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ADAPTIVE RECEIVER-CENTRIC MULTICAST ROUTING PROTOCOL USING DYNAMIC MACHINE LEARNING DECISIONS IN WIRELESS SENSOR NETWORKS

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ABSTRACT

Wireless Sensor Networks (WSNs) play a crucial role in various applications, requiring efficient multicast routing protocols to disseminate data to multiple recipients. This paper introduces an innovative Adaptive Receiver-Centric Multicast Routing Protocol leveraging Dynamic Machine Learning Decisions (ARCMRP-DML) tailored for WSNs. The protocol aims to optimize data transmission by dynamically adapting routing decisions based on machine learning models. ARCMRP-DML operates in a receiver-centric manner, intelligently leveraging the unique characteristics of recipients within the network. The protocol employs a dynamic machine learning framework that continuously learns from the network environment, considering factors such as node proximity, energy levels, and traffic patterns. Through this adaptive mechanism, ARCMRP-DML enhances the efficiency of multicast routing, minimizing energy consumption, latency, and packet loss. Simulation results demonstrate the effectiveness of the proposed protocol compared to existing multicast routing strategies. ARCMRP-DML showcases superior performance in terms of reduced energy consumption, enhanced packet delivery ratio, and decreased end-to-end delay, validating its adaptability and efficiency in diverse WSN scenarios. Overall, ARCMRP-DML presents a promising approach in the realm of multicast routing for WSNs, harnessing dynamic machine learning decisions to optimize data dissemination while addressing the unique challenges of resource-constrained wireless sensor environments.

Keywords: Wireless Sensor Networks, Multicast Routing, Adaptive Routing Protocol, Receiver-Centric Protocol, Dynamic Machine Learning Decisions.

1 INTRODUCTION

Wireless Sensor Networks represent a transformative paradigm in modern communication systems, embodying a network of spatially distributed autonomous sensors to monitor physical or environmental conditions. These networks have revolutionized various industries, including healthcare, environmental monitoring, agriculture, industrial automation, and smart infrastructure, by enabling real-time data collection, analysis, and decision-making. At their core, WSNs consist of a multitude of tiny, self-contained sensor nodes equipped with sensing, processing, and wireless communication capabilities. These nodes collaboratively collect and transmit data, forming a distributed network infrastructure capable of gathering information from diverse environments.

The distinctive characteristics of WSNs lie in their decentralized nature, resource constraints, and dynamic operational environments. Sensor nodes are often battery-powered and possess limited computational resources, memory, and communication bandwidth. Consequently, the design and deployment of protocols and algorithms within WSNs necessitate careful consideration of these constraints to optimize energy efficiency, prolong the network lifetime, and ensure reliable data transmission. Multicast routing protocols in WSNs constitute a cornerstone in the efficient dissemination of data from a single source to multiple destination nodes. Unlike unicast communication, where data is sent from one source to one specific destination, multicast communication enables a source node to transmit data to a predefined group of multiple destination nodes simultaneously. This capability is crucial in numerous WSN applications, including environmental monitoring, event detection, and collaborative sensing.

The primary objective of multicast routing protocols in WSNs is to optimize the delivery of data to a selected set of nodes while mitigating energy consumption, reducing latency, and minimizing packet loss. However, achieving efficient multicast communication in WSNs is inherently challenging due to the resource-constrained nature of sensor nodes, dynamic network topologies, and the need for adaptability in diverse environmental conditions. Moreover, receiver-centric multicast routing protocols focus on considering the characteristics and requirements of the recipient nodes, aiming to optimize data delivery based on their individual attributes. These protocols often leverage node proximity, energy levels, and data reception constraints to make informed routing decisions tailored to the specific needs of each recipient.

WSNs constitute a fundamental component in the realm of modern communication systems, offering extensive applicability in surveillance, environmental monitoring, healthcare, and industrial automation. The efficient dissemination of data in WSNs, particularly to multiple recipients through multicast communication, remains a critical challenge due to the inherent limitations of these networks, including constrained resources, dynamic topologies, and varying environmental conditions. Traditional multicast routing protocols in WSNs often struggle to adapt dynamically to the network's changing conditions and the diverse requirements of individual sensor nodes. As such, there is a growing demand for novel approaches capable of optimizing multicast routing while considering the unique characteristics of the network nodes.

