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HEURISTIC LEARNING APPROACH FOR RELIABLE MULTI HEAD COMMUNICATION IN WIRELESS SENSOR NETWORK

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ABSTRACT

In recent time, Wireless sensor network has gained a large usage in many Real-time applications. The capability of exchanging data with no pre infrastructure support has given a boost for the usage of wireless sensor network (WSN) in various practical application. Sensor nodes interfaced in WSN are inter-linked to each other and exchange data via different mode of communication wirelessly. Most popular mean of data exchange in WSN is a cluster-based communication, where large monitoring area is sub divided into small clusters for exchanging data. Cluster based communication involve head nodes, which act as a major link point in exchange of data. Optimal Selection of head node in WSN is a critical task for efficient communication. Heuristic learning approach such as Reinforcement learning is proposed for optimal selection of head node in WSN. Existing learning methods were developed with the objective of offering high throughput with energy conservation in the network. However, the reliability of the head node in data exchange is not addressed. Reliability factor is observed to be an important factor in WSN because of the sensitiveness of senor data in the network.

For developing a reliable head node selection in WSN, this paper contributes in developing a new 'Reliable Head Node Routing' (RHNR) approach for optimal head selection in WSN with reliability factor consideration. Proposed RHNR method process on observatory metric of data forwarding at each node in the network and develop a reliability factor updating existing reward factor for Head selection in WSN. The existing Reinforcement approach using Q-Learning is updated with the metric of forwarding factor in selection of a reliable head node in WSN communication. Simulation observations of developed method obtained increase in network throughput and node life time with varying node counts and payload in the network. The End-to-End (E2E) delay metric decreased with the proposed RHNR method resulting into a faster and more reliable packet exchanging in WSN communication.

Keywords: *Wireless Sensor Network, Heuristic Learning method, Reliable Head Node routing, Multi Head Communication*.

1. INTRODUCTION

Wireless sensor network has shown a greater advantage in exchange of monitoring parameter in real time usage. Regions with difficult access such as testing fields, nuclear radiating zone, high altitude locations, medical data monitoring etc. find WSN as an efficient mean of monitoring vital parameters in such fields. Wherein demand of WSN usage is increasing rapidly, various issues associated in data exchange were observed in WSN. Wireless sensor network demands for a high precision, low latency and high throughput network, due to the criticality of monitoring data in the network. Different approaches were developed in past addressing the required constraint for data exchange in wireless sensor network. Cluster based communication is developed as a suitable mean of communication in WSN. Various approaches of cluster-based communication were developed in past [1-4] addressing the formation of clusters and

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routing approaches. Data exchange in a cluster-based communication is performed via selected centralized node called as head Node. Wherein all interfacing nodes are remotely deployed, energy source is a major constraint in this network. In conserving node power for longer time, nodes with higher energy value are selected as Head in exchange of data from all other registered node [5,6]. Selection of head nodes and routing for data exchange in WSN is a major topic of research in this filed. In routing, low energy adaptive clustering hierarchy (LEACH) algorithm outlined in [7] is most efficiently been used. LEACH approach is an energy poling method where all nodes in a cluster participate for head node selection based on current energy levels. The poling process is a search mechanism in finding node with highest energy kevel. LEACH based head selection and communication is observed in various past literatures [8]. However, the energy poling is limited to energy level and other factor such as interference, overhead, traffic conditions etc, were not observed. This limitation decreases the efficiency of data exchange in WSN.

Towards improving head selection in cluster based communication various modified approaches were developed in past [9-12]. Methods using residual energy, coverage range, node distribution etc, were used in defining an optimal head node in the network. In [13] threshold based approach for head selection is proposed which is process on head selection based on matching of residual energy with a defined energy level. This approach gives more probability of head nodes in the network and improves the search performance. However, the variation in energy level with varying network property is not considered. In [14] sensing based method is applied for head selection where in addition to energy level, node interference and overhead is considered for head selection. The method significantly improved the selection performance, however, the computation complexity is observed to be high which impact the overall network lifetime.

Similar approach of interference based approach is outlined in [15, 16] where a weight based data exchange is proposed. A modified method of LEACH approach is defined in selection of head node. The selection process correlates the aggregated energy level in selection of head node in the network. The aggregation needs an additional computation in monitoring of wide distributed nodes in the network which increases the overhead and faster energy dissipation. The dynamic changes in network property such as node distribution, varying cluster size, and random change in resources constraints the existing approaches in searching of an optimal head node. Advance learning methods were hence used in recent past to overcome the dynamic issues in WSN. Method such as particle swarm optimization (PSO) [17], wolf optimizer method [18], fuzzy based approach [19], fire fly method [20] were proposed to optimize head selection in WSN. The random distribution were converged to minimize the search overhead, wherein modified K-mean method is used in optimal cluster minimizing for head node selection. The wolf optimizer approach process head selection based on routing and data exchanged in the network. However, the optimization approaches has no observation on the characteristic monitoring of node operation with change in communication period. They dynamic variation of node characteristic result into a higher processing overhead in the network. In recent a heuristic machine learning approach using Q-learning method is outlined in [21]. This method process to minimize the overhead for a head selection in a communication time period. Variation in node characteristic is governed using a reward metric computed as a function of residual energy and varying action in the network. Outlined method illustrated a significant mean of head selection under varying node which is much suitable in practical usage. However, the outlined method operates only on the node characteristics and no traffic condition or packet flow performance is observed in head selection process. This impacts the reliability of data exchange and builds a large overhead in the network. The measure of reliability packet exchange is observed and a enhancement to the presented approach is outlined in this paper. A new method called 'Reliable Head Node Routing' (RHNR) is proposed monitoring traffic condition and forwarding characteristic of node in the network. The major problems observed with past works,

