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Enhancing the Longevity and Reliability of Wireless Sensor Networks through Optimized Routing Strategies

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ABSTRACT
To maintain reliability, endurance, and energy conservation, wireless sensor networks (WSNs) require effective routing. The lifetime of the WSN depends on the battery power, the distances between nodes and the proximity of the data sink. Improved energy efficiency and energy balance depend on optimized node-sink connections. First, the study begins with the proactive routing method Ant Colony Optimization (ACO), which is based on favorable distance metrics and determines the minimum average node power consumption for optimal throughput. Our study uses a sectored network model and a carefully developed manual node placement method that includes uniform and random procedures. Later, the study uses an AI-based distributed network reinforcement learning method to apply WSNs to the medical field through a complicated cluster network to improve reliability. WSNs have an excellent sensor interface for detecting and transmitting medical information, but latency and packet loss make monitoring sensitive data difficult. We present a reinforced learning-based Low-Risk Reliable Routing (LLRR) strategy for secure and reliable data exchange between WSNs. This strategy improves network throughput, uptime, and end-to-end latency. Therefore, the proposed methods use optimized routing approaches to improve the performance of WSNs.

Keywords – Wireless sensor networks, Ant colony Optimization, Reinforcement learning, Routing, Reliability.

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I. INTRODUCTION

Wireless sensor networks (WSNs) are transforming industries such as healthcare, military operations, environmental monitoring, and automation [1] [2]. Sensor nodes actively collect and analyze data within these networks for immediate monitoring and control. Each sensor node houses both sensors and actuators and serves as the backbone of the system. Since the battery life of sensor nodes is limited, energy conservation within WSNs is crucial. To solve this problem, solutions such as using battery-powered nodes with solar panels have been deployed to extend their operational lifespan. Clustering, duty cycling, routing optimization, data compression, sleep scheduling and energy harvesting are key techniques to improve energy efficiency and extend the lifespan of these networks.

Because of resource limits in sensor nodes, Wireless Sensor Networks (WSNs) use a reduced five-layer paradigm, similar to the OSI model, with three cross-layers [3]. These inter-layer links improve network performance by allowing for data interchange. Cluster and sector-based models are used to optimize energy in WSNs. Data aggregation and transmission is enabled by clustering sensor nodes, which is controlled by selecting a cluster leader. Sector-based approaches, on the other hand, conserve energy by segmenting the network into sectors and limiting inter-node communication. The LEACH method is a well-known low-energy clustering algorithm in WSNs. To ensure equitable energy distribution, it dynamically forms clusters and appoints cluster chiefs based on energy levels. These cluster heads then communicate with a data collection base station. Power management, routing protocols, and connection oversight must all be carefully considered when managing sophisticated wireless sensor networks [4]. Customizing routing protocols necessitates taking into account computer power, storage capacity, and energy consumption. To increase network throughput in hazardous environments, effective security systems and strategic node deployment are required [5].

This comprehensive design includes hardware, security measures, power optimization, and data management, quality of service concerns, node specialization, and fault tolerance mechanisms to ensure reliability. Energy management in WSNs necessitates the use of performance models. Battery life, energy usage during signal processing, conversion, and A/D conversion all have a direct impact on node longevity. Furthermore, data amount and transmission distance affect dynamic voltage scaling, which optimizes power utilization. Deactivating dormant components and minimizing duty cycles improves energy management even further.

To address the issue of multiple-hop routing in WSNs, energy-efficient solutions must be deployed in order to extend the network's lifespan. Data transmission loss, control packet overhead, network abnormalities, and inactivity monitoring all contribute to power consumption, efficiency, and durability difficulties with WSNs. To address these concerns, low-heat materials are being used, sensor elements are being optimized, data redundancy is being eliminated, and communication overhead is being reduced. Furthermore, implementing routing, clustering, and hierarchical topologies is a powerful method for conserving power and extending network life.

