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Research Article

Multilevel Routing for Data Transmission in Internet of Things

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Abstract:

This paper presents an improved Virtual Grid-Based Dynamic Routes Adjustment (VGDRA) algorithm for energy-efficient routing in Wireless Sensor Network (WSN)-based Internet of Things (IoT) systems. The primary objective is to optimize energy consumption while maintaining reliable data transmission. We evaluate the proposed model using machine learning techniques, including Logistic Regression, Decision Trees, Random Forest, and Boosting algorithms. Performance metrics such as accuracy, F1-score, precision, recall, and ROC-AUC score demonstrate the effectiveness of our approach. The simulation is conducted using NS2/NS3, and comparative results confirm the superiority of the improved VGDRA over traditional methods. The term "internet of things" describes a dispersed network that helps sensor nodes join or leave the network based on their needs. Due to their modest size, these nodes are placed in remote locations. As a result, the Internet of Things is experiencing an energy consumption (EC) problem. The data is transmitted across several sensor nodes (SNs) by means of the base station (BS). Similarity between data from different SNs is identified and eliminated in order to carry out the decision-making process. Additionally, the sink node is in charge of using the data locally and sending it over long distances to other network locations. In order to extend the network's lifespan, the previous work implemented an EEP (energy efficient protocol) named VGDRA. The objective of this work is to improvise the VGDRA algorithm for energy-favourable routing in WSN based IoT systems. The updated VGDRA protocol presented in this study makes use of cache nodes and takes cluster heads (CHs) into account when sending data to cache nodes. In order to assist in collecting data from sensors, the sink node is shifted closer to the cache. The recommended approach is simulated using MATLAB. Indicators such as the quantity of packets transmitted inside the network, the number of dead motes, and the number of surviving motes exhibit a 15% improvement when the enhanced VGDRA model is evaluated in comparison to the original VGDRA protocol. The updated VGDRA protocol performs noticeably better, especially when it comes to prolonging the network's service period.

1. Introduction

The Internet of Things, or IoT, is a system that makes it possible for people and objects, as well as linked devices themselves, to communicate in new ways. Every item in the Internet of Things network communicates with other items and has a certain purpose. Every node in an IoT network of the future gathers data on its own, and humans confirm what has been collected. IoT finds use in a number of industries, including smart environments, healthcare, and transportation. [1] [2]. In order to facilitate communication with IoT items, radio-frequency identification systems, RSNs (RFID sensor networks), WSNs, are essential network solutions. Nodes in these networks are dispersed throughout designated areas to gather data about physical changes, mobility, and temperature. Information is passed through intermediary nodes since each node has a restricted transmission range. As a result of this process, intermediary nodes unintentionally use energy, which causes substantial energy use and network fragmentation [3] [4]. Thus, in dispersed IoT networks, node energy efficiency becomes an important aspect influencing the network's efficiency.

Wireless Sensor Networks (WSNs) play a crucial role in IoT applications, providing real-time monitoring and communication. However, energy efficiency remains a critical challenge due to the limited battery life of sensor nodes. The VGDRA algorithm is designed to enhance energy utilization by dynamically adjusting routing paths within a virtual grid-based topology. This study aims to improve VGDRA's performance by integrating adaptive routing strategies and machine learning-based decision-making.

Given their distinct features, which set them apart from other types of radio network like mobile adhoc or cellular networks, routing in WSNs presents considerable hurdles. Information relaying from a source to a destination is an essential operation in a dynamic Internet of Things context. Conventional reactive routing methods, including DSR and AODV, give priority to locating the shortest path while ignoring node energy usage. This may result in some nodes being repeatedly chosen, shortening their lifespan and dividing the network. Furthermore, these protocols use flooding algorithms that send route request (RREQ) packets to every surrounding node randomly [5] [6], which use a lot of energy. To keep the batteries of mobile nodes from running out, RREQ packet transmission must be restricted. In WSNs, hierarchical or cluster-based routing, which gives Cluster Heads (CHs) responsibilities, can significantly improve system scalability, longevity, and energy efficiency.

