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Research Article

A Multi-Objective Direction of Arrival Estimation Technique Minimizing Energy Consumption in Wireless Sensor Network

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Abstract: Wireless Sensor Network (WSN) demand for secure communication is challenging due to its limited resource constraints. Hence, this research developed an effective distributed DOA estimation model through Direction Optimization Integrated Ranking Voting (DOIRV) to improve the performance of WSNs. The developed model comprises the multi-objective optimization model with the Whale technique for the WSN. The constructed DOIRV model uses objective function estimation with branch-and-bound for effective data transmission. The developed DOIRV model uses the Artificial Intelligence-based machine learning model for the DOA routing path computation and estimation. Finally, the DOIRV estimation is evaluated for the performance analysis with the consideration of the Cramer-Rao analysis for the data transmission in the WSN model. Simulation results stated that the proposed weighted technique significantly improves the network performance such as packet delivery ratio, throughput, and network delay. Analysis of the technique expressed that the proposed DOIRV technique exhibits effective performance rather than the conventional technique in terms of network delay, throughput, and packet delivery ratio. The comparative analysis stated that the performance of the proposed DOIRV model is ~13% higher than the conventional technique in terms of packet delivery ratio and ~18% higher for the throughput.

Keywords: - Wireless Sensor Network (WSN); Direction of Arrival (DOA); Multi-Objective Optimization; Cramer-Rao; Ranking

1 Introduction

A Wireless Sensor network (WSN) is simply defined as wireless devices connected in a network with minimal size and reduced complex network, this is defined as a node for sensing and communication. The nodes are involved in gathering and monitoring information in as system with wireless channel [1]. Through nodes, data were forwarded through consideration of relay with multiple hop into consideration with the communication between sink and node or other devices in the network. Initially, WSN network was framed for military application [2]. The WSN network involved in offering minimal power, maintenance and low power consumption methods for sensor to exhibit undesirable performance. Generally, sensor network are resource constraints with multiple nodes connected in a network with effective sensing and processing based on the objective of the application into consideration [3-5]. The connection between nodes are framed due to interconnection of infrared devices or radio channels[6].

Wireless Sensor Network (WSN) routing protocols are primarily categorized into two types: single path routing and multipath routing [7]. These protocols enable sensor nodes to transmit packets from source to destination within the WSN using intermediary nodes. In WSNs, delivering packets to the sink node through multiple hops relies on maintaining energy efficiency and network load balancing. To achieve efficient routing, protocols aim to strike a balance between factors such as delay, energy consumption, and load distribution. Single path routing protocols evaluate all available paths to the sink node and opt for a single path for packet routing. Conversely, multipath routing protocols analyse all potential routes and select multiple paths for routing purposes. Single path routing protocols may be less effective in environments with higher levels of noise. In contrast, the flexibility of multipath routing protocols in utilizing numerous routing paths equips them to effectively manage network loads. Moreover, multipath routing enhances the network's bandwidth and reliability, contributing to an overall improved performance of the WSN [8].

Wireless sensor networks (WSN) subjected to vast range of challenges due to its limited resource and power constraints for different network topologies of the network. The major challenge associated with wireless sensor network (WSN) is optimization which leads to increased communication and overhead. To resolve those limitations in WSN network vast range of research has been conducted for effective optimization or minimization of Distributed Direction of Arrival (DOA). Further WSN dynamic nature is considered as essential characteristics for optimization of resources, monitoring application and military surveillance of the network [9]. In WSN network secure communication is challenging due to its limited resource constraints nature and wireless behaviour of transmission system [10]. A Wireless Sensor Network (WSN) comprises randomly distributed sensor nodes tasked with transmitting data to specific target areas through network communication capabilities. The positioning of these nodes holds crucial significance across diverse applications, including medical care and agriculture. Furthermore, node positioning plays a pivotal role in achieving load balance within the WSN network, thereby enhancing overall network efficiency [11]. However, given the limited resources, cost considerations, and constraints associated with node placement, optimizing energy consumption becomes imperative [12]. This optimization hinges on the Direction of Arrival (DOA) estimation, where sensor nodes play a pivotal role in ensuring efficient data transmission.