ACO and RL make important contributions to the endurance and reliability of wireless sensor networks (WSNs). ACO optimizes node routing and placement to save energy and extend network lifespan. On the other hand, RL, a subclass of machine learning, emphasizes the ability to make autonomous decisions. The combination of ACO and RL has a synergistic effect that significantly improves both energy economics and reliability within WSNs. A recent study offered strategic transmission design, balanced power node spacing, AI-driven energy uncertainty management, and route management and load balancing algorithms. These insights have the potential to transform WSNs and ensure their long-term operation, especially in vital areas such as medicine. WSNs have three main problems that limit their durability and reliability:

- Energy Uncertainty: Accurately estimating power consumption is difficult due to variations in hardware and sensor performance. This can affect node operations and data distribution.
- Route Management Gap: Inefficient node selection for data routing can lead to network congestion and node failures.
- Load Balancing Deficiency: Uneven distribution of network traffic can cause some nodes to exhaust their energy resources prematurely.

To address these challenges, the study proposes the following solutions:

- Design transmission plans that optimize node spacing to minimize energy consumption.
- Utilize AI-based machine learning techniques to improve WSN reliability in medical applications.
- Establish criteria for selecting cluster heads to distribute network load more effectively.
- Define criteria for adding nodes to the network to enhance its dynamics and adaptability.

Objectives of the Study:

- Maximizing WSN network lifetime through most favorable distance (MFD) based ACO.
- Improving reliability with low risk reliable routing (LLRR) using reinforcement learning.
- Analysis of proposed approaches, comparing parametric performance with existing approaches through simulation.

Prioritizing reliability is critical to the continued success of wireless sensor networks (WSNs). This requires optimizing performance, distances, configuration and routing to mitigate data issues and extend network longevity. Techniques such as proactive heuristic routing, energy conservation, and machine learning-based routing are crucial for expanding wireless sensor networks (WSN), thereby significantly improving their reliability and durability. To achieve these goals, the study follows a comprehensive strategy. The study evaluates routing protocols, leverages Ant Colony Optimization (ACO) techniques to extend network lifespan, promotes reliability by implementing Low Latency and Reliable Routing (LLRR), and improves energy efficiency. The aim of this study is to optimize wireless sensor networks (WSNs) by conducting simulations and comparing different approaches with existing protocols. This requires the use of optimization approaches and energy-saving algorithms to improve the capabilities of wireless sensor networks (WSNs).

II. RELATED WORKS

By monitoring physical events using small, autonomous wireless sensors, wireless sensor networks (WSNs) have revolutionized technology. To maximize the lifetime of the WSN, a proactive Ant Colony Optimization (ACO) is used. The lifetime of the sensor battery is of great importance. To improve WSN reliability, Reinforcement learning based low risk reliable routing (LLRR) is used. This has shown promise for optimizing network performance. The following studies examine how some articles describe the high-performance WSN network based on traditional ACO and reinforcement learning approaches.

S. Okdem et al. [6] state that ACO is based on the behavior of real ants, which use pheromones to communicate with each other and find the shortest path between a food source and their nest. The ACO algorithm uses a swarm of artificial ants to roam the network, leaving pheromone trails behind. The attractiveness of a route depends on the concentration of pheromones on it. Over time, the concentration of pheromones on the shortest path increases while the other paths are abandoned.

Deepa and Senthilkumar et al. [7] discuss the basic Ants system and algorithm. To enable optimal route finding, a swarm intelligence-based mechanism and an ACO algorithm based on ant behavior, coordination and synchronization are developed. Although the strategy addresses NP-hard problems, probabilistic approaches for improved learning and optimization, dynamic networks, and multi objective reasoning must be considered. Since the longevity of the network depends on this, information in the WSN must be transmitted reliably and with optimal energy.

Cheng et al. [8] provide an Energy Aware Ant Colony Algorithm (EAACA) as a routing protocol specifically designed for wireless sensor networks. This algorithm considers two key factors, namely the residual energy of the nearest node and the average energy level of the path, to optimize the routing process. Comparing the simulation results with those of traditional Ant Colony Optimization (ACO), it is clear that the proposed approach has superior efficiency and increases the longevity of the network.