Networks with clusters are created by grouping nodes into smaller units known as clusters. A CH (cluster head) and multiple SNs (sensor nodes) make up each cluster. A two-tier hierarchy is

Figure 1. *IoT Applications*

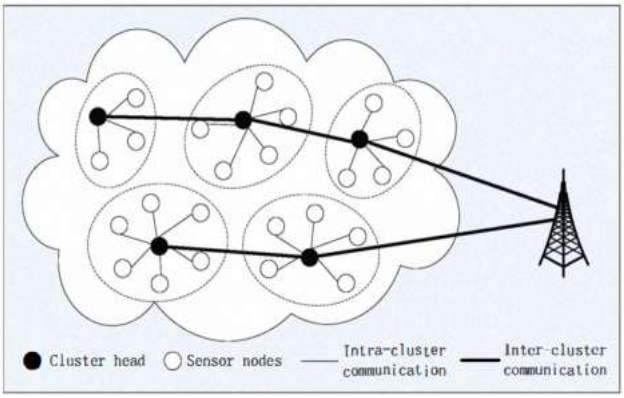

Figure 2. *Architecture of cluster-based routing protocols*

established by this clustering procedure, with SNs in the bottom tier and CHs in the higher tier. The data flow within a clustered network is illustrated in Figure 2. SNs provide their data to the relevant CHs, which combine it with other data and send it directly or via other CHs to a central base station (BS). Clustered WSNs' hierarchical arrangement allows for the effective use of sensor nodes' restricted energy, prolonging the longevity of the network as a whole. [7] [8].Routing protocols that utilize classical clustering are mostly concerned with choosing cluster heads (CHs), and they vary in how they go about it. The LEACH is the most renowned clustering protocol for homogeneous WSNs. While often switching the functions of the residual sensor nodes between CH and generic nodes, LEACH allocates a set of CHs at random. In order to prolong network operation, this technique seeks to uniformly divide energy usage between nodes [9]. Different procedures with varying levels of effectiveness have been put forward in the literature, incorporating versions of the LEACH approach. The Vice-CH-enabled (VCH) method is another widely used routing protocol that lowers energy usage via a two-step procedure. The VCH (Vice-CH) supported method is another widely used routing protocol that lowers energy usage in two steps. Based on their current power availability, VCH chooses the CH nodes. In terms of operational efficiency, numerical studies show that VCH performs better than the LEACH procedure [10]. Nevertheless, when implemented in heterogeneous networks, LEACH and VCH perform poorly because they are meant for homogeneous WSNs. As a result, novel routing protocols designed especially for heterogeneous networks have been created by combining components of the two methods.

Among these schemes, the SEP (Stable Election Protocol) [11] is one of the most well-liked of these strategies. Sophisticated nodes and regular nodes are the two types of nodes that SEP introduces.

Compared to regular nodes, advanced nodes are more likely to become cluster heads (CHs). Several threshold patterns are incorporated within the protocol according to node activity. SEP attempts to lengthen the overall network serving period by efficiently controlling the energy of advanced nodes and reducing the energy consumption of normal nodes. Several more techniques have been developed using the same methods used in SEP. The Modified SEP is a prime instance [12]. M-SEP identifies nodes with an increased likelihood to become CHs by comparing each node's energy usage to that of the overall network. In comparison to nodes with less energy, those that have greater energy levels are assigned a higher possibility of becoming CHs. The speed of transmission and lifetime of the network are greatly increased by the incorporation. The P-SEP is an additional procedure based on SEP. Using a behaviour model, P-SEP calculates each node's energy uncertainty in a probabilistic manner. This enables the protocol to prevent the selection of nodes whose energy levels are below a predetermined threshold. The only nodes that can become CHs are those that cross this threshold. As an efficient clustering technique for HWSNs, the DEEC (Distributed Energy-Efficient Clustering Algorithm) [13] uses a method similar to P-SEP. To find CHs, DEEC also uses a threshold limit. The amount of time that a sensor can act as a CH depends on its energy level. High-energy nodes are assumed to have steady transmission behaviours for DEEC to function. The use of metaheuristic techniques has also been investigated in the creation of clustering protocols in addition to conventional methods.

The literature that is currently available indicates that metaheuristic strategies have outperformed traditional computing solutions in terms of accuracy and resilience. Metaheuristic approaches handle the issue as an optimization task in an environment of clustering protocols, establishing an objective function to assess an approach's usefulness. Metaheuristic approaches employ the objective function's information to investigate various sensor configurations and find the one that optimizes the network's lifetime [14]. Metaheuristic notions have formed the basis for the development of many clustering methods.