1. Reliability of packet exchange is not observed.
2. Traffic conditions and forwarding characteristic is not observed in head selection.
3. Optimization of cluster formation in node registration is not addressed resulting into overhead.

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Observing the past problems addressed, this paper contributes following factors in optimal head selection and data exchange in WSN.

1. A new head selection approach is proposed monitoring node forwarding characteristic.
2. An optimal cluster formation is presented monitoring traffic constraint.
3. Efficient data exchange improving reliability and network performance is presented.

To present the outlined work, this paper is presented in 5 sections. Past developed approaches and limitations to the past work is presented in section 1. The problems observed with the existing approaches were summarized and a contribution to the presented work is outlined. Section 2 outlines the recent machine learning approach of head selection using reinforcement method in WSN communication. Section 3 outlines the proposed method for head selection with updated reward factor and risk analysis. Section 4 present the result observations of the outlined work and section 5 conclude the presented work in conclusion section.

2. LEARNING METHOD FOR HEAD SELECTION AND ROUTING IN WSN

Wireless senor network has evolved to a large extend, as the infrastructure less communication has given a additional advantage of deploying of such network to many remote applications. Various real time applications has deployed the WSN in its monitoring and control operation such as agriculture sector, industrial sector, military applications, navigation etc. WSN is a self deployed and follows a dynamic routing mechanism for data exchange with support of interfacing nodes. Each node interlinks each other in data exchange. The most recent approach of WSN use cluster based communication in data exchange where all nodes in a zone form small clusters and exchange data via cluster heads. Cluster heads are nodes satisfying multiple criterion such as the coverage range, energy etc. in the network for communication. Head based communication has gained advantage in cluster based communication where energy conservation and extension of node life is observed. In recent approach multiple head nodes were used in data exchange for more reliable communication. One of the challenging tasks is the selection of head node in the network. With evolution of new technologies, approaches such as machine learning were introduced in head selection. In recent heuristic method of head selection using machine learning is outlined in [21]. The outlined method used reinforcement learning approach for head selection and routing in WSN.

An approach of data exchange in WSN using cluster based communication using head node is illustrated in figure 1. Nodes in a cluster wake for communication from sleep phase and link with head node to deliver data to registered head node. The member node returns to sleep mode once the packets are delivered to head node. Head node intern forward the packet to the receiving cluster head and vice versa.

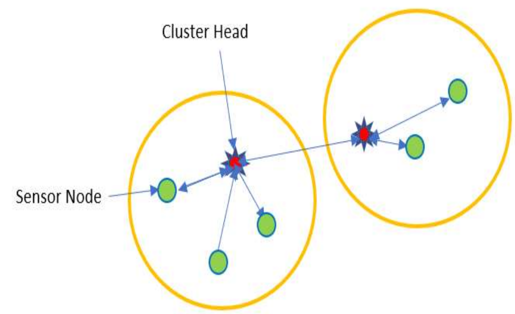

Figure 1. Data exchange in WSN using cluster heads interface

To keep a monitoring on data exchange, a centralized node observing different cluster is used as a monitoring unit which records the communication status of data exchange of all head nodes. The updated parameters are used in monitoring of traffic flow and energy level among different clusters. Illustration of centralized monitoring in cluster based WSN communication is presented in figure 2.

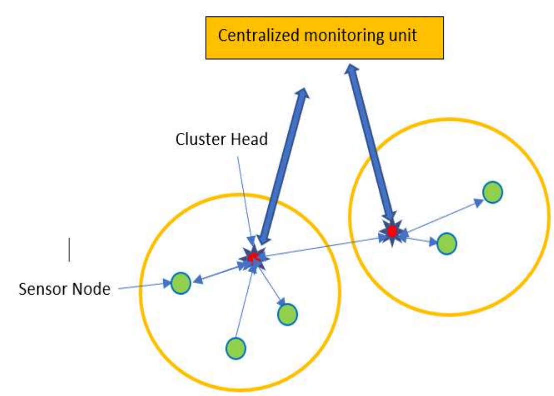

Figure 2. Centralized Monitoring Of Multiple Cluster Head Communication

Approach of cluster based communication is primarily depending on the selected node. Hence, head node selection is a critical part of wireless sensor network. The most popularly used head selection approach is the LEACH algorithms [7] which perform head selection based on the energy level among the nodes. The approach of LEACH has improved network lifetime by 15% in WSN network using energy based selection. However, with wide distribution, random deployment of nodes and dynamic varying nature of network head selection by LEACH is limited and hence new selection approaches were introduced.

