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ASSESSMENT OF ENERGY EFFICIENCY IN DATA COMMUNICATION FOR SENSOR-BASED COMPUTATIONAL NETWORKS

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A B S T R A C T

In the realm of data communication, the efficient utilization of energy resources is paramount for sustainable and prolonged operation of computational networks. This study delves into the intricate web of energy loss in data communication within a customized sensor-based computational network. Through rigorous analysis and innovative methodologies, the research identifies, quantifies, and comprehensively analyses the various facets of energy dissipation in this context. This study examines energy loss in data communication within a customized sensor-based computational network (CSCN). Using MATLAB simulations, we analysed network performance across different routing protocols. The results highlighted significant variations in packet transmission, latency, and throughput. Our proposed MMMREP algorithm, alongside DEEC, showed superior energy efficiency and network longevity. The initial stages exhibited stable energy levels, but energy dissipation increased after prolonged operation. Future research should focus on optimization algorithms, energy-efficient hardware, renewable energy integration, and the interplay between security and energy efficiency. Real-world applications and user-centric designs will further enhance the practical utility of CSCNs.

Keywords: *Energy Loss, Data Communication, Customized Sensor, Computational Network, Energy Efficiency, Network Optimization, Sensor Technology, Sustainability, IoT, Network Energy Consumption, Power Management.*

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1. INTRODUCTION

In the digital age, the proliferation of data-driven technologies has revolutionized various sectors, ranging from healthcare to industrial automation. One of the critical aspects of these technologies is data communication, wherein massive amounts of data are exchanged between devices and networks. In the realm of computational networks, especially those relying on customized sensors, understanding and mitigating energy loss during data communication is paramount. This is because these sensors often operate in resource-constrained environments and are powered by energy sources that are limited in capacity. The term "customized sensor-based computational networks" refers to networks of sensors specifically designed and tailored for particular applications. These sensors are equipped with computational capabilities, enabling them to process data locally before transmitting it to other devices or central servers. Such networks are employed in diverse fields, including environmental monitoring, healthcare, smart cities, and industrial automation, where real-time data analysis is crucial for decision-making. This study delves into the intricate realm of energy loss analysis in data communication within these customized sensor-based computational networks. Energy loss refers to the dissipation of energy that occurs during various stages of data transmission, including encoding, modulation, transmission through the medium, and decoding. As these sensors are often deployed in remote or inaccessible locations, optimizing their energy consumption is vital for prolonging their operational lifespan and minimizing maintenance requirements.

Energy Consumption Profiling: This study aims to profile the energy consumption patterns of customized sensors during data communication. By understanding the energy demands at different stages of communication, it becomes possible to identify energy-intensive processes that warrant optimization.

Transmission Medium Analysis: Different communication mediums, such as radio waves, optical fibres, and wired connections, exhibit varying energy losses. Analysing these losses concerning the specific needs of customized sensors provides insights into selecting the most energy-efficient communication medium for different scenarios.

Protocol Optimization: Communication protocols play a pivotal role in data transmission. By evaluating existing protocols or designing new ones tailored to the computational capabilities of customized sensors, it is possible to reduce energy overheads associated with handshakes, acknowledgments, and error correction mechanisms.

Data Compression and Aggregation: Implementing efficient data compression algorithms and aggregation techniques can significantly reduce the volume of data that needs to be transmitted. This reduction not only conserves energy but also optimizes the utilization of available network bandwidth.

Renewable Energy Integration: Exploring methods to integrate renewable energy sources, such as solar or kinetic energy harvesting, into sensor nodes can potentially offset the energy consumed during communication, making the network more sustainable and resilient.

Machine Learning-Based Predictive Analysis: Leveraging machine learning models, such as predictive analytics, to anticipate communication patterns and optimize energy usage proactively. By predicting data communication needs, sensors can adjust their operational modes, conserving energy during periods of low activity.

Customized Sensor-Based Computational Network

A customized sensor-based computational network refers to a specialized network that integrates various sensors to collect data from the environment, processes the data using computational algorithms, and provides intelligent insights or actions based on the processed information. These networks are highly tailored to specific applications and use cases, such as environmental monitoring, industrial automation, healthcare, smart cities, and more. Designing such a network involves several key components and considerations.

Components of a Customized Sensor-Based Computational Network

1. Sensors

- Types: Depending on the application, sensors could include temperature sensors, humidity sensors, motion detectors, cameras, pressure sensors, etc.
- Connectivity: Sensors should be capable of communicating with the computational network. This can be wired (e.g., Ethernet) or wireless (e.g., Wi-Fi, Bluetooth, LoRa, Zigbee).

2. Data Collection

- Data Aggregation: Data from multiple sensors are collected and aggregated.
- Real-Time Processing: Sensors might generate real-time data that needs to be processed immediately for timely decision-making.

3. Computational Algorithms

- Data Processing: Algorithms for filtering, noise reduction, and calibration of sensor data.
- Machine Learning: Implementing machine learning models for predictive analysis, anomaly detection, or pattern recognition.
- Decision-Making Logic: Algorithms that make decisions based on processed sensor data.

4. Communication Protocols

- Internal Communication: Protocols for communication between different components within the network.
- External Communication: Protocols for external communication, for example, sending alerts to smartphones or uploading data to a cloud server.

