

Node Localization and Routing Schemes in Wireless Sensor Networks

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CERTIFICATE

This is to certify that the thesis entitled "Node Localization and Routing Schemes in Wireless Sensor Networks" being submitted by Yogendra Mohan (Reg. No.: 2K19/PHDCO/15) for the award of degree of Doctor of Philosophy to the Delhi Technological University is based on the original research work carried out by him. He has worked under my supervision and has fulfilled the requirements that to our knowledge have reached the requisite standard for the submission of this thesis. It is further certified that the work embodied in this thesis has neither partially nor fully submitted to any other university or institution for the award of any degree or diploma.

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ABSTRACT

Numerous applications of wireless sensor networks (WSNs) highly depend on the node location, such as maritime rescue, agriculture, and hazardous environments. GPS-enabled sensors are neither cost-effective nor energy-efficient. Finding the position of a target node (an unknown node) is known as node localization. Henceforth, the precise location of sensor nodes significantly impacts the performance of WSNs.

Energy efficiency and network life are crucial concerns in WSNs due to the limited battery life of the sensor nodes. An efficient cluster head (CH)-based routing is a need of WSNs. Security is a major challenge in WSNs. Malicious nodes cannot be ignored in the hostile environment of WSN operations.

Firstly, the thesis proposed an RSSI-based node localization. The localization error estimated using the RSSI and trilateration method is chosen as a fitness function for the Seagal Optimization Algorithm (SOA) for further minimization of the localization error. The SOA is modified using logistic chaotic maps and Lévy flights, known as C-SOA and LF-SOA. The simulation results illustrate that the performance of the LF-SOA is better than the C-SOA and SOA.

Secondly, to improve the life of the sensor nodes, a cluster head selection (CHS)-based routing scheme is proposed. The Pelican Optimization Algorithm (POA) is modeled for an energy-efficient CHS and routing. The CHS is based on five fitness functions: energy of the sensor nodes, distance between cluster members (CMs) and cluster head (CHs), distance between CHs and base station (BS), node degree, and node centrality. These five fitness functions are applied to the POA to select the CHs. Further, the selected optimal CHs are participating in the routing process to send the aggregated data from the neighbor's nodes (CMs). To choose the optimal path between CHs and BS (sink node), three fitness functions (residual energy of the CHs, distance between CHs and BS, and distance between CMs and CH) are chosen to model POA for optimal routing. The outcome of the proposed scheme (POA_Proposed) is energy-efficient, which enhances the network life.

Lastly, a trust-aware node localization scheme (TANLS) is proposed. This work presents a novel model to resolve the shortcomings of existing localization techniques in WSNs. TANLS leverages trust-based approaches to accurately estimate the positions of sensor nodes while

mitigating the impact of compromised or malevolent nodes on localization accuracy. The trust values of anchor nodes are evaluated against the reputation value of the anchor nodes. The highly trustworthy anchor nodes are subsequently selected as legitimate nodes for the localization process, and the unknown nodes get information from highly trustworthy anchor nodes to perform the NL. To enhance the performance of the localization, the Coati Optimization Algorithm (COA) is modeled using suitable fitness functions, and its performance is compared with the butterfly optimization algorithm (BOA) and particle swarm optimization (PSO). The simulations are performed using the COA_Proposed, BOA, and PSO. The comparative analysis among the COA_Proposed, BOA, and PSO demonstrates that the COA_Proposed outperforms the compared algorithms in terms of localization, localization computation time, and localization error.

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LIST OF ABBREVIATIONS

SN	Abbreviation	Description
1	<i>ABC</i>	Artificial bee colony
2	<i>ABCOA</i>	Artificial Bee Colony Optimization Algorithm
3	<i>ACO</i>	Ant Colony Optimization
4	<i>AEC</i>	Average Energy Consumption
5	<i>ALOC</i>	Ant Lion Optimization for Clustering
6	<i>ALNs</i>	Active/Alive nodes
7	<i>AN/ANs</i>	Anchor Node/Anchor Nodes
8	<i>ANLe(m)</i>	Average Node Localization Error in Meter
9	<i>ANL_t(s)</i>	Average Node Localization Computation Time in Second
10	<i>AOA</i>	Angle of Arrival
11	<i>APIT</i>	Approximation-Point-In-Triangulation Test
12	<i>ATNL (%)</i>	Average NL Accuracy
13	<i>BOA</i>	Butterfly Optimization Algorithm
14	<i>BOAACO</i>	Butter fly Optimization Ant Colony Optimization
15	<i>C_{AB}</i>	Set of common neighbors of Nodes A and B
16	<i>CH/CHs</i>	Cluster Head/Cluster Heads
17	<i>CHS</i>	Cluster Head Selection
18	<i>CM/CMs</i>	Cluster Member/Cluster Members
19	<i>COA</i>	Coati Optimization Algorithm
20	<i>dBm</i>	Decibel milliwatts
21	<i>DALO</i>	Discrete Ant Lion Optimization
22	<i>DEEC</i>	Distributed Energy Efficient Clustering
23	$(D_A^B(t))$	Direct trust of node B estimated at node A at time t
24	$DT_A^C(t)$	Direct trust of node C estimated at node A at time t
25	$DT_B^C(t)$	Direct trust of node C estimated at node B at time t
26	<i>DTN</i>	Distance to neighbors
27	<i>D_{tr}</i>	Distance between transmitter and receiver
28	<i>DV-Hop</i>	Distance-Vector Hop Count
29	<i>E_{afs}</i>	Energy consumed when free space model is used
30	<i>E_{amp}</i>	Energy consumed when multipath fading model is used

31	E_{trans}	Energy lost to operate transmitter
32	E_{receiv}	Transmission amplifier's energy dissipation
33	E_{edtr}	Energy dissipated at transmitter receiver
34	E_{afs}	Energy consumed when free space model is used
35	<i>ER-SR</i>	Energy-efficient region source routing
36	<i>EEICS</i>	Energy-Efficient intra-cluster data communication scheme
37	<i>EEYSGPO</i>	Energy Efficient Yellow Saddle Goatfish POA
38	<i>FCGWO</i>	Firefly Cyclic Grey Wolf Optimization
39	<i>FFOA</i>	Firefly Optimization Algorithm
40	<i>FF</i>	Fitness Function
41	ff_{CH}	Fitness Function for CHS
42	ff_R	Fitness Function for Routing
43	<i>FND</i>	First node dead
44	<i>GIT</i>	Greedy Incremental Tree Algorithm
45	<i>GA</i>	Genetic Algorithm
46	<i>GIT</i>	Greedy Incremental Tree Algorithm
47	G_t	Power Gain at Transmitter Node
48	G_r	Power gain at Receiver Node
49	<i>HGWCSOA-OCHS</i>	Hybrid GOA and CSOA-based optimal CHS
50	<i>HABC</i>	Hybrid Artificial Bee Colony
51	<i>HEED</i>	Hybrid Energy-Efficient Distributed Clustering
52	<i>ICOA</i>	Improved Coyote Optimization Algorithm
53	<i>IJO-LF</i>	Improved Jaya Optimization Algorithm with Levy Flight
54	<i>ICOA</i>	Improved Coyote Optimization Algorithm (ICOA)
55	<i>IJOA</i>	Improved Jaya Optimization Algorithm
56	L	Losses at antenna
57	<i>LMDS</i>	Local Multipoint Distributed Service
58	<i>LND</i>	Last Node Dead
59	<i>LEACH</i>	Low Energy Adaptive Clustering Hierarchical Routing P
60	<i>LEACH-C</i>	LEACH Centralized
61	<i>MHOA(s)</i>	Meta-heuristic Optimization Algorithm(s)
62	<i>MMDS</i>	Multi-channel Multi-point Distributed Service

63	MN/MNs	Malicious Node/ Malicious Nodes
64	NL	Node Localization
65	$NLE(m)$	Node Localization Error in Meter
66	$NLT(s)$	Node Localization Computation Time in Second
67	$NT_A^B(t)$	Node trust of node B estimated at node A
68	N_p	Total no of trails for a particular node set (AN, TN, MN)
69	Obj_Fun	Objective Function
70	$ODTD-LI$	Optimal data transmission with data-location integration
71	$PEGASIS$	Power-Efficient Gathering in Sensor Information Systems
72	$PEDAP$	Power Efficient Data Gathering and Aggregation Protocol
73	POA	Pelican Optimization Algorithm
74	PSO	Particle Swarm Optimization Algorithm
75	PDR	Packet Delivery Ratio
76	$R_A^B(t)$	Recommendation credibility of node B estimated at node A
77	$R_{AN_{ij}}^{t+1}$	Reputation of the anchor node i computed by node j at the time t+1.
78	RE	Residual Energy
79	ROA	Raccoon Optimization Algorithm
80	$RSSI_d$	RSSI value at the distance d from the reference point
81	SA	Search Agent
82	SN/SNs	Sensor Node(s)
83	$TANLS$	Trust-Aware Node Localization Scheme
84	$TDOA$	Time Difference of Arrival
85	$TEEN$	Threshold-sensitive energy-efficient sensor network
86	TN/TNs	Target Node/Target Nodes
87	ToA	Time of Arrival
88	$YSGA$	Yellow Saddle Goatfish Algorithm
89	$WSNs$	Wireless Sensor Networks

LIST OF SYMBOLS

SN	Symbols	Description
1	β	Chaotic Index
3	c_r	Chaotic pseudo-random number
4	e	Euler number
6	fc	Frequency-controlled
7	κ	Proportionality constant
8	θ	Random number between $(0, 2\pi)$
9	u	Correlation constant
10	v	Correlation constant
13	μ	Chaotic logistic map constant
14	φ_i	weighted values for routing
15	ω_i	weighted values for clustering

LIST OF PUBLICATIONS

Journal

1. Yogendra Mohan, Rajesh Kumar Yadav, Manisha Manjul, “Seagull Optimization Algorithm for Node Localization in Wireless Sensor Networks”, *Multimed Tools Appl* (2024). <https://doi.org/10.1007/s11042-024-18331-8>. (SCIE I.F.=3.0).
2. Yogendra Mohan, Rajesh Kumar Yadav, Manisha Manjul. EECRPOA: energy efficient clustered routing using pelican optimization algorithm in WSNs. *Wireless Networks* 31, 3743–3769 (2025). <https://doi.org/10.1007/s11276-025-03970-y>. (SCIE I.F.=1.9).
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2. Yogendra Mohan, Rajesh Kumar Yadav, Manisha Manjul, “Distributed Node Localization Techniques in Wireless Sensor Networks: A Review,” 2nd International Conference on Networks and Cryptology (NETCRYPT2020), JNU, New Delhi, INDIA.
3. Yogendra Mohan, Rajesh Kumar Yadav, Manisha Manjul, “PATANLS: Performance Analysis of Trust-Aware Node Localization in WSNs,” 4th International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2024. [DOI:10.1109/ICTACS62700.2024.10840803](https://doi.org/10.1109/ICTACS62700.2024.10840803) IEEE. (SCOPUS).

