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Energy-Aware RPL-Deep Learning Protocol for Multisink Wireless Sensor System

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Abstract

Wireless Sensor Networks (WSNs) are increasingly deployed across various application domains. Despite their potential advantages, WSNs face persistent challenges due to the resource-constrained nature of sensor nodes, particularly in energy efficiency, routing optimization, and reliable data delivery. This study proposes a machine learning-enhanced RPL protocol to optimize energy-aware routing in WSNs. Two methodologies were developed: the first one is a baseline implementation of RPL-OF0, and the other one is integrating Random Forest (RF) and Support Vector Machine (SVM) algorithms with RPL for dynamic path selection. The framework was across two topologically distinct scenarios—uniform and random node distributions—using metrics such as energy consumption, and end-to-end (E2E) delay. Key parameters included 26–50 nodes, 200–400m deployment areas and energy models accounting for transmission, reception, and aggregation costs,and using one sink and two sink techniques The results indicated that the integration of RF with the RPL protocol significantly outperformed both SVM-enhanced RPL and standard RPL-OF0 in one sink , achieving the most significant reduction in energy consumption across all scenarios. Specifically, RPL-RF achieved a 24.7% reduction in average energy consumption in dense networks. While RPL-SVM showed moderate improvements in E2E delay, Moreover, the adoption of a two-sink architecture produced substantial additional energy savings over single-sink deployments, with average power consumption further reduced by 38–43% across all scenarios and routing protocols, particularly in large-scale and randomly deployed networks. This demonstrates that combining multi-sink deployment with machine learning-driven routing substantially enhances energy efficiency and scalability in WSNs.In all cases and in every part of the network, the SVM method shows the best way to cut delays and grow, followed by RF. The RF method also usually does better than the old OF0 rule.In all cases and in every part of the network,the E2E delay in two sink is better than one sink by almost 20%. Overall, these findings demonstrate that integrating machine learning-driven enhancements into the RPL protocol substantially improves energy efficiency, path reliability, and network longevity in WSNs.

Keywords: WSNs, RPL, IOT, Machine learning, Random Forest, Support Vector Machine

1. Introduction

In recent years, significant advancements in information technology and the rise of the Internet of Things (IoT) have facilitated the integration of the physical environment with digital systems, allowing smart applications to communicate with each other in real-time, which results in improvements in automation, enhanced efficiency, and solutions to various problems across different sectors in daily life [1]. Wireless sensor network (WSN) is considered a cornerstone of IoT that consists of many distributed autonomous sensors responsible for monitoring environmental conditions such as temperature, humidity, light, motion, and sound. WSNs play a significant role in collecting and transmitting data through sensors that communicate wirelessly [2]. There are several disadvantages to sensor technology, including its cost-effectiveness and the limited resources available for storage/computing on/off and energy consumption. Nonetheless, these resources facilitate user engagement in reacting promptly to changing environmental circumstances. They also help to develop effective strategies for addressing environmental issues [3]. A WSN faces several challenges, including high power consumption, high bandwidth demand and data security concerns. Furthermore, wireless communications are often subject to interference from other devices, resulting in poor data transmission quality. Among all these challenges, energy efficiency remains the most critical in WSN design. To overcome the above challenge inexpensive,low-power, multi-functional sensor nodes based on energy-efficient control protocols have been designed to ensure long-term operation and improve overall network performance by selecting protocols that contribute to reducing energy consumption, effectively improving data distribution and achieving excellent reliability[4].

2. Methods and Materials

This section presents a concise description of the material, protocol, algorithm, and network used in designing the proposed system.

2.1 Routing Protocol Low (RPL)The Routing Protocol for Low-Power and Lossy Networks (RPL) utilizes a hierarchical structure known as Destination-Oriented Directed Acyclic Graphs (DODAGs), which are a specific form of Directed Acyclic Graph (DAG) with a single destination root[5,6].RPL used four primary control messages types to manage network topology and communication, as outlined in [7,8,9]:

•DODAG Information Object (DIO): This message includes routing metrics and the objective function (OF) used by nodes to advertise RPL instances. It allows neighboring nodes to discover an RPL instance, obtain configuration parameters, and select a preferred parent within a Destination Oriented Directed Acyclic Graph (DODAG).