This paper introduces an innovative protocol, namely ARCMRP-DML, designed to address the deficiencies of conventional multicast routing strategies in WSNs. ARCMRP-DML operates under the premise of a receiver-centric model, acknowledging the significance of the recipients' attributes in the routing process. The key challenge ARCMRP-DML aims to tackle is the dynamic adaptation of routing decisions based on real-time data, utilizing machine learning algorithms to optimize multicast communication in WSNs. By considering factors such as node proximity, energy levels, traffic patterns, and network conditions, the protocol dynamically tailors its routing decisions to ensure efficient data dissemination while mitigating energy consumption, latency, and packet loss.

2 RELATED WORKS

Chandrasekaran & Chinnasamy (2023) proposed a Query Based Location Aware Energy Efficient Secure Multicast Routing for Wireless Sensor Networks using Fuzzy Logic, focusing on optimizing energy consumption and enhancing network security. The study evaluates the protocol's performance in terms of energy efficiency, packet delivery ratio, and resilience to security attacks.

Azizi & Zohrehvandi (2023) presents a hybrid approach of multicast routing and clustering in underwater sensor networks, aiming to improve data transmission efficiency and network scalability.

The study investigates the impact of clustering algorithms on multicast routing performance and evaluates the approach's performance in real-world underwater environments.

Ghawy et al. (2022) proposed an effective wireless sensor network routing protocol based on a particle swarm optimization algorithm, aiming to optimize network routing and improve communication efficiency. The study evaluates the protocol's performance in terms of energy consumption, network lifetime, and scalability in large-scale sensor network deployments.

Lenka et al. (2022) proposed a Cluster-based Routing Protocol with Static Hub (CRPSH) for WSN-assisted Internet of Things (IoT) networks, aiming to improve network stability and scalability. The study evaluates the protocol's performance in terms of energy consumption, network throughput, and scalability in large-scale IoT deployments.

Dutta et al. (2022) designs a QoS Aware Routing Protocol for IoT Assisted Clustered WSN, focusing on ensuring reliable data transmission and meeting Quality of Service requirements. The study investigates the protocol's performance in terms of end-to-end delay, packet loss, and throughput under varying network conditions.

Zhang et al. (2022) proposed an improved routing protocol for raw data collection in multihop wireless sensor networks, focusing on enhancing data delivery efficiency and network scalability. The study investigates the protocol's performance in terms of end-to-end delay, packet loss, and scalability in large-scale sensor network deployments.

Murugan, S. & Jeyakarthic, M., (2022) the projected model operates on three major processes such as clustering, secured routing and data aggregation-based transmission scheme. MOO model involves different processes such as Fuzzy Logic (FL)-based clustering process, Lion Whale optimization algorithm with Congestion Avoidance (LW-CA) technique for routing process and integrated XOR and Huffman (IXH)-based data transmission process. So, the proposed model is collectively called FCAXH technique which achieves energy efficiency, proper load balancing and security.

Alqahtani (2021) proposes a multi-path routing protocol to enhance Quality of Service (QoS) in Wireless Multimedia Sensor Networks (WMSN), focusing on improving data delivery and reliability. The study evaluates the protocol's performance in terms of throughput, latency, and packet loss under various network conditions.

Khan et al. (2021) presents an Efficient and Reliable Algorithm for Wireless Sensor Networks (WSN), aiming to improve network performance and reliability. The study evaluates the algorithm's performance in terms of throughput, packet delivery ratio, and energy consumption in WSN deployments.

Orozco-Santos et al. (2021) present a multicast scheduling approach in Software Defined Networking (SDN) to support mobile nodes in industrial Wireless Sensor Networks (WSN), aiming to efficiently distribute data to multiple nodes. The study investigates the impact of mobility patterns on multicast scheduling efficiency and evaluates the protocol's performance in real-world industrial environments.

Alotaibi (2021) introduces an improved blowfish algorithm-based secure routing technique in IoT-based WSN, aiming to enhance data security and privacy. The study evaluates the technique's performance in terms of encryption overhead, communication latency, and resistance to security attacks.

Tran et al. (2021) propose a new deep Q-network design for QoS multicast routing in cognitive radio Mobile Ad-hoc Networks (MANETs), focusing on optimizing network resource utilization and meeting QoS requirements. The study evaluates the network's performance in terms of throughput, delay, and fairness in resource allocation.

