Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 8, August : 2023

Enhanced Data Exchange in Wireless Sensor Networks for Centralized Medical Monitoring: Low-Risk Reliable Routing with Reinforcement Learning

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Abstract: The medical sector is one of the most rapidly expanding areas of wireless sensor network (WSN) application. Continuous monitoring of patient vitals is required in big hospitals with widely dispersed units. When manual monitoring is difficult and needs a big number of people, centralized monitoring is preferable. The wireless sensor network offers the best sensor interface for detecting and communicating crucial values for a centralized monitoring system. The communication system exchanges data across a wireless channel with no pre-infrastructure assistance. WSN's self-creating property provides an opportunity to monitor critical parameters in a medical sector. However, delay and packet loss are crucial for monitoring critical metrics. A low-risk reliable routing (LLRR) strategy is presented to provide a reliable data exchange over WSN. In WSN communication, the LLRR technique presents an updated reward metric in a reinforcement learning strategy for optimum clustering and head selection. When compared to previous cluster-based routing systems in WSN, the performance of the WSN interface employing LLRR for crucial parameter exchange improved network throughput and network life time while decreasing E2E latency.

Key words: Cluster formation, Head selection, Low-risk Reliable routing (LLRR), Medical sector, Reinforcement learning strategy, Wireless sensor network.

I. Introduction

Monitoring crucial metrics across a large region has become a significant task in today's applications. In actual circumstances, the sensitivity of the detected data and the accuracy of transmission present a twin difficulty in the management and interchange of sensor data. Various technologies have been introduced in response to the increased demand for quicker and more accurate data sharing. Wireless sensor networks (WSN) have shown to be more advantageous in the interface of data sharing for sensor data in a broader sense. While wireless monitoring and dynamic network adaptation provide WSN an edge, data interchange performance has many limits to overcome for sensitive applications. To increase data interchange performance in WSN, many routing schemes have emerged. Nodes are the interface devices in wireless sensor networks that acquire sensory input and communicate. At the node level, each node is capable of data transmission, reception, and exchange. [1,2]. The distant deployed device, on the other hand, has power limits, which is a critical concern in WSN [3] for efficient wireless communication. Several WSN routing algorithms were described, with clustering-based routing [4-6] being the most favored due to the benefits of optimum resource monitoring and energy savings.

Nodal communication is based on tiny cluster zones in which all nodes interact with one another via an elected cluster head. The low energy adaptive clustering hierarchy (LEACH) methodology is a popular cluster-based communication method in WSN [7]. This method uses an energy polling mechanism to pick cluster heads in a probabilistic manner. The cluster head is chosen at random, and the node with the most energy is chosen as the head node. Following selection, the head node publishes an update request to all neighboring nodes. For data sharing, all registered nodes interact through the designated head [8]. The use of a maximum energy node enhances network life by reducing dissipation for low energy devices. The downside of random selection of the head node is that it does not optimize traffic circumstances, resulting in delays and increased power dissipation. Energy-saving approaches in WSN were given in [9-12] using various ways of cluster head selection. The cluster head selection is displayed and is unevenly distributed in the network based on a node's residual energy. A threshold-based strategy was presented in [13] to optimize cluster head selection by constraining the head selection with residual energy and the number of clusters in the network. To reduce processing overhead in [14], a simplified sensing technique for data was developed.

The conversation is shown. [15] describes a method for weighting data packet communication depending on interference in a zone for improved estimate at the destination node. [16] describes an improvement to the leach algorithm (ILEACH) for power optimization, which establishes a threshold for cluster head selection based on total network energy usage. The equalization mechanism in the network is used to generate the threshold for head selection. To save energy in WSN, various learning approaches were used. [17] described a learning strategy for cluster head selection based on partial swarm optimization (PSO). The approach selects cluster heads from a network of uniformly dispersed nodes. The Wolf optimizer technique for selecting cluster heads and routing for data exchange on a network is developed in [18]. [19] describes a fuzzy-based approach for cluster head selection. A modified k-mean strategy for the optimal selection of cluster heads in a widely dispersed WSN is described. [20] describes a fire fly technique to cluster creation.

This method improves cluster formation in a network with a heterogeneous node distribution. [21] recently described a heuristic machine learning strategy based on reinforcement learning. This method provided a multi-head solution for cluster head selection and data sharing. The Q-Learning method is used to calculate a monitoring factor depending on reward value. The value of the reward is calculated as a function of leftover energy. Because of dynamic head selection, the presented strategy increased network performance and node life time. The proposed technique, however, does not assess the dependability of data sharing via the head node. Because of the sensitivity of data flow, reliability is a vital component in WSN. This paper describes a technique for low-risk reliable routing (LLRR) in WSN for determining cluster head based on network reliability and risk variables. The measure of dependability in terms of packet forwarding success improves the performance of cluster node registration and cluster head selection.