In recent machine learning has evolved as an optimal solution in mining and decision making approaches. For a randomly distributed observation, machine learning performs a mining of distributed data in making decision. In recent towards head selection, reinforcement based mining approach is outlined in [21]. This approach is developed using Q-Learning method [22] which is a markovian based learning approach used in reinforcement approach.

Q-Learning based approach optimizes route selection based on the action performed by nodes in the network and compute monitoring Q parameter in making decision. The monitoring parameter is developed using reward value ($R_\emptyset^t$) defend for a action ($\emptyset_t$) performance in the network. The reward values is defined as,

$$Q_t(\emptyset_t) = (1-\delta)Q_t(\emptyset_t) + \delta[R_\emptyset^t(\emptyset_t+1) + \beta \times \max\big(Q_t(\emptyset_t)\big) \quad (1)$$

The computation process of the Q parameter is defined by the learning parameter δ and a discount factor β applied for an action $\emptyset_t$ preformed in communication phase in the network. $R_\emptyset^t$ is the reward factor defend for an action given as,

$$R_\emptyset^t = \frac{\sum(\min(E(p)+\sum E(p))}{\sum p(pth)} - t \quad (2)$$

Where E(p) is the residual energy at a node after data exchange, which is defined as,

$$E(p) = E_i^t - D \times E_c^t \quad (3)$$

Where,

E_i^t is the residual energy at node k in the observing time t.

D is the data volume to be exchanged over the network

E_c^t Defines the energy value required in communication for a signals data packet

The selection of optimal path for data exchange is perfumed based on the reward values obtained. In selection of optimal path with selected head, computed reward value is compared with a limiting value ϵ given by [21] as,

$$\epsilon = \frac{P(n)}{1-P(r \, mod\left(\frac{1}{P(n)}\right)} \quad (4)$$

The probability of a head node selection at i[th] iteration is defined by $P(n)$

Nodes with reward value above the threshold limit is used in selection of a head node and it associated path in data exchange. The presented Q learning approach for head selection for data exchange is more robust in path selection and data exchange in WSN, however, the reliability factor of the node in data exchange is not observed. Reliability of data exchange is a critical need in WSN due to the selective data exchange over the network. However, the presented method does not consider the reliability factor which constraints the performance in communication in WSN. To improve the communication performance, a new method of route selection with associated head is proposed in consideration with reliability factor.

3. RELIABLE HEAD NODE ROUTING (RHNR) IN WSN

To avoid failure of packet loss, multi head communication is adopted. Multi head communication offers a higher guarantee of forwarding packet delivery in WSN. A two head communication based on Q-leaning is outlined in [21]. Node with higher reward factor is selected as the primary clatter head for data exchange. Node having similar observation is selected as secondary head for communication. In data exchange if selected primary head node fails in forwarding data, secondary head node is switched. In this the selection of head node for data exchange is defined by a reward factor measured based on action in the network. However, varying condition of WSN during data

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exchange has impact on multiple factors which affects the data exchange performance in WSN, such as the energy dissipation, interference observed and the traffic flowing through the head node at a time interval and the density of nodes in a cluster. Random variation of these factors, constraint the communication performance effecting accuracy of data exchange in WSN. Proposed approach defines a monitoring parameter to the existing reward metric in improving reliability of selected head node. A controlling and decision unit is interfaced with the existing monitoring unit to monitor the reliability factor of each node, used in the selection of head node. Figure 3 illustrates the proposed approach of reliable monitoring in WSN.

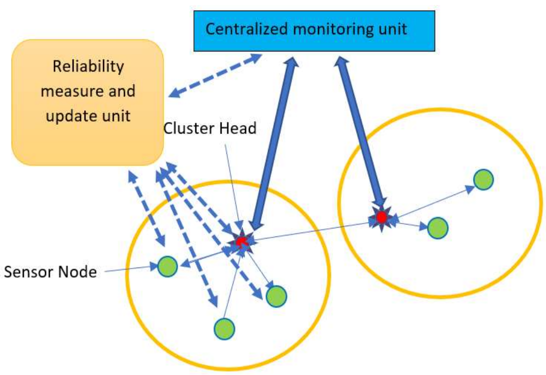

Figure 3. Interface For WSN Nodes Reliable Factor

The decision unit reads the status of packet forwarding using sensing signal from each node, which is generated on request for updated value of forwarding parameter measured at the node. The decision unit generates a control signal for reading the status of forwarding parameter from each node. Signal flow for proposed approach in WSN is illustrated in Figure 3.

Outline method define two monitoring parameters to monitor packet forwarding conditions. For a successful forwarding of packet a forward parameter Φ and on blockage a parameter Ω is used. During data exchange, head node update these parameters and process for a suitable path using decision unit. During each packet exchange time 't', the two parameters are continuously updated at the decision unit which are defined as,

$$\Phi t = (\Phi + \Phi') + \gamma \qquad (5)$$

$$\Omega t = (\Omega + \Omega') + (1 - \gamma) \qquad (6)$$

Where, the updation factor γ is used to define the status of packet forward condition. For successful packet forwarding the value is set to 1 wherein for packet blockage value 0 is assigned.