•DODAG Information Solicitation (DIS): A node transmits this message when it intends to join a DODAG but has not received any DIO announcements. The DIS message triggers neighboring nodes to respond with DIOs.
•Destination Advertisement Object (DAO): This message is used by a child node to advertise downward routes. In storing mode, DAO messages are unicast to selected parent nodes, which store routing tables. In non-storing mode, DAO messages are forwarded directly to the DODAG root for centralized route management.
Destination Advertisement Object Acknowledgment (DAO-ACK): This control message serves as a confirmation from the recipient node, indicating the successful receipt and processing of a previously transmitted Destination Advertisement Object (DAO) message. The objective function (OF) in RPL governs how nodes construct the DODAG, select optimal paths, and calculate their ranks [10-12]. It evaluates both link and node metrics to determine the most suitable parent for routing. RPL defines two standard objective functions:Objective Function Zero (OF0) [13]: Selects routes based on hop count, favoring paths with the fewest hops to the root.
• Minimum Rank with Hysteresis Objective Function (MRHOF) [14]: Chooses paths based on the Expected Transmission Count (ETX), which measures link reliability.Additional metrics, such as energy consumption and Received Signal Strength Indicator (RSSI), may also be considered [15].

2.2 Machine learning ML

Machine learning (ML) is a subset of artificial intelligence that enables systems to learn from data and make informed decisions without needing programming. In wireless sensor networks (WSNs), ML has been extensively employed to enhance Quality of Service (QoS) and security, including applications such as traffic classification, anomaly detection, intrusion detection, and network optimization [16].

2.2.1Random Forest

Random forest Classifier is a collection of decision trees, where each tree is trained on a different subset of the data. When it comes to making a prediction, each individual tree "votes" for a class label, and the class with the most votes becomes the final prediction of the random forest.

• Ensemble learning means using multiple models (in this case, decision trees) to improve the performance over a single model.
• Bootstrap aggregating (Bagging) is the technique that Random Forest uses to create each tree by training on random samples of the data.

• Random feature selection is used when building each tree, ensuring that trees are diverse and independent of one another.

2.2.2 Support Vector machine (SVM)

A Support Vector Machine (SVM) is a supervised machine learning algorithm commonly used for classification tasks, although it can also be applied to regression problems. The main idea of SVM is to find a hyperplane that best separates the data into distinct classes. It is particularly effective in high-dimensional spaces and is known for its ability to handle complex, non-linear decision boundaries using a technique called the kernel trick.

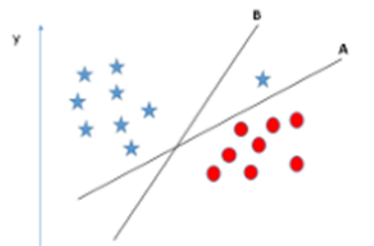

Fig 1. The SVM Technique.

3. Contributions of this paper

Energy limitation is one of the most important challenges facing WSNs and is a major concern as the network expands. Therefore, we are developing key energy efficiency measures to manage energy consumption within the network effectively. This research contributes to addressing this issue.

- Development of a low-power routing protocol (RPL) based on machine learning in WSNs that support the IoT aimed to reduce energy consumption.
- The proposed model classifies the available paths from the source node to the target based on the total energy consumption, ensuring that messages are delivered with the lowest possible energy usage.
- We used two models: one that used the RF algorithm and the other that used the SVM algorithm.

4. Simulation Parameter

Parameters are critical variables that influence the behavior and overall performance of the network. The appropriate selection and precise configuration of these parameters are vital for enhancing the network's operational efficiency and achieving optimal system performance. Various measurements are collected, including the power consumption, and end-to-end delay (E2E) . The RPL protocol was evaluated through simulation under two distinct scenarios :uniform, and random distribution.

Table 1. Simulation Parameters

Parameter	Value
Number of Nodes in the field	26, 50
Number of Sink	1,2
Maximum number of rounds	300
WSN deployment Area	100
Radio Range	120
Maximum number of rounds (r max)	max Rounds
Data packet size (Packet Size)	400
Hello packet size (Hello Packet Size)	100
Number of Packets to be sent in steady-state phase (Num Packet)	100
Initial Energy in Joules (E_0)	0.5
Transmission and receiving energy consumption (E_x, E_r)	Ex=50×10−10E_x = 50 \times 10^{-10}, Er=50×10−10E_r = 50 \times 10^{-10}
Transmit Amplifier energy consumption (SRAEC)	10−1110^{-11} Joules
Long range Amplifier energy consumption (LRAEC)	13×10−1813 \times 10^{-18} Joules
Threshold distance (d□h)	877.0580 (unitless)

5. Result and discussion

In this section, we present the results of implementing the proposed model that aimed to improve energy consumption in WSNs.