CHAPTER-1

INTRODUCTION

1.1. Wireless Sensor Networks: Wireless Sensor networks (WSNs) have emerged as a substantial high-tech advancement in node localization (NL) [1-4], clustered routing (CR), and trust management (TM). The WSNs contain numerous sensor nodes, distributed in the environment to sense, evaluate and receive data. WSNs are composed of a set of nodes that are deployed in a region of interest to find a certain phenomenon like pressure, wind direction and speed, chemical concentrations, temperature, humidity, illumination intensity, vibration intensity, power-line voltage, sound intensity, pollutant levels and vital body functions of the environment. WSNs have potential applications in many areas like greenhouse monitoring, machine health monitoring, home automation, military, environment, etc. The sensor networks are used to collect data from autonomous sensors, process the data, and send it to the base station or sink node. The Fig. 1.1 represent the general architecture of WSNs for NL. The anchor node (AN) is GPS embedded which is self-capable to known its position deployed in the network field where as normal sensor node also known as target node (TN) is not GPS embedded and TN is not self-capable to known its position. The Base station (BS) is a transceiver.

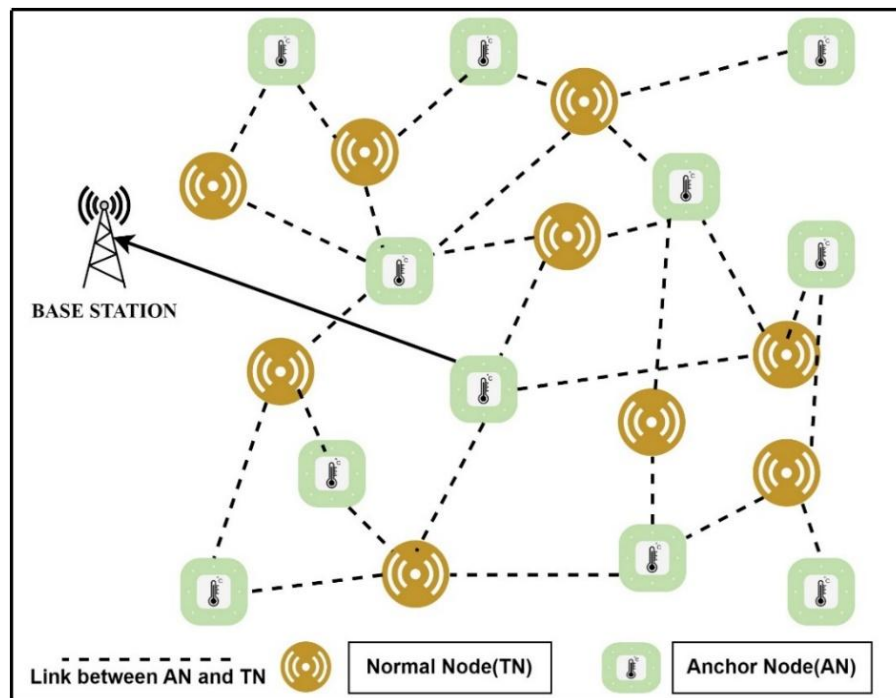


Fig 1.1 Architecture of WSNs

1.2. Node Localization: The location of nodes in WSNs is a crucial factor that affects their usefulness and performance. Localization is the procedure of ascertaining the precise geographical coordinates of sensor nodes inside the network. Precise localization is crucial for several WSN applications, such as environmental monitoring, target tracking, and navigation. The coordinate-based localization can be broadly classified into two categories. Centralized localization is one type of localization in which the base station controls all surrounding sensor nodes whereas distributed localization is another type of localization in which the beacon nodes coordinate with an unknown node to find the position of the unknown nodes. Distributed node localization can be further classified into two categories: range-free and range-based localization. Examples of range-based localization [5-7] are AoA, ToA, TDoA, and RSSI. The AoA, ToA, and TDoA are not cost-effective because of hardware dependency whereas hardware is not mandatory for RSSI-based localization.

1.3. Meta-Heuristic Optimization Algorithm (MHOA): Meta-heuristics are algorithmic frameworks that offer a set of strategies for developing heuristic optimization techniques [8-11]. Meta-heuristics are problem-independent and work at a high level. They are especially valuable for resolving intricate optimization problems where conventional methods are not effective. Metaheuristic optimization methods are highly efficient tools for handling various optimization challenges associated with node localization in WSNs. By utilizing the properties of algorithms, substantial enhancements in energy efficiency, network lifespan, fault tolerance, and data aggregation can be attained. MHOAs have numerous fundamental qualities that distinguish them from other types of optimization approaches. The MHOAs are nature-inspired algorithms. The processes are stochastic. The algorithms have global search capability. There is a balance between exploration and exploitation phases. The metaheuristic algorithms are problem independent. The process is iterative. The algorithms are flexible, scalable, heuristic, simple to implement, and adaptable.

1.4. Trust Management: Trust management in WSNs is essential for guaranteeing the security and reliability of the sensor nodes.

Trust Models for Node Localization: The reputation-based model observes the past behavior of the nodes, the certificate-based model requires a digital signature to prove the legitimacy of the node, and the behavior-based model observes the packet forwarding behavior and communication pattern.

Common Attacks in WSNs: The most common attacks in WSNs are sybil, wormhole, selective forwarding, and replay attacks.

1.5. Motivation: WSNs play a vital role in several sectors, such as manufacturing, healthcare, agriculture, and energy. Their functionalities, such as impact sensing, location-based services, and real-time monitoring, are extensively utilized. Impact sensing is crucial for monitoring the structural integrity and analyzing vibrations. Location-based services facilitate the tracking of assets and the determination of their geographical location. Continuous patient monitoring is essential in healthcare, and real-time monitoring plays a vital role in achieving this. The market for WSNs is experiencing significant growth because of increasing demand for Internet of Things (IoT) applications, automation, and the adoption of sophisticated technologies such as 5G and LoRa. WSN vehicles are gaining popularity in the context of smart cities and intelligent transport systems. Integrating WSNs with security is hard, considering privacy and security considerations.

The WSN market is positioned for large development due to IoT demand, automation, and improved tech, despite hurdles including privacy security and integration across industries. The market size of WSNs is projected to increase by USD 92.39 billion at a compound annual growth rate (CAGR) of 17.32% from 2022 to 2027. In 2023, the market size of wireless sensors in the United States was assessed at USD 5 billion. It is projected to expand at a CAGR of 21.2% from 2023 to 2032, reaching USD 28.21 billion by 2032, as presented in Fig. 1.2(a). The global wireless sensors market encompasses a wide range of product types, including temperature sensors (including biosensors), motion and positioning, humidity, pressure, level sensors, gas, flow sensors, and others. These sensors are utilized in various industry verticals such as industrial, consumer electronics, aerospace and defense, automotive and transportation, healthcare, agriculture, and others. The market is analyzed based on factors such as industry analysis, growth, trends, size, regional outlook, share, and forecast for the period of 2023-2032.