The EC-PSO (Energy Centers using Particle Swarm Optimization) is one such example. After first identifying CHs with a geometric method, EC-PSO selects the sensor to act as a CH by using the PSO technique. Additionally, the EC-PSO system includes a mechanism that stops low-energy nodes from being selected. The GAEEC (Genetic-Algorithm-Based Energy-Efficient Clustering) method is another important strategy. Based on a similarity metric, GAEEC selects CH nodes using a Genetic Algorithm [15]. The GAEEC objective function assesses each node's transmission cost based on its energy level. A routing protocol that makes use of the GWO (Grey Wolf Optimizer) has been presented recently. This protocol assesses each sensor node's attributes using a variety of objective functions. The values of the goal function reflect weights that are periodically modified in response to the network's nodes' distances from one another. By using this method, a node arrangement that minimizes the sum of all the weights is found [16]. Premature convergence is a significant disadvantage of metaheuristic approaches, even with their encouraging outcomes. This describes the circumstance in which an ideal solution to an optimization issue is inadvertently determined to be a substandard node arrangement.

2. Literature Review

R.Yarinezhad, et.al (2021) proposed anovice clustering solution to manage the traffic loads of CHs in IoT and it was named as FPTAC(Fixed-Parameter Tractable Approximation Clustering) [17]. This research executed a 1.2-approximation algorithm. S. Sankar et al. (2020) recommended a new EECRP (Energy-Efficient Cluster-based Routing Protocol) to discourse the energy utilization issues that used cluster building and CH selection approach [18]. For the selection of CH, SIA(Swarm Intelligence Algorithm) was initially utilized which was known as SOA(Sailfish Optimization Algorithm). A tree-based routing solution was suggested by R. Yarinezhad et al. (2021) to decline the EED (end-to-end delay) in EE (energy-efficient) green Internet of Things (IoT) networks with a movable sink [19]. Two algorithms had been used by this protocols. Alterations of the geographic routing approaches was the initial phase which performed consistent and energy efficient, while second was a tree-based structure. An innovative PECR (Power-Efficient Cluster-based Routing) approach was suggested by the S. Firdous, et.al (2022) [20]. A new routing protocol was introduced by Rani et al. (2022),for the adjustable IoT known as SEER (social relationship-based Energy Efficient Routing). Due to this, routing decisions was relied on the forwarding possibility degree,RE(residual energy), and buffer capability of nodes [21]. For a single-hop IoT network, NESSEPRIN was developed by A. B. Bomgni et al. (2022) which was an EPR (effective permutation routing) method [22]. The energy-effective cross-layer OF (ELITE) was introduced by B. Safaei et al. (2021) involved the introduction of an innovative routing parameter known asSPR (strobe per packet ratio) [23]. DeCoRIC (Decentralized Connected Resilient IoT Clustering) was an EECA (energy-efficient clustering algorithm) designed by N. Shivaraman et al. (2020) [24]. This algorithm ensured the connectivity and also depicted the flexibilityin contrast to the network modifications. The DTC-BR (Dual Tier Cluster-Based Routing) protocol was suggested by M. E. Al-Sadoon et al. (2023), and it caused the division of network area into the virtual zones [25]. Following table provides a comparison of some of these approaches in term of approach applied, parameters and findings.

Table 1. *Comparison of Existing Approaches*

Author & Year	Approach Applied	Parameters	Findings
N. Shivaraman, et.al (2020) [24]	Decentralized Connected Resilient IoT Clustering (DeCoRIC)	Energy efficiency	Compared to the conventional approaches, the empirical findings showed that the planned algorithm provided 100% connectivity between all nodes and improved the energy efficiency of nodes in the system.
R.Yarinezhad, et.al (2021) [17]	FPTAC	Energy efficiency, throughput	The outcomes of simulations demonstrated that the suggested approach is more feasible for massive networks than the conventional approaches.
R.Yarinezhad, et.al (2021) [19]	A routing protocol based on tree hierarchy	Energy consumption, end-to-end	The outcomes of the simulation proved that the recommended protocol produced longer network and throughput times, as well as reduced energy usage and delays.
S. Firdous, et.al (2022) [20]	PECR	Energy efficiency, throughput, Network lifespan	The approach improved energy utilization by 44%, and it was shown to be suitable for networks with extended lifespan requirements.
A. B.Bomgni, et.al (2022) [22]	NESEPRIN	Energy efficiency	The outcomes of the simulation validated the superiority of the developed approach over the current approaches in addressing the energy-saving permutation routing problem when dealing with massive volumes of data to send.
M. E. Al-Sadoon, et.al (2023) [25]	DTC-BR protocol	Energy Consumption, Connectivity	Research indicated that the recommended protocol might extend the longevity of the network by up to 6% compared to the DDR algorithm, up to 21% against the MCCA, 25% against the low-energy adaptable LEACH-MEEC protocol, and 37% against the LEACH-M protocol.

