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ENERGY OPTIMIZED ROUTE SELECTION IN WSNS FOR SMART IOT APPLICATIONS

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ABSTRACT

Interest in the IoT and smart cities has been growing as people learn about its potential applications in fields as diverse as healthcare, remote monitoring, and transportation. In these Internet of Things (IoT)-based systems, wireless networked sensors (WSNs) gather data critical to the operation of smart surroundings. IoT-enabled WSNs face challenges such high latency, low bandwidth, and short network lifespan due to the copious amounts of data generated by a wide variety of sensors. This study presents a deep reinforcement learning-based efficient routing method for IoT-enabled WSNs to combat latency as well as electricity consumption (DRL). The proposed strategy separates the network into unequal cluster according to the present data transmission existing in the sensors, hence preventing the network from collapsing prematurely. Extensive testing has been performed in ns3 using the recommended strategy. The results of the experiments are contrasted to the state-of-the-art methodologies to demonstrate that the proposed method is effective in the areas in received packets, connectivity latency, clean energy, and the amount of living nodes within a network.

Keywords: Energy Efficiency, Routing, Wireless Sensor Networks and Smart IoT Applications.

I. INTRODUCTION

Several fields might benefit from the cutting-edge web of linked gadgets known as the "Internet of Things," including security, medicine, and "smart cities." Sensors are crucial to the functioning of the Internet of Things because they allow information to be gathered and sent from anywhere in the globe. Since sensor technology has rapidly advanced in recent years, sensor nodes have grown to be an essential component of the IoT. Nevertheless, owing to the large coverage area needed and the restricted transmission range of sensor, WSNs with a single sink may not prove to be the ideal solution when it comes considering application like smart cities. Therefore, it appears that multi-sink WSN devices are appropriate for these uses. As the throughput, longevity, and power consumption of

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WSNs have increased, multi-sink WSNs have become increasingly widespread. In addition, multi-hop routing is crucial to the WSNS's ability to quickly gather data from sensor nodes and transport it to the sink node, where it can be analyzed. There was little concern about latency, hence many multi-sink WSN routing methods were developed with longevity in mind. Nevertheless, this approach is not suitable for use with applications that want data packets to reach sink nodes within a certain real-time window. However, the majority of preexisting routing algorithms entirely ignore the impacts of external environmental factors like temperature and humidity and the dependability of real-time data transfer. The effectiveness of the network may be drastically impacted by these problems. The proliferation of IoT use cases is a direct result of technological progress in many fields. IoT devices rely on WSN, which are networks of cheap and small sensors. Wireless sensor networks (WSNs) collect data from sensors and send it to the user's device for a variety of Internet of Things (IoT) uses, including monitoring, surveillance, and gps tracking. Nevertheless, smart gadgets have limitations in areas like battery life, data transfer speeds, storage space, and computational power. There is a challenge for IoT-based WSNs in optimizing network lifetime while decreasing energy consumption. Wireless sensor networks (WSNs) and the Internet of Things (IoT) might revolutionize next-generation, real-time, intelligent applications. IoT has risen to the forefront of modern society because it can make otherwise tedious activities more manageable and even enjoyable. WSN has a wide range of practical applications, including surveillance, patient care, practical monitoring, pollution monitoring, etc. Consists of a network of small electrical nodes, or sensors (SN). In general, these SNs are not very powerful. The energy needed for SN transmission rises when WSNs are included. Existing network protocols all operate by partitioning the available channels of communication into smaller, more manageable chunks. There is a significant discrepancy in SN deployment between regions, and no existing approaches can account for this. To reduce the network's dependency on SNs' power and increase their availability, a new energy-efficient SN deployment technique for two-stage routing algorithm (EE-DSTRP) has been created. The authors suggest a new approach to deploying SNs that takes into consideration the golden ratio. A network's energy consumption might be lowered by switching to a different method of deployment. The proposed EE-DSTRP protocol has been shown to beat its competitors in a number of computer simulations. Rapid advances in wireless technology are making the IoT a reality in which smart wireless devices may communicate with one another. Now more than ever, sensor nodes, also referred to as smart gadgets, are essential to the smooth operation of the Internet of Things. Therefore, the WSN has emerged as the standard technology for enabling Internet of Things applications. For this technology to be practical, it requires the ability to handle and send large volumes of data consistently across the internet. The primary objective is to increase the network's lifespan, which is proportional to the number of active wireless sensor nodes divided by the average remaining battery life of those nodes. IoT-enabled Wsn's system lifespan is significantly impacted by the clustering approach adopted. Twenty years have passed since academics first began investigating ways to increase the longevity of WSNs for usage in the Internet of Things (IoT). Real-time Internet of Things applications are becoming more important in the fields of monitoring and advanced analysis. Energy constraints posed by sensor network battery backup in the IoT must be taken into

