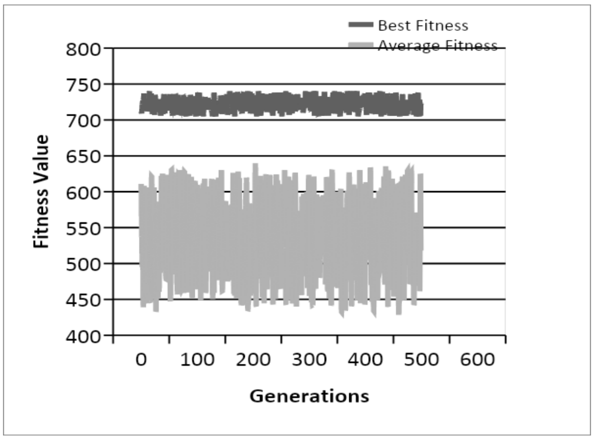

Fig. 3 Fitness value with respect to Generations

The weights that can provide the number of transmissions in the network are initially chosen by brute force estimation. As the generation proceeds in the evolutionary approach correspondingly the best and average fitness values will be increased. The best fitness values have only a small variation and the greater variations are observed in the average values due to filtering of low fitness chromosomes during the selected time. The chromosomes with the best fitness value only survive for the next generation.

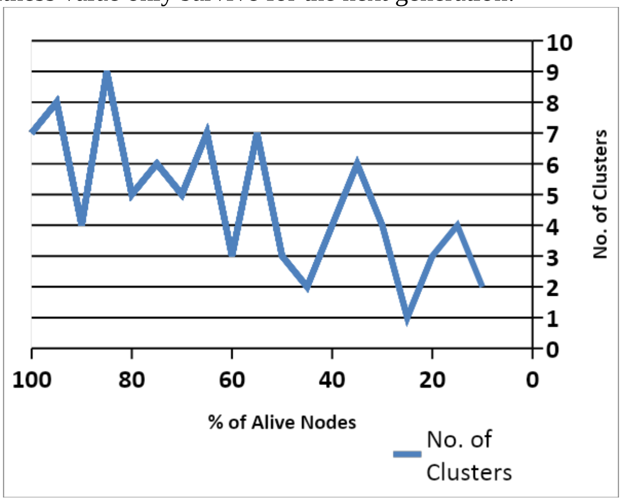

Fig. 4 GA determined no. of clusters

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The Fig. 4 presents the variation in the number of clusters formed and the corresponding percentage of live nodes available in the network. It is found that the number of clusters is higher when the percent of live nodes is higher. The number of clusters formed in the network varies between 4 to 6 when there were approximately 50% of live nodes available in the network. In the simulation 100 transmissions were simulated in each round. The random nature of the evolutionary approach of Genetic algorithm causes some spikes in the cluster formation. Similarly, due to the same reason the energy consumed is also higher at times. The energy consumption is presented in the Fig. 5 for each of the rounds. Poor average fitness of the final population is also another reason for the sudden high energy consumption. During the simulation both grid layout and random layout are followed and in both the cases there is no much difference in percentage of live nodes available in the network after all data transmissions. IN the simulation, it is found that the number of live nodes decreases with respect to time and the total amount of energy consumed is also decreasing as there are only a few nodes for transmission.

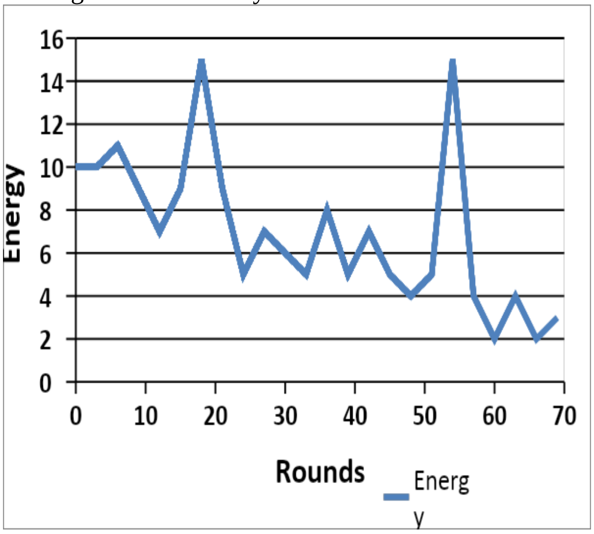

Fig. 5 Energy Consumption in each transmission rounds.