In real-time applications, WSNs transmit data through a single sink to facilitate effective communication [13]. However, this approach can lead to network congestion due to the simultaneous data flow, causing a strain on the system. At higher data reception rates, sensor nodes must handle extra data that surpasses their transmission capabilities, necessitating data storage in buffers [14]. The confined buffer space often results in data packet drops due to congestion, consequently diminishing network performance. The complexities of a multi-path environment introduce challenges such as collision, channel access rate, and coupling, which further degrade network efficiency [15]. These challenges can be mitigated through the estimation of DOA within WSNs, enabling optimized data transfer rates and improved network performance characteristics. The role of DOA estimation in enhancing network attributes is particularly noteworthy [16]. DOA estimation plays a crucial role in minimizing data transfer rates while bolstering network performance characteristics [17]. Network congestion, a prevalent issue, triggers a negative impact on the WSN, leading to elevated delays, reduced delivery ratios, increased packet energy consumption, and decreased throughput [18-20]. To counteract these adverse effects, focusing on DOA within the sensor network becomes essential, promising enhanced network attributes. Nonetheless, existing DOA estimation techniques exhibit shortcomings like slow convergence rates and elevated energy consumption, necessitating further refinements.

2 Overview of Proposed Direction Optimization Integrated Ranking Voting (DOIRV)

Even though WSN has been used in broad area of research it has been limited to certain factors such as limited bandwidth, limited battery level, security issues and so on. In order to resolve those limitation and optimal performance of the WSN network this research focused on development of optimization algorithm known as Whale algorithm. This is kind of optimization approach belongs to metaheuristics optimization algorithm which involves mathematical formulation. The developed weighted Whale algorithm is based on the characteristics of aggregation without parallel arrangement as WSN also arranged without any orientation. Also, another attractive functionality of Whale is space scale 10s to 100s meters with capability of forming larger swarms. The process of Whale is adopted in WSN network with consideration of three basic functionalists such as formulation of objective function, movement induced by whale, foraging activity and random diffusion. Based on this activity neighbours of sensor are evaluated for data transmission. With respect to formulation of objective function distance between sensor nodes are estimated and evaluate the power level of the sensor node. Once the distance and energy level of nodes are identified data were transmitted between nodes. Since data were transmitted through optimal path WSN it effectively improves the performance especially in terms of energy consumption, data transmission and collision shown in Figure 1.

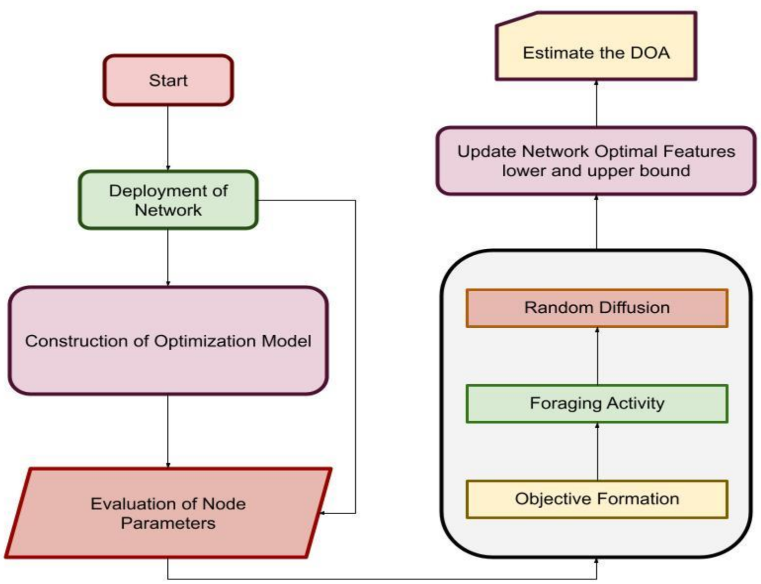

Figure 1: Flow chart of DOIRV

To improve the performance of WSN network this research primarily focused on construction of WSN. The constructed network parameters covered distance of 50 meters with node count of 50. The constructed node level is presented in below table. The Whale algorithm plays a role in the creation of different marine animal species by employing non-random and under-dispersed factors. The primary element underpinning the weighted whale technique is its capability to enhance feeding, reproduction, predator protection, and sensitivity to environmental conditions. This algorithm draws inspiration from Antarctic studies while considering the characteristics of marine animals. The algorithm assesses whale hearing and orientation without any aggregation, considering various species within a spatial range of 10 to 100 meters.