The approach is explained in five sections. Section II describes how to use a wireless sensor network to pick cluster heads. Section III describes the suggested method of dependable routing. Section IV presents observations on the suggested technique, and Section V provides a brief conclusion to the proposed strategy.

II. Wireless Sensor Network Head Selection and Routing

Practical applications have increased wireless sensor network use. The self-deploying and data sharing properties of WSN are advantageous in remote places where pre-infrastructure construction is impossible. WSN uses indoor and outdoor interfaces. WSN consists of nodes interfaced with sensors that capture and process data from the interfaced unit and process it wirelessly. An combined codec-sensor unit concept forms nodes. Over wireless medium, intermediate nodes forward packets to the destination containing encoded data. The self-creating nature allows distant use and no pre-infrastructure need. However, data exchange pathways are very dynamic, reducing network dependability in crucial applications. The limited energy supply and variable traffic circumstances hinder real-time WSN usage. Due to sensitive sensor node data processing, this network needs reliable routing. WSN communication is cluster-based. Clusters emerge based on node coverage. Data exchange is concentrated at a head node for optimal coverage and energy. Only head nodes connect with all sensor nodes. WSN node features like data sensitivity and gain factor require optimal clustering. For better data interchange, traffic control, and energy dissipation, WSN cluster heads should be efficient. Need reliable routing under variable network circumstances for low latency and high accuracy. Cluster formation, head selection, and routing were designed with communication range and energy restrictions. Reinforcement learning-based machine learning algorithms were presented to optimize WSN head selection and routing. The reinforcement technique optimized WSN routing employing latency, energy, and node density limitations. Figure 1 shows cluster-based data sharing in wireless sensor networks with member and head nodes interfaced. In WSN, dependable and efficient communication requires excellent cluster formation and head selection.

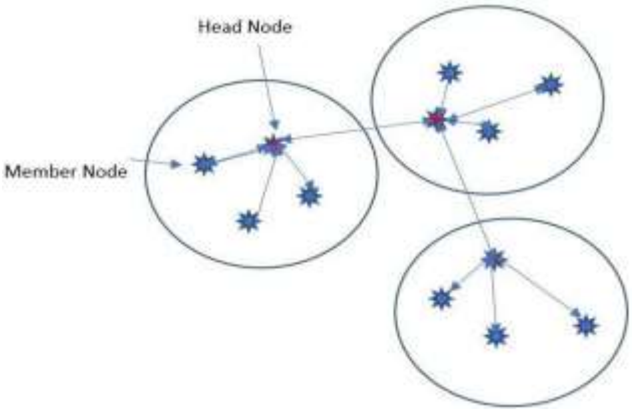


Figure 1. Communication scenario in a wireless sensor network

This proposal addresses cluster location and head node selection. Current WSNs exchange data utilizing cluster-based communication. Clusters are used to communicate in faraway WSNs. Current cluster-based communication uses range restrictions (device power and protocol specify maximum coverage range). The head node controls all cluster nodes' communication. Maximum power and coverage determine head nodes. The head node selection is crucial in cluster-based WSN communication. The head node's constant data interchange increases the likelihood of node draining and maximal interference, which accelerates power dissipation. This paper proposes a novel cluster head selection and node placement method to reduce power dissipation and increase network life. Nodes between clusters have a chance to join any cluster. However, haphazard placement increases interference and power loss. Figure 2 shows each head node sharing data with a central monitoring unit.