From the simulation it was observed that the number of clusters formed was reduced to a lower number after 25% of nodes have died. As the GA follows a cross layer optimization; it is adaptable for any energy levels of the sensor nodes. The number of transmission rounds in the network was increased considerably. The performance of the proposed approach in terms of throughput and packet delay is analyzed by comparing it with the performance of the other conventional cluster routing protocols. Throughput represents the successfully received data packets in the destination node. The throughput comparison is presented in Fig. 6.

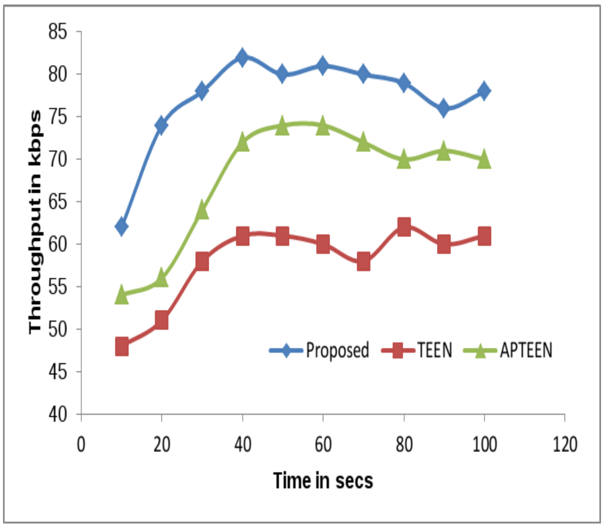

Fig. 6 Throughput Analysis during simulation

The proposed approach does not suffer from overhead issues. During simulation after a certain time the throughput starts reducing. This is due to the traffic increase and subsequent high energy consumption in the network, especially among the nodes closer to the BS.

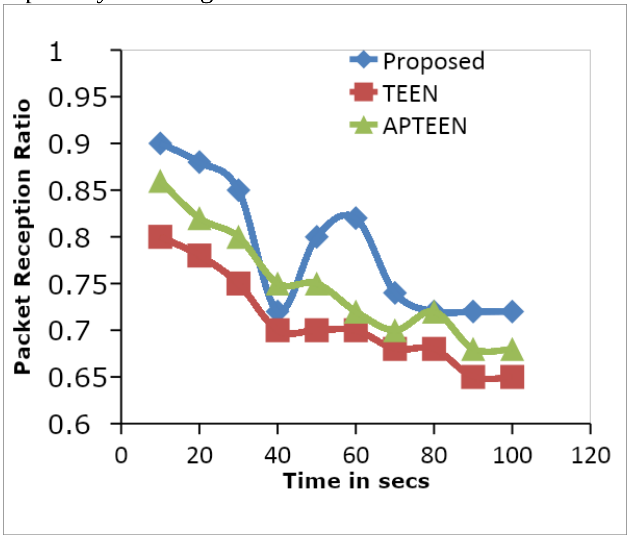

Fig. 7 Comparison of Packet Reception Ration

Packet Reception Ratio gives the percentage of successfully received data packets at the destination end. The sudden dip in the PRR is due to packet loss caused by node mobility [Fig. 7]. The data traffic gets increased during simulation and more nodes are involved in the transmission; so the average energy consumption in the network is increased linearly.

VI. CONCLUSION

This paper proposed an efficient clustering approach based on genetic algorithm which as expected, performs better than the other protocols available in the literature. The algorithm is designed with optimal chromosome representation, random initial population generation with equal weights, chromosome selection and cross over mutation operations with an efficient Fitness Function (FF). The FF is formed by using multiple attributes that can possibly influence the energy spending in the network.

From the analysis of simulation output it is observed that the clustering method proposed is better when compared with other routing approaches reviewed in the literature. The overall network lifetime is increased by lessening the energy spending in the network. This is analyzed using performance measures such as throughput, packet reception ratio, and mean energy spending in the network. In future the cross layer optimization will be researched to build optimal routing strategies. The work can be scaled by adding multi hop communication among the Cluster Heads.

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