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account while engaging in a wide variety of tasks. The difficulty of extending the useful life of nodes in the network has increased. Life-time protocols have been studied in the past to increase the lifespan of network nodes, but this has come at the price of solving other challenges, such as sensor diversity, scheduling, and high-speed network access. Industry, environmental control, security, and even home automation all rely heavily on the IoT. Data transmission while minimizing energy consumption is difficult during an emergency evacuation due to a power outage. Among the many advances made possible by recent developments in WSN technology is the Internet of Things. Implementing all use cases in the actual world may face obstacles. The fundamental problem is the burden that data transmission places on sensors with limited resources. Network like WSN and Underwater WSN are made possible by the IoT, allowing for a wide range of high-level monitoring applications (UWSNs). By using the IoT, UWSNs were able to facilitate a broad range of underwater uses, such as data collecting, monitoring, cinematography, and more. In addition to radio and optical communications, acoustic signals have also been used by IoT-UWSNs for network-wide interaction. Lower bandwidth, greater energy consumption, longer transmission delays, and lower network lifetimes are only some of the numerous problems that arise when employing acoustic waves to convey data. Recently offered data relays and aggregating procedures seek to improve UWSN's capabilities. Smart cities, healthcare, and agriculture are just a few of the intriguing new sectors where Internet of Things-based WSNs are being put to use. In order to be truly sustainable, electricity WSNs (EH-WSNs) must satisfy stringent standards. IoT sensors have been difficult to design because to the limited availability of their power source, thus scientists are exploring for ways to alleviate this issue. New energy-harvesting routing methods that maintain the network's reliability must be found. Monitoring and security systems, traffic management, smart infrastructure, and weather prediction are just a few of the many real-world uses for the IoT. Current devices fall short, notably in terms of extended battery life and reduced emissions, despite the vast opportunities presented by these applications. While research is underway to find solutions, wireless IoT networks currently lack the ability to guarantee constant network presence and comprehensive sensor coverage. It's also important to note that the solutions proposed in the literature are complex and difficult to put into reality. As a result, it's important to look at a straightforward method for achieving power routing in mobile Smart sensors systems.

The most significant conclusion of this study is outlined briefly below:

This research offers a clever routing method for IoT-enabled WSNs that utilizes Inter Deep Reinforcement Learning (DRL) to significantly reduce communication time and message overhead. Additionally, a novel load balancing strategy for IoT-enabled WSNs is presented, which enhances network speed and lifespan.

In the end, detailed simulations demonstrate the efficacy and success of the proposed approach.

This is a summary of the paper's remaining parts.

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The provincial algorithm and related work are discussed in the second part of this article. In this third section, we outline the simulation and the underlying assumptions. Part IV contains a detailed explanation of the next steps to be taken. Part V provides an analysis of the outcomes achieved by adopting the suggested approach. The results and design of the simulation are discussed in Section VI. In Section VII, we wrap up the paper.