Proposed method defines a monitoring parameter 'ρ' at decision unit which relate the two monitoring parameters in updation of reward factor given by,

$$\rho = \frac{\Phi t}{\Omega t} \qquad (7)$$

The existing reward parameter for an action ∅ is updated by the observation of proposed monitoring parameter ρ which is given by,

$$R_{\emptyset}^{updt} = R_{\emptyset}^{t} \times \rho \qquad (8)$$

Which is given as,

$$R_{\emptyset}^{updt} = R_{\emptyset}^{t} \times \frac{\Phi t}{\Omega t} \qquad (9)$$

Change in packet forwarding parameters γ , Φ effect the reward factor and the path selected for communication. Using the outlined method, path selected for communication is energy efficient and reliable for data exchange as the reward factor is defined by residual energy and packet forward factor. A random clustering and node registration into cluster results into an improper loading into the network. To minimize random loading into network a monitoring risk factor 'φ' is measured given by,

$$\varphi(n) = (P(\sum E(p) + E(n)) - P(\vartheta \times D) \qquad (10)$$

Where,

The risk factor is defined as a probabilistic function P(.), of aggregated energy of current nodes (p) and adding node (n) in the network and the probability of data volume $(P(\vartheta \times D))$ increased due to adding of nodes. The new node count ϑ after the addition of new node in the cluster is given by,

$$\vartheta = n + p \qquad (11)$$

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with p and n are the available and updating nodes in the cluster.

Proposed monitoring factor is measured by correlating the aggregated energy gain in a cluster with the packet exchange overhead due to additional nodes n in the network. To perform the decision of selection, measured parameter is compared to a tolerance value (ϵ) and a node with risk value below limiting value is registered into the cluster. Nodes with risk factor above limiting value (ϵ) is discarded for registering onto current cluster and processed for neighboring cluster. The tolerance limiting value is updated for the decision system defined as,

$$\epsilon = \frac{P(n)}{1-P\left(r \, mod\left(\frac{1}{P(n)}\right)\right)} \times \frac{E(n)\times n}{E(p)\times p} \qquad (12)$$

The limiting constraints are measured as a probabilistic function of adding node probability into a cluster in comparison of energy due to added node in the cluster over available energy level. Nodes which are constraint within the defined limit are added into the cluster. Optimal clustering and reliable head selection offers high performance operation into WSN, which increase the scope of WSN application in various real time usages. Reliable head selection and node with lower risk factor contributes in faster and more accurate data exchange which is much needed in various critical applications. Observation of the proposed work for data packet exchange in WSN is outlined in following section.

4. RESULT OBSERVATIONS

Evaluation of the proposed approach is developed for a randomly distributed network with network parameters listed in Table 1. The simulated network is randomly distributed with nodes placed at random locations in the network area. Powers assigned to the nodes are randomly allocated to have a nonlinear distribution of power levels in the network.

Table 1. Simulation Parameter For Evaluation Of Outlined Method

Network parameter	Values
Node layout	Random
Route discovery	AODV
MAC interface	IEEE 802.11
Power in the node	Random
Communication range	45 m
Area of Network	200 × 200
Node counts	10-100

Figure 6 show the simulated network for analysis of the outlined method where nodes are randomly placed in a 200×200 m^2 network area. Nodes in the network are allotted with distinct IDs, communicating spectrum and varying power level. Nodes with a range of 45m in distance are declared as direct link nodes. All link nodes exchange their registered link nodes

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to form possible paths for communication as shown in Figure 7. Proposed risk factor is computed to form sub cluster as shown in Figure 8 below. Based on the power level and reward factor shared head node is selected and all linked nodes are registered to the head node for data exchange selecting a suitable path as shown in Figure 8.