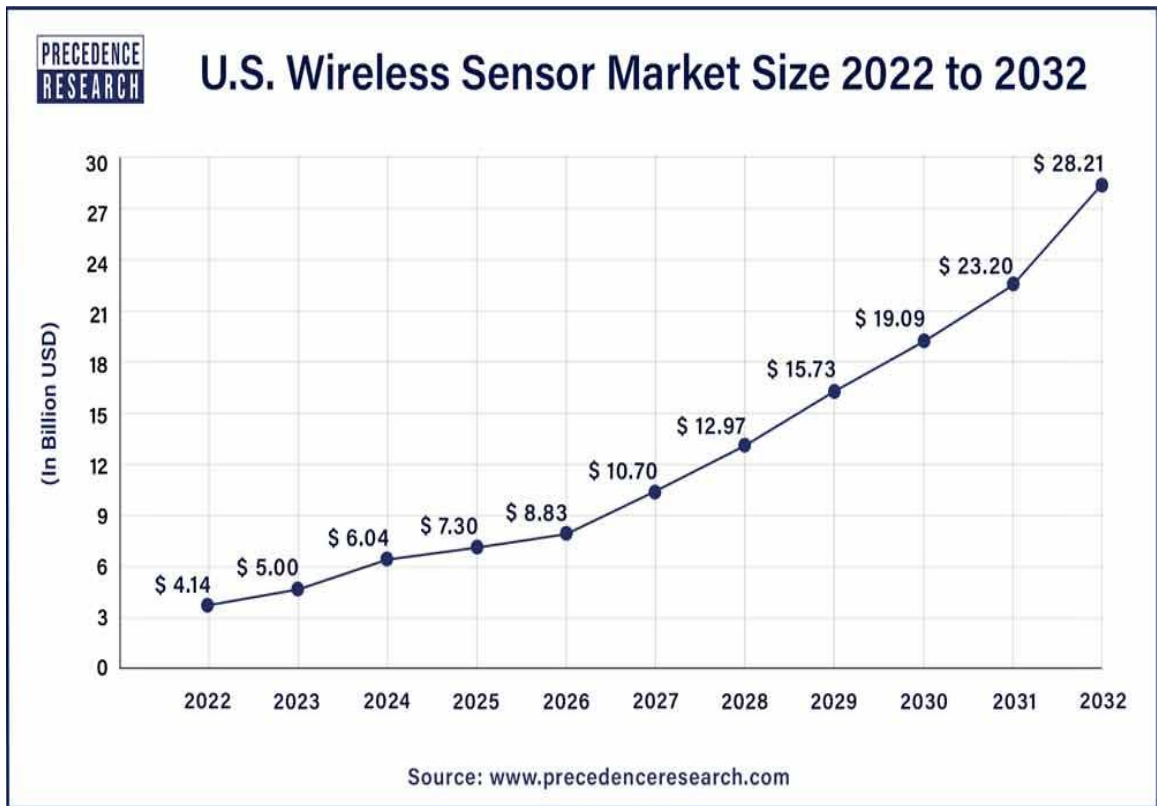


Fig 1.2(a) US Wireless Sensors Market Size

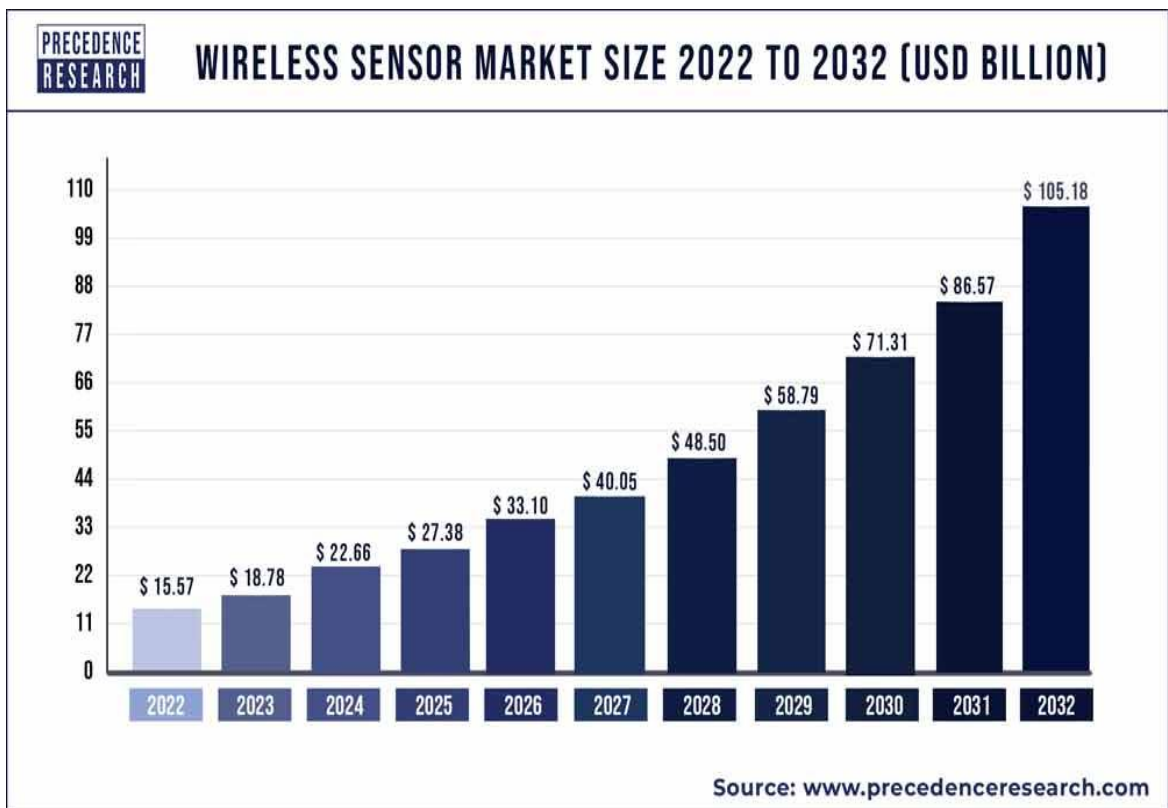


Fig 1.2(b) Global Wireless Sensors Market Size

1.6. Application of WSNs: WSNs have extensive use in diverse domains owing to their capacity to remotely monitor, gather, and send data without relying on physical connections. WSNs have several important applications:

Industrial Automation for Industry 4.0: WSNs are one of the main components of Industry 4.0. This will provide real-time data, which is a cost-effective approach at the low power consumption.

Environmental Monitoring: WSNs are extensively employed to monitor several environmental factors, including humidity, temperature, quality of the air, moisture in the soil, and pollutant levels. They assist in the examination of natural ecosystems, identification of environmental fluctuations, and management of natural resources.

Industrial Automation: WSNs are applied for process control and monitoring, condition of equipment monitoring, management of inventory, and tracking of assets. They make industrial operations safer, more efficient, and less prone to downtime.

Healthcare: Medical asset tracking, remote patient monitoring, and smart healthcare systems are some very popular applications.

Smart Agriculture: Monitoring of crop health, soil conditions, weather patterns, and irrigation systems are some very popular examples in the agriculture sector.

Home Automation: Energy management systems, smart home systems, security systems, control of household appliances, and remote monitoring are widely used applications.

Structural Health Monitoring: To monitor the structural integrity of dams, bridges, buildings, and other civil infrastructure to identify and assess structural failures, and degradation, and permit prompt maintenance and repairs.

Military and Defense: WSNs are utilized for personnel monitoring in the military, perimeter security, reconnaissance, and battlefield surveillance.

Wildlife Tracking: WSNs are widely used in tracking the movement activity of wildlife species, and wildlife management.

Smart Cities: Intelligent street lighting, air quality monitoring parking management, waste management, and traffic monitoring are very popular applications of WSNs.

Disaster Management: Disaster management systems like monitoring natural phenomena (like earthquakes, floods, and wildfires) by providing early warning systems, coordinating rescue and relief operations, and assessing damage are popular applications of WSNs.

1.7. Challenges of WSNs: Low bandwidth connectivity, distributed processing, device heterogeneity, large-scale sensor coordination, and real-time computation are the primary obstacles to WSN design. In addition to design issues, there are certain operating challenges. Limited energy, noise measurements, scalability, node failure, storage constraints, and computational and communicational overhead are the difficulties.

1.8. Problem Formulation: A sensing unit, a processing unit, a transceiver unit, and a power supply are the four essential parts of every sensor. In order to enable location-aware applications of WSNs, the nodes may optionally include a GPS or a number of built-in sensors. Each additional feature, however, raises the node's cost, power consumption, and physical dimensions. Cost-effective and secure localization are essential requirements. Cost-effective routing is another challenge in WSNs. Cluster-based efficient routing is the solution to the problem.

1.9. Research Methodology: An extensive literature survey has been carried out in node localization, clustered routing, and trust-awarded localization, and problems are formulated. The problem is divided into three sub-problems as shown in Fig. 1.3. The three models have been proposed and simulated using MATLAB2021a, and the result evaluation and comparative analysis are carried out.

1.10. Simulation Tools: In this thesis, all the simulations are carried out using MATLAB 2021a and processor 11th Gen Intel(R) Core (TM) i7-1165G7 @ 2.80GHz, 2803 MHz, 2-Core(s), 4-Logical Processor(s). There are two approaches commonly used in WSNs for the simulations. They are discrete-event-driven and trace-driven. The discrete-event-driven simulations are easy and mostly preferred. Trace-driven simulations are preferred in real-time systems. Trace-driven simulation has more credibility. MATLAB is a high-performance computing and visualization tool. MATLAB is widely used for scientific research. It has analysis capability, flexibility, and reliability. It is a high-level language and interactive environment that has dependable and accurate mathematical functions that are built into the software. These functions solve mathematical problems in signal processing, complex arithmetic, matrix algebra, linear systems, and many other scientific evaluations.

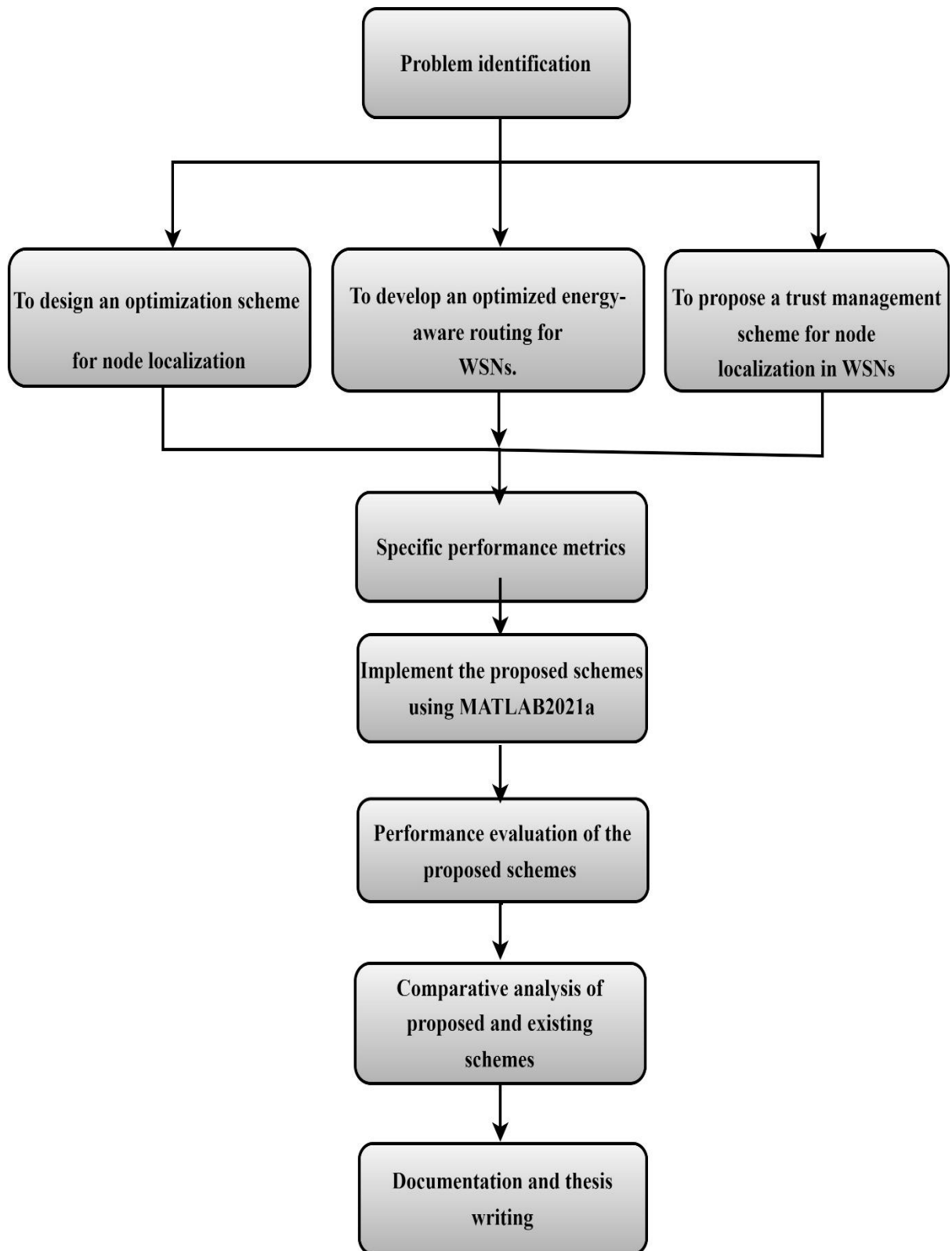


Fig. 1.3 Research Methodology

1.11. Contributions: This thesis has made significant contributions that have greatly influenced the progress of localization, energy-efficient routing, and trust-aware localization in WSNs.