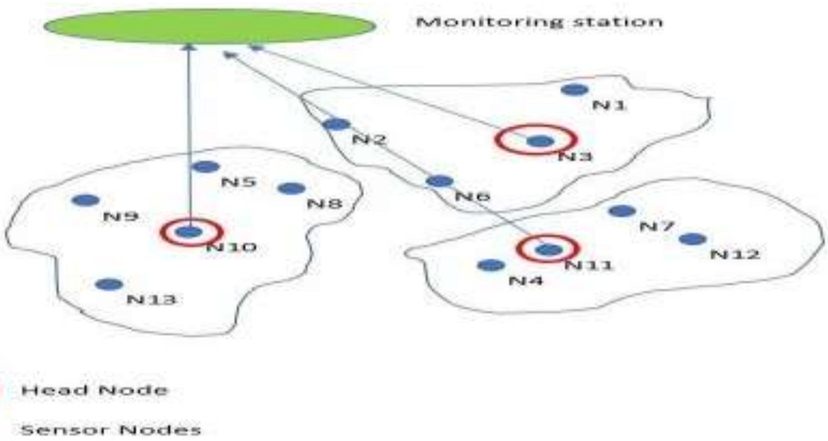


Figure 2. Monitoring of sensor data in a wide area application

WSN communication is carried out utilizing a cluster-based technique. The network's nodes are divided into zones, and each zone elects a head node to share data with other nodes. The noncurrent strategy that uses maximum energy and coverage range poling in head node selection is concerned with two primary issues: optimal cluster head selection and node registration into a cluster. The Node with the highest energy level and the greatest coverage is designated as the head. All adjacent nodes are considered members and communicate through the head node. The LEACH method, which chooses head nodes based on maximum energy level [7], is the most widely used head selection technique. LEACH achieves a 15% increase in network lifespan.. However, LEACH has various limitations as outlined:

1. Random head selection for clusters
2. Observable cluster formation
3. Significant power loss
4. Extremely prone to topological fluctuation

To overcome the listed issues, a reinforcement learning approach was introduced in [21]. Reinforcement learning is a significant subfield of machine learning which concentrates on action learning for expected outcome. The Q-Learning approach [22] is an optimal method used in reinforcement learning which is based on the decision process from the Markovian approach with no prior knowledge. The Q-Learning algorithm determines the ideal route under dynamic network conditions, performs operation on action (a), and develops a Q-value which correlated to the reward value for an action at iteration t, given as:

$$Q_t(a_t) = (1-\alpha)Q_t(a_t) + \alpha[R_t(a_t+1) + \tau \times \max Q_t(a_t)] \quad (1)$$

Where α is the learning rate and γ is the discount factor. R_t is the reward value for action α_t.

The reward function is defined by the energy usage and the data transfer latency which is given as:

$$EE_k^t = E_k^t - dt_k^t \times E_{cast}^t \quad (2)$$

Where, E_k^t - Available node energy.

dt_k^t - Data volume in the buffer.

$E_{\cos t}^t$ - Energy cost for ending unit data.

t - time slot.

The path selection in a multi path scenario is developed based on highest reward factor defined by:

$$R_a^t = \frac{\sum(\min(E(n) + \sum E(n))}{\sum n(P_{th})} - t \quad (3)$$

The path with the highest power weight specified by the leftover energy is chosen as the ideal path for data transmission. The communication channel chosen accomplishes data exchange via cluster heads, which are chosen depending on the residual energy of the network's nodes. The choice of head node is limited by a threshold value. [21] proposes a dynamic threshold calculation for head node selection, which is provided as:

$$Th_n = \frac{prob(p)}{1 - prob \times \left(r \bmod \times \left(\frac{1}{prob} \right) \right)} \quad (4)$$

Where, $prob(p)$, is the probability of cluster heads at r iterations

All member nodes in a cluster with a reward factor greater than the determined threshold are designated as the head. Data is sent between registered cluster member nodes via designated head nodes. The head node is chosen based on residual energy, however the dependability of the chosen head node in data exchange is not monitored. In sensitive data monitoring, data interchange reliability is crucial. An enhanced reinforcement learning strategy with an updated reward factor is suggested to establish reliable routing in WSN.

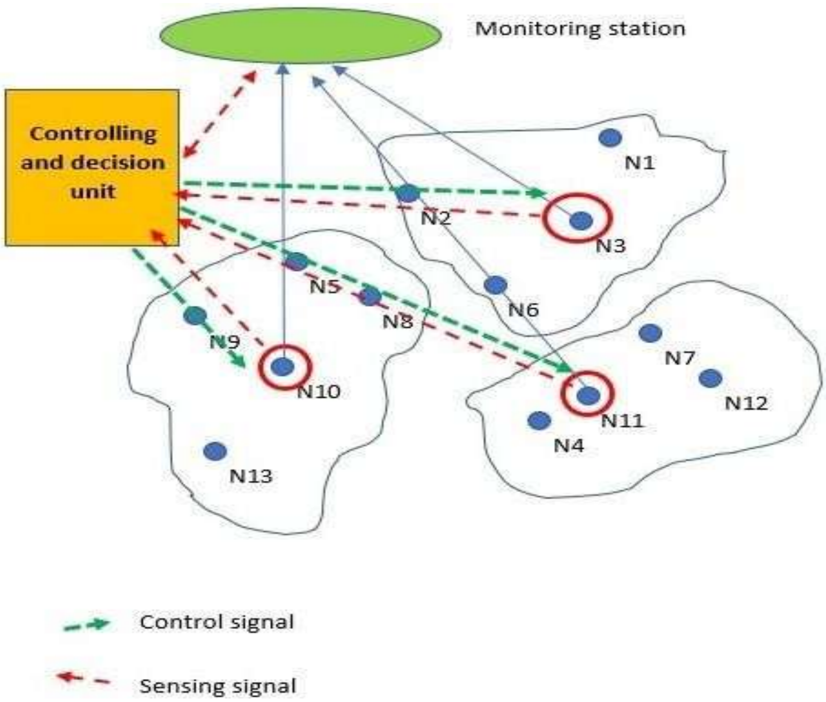
III. Low Risk Reliable routing (LLRR)