Xu YH et al. [9], the authors propose a reinforcement learning-based strategy to increase the longevity of a network by using harvesting methods. The authors' goal is to increase the longevity of the network by balancing the power consumption of all sensor nodes. Energy harvesting nodes effectively address the challenge of resource allocation by alleviating the problem of energy efficiency. The problem is conceptualized as a Markov decision process and a reinforcement learning approach is developed to determine the optimal transmission method for individual sensor nodes. Factors such as residual energy, distance to sink and channel quality are considered in determining the transmission power and rate in the proposed technique. This research shows that the proposed strategy creates an optimal trade-off between energy consumption and network lifetime compared to traditional transmission technologies.

Hashmi, Mohammad Farukh et al. [10] presents a routing system that uses reinforcement learning techniques to optimize the lifetime of wireless sensor networks (WSNs). The authors propose a Q-learning methodology for sensor nodes to optimize path selection based on power consumption considerations and network characteristics. The performance of the proposed protocol is evaluated and compared with the performance of alternative routing protocols using simulated tests.

Bouzid, S.E. et al. [11] The goal described in is to study and propose an energy-efficient routing approach for wireless sensor networks (WSNs) that leverages reinforcement learning. The researchers present a Q-learning based routing method in which nodes acquire the ability to choose the path that maximizes energy efficiency. The simulation results show the effectiveness of the proposed protocol in terms of energy consumption and network lifetime

The purpose of this study is to look into Ant Colony Optimization (ACO) algorithms for improving the efficiency of wireless sensor networks (WSN), with a focus on energy efficiency and adaptability in dynamic environments. Furthermore, reinforcement learning methods are being developed to improve energy efficiency and dynamic routing to enhance the reliability in WSNs. Implementation complexity, parameter sensitivity, and scalability are key challenges. Overall, these studies provide useful information for improving WSN performance in a variety of applications.

III. PROPOSED APPROACHES

To overcome the problems listed above, strategies that effectively improve the performance of WSNs can be proposed based on previous studies.

3.1 Maximizing Longevity using a proactive ACO

The study utilizes the proactive strategy of Ant Colony Optimization (ACO) to improve the durability of wireless sensor networks (WSNs). The aim of this study is to identify, through a comprehensive evaluation of the existing literature, the areas that have not been sufficiently explored in ACO (Ant Colony Optimization) study and to highlight the notable strengths of the studies conducted on WSN (Wireless Sensor Networks). To investigate fundamental questions about the influence of ACO on the longevity of wireless sensor networks (WSNs), particularly examining parameters such as network size and topology. To assess this, simulations were performed using MATLAB to compare the performance of the algorithm and its impact on energy consumption. The goal is to optimize energy savings while ensuring network connectivity and maintaining a high standard of service quality.

In order to achieve this method involves formulating mathematical models that prioritize power consumption, connectivity, quality of service and environmental factors to guide optimization procedures. The proactive ACO algorithm consists of various components, including ant behavior, pheromone updates, heuristic functions, and mechanisms for local and global search. Optimizing these parameters is essential to achieve optimal results. In practice, the ants move effectively via wireless sensor networks (WSNs) by adhering to the defined algorithm and process and using clever energy saving techniques. The aim of this path finding algorithm is to minimize the energy consumption of nodes, thereby increasing the overall network lifetime. Therefore the focus of this study is on extending the lifespan of wireless sensor networks by employing Ant Colony Optimization (ACO) and using various mathematical models to evaluate the durability of WSNs

3.1.1 Energy Consumption Model

Energy required transmitting a packet of size P from node i to node j:

$$E_{ij} = Ce * d_{ij} * P \qquad 3.1$$

Energy consumed for the amplifier's transmission and reception:

$$E_{amp} = \varepsilon_{amp} * P * d_{ij}^{2} \qquad 3.2$$

Energy consumed to transmit a packet between nodes is crucial in wireless sensor networks (WSNs). The energy consumption model describes this energy consumption. Equ. 3.1 indicates the energy needed to send a P-sized packet from node i to node j. The constant factor Ce, node distance d_{ij}, and packet size P determine energy consumption. It summarizes data transmission energy costs, including coding, modulation, and amplification. Amplifier energy is added to the energy consumption model in Equ. 3.2. This equation accounts for amplifier energy used to send and receive data. Constants elec and amp measure energy loss during electrical and amplifier operation, respectively. d_{ij} indicates communication node distance.