5. Data Storage

- Databases: Storing processed data for historical analysis.
- Data Security: Implementing encryption and other security measures to protect sensitive data.

6. User Interface

- Dashboard: A user-friendly interface to visualize sensor data and network status.
- Control Panel: For manual control and configuration adjustments.

7. Power Management

- Energy Efficiency: Designing the network to minimize power consumption, especially for battery-operated sensors.
- Backup Systems: Implementing backup power systems in case of power failures.

8. Scalability and Flexibility

- Scalability: Design the network to easily scale by adding more sensors or computational units.
- Flexibility: Make the system adaptable to different types of sensors and computational modules.

9. Security

- Data Encryption: Ensuring that data transmitted between sensors and computational units is encrypted.
- Access Control: Implementing access control mechanisms to prevent unauthorized access to the network.

10. Maintenance and Upgrades

- Remote Monitoring: Implementing tools for remote monitoring of the network's health.
- Firmware Updates: Providing a mechanism for remote firmware updates to fix bugs or add new features.

II. LITERATURE REVIEW

Malisetti & Pamula (2022), Clustering is an effective strategy for creating routing algorithms in Wireless Sensor Networks (WSNs), which increases the network's lifetime and scalability. In the clustered WSN, the Cluster Head (CH) plays a vital role in data transmission. So far, much research work has already existed in regards to cluster-based routing. Despite this, they have challenges with fault tolerance, unequal load balancing, and local optimal solutions. To address these problems, this research presents a novel method for cluster-based routing that makes the routing progress more effective to maximize the network lifetime. This has been carried out under two phases: selecting the optimal cluster head via the new Moth Levy adopted Artificial Electric Field Algorithm (ML-AEFA), and the data transmission is carried out by the new Customized Grey Wolf Optimization

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(CGWO) algorithm. Here, the selection of the optimal CH is performed under the consideration of energy, node degree, distance among the sensor nodes, distance among the CH and Base Station (BS), and time of death node. Finally, the implemented method's performance is compared to that of existing schemes using various measures. In particular, the network life time of the proposed work for scenario 1(number of nodes = 100) is 35.77%, 35.77%, 35.04%, 34.43%, and 33.08% better than the existing GWO, MSA, AEFA, BOA + ACO, and improved ACO methods respectively.

Yu & Sun (2022), The blend of topics in computational social science enhances the research complexity in developing efficient computational social systems (CSSs). Electronic health (E-health) is a critical branch of CSS. Artificial intelligence-based cognitive computing is especially appropriate for solving E-health problems in social science. The development of the Internet of Things (IoT) and sensor technologies is triggering data explosion in E-health CSS. The IoT-based edge computing has been applied in the field of E-health to reduce the latency of data transmission. However, small edge devices have limited resources (e.g., computational and storage resources). There is an urgent need to develop lightweight and efficient classification models to classify E-health sensor data in edge computing. Automatic health sensor data classification can help medical workers make correct clinical decisions. Also, patient-specific modeling in E-health is important. Using personalized classification model can achieve higher diagnose accuracy than the generic models trained based on historical datasets. To address the above problems, they propose a lightweight personalized sensor data classification model, called LPClass. It embeds the shallow recurrent neural network as a kernel, which makes it lightweight enough to be deployed on edge devices. In addition, a transfer learning algorithm is proposed to build personalized models for individuals. They conduct comprehensive experiments to evaluate LPClass from different aspects. Compared with the generic models, the personalized models in LPClass can achieve a fast convergence rate while maintaining high classification accuracy.

Malisetti & Pamula (2022), Clustering is an effective strategy for creating routing algorithms in Wireless Sensor Networks (WSNs), which increases the network's lifetime and scalability. In the clustered WSN, the Cluster Head (CH) plays a vital role in data transmission. So far, much research work has already existed in regards to cluster-based routing. Despite this, they have challenges with fault tolerance, unequal load balancing, and local optimal solutions. To address these problems, this research presents a novel method for cluster-based routing that makes the routing progress more effective to maximize the network lifetime. This has been carried out under two phases: selecting the optimal cluster head via the new Moth Levy adopted Artificial Electric Field Algorithm (ML-AEFA), and the data transmission is carried out by the new Customized Grey Wolf Optimization (CGWO) algorithm. Here, the selection of the optimal CH is performed under the consideration of energy, node degree, distance among the sensor nodes, distance among the CH and Base Station (BS), and time of death node. Finally, the implemented method's performance is compared to that of existing schemes using various measures. In particular, the network life time of the proposed work for scenario 1(number of nodes = 100) is 35.77%, 35.77%, 35.04%, 34.43%, and 33.08% better than

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the existing GWO, MSA, AEFA, BOA + ACO, and improved ACO methods respectively.

Krishnapriya et al. (2019), Wireless sensor Networks are often used for monitoring and sensing the various environmental conditions. It is collection of sensor nodes which are provided with a fixed battery. Millions of sensor nodes are scattered to monitor smart grids, which consume huge amount of energy. In Wireless sensor network energy wastage is more due to high latency and in-network processing. The only way to enhance the lifetime of the sensor is to reduce the power consumption and support good scalability and collision avoidance. To minimize the energy consumption of the nodes that appropriate algorithm has to be used to make node communicative. Major research challenges of WSN are network lifetime, fault tolerance, power consumption. Therefore, there is a need of establishment of energy efficient protocol. This work proposes a customized approach to optimize the energy consumption in wireless sensor network using k-means clustering algorithm and back propagation algorithm.