The node with the highest reward is chosen as the primary cluster head, and the others as subordinate heads. Secondary heads are used during data interchange to transfer data when the primary head fails to do so. The dynamic selection head and pathways resulted in increased data delivery, enhanced throughput, and lower network latency. However, the current head selection method does not address the dependability of the chosen head node. The chance of maximal data interchange is higher for selected head nodes based on energy restrictions. However, a variety of factors influence the performance of the head node during communication.

The following factors have a higher influence on network performance:

1. Power dissipation rate
2. The flow of traffic through the head nodes
3. Interference at the head node detected
4. Cluster density

To increase data exchange reliability, the variables head node selection and communication path need to be monitored concurrently. This paper suggests a new forwarding factor to the existing reward metric, for the best path selection in WSN, in order to provide a trustworthy way for data exchange. In figure 3, the suggested method for reliability monitoring in WSN is shown.



Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 8, August : 2023
Figure 3. WSN interface for reliability measure in WSN

The suggested technique specifies two packet forwarding and blockage parameters as φ and ρ, respectively. During communication, the head node updates two monitoring factors and communicates path selection with the member nodes.

The updation of the two factors is given as:

$$\varphi t = (\varphi + \varphi') + \delta \quad (5)$$

$$\rho t = (\rho + \rho') + (1 + \delta) \quad (6)$$

Where δ is the updating factor which is given value 1 on forwarding and 0 on blocking.

The monitoring factor (M) for a path is defined as:

$$M = \frac{\varphi t}{\rho t} \quad (7)$$

The monitoring factor (M) is introduced to the reward function which is updated as:

$$R_a^{t-update} = \left(\frac{\sum(\min(E(n) + \sum E(n))}{\sum n(P_{th})} - t \right) \times M \quad (8)$$

Which is defined as:

$$R_a^{t-update} = \left(\frac{\sum(\min(E(n) + \sum E(n))}{\sum n(P_{th})} - t \right) \times \frac{(\varphi + \varphi') + \delta}{(\rho + \rho') + (1 - \delta)} \quad (9)$$

The change in the forwarding condition update, which has an influence on the prize. The suggested technique selects the path with the maximum power weight and the best reliability factor. As path selection at the node level is built with previous knowledge about head operational circumstances, this gives a better chance of path existence for a longer period of time. Route request overhead due to random selection is avoided. This provides a significant reduction in power dissipation at the head node and enhances overall network life time. A risk factor is added for node registration into a cluster, which is specified as:

$$Risk(Nr) = (\Pr ob(\sum E(n) + E(nr)) - (Nc) \times D \quad (10)$$

Where,
E(n) + E(nr) indicates the aggregated energy due to a registering node Nr in the network.
$(Nc) \times D$ Indicates the volume of data increases due to Nr nodes, (Nc = (N +Nr)) (for N available node in a cluster.
Here,
A risk factor is calculated by comparing the network's overall energy benefit to the volume of data overhead that grows with the addition of Nr nodes. If the risk is less than the limiting value (Lc) of registration gain, the node is included to the cluster; otherwise, it is dropped in favor of another cluster selection.
The limiting value L_c for a cluster C is defined by,

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$$L_c = \frac{prob(p)}{prob \times (r \bmod \times (1/prob)} \times \frac{E_{nr} \times Nc}{E_{ini} \times Nc} \quad (11)$$

The overall network energy and the initial energy are denoted by the symbols Enr and Eini. This dependable routing provided improved network performance in terms of network throughput and data exchange latency. The suggested routing strategy is used to monitor vital signs in a wide-area hospital interface. Figure 4 depicts the arrangement of the monitoring unit.