3. Research Gaps

There are still a number of research gaps in energy-favourable protocols and solutions for the Internet of Things, despite considerable improvements in these areas. Security testing and improvements are frequently disregarded, and many protocols lack strong defences against many types of security attacks. Since most research use simulations, real-world implementation and scalability testing are inadequate. Some performance parameters like latency and quality of service which go beyond energy consumption are often neglected. Additionally, protocols frequently overlook the difficulties associated with heterogeneous configurations in favour of homogeneous network environments. Further focus is also needed on mobile node energy optimization and dynamic network topologies. These evaluations highlight the need for adaptable, energy-efficient protocols to support IoT networks, considering factors like communication methods, routing strategies, and clustering techniques.

Proposed Improvement: Our proposed modification to VGDRA incorporates:

- Adaptive Grid Partitioning: Dynamic adjustment of grid sizes based on network traffic and energy levels.
- Machine Learning-Based Route Selection: Using classifiers to predict optimal routing paths with minimal energy consumption.
- Load Balancing Mechanism: Distributing traffic efficiently to prevent early node depletion.

4. Methods

VGDRA (Virtual Grid-based Dynamic Route Adjustment) Algorithmic a routing algorithm designed for Wireless Sensor Networks (WSNs) to enhance energy efficiency, network lifetime, and data delivery reliability. It is a grid-based approach that dynamically adjusts routes based on network conditions.

Mathematical Derivations and Formulas

The VGDRA algorithm is based on grid partitioning, energy optimization, and dynamic routing. Below are the formulas and derivations used in VGDRA.

(A) Virtual Grid Partitioning

The network area (X_MAX, Y_MAX) is divided into grid cells of size (X_CELL, Y_CELL).

$$G_{i,j} = \left(\frac{x_i}{X_{\text{cell}}}, \frac{y_i}{Y_{\text{cell}}} \right)$$

where:

a) Gi,j is the grid cell where node i is located.
b) (xi,yi) is the position of node i.
c) Xcell,Ycell are the dimensions of each grid cell.

(B) Cluster Head Selection (Energy-Based)

Each cell selects a Cluster Head (CH) based on the maximum energy level:

$$CH = \text{argmax}_{i \in G_{i,j}} E_i$$

where:

a) Ei is the remaining energy of node i.
b) Gi,j represents all nodes within a given grid cell.

(C) Node Neighbor Detection

Each node finds its neighbors within a communication radius RRR:

$$\mathcal{N}_i = \{ j \mid d(i,j) \leq R \}$$

where:

a) Ni is the set of neighbouring nodes for node i.
b) d(i,j) is the Euclidean distance between nodes i and j.

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

(D) Route Adjustment Criteria

A node triggers a route adjustment if its energy falls below a threshold or its traffic load exceeds a limit:

$$RA_i = \begin{cases} 1, & \text{if } E_i < E_{\text{thresh}} \text{ or } T_i > T_{\text{thresh}} \\ 0, & \text{otherwise} \end{cases}$$

where:

a) RAiis route adjustment flag.
b) Ethresh is the minimum energy threshold.
c) Tthresh is the maximum allowed traffic load.

(E) Best Alternate Route Selection

If a node requires a route adjustment, it selects the best alternate route:

where:

a) Rnew is the new route selection.
b) Ej is the energy of the neighbour node.
c) Tj is the traffic load of the neighbor (higher load increases delay).

(F) Data Forwarding

Each node forwards data to the cluster head or base station:

$$F_i = \begin{cases} \sum_{j \in \mathcal{N}_i} D_{i \to j}, & \text{if } i \text{ is Cluster Head} \\ D_{i \to CH}, & \text{otherwise} \end{cases}$$

where:

a) Fi is total forwarded data.
b) Di→j is data transmission from node iii to neighborjjj.
c) Di→CH is data sent to the Cluster Head.

