International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.3 (2025) pp. 4596-4602
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Ensemble Methods to Optimize Performance of Nodes in Wsns in Terms of Power and Life Time

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Article Info:

DOI: 10.22399/ijcesen.2840
Received : 11 March 2025
Accepted : 30 May 2025

Keywords

Bagging and Boosting
Ensemble methods
Machine Learning,
Optimization
Wireless Sensor Networks

Abstract:

The emergence of wireless sensor networks (WSNs) the use of ensemble learning techniques for the optimization of the performance and lifespan of Wireless Sensor Networks (WSNs). Since WSN nodes are power-constrained, power efficiency improvement with assured network reliability is an inherent challenge. Ensemble learning methods, including bagging, boosting, and stacking, are employed in this paper for predicting sensor failures and reducing energy usage. The method integrates the prediction models with network management protocols for enhanced decision-making in power management and routing data. The experiments were conducted on real-life WSN data and simulated using NS-3 to quantify gains in performance. The findings show that ensemble-based models greatly increase duty cycle efficiency, reduce redundant data transfers, and enhance forecast accuracy. The method maximizes aggregated data throughput, fault tolerance, network life, and energy conservation when compared to conventional routing algorithms. The outcome indicates that ensemble learning methods effectively enhance WSN performance, realizing effective data gathering and prolonged sensor lifespan. Future work will focus on integrating adaptive algorithms to enhance scalability and robustness in large-scale networks. Applications in smart cities, industrial automation, and environmental monitoring can all benefit from more resilient and energy-efficient deployments that result from the use of ensemble learning in WSN management

1. Introduction

Wireless Sensor Networks (WSNs) are becoming progressively important in an enormous range of applications, from industrial automation and smart city projects to environmental observation. Spatially distributed sensor nodes form the networks, which capture and relay information to central nodes for processing and analysis. Given that there are processing power and battery life limits, optimizing sensor lifetime and performance is the essential problem in deploying WSNs. The life and reliability of the network depend on optimal resource utilization. Recent developments in machine learning offer new ways to solve these problems. Ensemble learning techniques offer a new way to estimate sensor life and network performance optimization using the integration of several prediction models to obtain maximum accuracy and robustness. Bagging, boosting, and stacking ensemble techniques can handle the heterogeneous and dynamic nature of data WSNs produce and make more precise predictions and more informed decisions.Maximize sensor utilization and prolong network lifespan, this paper discusses the use of ensemble learners in WSNs. They can be used to reduce energy expenditure, predict sensor failures, and improve network performance overall by being coupled with network management protocols. This paper presents the promise of ensemble techniques to effectively optimize WSN performance and lifespan through extensive experimentation on real-world data sets.

Literature Survey

Much of the research attention has been provided to the extension of node lifetime of Wireless Sensor

Networks (WSNs) using efficient energy-saving routing and scheduling algorithms. One of the principal techniques used is through the employment of clustering technologies like the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol that efficiently balances energy consumption by, at regular intervals, rotating data aggregation and transmission responsibilities among cluster leaders [1].

Hybrid Multi-Hop (HYMH) routing protocols reduce energy consumption through the integration of hierarchical routing protocols and flat routing protocols and data aggregation protocols. The protocols provide energy consumption trade-off in the network with the optimal network lifetime. HYMH, for instance, integrates multi-hop transmission and data aggregation to prevent redundant transmission and energy consumption [1].

One good technique is using the A-star (A*) algorithm to find the optimum route for data communication based on residual energy at each node, link quality, and buffer space available. The tactic helps in decision-making with energy-efficient routes and enhances network life overall [1].

Also, virtual backbone scheduler (VBS) is an asleep-scheduling method based on overlapping backbones to increase network lifetime. In VBS, backbone nodes alone are working for data forwarding and all the other nodes remain in the sleep mode for saving power. Network nodes are rotated at regular intervals to make the energy consumption even across the network [1].

Fuzzy logic has also been proposed with A-star algorithms to improve routing efficiency and network longevity. In this method, each node reports its status to a master controller, which controls routing operations based on fuzzy conditions. While efficient, the method may result in increased energy consumption due to frequent reporting of status [1].