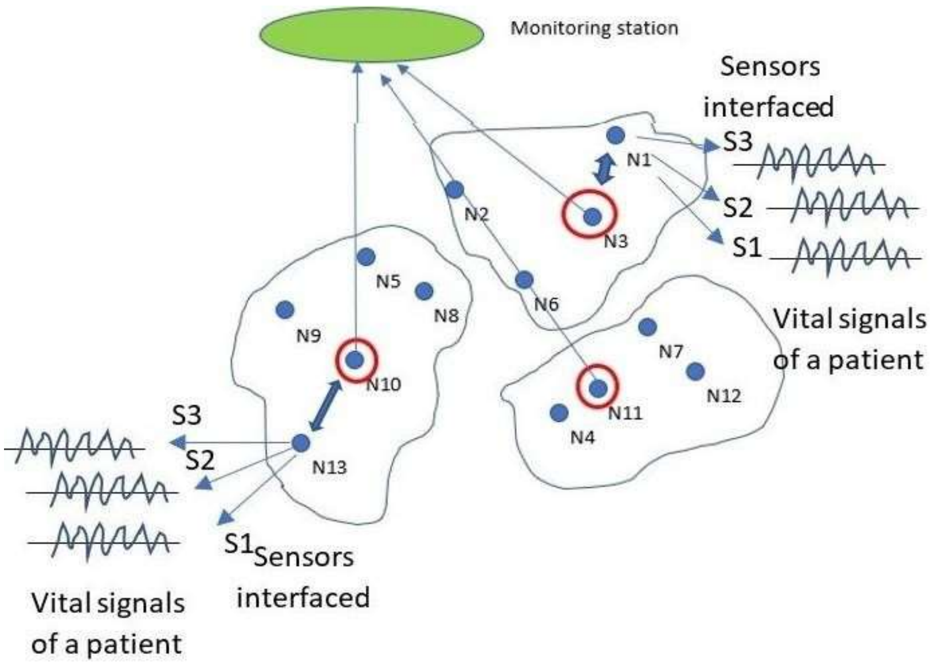

Figure 4. Multi vital parameter monitoring using adaptive routing for WSN in medical data interface

The suggested method connects sensor data from many patients and sends it to the central monitoring unit via chosen cluster heads. Figure 5 depicts the flow diagram of the suggested technique for crucial data interfacing.

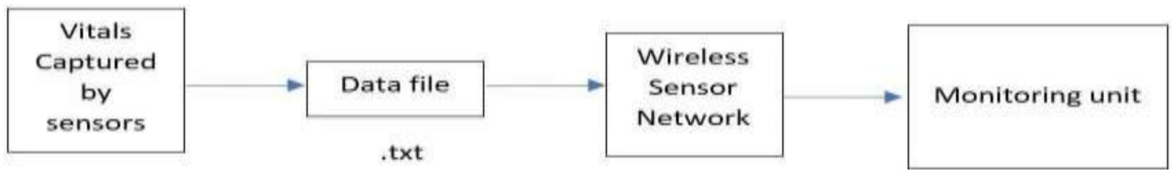

Figure 5. Flow diagram of vital monitoring using WSN interface

In this study, the suggested WSN routing interface monitors three crucial data points: temperature, ECG, and oxygen level. The interfaced sensors' sensor data is stored into a.txt file, which is read by the encoding unit and delivered over wireless means. The gathered data is sent to the monitoring unit through a designated head node over the channel.

IV. Result Analysis

The suggested technique is evaluated using a randomly deployed network with the network parameters provided in table 1. The simulated network is distributed randomly, with nodes put in random locations. The power distributed to the nodes is distributed at random, resulting in a nonlinear power distribution. The network is simulated for a network area of 200x200 with a communication range of 45m. The suggested approach's simulation is evaluated for various number of nodes in the network and varied payload size in the network. For the specified variable parameters, the network is tested for network speed, network longevity, latency, and number of living nodes. The simulation model observations are depicted in the images below.