IoT (Internet of Things) Denial-of-Service (DOS) estimation, upper and lower bound estimation techniques are essential for assessing the potential impact of malicious attacks on the system. The upper bound estimation represents the worst-case scenario, indicating the maximum potential damage or disruption that a DOS attack could inflict on the IoT infrastructure. This involves considering the highest possible intensity and duration of the attack, as well as the vulnerabilities of the targeted devices. On the other hand, lower bound estimation provides a more conservative outlook, taking into account factors such as mitigation measures and resilience mechanisms that may limit the impact of an attack. To enhance the accuracy of these estimations, a weighted model is often employed, assigning different weights to various parameters based on their significance in influencing the DOS impact. This weighted approach allows for a more nuanced and realistic evaluation of potential threats, enabling IoT system administrators to better prepare for and mitigate the risks associated with DOS attacks. Direction of Arrival (DOA) estimation plays a crucial role in detecting and classifying attacks. Leveraging a Voting Classifier is an effective strategy to enhance the accuracy of the detection and classification process. The Voting Classifier combines the outputs of multiple individual classifiers, each trained on specific features or aspects of the data, to make a consensual decision. In the realm of DOA estimation for IoT attack detection, the Voting Classifier can integrate diverse algorithms, such as machine learning models and statistical methods, each tailored to identify different attack patterns.

3 Weighting model for Whale for WSN Environment

The assessment of the multi-objective path identification optimization algorithm, explored within this study, relies on an objective function that is defined as follows in equation (1) and (2)

$$F(x) = [F_1(x)F_2(x).....F_k(x)]^T \quad (1)$$

$$g_j(x) \leq 0; j = 1...m \quad (2)$$

In the given equation (1) and equation (2), "m" represents inequality constraints, and "k" signifies the objective function of the established Wireless Sensor Network (WSN). The conventional whale involved in minimization of density of whale and estimation of distance between the swarm and location of food. During the initialization phase of KH this system involved in consideration of fitness function through combination of food at different distance of whale. The major functionality related to KH is defined as:

- Induced movement of whale
- Activity of foraging and
- Random diffusion of Whale

Through consideration of constructed WSN in the context of optimization, the concept of arbitrary dimensions comes into play, considering the scope of the search space. The weighted function of the Krill is formulated as follows in equation (3)

$$\mathrm{U} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w_i F_i(x)} \quad (3)$$

This weighted function of the network hinges on the network's operational attributes. The assessment is grounded in the principles of Pareto Optimality conditions. The determination of the network's path is outlined as follows in equation (4)

$$\frac{\mathrm{dX_i}}{\mathrm{dt}} = \mathrm{N_i} + \tau_\mathrm{i} + \mathrm{D_i} \quad (4)$$

Where, N_i individual whale motion induced is denoted; $\tau_i$is the foraging motion, and $D_i$is the physical diffusion of the whale individuals.

3.1 Path formulated by the Whale to estimate DOA

The whale endowed with a weighted function exhibits a tendency to migrate towards regions of higher density, while accounting for the interplay of mutual effects. This movement direction is influenced by factors such as the induced motion, estimated swarm density, target density, and the repulsive density of the swarm. The locomotion pattern of the whale is expressed as follows in equation (5)

$$\mathrm{N}_\mathrm{i}^{\mathrm{new}} = \mathrm{N}^{\mathrm{max}_{\mathrm{i}_{\mathrm{n}_\mathrm{i}}}}{}^{\mathrm{old}} \quad (5)$$

Where, $\alpha_\mathrm{i} = \alpha_\mathrm{i}^{\mathrm{locadl}} + \alpha_\mathrm{i}^{\mathrm{target}}$, the maximal induced speed is denoted as Nmax; Direction of whale is defined as αi, inertia weight is defined as ωn; last motion induced is defined as Niold; Effect of neighbor locally is stated as αi and target effect of individual whale is defined as αitarget. The foraging motion induced by the proposed approach is whale induced towards food of attraction which means nodes with higher energy level this can be denoted as in equation (6)

$$\mathrm{F}_\mathrm{i} = \mathrm{V}_\mathrm{f}\beta_\mathrm{i} + \omega_\mathrm{f}\mathrm{F}_\mathrm{l}^{\mathrm{old}} \quad (6)$$

In the above equation, foraging speed is defined as Vf, inertia weight as ωf, last foraging motion is stated as Fi old; higher food or energy level is stated as βi

3.2 Upper Bound and Lower Bound Estimation

Initially, number of packets in the WSN queue is considered as 50 and adaptive MAC protocol design is estimated using NS-3 in multi-hop scenario. With utilization of middle-order MAC protocol queue with consideration of infinite scenario. Based on consideration of MAC protocol queue length of packet with consideration of arrival time is presented in table 1. The consideration of queue length and packet arrival time is presented in table 1.