The thesis **primarily** addresses an essential component of localization in WSNs, and an extensive survey is carried out on various node localization schemes. A survey paper is presented at the 2nd International Conference on Networks and Cryptology (NetCypT-2020) on 6th December 2022. An optimized node localization scheme is proposed for the performance analysis of localization, and the paper is presented at the 3rd International Conference on ICTACS – 2023 in Tashkent, Uzbekistan, on 3.11.2023. This work has been published in the IEEE Xplore Digital Library. “Mohan, Yogendra, Rajesh Kumar Yadav, and Manisha Manjul. "PANLS: performance analysis of node localization scheme in WSNs." In 2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS), pp. 950-956. IEEE, 2023.

DOI: 10.1109/ICTACS59847.2023.10390138."

The thesis aims to enhance localization, localization computation time, and minimization of localization error using RSSI value and modified meta-heurist optimization algorithm. This work has been published in Multimedia Tools and Applications.

“Mohan, Yogendra, Rajesh Kumar Yadav, and Manisha Manjul. "Seagull optimization algorithm for node localization in wireless sensor networks." *Multimedia Tools and Applications* 83, no. 28 (2024): 70793-70814”. **DOI: <https://doi.org/10.1007/s11042-024-18331-8>** (Pub.: Springer), [SCIE Indexed].

Secondly, the thesis focuses on cluster formation and cluster head selection using POA. The cluster heads are used to get data from cluster members and send data to the Base Station using the modeled POA. The cluster-based routing schemes is an energy-efficient. This work is published in Wireless Networks journal.

“Mohan, Yogendra, Rajesh Kumar Yadav, and Manisha Manjul. "EECRPOA: energy efficient clustered routing using pelican optimization algorithm in WSNs." *Wireless Networks* (2025): 1-27.” **DOI: <https://doi.org/10.1007/s11276-025-03970-y>**.

Lastly, the thesis contributed by modeling a scheme that ensures the legitimacy of the sensors and ensures that only trustworthy sensors are involved in the localization process. The trust management scheme has been modelled for secure localization, and the Coati optimization algorithm (COA) is modeled using a suitable fitness function to enhance the accuracy of the localization, minimize the localization error, and reduce computation overheads. “Mohan, Yogendra, Rajesh Kumar Yadav, and Manisha Manju. "PATANLS: Performance analysis of trust-

aware node localization in WSNs." In 2024 4th International Conference on Technological Advancements in Computational Sciences (ICTACS), pp. 1483-1491. IEEE, 2024." DOI: 10.1109/ICTACS62700.2024.10840803.

Ultimately, these contributions greatly enhance the comprehension and application of localization, routing, and trust in WSNs. The thesis provides significant insights and concrete ways to enhance performance, reliability, and durability. This is achieved by extending the network's lifespan, refining existing algorithms, optimizing cluster formation, and ensuring secure localization.

1.12. Thesis Organization: The thesis work emphasizes the localization of nodes and the development of a cluster-based routing scheme in WSNs. The work is structured into discrete chapters, with each chapter's contributions being briefly stated as follows:

This **chapter 1: Introduction** represents the basics idea of WSNs, node localization, applications of WSNs, architecture of WSNs, trust management, meta-heuristic optimization algorithms, challenges of WSNs, problem formulation, and research methodology.

Chapter-2: Background and Literature Review have two sections. Section one is preliminaries which describe the node localization taxonomy, basic ideas about the meta-heuristic optimization algorithm. Section two represents the literature review which include survey on node localization, cluster based optimized routing and trust-aware localization in WSNs.

Chapter-3: Design an optimization scheme for node localization

This chapter modeled SOA using suitable fitness function and analyzed an optimization scheme for node localization under the six different scenarios. The localization accuracy, error, and computation time of the modified (C-SOA and LF-SOA) schemes are improved.

Chapter-4: Develop an optimized energy-aware routing for WSNs

In this chapter, Pelican optimization algorithm is modeled using five suitable fitness function for clustering and three suitable fitness function for routing. The performance of the POA_Proposed is better in terms of network life and transmission of the data to the base station.

Chapter-5: Propose a trust management scheme for node localization in WSNs

In this chapter, a trust management scheme is proposed for trust estimation of the anchor nodes. The nodes are localized using only trust worthy anchor nodes. The localization error is a fitness function applied in COA_Proposed Algorithm. The performance of COA_Proposed for the secure localization is better than existing schemes.

Chapter-6: Conclusion and Future Work

This chapter illustrates the conclusion and future scope, summarizes the findings and outcomes derived from the models, methods, and algorithms presented in the proposed work. It also delves into an extensive discourse on prospective avenues for future research and development.

CHAPTER-2

BACKGROUND AND LITERATURE REVIEW

In this chapter, illustrated fundamental of the localization, meta-heuristic optimization techniques, taxonomy of meta-heuristic optimization, taxonomy of clustering protocols, taxonomy of routing protocols, trust management, and Taxonomy of trust management. The intensive literature survey is carried out in this chapter on node localization in WSNs. The survey is classified into three sections. The first section is a survey on localization using meta-heuristic optimization, the second section is a survey on cluster-based routing in WSNs, and the third section is a survey on trust-aware localization in WSNs.

2.1.Taxonomy of Sensor Networks: Wireless networks are specifically intended to fulfil distinct functions and meet diverse use cases. The primary categories of wireless networks are shown in Fig. 2.1 and illustrated as follows:

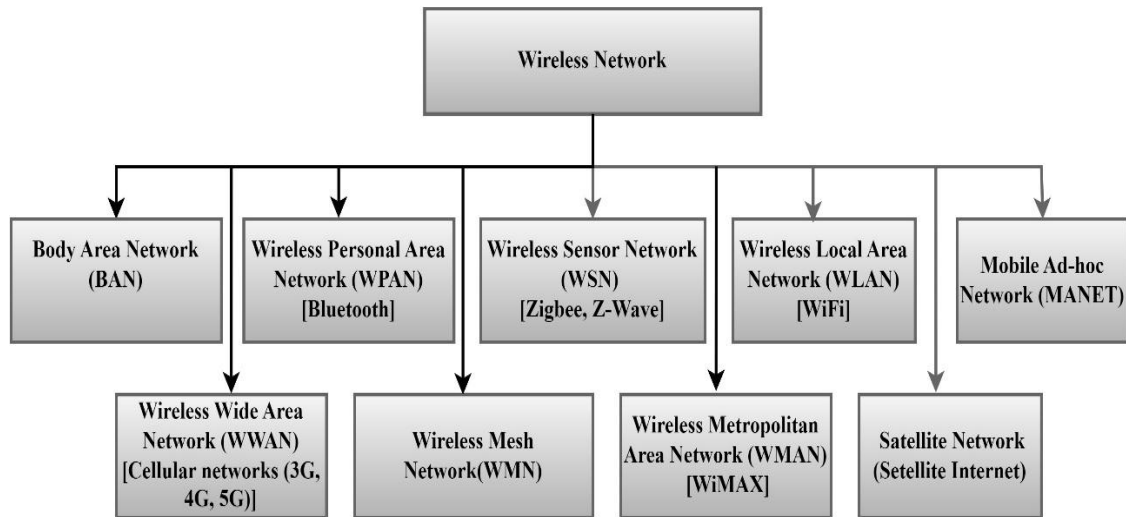


Fig. 2.1 Taxonomy of Sensor Networks

Zigbee and Z-Wave are example of WSNs. The open-standard Zigbee protocol is used on mesh networks to wirelessly connect smart devices at home, offices, and hospitals. With Zigbee, signals can hop between devices in an open topology without connecting them to a hub. Zigbee is the IEEE 802.15.4-based protocol. Zigbee is the solution to the high-power consumption for building automation, medical care, gaming, and home automation. The Zigbee(2.4GHz) standard connects approx. 65,000 devices. Zigbee is a cost-effective and low power consumption

technology. Z-Wave is like Zigbee but Z-wave is reliable and secure due to closed network standards. Bluetooth is a cost-effective, energy-efficient, and robust connecting device. The frequency band of the Bluetooth is 2.4GHz and the transmission range is less than 10 meters. The Wi-Fi is an example of Wireless Local Area Network (WLAN) useful to connect personal devices like laptops smartphones, tablets, and wireless peripherals such as mice and keyboards. The frequency band of the Wi-Fi is 2.4GHz and 5 GHz. MANET is a network that is suitable for data, audio, and video transmission. The network is ad-hoc as it is independent on any pre-existing network. Data traverses from one node to another until it reaches its destination. WWAN uses distinct infrastructure and technologies compared to WPAN and WLAN. WPAN uses Bluetooth and WLAN uses Wi-Fi technology, WWAN uses cellular technology (GSM, CDMA, or LTE) to link devices. The Table 2.1 represent the types of wireless networks.

