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Design and Implementation of Integrated RPL Protocol and Deep Learning for Energy-Aware Wireless Sensor Networks

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Abstract: A wireless sensor network (WSN) represents a significant and contemporary technology that has recently emerged, playing a crucial role in enabling the Internet of Things (IoT) to bridge the gap between the physical environment and the digital domain. The major challenges facing WSNs include limited power, data security and reliability, and node failure, along with limitations in data storage, processing, analysis, power management, and security. WSNs with limited physical capabilities employ the low-power lossless routing (RPL) protocol, which employs various processes to simplify communications and network design. Despite its importance and effectiveness, the RPL protocol faces several challenges, including handling high traffic and load balancing, which can lead to service interruption. This paper proposes a machine learning model to address the challenges of energy consumption and efficiency in the RPL protocol. The proposed model is based on the use of Random Forest (RF) and Support Vector Machine (SVM) to identify the optimal path from source to interface, enhancing the network lifetime and delivering data packets in an energy-efficient manner. The model is implemented in two scenarios, one with uniformly distributed nodes and the other with randomly distributed nodes. The results demonstrate that the proposed system outperforms the standard RPL protocol and other protocols in terms of extending the network lifetime and enhancing energy efficiency.

Keywords: Wireless sensor networks, Machine learning, Random forest, Support vector machine, RPL, IOT

Introduction

As a result of the rapid development of information and communications technology, computer networks, the mobile phone industry and the emergence of IoT there has been significant advancement in daily life and smart cities. Wireless devices that support IoT play a crucial role in collecting, transmitting and processing data. Among these technologies, WSN is one of the most important and recent innovations for connecting the physical environment to the digital world. They are extensively utilized across a range of applications in multiple domains, such as environmental monitoring, healthcare, industrial automation, agriculture, and smart cities (Vlajic et al., 2011). A WSN consists of a collection of sensor nodes and actuators that interact with and control the physical environment and sensor nodes have limited energy storage capacity and low processing speed with limited communication bandwidth, which makes the design and maintenance of sensor networks difficult after energy consumption (Gaber et al., 2018). 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 (Dai et al., 2020).These protocols are either static or dynamic and are the backbone of the Internet of Things (IoT), the most important of which is the Routing

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Protocol for Low Power Networks (RPL), which aims to improve overall network performance, and focuses on the use of low-power networks, and high loss rates due to its flexibility and suitability for different IoT, but it is not without limitations and drawbacks, especially in terms of service efficiency. Recently, machine learning (ML) and deep learning (DL) algorithms have been integrated with the RPL protocol to design hybrid systems to contribute to solving the shortcomings and problems (Zahra et al., 2022). This Study presents a methodology for WSNs based on the development of a low-power routing protocol (RPL) model that utilises machine learning. The target is to achieve energy efficiency by classifying available paths and determining the optimal path for delivering messages to a target with minimal energy consumption.

Literature Survey

Many studies have contributed to providing solutions to the challenges facing WSNs using different technologies. These efforts mainly focus on designing aggregation and routing protocols to reduce energy consumption, enhance security, and select the best path in the network, as detailed below:

Abdelhadi et al. (2019): A minimal hierarchical objective function (MRHOF) and zero-order objective function (OFO) evaluation scheme are proposed for large-area scenarios and realistic topologies, considering reliability in terms of packet delivery ratio, power consumption, average end-to-end delay, and radio activity ratio. COOJA is used as a wireless sensor network simulator, simulating the software and hardware levels of embedded nodes using Contiki OS. Based on the simulation results, it is concluded that the choice of the given objective function has an impact on PDR and delay and can achieve energy saving. Finally, the development of an objective function with hybridisation of more than one metric is proposed as future work to balance PDR and power consumption (Somula et al., 2022). The proposed method may not be ideal in some real-world large scenarios requiring a balance between PDR and power consumption may increase computation complexity.

Somula et al. (2021): A system based on the Seagull Optimisation Algorithm-based Energy Aware Cluster Routing (SOA-EACR) routing protocol and the (SEAGULL) optimisation algorithm was proposed. The system aims to extend the network lifetime and reduce the delay, as the network lifetime was improved by 20% with an increase in the packet delivery ratio from 2-5%. The simulation was performed using MATLAB 2019. The system performance was divided using similar optimisation algorithms based on the fitness function that takes into account the appropriate network parameters to choose the optimal channel among other nodes in the network (Gurram et al., 2022). The proposed method did not mention computational complexity or real-world applicability

Suliman et al. (2022): This study aims to propose the (EAFTC-RIS) technique which consists of three main processes which are (MFO), fault loading process and (SSO)-based routing to determine the communication channels and optimal paths towards the destination for efficiency and safety. The simulation results indicated that the technique is better compared to other methods and can be used as a skillful method to achieve maximum survivability of wireless sensor networks (Suliman et al., 2022). This research presents limited comparisons with other techniques and scalability concerns.

Nilabar et al. (2023): The authors proposed a system based on the SCORE BASED LINK DELAY AWARE ROUTING (SBLDAR) protocol and Modified Salp Swarm Optimisation (MSFO) algorithm to select the best routing path for secure data communication, distinguish between hostile and normal nodes, and allow collision-free data exchange. The results demonstrate that the protocol, used with a hybrid message authentication code (MAC) environment, reduces energy, improves network lifetime, and improves overall performance (Nilabar,et al, 2023). Different network conditions do not display the performance metrics in full detail.

Abubakar et al. (2024): This study proposed a system combining the RPL protocol with machine learning algorithms to enhance the security and quality of service (QOS) of RP networks in WSNs supporting IoT applications. The system results confirmed that the additional computational overhead is reasonable and acceptable, ensuring improved security and QoS without affecting the overall performance of WSNs. Thus, the system greatly enhances the QoS and secures the data transmission in WSNs supporting the IoT (Wakili et al., 2024). The proposed system has additional overhead that might impact resource-constrained nodes in large-scale networks.