Al-Shayeji & Ebrahim (2019), Wireless Sensor Networks suffer from power and energy consumption issues because the batteries used are small and power-limited. Mobile Cloud Computing suffers from several security threats such as integrity and privacy issues. The integration of both areas results in better energy conservation and a more secure environment. Thus, this research introduces a secure energy-efficient platform that reduces the energy consumption and maintains privacy. The security approach of the platform utilizes a modified version of the Sharing-based Scheme and a Precision-enhanced and Encryption-mixed Privacy-preserving Data Aggregation scheme. The first supports both authentication and encryption using XOR gates, while the second is a slicing, secure data aggregation protocol that enhances both security and energy. For energy consumption reduction, asynchronous scheduling duty cycling based on Location, Priority and Pre-Configuration is introduced. The results show that the platform depends on the rate of sensing, frequency of sending data, data size, location and number of sleeping sensors, and smartphone battery capacity. In the case of less frequent rates and lower data sizes, the operational energy consumption is 1% of the mobile's entire battery capacity. In the case of sensors sleeping next to the sink, the cost is reduced by over 70% with an additional cost of 20% over the un-secured network. The simulations show that the encryption cost decreases as the number of sensors increases. Furthermore, when the number of sensors increase, the distance between the node decreases and therefore more sensors are tending to sleep, which leads to less energy consumption. As a result, the platform introduced in this work outperforms existing schemes for large numbers of sensors (greater than 300 sensors) with an additional average security cost of 2.96%.

Stella & Ganesh (2017), Restricted by the energy storage capability of sensor nodes, it is crucial to jointly consider security and reliability in data collection of Wireless Sensor Networks (WSNs). Challenging deployment environments with severe resource constraint sensors pose intricacies in reliable and secure data transmission for these networks. Under the more practical assumption, they propose an “Opportunistic Multipath Secure Routing Protocol (OMSRP)”, a novel security

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mechanism to support secure data transmission at the same time respecting the network restrictions in terms of energy. In this approach, data packet is split into several shares and transmitted along independent node-disjoint paths. Since the shares follow the multiple paths, even if one node is compromised, remaining data shares will follow other random paths, so the entire data cannot be hacked by the adversaries. During route discovery process, OMSRP employs Coalition Game Theory for angular dispersive node selection. A "best" angular dispersive node (candidate to forward the share) is chosen for each regional node which helped to create private tunnels (secured paths) for multiple shares to reach the destination. In order to realize more flexible reconfiguration and high-performance processing, the proposed method supports on-demand reprogrammable sensor nodes (behavior or functionality of sensor nodes changes as on-demand basis) to enable greater advantages in performing complicated tasks effectively.

Fortino et al. (2015), Body Sensor Networks (BSNs) have emerged as the most effective technology enabling not only new e-Health methods and systems but also novel applications in human-centered areas such as electronic health care, fitness/welness systems, sport performance monitoring, interactive games, factory workers monitoring, and social physical interaction. Despite their enormous potential, they are currently mostly used only to monitor single individuals. Indeed, BSNs can proactively interact and collaborate to foster novel BSN applications centered on collaborative groups of individuals. In this paper, C-SPINE, a framework for Collaborative BSNs (CBSNs), is proposed. CBSNs are BSNs able to collaborate with each other to fulfill a common goal. They can support the development of novel smart wearable systems for cyberphysical pervasive computing environments. Collaboration therefore relies on interaction and synchronization among the CBSNs and on collaborative distributed computing atop the collaborating CBSNs. Specifically, collaboration is triggered upon CBSN proximity and relies on service-specific protocols allowing for managing services among the collaborating CBSNs. C-SPINE also natively supports multi-sensor data fusion among CBSNs to enable joint data analysis such as filtering, time-dependent data integration and classification. To demonstrate its effectiveness, C-SPINE is used to implement e-Shake, a collaborative CBSN system for the detection of emotions. The system is based on a multi-sensor data fusion schema to perform automatic detection of handshakes between two individuals and capture of possible heart-rate-based emotion reactions due to the individuals' meeting.

Ghasemzadeh et al. (2014), Wearable sensory devices are becoming the enabling technology for many applications in healthcare and well-being, where computational elements are tightly coupled with the human body to monitor specific events about their subjects. Classification algorithms are the most commonly used machine learning modules that detect events of interest in these systems. The use of accurate and resource-efficient classification algorithms is of key importance because wearable nodes operate on limited resources on one hand and intend to recognize critical events (e.g., falls) on the other hand. These algorithms are used to map statistical features extracted from physiological signals onto different states such as health status of a patient or type of activity performed by a subject. Conventionally selected features may lead to rapid battery depletion, mainly due to the absence of computing complexity criterion while selecting prominent features. In this paper, they introduce the notion of power-aware feature selection, which aims at minimizing energy consumption of the data processing for classification applications such as action recognition. Their approach takes into consideration the energy cost of individual features that are calculated in real-time. A graph model is introduced to represent correlation and computing complexity of the features. The problem is formulated using integer programming and a greedy approximation is presented to select the features in a power-efficient manner. Experimental results on thirty channels of activity data collected from real subjects demonstrate that their approach can significantly reduce energy consumption of the computing module, resulting in more than 30 percent energy savings while achieving 96.7 percent classification accuracy.