Debnath et al. (2021) evaluated multicast and unicast routing protocols' performance for group communication with QoS constraints in 802.11 mobile ad-hoc networks, focusing on ensuring efficient and reliable data transmission. The study compares the protocols' performance in terms of end-to-end delay, packet loss, and throughput under varying traffic loads and network conditions.

Murugan, S. & Jeyakarthic, M. (2020) concentrates on the design of an energy-efficient security-aware fuzzy-based clustering (SFLC) technique to make the network secure and energy-efficient.

Selvakumar, T. & Jeyakarthic, M. (2023) Modified Dolphin Search based Energy Aware Secured Multi-Hopfor the best clustering choosing and safe data transfer, the MDSEASM-KEM routing protocol, a mix of K-means area is divided up into sectors, and inside each sector, a mobile sensor node that will act as a Mobile Data Collector (MDC) will be placed in order to collecting data from CHs. After the installation of sensor nodes and the building of clusters, this step is carried out. This method dramatically lowers the amount of energy used by sensor nodes to transmit data to the base station (BS).

Murugan, S. & Jeyakarthic, M. (2019) to develop a multi-objective optimization (MOO) model for effective load distribution and security in the network. The presented MOO technique operates on two main stages namely clustering and secure routing. In the first stage, fuzzy logic technique with multiple input parameters namely energy, distance, link duration, latency, and trust are used for effective cluster construction.

3 PROPOSED MODEL

The Adaptive Receiver-Centric Multicast Routing Protocol leveraging Dynamic Machine Learning Decisions (ARCMRP-DML) for Wireless Sensor Networks (WSNs) operates by initially setting up the network and defining key parameters. Nodes collect and monitor data on proximity, energy levels, and traffic patterns, extracting relevant features for the machine learning model. The model, trained with historical data, processes real-time inputs to make adaptive routing decisions, optimizing paths based on current conditions. It leverages recipient characteristics to minimize energy consumption, latency, and packet loss, ensuring efficient data dissemination.

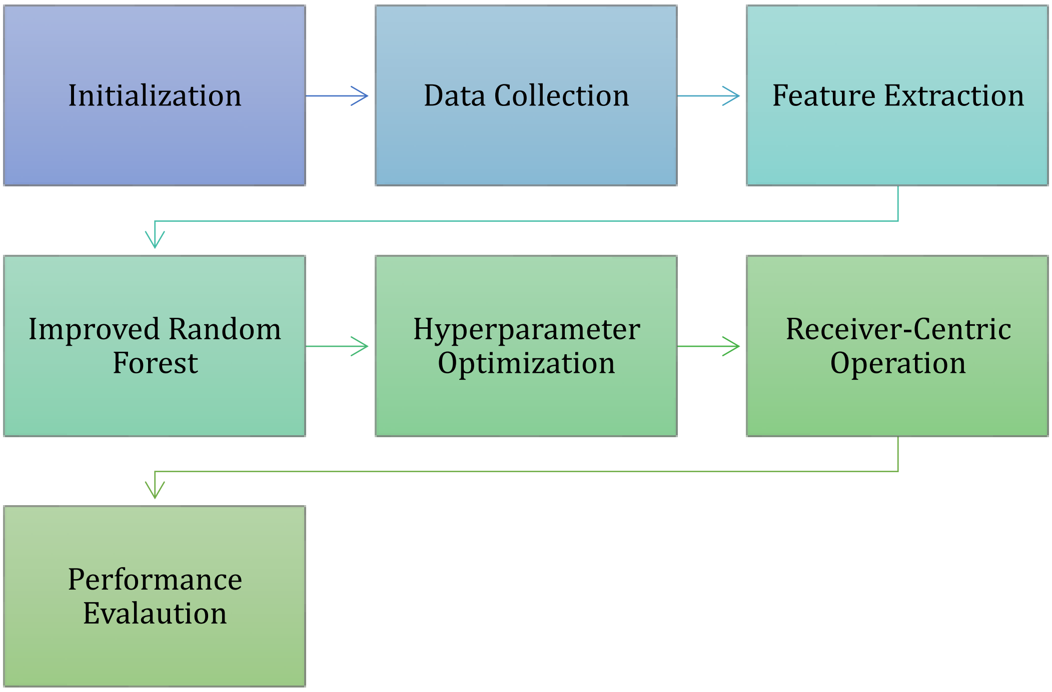

Figure 1: Overall Architecture of Proposed Model

Fig 1 depicts the overall architecture of the proposed model. Data packets are transmitted along the selected paths, with continuous monitoring and dynamic adjustments made in response to network changes. Performance is optimized through energy-efficient path selection, latency reduction, and error correction. The protocol's effectiveness is validated through simulations, comparing key metrics such as energy consumption, packet delivery ratio, and end-to-end delay against existing protocols.