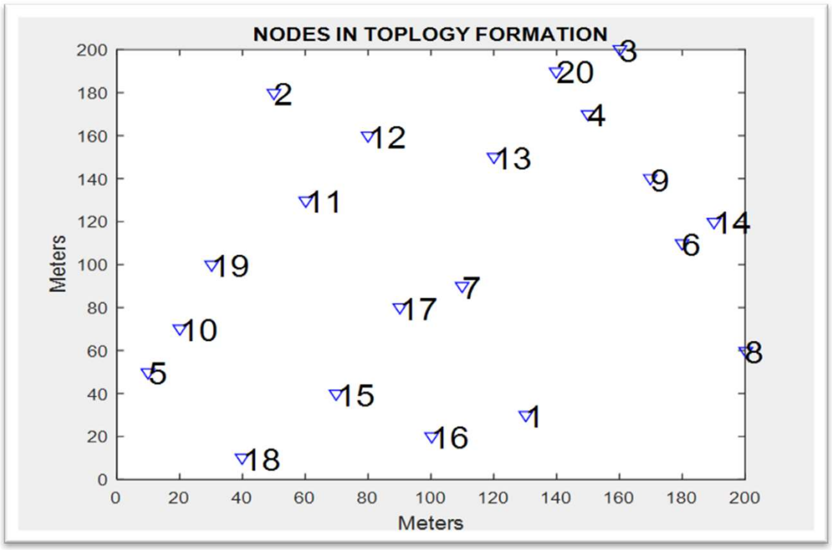

Figure 6. Layout Of Sensor Node Distribution In Simulating Network

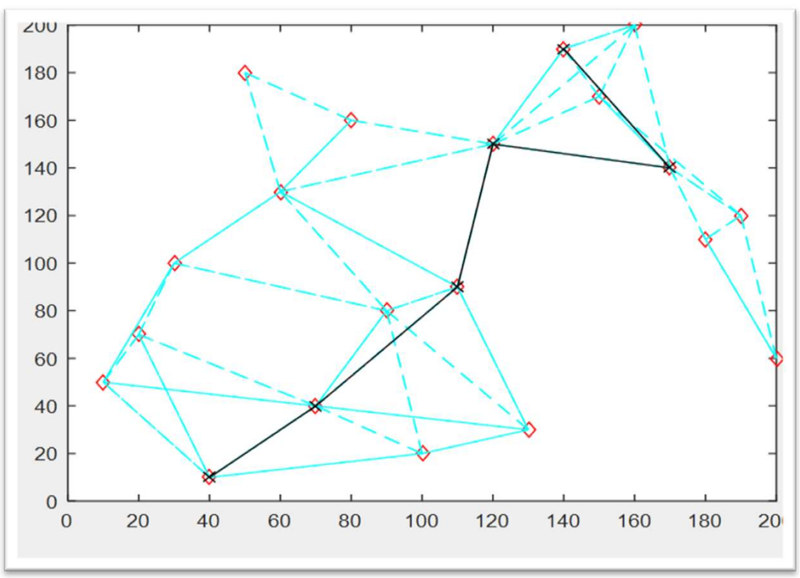

Figure 7. Observed Link For Data Exchange Based On Communication Range Constraint

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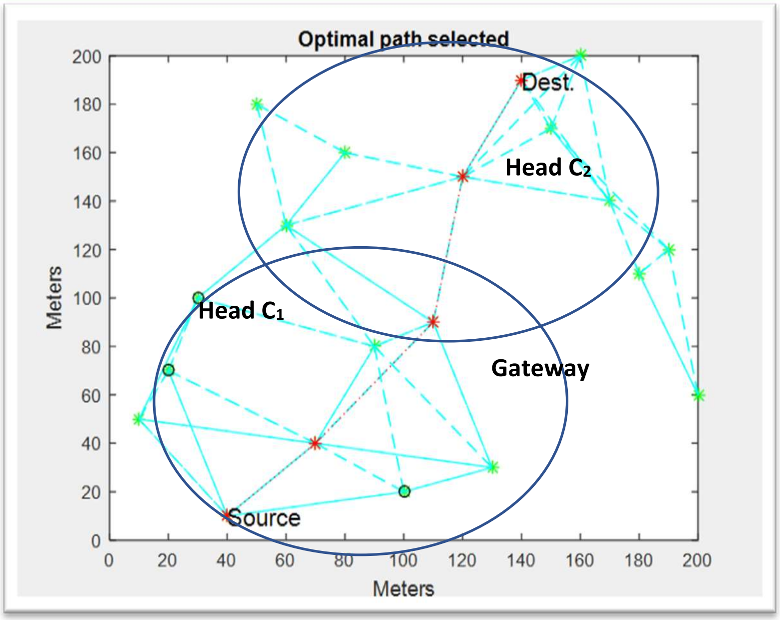

Figure 8. Optimal Path Selected Using Proposed Method For Data Exchange

In exchanging packets form source to destination head node are interfaced in exchange of data form one cluster to other. In computing the observing parameters, volume of packet exchanged and time taken in exchange of data is observed to define network metrics. Observation of measured metrics with the variation of number of node counts and exchanging packets n the network is presented in figure 9-14. With increase in node counts in the network, the throughput defined as the volume of data exchanged over the network for a defined time interval is observed to increase by 14800 Kbps as compared to 10000 Kbps for existing LEACH-FET [21] method. As the outlined method offers a reliable path in data exchange, minimum blockage of data is observed in the network with rise in node count. This result in lower congestion and faster data flow in the network resulting in increase of throughput in the network as illustrated in figure 9.