5.1 Average power consumption

In two sink, The OF0 approach consistently shows the highest power consumption across all node densities, both RF and SVM significantly outperform OF0 in terms of energy consumption, with SVM achieving the best energy profile. The using of two sink show more power efficient by almost 50% than using of one sink in all algorithms, and across all node densities the power consumption in area 200 is better than 400 in two sink across all node densities.

In one sink the integration of the Random Forest (RF) algorithm with the RPL protocol consistently achieved the lowest energy consumption across all tested scenarios, regardless of differences in network topology and configuration. The reason is because the RF algorithm that the following advantages: Simple implementation, effective use of data, it work well when there's noise in the data, and work quickly in training.

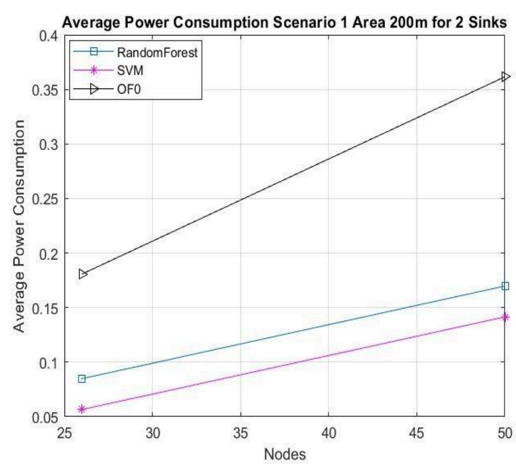

Fig 2. Average power consumption scenario 1 Area 200m 2sink.

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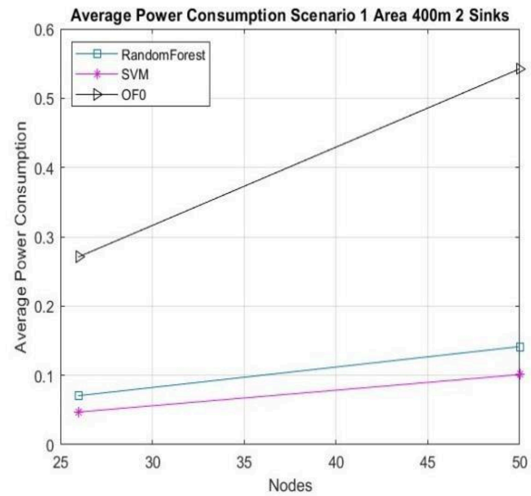
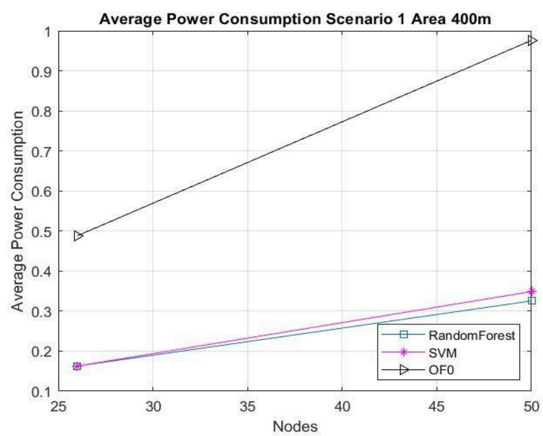


Fig 3. Average power consumption scenario 1 Area 400m 2sink .



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PP 151-166

Fig 4. Average power consumption scenario 1 Area 400m 1sink.

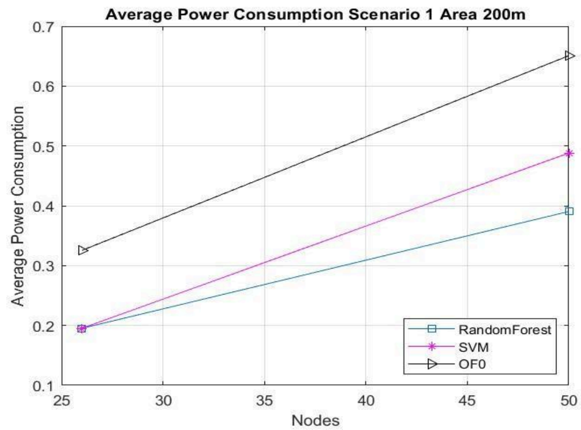

Fig 5. Average power consumption scenario 1 Area 200m 1sink.