Table 1: Queue Length and Packet inter arrival time

Traffic	**Packet**	**Number of Packet in queue**	**Traffic arrival (sec)**	**Packet**	**Number of packets in queue**
Extremely High	Extremely High	Very High	0.01	100	50
High	High	High	0.1	10	20
Medium	Medium	Medium	1	1	2
Slightly Low	Slightly Low	Low	10	0.1	1
Low	Low	-	20	0.05	-
Extreme low	Extreme low	-	30	0.03	-
Extremely Low	Extremely Low	-	40	0.02	-

The length of queue is estimated using equation (7) shown below.

$$Queue\ Length\ (QL) = 0.48 \times (packets/sec) + 2.27 \quad (7)$$

The construction of duty cycle for node with consideration of residual energy is adopted with certain set of rules those are expressed as follows: If residual energy >700J considered as high duty cycle

If residual energy between 500 J - 700 J then the duty cycle is medium and low traffic with duty cycle of 20%.

If residual energy < 500J consider higher rate of traffic with duty cycle of 20% for medium and low traffic with duty cycle of 10%.

In estimation of duty cycle middle-order based adaptive MAC protocol is considered as run time based on consideration of node residual energy and queue length. The duty cycle of nodes is stated in equation (8) as follows:

$$Duty\ Cycle\ (d) = f\ (node\ residual\ energy, queue\ packet\ count) \tag{8}$$

With application middle -order based residual energy estimation space and time complexity is estimated with duty cycle. The factor involved in estimation of residual energy using equation (9) as follows:

$$Duty\ factor\ cycle = (0.046195 \times RE) + (0.152679 \times QL) + 3.489007 \tag{9}$$

Initially, the MOEEP protocol computes node locations and mobility for the purpose of cluster head election. The weighted function facilitates the estimation of node power probabilities by utilizing estimated middle-order distances. Through the calculated weights, data hopping and data loss within the network are determined. The middle-order head initiates SYNC transmission to enable node residual energy estimation. The estimated weighted function contributes to a probabilistic approach for enhancing node distance and power level estimations, thereby extending the network's lifetime. The developed MOEEP protocol employs SYNC packets for node selection. This selection process is based on distance estimates derived from Equation (10). Nodes chosen for SYNC undergo further evaluation for duty cycle adjustment, considering the estimated queue length and residual node values. The allocation of dynamic duty cycles is maintained through an adaptive MAC schedule. The MOEEP protocol encompasses diverse scenarios for duty cycle computation, with Equation (2) serving to compute node duty cycles along with node scheduling. Employing the outlined criteria for mode selection augments the network's lifespan. The SYNC packet is integral to residual energy estimation, involving queued neighboring node packets. Synchronization of node packets hinges on the residual energy of nodes, which is stored in an array. The subsequent steps for synchronizing duty cycles are presented as follows:

The overall process involved in MOEEP is explained in steps as follows:

First Phase

Step 1: Establish a network comprising 50 nodes.

Step 2: Assume that all nodes are initially in a sleep state.

Step 3: Determine the scheduling of nodes, considering sleep and wake-up cycles.

Step 4: If specific nodes do not receive any schedule, they are engaged in the role of synchronizers for other nodes.

Step 5: In scenarios where two nodes utilize distinct schedules, the node will be involved in implementing both schedules.

Step 6: Utilize mini time slots to sense channel activity and node listening periods.

Step 7: Estimate transmission variables, factoring in the sensed values.

Step 8: In cases of previous successful transmissions, adjust the contention window size downwards.

Step 9: If a transmission attempt fails, increase the size of the contention window.

Step 10: When the channel is idle, a transmitting node sends a Request to Send (RTS) to its corresponding receiver.