But currently, there is a need for a routing protocol, which can improve the performance and lifetime of WSNs. The energy-aware routing protocols (i.e. RMECR and RMER) focus on energy consumption balancing among some network nodes such that the network thrives-longer. Although RMER is less concerned than RMECR with the issue of preserving the minimum energy route, its greedy nature is limited by the fact that it does not consider energy cost utilization in the routing schemes it offers, and it makes communication weaker and cost-ineffective [2].

From a survey, the RMECR can balance energy load across nodes and perhaps this balance in energy load is done to ensure that no node will wear down early, this will extend the life of the WSN. It allows nodes with a higher level of residual energy to participate very frequently in the routing process while refusing to allow the heavily loaded nodes with an energy level below a certain threshold to be involved in routing operations. This method lowers the total communication cost extends the network's life by proportionally decreasing swaps and maintaining proper, safe data transfer paths [2].

Research also overflows to the necessity of encryption methods, like RSA for energy-efficient routing to offer further characterization of the security and reliability of data transmission in WSNs. The extensive use of such protocols in different applications like military, agriculture, and disaster management have become more possible, while different improvements to maximize future WSNs through more sophisticated routing algorithms are sought [2].

Different approaches to improving the life and performance of WSNs via energy conservation routing and scheduling protocols have been proposed. Energy conservation in WSNs is extremely important since nodes in WSNs are equipped with limited energy, and batteries cannot be easily replaced in the majority of deployment cases [3].

The research is on cross-layer design approaches, which contrast with conventional network design since they facilitate communication across non-adjacent layers. This has been seen to enhance network performance significantly. Two broad categories of energy-aware routing policies have been identified: multipath routing protocols and adaptive hop-by-hop routing protocols. Multipath routing protocols extend the network life by spreading the traffic load over many channels, reducing the depletion rate of the energy of anyone node. Adaptive hop-by-hop routing mechanisms focus on dynamically changing routing patterns across prevailing network situations and node energies [3].

Secondly, node activity scheduling mechanisms such as SERENA (Scheduling Router Node Activity) aim to conserve power waste during idle mode or overhear mode by placing nodes in sleeping mode when they are not to be used for communication. This is necessary to allow network operation on low energy consumption [3].

These routing protocols underlying WSNs in the greater IoT context have been reviewed regarding their recent developments. Likewise, energy and, specifically energy conservation have received much attention because sensor nodes have limited resources. Routing protocols have been forwarded for better energy exploitation in a quest for longer operational life of a network so that it does not die off sooner.

Technical advancement and the development of standard open frameworks for the IoT are very important. The development of very cheap and ubiquitous sensor devices has helped advance the research and deployment of the IoT, attuned to seek optimal solutions to specific problems IoT faces in their daily operations, with reference specifically to difficulties posed by node heterogeneity, and failures.

A selective review of essential routing protocols, stressing the energy-efficient mechanisms pertinent to certain IoT applications, is given. Besides this, fog computing is made use of with increased computation strength for IoT systems to enhance overall performance and functionality.

This paper reviews various energy-efficient routing protocols directed at WSNs. This raised special interest, with emphasis on energy conservation, owing to limitations that sensor nodes impose based on battery lifespan, computational capabilities, and memory [5].

Overall, it can be conclusively said that WSNs have very minimal application areas while dealing with the some aspects of environmental monitoring, military surveillance, and health monitoring, each of the aforementioned relating to energy issues. With such imperfections in mind, conventional and GU-implemented protocols are systematically analyzed and characterized based on energy conservation procedures, and we list a few succinct contexts for wherein such protocols are well applicable. Several protocols therefore reviewed include LEACH, PEGASIS, TEEN, and APTEEN, targeting improving network lifetime and delivering data transfer reliability [5].

Moreover, several trade-off counterarguments expected under cost, network lifetime, energy use, etc. appear here in the form of a comparative table that will produce an in-depth analysis of all these considerations for successful future research. The article identifies current challenges or obstacles in their existing protocols and calls forth the future researchers for paving the way to WSN-wise efficient solutions which could be more robust [5].