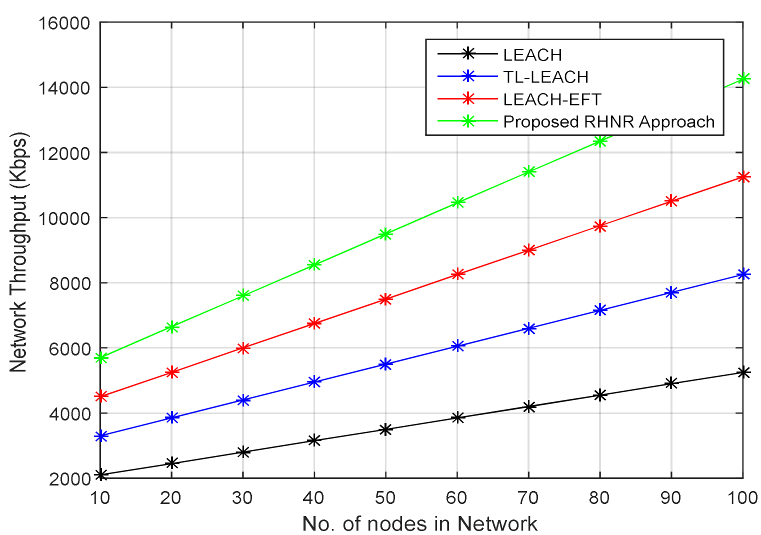

Figure 9. Observation For Network Throughput With Change In Node Count

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Alive node defined as the number of node available in data exchange. With exchange of packets in network node dissipates energy resulting into deceasing the life time. The aggregated node counts available with energy level above communication energy are counted to observe alive nodes in the network. With increase in node counts, the available nodes were increased however, the increase in node count also increase the date exchange probability in the network which increases high traffic resulting in faster energy dissipation. The proposed method observes the forwarding probability before exchange of packet decreasing the energy dissipation of re-transmission. This improves the node life time and overall available node counts as observed in figure 10.

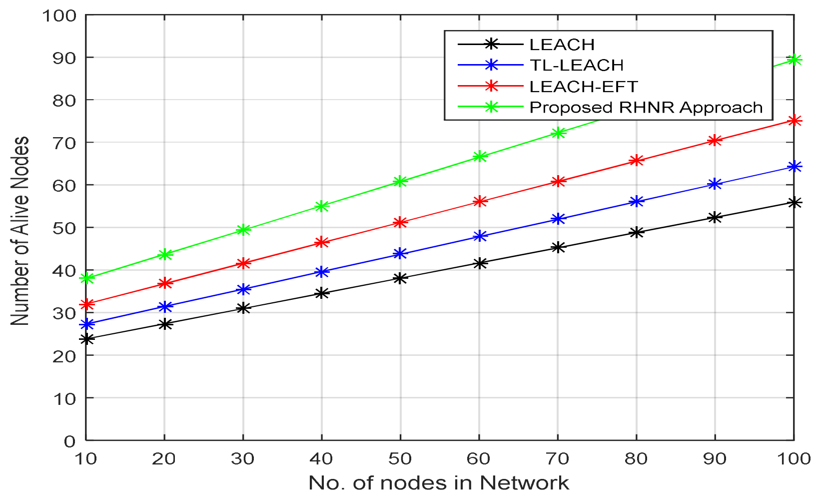

Figure 10. Count Of Node Alive In The Network With Change In Node Count

Observation of network lifetime with change in node counts in the network is illustrated in figure 11. Network lifetime is defines as the total time available for member nodes in the network which is computed by the energy available and the utilizing transmitting and receiving energy level. the lifetime for the network with proposed method is observed to 100msec and 33, 85,76 mSec for the existing LEACH, LEACH-EFT and TL-LEACH method respectively.

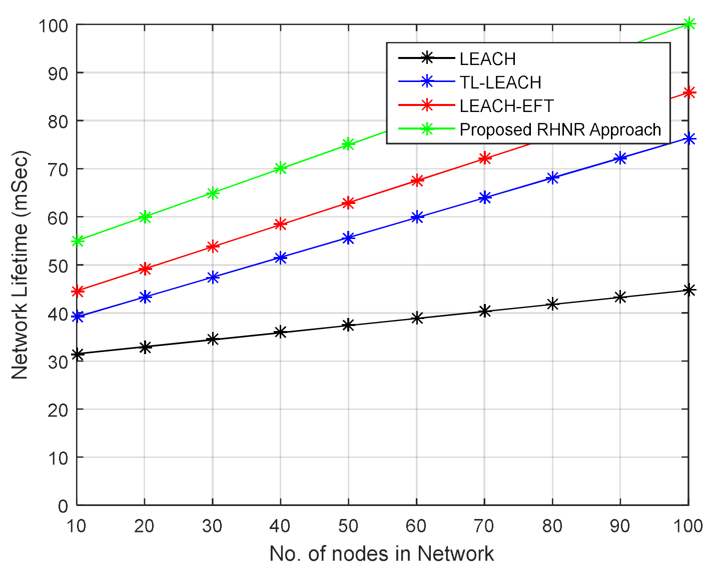

Figure 11. Variation In Network Lifetime With Change In Nodes In Network

The delay metric observed for data exchange over the network from a source to sink is observed as end to end delay in the network. Observation of End to End delay is illustrated in figure 12. Observation of the simulation model illustrated a decrease in end to end delay by 19 Sec in comparison to existing energy efficient LEACH method. The network with selected head node offers a faster data exchange due its selection based on forwarding factor. This monitoring results into lesser blockage of packet and decreases the observing delay parameter. Comparison of the delay parameter for proposed RHNR method compared to existing LEACH, TL-LEACH and LEACH-EFT method is shown in Figure 12.