Step 11: Upon receiving the RTS, the receiver awakens and responds with a Clear to Send (CTS) signal.

Step 12: Following the establishment of communication, neighboring nodes of the communicating pair revert to a sleep state.

4 Proposed DOIRV Classifier for attack detection and classification

The assessment of cyber-attacks and polymorphic attacks through the implementation of a stacked classifier integrated with a voting scheme. The research utilizes machine learning techniques for attack classification, incorporating four classifiers—AdaBoost, Artificial Neural Network (ANN), Decision Tree, and Support Vector Machine (SVM)—integrated with the voting scheme. The stacked classifier developed in this research involves several sequential steps, including input data acquisition, data pre-processing, feature extraction, feature selection, and classification. The proposed approach encompasses the DOIRV classification for zero-day and polymorphic attacks. The procedural steps of the proposed mechanism are detailed as follows:

- Input Data: The dataset collected from Kaggle is employed in the machine learning process for data analysis.
- Data Evaluation: During this phase, the Kaggle dataset is assessed to eliminate redundant information.
- Feature Extraction: Extracting relevant data features to facilitate subsequent machine learning processes.
- Feature Selection: Identifying and removing irrelevant features from the extracted data to reduce computational complexity and enhance accuracy.
- Attack Classification: This stage involves determining the presence of attacks in the provided data and comprises two key phases:
- Training: Machine learning algorithms are trained to comprehend the extracted features, with classifier parameters tuned to optimize the model.
- Testing: The dataset undergoes classification using the trained classifiers. In the proposed DOIRV mechanism, data features collected are processed through various machine learning stages. The DOIRV scheme incorporates four classifiers—AdaBoost, Artificial Neural Network (ANN), Decision Tree, and Support Vector Machine (SVM)—with a stacking approach in the machine learning process.

The DOIRV mechanism focuses on attack classification. Initially, attack classification is conducted using AdaBoost, SVM, Decision Tree, and ANN classifiers. If an attack is identified by two classifiers and not identified as an attack by another classifier, the DOIRV scheme proceeds with the Decision Tree for evaluation. The Decision Tree algorithm contributes to the final determination of whether the file is an attack or not. The network system's decision is then made based on the classification results from the Decision Tree algorithm, resulting in the estimation of an attack or not using a voting mechanism. The proposed DOIRV trains the model using classifiers such as AdaBoost, ANN, SVM, and Decision Tree. This model, trained by the classifiers, is then applied to a predictor for attack computation. Predictors assess the predictor vector of each classifier and update the voting mechanism. The voting process determines whether the network is classified as an attack based on the scores obtained from the four classifiers. In cases where two classifiers identify an attack, the DOIRV mechanism employs the Decision Tree process for further analysis. The proposed DOIRV relies on a voting mechanism to make decisions.

The voting scheme plays a key role in attack estimation. The analysis involves summing up classifier values to determine if an attack has occurred. The voting scheme relies on classifier scores, considering specific conditions for classification decisions:

if estimated score>2; then attack

else 0; not attack

The voting values is calculated with the computation of classifier values. Based on computed values, the proposed DOIRV determines whether the data corresponds to an attack or normal data.