Table 1. Parameters of network for simulation

Network Parameter	Values
Node Layout	Random
Route Discovery	LLRR
MAC Interface	IEEE 802.11
Communication Range	45m
Network Area	200 x 200 m^2
Node Counts	10-100

Observations of the presented approach illustrate the validation of the proposed work

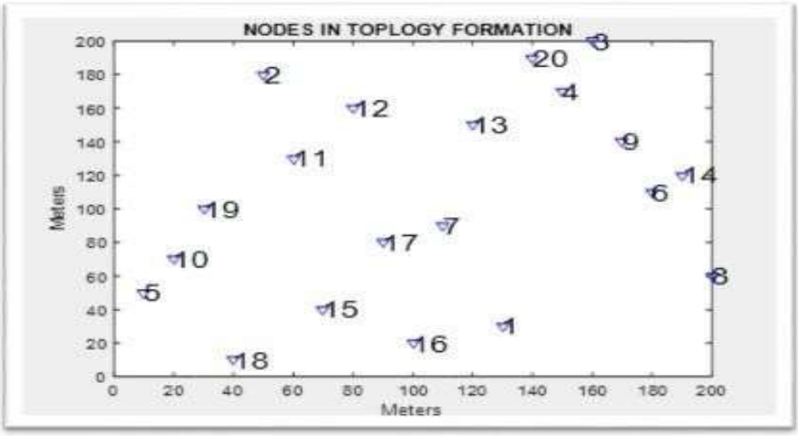

Figure 6. Layout network for communication

Figure 6 depicts a simulated network with randomly dispersed nodes in a 200 × 200 m2 network region. Each node in the network is assigned a unique node ID. Each node in the network is given random power and bandwidth.

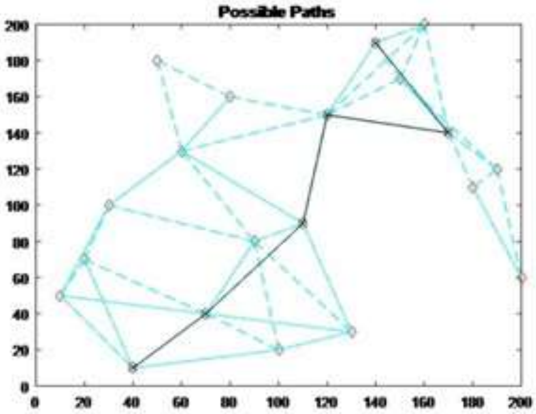

Figure 7. Possible links in the network with communication Constraint range (R=45 m)

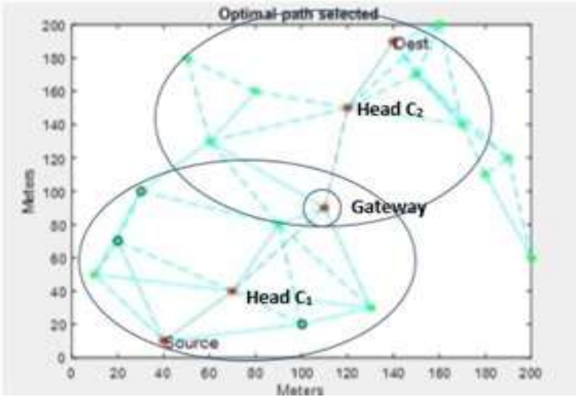

Figure 8. Optimum path selected for commutation

Route discovery in networks is accomplished by cluster-based communication, with clusters determined by the node communication range. In the network, nodes with direct connection access to one another constitute a cluster. Based on the risk factor, all nodes in the network are assigned to a cluster. The nodes in a cluster area pick a head using the suggested LLRR technique. Figure 8 shows the selected head and route for data exchange as indicated nodes. The detected data is sent via the network to the destination through an interfacing head and a gateway node. The packet transmitted as well as the time required for data exchange are both logged. Figure 9-12 depicts network performance as assessed by various node numbers and packet sizes. Figure 9 depicts network throughput observations with different node density. The volume of data exchange over an observation time period defines the simulated system's network throughput. The suggested LLRR strategy achieves superior network throughput of 14800 Kbps, whereas the LEACH-EFT [21] approach achieves 10000 Kbps. Reliable head nodes increase the likelihood of data exchange while minimizing obstruction, leading in a larger volume of data flow. The suggested technique makes the cluster more optimum through risk monitoring as node density in the network increases, resulting in reduced packet blockage. This increases throughput in the test network.