Methods and Materials

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

Routing Protocol Low (RPL)

RPL is an IPv6-based protocol specifically designed for low-power and lossy networks (LLNs), facilitating routing across multiple layers (Hassani et al., 2019) and supports various modes such as store-and-no-store, transport and local repair (Culler et al., 2004). However, the protocol has several limitations and drawbacks concerning QoS,security, reliability, delay, jitter, packet loss, and power consumption (Porcus, et al., 2010). The primary objective of RPL is to establish optimal routing paths between multiple nodes and a single destination node or edge router, which serves as the gateway to the Internet. Unlike conventional routing protocols, RPL determines paths through an objective function that delineates a set of metrics and constraints for identifying the lowest-cost routes within a specific RPL instance. Despite certain limitations, RPL possesses several significant features, including support for automatic configuration via ICMPv6 messages, the ability to detect and prevent loops in the network by constructing multiple Directed Acyclic Graphs (DAGs) within a Destination-Oriented DAG (DODAG), and the utilization of rank values assigned by each node in the network. Additionally, RPL demonstrates the capability to adapt to changes in topology and effectively manage node failures. The following points outline the key aspects of the RPL protocol (Figure 1).

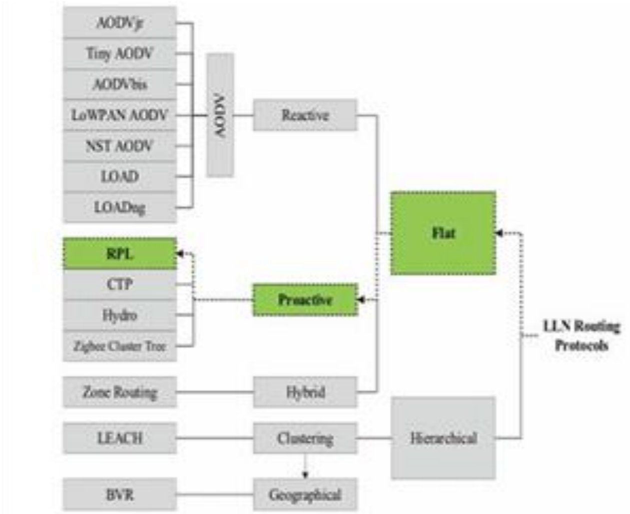


Figure 1. Classification of routing protocols for low-power and lossy networks.

We maintain DODAG by computing the rank of each node within the network and choosing its preferred parent. As illustrated in Figure 3, the rank of nodes decreases along paths leading to the root node. RPL employs Objective Functions (OFs) to determine the criteria for path selection, rank assignment, and parent selection. The process of constructing a DODAG using RPL is also represented in Figure 2.

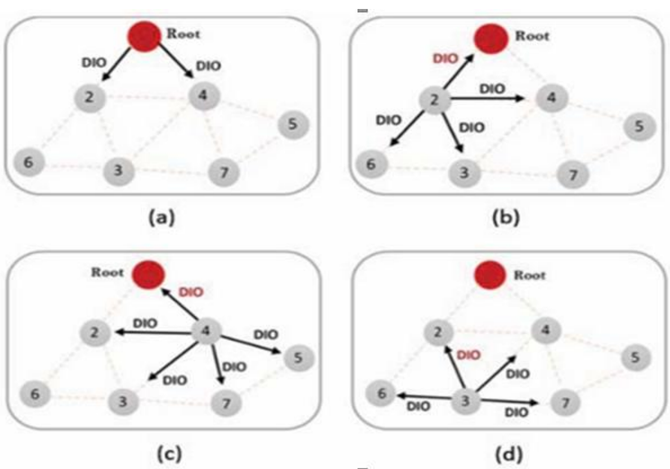


Figure 2. Structure of building DODAG with RPL

Designing an OF remains an active area of research to improve the performance of the routing protocol. In this context, the Routing Over Low Power and Lossy Networks (ROLL) working group designed two basic objective functions. The first one is OF0, which is based on the hop count metric that follows the philosophy of the famous algorithm of Dijkstra to select the nearest path first. The second one is MRHOF, which selects routes that minimize a metric relative to link paths. Figure 3. RPL utilizes OF, which outlines the process of selecting the computing path.

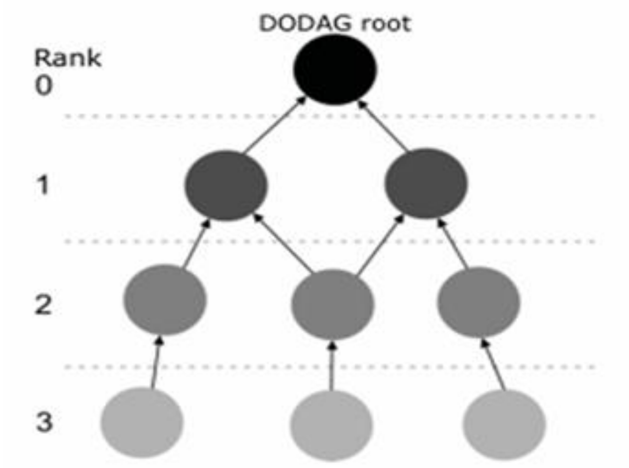


Figure 3. Ranks using DODAG.

Objective Function Zero (OF0)

OF0 is based on reducing hop count to ensure connectivity for a substantial number of nodes within the network and to facilitate the routing of data packets to the root. The overall path selection process initiates with the computation of a variable referred to as Rank Increase for each node, as defined in Eq. (1).

Rank node = Rank parent + Rank increase (1)

Where Rank parent refers to the rank of the preferred parent node, while the variable Rank increase is determined according to Eq (2).

Rank _increase = Min Hop Rank Increase *Step (2)

Where Step is a scalar value that indicates the magnitude of rank increment along a path within the DODAG, while Min Hop Rank Increase specifies the unit of rank increase.

Minimum Rank Hysteresis Objective Function (MRHOF)

The MRHOF is based on a standardised routing metric known as Expected Transmission Count (ETX) which represents the anticipated number of transmissions required for a node to successfully deliver a packet to its destination. The calculation of ETX for potential parent nodes is expressed in Eq. (3):

ETX = 1 / (Df * Dr) (3)

Where Df denotes the probability of packet reception by the neighbor, while Dr represents the acknowledgment probability for a successfully received packet. The rank of the node is subsequently computed using Eq (4):

Rank node = Rank parent + ETX (4)

Where Rank parent refers to the rank of the parent node and ETX indicates the expected transmission count to this parent node.