Table 2.1 Wireless Network Types

Type	Technology	Bandwidth	Coverage	Standards
WPAN	Bluetooth	0.25 to 20 Mbps	>30 Meters	IEEE 802.15
WLAN	Wi-Fi	2.4, 3.6, 4.9, 5, 5.9 GHz	> 100 Meters	IEEE802.11, Wi-Fi, HiperLAN
WMAN	WiMAX	2.3, 2.5, 3.5, 5.8GHz	< 50 K. Meters	IEEE 802.16
	LMDS	25-31 GHz		
	MMDS	(2.7-2.8 GHz		
WWAN	Cellular Technology	2G,3G,4G,5G	>50 Meters	IEEE 802.16
WSN	Zigbee	915 MHz, 2.4 GHz	<100 Meters	IEEE 802.15.4
	Z-Wave	800-900 MHz		

2.2.Taxonomy of Node Localization in WSNs: To estimate the position of the target node is known as Node Localization (NL). NL is a popular scheme in wireless sensor networks. NL can be classified into centralized and distrusted. Range free and range based are the distributed NL schemes. The accuracy of the range-based NL is low as compared to centralized. In the range-

based node localization (RBNL) method, the distance or angle between two nodes is estimated. The taxonomy of Node Localization is shown in Fig.2.2. The sensors can be deployed on earth, underground, or underwater. It is difficult to localize the sensors deployed and the sensor node's battery equipped with limited battery power is difficult to recharge. The RBNL is as follows:

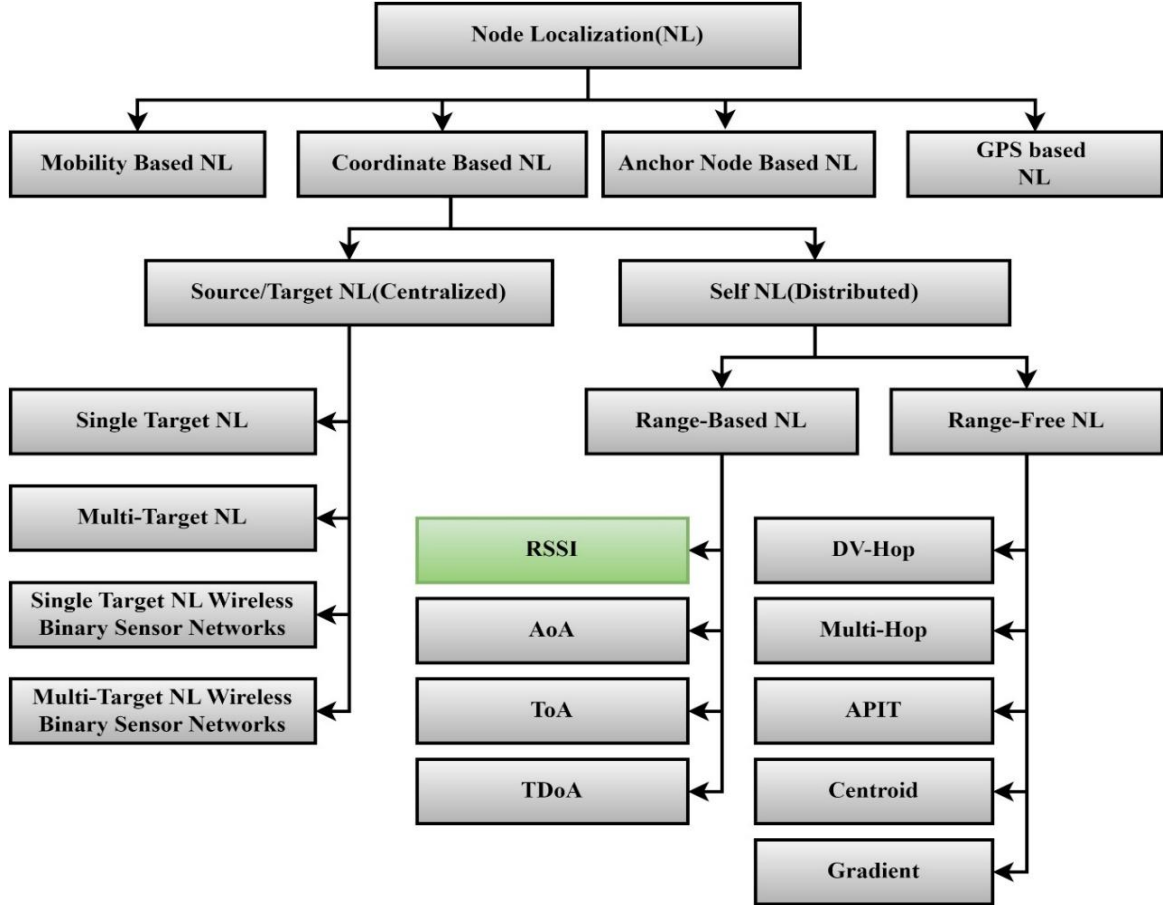


Fig. 2.2 Taxonomy of Node Localization in WSNs

Angle of Arrival (AoA): The angle of Arrival (AoA) is used to estimate the location of unknown nodes. The AoA pertains to the specific direction from which a signal is received at a target sensor node. The location of the target sensor node can be approximated by estimating the Angle of Arrival (AoA) of signals from anchor nodes. Signals are transmitted by anchor nodes, and the unknown node is the recipient of these signals. There is also the possibility that the unknown node will send out signals that will be received by several anchor nodes. The radio signals transmitted by anchor nodes are received by an unknown node. An unknown node can also send signals to surrounding anchor nodes. The AoA method gives high accuracy but requires hardware which is not cost-effective.

Time of Arrival (ToA): The ToA technique is used to evaluate the position of the sensor nodes in WSNs. An anchor node sends a signal to target node at a known time (T_{trans}). The target node records the received signal time (T_{rec}). The signal propagation time (Δt) is the difference between these times ($T_{rec} - T_{trans}$). To estimate the distance between sensors, and multiply the time difference by 3×10^8 (speed of light). Finally, the target node position can be estimated using the trilateration or multi-lateration method. The advantage of using AoA method for localization is high accuracy and challenges of using ToA are clock synchronization and interference due to signal propagation effects.

Time Difference of Arrival (TDoA): The TDoA technique is used to estimate the position of target nodes using the differences in arrival times of signals at various reference nodes in WSNs. The ToA measures the actual time taken by the signal to travel from a source to a destination ((transmitter to receiver) but the TDoA measure the relative time differences between multiple anchor nodes(receivers) as shown in Fig.2.3. A signal propagates from the target node and is received by several anchor nodes deployed at different locations.

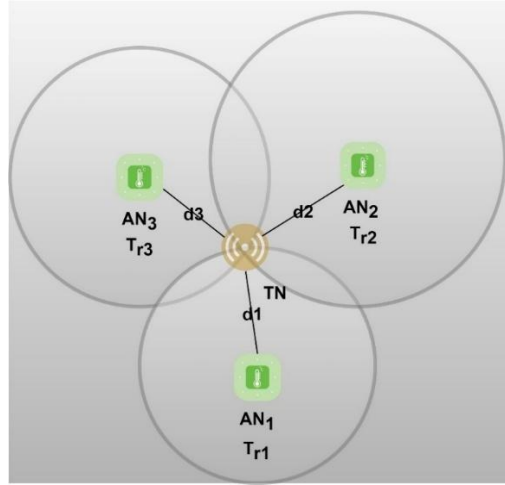


Fig. 2.3 Time Difference of Arrival (TDoA) in WSNs

The signal received at anchor nodes AN_1 , AN_2 , and AN_3 are T_{r1} , T_{r2} , and T_{r3} . The distance from AN_1 , AN_2 , and AN_3 to target node (TN) are d_1 , d_2 , and d_3 .

The time difference between AN_1 , and AN_2 is shown in equ. (2.1) as follows:

$$\Delta T_{12} = T_{r1} - T_{r2} \quad (2.1)$$

Similarly, the time difference between AN_1 , and AN_3 is shown in equ. (2.2) as follows:

$$\Delta T_{13} = T_{r1} - T_{r3} \quad (2.2)$$

The distance difference between AN_1 , and AN_2 can be estimated using equ. (2.3) as follows:

$$d_1 - d_2 = propagation_{speed} * \Delta T_{12} \quad (2.3)$$

Similarly, the distance difference between AN_1 , and AN_3 can be estimated using equ. (2.4) as follows:

$$d_1 - d_3 = propagation_{speed} * \Delta T_{13} \quad (2.4)$$

The distance differences $d_1 - d_2$ and $d_1 - d_3$ creates hyperbolic equations. The unknown node position can be estimated using above hyperbolic curve. The computational complexity is high due to hyperbolic curve and the synchronization between the anchor nodes is not easy due to environmental-effects.

Received Signal Strength Indicator (RSSI): The unit of RSSI is decibel milliwatt (dBm) on a logarithmic scale. Zero dBm is equivalent to one milliwatt. The best signal range is lies between -30 to -55 dBm, where -35 is better than -55. The RSSI based technique is used for node localization in WSNs which measures the power level of a received signal. As the distance between the transmitter and receiver increases, the strength of the RSSI signal decreases. There is a relationship between RSSI and distance, and modeled empirically that represents a relationship between RSSI and distance is known as the log-distance path loss model, shown using equ. (2.5) as follows:

$$P_d^R = P_{d_0}^T - 10 * n \log \left(\frac{d}{d_0} \right) \quad (2.5)$$

Where P_d^R is the signal strength received at receiver located at distance d and $P_{d_0}^T$ is the signal strength received at reference distance d_0 . The path loss exponent(n) is a constant which is varies between 2 to 5 depending on the environment. The trilateration method can be used to estimate the location of target nodes in a two-dimensional environment field.

Cluster-based Routing in WSNs: Cluster-based routing [12] is a prevalent way for effective communication among sensors. The nodes are grouped into clusters, where each cluster typically comprises a cluster head (CH) and several cluster members (CMs). Cluster heads (CHs) function as agents between CM nodes and the BS (sink) by aggregating data from CMs and transmitting it to the BS. Here is an overview of cluster-based routing in WSNs:

Cluster Formation: Sensor nodes self-organize into clusters according to parameters, including energy level or closeness. There are many clustering algorithms like HEED, LEACH, PEGASIS, and many MHOAs.

Cluster Head Selection: CHS may depend on several parameters like residual energy, node density, node centrality, and closeness to the BS. The fitness

Data Aggregation: CHs aggregate data gathered from CMs within their clusters to decrease the amount of data transmitted to the BS and the scheme may be energy efficient, and reduce network congestion.

Routing Protocol: CHs are liable for routing data to the BS. Various routing methods can be implemented for this purpose, including direct transmission, data-centric routing, hierarchical routing etc.