II. SUMMARY OF PREVIOUS WORKS

In this research, we develop a routing strategy that minimizes resource usage while yet meeting all of the requirements of the overall system. Paths are chosen after considering a number of criteria. This includes things like the strength of the wireless network, the influence of the surroundings, and the amount of time left before the deadline. Integer linear programming is used to get the best answer (ILP). Scientists in the field of sensor networks may use this issue description to better understand the scope of the challenge and the most important limitations that must be met. Moreover, the optimal solution for small-scale situations might be utilized to evaluate the efficacy of potential heuristics for dealing with the same issue. The paper continues by proposing a swarm intelligence-based heuristic approach to the optimization challenge facing large-scale multi-sink WSNs. We use comprehensive experimental data to compare our proposed method to the two most comparable recent algorithms, SMRP and EERP. The collected information suggests that the suggested algorithm offers many benefits over its rivals. The pace at which packets are delivered, the average end-to-end delay, the lifespan of the network, and the energy imbalance factor are all improved. If we compare the suggested technique to others in the same vein, we find that it requires more processing effort [11]. Thus, clustering and routing protocols are often used in the IoT to drastically reduce power consumption. For IoT-enabled WSNs, the authors here provide Energy Conscious Clustering and Multihop Routing Protocol with Mobile Sink (EACMRP-MS). The EACMRPMS method was developed to lessen the energy consumption of IoT sensor nodes and hence improve the efficiency of the whole IoT network. In the proposed EACMRPMS method, the CHs to be used in the cluster creation process are first selected using the Tunicate Swarming Algorithms (TSA). The most effective multi-hop routes are discovered with the use of the type II fuzzy logic (T2FL) method, which requires just a few input parameters. To further improve the effectiveness of the IoT program, the study describes a mobile sink equipped with a mechanism for adjusting course. This method further reduces energy use by adapting pathways to the path taken by the mobile sink. Experimental and simulated studies have revealed that the EACMRPMS methodology outperforms state-of-the-art approaches on a number of assessment measures [12]. This research makes advantage of a clustering topology to provide and cross-layer routing protocol (CLRPLEACH) and Fuzzy-based routing mechanism (FRPLEACH). The suggested algorithms, in particular, have been tailored to meet the needs of IoT healthcare infrastructure. Such methods provide a suite of cutting-edge, cloud-based patient care services and protections against threats to the healthcare and paramedical sectors, such as the current COVID19 pandemic. We present a fuzzy logic-based energy-efficient routing approach for IoT sensor networks to overcome these obstacles. We demonstrate the superiority of the proposed

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algorithms over the state-of-the-art fuzzy logic-based cluster-based routing protocols [13] by extensive simulations. With the purpose of reducing the network's overall power consumption and extending its useful life, we suggest an unique energy efficient routing system (EERS) for duty cycled nodes. The packet delivery rate and the nodes' energy efficiency are both improved by this strategy's consideration of sleep/awake mode and enhanced data rates. Based on each node's energy level, coverage area, and total amount of time it has been active, the sink node regularly assigns sleep/awake states [14]. As part of the study, an Energy Efficient Emergency Rescue System is developed and evaluated to provide the secure transmission of data at high transfer rates and low latency in the Internet of Things (EEERS). MATLAB is used for simulating networks with a sensor density of 100-500 nodes. Edge latency, bandwidth, energy utilization, packet loss, and average throughput are evaluated between the proposed routing system EEERS and the existing routing algorithms SAR and SPEED. The simulation findings demonstrate that in the context of emergency rescue through the Internet of Things, EEERS reduces. The long lifetime that EEERS provides might be especially useful for large networks [15]. This study presents a cluster-based IoT routing system capable of estimating power consumption. We developed a multi-population ensemble swarm - based optimizer for selecting and updating cluster heads. Simulations were run in MATLAB, and the results show that it is superior to other methods [16]. For efficient, low-power data transfer between submerged sensor nodes and surface sinks, this research provides a unique Swarm Intelligence-based routing technique (SI). Energy Optimization by Routing Optimization, or EORO for short, is the name of the game here. Optimization of UWSNs was achieved by the selection of the optimal forwarder node utilizing Effective Fitness Function-based Particle Swarm Optimization (EFF-PSO). For EORO to work, the sender node must first use its location information to identify appropriate relay nodes. Next, the EFF-PSO algorithm takes into account all of the potential outcomes to choose the best relay node. The health of a network's forwarder nodes depends on factors including how much juice they have left, how many packets they can send, how many other nodes they're connected to, and how far away they are from the hub. By fine-tuning these settings, we may reduce power consumption and increase throughput by reducing the likelihood of packet collisions. Extensive research [17] shown that the EORO protocol beat the underlying routing approaches in regards to Packet Delivery Ratio (PDR), throughput, latency and energy consumption. Our increased energy greedy boarder stateless routing system is an effective solution to the problem of low sensor power (EH-GPSR). Energy harvesting rate (EH rate) is used as a cost function in EH-GPSR, a variant of the randomized minimum path recovery time (R-MPRT) algorithm. Long-term, it's superior than the greedy routing system. The next hop is chosen in an adaptive fashion taking into account both the present hop cost and the projected hop rate. The results of our simulations show that compared to GPSR methods [18], our protocol EH-GPSR significantly extends the lifespan of the network and speeds up the delivery of data packets. In this study, we provide a threshold-based data collecting hybrid grouping and routing technique for dispersed wireless sensor networks. Our suggested paradigm divides the network into zones where nodes are either all the same or all different. When there is little difference between a simulation and its real-world applications, we offer threshold-based criteria to restrict data transfer. We find that the network is more stable in both dense and