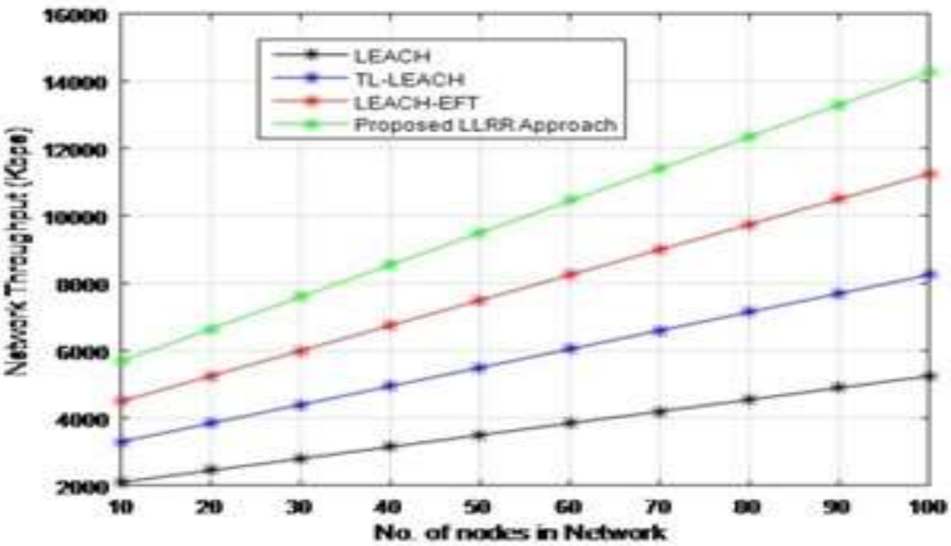

Figure 9. Network throughput with varying node counts in the network

Figure 10 depicts the number of living nodes in the network with varied nodes. As energy is

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ISSN: 0970-2555
Volume : 52, Issue 8, August : 2023

dissipated with each packet exchange, nodes with lower energy levels drain quicker and are removed from the network. The node alive count represents the total number of nodes in the network at the moment of observation. The suggested LLRR methodology has 90 living nodes, while the current LEACH-EFT, TL-LEACH, and LEACH approaches have 79, 65, and 55 alive nodes, respectively. The dependability metric minimizes the likelihood of packet drops, lowering the retransmission rate. Reduced retransmission rate protects each node's energy level, resulting in more living nodes in the network.

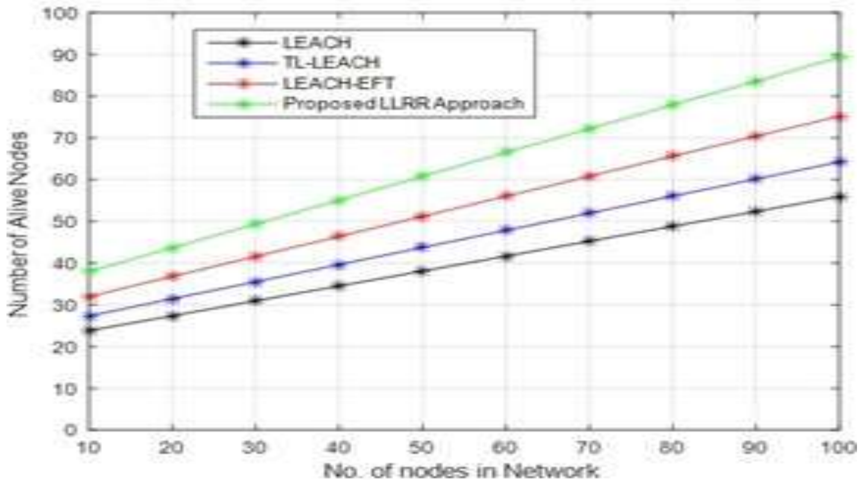

Figure 10. Alive node counts in the network for varying node count

Figure 11 depicts the observed network life time for various network node counts. The suggested LLRR methodology has a network lifetime of 100msec, whereas the LEACH, LEACH-EFT, and TL-LEACH approaches have lifetimes of 35, 88, and 78msec, respectively. As seen, an increase in the number of living nodes in the network resulted in a longer network lifespan.