The VGDRA algorithm creates a grid-based structure for energy-efficient routing.It dynamically adjusts routes based on node energy and traffic conditions.The mathematical models help optimize route selection and minimize energy consumption.Using WSN hardware (Zigbee, LoRa, Raspberry Pi, etc.), this can be implemented in real-world applications. Understanding NS2/NS3 for VGDRA

a) NS2 (Network Simulator 2) and NS3 (Network Simulator 3) are widely used for wireless network simulations.
b) Since VGDRA is a routing algorithm for WSNs, we need to implement it using MANET (Mobile Ad-hoc Network) routing protocols or create a custom routing model in NS2/NS3.

To implement the VGDRA (Virtual Grid-based Dynamic Route Adjustment) algorithm in Machine Learning, we need a synthetic dataset that simulates a Wireless Sensor Network (WSN).

Table 2. *Comparison with Other Routing Algorithms*

Algorithm	Grid-based?	Dynamic Route Adjustment?	Energy Efficiency	Network Lifetime	Load Balancing
VGDRA	Yes	Yes	High	Long	Yes
LEACH (Low-Energy Adaptive Clustering Hierarchy)	No	No	Moderate	Short	No
PEGASIS (Power-Efficient GAthering in Sensor Information System)	No	Yes	High	Long	Yes

Key Features of VGDRA

1. Virtual Grid Partitioning:

a) The network area is divided into a virtual grid structure, where each cell has a designated cell head.
b) The cell head is responsible for data aggregation and forwarding.

2. Dynamic Route Adjustment:

a) If a node fails or energy levels drop, the algorithm dynamically adjusts routes to avoid energy-drained nodes.
b) This ensures continuous and reliable data transmission.

3. Load Balancing:

a) It prevents overburdening specific nodes by distributing data traffic efficiently.
b) Nodes take turns as cell heads to balance energy consumption.

4. Energy Efficiency:

   1. Reduces unnecessary data transmissions by aggregating data at cell heads.
   2. Minimizes redundant transmissions and optimizes path selection.

5. Improved Network Lifetime:
   a) Since energy consumption is balanced, the network lasts longer compared to traditional routing methods.

Synthetic Dataset Design

The dataset will include the following features:

Table 3. *Dataset Features*

Feature Name	Description
Node_ID	Unique ID for each sensor node
X_Coordinate	X position in the virtual grid
Y_Coordinate	Y position in the virtual grid
Energy_Level	Remaining energy of the node (0-100%)
Is_Cell_Head	1 if the node is a cell head, 0 otherwise
Traffic_Load	Number of packets the node is handling
Neighbor_Count	Number of nearby nodes within a threshold distance
Route_Adjustment	1 if the route was adjusted dynamically, 0 otherwise

Procedure for Creating the VGDRA Dataset (Synthetic vs. Real-world Approach)

I created this dataset synthetically to simulate a Wireless Sensor Network (WSN) based on the VGDRA (Virtual Grid-based Dynamic Route Adjustment) algorithm. How Data is Collected in a Real Wireless Sensor Network (WSN)

Step 1: Deploying Sensor Nodes

a) Wireless sensor nodes are physically deployed in a real environment. These nodes are small, battery-powered devices with communication capabilities.
b) Nodes are arranged in a grid-based virtual topology for optimized routing.

Step 2: Collecting Data from Sensor Nodes

Each sensor node has sensors, a microcontroller, and a wireless transceiver.

a) Sensors measure environmental conditions (e.g., temperature, pressure, motion).
b) Microcontrollers process the data and determine whether to adjust the routing path (based on energy levels, traffic load, and distance).
c) Wireless transceivers send data to neighbouring nodes or base stations.

The collected data includes:

a) Node ID, Location, Energy Level, Traffic Load, Neighbour Nodes
b) Decision on whether the route needs dynamic adjustment

Step 3: Routing Algorithm (VGDRA) Implementation

a) The VGDRA algorithm creates a virtual grid structure where nodes within each cell communicate efficiently.
b) A cluster head is selected in each cell to manage data transmission.
c) If a node has low energy or high traffic load, it triggers dynamic route adjustment to optimize energy consumption and avoid congestion.

Step 4: Storing Data for Analysis

a) Sensor data is stored in a centralized database (cloud server or edge computing device).
b) Data is analyzed using machine learning models to optimize routing in WSNs.