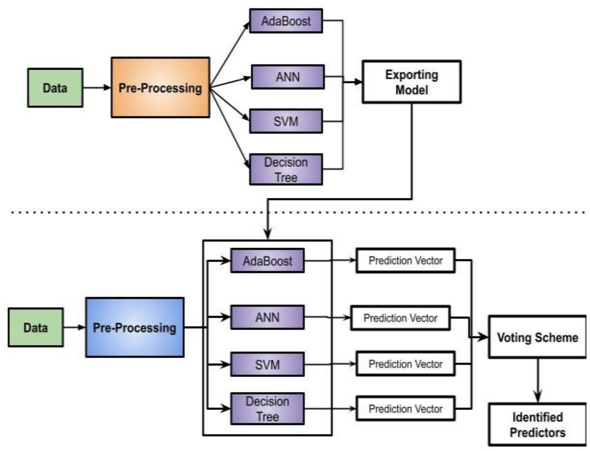

Figure 2: Flow in Proposed Model

Algorithm 1: Classification with DOIRV
Input: CICIDS 2020 dataset Output: Classification cyber-attacks with predictors Steps: Read data in batches for data processing. Extract features for classifying attacks. Retrieve a trained model and assess the predicted values of the data. Combine the prediction parameters from the estimated model to obtain prediction results. Initialize with Xavier (θ_c) at epoch 0. While epoch is less than or equal to 5, execute the following steps: Apply predicted vectors to voting. Convert feature vectors into the desired shape. Estimate prediction features using the Rectified Linear Unit (ReLU) activation function. Utilize SoftMax for predicting features. as $f\left(\alpha^{i}\right) = \frac{e^{\alpha_i}}{\sum e^{\alpha_i}}$ Compute score of voting proposed DOIRV classifier if predictor score is >2 considered as attack else predictor score = 2 evaluate decision tree

```
else if
predictor score <2 considered as normal data
end
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5 Simulation Results and Discussions

In this section presented about dataset considered for evaluating the performance of proposed sigmoidal based approach. For evaluation this research uses Kaggle dataset for attack identification and prevention in WSN network. Based on the constructed algorithm 1 nodes are deployed in the WSN network. The simulation values are presented in below table as follows:

Table 2: Construction of Weighted WSN

Parameters	**Values**
Network Topology	Mesh
Number of nodes	100
Type of Channel	Wireless Channel
Simulation Area	100*100
Simulator	MATLAB 2019a
Mobility Model	Radio Propagation Model (2-way)
Coordinates of Base Station	50,50
Initial Energy (E0)	0.5 Joules
Data Aggregation Energy (EDA)	5*0.000000001 Joules
Packet Size	4000 bits

Based on the defined parameters network is deployed those deployed networks is presented as follows:

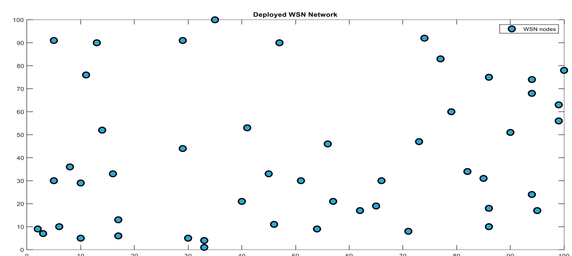

Figure 3: Deployed WSN for the 100x100 meters

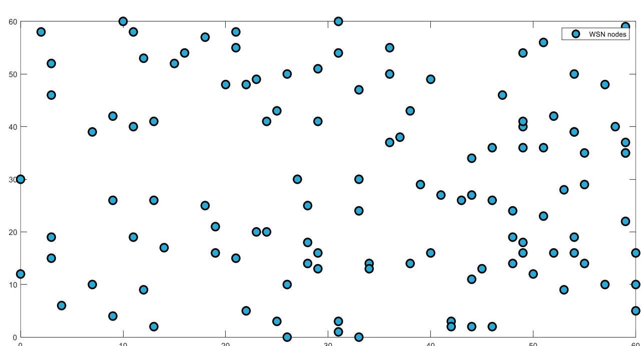

Figure 4: Constructed WSN with coverage of 60x60

The above figure 3 demonstrate the deployed WSN network for 50 wireless nodes. The coverage area considered for analysis is 100meter in x-axis and 100 meter in y-axis which means node able to transmit data within this energy range. The nodes in the WSN is deployed in random manner with the specified coverage range. In figure 4 WSN nodes data transmission is illustrated in which node with higher energy level is considered as cluster head. Data transmission among cluster head are shown in figure as red circle which demonstrate the data transmission among the nodes based on the proposed weighted Whale based optimization approach data were transmitted among the nodes. In below figure 4 presented about the screenshot related to assigned energy level for the nodes. Even this provides a path loss exponent value, maximal iteration value and compression energy. The below figure 5 provides the residual energy level of the nodes in the deployed WSN network. In this figure x-axis denoted the number of iterations conducted through the proposed weighted Whale algorithm. The simulation is performed for 5000 iterations in which number of nodes in WSN is evaluated with consideration of residual energy in the system. Through evaluation of simulation approach, it is observed that for 100 nodes as iteration increases residual energy decreases drastically even which has energy level till completion of 5000 iteration in the system.