3.1.2 Distance Model

Effective energy distance for sector Si:

$$E_{i\_eff} = (\Sigma_{j \neq i} \Xi_j * dij) \;/\; (\Sigma_{j \neq i} \Xi_j) \qquad 3.3$$

Balanced energy distance for sector Si:

$$E_{i\_bal} = (\Sigma_{j \neq i} \Xi j * dij) \;/\; (\Sigma_{j \neq i} \Xi_j^{2})\;) \qquad 3.4$$

Node distances are essential for optimizing energy consumption and routing. The distance model in equations 3.3 and 3.4 shows how distances affect energy-efficient communication. The effective energy distance for sector Si is given by Equ 3.3. This distance metric considers data transmission Ξ_j and distance d_{ij} between neighboring sectors. The average energy distance nodes within a sector experience when communicating with neighboring sectors is evaluated. Equ. 3.4 introduces balanced energy gap. This metric measures the squared data volumes Ξ_j^2 of neighboring sectors. Squaring data volumes shows how they affect energy consumption. Balanced energy gaps provide a comprehensive view of energy-efficient sector communication.

3.1.3 Routing Model

Probability of transition of ant moving from sector Si to sector Sj:

$$P_{ij} = (I_{ij}^{\alpha} * H_{ij}^{\beta}) \;/\; \Sigma_{Sj \in DISj} (I_{ij}^{\alpha} * H_{ij}^{\beta}) \qquad 3.5$$

I_{ij} is the pheromone concentration, H_{ij} is the heuristic information and α, β are control parameters. The routing model plays a fundamental role in determining the paths through which data traverses the network. The model includes pheromone concentrations and heuristic information, as captured in Equ.3.5.This will summarizes the probability of an ant moving from sector Si to sector Sj during a given iteration. This probability is influenced by both pheromone concentration (I_{ij}) and heuristic information (H_{ij}). The parameters and enable control over the respective contributions of pheromones and heuristic factors in the decision-making process. By evaluating these probabilities, the algorithm guides the ants toward paths that maximize the energy efficiency and longevity of the network.

3.1.4 Objective Function for Network Lifetime

Network longevity ratio (LR):

$$L\,R = \frac{(\Sigma\,(INITIALENERGY \,/\, AVERAGEENERGY\_I))}{(N * INITIALENERGY \,/\, MAXAVERAGEENERGY)} \qquad 3.6$$

Where N is the number of sectors, Initial Energy is the initial energy supply, Average Energy_i is the average energy consumption in sector Si, and Max Average Energy is the highest average energy consumption across all sectors.

The objective function in the equation assesses the network's longevity by comparing initial energy use to sector energy consumption. It reflects the network's power balance. The terms Initial Energy, Average Energy_i, and Max Average Energy drive this calculation, measuring overall energy efficiency and network lifespan. These mathematical models underpin research on energy consumption, routing decisions, and network performance, enabling algorithm development for wireless sensor networks. They are crucial for optimizing energy use, transmission distances, and routing strategies, enhancing research understanding.

This method aims to achieve balanced and optimal routing by minimizing energy consumption, maximizing network lifetime, and enhancing throughput while maintaining a sufficient number of active nodes.

Key Points

- Simulations conducted using MATLAB's M-Script demonstrate the effectiveness of ACO in optimizing WSN routing.
- Parameters considered in the simulations include node radius, node count, and number of ants, energy consumption, data rate, and energy level of the transmission range.
- The average energy consumption per node (ECPN) at different distances and energy levels is analyzed.
- The impact of network radius on network lifetime is discussed.