Energy Efficiency: One of the most important goals of cluster-based routing is to enhance energy efficiency and extend the network lifetime. To achieve the task, efficient MHOA may be the optimal solution to the problem if the fitness function is chosen wisely for the optimization of the proposed work. The taxonomy of Energy-Efficient Routing is shown in Fig.2.4.

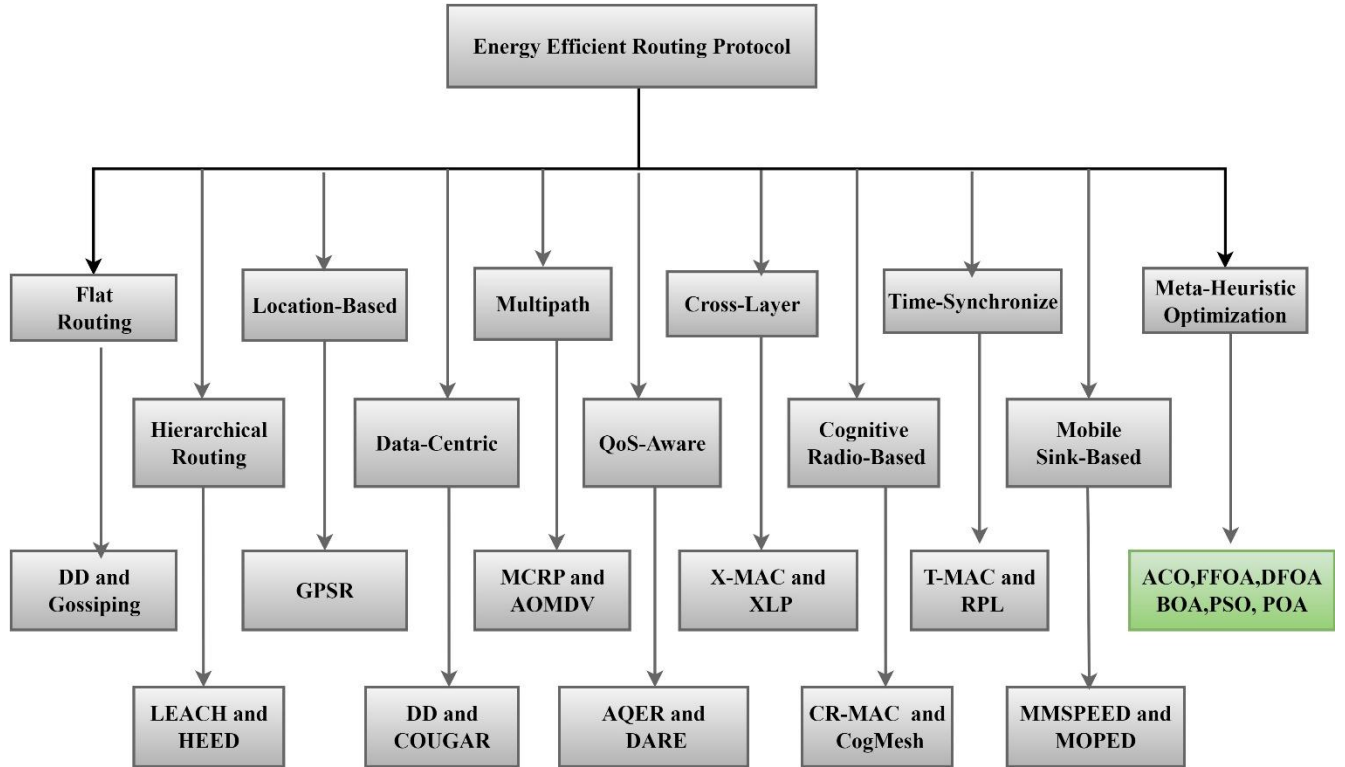


Fig 2.4 Taxonomy of Energy-efficient Routing Protocol

2.3.Trust Aware Node Localization in WSNs: Trust-aware localization is a process of finding the position of sensor nodes in an environment field while considering trust-related criteria. Traditional localization techniques typically rely on distance estimate, triangulation, or multi-lateration methods. However, these systems may be subject to numerous assaults, such as hostile nodes supplying misleading location information or manipulating with distance calculations. In trust-aware localization, the reliability of the information provided by individual nodes is considered during the

localization process. This involves analyzing the trustworthiness and credibility of the localization-related data, including distance measurements, and other required information.

2.4.Trust Management in WSNs: A trust management (TM) in WSNs is used to detect the malicious nodes in the network. It assists the network's nodes in making choices based on metrics or trust values. It mitigates the security threats. It increases the network's resilience. Traditional research work in WSNs is mostly based on the assumption of the trusted environment which may not be realistic in every application. The traditional research work in WSNs is mostly based on the assumption of the trusted environment, which may not be realistic in every application. The conventional methods of trust management that have due to their higher memory and power consumption, wireless ad hoc networks are not appropriate for use in WSNs. To increase the network's resilience and dependability, a lightweight trust management system is required. The taxonomy of the TM is presented in Fig. 2.5.

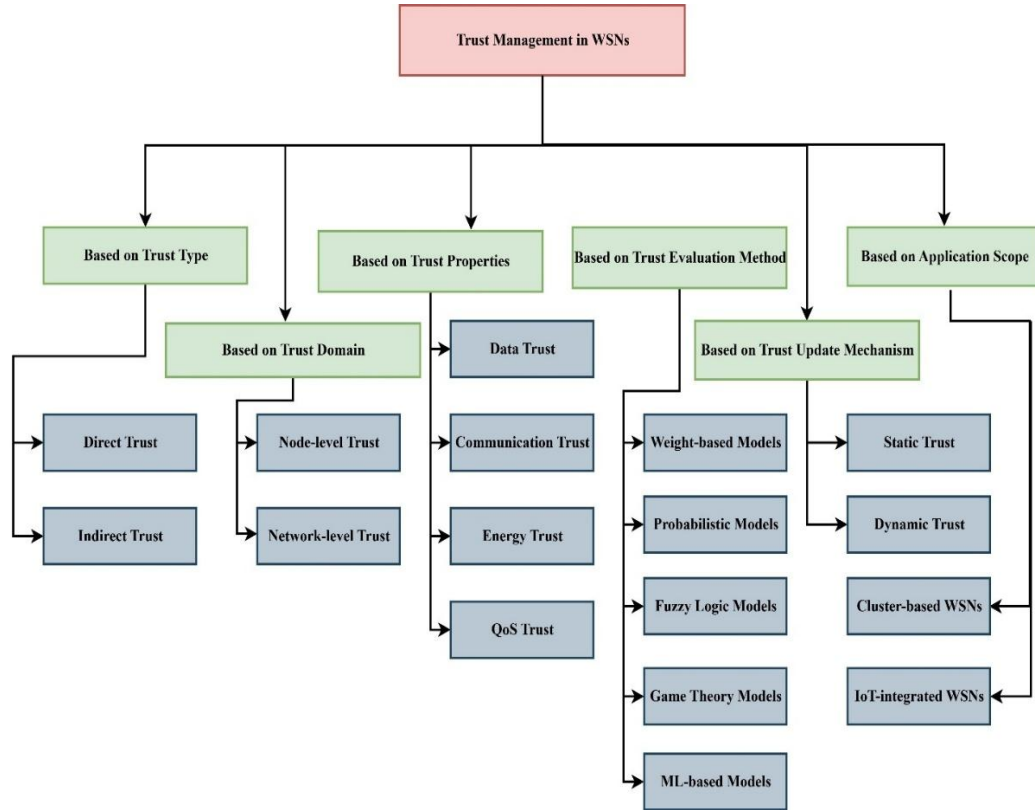


Fig. 2.5 Taxonomy of Trust Management in WSNs

Types of Attacks in TM: The most common attacks in trust management systems for WSNs are bad-mouthing attacks, on-off attacks, selective behavior attacks, Sybil attacks, and newcomer attacks.

Sinkhole Attack: Sinkhole attack belongs to DoS attacks in WSNs. The malicious node must appear to other nodes as attractive by presenting optimal routes to attract packets as much as possible to control most of the data circulating in the network. Thus, a malicious node creates a black hole in the network by acting as a base station by drawing data packets and stopping them from moving forward.

Flooding Attack: The goal of this attack is to shorten the lifespan of the network by causing a denial of service.

Sybil Attack: The malicious node has multiple identities behaves like a legitimate node and participates in communication.

Characteristics of TM in the WSNs: The characteristics of trust depend on type of networks and management algorithm used to mitigate the security issues arises in the hostile WSN networks. They are some common characteristics of trust as follows:

Dynamic: Depending on the nodes' successful and unsuccessful interactions, trust may increase or decrease over time.

Intransitive: Trust is not transitive. If node- N_1 trusts node N_2 , node N_2 trusts Node N_3 then node N_1 may not trusts on node N_3 .

Asymmetric: The trust score is based on the trust mechanism applied. Trust values of the nodes are distinct.

2.5.Taxonomy of MHOA: MHOA in WSNs is essential for improving several elements of network function, such as node localization, clustering, energy consumption, routing, network coverage, and data aggregation. These algorithms provide adaptable and effective solutions to complex optimization problems; here is a concise summary of meta-heuristic algorithms. The taxonomy of the MHOA is presented in Fig. 2.6.

Nature-inspired Optimization: MHOAs draw inspiration from natural phenomena or social behavior. They imitate the mechanism of natural selection, swarm intelligence, or other biological principles to systematically investigate the range of possible solutions and discover ones that are very close to being optimal.

Global Optimization: MHOAs differ from deterministic optimization techniques in that they avoid being trapped in local optima by exploring the whole solution space to locate global optima or solutions that are close to optimal. This is especially advantageous in WSNs because the structure of the network and the surroundings might undergo dynamic changes.