Machine Learning (ML)

ML is a subfield of artificial intelligence (AI) that enables systems of learning and analysing data (Dunkels et al., 2004) (Dimarco et al., 2010). It offers the flexibility to discover different network characteristics and determine optimal path solutions within a network (Santos et al., 2023). We have used machine learning (ML) techniques to solve wireless problems,ensuring timely and effective decision-making in complex situations. It also helps to enhance the efficiency of wireless sensor networks as well as reduce human intervention or reprogramming. This research has used Random Forest (RF) and Support Vector Machine (SVM) algorithms to design and implement the proposed system.

Support Vector Machine (SVM)

SVM is a non-probabilistic classifier that is formally characterized by a separating hyperplane. The training dataset is labeled through a supervised learning process,whereby the algorithm identifies an optimal hyperplane that maximizes the distance from the support vectors. In a two-dimensional space, this hyperplane manifests as a line that divides the plane into two distinct classes. The tuning parameters for the SVM classifier include epsilon, regularization and kernel parameters (Zidi et al., 2017) Figure 4 shows the technique of SVM.

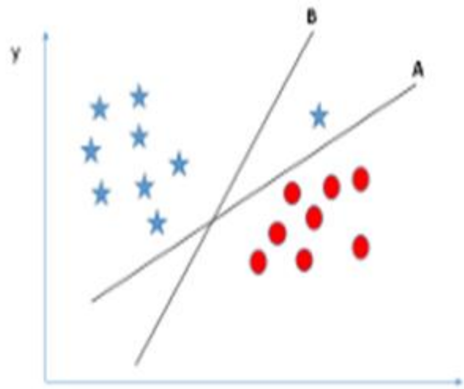


Figure 4. The SVM technique.

Random Forest (RF)

The Random Forest (RF) is an ensemble learning method used for classification, regression, and other predictive tasks. It operates by constructing decision trees during the training phase and producing a class based on the mean prediction of individual trees. In RF, there is a directly proportional relationship between the number of trees in the forest and the resulting accuracy. The RF algorithm consists of two main steps:
The first step is to create an RF tree, which involves five stages:

- Select K random features from the total features m, where K is less than the total number of features (m).
- Within the selected features, determine node d using the best split point.
- Distribute the nodes into daughter nodes through the best split.
- The first three steps are repeated until the number of nodes is obtained
- All of the above steps are repeated n times to achieve p number of trees, where n is not equal to p.

Next, we classify the data using the RF tree we created in the first step. It has the following stages:

- The rules created for each randomly formulated decision tree and test features,
- data are classified
- The votes are calculated for each target value.
- The highest voted prediction target is considered to be the final result of the RF algorithm (Zhang,et al,2018).

Figure 5 shows the RF algorithm.

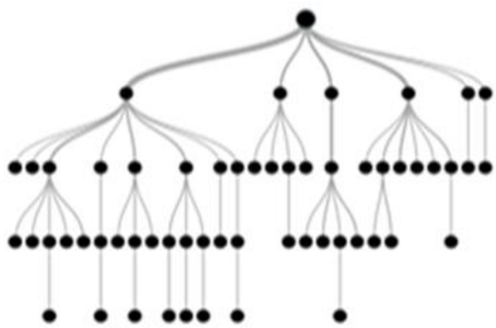


Figure 5. The RF technique.

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.

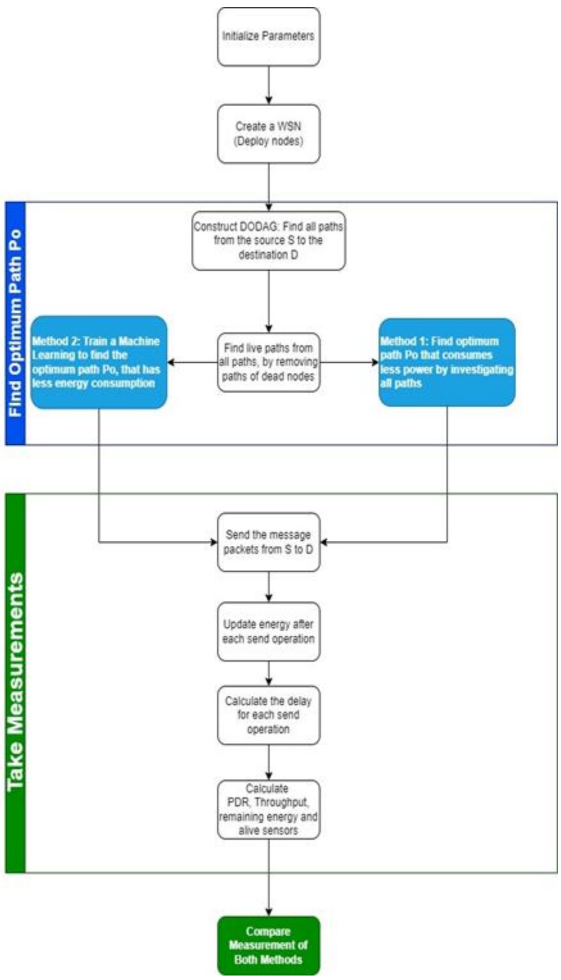


Figure 6. The framework of the proposed model.