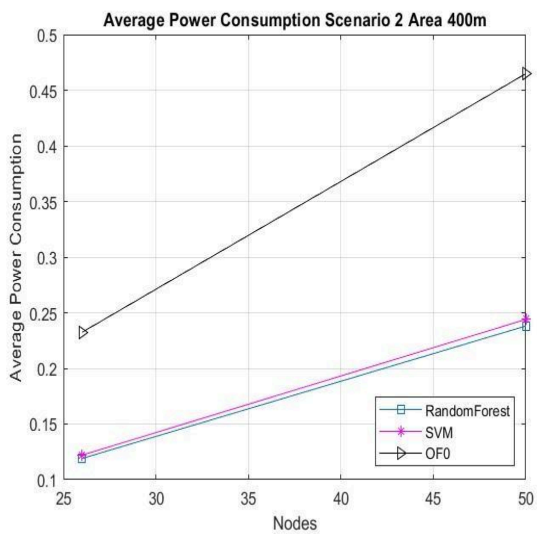

Fig 6. Average power consumption scenario 2 Area 400m 1sink

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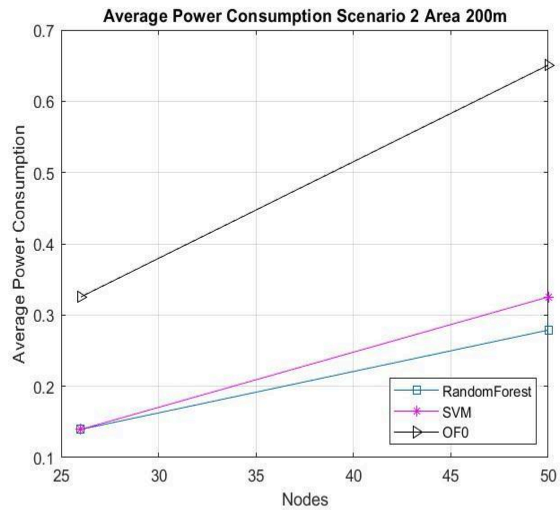

Fig 7. Average power consumption scenario 2 Area 200m 1sink

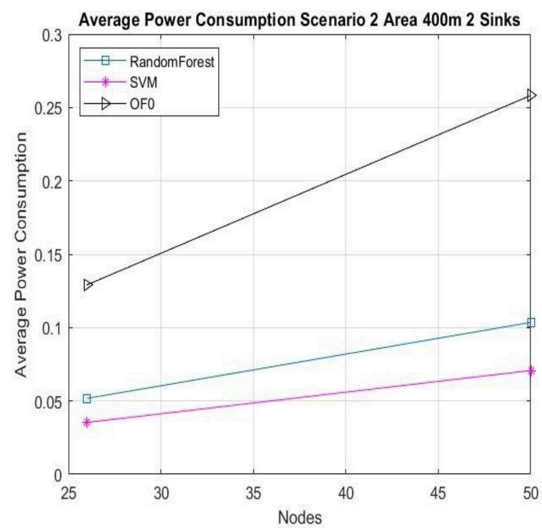

Fig 8. Average power consumption scenario 2 Area 400 m 2sinks

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PP 151-166

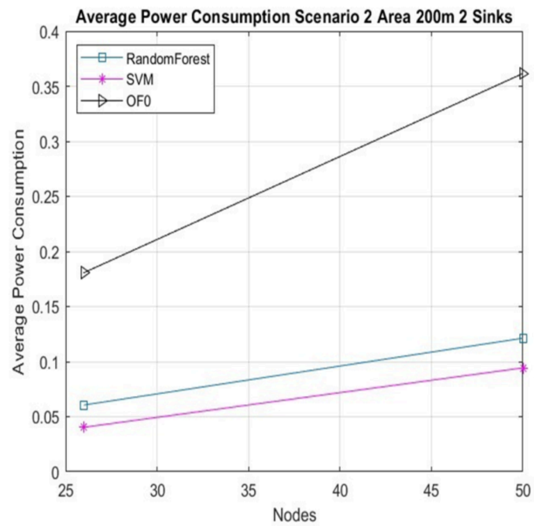

Fig 9. Average power consumption scenario 2 Area 200m 2sink.