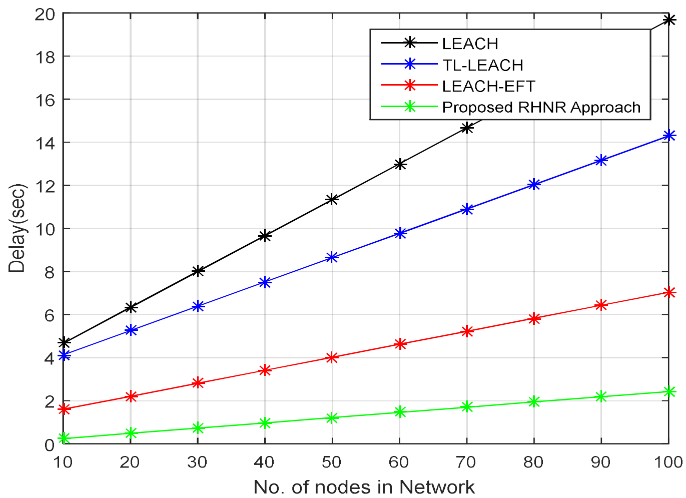

Figure 12. End To End Delay With Change In Node Counts

Performance of the WSN for change in forwarding packets is evaluated as shown in Figure 13-16. Setting node count of 100 in the network, volume of packet counts for exchange is evaluated. Different packet size in communication has variation in the monitoring parameter which affects the accuracy of cluster formation and optimal head selection. Observations of monitoring parameters with varying packet counts in illustrated in following figures.

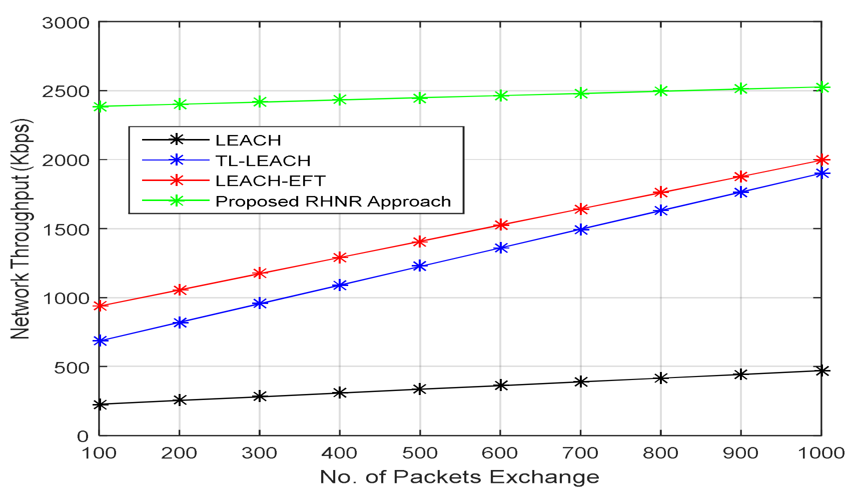

Figure 13. Observation Of Network Throughput With Increase In Packet Exchange

Network throughput is observed to be increased using the proposed method compared to existing approach as shown in figure 13. Volume of packet exchange has an impact on the traffic flow and resource allocation. Wherein existing approaches focus on energy-based head selection and data exchange, reliability of packet forwarding is not observed. Head node with higher energy level could be blocked due to other factors in the network such as the interference and traffic congestion. The proposed selection of head is governed by power and blockage level which optimally select path with higher reliability. This factor improves the throughput parameter in the network as shown in Figure 13.

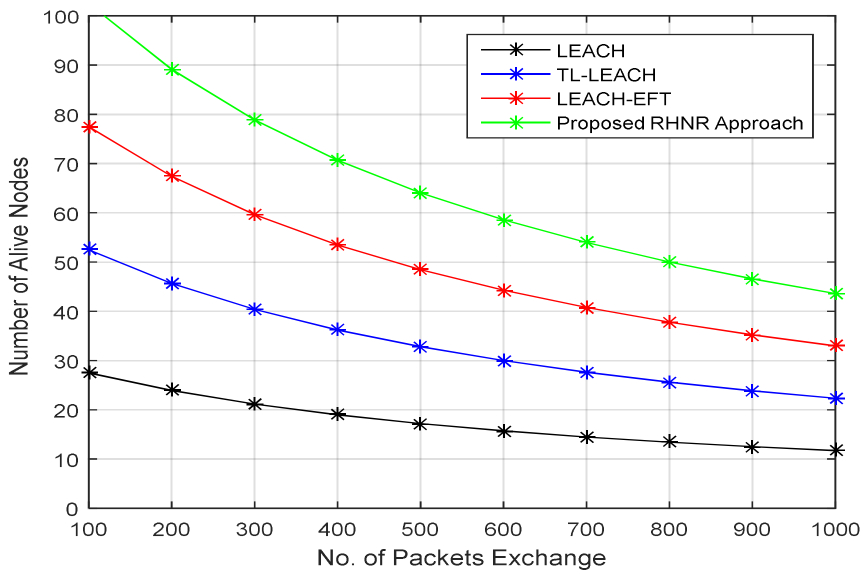

Figure 14. Node Counts Available In Network With Increase In Exchange Of Packets

Faster data exchange minimizes the blockage probability, which intern reduces power dissipation at each node in the network. Lower power dissipation increases the number of node alive counts, and network life time. A comparison of node alive count and network lifetime is shown in Figure 14 and 15 respectively.