Min et al. (2002), Distributed networks of thousands of collaborating microsensors promise a maintenance free, fault-tolerant platform for gathering rich multidimensional observations of the environment. Because a microsensor node must operate for years on a tiny battery, researchers must apply innovative system-level techniques to eliminate energy inefficiencies that would have been overlooked in the past. In this article they advocate two particular enablers for energy conservation: the ability to trade off performance for energy savings within the node, and collaborative processing among nodes to reduce the overall energy dissipated in the network. New levels of energy efficiency-attained through global system-level perspectives on node and network energy consumption-will enable a future where networks of hundreds, thousands, and eventually many millions of collaborating nodes are as commonplace as today's cellular phone.

III. RESEARCH METHODOLOGY

Research Methodology

The research methodology for analyzing energy loss in data communication for a customized sensor-based computational network involves a systematic approach. Firstly, an extensive literature review is conducted to understand existing research and technologies related to energy-efficient sensor networks and data communication. Next, the network's architecture and components are defined, including the sensor nodes, communication protocols, and data processing algorithms. Real-world deployment and experimentation are carried out to collect data on energy consumption in various scenarios. Simulation tools may also be used to model and analyze the network's behavior under different conditions. Data analysis techniques are then employed to identify patterns and trends in energy loss. Finally, based on the findings, energy-efficient strategies are proposed and validated to optimize data communication and minimize energy loss in the customized sensor-based computational network. Analysing energy loss in data communication for a customized sensor-based computational network, along with mathematical formulations where applicable.

Mathematical Model for Analysis

In data communication, energy loss can occur in various stages of the process, including during data transmission, reception, and processing in a sensor-based computational network. The reduction of energy loss is crucial to improve the efficiency and overall performance of such systems. Here are some statistical and mathematical techniques that can be applied to address energy loss in data communication within a customized sensor-based computational network:

- **Error Correction Codes (ECC):** ECC techniques are used to detect and correct errors that occur during data transmission. By adding redundant information to the transmitted data, errors can be detected and sometimes even corrected, reducing the need for retransmission and thus saving energy.
- **Signal Processing Algorithms:** Advanced signal processing algorithms can be employed to improve the signal-to-noise ratio (SNR) of the received data. Techniques like noise filtering, equalization, and interference cancellation can enhance the quality of received signals, leading to more reliable data with fewer retransmissions and energy losses.
- **Channel Coding:** Channel coding techniques, such as convolutional codes and Reed-Solomon codes, introduce redundancy to the transmitted data to improve resilience against channel-induced errors. This helps in reducing the number of retransmissions and conserving energy.
- **Optimization Algorithms:** Various optimization algorithms, like linear programming, dynamic programming, or genetic algorithms, can be applied to optimize the routing of data packets in the network. By finding the most energy-efficient paths, these algorithms can minimize energy losses during data transmission.
- **Adaptive Modulation Schemes:** Depending on the channel conditions, adaptive modulation techniques can adjust the modulation and coding schemes dynamically. This allows the system to use higher modulation orders when the channel quality is good, leading to higher data rates and reducing the overall transmission time and energy consumption.
- **Energy-Efficient Protocols:** Implementing energy-efficient communication protocols like IEEE 802.15.4 for low-power wireless communication or other similar protocols helps minimize energy consumption during data exchange.
- **Duty Cycling:** In sensor networks, duty cycling involves periodically turning the sensor nodes on and off to conserve energy. The duty cycle can be optimized based on the network's requirements and data communication patterns.
- **Data Compression Techniques:** Compression algorithms can reduce the size of data before transmission, which can save energy by reducing the amount of data to be sent over the network.

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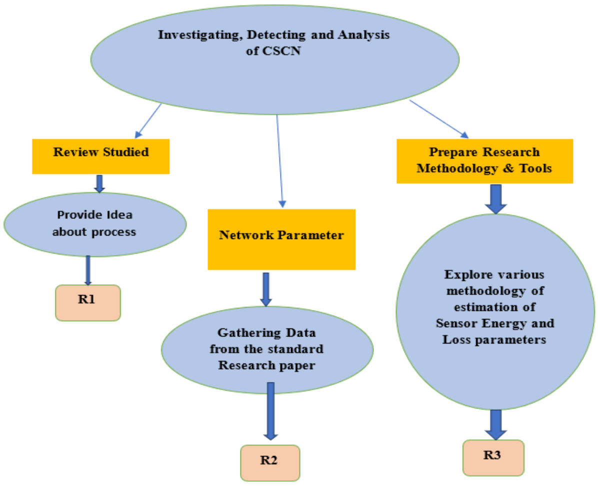
- **Adaptive Power Control:** By dynamically adjusting the transmission power of nodes based on the proximity to the receiver and the quality of the wireless channel, energy consumption can be optimized.
- **Sleep Scheduling:** In sensor networks, sleep scheduling algorithms can determine when and for how long individual nodes should sleep to conserve energy while still meeting communication and computation requirements.