The following figure shows the network lifetime for the different radii

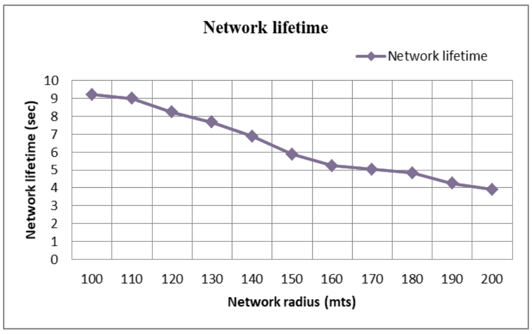

Figure 3.1: Plot showing Network radius versus Lifetime

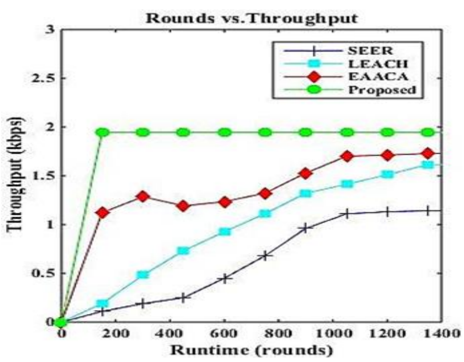

Figure 3.2: Plot showing Network throughput

Manual node deployment extends network lifespan compared to random deployment. Ant-based routing achieves better energy balance and longer network lifetime compared to other protocols. The proposed method optimizes energy efficiency and results in longer node lifetime and stable throughput compared to other protocols. The study focuses on enhancing WSN efficiency by simulating and comparing routing protocols and strategies. The proposed ACO-based algorithm surpasses existing protocols by balancing energy consumption and extending network lifespan. It exhibits resilience against performance fluctuations and can be applied to larger networks, subnets, and time-constrained scenarios.

3.2 Enhancement of reliability using LLRR

Due to their self-configuration, data sharing, and encryption, wireless sensor networks (WSNs) are becoming increasingly popular in remote and demanding environments. Nodes equipped with sensors with wireless transmission are used both indoors and outdoors. WSNs are self-contained and portable, but dynamic data paths can compromise reliability. Due to performance and traffic limitations, real-time WSN usage requires reliable routing. Cluster-based methods, where a master node connects others, improve data reliability and energy efficiency. Routing strategies are critical given communication range and performance limitations. Machine learning, particularly reinforcement learning, optimizes the selection and routing of WSN cluster heads. A low-risk reliable routing (LLRR) approach improves path reliability, while a Q-learning model achieves energy and latency benefits. This method enabled early disease detection and energy sustainability for longer network lifespan when monitoring patients remotely

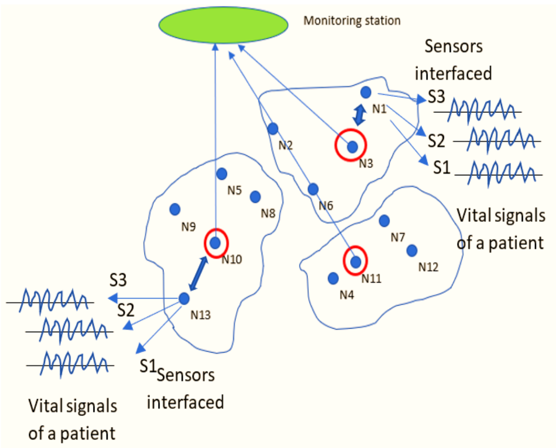

Figure 3.3. Multi vital parameter monitoring using adaptive routing for WSN in medical data interface

3.2.1 Proposed Method Structure

The proposed method combines sensor data from multiple patients and delivers a signal to the central monitoring unit via specific cluster heads. Figure 3.4 depicts the flow diagram of the suggested strategy for the interface for critical data.

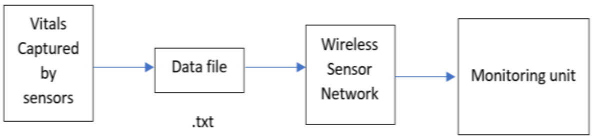

Figure 3.4. Flow diagram of vital monitoring using WSN interface

This study examines dynamic and distributed wireless sensor network clustered topologies. The study examines dynamic wireless sensor network cluster head reliability. They use a novel node and route selection system to handle massive data rates and reliability. After eliminating an energy-depleted routing node, Q-Learning chooses the best. Wireless sensor network cluster nodes communicate locally. In some cases, intermediate clusters improve coverage. Data from sensor nodes is amplified and sent to cluster headers. Medical cluster head selection and transition problems are solved in wireless sensor networks (WSN). See Figure 4.2 for the proposed method framework.