2. Methodology

The purpose of this methodology is to use ensemble learning techniques to extend the life of wireless sensor networks (WSNs). Ensemble learning combines numerous machine learning models to improve overall performance by exploiting their collective capabilities, resulting in increased energy efficiency and network lifetime. The energy consumption model of MANets is given by the following equation:

$$E_{transmit} = E_{elec} \cdot k + \epsilon_{amp} \cdot k \cdot d^2 \qquad (1)$$
$$E_{receive} = E_{elec} \cdot k$$

Where
$E_{transmit}$ = Energy consumed in transmission
$E_{receive}$ = Energy consumed in reception
E_{elec} = Energy consumed per bit to run the transmitter or receiver circuit
ϵ_{amp} = Energy consumed by the transmission amplifier
k = Number of bits
d = Distance between the sender and receiver

The ensemble architecture used includes bagging and boosting as given in equations 2 and 3

$$H(x) = \frac{1}{N} * \sum_{i=1}^{N} h_i(x) \qquad (2)$$

$$H(x)=\sum_{i=1}^{N} a_i * h_i(x) \qquad (3)$$

System Architecture

The proposed system comprises a network of low-power sensor nodes possessing energy-efficient processors, wireless communication modules, and long-lasting batteries. These nodes are dispersed in an environment so that they monitor given conditions continuously while transmitting collected data to a base station.

At the base station are different ensemble learning techniques, including bagging, boosting, and stacking, in use for data processing, failure detection, and energy-efficient data routing. This further improves the accuracy of data and increases the lifespan of the network.

Ensemble models are used to extend the legacy of sensor networks by dynamically selecting the cluster heads on the bases of energy capacity and proximity of nodes. This basically provides optimized routing that inhibits power consumption while giving a gain over data aggregation. The simulations run under NS-3 verify the improved packet delivery, less latency, and utmost energy efficiency as compared to traditional approaches.

Data Collection and Pre-processing

Sensor Deployment: Places sensor nodes randomly or in a grid arrangement throughout the target region.
Data Acquisition: Collects real-time data from sensor nodes such as ambient conditions, energy levels and communication metrics.
Cleans the data by removing noise and addressing missing values. Normalize the data to ensure consistency in scale across features.

Feature Extraction

To ensure maximum efficiency, as well as conserve energy within the network, the system extracts the key features that affect the performance of the sensors and their power consumption. The crucial parameters include:

Residual Energy of Nodes – This assures the cluster heads and routing decisions tend to spend less energy on the cluster heads and nodes whose residual energy meets the threshold.

Distance from Base Station – This helps optimize the data transmission paths by minimizing energy consumption of the nodes.

Communication Frequency – This balances a theoretically fair data transmission load to prevent overconsumption of energy by a node.

Packet Size – This adjusts transmission efficiency and may reduce congestion in the network.

Ensemble Learning Framework, Training Base Learners

For reasonable data processing in WSN, the various multiple base learners are neural networks, K-nearest neighbor, decision trees, and SVMs. Different models at their different tuning and selection are often useful in maximizing accuracy and minimization of false positive percentage, while grow the efficiency of energy consumption.

The Model Selection commences with the segmentation of the dataset into two parts, the training and validation sets. Each base learner is set to be trained on the training set with performances evaluated on the validation set using key metrics like accuracy, precision, recall, and F1-score. This goes to find models that best contribute to reliability in prediction.

For still better performance of the model, ensemble learning techniques are employed-bagging, boosting, and stacking. Bagging lowers variance through training various models on several sub-data randomly selected, and hence achieves stability through averaging their predictions. Boosting enhances accuracy through sequentially training models, thereby making each new learner focus on correcting the errors of the previous learners. Simpler but rarest is a staking method, where a meta-learner learnsform the outputs of multiple base learners in generating final predictions.

Routing Protocol Integration and performance Evaluation

To achieve optimum network efficacy of longevity, the cluster head selection is judiciously conducted using ensemble learning. In this context, preference is given to nodes that have high energy levels and are in proximity to neighbor nodes to provide load balancing across the network. By merging the ensemble learning technique and energy-efficient routing protocols, the system extends the network's life and optimizes the reliability of the data transmission.