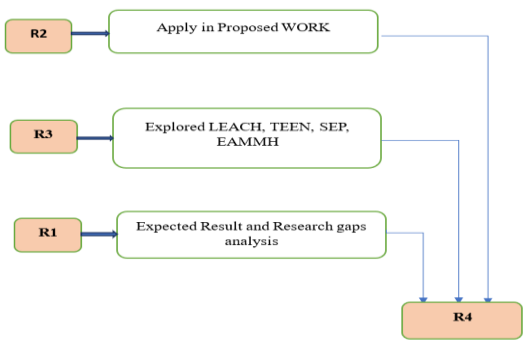
IV. SIMULATION AND RESULTS

With digital packet radios, a digital multi-hop network is a network of nodes linked by wireless communication connections amongst each other. Due to the fact that a node cannot directly connect with every other node in the network, it uses intermediary nodes to send packets on their way. Send, receive, and relay packets are all capabilities of a node. A wireless network's performance might be enhanced with the use of an optimum routing measure.

1. Proposed Framework



Process 2: Middle



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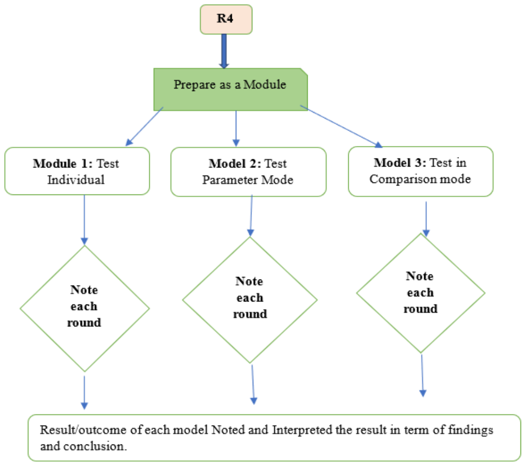
Process 3: Final



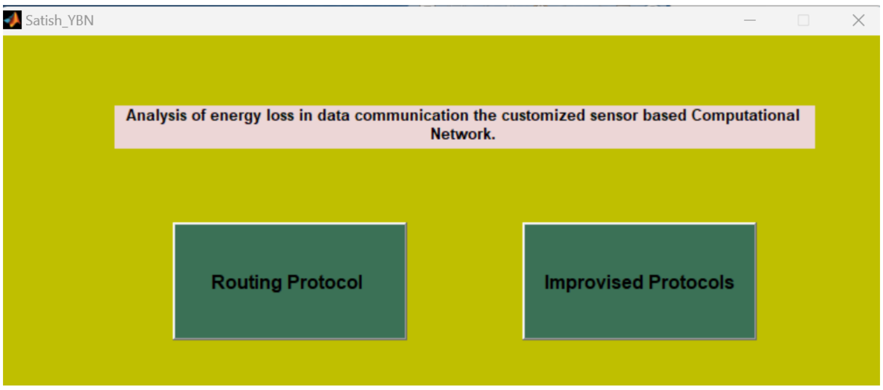


Fig 1: Protocol for Project Routing and Custom Protocol Design

The nodes of CSCNs are distributed at random. Each sensor node contains instructions that may be based on the best knowledge about its processing, communication, and energy resources on a specific job or mission. Each node may transmit and receive data to and from the base station.

Proposed Work

This research introduced two different analyses as one is for energy analysis and second is for data analysis. As we have contracted the GUI in MATLAB with two different execution buttons. As the presented below the GUI constructed in MATLAB.

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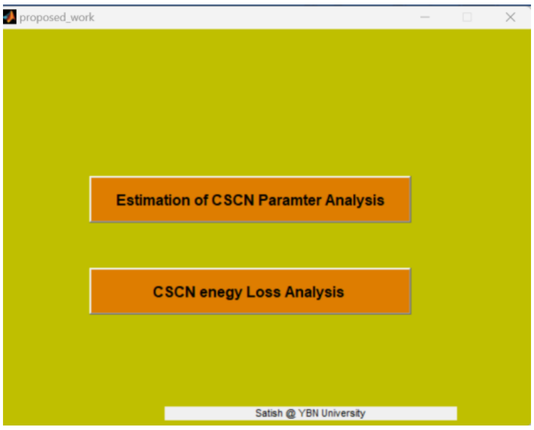

Fig 2: Overview of Proposed Diagram

Execution of Button 1(Estimation of CSCN packet Analysis). The network parameters which have been taken for this analysis as below

Table 4.1: Parameters Used

Sr. No	Parameters	Value
1	Total Number of nodes	100
2	Coverage Range	<400 m
3	Placement of Nodes	Fixed Topology
4	Initial Energy	0.5 J
5	Energy Transmitted	50*0.000000001
6	Energy Received	50*0.000000001
7	Total Area	100

Table 4.2: Packet Transmitted, Packet Drop, PDF, Latency And Throughput for Different Trials

Sr. No	Packet Transmitted	Packet Drop	PDR	Latency	Throughput
1	190	9	9995.30	0.00010610	1790800.00
2	210	9	9995.70	0.00006590	3186600.00
3	190	6	9996.80	0.00006810	2790000.00
4	180	7.5	9995.80	0.00010450	1722500.00
5	170	3	9998.20	0.00006680	2544900.00
6	170	9	9994.70	0.00010410	1633000.00
7	190	6	9996.80	0.00007030	2702700.00
8	150	0	10000.00	0.00003200	4687500.00
9	180	4.5	9997.50	0.00006650	2706800.00
10	150	0	10000.00	0.00002400	6250000.00
11	150	0	10000.00	0.00002420	6198300.00