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sparse environments after adopting a multi-hop approach. Our proposed model outperforms previous proposals such as the, thresholds dispersed energy-efficient clusters (TDEEC), threshold-sensitive stable election protocol (TSEP) and the, and low-energy adaptive clustering hierarchy (LEACH), and the energy-efficient sensor network (TEEN) [19]. In this study, we created a hybrid strategy that utilizes elements of both clustering and routing. We provide a simulated environment whereby nodes may exchange data with one another. For dependable and efficient data gathering in massive wireless sensor networks, a hybrid clustering and routing (HCR) protocol was developed. HCR's theoretical modeling and analytical findings will demonstrate the network's functionality and connection. Criterion Indicators Sensor networks that communicate wirelessly the formation of a conglomerate Energy throughput as a measure of a node's lifespan in routing [20].

III. PROPOSED MODEL

A. Model System

Unequal cluster formation and smart data routing are the two stages that make up the proposed work. The distributed sensor nodes' energy consumption rates are balanced by forming uneven clusters inside the network. A multi-objective DRL is presented for intra-cluster and cross routing to drastically improve network performance and decrease communication time during the data routing phase. Careful goal selection is used to deal with sensor nodes with limited energy resources and to distribute the burden across the available supernodes.

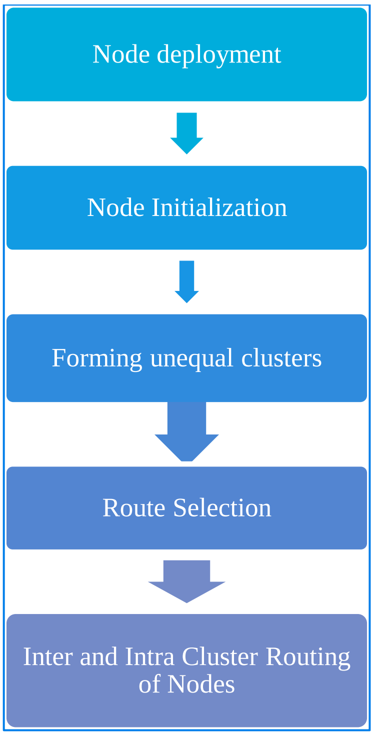

Fig.1: Proposed Solutions Flow Diagram

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B. Model Energy

To estimate the amount of power being wasted by the scattered sensors, a radio-based energy-consumption model is used. Power required for transmission of l-bit distance data d, is demonstrated by E_{tx} and it is calculated as follows:

$$E_{tx} = \begin{cases} (E_{\mathrm{elc}} + \epsilon_{\mathrm{efs}} \times d^2) l_i & \text{if } d < d_0 \\ (E_{\mathrm{elc}} + \epsilon_{\mathrm{amp}} \times d^4) l_i & \text{if } d \geq d_0 \end{cases}$$

E_{rx} is an required energy to receive l-bit message and it is calculated as follows:

$$E_{rx} = l \times E_{elc}$$

$$d_o = \sqrt{\epsilon_{efs}/\epsilon_{amp}}$$

Each individual node in a cluster's energy requirements are E_{cm} which depends on l pieces of information sent to the CH. As a result, the quantity of energy used by every cluster member $(E(CM))$ is given as follows:

$$E(CM) = l \times E_{elc} + l \times \epsilon_{amp} \times d_{ch}^2$$

The total amount of energy dissipated by CH is proportional to the total number of packets of data received from cluster member nodes, the total amount of data aggregated, and the total amount of data sent to BS. Hence, the amount of energy used by each CH during uneven clustering as a result of the intracluster process is calculated as follows:

$$E_{\text{intra cluster}}(\mathrm{CH}_i) =$$
$$CM_i \times E_{rx} + (CM_i + 1) \times E_{agg} + E_{tx}\big(CH_i, NH(C_i)\big)$$

Furthermore, CH_i Similarly, it serves as a load-balancing intermediary for traffic between clusters. As a result, the energy needs of CH_i as a result of a process occurring between clusters, we get:

$$E_{\text{inter cluster}}(\mathrm{CH}_i) =$$
$$\mathrm{z}(i) \times E_{rx} + \mathrm{z}(i) \times E_{tx}\big(\mathrm{CH}_i, \mathrm{NH}(\mathrm{CH}_i)\big)$$

C. Conventions

The following are some of the foundational assumptions of the suggested method:

- Random placement of sensor network and supernodes in $M \times M(m^2)$ square area.
- The energy capacity and mobility of sensor nodes are both low.
- Infinite power is expected to be available at the base station.