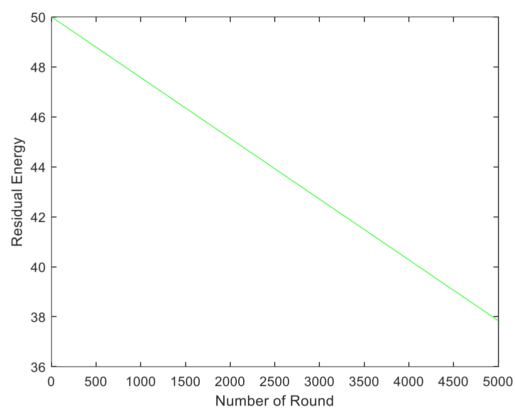

Figure 5: Objective Function estimation

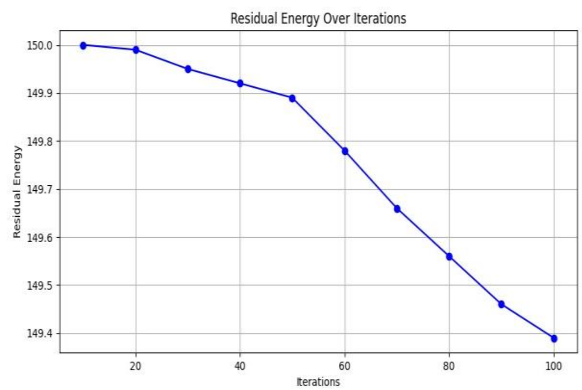

Figure 6: Residual Energy Level

In figure 6 represented the normalized energy level per round with respect to consideration of number of iterations in the system. Normalized energy level of network is observed as 1 for initial iteration. With increase in number of iterations normalized average energy of network decreases drastically even for proposed weighted Whale algorithm normalized energy reaches value of 0.75 for increased number of iterations using the proposed approach. This implies that normalized energy is significant for proposed weighted whale algorithm which significantly improves the deployed WSN network.

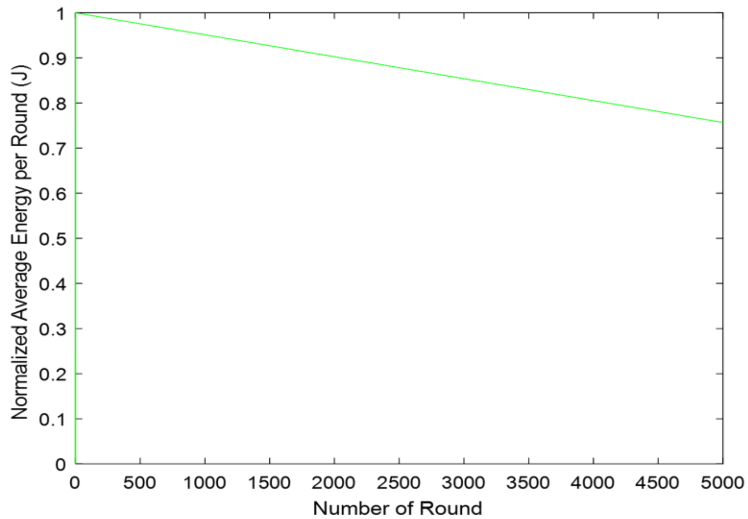

Figure 7: Estimation of Energy

The Figure 7 illustrated the estimated energy level of the nodes for the variation in the rounds. The below figure 8 presented that number nodes alive for every iteration in the network. The number of nodes while initiating iteration is 5000 after completion iterations it is observed that number of nodes alive is observed as 100 which defines that even energy level able to decreases significantly but all nodes alive in the network. This implies that proposed weighted whale algorithm effectively improves the performance of constructed WSN network.

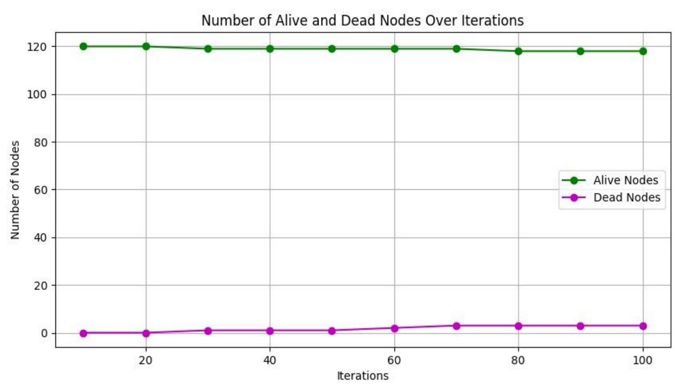

Figure 8: Number of Alive and Dead Nodes

It is evident that in the case of the structured weighted whale method, the number of dead nodes is effectively reduced to zero. This observation indicates that none of the nodes within the network are non-operational. The graph visually demonstrates that as the number of iterations increases, the occurrence of non-functional nodes diminishes, showcasing a remarkable reduction compared to alternative approaches.

Table 3: Comparison of Performance Characteristics

Iteration	Residual Energy	Normalized Energy	Number of alive nodes	Number of dead nodes
10	150	0.98	120	0
20	149.99	0.97	120	0
30	149.95	0.97	119	1
40	149.92	0.96	119	1
50	149.89	0.96	119	1
60	149.78	0.95	119	2
70	149.66	0.95	119	3
80	149.56	0.95	118	3
90	149.46	0.94	118	3
100	149.39	0.93	118	3

The above table illustrated performance measures of proposed weighted whale algorithm for constructed WSN. For framed iteration initiated from 0 to 5000 are range with normalized energy level of 0.75 which involves number of alive nodes 100 and dead nodes are 0 this implies that proposed weighted approach effectively improves the performance of WSN network.

Table 4: Comparison of Performance based on energy consumption

Run	Energy Consumption (Joules)	Average Energy Consumption	Coverage Area m2	No.of Nodes
1	150.2	149.8	500	50
2	148.5	149.8	490	49