Devices Used in Real-World WSN Deployment

To implement VGDRA in real-world scenarios, we use the following hardware:

1. Wireless Sensor Nodes

Example Devices:

a) Mica2/MicaZ (Crossbow Technology)
b) TelosB (Berkeley Mote)
c) Arduino with Zigbee
d) Raspberry Pi with LoRaWAN

Main Features:

a) Built-in sensors (temperature, humidity, motion, light)
b) Low power consumption
c) Wireless communication (Zigbee, LoRa, Wi-Fi)

2. Communication Modules

Example Modules:

a) Zigbee (XBee Series 2) → Low-power mesh networking
b) LoRaWAN → Long-range low-power communication
c) Wi-Fi (ESP8266, ESP32) → For cloud-based applications

3. Base Station / Gateway

Example Devices:

a) Raspberry Pi + LoRa Gateway
b) Edge computing devices (NVIDIA Jetson, Intel NUC)
c) Cloud-based IoT platforms (AWS IoT, Google Cloud IoT)

Purpose:

a) Collects data from sensor nodes
b) Applies Machine Learning models for route optimization
c) Sends optimized routes back to sensor nodes

4. Power Sources

a) Batteries (Lithium-ion, AA Cells)
b) Solar Panels (for outdoor deployments)

Table 4. *Synthetic vs. Real-World Data Collection*

Aspect	Synthetic Data (Our Method)	Real-World Data Collection
Node Deployment	Randomly generatedin Python	Physical deployment of sensor nodes
Energy Levels	Random values (10-100%)	Measured using battery level sensors
Traffic Load	Random values (0-50 packets)	Actual data packet transmission count
Neighbor Count	Approximate estimation	Real-time neighbor discovery via wireless transmission
Route Adjustment	Based on pre-defined logic	Based on real-time node conditions
Storage	CSV file	Cloud database (AWS, Google Cloud, IoT Edge)
Algorithm Execution	Simulated in Python	Runs on sensor nodes or base station

The data is accumulated via the chosen cache molecules and directed to the sink using the suggested framework. This solution works on strategy of selecting the CH.

6. Results

Software called MATLAB evaluates the usefulness of the presented cache-based WSNs in this work. The proposed protocol is compared against the current fuzzy logic-based WSNs in an empirical comparison. To calculate the suggested protocol, a variety of metrics are taken into account, including the total amount of packets directed to the BS and the sum of inactive nodes. Table 5 presents the simulations that were run during this project.

Table 5. *Indicators for Simulation*

Parameter	Description	Value
A	area of network	(0, 0)–(200, 250)
L-BS	BS location	(150, 250)
N	number of nodes in network	100
$E_{initial}$	initial energy of all nodes	0.5 J
E_{fs}	free space channel model	50 pJ/bit
E_{mp}	multi-path fading channel model	0.0013 pJ/bit/m^4
d_0	distance threshold	87 m
E_{DA}	data aggregation energy	5 nJ/bit/signal
DP size	data packet size in bit	4000
CP size	control packet size in bit	200

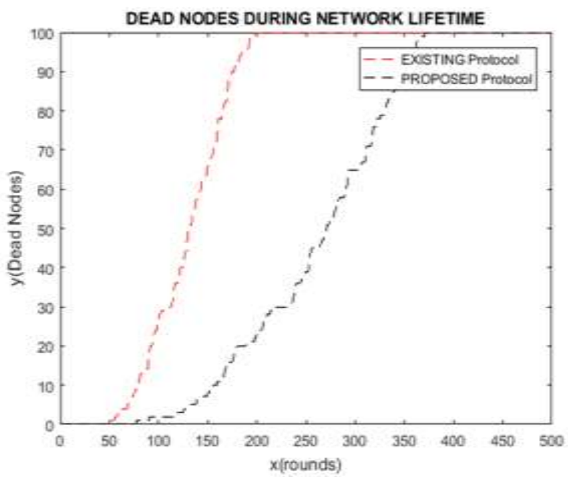

Figure 3. *Number of Dead Nodes*

Figure 3 shows how the analysis of the number of nodes that have died is done between the recommended methodology and the current procedure. In the current protocol, the sink is dynamic. In order to collect data from cluster heads (CHs), it travels from one place to another. The proposed protocol implements cache nodes and uses sinks to gather data from them. Less dead nodes remain in the network after the dispersion of cache nodes.