The Journal of Computational Science and Engineering (TJCSE)
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PP 151-166

5.2 The percentage E2E delay

Figures 10-13 show the percentage delay in data transmission from the source to the interface across the various simulation scenarios using one sink. The results indicate that delay increases proportionally with the number of nodes in the network in area 200. For both the RF and SVM algorithms, the observed delay percentages are relatively close, ranging between 10% and 50%, depending on the number of nodes deployed.E2E delay decrease when the number of node increase. Figures 14-17 show the percentage delay in data transmission from the source to the interface across the various simulation scenarios using two sink. While OF0 gets better with more nodes in area 400m, it still does not beat RF and SVM. In all cases and in every part of the network, the SVM method shows the best way to cut delays and grow, followed by RF. The RF method also usually does better than the old OF0 rule. In all cases and in every part of the network,the E2E delay in two sink is better than one sink by almost 20%.

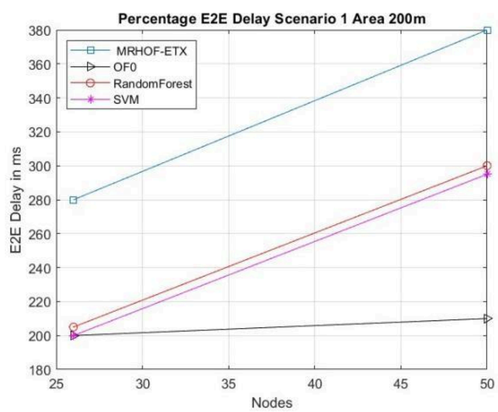

Fig 10.Percentage E2E Delay scenario 1 area 200 m 1 sink

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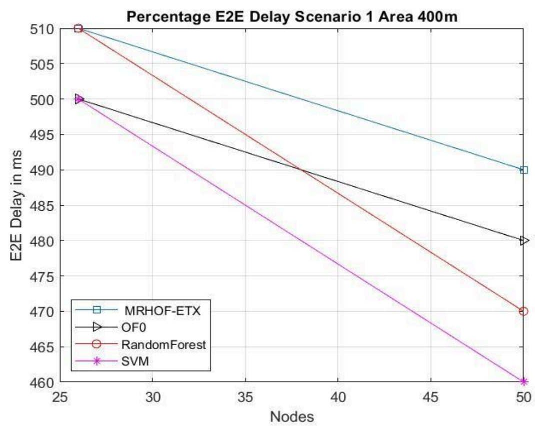

Fig 11. Percentage E2E Delay scenario 1 area 400 m 1 sink

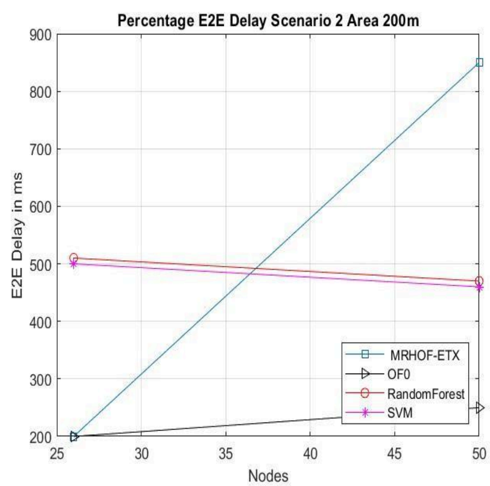

Fig 12.Percentage E2E Delay scenario 2 area 200 m 1 sink

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ISSN 2583-9055 (Media Online)
Vol 3, No 10, October 2025
PP 151-166

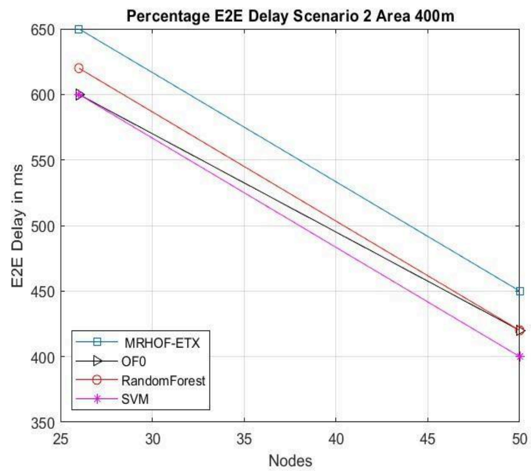

Figure 13. Percentage E2E Delay scenario 2 area 400 m 1 sink.