3	151.0	149.8	505	51
4	149.8	149.8	498	50
5	150.5	149.8	502	52
6	149.2	149.8	496	51
7	150.8	149.8	508	53
8	149.7	149.8	503	52
9	150.3	149.8	499	50
10	148.9	149.8	491	49
11	150.2	149.8	500	50
12	149.4	149.8	494	51
13	150.6	149.8	506	52
14	149.1	149.8	495	50
15	150.9	149.8	509	53
16	148.7	149.8	487	48
17	150.4	149.8	504	52
18	149.3	149.8	497	51
19	150.2	149.8	500	50
20	149.8	149.8	503	52

The recorded energy consumption values, both for individual runs and their average, indicate a relatively consistent level around 149.8 Joules, showcasing stability in the system's power utilization. The associated coverage area and the number of nodes vary in response to changes in energy consumption, revealing the system's adaptability and responsiveness to energy alterations. Across the 20 runs, the coverage area spans from 487 to 509 square meters, illustrating the system's ability to accommodate fluctuations in energy consumption while maintaining a broad coverage footprint. The number of nodes fluctuates between 48 and 53, demonstrating the network's flexibility to sustain varying quantities of nodes under different energy scenarios. These fluctuations in coverage area and the number of nodes highlight the dynamic nature of the system, where energy consumption adjustments influence the network's capacity and reach. The tight clustering of energy consumption values around the average, coupled with the corresponding variations in coverage area and the number of nodes, suggests that the system can effectively adapt to changes in energy availability. The consistent average energy consumption value of 149.8 Joules indicates that the system is operating at a stable energy usage level. The observed patterns in coverage area and node count showcase the system's ability to dynamically allocate resources in response to varying energy conditions, underscoring its resilience and efficiency in managing resources while sustaining network performance.

6 Conclusion

This paper presents a novel multi-objective Direction of Arrival (DOA) estimation technique, utilizing the Direction Optimization Integrated Ranking Voting (DOIRV) model to enhance the performance of Wireless Sensor Networks (WSNs) while minimizing energy consumption. The research successfully integrates the Whale Optimization Algorithm (WOA) with advanced artificial intelligence-based machine learning models to optimize DOA routing paths and data transmission. Through a comprehensive simulation using MATLAB, the proposed DOIRV model demonstrated significant improvements in key performance metrics including packet delivery ratio, throughput, and network delay. The comparative analysis reveals that the DOIRV model outperforms conventional techniques, achieving approximately 13% and 18% higher performance in packet delivery ratio and throughput, respectively. Additionally, the effectiveness of the Whale-based approach in reducing energy consumption and enhancing node longevity is evident from the simulation results, which show a substantial reduction in the number of dead nodes and improved residual energy levels over iterations.

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