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- Unlike the mobile sensor nodes, the supernodes never move and always have more power than the others.
- There are a lot fewer supernodes than sensor nodes.

D. Cluster of Formation Phase

According to the suggested architecture, the nodes at the top of the network would serve as the leaders of groups of nodes (CHs). Upon setting up, the BS sends out a Beacon messages to the other nodes in the network. When a request is made by BS, the supernodes send back a RESPONSE message with details like their ID, where they are, and how much energy they have left. As a result, the locations of the supernodes and BS are shared knowledge. The BS maintains a table of supernode IDs and distances, sorted in a non-decreasing order based on distance from the BS to the supernodes (D_{bg}). Supernodes are in charge of cluster creation. The initial value of C_r is set to R. If the value of D_{bg} If constant, then the cluster radius is also constant at that value. So, if the worth of D_{bg} If unique, the cluster radius is determined by the formula below.

$$C_r[i+1] = C_r[i] + R/i + 1 \forall i \in [1,2, \ldots m]$$

Each supernode evaluate a C_r depending on D_{bg} and sends Cluster Formation Message (CFM) within the C_r. The ID, position, and energy status of each supernode are all stored in CFM. A JOIN message is sent from any receiving sensor node to the receiving supernode in response to a CFM. The JOIN packet includes data about the sensor's identifier, position, and power reserve. A sensor node will choose the closest supernode as a CH if it gets a CFM request from a different supernode. All of the data packets from the other mesh nodes and sensor network within the cluster's radius are concentrated on the supernodes closest to the BS. In order to evenly distribute work between the closest BS cluster and the furthest cluster, Eq. 7 is used. Smaller clusters closer to the BS are used to balance the strain brought on the combined data from the cluster's members and the inter-cluster heads in the proposed architecture. To maintain a constant rate of energy dissipation between the CH and its member nodes as their distance from the BS grows, the cluster radius grows proportionally. The uneven clustering technique suggested between mesh nodes and deploying sensor nodes is shown in Fig. 1. In the process of cluster formation, sensor nodes are considered "free" if they are located in an overlapping area of the cluster radii of neighbouring super nodes. Nodes in the FREE sensor network may choose to join any of the two neighbouring groups. They choose the CHP with the most available power. Uneven clustering is proposed, and its pseudo-code is shown in Algorithm1.

E. Phase of Routing

Finding the optimal routing route in IoT-enabled WSNs seems to be a multiple objective issue that depends on a wide variety of network characteristics. When it comes to the routing in the suggested system, it's all handled via reinforcement learning. The cluster's sensor nodes serve as many agents,

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directing packets of data to the CH. Together, sensor networks and supernodes optimise intra-cluster routes using multi-objective dynamic programming. Model of the proposed multi-agent system, shown in Fig. The proposed work strategically chooses goals for intra-cluster routing. The primary goal is to extend the runtime of a battery-powered sensor node as much as possible. Throughput optimization in the network is the secondary goal. As a third goal, we've settled on reducing the amount of time spent in communication. These goals are inherently at odds with one another. Hence, multi-objective DRL using Pareto optimality may address the issue.

An arrowed graph is used to depict the inter-cluster system model G. It is ordered pair of (V, E), where V is a set of supernodes and $E \in (V_x, V_y), x \neq y$ the connection that relies on radio waves. Many origin nodes provide information to the central hub (CH) via additional nodes. If the sensing node $V_i \in R$ range of transmission CH then it connects directly to it. Otherwise, if sensor node $V_i \notin R$ then it communicates via other neighbour sensor nodes V_j, so V_j in the role of intermediary nodes. Because of the inherent unpredictability of the IoT-enabled WSNs ecosystem, the suggested strategy uses Markov Decision Processes (MDP) as its optimization model. States are characterised in MDP as $s_x \in S$, action $a_x \in A$, the associated transition probability $p(s_y \mid s_x, a_x) \in P$ and rewards are $R(s_x, a_x)$. Multi-objective optimization using the multi-objective - MDP is used to simulate interactions across clusters. The following are the state, action, and reward definitions for intra-cluster routing in the proposed architecture:

- State space of sensor agent: The packet that need to be transferred at time t by agent a represents the current packet being sent. Sensor agent state space is defined as $s_t^a = \{\mathrm{D}^g, I^a, I^n\}$, where D^g sensor node packet's final destination CH, I^a is agent a information and I^n does it have data on neighbouring nodes.
- Action space of sensor agent: Definition of the Action Space $a_t^i = \{\mathrm{N}^i\}$, where $\{\mathrm{N}^i\}$ consists of the agent's nearest neighbours from inside the cluster.
- Rewards: Several goals of the planned effort are in direct opposition to one another. Those that dole out these bonuses include reward_t^1, reward_t^2 and reward t_t^3 such that they fit within the parameters that have been established.

reward_t^1: maxLifetime $= v/(\mu \times \gamma)$
reward_t^2: minDelay $= \alpha + \beta$

IV. EXPERIMENTAL RESULTS

The proposed method is put to the test versus LEACH and M-LEACH on a virtual network created in ns3.29. The Ubuntu 20.04 server ran the simulation software. The Intel Core i3 had a clock speed of 3.07 GHz. There is a need for 8 GB of RAM for simulations. A region 100 cm2 in size has both supernodes and sensor network spread out at random. The coordinates (0,0) and (1,000,1,000) denote the position of sensor networks and supernodes, respectively (100,100). In the starting experimental

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run, a thousand sensor nodes are dispersed over the field of view, with the ground station (BS) situated in the geographic center of the networks (50,50). The next modeled case involves removing BS from the network and randomly placing 150 sensor nodes throughout the field of view. Keeping track of where the BS is (150,60). Specifically, we look at two scenarios to gauge the performance of the suggested method: I a network of 100 sensors having 7 supernodes and (ii) a network of 150 sensors with 18 gateways. Table 1 provides additional options for modeling the recommended and state-of-the-art methods.

Table 1: Simulation Parameters

Factors	Worth
Physical Medium	Wireless
Supernodes	$7 - 18$
Nodes/Devices	$100 - 150$
MAC	802.11
Energy of Sensor nodes	0.5 J
Traffic Style	CBR, FTP
E_{elc}	50nj/bit
Nodes Position	Between (0,0) and (100,100)
Radio model of Propagation	Two ray ground
energy of Supernodes	5 J
ϵ_{efs}	10pj/bit/m^2
Base station	(50,50)and(150,60)
$E_{aaa}(l)$	5 nJ/bit
packet size Data	512bits
ϵ_{amp}	0.0013pj/bit/m^4

A timeline of packet delivery is shown in Fig. 2. Data from = demonstrates an increase in packet delivery rates of 45% over LEACH and 85% over M-LEACH. Figure also shows that compared to LEACH and M-LEACH, the suggested system improves packet delivery rates by 43.4% and 84.1%, respectively. DRL-based data routing protocols, in which the ideal data routing route is generated based on many criteria like residual energy, waiting time, packet size, traffic rate, etc., are responsible for the improved packet delivery.

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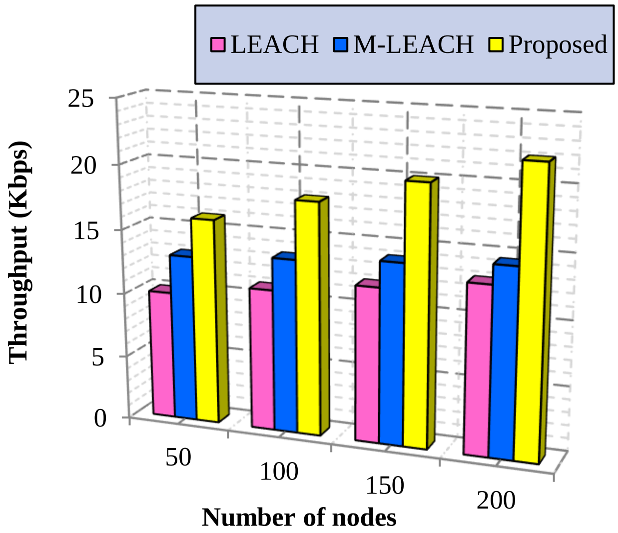
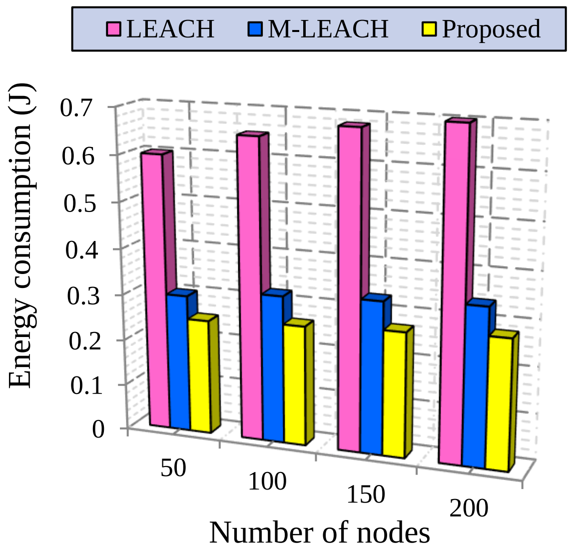