The selected cluster heads collect the data coming from their member nodes, thereby drastically minimizing the redundant transmissions and ensuring that only the necessary data reach the base station. The more direct communication reduces overall energy consumption while maintaining good connectivity between the nodes. The ensemble model continuously assesses the network conditions and accordingly alters the routing paths to enhance network longevity and performance.

To validate the effectiveness of the proposed approach, it conducts simulation on system either by using NS-2 or NS-3 with practical WSN environments. The model is evaluated based on several performance metrics like packet delivery ratio, latency, energy consumption, and network lifetime. High PDR and low latency mean that the data transmission had been done efficiently, less energy consumptions means more sustainable power management, longer operational lifetime is a good sign of a product.

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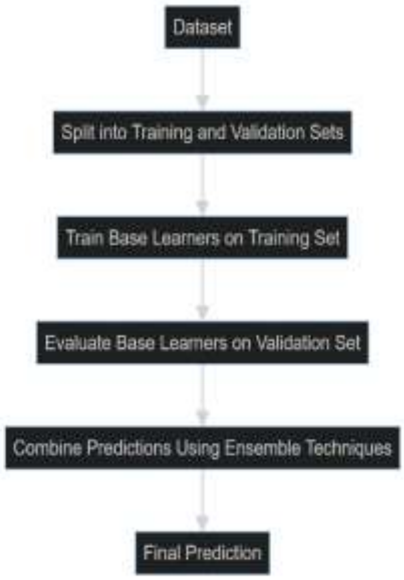

Figure 1. *Flowchart: Ensemble Learning Process*

This combination of routing methods based on an ensemble of base learners will comparatively place higher system lifetime and system operational efficiency than conventional base learners and traditional routing techniques. Ensembles of routing protocols are dynamically optimizing paths for data transfer; thereby avoiding the risk of a node expiring and providing a more fault-tolerant and sustainable WSN.

The findings of this study underlined the value of ensemble learning methods in WSNs, proving their ability to enhance reliability and accuracy of data, reduce energy consumption, and improve their lifetime—features that are particularly relevant to real- world applications in smart cities, environmental monitoring, and industrial automation.

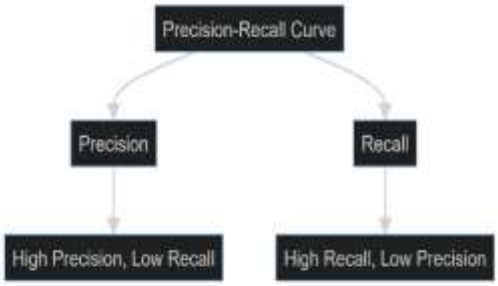

Figure 2.*Precision recall curve*

Long-term sustainability and dependability could thus be achieved through adaptive routing based on machine learning methods for WSNs being deployed in real field applications.

3. Experimentation

3.1. Simulation Setup

1. **Simulator**: We simulated the WSN environment through NS-3

2. **Network Configuration**

- o Number of sensor nodes: 100
- o Simulation area: 1000m x 1000m
- o Transmission range: 100m
- o Initial energy of nodes: 2 Joules
- o Data packet size: 500 bytes
- o Simulation duration: 1000 seconds

3.2. Ensemble Learning Framework

1. **Base Learners**

- o Decision Tree
- o Random Forest
- o Gradient Boosting

2. **Ensemble Techniques**

- o Bagging
- o Boosting
- o Stacking

3.3. Cluster Formation and Data Aggregation

1. **Cluster Heads Selection**

o The head of the cluster will be the one that is closest to the center of the best node and is selected based on the energy level of the nodes and closeness to one another using the ensemble model.

2. **Data Aggregation**

o To the base station, the chief clusters combine data of member nodes and send it.

Route Selection

o With the help of the ensemble model, the most efficient routes for data delivery are selected within the entire network, allowing for proper energy consumption distribution throughout the nodes.