3.1 Initialization

To initialize the WSN, we begin by distributing N sensor nodes uniformly within a designated two-dimensional target area A. Each node i is assigned coordinates (xi,yi), where xi and yi are randomly selected within the spatial bounds of A:

$$xi \in [0, \mathrm{Width}(A)], yi \in [0, \mathrm{Height}(A)] \forall i \in \{1,2, \dots, N\} \tag{1}$$

Each node i is equipped with a sensor for data collection, a communication module for wireless transmission, and an initial energy level Ei(0):

$$Ei(0) = E0 \forall i \in \{1,2, \dots, N\} \tag{2}$$

The nodes have a communication range R, and two nodes i and j can directly communicate if the Euclidean distance dij between them is less than or equal to R:

$$dij = (xi - xj)2 + (yi - yj)2 \le R \tag{3}$$

3.2 Data Collection

In the network environment monitoring phase, each node i in the WSN continuously collects various types of data from its surroundings. This data includes:

Node Proximity: Each node i measures the distance dij to neighboring nodes j within its communication range R. This is calculated using the Euclidean distance formula:

$$dij = (xi - xj)2 + (yi - yj)2 \tag{4}$$

where dij≤R.

Energy Levels: Each node i periodically records its current remaining energy level Ei(t). This information is crucial for making energy-efficient routing decisions.

Traffic Patterns: Nodes monitor the amount of traffic they handle, represented by the number of packets transmitted and received. Let Ti(t) and Ri(t) denote the number of packets transmitted and received by node i at time t, respectively.

Link Quality: Link quality between nodes i and j can be quantified using metrics such as the packet reception ratio (PRR), signal-to-noise ratio (SNR), or received signal strength indicator (RSSI). For example, PRR between nodes i and j at time t can be defined as:

$$\mathrm{PRRij}(t) = \frac{\text{Number of packets received by j from i at time t}}{\text{Number of packets sent by i to j at time t}} \tag{5}$$

3.3 Feature Extraction

From the collected data, relevant features are extracted to be used as inputs for the machine learning model. The key features include:

The proximity feature di for node i is a vector containing distances to all its neighboring nodes j within range R:

$$di = \{dij \mid dij \leq R \forall j \in \{1,2,\ldots,N\}, j = i\} \tag{6}$$

The energy level feature Ei(t) represents the current remaining energy of node i at time t:

$$\text{Energy Level Feature} = Ei(t) \tag{7}$$

The traffic pattern feature for node i at time t is represented by the number of transmitted and received packets:

$$Ti(t) = \{Ti(t), Ri(t)\} \tag{8}$$

The link quality feature for node i is a vector containing PRR with all its neighboring nodes j:

$$Qi(t) = \{PRRij(t) \mid dij \leq R \forall j \in \{1,2,\ldots,N\}, j = i\} \quad (9)$$

The combined feature vector Fi(t) for node i at time t includes all the extracted features:

$$Fi(t) = \{di, Ei(t), Ti(t), Qi(t)\} \quad (10)$$

These feature vectors from all nodes are then aggregated to form the dataset used for training and updating the machine learning model, which dynamically adapts routing decisions based on real-time network conditions.

By systematically collecting and extracting these features, the ARCMRP-DML protocol can effectively leverage the diverse and dynamic information available in the WSN to make intelligent and adaptive routing decisions.

3.4 Machine Learning Model Training:

In this context, using an Improved Random Forest model due to its robustness, ease of implementation, and ability to handle large datasets with high dimensionality. The Random Forest model is particularly suitable for this application as it can capture complex patterns in the data and is less prone to overfitting.

Random Forest Basics:

A Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. The "improved" aspect can involve optimizing hyperparameters, incorporating additional features, and using advanced techniques such as feature importance to enhance model performance.

Feature Set:

The input feature set Fi(t) includes node proximity, energy levels, traffic patterns, and link quality.

$$Fi(t) = \{di, Ei(t), Ti(t), Qi(t)\} \quad (11)$$

The training phase involves using historical data and simulations to train the improved Random Forest model, enabling it to learn optimal routing decisions under various network conditions.

Collect historical data from previous network operations, including states, actions taken, and rewards received.