Choose cluster heads carefully in wireless sensor networks. Communication and data aggregation are difficult in dynamic networks, but the popular LEACH algorithm linearly selects primary cluster nodes. This study improves stress-related network reliability with reinforcement learning (RL). Variant RL Channel selection is optimized by Q-Learning. Uniquely, secondary cluster heads activate when the primary head overloads or becomes unstable. Healthcare needs transmission of reliable data. Backup head nodes and communication links improve wireless sensor network accuracy. AI-powered Reward points rotate primary and secondary cluster headers in Q-Learning. Graphs show node power use. Q-Learning uses Alpha (α) and Gamma (γ) to adapt to changing conditions. The study improves cluster head selection, adds multi-stage transitions, and seamlessly integrates local nodes for flexibility.

Advances make cluster heads and network architecture reliable.MATLAB simulations validate and improve technology. This study improves cluster head selection and wireless sensor network performance.

3.2.2 Observations

Our methodology has been extensively tested in the complex domain of wireless sensor networks (WSNs) designed for health monitoring. The chosen approach was tested extensively in 200 x 200 square meter network architecture with randomly distributed nodes. The dynamically assigned power levels of each node resulted in a differentiated and nonlinear power distribution. We evaluated performance in several areas within a communication radius of 45 meters using several indicators.

3.2.3 Performance Evaluation based on Node Counts

While conducting an in-depth analysis, we tried to explore the complex relationship between network performance and the different number of nodes within the system. During the course of our investigation, we have found that our Low risk reliable Routing (LLRR) approach demonstrates exceptional superiority compared to its competitors LEACH-EFT, TL-LEACH and LEACH on key performance criteria.

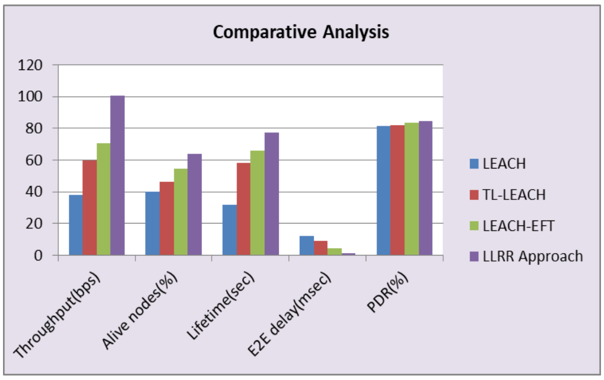

Figure 3.5 : Comparative analysis using LLRR

Throughput: The study we conducted placed great emphasis on throughput, which is a crucial aspect of data transfer. It is considered to be the essential component that enables the smooth flow of data. LLRR demonstrated its dominance in this space by demonstrating exceptional data sharing capability and exceeding the performance standards set by LEACH-EFT.

Active Nodes: A fundamental component of a network's continued effectiveness is the state of its nodes and the level of activity they maintain over time. In this environment, LLRR outperformed comparable nodes LEACH-EFT, TL-LEACH, and LEACH in its amazing ability to cultivate an atmosphere of sustained activity. Specifically, LLRR significantly outperformed over LEACH.

Network Lifetime: Another key part of the investigation was the length of time the network was operational. In this area, the LLRR demonstrated an impressive ability to expand the functioning of networks and to clearly outlast the time limits set by its contemporaries.

End-to-End Delay: In the complex area of data transmission, the so-called end-to-end delay has proven to be a critical factor. In this study, LLRR showed a remarkable ability to reduce delays and accelerate packet exchange, thereby improving the efficiency and reliability of data transmission.

PDR: Another important part of the study was the network's PDR, which estimates the number of successfully transmitted packets from source to destination. In this study, the LLRR performs better compared to LEACH-associated techniques.

The above parameter values in the simulation show extensive observations and remarkable achievements. The LLRR has effectively assumed the role of a pioneering strategy, significantly improving network performance and consolidating its position as an innovative solution in the field of wireless sensor networks. This section examines the stability of the routing protocol and the efficiency of reinforcement learning. In greedy mode, nodes choose optimal paths based on probabilities. This allows the data transport routes to be localized step by step. Simulations are used to validate the optimization of data routing, latency, power consumption and energy production. For real-time reinforcement learning, the study proposes centralized WSN unpredictability management. To enforce routing policies and prevent data loss due to node power outages, central controllers change transmission channels. At data initiation, routes are selected instead of hops, and transmission updates the node data for the next learning cycle. Data fusion reduces power consumption and increases WSN lifetime. Real-time Q-learning routing reduces downtime and increases efficiency. With performance-based adaptive routing, reduced node failures improve energy efficiency and latency. Power consumption and network lifespan are significantly reduced in simulations. Medical diagnosis is precise with LLRR.