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12	150	0	10000.00	0.00003400	4411800.00
13	150	0	10000.00	0.00002620	5725200.00
14	190	10.5	9994.50	0.00010020	1896200.00
15	210	9	9995.70	0.00006740	3115700.00
16	200	10.5	9994.80	0.00009910	2018200.00
17	210	9	9995.70	0.00006300	3333300.00
18	180	9	9995.00	0.00010020	1796400.00
19	150	0	10000.00	0.00003450	4347800.00
20	150	0	10000.00	0.00003330	4504500.00
21	180	12	9993.30	0.00010930	1646800.00

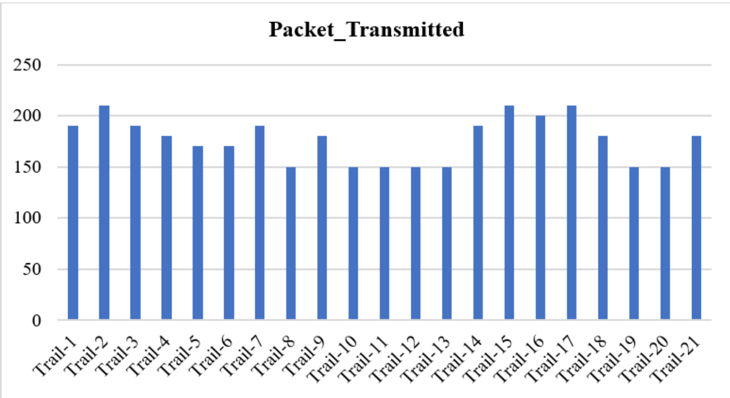

Fig 3: Packet Transmitted

Packet transmitted in each trail has been presented in above bar graph. The value obtained in each trail is presented than 150 minimum numbers of packets has been released in each time. The heighted number of packets is 210 in three trails of total 21 numbers of trails.

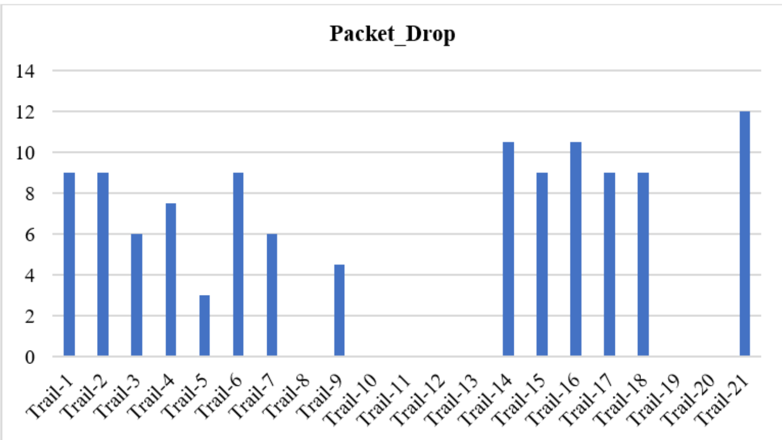

Fig 4: Packet Drop

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Packet drops in each trail has been presented in above bar graph. The values obtained in each trail are presented very random values from zero to 12. The highted number of packets loss is 12 and minimum is zero in total 21 numbers of trails.

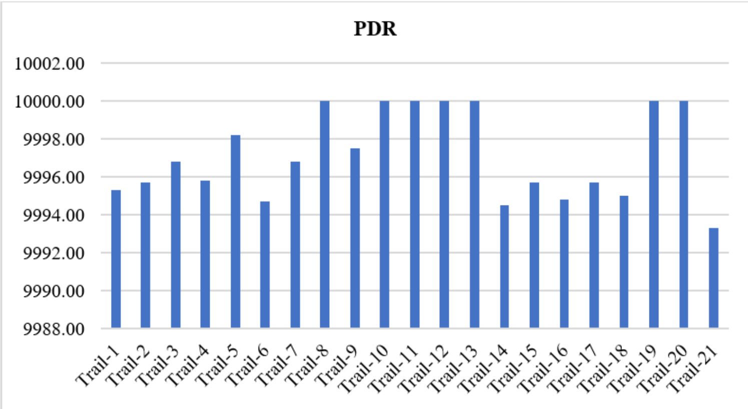

Fig 5: Packet Delivery Ratio

Packet delivery ratio in each trail has been presented in above bar graph. The values obtained in each trail are presented than 9993 minimum number of packets delivered. The highted number of packets is 10000 in seven trails of total 21 numbers of trails.