The Proposed Model

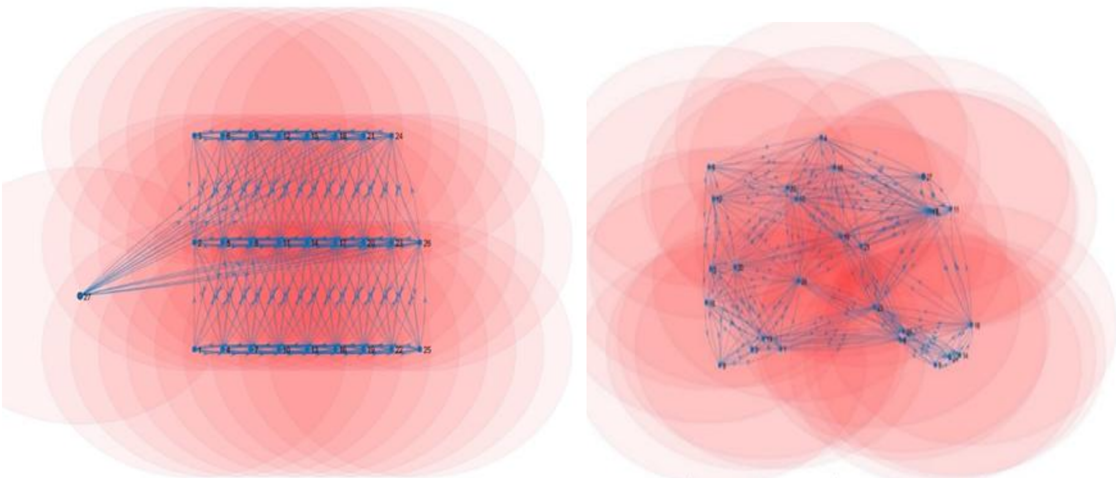
This article presents a methodology for WSNs based on the development of a low-power routing protocol (RPL) model that utilises machine learning. The target is to achieve energy efficiency by classifying available paths and determining the optimal path for delivering messages to a target with minimal energy consumption. The proposed model divides into four stages, as depicted in Figure 6.

- Stage 1: Building the wireless sensor network and determining the initial parameters.
- Stage 2: Finding the optimal path.
- Stage 3: Implementing dependent measures.
- Stage 4: Conducting comparisons

Below is a detailed explanation of each stage along with subsequent partial steps.

Building the WSNs and Initial Parameters

This stage includes a brief overview of all the initial parameters selected for the simulation, which was implemented in two scenarios with different topologies. Choosing the parameters carefully ensures that the wireless sensor network performs well, as choosing the parameters of signal strength, data transfer rate and speed reduces energy consumption, increases the battery life of the nodes, improves the quality of the connection and the stability of the network, and reduces the failure rate, data transfer time, error rate, and the risk of hacking. Additional factors that contribute to ensuring acceptable network performance include the method used to select the network design scenarios and topologies. Figure 7 illustrates these factors, along with the simulation scenarios and scripts.



a) b)

Figure 7. a) Scenario 1: Uniform distribution. b) Scenario 2: Random distribution.

Send and Receive Packets

After initializing the WSN, the simulation starts sending data packets from the sender node to the receiver node. The packet may pass through many nodes till it reaches its destination. Between each pair of neighbouring nodes, the packet is transmitted through the channel by the transmitter, which consumes energy of E_TL Joules. The transmitter consumption loss energy E_TL is calculated based on the distance between them d as follows:

$$E_{TL} = \begin{cases} E_{Tx} + LRAEC \times PacketSize \times d^4 & if\ d > d_{th} \\ \\ E_{Tx} + SRAEC \times d^2 & if\ d < d_{th} \end{cases} \quad (5)$$

where E_Tx is the initial energy consumption of the transmitter, d is the distance between the transmitter and the receiver. In any case, where the distance is less or greater than the threshold d_th, the receiver consumes the following energy:

$$E_{RL} = (E_{Rx} + EDA) \times PacketSize \quad 6$$

where EDA is the Data Aggregation Energy, which is set in the initialization step.

Finding the Optimal Path Stage

After establishing the first stage by selecting the appropriate parameters, designing topology scenarios, and deploying the nodes, this stage involves identifying all paths from the source(s) to the interface (D) and determining the direct paths by eliminating the paths of neglected nodes through the construction of DODAG. The optimal path from the source to the interface is determined using two methods: the first uses the standard RPL protocol technology and uses the OF0 algorithm, while the second method involves ML techniques using the RF and SVM algorithms. Figure 8 shows the flowchart of this stage.

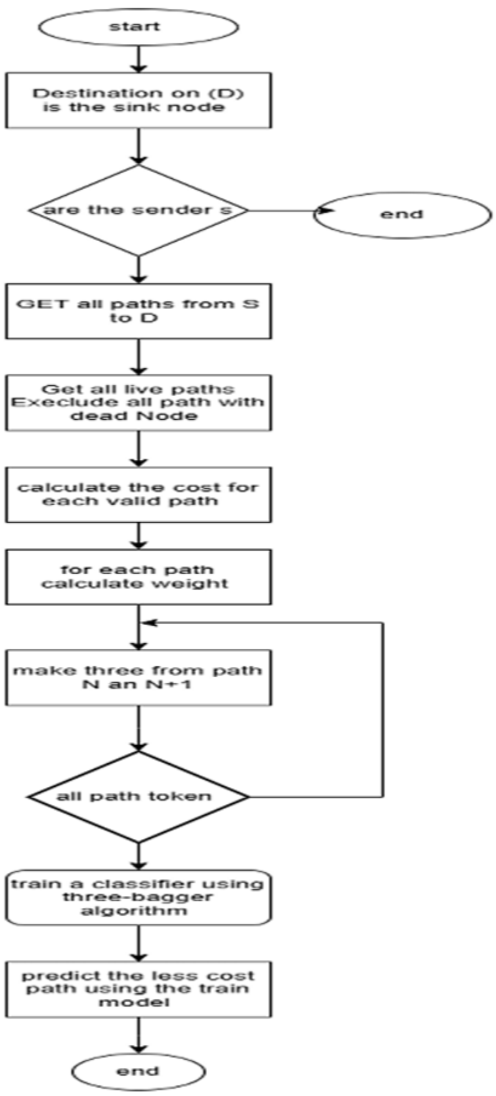


Figure 8. Flowchart of finding the optimal path.

Approach 1: The low-power lossless RPL protocol with the objective function OF0 determines the optimal path from the source to the interface in a WSN by identifying the immediate neighbour nodes, calculating the link cost between these neighbours, then constructing the tree for each node after identifying its immediate parent through the link quality. The objective function OF0 is calculated as follows:

OFO = min (Rank, Parent _ Rank) (7)

where Rank is the rank of the current node, and Parent Rank is the rank of its direct parent. After calculating the objective function OF0, the optimal path with the lowest cost is determined, and the tree is then cyclically checked to ensure that the optimal remains valid.