IV. CONCLUSION

Wireless sensor networks (WSNs) are used both indoors and outdoors, particularly in areas with little infrastructure where challenges such as limited battery life and reliability prevail. A recent study aims to address these challenges by proposing optimization strategies and practical applications. To address this problem, a proactive Ant Colony Optimization (ACO) algorithm was developed. This algorithm efficiently discovers energy-saving paths, promoting a balanced and efficient WSN network while ensuring maximum longevity. A comparative analysis with traditional routing methods shows the significant value and superior performance of the proactive ACO algorithm. Improved machine learning in the medical field monitors vital signs using probabilistic models, improving data reliability. Low Risk Reliable Routing (LLRR) optimizes network properties for efficient sensor data exchange. Future directions include integrating WSNs with cloud computing, expanding IOT capabilities, exploring energy harvesting, refining machine learning, conducting real-world testing, and creating energy-efficient communication protocols.

REFERENCES

[1] Evolution of communication: http://telecom.alexwiddowson.co.uk/1951-2000.html

[2] Shafiullah Khan, Al-Sakib Khan Pathan and Nabil Ali Alrajeh. Wireless Sensor Networks: Current Status and Future Trends. November 16, 2016 by CRC Press. https://www.routledge.com/Wireless-Sensor-Networks-urrent-Status-and-Future-Trends/Khan-Pathan Alrajeh/p/book/9781138199873.

[3] Singh AP, Luhach AK, Gao X-Z, Kumar S, Roy DS. Evolution of wireless sensor network design from technology centric to user centric: An architectural perspective. International Journal of Distributed Sensor Networks. 2020;16(8). doi:10.1177/1550147720949138.

[4] Jain, Khushboo & Sikka, Vaishali. Design Issues and Challenges in Wireless Sensor Networks. International Journal of Computer Applications. Volume 112. 2015. 10.5120/19656-1293.

[5] S. Okdem and D. Karaboga, "Routing in Wireless Sensor Networks Using Ant Colony Optimization," First NASA/ESA Conference on Adaptive Hardware and Systems (AHS'06), 2006, pp. 401-404, doi: 10.1109/AHS.2006.63.

[6] O. Deepa and A. Senthilkumar, "Swarm intelligence from natural to artificial systems: Ant colony optimization," Networks (Graph-Hoc), vol. 8(1), pp. 9–17, 2016.

[7] Cheng, D., Xun, Y., Zhou, T., Li, W. (2011). An Energy Aware Ant Colony Algorithm for the Routing of Wireless Sensor Networks. In:

Chen, R. (eds) Intelligent Computing and Information Science. ICICIS 2011. Communications in Computer and Information Science, vol 134. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-18129-0_62.

[8] Xu YH, Xie JW, Zhang YG, Hua M, Zhou W. Reinforcement Learning (RL)-Based Energy Efficient Resource Allocation for Energy Harvesting-Powered Wireless Body Area Network. Sensors (Basel). 2019 Dec 19;20(1):44. doi: 10.3390/s20010044. PMID: 31861735; PMCID: PMC6983140.

[9] Mohammad Farukh Hashmi, Tripti Sharma, Archana Balyan, Rajit Nair, Paras Jain, Shivam Arora, Fardin Ahmadi., "ReLeC: A Reinforcement Learning-Based Clustering-Enhanced Protocol for Efficient Energy Optimization in Wireless Sensor Networks", Wireless Communications and Mobile Computing, Hindawi. VL - 2022, 2022. https://doi.org/10.1155/2022/3337831.

[10] S. E. Bouzid, Y. Serrestou, K. Raoof and M. N. Omri, "Efficient Routing Protocol for Wireless Sensor Network based on Reinforcement Learning," 2020 5th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Sousse, Tunisia, 2020, pp. 1-5, doi: 10.1109/ATSIP49331.2020.9231883.