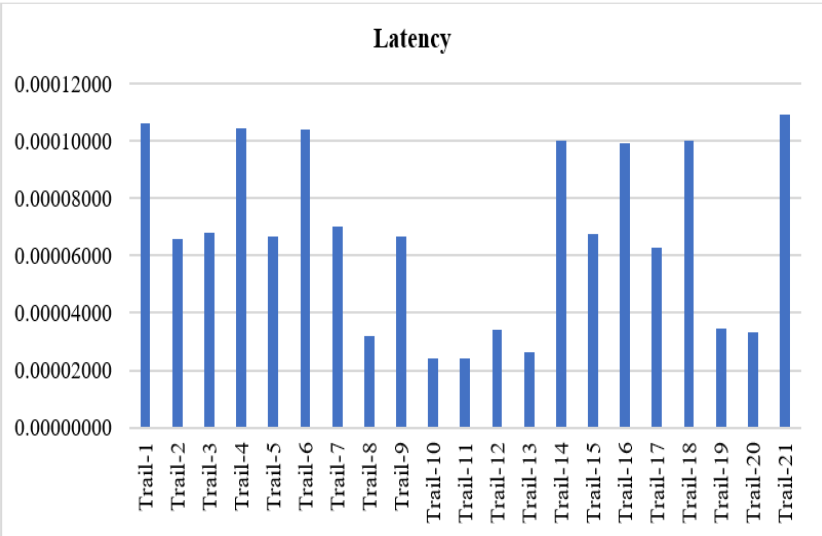

Fig 6: Latency

Latency in each trail has been presented in above bar graph. The value obtained in each trail are presented is greater than$24*10^{-6}$second. The highted time of packets delivery time as latency is $109.30 * 10^{-6}$second in total 21 numbers of trails.

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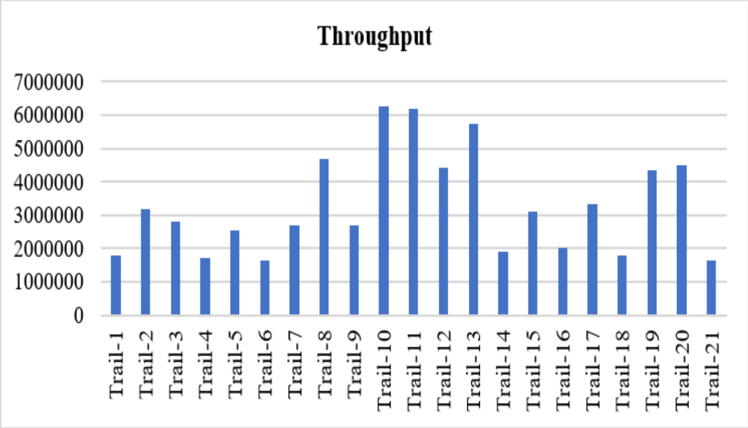

Fig 7: Throughput

Throughput in each trail has been presented in above bar graph. The values obtained in each trail are presented very random values from zero to 12. The highted number of packets loss is 12 and minimum is zero in total 21 numbers of trails.

Execution of Button 2 (Energy Analysis of proposed Work)

As the network energy analysis is most important exploration of our research. The average energy at the starting of the network has been as 100 which comes down as the round increases. The analytical result for LEACH, SEP, EAMMH, TEEN, DEEC and Proposed MMMERP has been estimated. The network energy has been estimated in this execution and the result has been drawn as below.

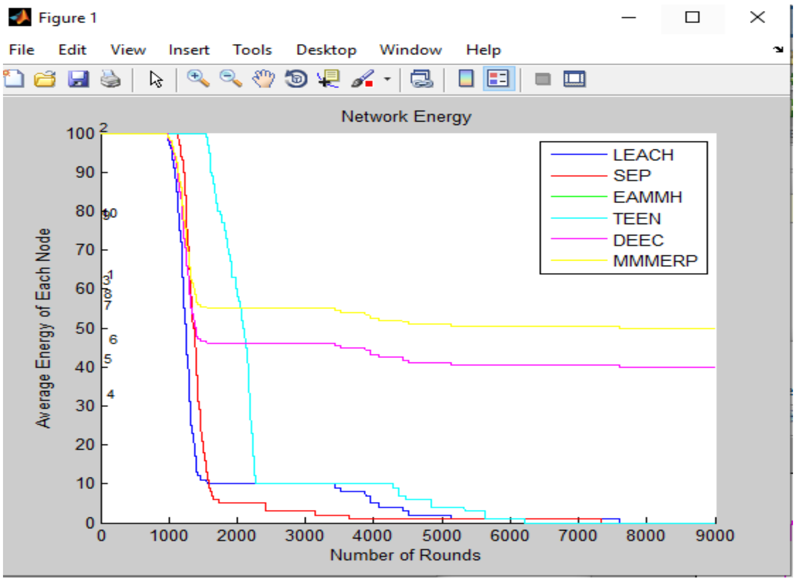

Fig 8: Average Energy of Each Node

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The above energy exploration of various routing algorithms is demonstrated as in graph as the initial 1200 round is very smooth and very less amount of energy falls, but after the 1200 rounds the fall of energy dissipation has been observed. Only DEEC and proposed MMMREP have been stagnant for long as compared to others.