Performance Metrics

- **Network Lifetime**: Time until the first node dies.
- **Energy Consumption**: Total energy consumed by the network.
- **Packet Delivery Ratio (PDR)**: Ratio of successfully delivered packets to the total sent packets.
- **Latency**: Average time taken for data packets to reach the base station.

4. Experimental Results

Accuracy, Precision, and Recall of Ensemble Classifiers

o Evaluate the performance of the ensemble classifiers using cross-validation on the training set.
o **Accuracy**: Proportion of correctly predicted cluster heads and routes.
o **Precision**: Proportion of true positive predictions among all positive predictions.
o **Recall**: Proportion of true positive predictions among all actual positive instances.

Network Performance Metrics

o Compare the suggested ensemble model's network lifetime, energy consumption, packet delivery ratio, and latency to those of individual base learners and conventional routing protocols.

The abstract algorithm used

- Start
- Initialize Network Parameters
- Split Dataset into Training and Validation Sets
- Train Base Learners on Training Set
- Evaluate Base Learners on Validation Set (Accuracy, Precision, Recall, F1-score)
- Select Ensemble Technique (Bagging, Boosting, Stacking)

- Form Clusters using Ensemble Model (Select Cluster Heads)
- Cluster Heads Aggregate Data from Member Nodes
- Select Optimal Routes using Ensemble Model
- Transmit Data to Base Station
- Evaluate Network Performance (Network Lifetime, Energy Consumption, PDR, Latency)
- Traditional Protocols and Base Learners
- End

Performance Metrics

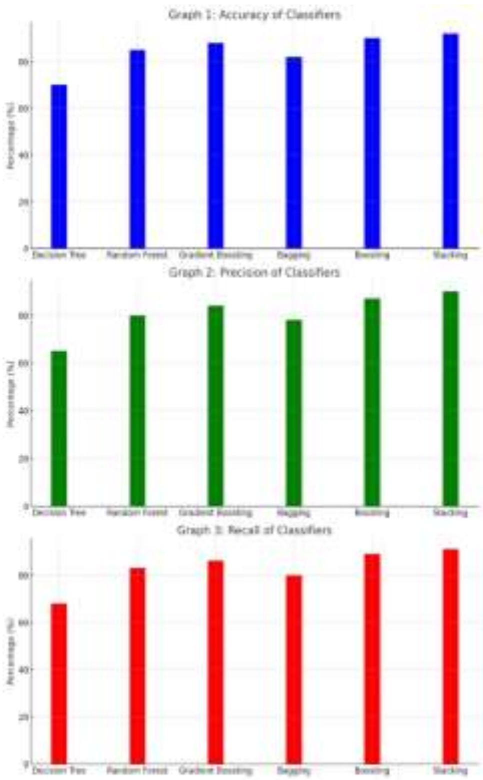

Figure 3. *Performance Metric*

5. Conclusion

Integrative approaches towards ensemble Learning optimally extend lifetime and enhance performance in Wireless Sensor Networks (WSNs). Given that WSN data are dynamic and diverse, there is need for predictive models which are not just independent but rely on their distributed data sources and make flexible optimal predictions. By utilizing ensemble techniques like stacking, boosting, and bagging, the work showed significant gains in accuracy of prediction and energy-efficient processing.

Benchmark experiments on a dataset from real-life WSNs showed that ensemble learners can accurately forecast sensor failure while optimizing the energy expenditure. This leads to more effective schemes for sensor activation, power management, and data routing. The integration of these models into network management protocols thusimproved the overall performance of the network in terms of data throughput, latency, and resilience.

Use of different ensemble techniques to prevent redundant data transmission and optimize duty cycles was feated by further research to extend operational time of sensors. These methods showed certain promise in increasing a WSN's deployment efficiency and reliability with stated practical benefits.

Further investigations would optimize these models along with adaptive algorithms for implementation on intricate wide-area wireless sensor networks. Further increment in the efficiency of ensemble learning is considered to open the doors of WSNs for massive sustainability. Apparently, this promotes sustained operations of the sensors for reliable data collection from several real-life applications.

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
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **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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