Approach 2: In this approach, the optimal path from the source to the interface is determined by combining machine learning models with the RPL protocol, using RF and SVM algorithms for comparison. When integrating either of the two algorithms into RPL, the process involves collecting and analysing data such as link quality, energy consumption, and data transmission time. Important features that affect the network performance are identified, and RF and SVM models are created based on these features. The models are trained using training datasets, optimising the path based on the trained model. This process is repeated multiple times to improve the network performance. Even the RF and SVM models have improved accuracy, still the SVM algorithm has limitations, including the complexity and time consumption of training data and determining the optimal parameters of the model.

Dependent Measures

Various measurements are collected, including the packet delivery ratio (PDR), power consumption, end-to-end delay (E2E Delay), and the percentage of time the radio is ON.

Comparisons

In the final stage of the proposed system, the overall performance of the network is compared among the RF algorithm, SVM, the standard RPL protocol with the objective function OF0 and the modified RPL protocol with Minimum Rank Hysteresis Objective Function (MRHOF).

Results and Discussion

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

Simulation Parameters

Table 1 shows the parameters used in simulating the proposed model

Table 1. Simulation parameters

Parameter	Value
Number of Nodes in the field	26, 50
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_th)	877.0580 (unitless)

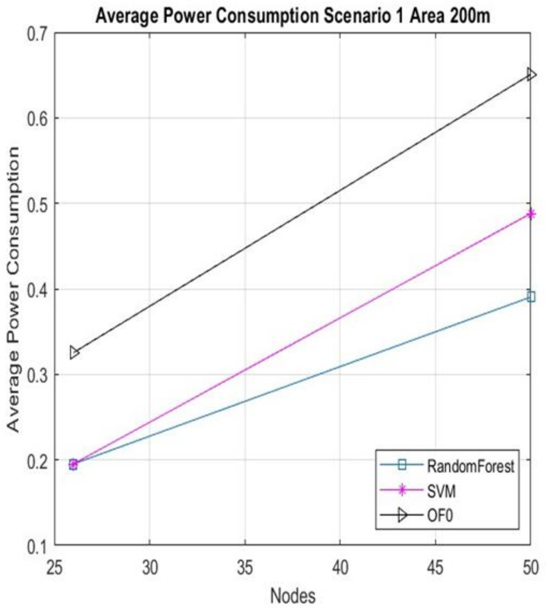


Figure 9. Average in scenario 1 with 26 nodes and a side area of 200 m.

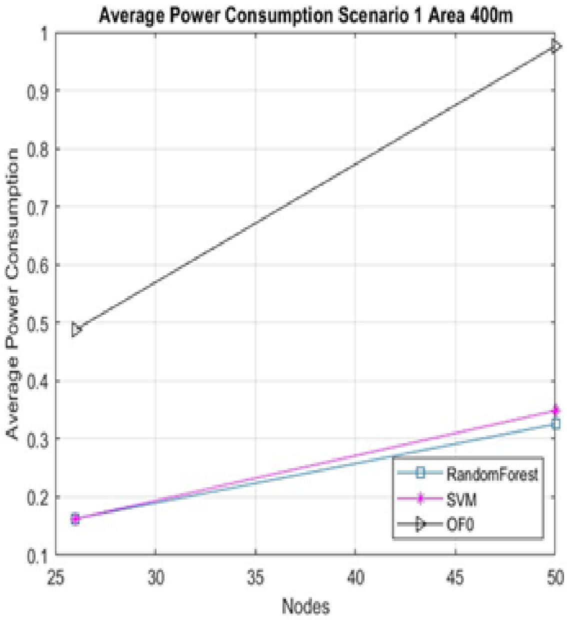


Figure 10. Average power consumpation scienario 1 area 400m

The Average Consumed Power

It is clear from figures (9-12) that the random forest algorithm is the best in terms of energy consumption for all scenarios, their topology, and components 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.

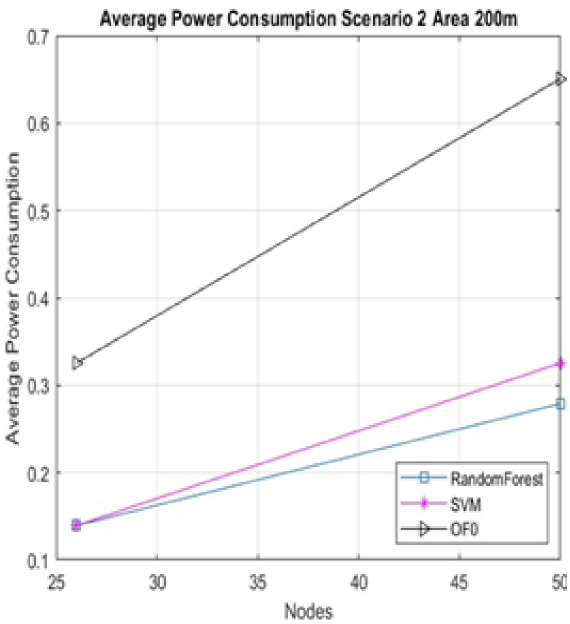


Figure 11. Average power consumption scenario 2, area 200m.

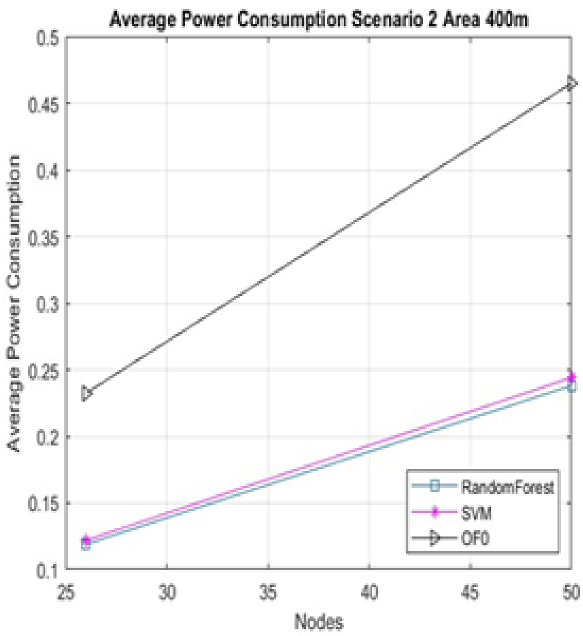


Figure 12. Average power consumption scenario 2 area 400m

Packet Delivery Ratio (PDR)

Figures (13-14) show that the RF algorithm is the best in terms of PDR in the two scenarios with an area of 200m. The reason is because the RF algorithm has the following advantages: Its ability to withstand data noise, rapid learning and dealing with non-linear, missing and heterogeneous data.