(a)



(b)

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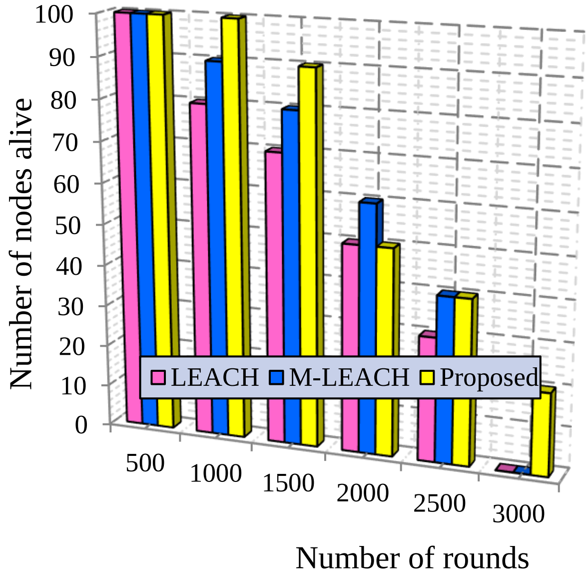
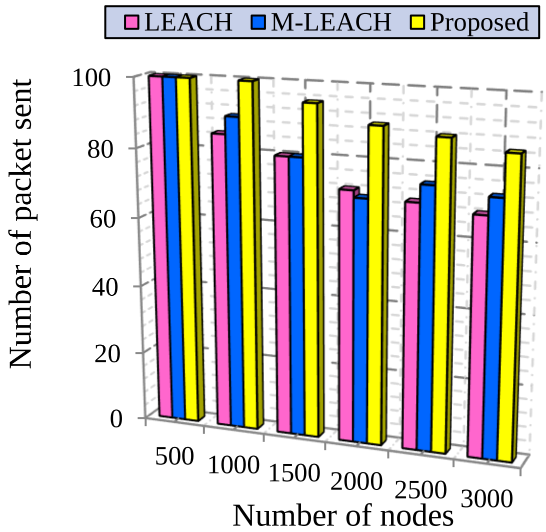


(c)



(d)

Fig. 2: (a) Throughput (b) Energy Consumption (c) No of Nodes Alive and (d) No of Packets Sent

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Fig. depicts the percentage of network nodes that are still active at various network epochs. Fig. The suggested approach increases the proportion of healthy nodes by as much as 65 percent compared to LEACH and 75 percent compared to M-LEACH, as shown by the value 5 in the previous sentence. Fig. shows that there is an increase of 66.2% in the proportion of healthy nodes compared to RLBR and a rise of 75.4% over the standard scheme.

V. CONCLUSION

In this paper, we provide a smart routing method for IoT-enabled WSNs that significantly reduces power usage. The proposed strategy uses an uneven clustering mechanism to keep the network alive, with the supernode taking on the role of cluster leader and coordinating the efforts of the dispersed sensor nodes. By distributing the workload, we can avoid power outages and divide the network into manageable chunks. We consider a wide variety of objectives, including lifetime, throughput, and latency, while planning intra-cluster routes. Both network dependability and performance might benefit considerably from inter-cluster routing, which takes many objectives into consideration. The effectiveness of the proposed technique has been evaluated using simulation data and integrated into the provided design. Through a series of simulations, the proposed method is shown to outperform two state-of-the-art algorithms, LEACH and M-LEAC, by a wide margin. This is true across a variety of metrics, including message transfer, energy efficiency, information sharing latency, and the percentage of nodes in the network that are still operational. The message complexity and running time of the proposed method are also analyzed. We want to improve the reliability of the proposed system by including a fault-tolerant mechanism into it throughout the course of our continuing study. Moreover, we suggest accounting for congestion and interference in the intermediate node's data scheduling. Smart cities, precision agriculture, healthcare, and even home automation is just some of the many places where the proposed method may be put to good use.