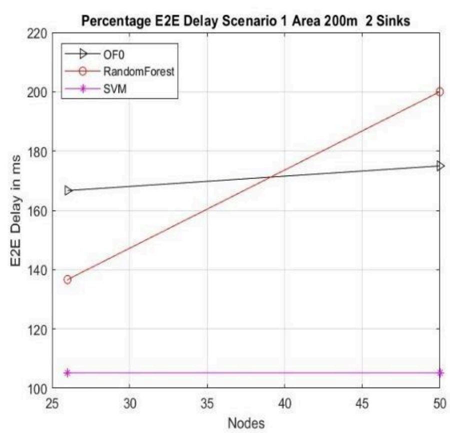

Fig 14. Percentage E2E Delay scenario 1 area 200 m 2sink

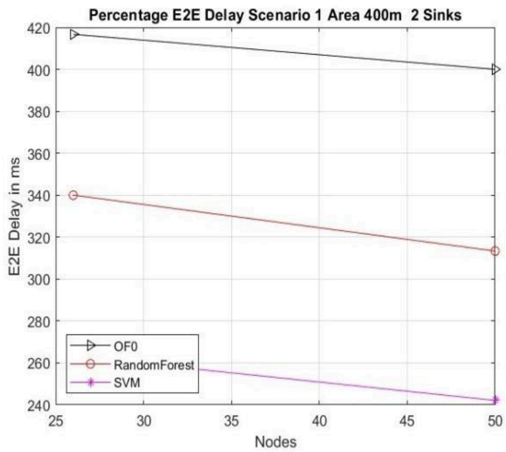

Fig 15. Percentage E2E Delay scenario 1 area 400 m 2sink.

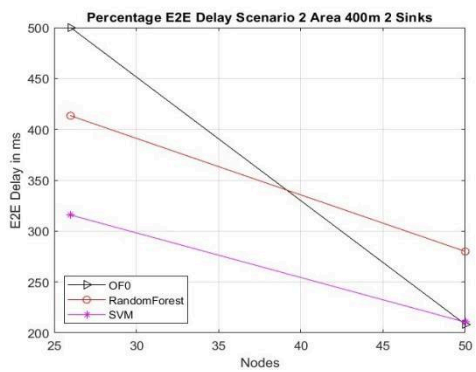

Fig 16. Percentage E2E Delay scenario 2 area 400 m 2sink

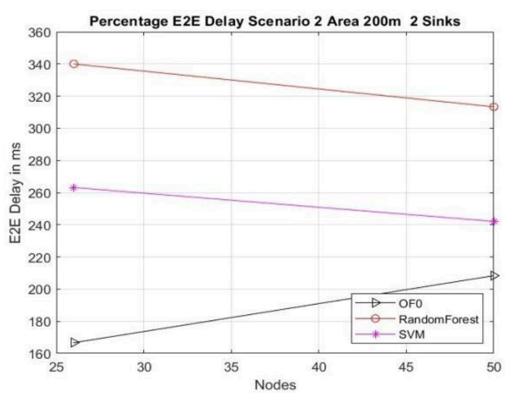

Fig 17.Percentage E2E Delay scenario 2 area 200 m 2sink.

7. Conclusions

One of the most significant challenges facing the WSN is energy consumption, which plays an important and effective role in the network's performance and extending its life. Therefore, it is important to choose the appropriate nodes, protocols and technologies to ensure the lowest possible power consumption. The low-power lossy routing protocol (RPL) has many uses in WSNs due to its ability to reduce energy consumption and improve routine quality This paper presents a model that combines machine learning techniques and the RPL protocol to improve the performance of standard RPL by identifying the best energy-efficient path for data transmission from the source node to the interface .while maximising data delivery rate and minimising latency. Simulation results demonstrate that The RPL-RF model reduced average power consumption by 22–38% and achieved better performance than the RPL-SVM and RPL-OF0 baselines for single-sink scenarios . With the implementation of a two-sink topology , average power consumption was further reduced by 38–43% across all routing protocols and network scenarios, demonstrating the significant benefit of a multi-sink framework for energy efficiency.

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