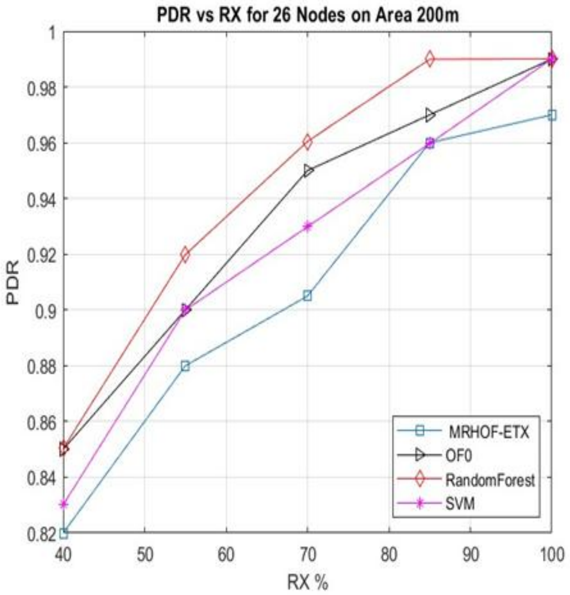


Figure 13. PDR vs RX in scenario 1 with 26 Nodes and side area 200m.

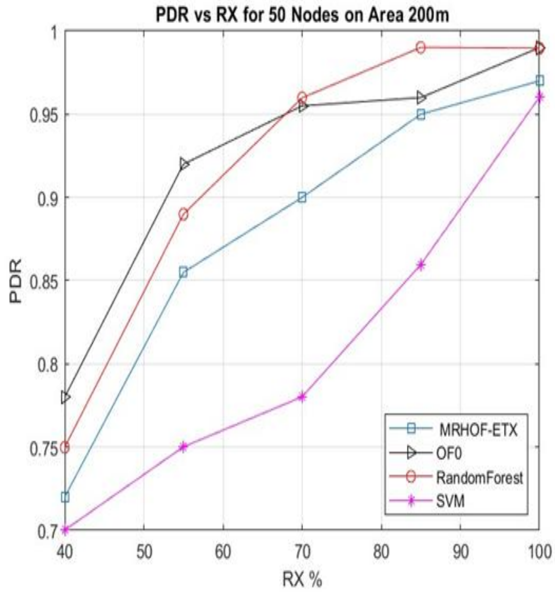


Figure 14.PDR vs RX in scenario 2 with 50 nodes and side area 200m.

The Percentage E2E Delay

Figures 15-18 show the percentage delay in data transmission from the source to the interface across the various simulation scenarios. The results indicate that delay increases proportionally with the number of nodes in the network. 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.

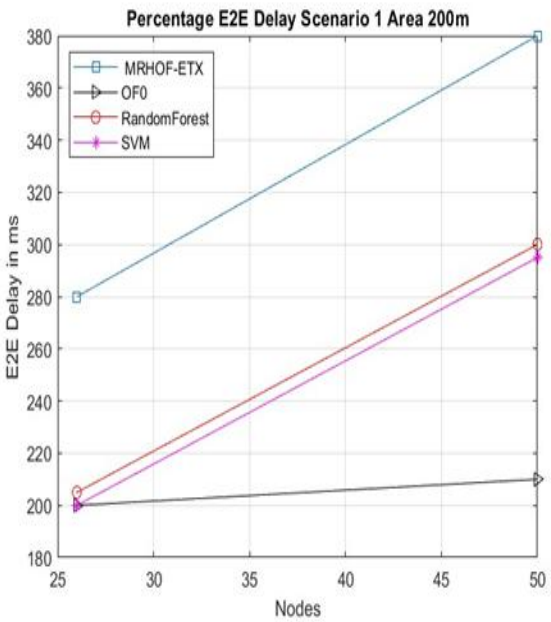


Figure 15. Percentage E2E delay scenario 1 area 200 m.

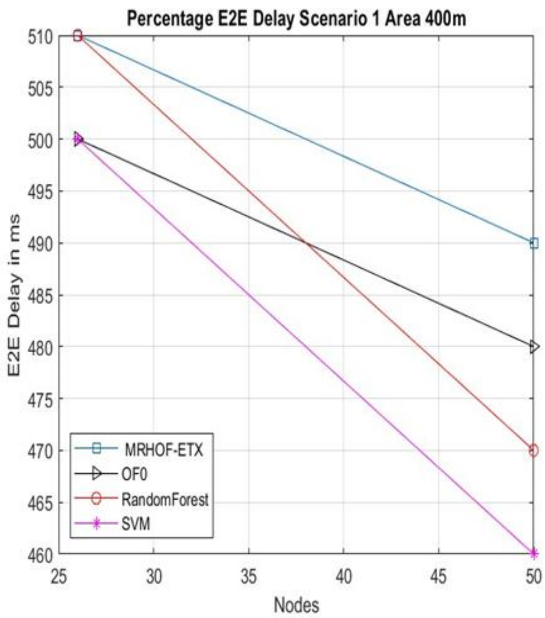


Figure 16. Percentage of E2E delay scenario 1 area 400m.

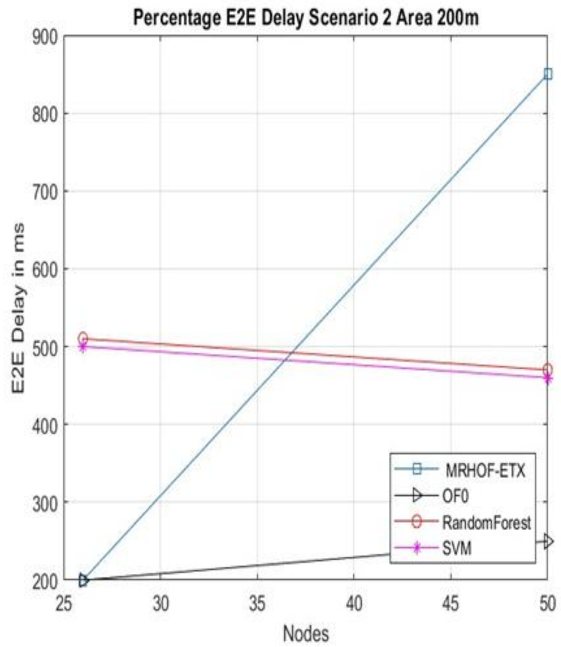


Figure 17. Percentage of E2E delay scenario 2 area 200m.