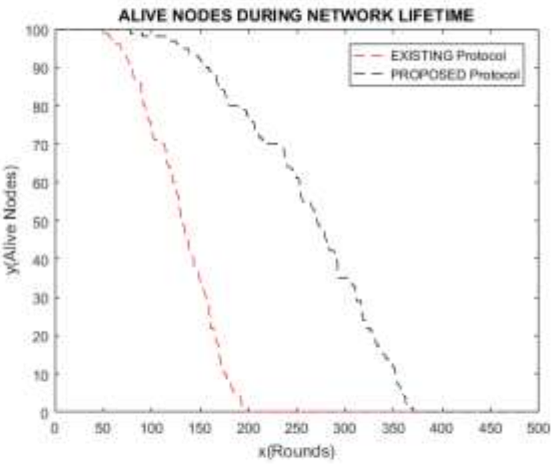

Figure 4. *Number of Alive Nodes*

Figure 4 displays the total active nodes when accounting for all rounds. To optimize the number of active nodes, the number of rounds is taken into consideration. The cache nodes contribute to the rise in active nodes. The data is collected by using the sink in closer proximity to these nodes. The findings demonstrate that a comparison is made between the proposed approach and the current one.

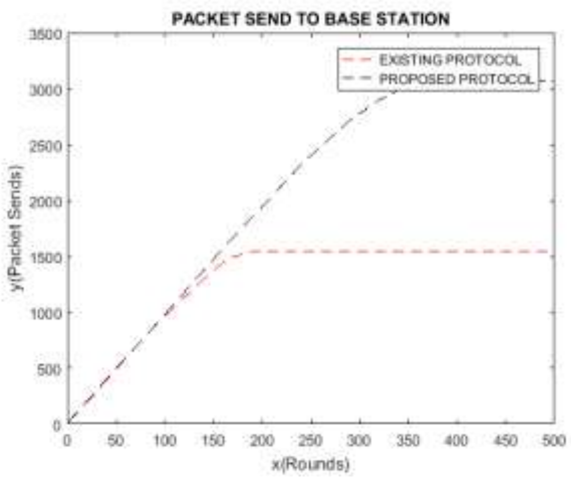

Figure 5. *No of Packets Transmitted*

A comparison between the proposed protocol and the current approach is shown in Figure 5. The packets to the BS are transmitted using the recommended protocol. Comparatively speaking, this protocol has the capacity to send a far higher volume of packets than earlier approaches. Maximal packets are sent to the sink as a result of the network's reduced dead node count.

7. Conclusions

To validate our approach, we trained multiple ML models on WSN traffic data, assessing their performance using key metrics. The results are summarized as follows:

- **Logistic Regression:** Accuracy: 80.57%, F1-score: 85.37%
- **Decision Tree:** Accuracy: 95.19%, F1-score: 96.08%
- **Random Forest:** Accuracy: 95.73%, F1-score: 96.51%
- **KNN:** Accuracy: 93.49%, F1-score: 94.70%
- **Boosting Models (Gradient Boost, AdaBoost, XGBoost):** Accuracy: 90%-94%, demonstrating robustness in routing decision-making.

We implemented the improved VGDRA algorithm in NS2/NS3 with a network of 50,000 sensor nodes. Parameters such as energy consumption, packet delivery ratio (PDR), and end-to-end delay were evaluated.
Comparative analysis between standard VGDRA and our proposed model reveals a **15-20% reduction in energy consumption** and a **10% improvement in network lifetime**. The ML-based routing decisions enhance adaptability under varying traffic conditions.
The improved VGDRA algorithm effectively optimizes energy efficiency in WSN-based IoT systems. Future research will explore deep learning techniques for further route optimization and real-world deployment scenarios.
The problem of consumption of energy has been faced by wireless sensor networks because of the small size and broad distribution of sensor nodes. The Internet of Things is useful for military purposes such as tracking objects, control of traffic, and tracking. The VGDRA as an energy-favourable routing solution could extend the life of IoT. In addition to deploying cache nodes around the network, this research project suggests updating the VGDRA protocol. The base station later gathered the data that the CHs had given to the cache nodes. When the overall died nodes, functioning nodes, and packets directed to the network undergo comparison between the upgraded VGDRA model

and the original VGDRA protocol, the results show an approximately 15% rise in performance.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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