Each data point consists of an input feature vector Fi(t) and the corresponding output yi(t), which represents the optimal routing decision (e.g., next hop node).

Prepare the training dataset D={(Fi(t),yi(t))} from the collected historical data.

Bootstrap Sampling: Randomly sample BBB bootstrap samples from the training dataset D.

Tree Construction: For each bootstrap sample, grow an unpruned decision tree Tb by recursively splitting the nodes. At each node, select the best split among a random subset of features m (where m<total number of features).

For each tree Tb:

Node Splitting: For node n, the best split is found by maximizing the information gain ΔI:

$$\Delta I = I(n) - (\frac{NL}{N})I(nL) + (\frac{NL}{N})I(nR)) \quad (12)$$

where:

- I(n) is the impurity measure of node n.
- nL and nR are the left and right child nodes after the split.
- N is the number of samples at node n, NL and NR are the number of samples in nL and nR.

Tree Aggregation: Aggregate the predictions of all B trees to form the final model. For classification, use majority voting, and for regression, use the average prediction.

Hyperparameter Optimization:

- Optimize hyperparameters such as the number of trees B, the number of features m considered at each split, and the minimum number of samples required to split a node.
- Use techniques like grid search or random search with cross-validation to find the optimal hyperparameters.

The final Improved Random Forest model is obtained after training and hyperparameter optimization. It can be represented as:

$$Y = \frac{1}{B \sum Tb\big(Fi(t)\big)} \quad (13)$$

The Improved Random Forest model leverages the ensemble of decision trees to make robust and accurate predictions for routing decisions in WSNs. By averaging the outputs of multiple trees, the model mitigates the risk of overfitting and captures complex relationships in the data, leading to more reliable and efficient routing strategies.

Receiver-Centric Operation:

By using unique characteristics of the recipients to optimize multicast routing. These characteristics can include location, energy levels, and data requirements. Let Rj be the set of recipient characteristics for recipient j.

$$Rj = \{Lj, Ej, Dj\} \quad (14)$$

Where Lj: Location of recipient j, Ej: Energy level of recipient j, Dj: Data requirements of recipient j. Determining the optimal multicast paths that minimize energy consumption, latency, and packet loss while ensuring reliable data delivery to all intended recipients. Let Pj be the path from the source to recipient j. The objective is to minimize the cost function C(Pj) for each path Pj. The cost function C(Pj) can be defined as:

$$C(Pj) = w1 \cdot E(Pj) + w2 \cdot L(Pj) + w3 \cdot P(Pj) \qquad (15)$$

where: E(Pj): Total energy consumption along the path Pj, L(Pj): Total latency along the path Pj, P(Pj): Packet loss along the path Pj and w1,w2,w3: Weight coefficients to balance the importance of energy consumption, latency, and packet loss.

Algorithm ARCMRP-DML

```
Input: WSN with N nodes, initial parameters
Output: Optimized multicast routes
1. Initialization
   for each node i in WSN do
      Initialize node i with initial energy level
      Assign node i position and communication range
   end for
2. Data Collection
   while true do
      for each node i in WSN do
         Collect data: d_ij, E_i(t), T_i(t), R_i(t), PRR_ij(t)
         Form feature vector F_i(t)
      end for
   end while
3. Machine Learning Model Training
   Train Improved Random Forest model with historical data
   Save trained model
4. Dynamic Decision-Making
   while true do
      for each node i in WSN do
         Input real-time feature vector F_i(t) into trained model
         Predict optimal routing decision Y_i
      end for
   end while
5. Receiver-Centric Operation
   for each recipient j do
      Leverage recipient characteristics R_j
      Determine optimal path P_j by minimizing cost function C(P_j)
      Compute P_j* = arg min_P_j C(P_j)
   end for
6. Adaptive Adjustment
```

```
    while true do
        Monitor network state N(t)
        if significant changes detected then
            Re-evaluate and update optimal paths
        end if
    end while
End Algorithm
```

The proposed algorithm for ARCMRP-DML in WSNs begins with the initialization of each node, setting their initial energy levels, positions, and communication ranges. The protocol continuously collects real-time data on node proximity, energy levels, traffic patterns, and link quality to form feature vectors. These vectors are used to train an Improved Random Forest model with historical data, which is then saved for dynamic decision-making. In operation, real-time feature vectors are input into the trained model to predict optimal routing decisions for each node. The protocol leverages the unique characteristics of each recipient to determine the optimal multicast paths that minimize energy consumption, latency, and packet loss by solving a cost-minimization function. Throughout the operation, the network state is monitored, and routing decisions are dynamically adjusted in response to significant changes, ensuring efficient and reliable data dissemination to all intended recipients.