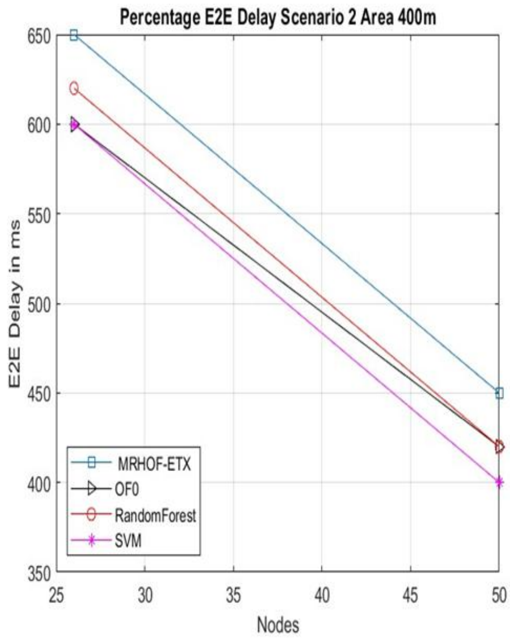


Figure 18. Percentage of E2E delay scenario 2 area 400m.

Percentage Radio ON

Figures (19-22) show the percentage of radio ON, which depends on the size of the network, the number of nodes and the link. In the RF algorithm, it ranges between 5% and 20%.

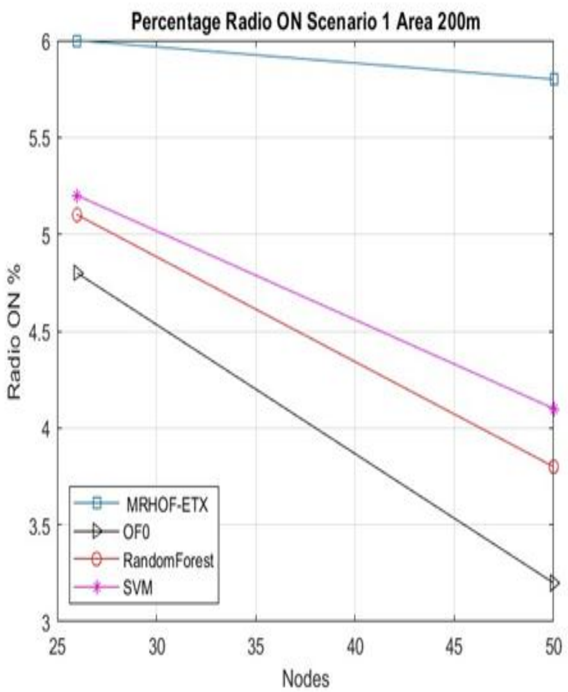


Figure 19. Percentage of radio ON scenario 1 area 200m.

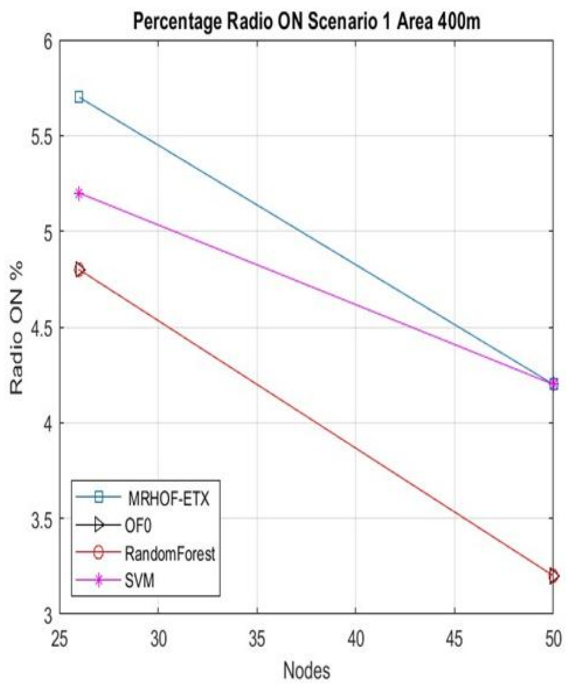


Figure 20. Percentage of radio ON scenario 1 area 400m.

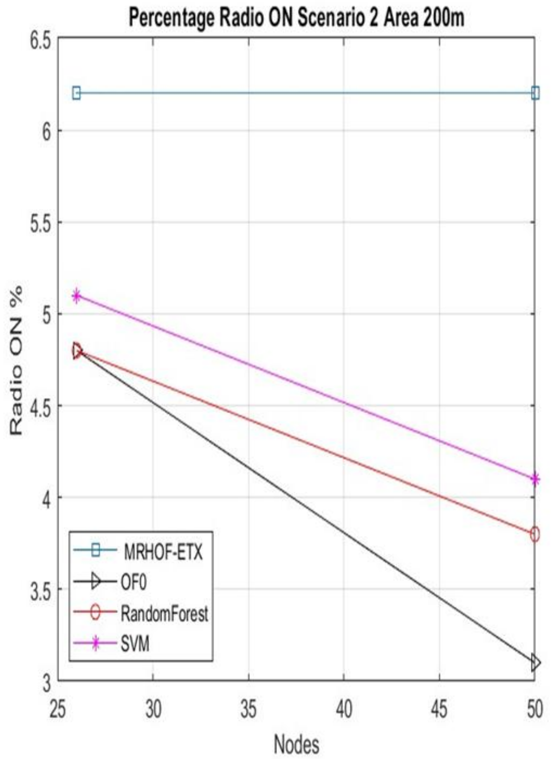


Figure 21. Percentage of radio on scenario area 400m.