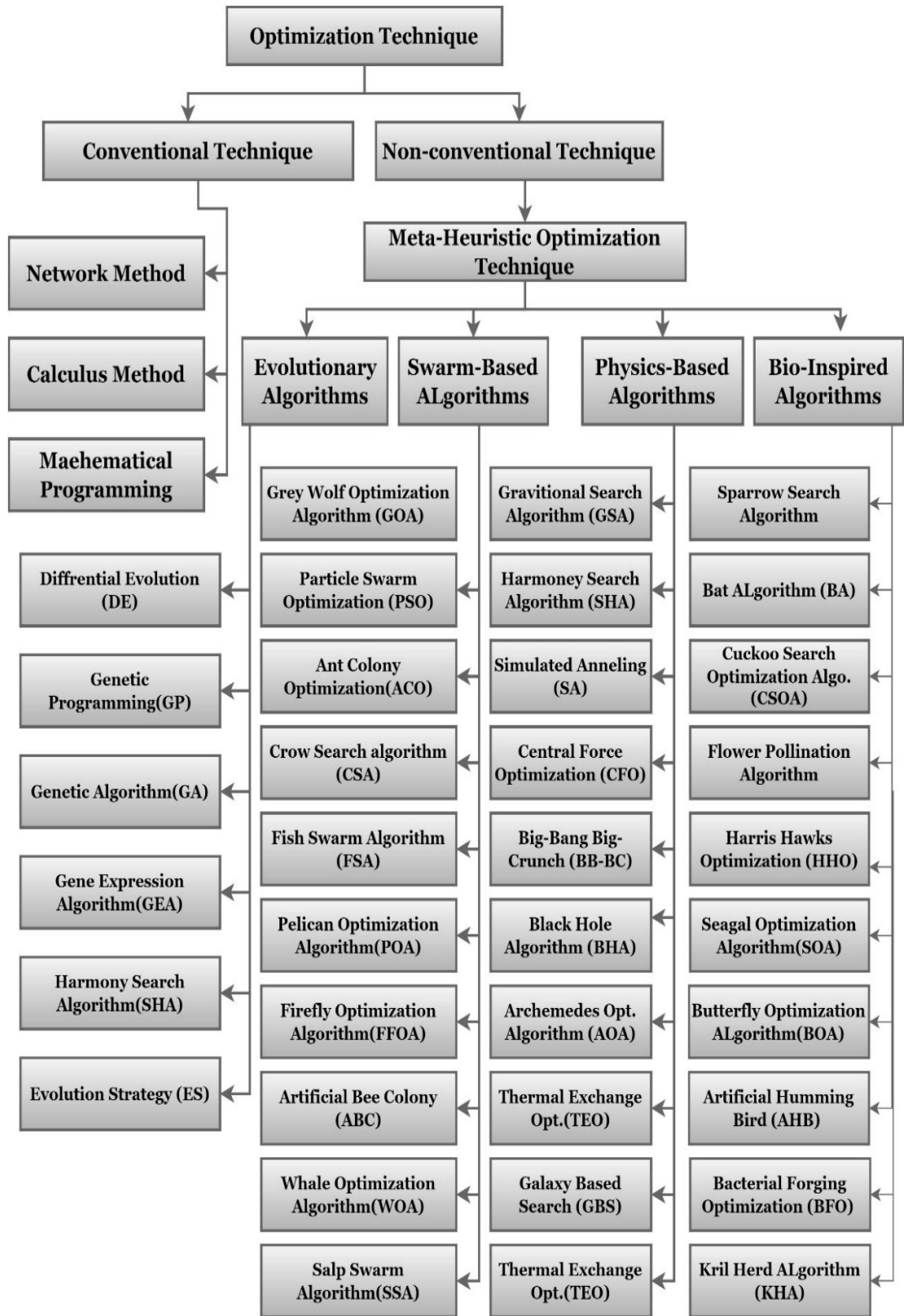


Fig 2.6 Taxonomy of MHOA

Adaptability: MHOAs reveal adaptation to several network settings. They can adapt their parameters or methods depending on real-time feedback, helping them to cope with changes in network topology, failures of nodes, or varying application requirements.

Efficiency: MHOAs are well known for their computational efficiency, making them suited for resource-constrained WSNs. They often require fewer computational resources compared to deterministic optimization algorithms, enabling them to be used on low-power sensors with limited processing capabilities.

Versatility: MHOAs can be applied to numerous optimization problems in WSNs, like node localization, energy-efficient routing, clustering, and data aggregation. Their adaptability makes them excellent for tackling varied issues faced by WSNs in diverse applications such as environmental monitoring, surveillance, healthcare, and industrial automation.

2.6. Seagal Optimization Algorithm (SOA): The mathematical model of SOA [13] mainly depends on exploration and exploitation. The exploration phase is accomplished with three conditions. Collision avoidance, movements toward the best neighbor's direction, and being close to the best search agent. To avoid collisions with other seagulls, variable A is employed to estimate the new position of the search agent(seagull) as follows:

$$C(t) = A * P(t); \quad (2.6)$$

where C(t) is the new position of the search agent and P(t) is the current position of the other search agent that does not collide with another search agent at iteration t. A represents the motion behavior of the search agent in each search space. A is a variable that represents the motion behavior of the search agent in each search space. The behavior of variable A is controlled using the frequency constant(fc) as shown in equ. (2.7). The value of fc is 2.

$$A = fc - t * \left(\frac{fc}{itrMax} \right) \quad (2.7)$$

where t is the iteration from 0 to itrMax, and the value of A decreases from fc to 0. Then search agent moves in the direction of the best solution as shown in equ. (2.8).

$$M(t) = B - P_{best}(t) - P(t) \quad (2.8)$$

where M(t) is the position of the search agent P(t) towards the best search agent PBest. B is a random number that balances the local and global search agents. B is estimated using equ. (2.9).

$$B = 2 * A^2 - rd \quad (2.9)$$

where the random number (rd) lies between 0 to 1. Now search agent moves in the direction of the best search agent as shown using equ. (2.10).

$$D(t) = M(t) + C(t) \quad (2.10)$$

where D(t) represents the best-fit search agent. The search agents can change the speed and angle for attacking the prey. While attacking the prey, the search agent moves in a spiral shape. The motion behavior of the agent 3-D planes is shown using equ. (2.11) as follows:

$$(x, y, z) = (r * \cos \theta, r * \sin \theta, r * \theta, \text{where } r = u * e^{\theta v}) \quad (2.11)$$

where the radius spiral is r and θ is a random angle between $[0, 2\pi]$. The correlation constants are u and v of the spiral shape, and e is the base of the natural logarithm. The attack position of the search agent is constantly updated using equ. (2.11).

$$P(t) = D(t) * x * y * z + p_{best}(t) \quad (2.12)$$

where P(t) saves the best solution and updates the position of other search agents.

2.7. Chaotic Maps: The meaning of chaos [14-20] is defined by properties of deterministic, nonlinear, semi-stochastic, and sensitive dependence. For best results, choosing the initial values carefully is crucial because chaotic maps are very sensitive to changes in the initial conditions. Chaos is the randomness of straightforward deterministic dynamic systems in mathematics, and chaotic systems can be thought of as sources of randomness. Chaos employs chaotic variables rather than random variables. Ergodicity and non-repetition are other valuable properties that enhance the search process. Chaotic can avoid reaching local maxima. Although the meta-heuristic optimization algorithm is robust, efficient, flexible, and very popular in the research community, it has a slow convergence speed. To improve the performance of the optimization scheme, the logistic chaotic map shown in Fig.2.7 is found to be more suitable out of the 10 chaotic maps shown in Table 2.2. Randomness is the basic property of the meta-heuristic optimization algorithms, which is modified using a chaotic map to improve the performance of the algorithm. A total 200 iterations are performed for the generation of the random number between 0 to 1.

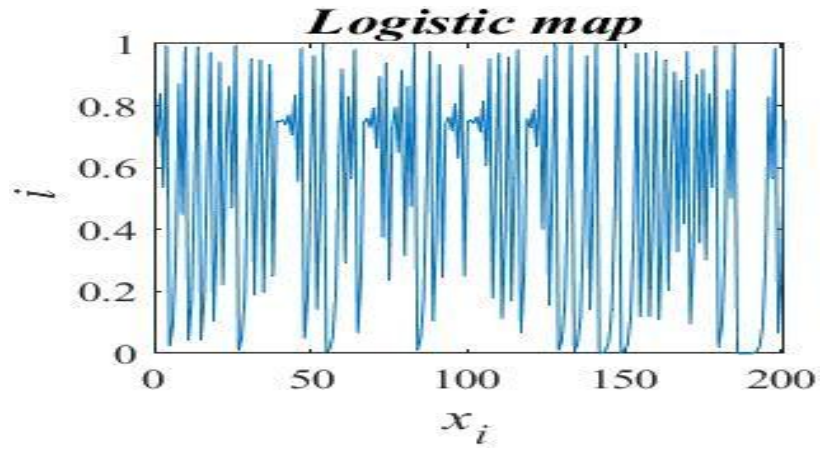


Fig. 2.7 Logistic map of the chaotic function

Table 2.2 List of Chaotic Maps

Sr.NO.	Name	Chaotic Map	Constant	Range
1	Tent map	$x_{i+1} = \begin{cases} \mu x_i, & \text{for } x_i < 0.5 \\ \mu(1 - x_i), & \text{for } x_i \geq 0.5 \end{cases}$	$\mu = 2$	(0,1)
2	Logistic map	$x_{i+1} = \frac{\mu}{4} x_i (1 - x_i)$	$0 \leq \mu \leq 4$	(0,1)
3	Sine map	$x_{i+1} = \frac{\mu}{4} \sin \pi x_i$	$0 < \mu \leq 4$	(0,1)
4	Kent map	$x_{i+1} = \begin{cases} \frac{x_i}{m}, & 0 < x_i < m \\ 1 - x_i, & m < x_i < 1 \end{cases}$	$0 < m < 1$	(0,1)
5	Circle map	$x_{i+1} = x_i + \mu - \frac{\tau}{2\pi} \sin 2\pi x_i \mod 1$	$\mu = 0.5, \tau = 0.2$	(0,1)
6	Cubic map	$x_{i+1} = cx_i(1 - x_i^2)$	$C=2.59$	(0,1)
7	Singer map	$x_{i+1} = \mu(7.86x_i - 23.31x_i^2 + 28.75x_i^3 - 13.3x_i^4)$	$0.9 \leq \mu \leq 1.08$	(0,1)
8	Gauss map	$x_{i+1} = \begin{cases} 1, & \text{if } x_i = 0 \\ \frac{1}{x_i \mod 1}, & \text{otherwise} \end{cases}$	$\mu = 6$	(0,1)
9	Square map	$x_{i+1} = (1 - \mu x_i^2)$	$\mu = 2$	
10	Sinusoidal map	$x_{i+1} = \alpha x_i^2 \sin \pi x_i$	$\alpha = 2.3$	(0,1)

2.8. Levy Flight: Levy flight is just a random walk with step lengths that adhere to the levy distribution, a probability distribution with a heavy tail depicted in Fig.2.8. Levy distribution is a series of small steps.