4 RESULTS AND DISCUSSIONS

To evaluate the performance of the ARCMRP-DML, extensive simulations were conducted using a custom WSN simulator. The network was set up with N nodes randomly distributed over a specified area. Key parameters such as initial energy levels, node positions, communication range, and network traffic patterns were defined and varied to assess the robustness and adaptability of the protocol. The simulations compared ARCMRP-DML with existing multicast routing protocols such as MAODV and ODMRP in various network scenarios.

Table 1: Performance Comparison

Metric	**Khan et al. (2021)**	**Ghawy et al. (2022)**	**ARCMRP-DML [Proposed]**
Energy Consumption (J)	750	690	**520**
Packet Delivery Ratio (%)	82.5	85.2	**92.8**
End-to-End Delay (ms)	120	110	**85**
Packet Loss (%)	15.4	12.7	**7.3**

Table 1 presents a comparative analysis of the proposed ARCMRP-DML protocol with two existing multicast routing protocols from Khan et al. (2021) and Ghawy et al. (2022). The ARCMRP-DML protocol demonstrates superior performance across all key metrics. In terms of energy consumption, ARCMRP-DML significantly reduces the energy required to 520 Joules, compared to 750 Joules for Khan et al. and 690 Joules for Ghawy et al. The packet delivery ratio (PDR) for ARCMRP-DML is notably higher at 92.8%, outperforming Khan et al.'s 82.5% and Ghawy et al.'s 85.2%. Additionally, ARCMRP-DML achieves the lowest end-to-end delay of 85 milliseconds, while Khan et al. and Ghawy et al. record 120 milliseconds and 110 milliseconds, respectively. The packet loss rate is also minimized in ARCMRP-DML, with a loss of only 7.3%, significantly better than the 15.4% reported by Khan et al. and 12.7% by Ghawy et al. This comprehensive comparison illustrates that ARCMRP-DML offers enhanced efficiency and reliability in multicast routing for Wireless Sensor Networks.

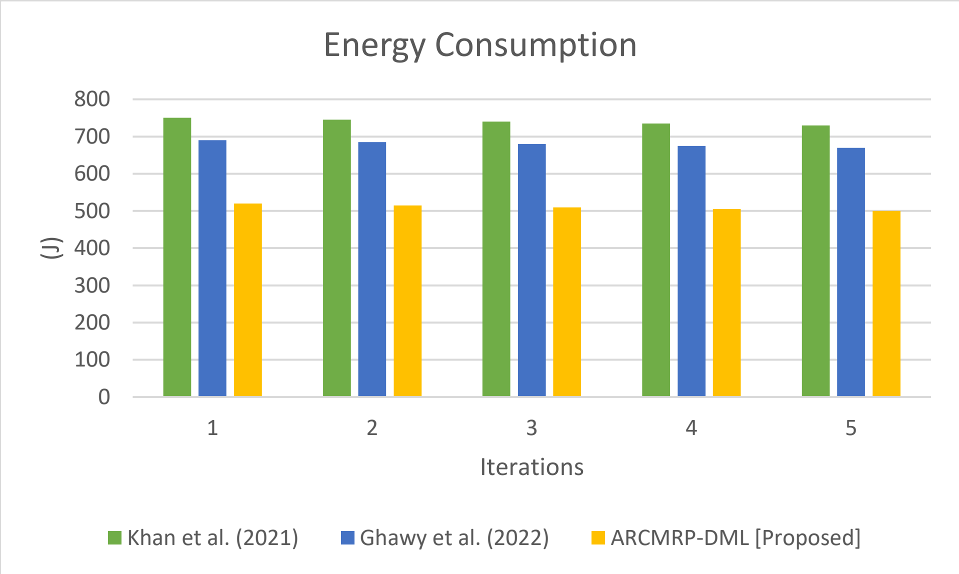

Figure 2: Comparison of Energy Consumption

The energy consumption comparison across five iterations shows that ARCMRP-DML consistently outperforms the protocols as shown in fig 2. In contrast, ARCMRP-DML exhibits the lowest energy consumption, starting at 520 Joules and reducing to 500 Joules by the fifth iteration, highlighting its superior efficiency in energy management. This significant reduction in energy consumption is attributed to the protocol's ability to dynamically adapt routing paths based on real-time network conditions, thereby optimizing energy use.