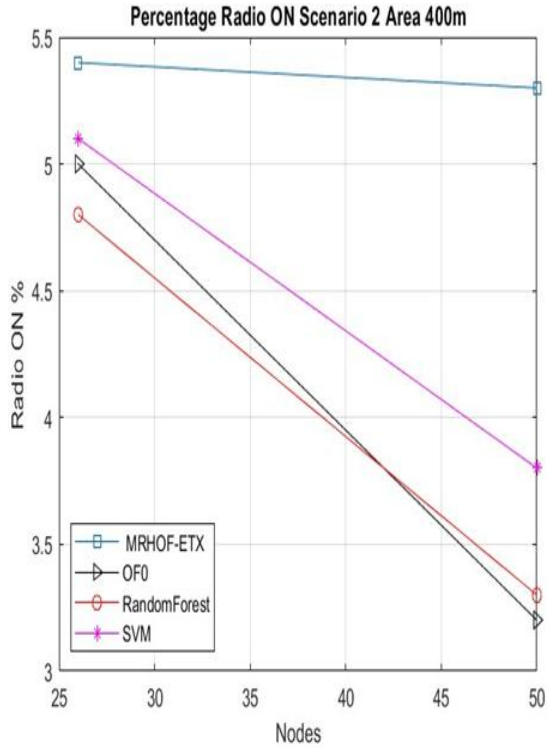


Figure 22. Percentage of radio ON scenario 2 area 400m

Conclusion

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 RF algorithm achieved superior performance compared with the SVM algorithm and the FRIPL protocols using the OF0 and MRHOF-ETX objective functions.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest.

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References

Culler, D., Estrin, D., & Srivastava, M. (2004). Guest editors' introduction: Overview of sensor networks. *Computer, 37*(8), 41-49.

Dai, H., Wu, X., Xu, L., & Chen, G. (2020). Practical scheduling for stochastic event capture in energy harvesting sensor networks. In *IEEE Wireless Communications and Networking Conference* (Vol. 18, pp. 85-100).

Dunkels, A., Gronnvall, B., & Voigt, T. (2004). Contiki- a lightweight and flexible operating system for tiny networked sensors. In *28th Annual IEEE International Conference on Local Computer Network*.

Gaber, T., Abdelwahab, S., Elhoseney, M., & Hassanien, E. (2018). Trust-based secure clustering in WSN-based intelligent transportation systems. *Computer.Network, 146*, 151-158.

Gurram, G. V., Stevanovic, D., & Spanogiannopoulos, G. (2022). Strategies for improving performance of IEEE 802.15.4/ZigBee WSNs with path-constrained mobile sink. *Computer Communication, 34*(6), 743-757.

Hassani, E., Sahel, A., & Badri, A. (2019). Assessment of a proactive routing protocol RPL in Ipv6 based wireless sensor networks. In *ICDS* (pp. 1-6).

Kundaliya, B., & Hadia, S. (2020). Enhancing network lifetime with an improved MOD-LEACH. *International Journal of Electrical and Computer Engineering, 9*(5), 3615-3622.

Kundaliya, B. L., & Hadia, S. K. (2020). Routing algorithms for wireless sensor networks: Analysed and compared. *Wireless Personal Communications, 110*(1), 85-107.

Nilabar, N. U., Manikandan, A., Venkataramanan, C., & Dhanapal, R. (2023). A score based link delay aware routing protocol to ımprove energy optimization in wireless sensor network. *Journal of Engineering Research, 11*, 192-219.

Ogundile, O., Balogun, M., Ijiga, O., & Falayi, E. (2019). Energy-balanced and energy-efficient clustering routing protocol for wireless sensor networks. *IET Communications, 13*(11), 1449-1457.

Park, P., Fischione, C., Bonivento, A., Johansson, K., & Sangiovanni-Vincent, A. (2011). Breath: An adaptive protocol for insutrial control applications using wireless sensor networks. *Mobile Computing, IEEE Transactions on, 10*(6), 821-838.

Santos, D. L. C., Mezher, M. A., Leon, A., Pabo, J., Cárdenas-Barrera, J., Guerra, E., & Meng, J. (2023). ML-RPL: Machine learning-based routing protocol for wireless smart grid network. *IEEE Access*, 57401-57414.

Sharma, R., Prakash, S., & Roy, P. (2020). Methodology, applications, and challenges of WSN-IoT. In *2020 International Conference on Electrical and Electronics Engineering (ICE3)* (pp. 502-507). IEEE.

Somula, R., Parvathala, B., Kolli, S., Pulipati, S., & Adita, S. S. T. (2021). SOA-EACR: Seagull optimization algorithm based energy aware cluster routing protocol for wireless sensor networks in the livestock industry. *Sustainable Computing Informatics and Systems, 33*.

Suliman, A. A., & Ahmed, J. O. (2022). High-quality clustering algorithm and optimal cluster head selection using fuzzy logic in wireless sensor networks. *Fuzzy Sets and Systems, 389*, 114-144.

Tahsien, S. M., Karimipour, H., & Spachos, P. (2020). Machine learning based solutions for security of ınternet of things (IoT): A survey. *Journal of Network and Computer Applications, 161*, 102630.

Vlajic, N., Stevanovic, D., & Spanogiannopoulos, G. (2011). Strategies for improving performance of ieee 802.15.4/zigbee wsn with path constrained mobile sink. *Computer Communication, 34*(6), 743-757.

Wakili, A. (2024). Machine learning for QoS and security enhancement of RPL in IoT-Enabled wireless sensors. *Wireless Networking Based Control*, 100289.

Zahra, F., Jhanjhi, N., Brohi, S. N., Khan, N. A., Masud, M., & AlZain, M. A. (2022). Rank and wormhole attack detection model for RPL-Based ınternet of things using machine learning. *Sensors, 22*(18).

Zhang, D., Qian, L., Mao, B., Huang, C., Huang, B., & Si, Y. (2018). A Data-driven design for fault detection of wind turbines using random forests and xg boost. *IEEE Access, 6*, 21020-21030.

Zidi, S., Moulahi, T., & Alaya, B. (2017). Fault detection in wireless sensor networks through SVM classifier. In *IEEE Sensors Journal, 18*(1), 340-347.

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