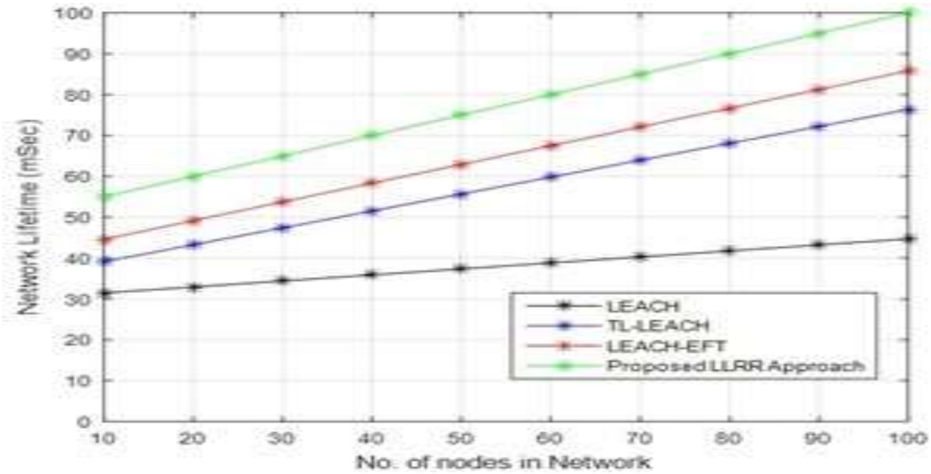

Figure 11. Network lifetime with varying node count in the network

The delay metric is defined as the time spent for data exchange from end-to-end communication. The observed delay parameter for the new LLRR technique is 19.1 sec, which is smaller than the current LEACH-EFT approach. Lower packet blockage meant quicker packet exchange, which reduced network end-to-end latency. Figure 12 depicts the observed delay metric for the simulated network for developed approaches.

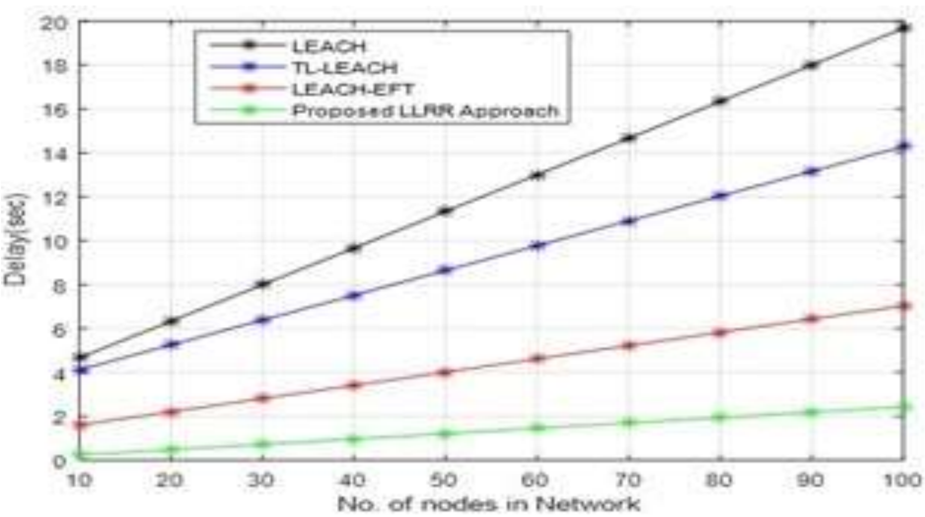

Figure 12. Observation of E2E Delay for varying node counts

The above study examines several network techniques inside a simulated system, focusing on key variables including throughput, node count, reliability, network longevity, and latency. The LLRR approach demonstrates superior throughput (14800 Kbps) compared to LEACH-EFT (10000 Kbps) as a result of the presence of dependable head nodes and a decrease in packet blockage. The LLRR protocol demonstrates a higher number of active nodes (90) in comparison to LEACH-EFT, TL-LEACH, and LEACH, which exhibit 79, 65, and 55 active nodes, respectively. These outcomes may be linked to the practice of risk monitoring, the optimization of cluster formation, and the reduction of retransmissions. The LLRR technique demonstrates an extended network lifespan of 100 milliseconds, surpassing alternative approaches with durations of 35, 88, and 78 milliseconds. This superiority can be attributed to the energy-efficient nature of the LLRR approach. The implementation results in a notable decrease in end-to-end latency, namely by a delay of 19.1 seconds, which is achieved through the mitigation of packet blockage. Therefore finally, it can be concluded that LLRR demonstrates superior performance compared to current methodologies, as seen by enhanced network efficiency, prolonged lifespan, and decreased latency.

V. Conclusion

This paper presents a novel approach for the selection of cluster heads and the construction of optimum clusters in wireless sensor networks, incorporating reliability concerns. The development of cluster formation and head selection is founded upon a modified reinforcement learning approach, with the objective of enhancing energy efficiency and network performance inside the network. In this study, a probabilistic prediction model is introduced that utilizes a learning technique to provide a dynamic threshold for head selection. The data exchange rate at the head node, which is crucial for vital monitoring in medical applications, was enhanced by the introduction of the suggested reliability factor based on the packet forwarding characteristic. The development of a simulated network aims to monitor critical metrics in sensing nodes that are randomly dispersed within the network. Additionally, the network facilitates the exchange of data through the use of the LLRR technique. The suggested LLRR technique has been seen to enhance network characteristics such as network throughput, life duration, and alive node count, while simultaneously minimizing the End to End delay in the network.

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