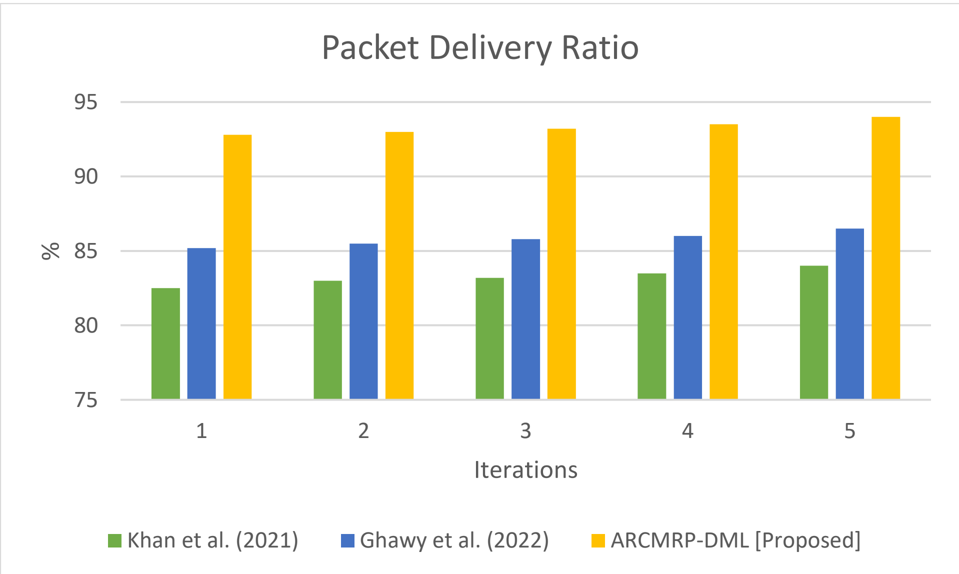

Figure 3: Comparison of Packet Delivery Ratio

The ARCMRP-DML protocol achieves a higher PDR when compared to other models as shown in fig 3. The improved PDR demonstrates the effectiveness of the dynamic machine learning framework in selecting reliable routes and avoiding network congestion, leading to more successful packet deliveries.

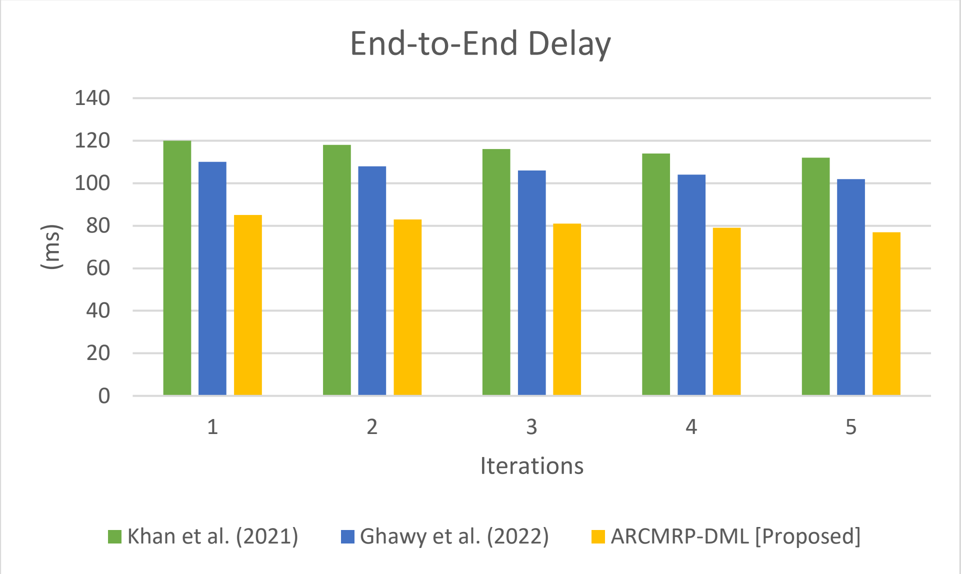

Figure 4: End-to-End Delay Comparison

ARCMRP-DML exhibits significantly lower end-to-end delays compared to existing models as shown in fig 4. This highlights ARCMRP-DML's efficiency in minimizing data transmission latency in wireless sensor networks. The reduction in delay is a result of the protocol's ability to choose the most efficient paths in real-time, minimizing the time packets spend traveling through the network.