REFERENCES

1. Chhabra, A., Vashishth, V., Khanna, A., Sharma, D.K., & Singh, J. (2018). An Energy Efficient Routing Protocol for Wireless Internet-of-Things Sensor Networks. ArXiv, abs/1808.01039.
2. Kaur, G., Chanak, P., & Bhattacharya, M. (2021). Energy-Efficient Intelligent Routing Scheme for IoT-Enabled WSNs. IEEE Internet of Things Journal, 8, 11440-11449.
3. Behera, T.M., Khan, M.S., Mohapatra, S.K., Samal, U.C., & Bhuiyan, M.Z. (2019). Energy-Efficient Routing for Greenhouse Monitoring Using Heterogeneous Sensor Networks. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 953-958.
4. Ismail, R.J., Ismae, S.J., & Ali, W.H. (2019). Energy Management in Wireless Sensor Networks for Internet of Things Applications. Cihan University-Erbil Scientific Journal.
5. Yadav, P.S., Singh, P., Kaur, G., & Chanak, P. (2021). An energy efficient hierarchical routing algorithm for IoT-enabled WSNs. 2021 Fourth International Conference on Computational Intelligence and Communication Technologies (CCICT), 302-307.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

6. Hamad, L.I., Dag, T., & Gucluoglu, T. (2022). Modulated relay based stable election protocol for large‐scale wireless sensor networks. International Journal of Communication Systems, 36.
7. Lazarevskal, M., Farahbakhsh, R., ManShakya, N., & Crespi, N. (2018). Mobility Supported Energy Efficient Routing Protocol for IoT Based Healthcare Applications. 2018 IEEE Conference on Standards for Communications and Networking (CSCN), 1-5.
8. Et. al., V.P. (2021). Improved energy efficient hierarchical cluster tree-based routing to prolong network lifetime.
9. Chan, L., Chavez, K.G., Rudolph, H., & Al-Hourani, A. (2020). Hierarchical routing protocols for wireless sensor network: a compressive survey. Wireless Networks, 26, 3291-3314.
10. Ramadan, R.A. (2020). Efficient Intrusion Detection Algorithms for Smart Cities-Based Wireless Sensing Technologies. J. Sens. Actuator Networks, 9, 39.
11. El-Fouly, F.H., Kachout, M., Alharbi, Y., Alshudukhi, J.S., Alanazi, A., & Ramadan, R.A. (2023). Environment-Aware Energy Efficient and Reliable Routing in Real-Time Multi-Sink Wireless Sensor Networks for Smart Cities Applications. Applied Sciences.
12. Subramani, N., Perumal, S.K., Kallimani, J.S., Ulaganathan, S., Bhargava, S., & Meckanizi, S. (2022). Controlling energy aware clustering and multihop routing protocol for IoT assisted wireless sensor networks. Concurrency and Computation: Practice and Experience, 34.
13. Nasri, M., Helali, A., & Maaref, H. (2021). Energy‐efficient fuzzy logic‐based cross‐layer hierarchical routing protocol for wireless Internet‐of‐Things sensor networks. International Journal of Communication Systems, 34.
14. Shreyas, J., H, D., K, U.P., Chouhon, D., N, S.N., & M, D.K. (2022). Energy Optimization to Extend Network Lifetime for IoT based Wireless Sensor Networks. 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), 90-93.
15. Rishiwal, V., & Singh, O. (2021). Energy efficient emergency rescue scheme in wireless sensor networks. International Journal of Information Technology, 1-8.
16. Adlak, R., & Meena, P. (2021). Multi-Population Ensemble Particle Swarm Optimizer based Energy Efficient Clustering Algorithms for IOT Applications. SMART MOVES JOURNAL IJOSCIENCE.
17. Gavali, A., Vaze, V., & Ubale, S. (2021). Energy Optimization using Swarm Intelligence for IoT-Authorized Underwater Wireless Sensor Networks. Microprocessors and Microsystems.
18. Khelifi, M., Lahreche, A., Grine, I., & Alioua, A. (2021). EH-GPSR: An Energy Harvesting Protocol for IoT-based Wireless Sensor Networks. 2021 12th International Conference on Information and Communication Systems (ICICS), 291-296.
19. Bilal, M., Munir, E.U., & Alarfaj, F.K. (2022). Hybrid Clustering and Routing Algorithm with Threshold-Based Data Collection for Heterogeneous Wireless Sensor Networks. Sensors (Basel, Switzerland), 22.
20. Mishra, P., & Khadagade, S.K. (2021). Hybrid Clustering and Routing Algorithm for Node Performance Improvement in Wireless Sensor Networks.