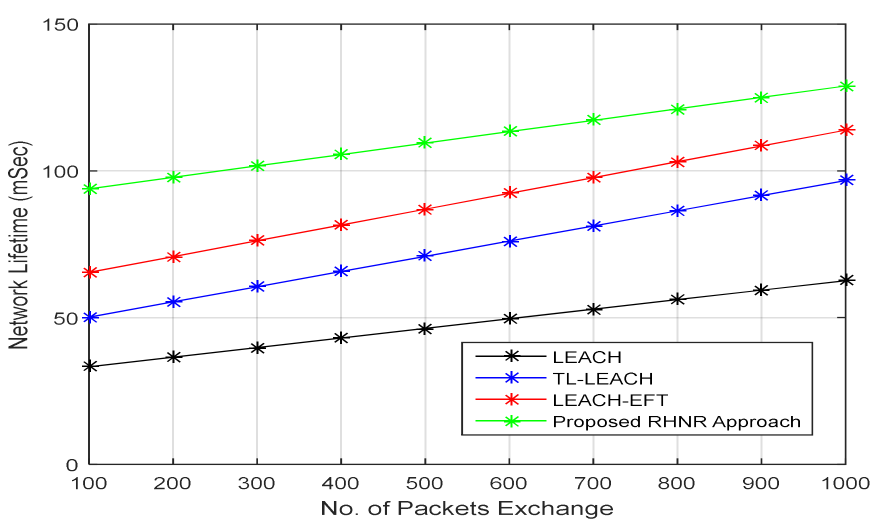

Figure 15. Observation Of Network Lifetime With Increase In Packet Exchange In The Network

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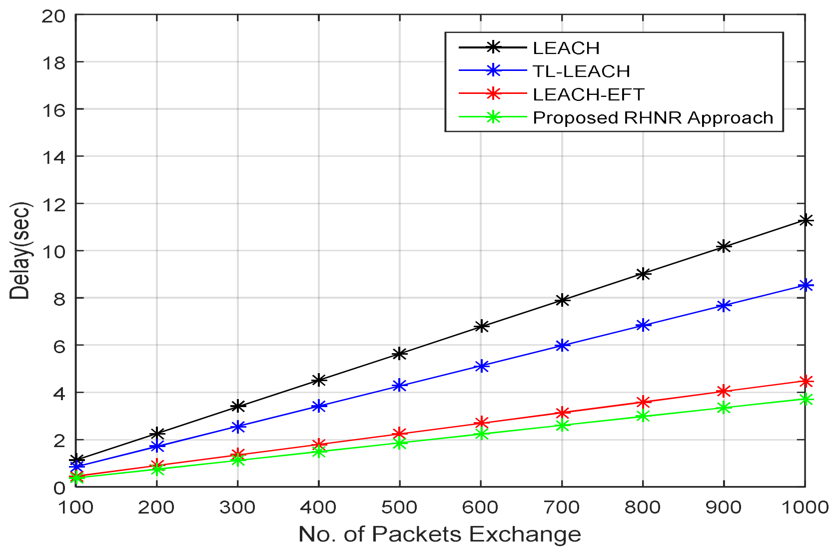

Figure 16. End To End Delay With Change In Exchanging Packet Count

The E2E delay parameter is measured as the time taken from encoding sensed data to delivering to the destination. The E2E delay is observed to reduce by RHNR method compared to LEACH, TL-LEACH and LEACH-EFT method. Observations illustrate an improvement in the lifetime, where the proposed approach observes an increase in lifetime by 96msec. communication delay is observed to reduce by 7.8 Sec resulting into increase in available node of 36 counts higher than the existing methods.

5. CONCLUSION

Selection of cluster head in data exchange is proposed. A new reliable reinforcement approach for optimal cluster formation and head selection is proposed in developing a new communication approach using energy monitoring parameter. Proposed approach defines a new method for path selection using packet forwarding characteristic in WSN. The proposed method improves the forwarding reliability in addition to energy constraint to offer a best selected path in communication, which improved the data accuracy and throughput in the network. For randomly distributed nodes in the network, low level congestive cluster with optimal path improves node life time and availability of nodes in link. Outlined RHNR method observes to increase network throughput by 4800 Kbps with minimization of End to End delay by 19 Sec in data exchange. Increase in network metrics increases the network lifetime by 100 mSec resulting into faster and reliable data exchange in WSN communication.

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