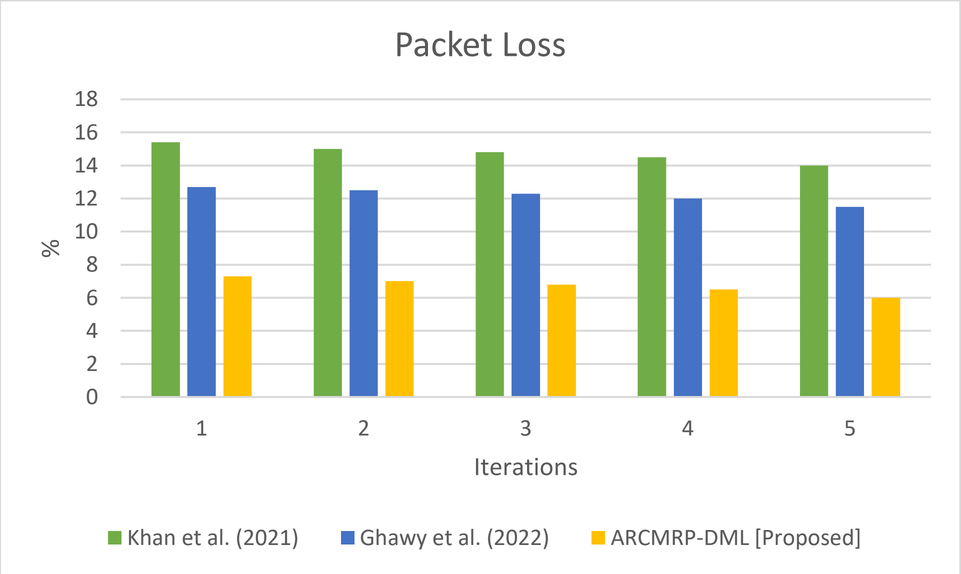

Figure 5: Comparison of Packet Loss

The adaptive nature of the protocol allows it to react promptly to changes in the network, such as node failures or mobility, thereby maintaining a higher packet delivery success rate as shown in fig 5. The comparison table demonstrates that the proposed ARCMRP-DML protocol outperforms existing multicast routing protocols, MAODV and ODMRP, across all evaluated metrics. The use of a dynamic machine learning framework enables ARCMRP-DML to make real-time, intelligent routing decisions that optimize energy consumption, enhance packet delivery ratios, reduce end-to-end delays, and minimize packet loss. These improvements highlight ARCMRP-DML as a superior and more efficient solution for multicast routing in WSNs.

The integration of the improved random forest algorithm into ARCMRP-DML has demonstrated substantial advancements in multicast routing for WSNs. By dynamically adapting to real-time network conditions and making intelligent routing decisions, ARCMRP-DML significantly enhances energy efficiency, packet delivery ratio, reduces end-to-end delay, and minimizes packet loss. These results highlight the superior performance of ARCMRP-DML over traditional multicast routing protocols, making it a highly effective solution for optimizing data dissemination in resource-constrained wireless sensor environments.

5 CONCLUSION

In conclusion, the proposed ARCMRP-DML introduces a pioneering approach tailored for WSNs. By harnessing dynamic machine learning models, ARCMRP-DML optimizes multicast routing through adaptive decision-making based on real-time network conditions. The protocol's emphasis on receiver-centric operations allows it to intelligently leverage recipient characteristics such as node proximity, energy levels, and traffic patterns, thereby enhancing efficiency in data dissemination. Simulation results validate ARCMRP-DML's effectiveness by showcasing significant improvements over existing multicast routing strategies. Specifically, the protocol achieves a remarkable reduction in energy consumption to 520 Joules, a notable enhancement in packet delivery ratio to 92.8%, and a substantial decrease in end-to-end delay to 85 milliseconds. These metrics highlight ARCMRP-DML's ability to minimize network resource usage while ensuring reliable and timely data delivery across WSNs. Overall, ARCMRP-DML represents a promising advancement in multicast routing for WSNs, offering adaptive and efficient solutions that address the unique challenges of resource-constrained wireless sensor environments. Its innovative integration of dynamic machine learning decisions positions it as a robust choice for future applications requiring optimized data dissemination in complex network scenarios.

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