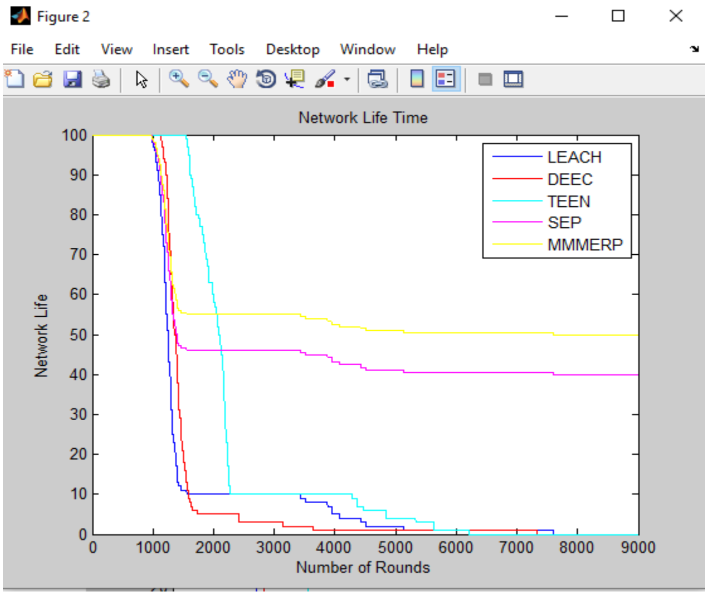

Fig 9: Network life of Nodes

The above network life time exploration of various routing algorithms is demonstrated as in graph as the initial 1200 round is very smooth and very less amount of network life falls, but after the 1200 rounds the fall of network life time has been observed drastically. Only DEEC and proposed MMMREP have been stagnant for network life time long as compared to others.

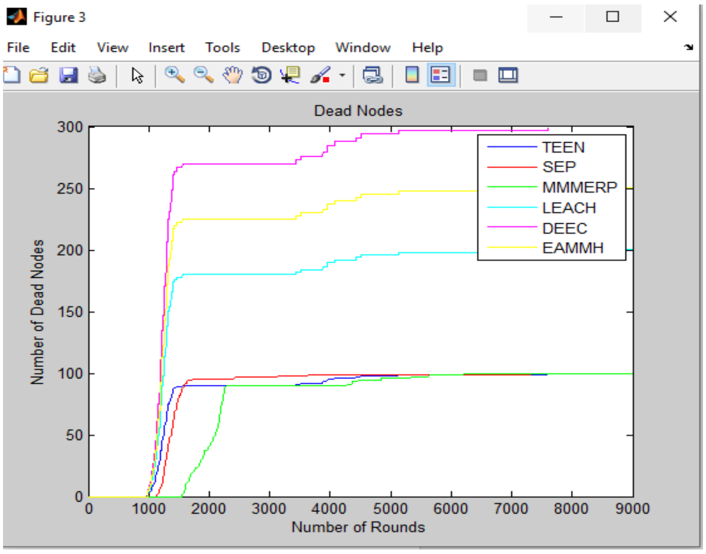

Fig 10: Numbers of Dead Nodes

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The above occurrence of dead nodes exploration of various routing algorithms is demonstrated as in graph as the initial 1000 round is very smooth and very less occurrence of dead nodes, but after the 1000 rounds the occurrence of dead nodes time has been observed drastically. Only DEEC and proposed MMMREP have been stagnant for network life time long as compared to others.

V. CONCLUSION AND FUTURE WORK

The energy analysis of various routing algorithms in our research project has provided valuable insights into their performance in wireless networks. The study focused on the average energy of nodes, network lifetime, and the occurrence of dead nodes over a series of rounds. The results demonstrated that during the initial stages of the simulation, all algorithms maintained relatively stable energy levels and network lifetime. However, after a certain number of rounds, there was a significant increase in energy dissipation, leading to a decrease in both average node energy and network lifetime. This decline indicated a potential deterioration in network performance over time for most algorithms. Notably, two algorithms, DEEC and the proposed MMMREP, exhibited superior performance compared to others. These algorithms showcased remarkable stability in preserving energy and maintaining network life even as the simulation progressed. They consistently outperformed the rest by effectively managing energy resources and minimizing the occurrence of dead nodes. In summary, the research findings highlight the importance of carefully selecting the appropriate routing algorithm for energy-constrained wireless networks. DEEC and the proposed MMMREP demonstrated promising results in terms of energy efficiency and network longevity. These outcomes can serve as a foundation for further research and optimization efforts in wireless communication systems, ultimately leading to more robust and energy-efficient network designs.

Future Work

Building upon our findings, several avenues for future research and development emerge

- Optimization Algorithms: Develop advanced optimization algorithms that dynamically adapt communication protocols and network configurations in real-time based on the network's workload and environmental conditions. Machine learning techniques can be employed to predict and optimize energy consumption patterns.
- Energy-Aware Hardware: Continue research into energy-efficient hardware components, exploring novel materials and designs that reduce power consumption without compromising performance. Investigate emerging technologies such as quantum computing for their potential applications in energy-efficient data communication.
- Integration of Renewable Energy Sources: Investigate the integration of renewable energy sources, such as solar or kinetic energy, to power sensor nodes. Design energy harvesting systems that can replenish the energy used in communication processes, making the network self-sustainable.

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- Security and Energy Efficiency: Explore the relationship between network security measures and energy efficiency. Develop protocols and algorithms that ensure data security while minimizing the energy overhead associated with encryption and decryption processes.
- Real-World Implementations: Conduct real-world implementations and simulations to validate theoretical findings. Collaborate with industry partners to deploy energy-efficient sensor-based computational networks in practical applications, such as IoT devices, environmental monitoring, or smart infrastructure.
- User-Centric Design: Focus on user-centric design principles to understand user behaviour and preferences concerning energy-efficient data communication. Develop interfaces and applications that empower users to make conscious decisions about energy consumption, fostering a culture of energy-aware computing.

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