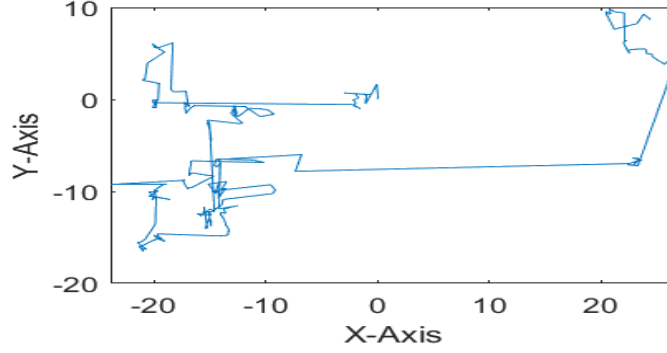


Fig.2.8 Randomness of Levy-light

When a walk is said to have a dimension more than once, the directions in which the steps are taken are isotropic. Lévy-flight can improve population diversity to speed up the convergence and reduce the local optimum. Better exploitation and exploration balance is made possible with the help of this strategy. A seagull follows the levy flight distribution. The levy flight can suddenly take a more extended step size.

$$p_i^{t+1} = p_i^t + \alpha \otimes \text{levy}(\lambda) \quad (2.13)$$

where p_i^{t+1} is the search agent's new position, p_i^t is the search agent's current position, α is the step size. The $\text{levy}(\lambda)$ is the levy exponent. The step size σ calculates how far a search agent can go for a fixed number of iterations. The step size affects the search agent's rate of convergence. The new position of the search agent would be very close to the present position if the step size is small, and it would be far from the current position if the step size is large. The step size of the levy flight is as follows.

$$\alpha = \frac{\sigma_u * u}{|v|^{\frac{1}{\beta}}} \quad (2.12)$$

where the variables u and v are stochastic. The values of the variables u and v , which follow the normal distribution, are as follows.

$$u = \text{rand} \cdot \sigma_u, 0 < u < \alpha_u^2 \quad (2.15)$$

$$v = \text{rand}, 0 < v < \alpha_v^2 \quad (2.16)$$

The standard deviation(σ_u) is as follows.

$$\sigma_u = \left(\frac{\gamma(1 + \beta) \cdot \sin\left(\pi \cdot \frac{\beta}{2}\right)}{\gamma\left(\frac{1 + \beta}{2}\right) \cdot \beta \cdot 2^{\frac{\beta-1}{2}}} \right)^{\frac{1}{\beta}} \quad (2.17)$$

The value of $\sigma_v=1$ and $\beta = 3/2$ are considered.

2.9.Literature Review: The literature survey is divided into three sections. The section-1 is a literature survey on optimized node localization, section-2 is the literature survey on cluster-based routing optimization, and section-3 is the literature survey on trust-aware optimized node localization. They are as follows:

2.9.1. Related Work on Node Localization: Yaming et al. [21] have proposed a scheme that is found suitable for environments where an offline calibration phase for the path-loss component is not feasible. The RSSI technique is used to estimate the distance between the anchor node (AN) and the target node (TN). The simulation results demonstrate that the suggested technique has a better NL accuracy than existing methods. The limitation of the proposed scheme is the same value of the path-loss exponent is taken for the different measurements which may affect the node localization accuracy. Ziwen et al. [22] have proposed a Multi-objective PSO for the NL. The localization accuracy and average node localization error are somewhat improved while the convergence rate is considerably improved. The performance parameters are convergence rate, node localization accuracy, and average node localization error. Sankalp et al [23] have proposed Butterfly Optimization Algorithm (BFOA) for NL. BFOA is compared with PSO and FFA. The performance of BFOA is better than PSO and FFOA. The trilateration method is used for distance computation between AN and TN but the value of the environment constant and Path loss component is not mentioned. The performance parameters are the mean of NL, mean of NL error, and mean of computation time. Mihoubi et al. [24] have proposed an RSSI-based Bat optimization algorithm (BOA) is used and the result obtained shows that the Bat algorithm is more efficient than PSO and DE. RSSI scheme is used for distance estimation between AN and TN but the value of environment constant and Path loss component is not mentioned. The performance parameters are mean NL error and mean NL time. The simulation result showed that the accuracy and convergence rate of the Bat algorithm is better than PSO and DE. Rajakumar et al. [25] have proposed a GWO algorithm for the simulation. To resolve the problems with the DV-Hop algorithm for NL, an improved DV-Hop method is proposed. The performance parameters NL accuracy, computation time, and minimum localization error are compared with PSO, and GWO. The convergence rate and NL accuracy are high as compared to the PSO and MBA, and NL error is low. Tu Li et al [26] have proposed a DV-HOP-based PSO algorithm. The chaotic map is hybridized to enhance the NL accuracy and minimize the computation delay. So many chaotic maps are available and a sine chaotic map is chosen for

simulations. It is not mentioned why only a sine map is chosen for it. The performance parameters are NL and NL Error. Huthaifa et al [27] have proposed an SSO algorithm for NL. Mean NL error, NL computation time, and the total number of nodes localized are the performance parameters of the proposed scheme. The NL accuracy is improved when the AN density increases concerning the number of TNs. The computation time for all localization methods is observed to grow as the number of TNs and ANs increases, although the SSOA has the fastest computation time when compared to PSO, BOA, FFA, and GWO. The performance of SSOA is better than BOA, FA, PSO, and GWO for all the performance parameters. Ju Liu et al. [28] have proposed a hybrid MCB-PSO algorithm for NL. The WSN environment is 3-dimensional. The anchor and target nodes are mobile. The convergence rate is improved. The main drawback of the MCB method is the random generation of node placements in an anchor box and there is no searching direction, which results in low localization efficiency and high computation time. The performance parameters are NL error and computation time. Ling Song et al. [29] have proposed the Monte Carlo NL algorithm which is hybridized with QUasi-Affine TRansformation Evolutionary (QUATRE) optimization. The advantage of the proposed algorithm is that only 30 anchor nodes are deployed for the localization of 320 target nodes, and the enhanced QUATRE optimization-based Monte Carlo NL scheme offers increased positioning accuracy and convergence rate. Although the proposed algorithm required some hardware still, the algorithm is cost-effective. Yeasir et al [30] have proposed a GWO-based compressive sensing (CS-GWO) algorithm. An energy-efficient bio-inspired NL algorithm and clustering algorithms are implemented in Unnamed Aerial Vehicles networks. The limitation of the proposed scheme is all sensor nodes are GPS enabled which consumes more power. The performance parameters are Node Localization, Mean Node Localization error, and clustering. Chuku et al. [31] have proposed utilizing outlier identification techniques to mitigate the impact of such disproportionately inaccurate distance estimates in RSSI-based location estimation. To effectively reduce node localization mistakes in shadowed environments, three distinct node localization methods are proposed that employ outlier identification. NL error is reduced in the proposed scheme. The distance between the AN and TN is estimated using RSSI of the RF signal but the environment constant and path loss component value is essential to the accuracy of node localization, the environment constant value lies between 2 to 5, and the fixed value of path loss exponent 2.3 is chosen without any calibration which may affect the NL accuracy. Pudi et al. [32] have designed Group Teaching Optimization Algorithm

(GTOA) for indoor NL. Comparative results of the GTOA are better than the PSO, krill herd algorithm (KHA), GWO, cuckoo search optimization (CSO), and firefly algorithm (FFA). The performance parameters are NL and NL Error. The KHA, PSO, CSO, GWO, and FFA-based NL algorithms have higher NL errors of 0.36, 0.57, 0.38, 0.53, and 0.51 respectively. The GTOA scheme for NL has achieved a reduced NL error of 0.16. Cheng et al [33] have proposed a DV-Hop-based Modified Archimedes optimization Algorithm (MAOA) for NL. The convergence speed is analyzed using 7 uni-modal and 6 multi-modal functions. NL of MAOA converges more quickly than DE and BOA. NL error is smaller than BOA, and DE. Rani et al. [34] have put out an NL topology for use in maritime search and rescue. RSSI-based SSA is proposed, RSSI algorithm is used to compute the distance between the AN and TN. The value of the environment constant and path loss component is essential to the accuracy of node localization and both values chosen for distance computation are not mentioned. SSA has 10% less NL error than BOA and PSO. The performance parameters are NL accuracy, localized nodes, NL errors, and computation time.

Table 2.3: Summery of the Related Work on Node Localization

Refer ence	Methodology/ Algorithm	Research Gap	Performance Parameter
[32]	GTOA	The optimization algorithm is mentioned only and the algorithm used for distance estimation between an anchor and target node is not mentioned.	NL, NL Error
[31]	RSSI	The RSSI method is used for distance estimation but the environment constant and path loss component value is essential to the accuracy of node localization and the constant value chosen lies between 2 to 5. The fixed value of path loss exponent 2.3 is chosen which may affect the NL accuracy.	Average NL errors and computation time
[30]	CS-GWO	All nodes are GPS enabled which consumes more power and cost-effective	NL, Mean NL error,

		approach.	
[29]	QUATRE	Required some hardware and not cost-effective.	NL accuracy, NL error
[28]	MCB, PSO	There is a defect in MCB algorithms. Because all the candidate positions are generated randomly in an anchor box, no searching direction exists, which makes the time cost quite high and localization efficiency low. It may not be suitable for high mobility requirements.	NL error, NL computation time
[27]	SSA	The NL is primarily needed and method used for NL is not mentioned.	NL accuracy, computation time and mean NL error
[25]	DV-HOP, PSO	So many chaotic maps are available and a sine chaotic map is chosen for simulations and it is not mentioned why only a sine map is chosen for it.	NL and NL Error
[33]	MAOA, DV-Hop	This paper only discussed the application of node localization based on the two-dimensional plane in WSNs.	Execution Time, Average NL error.
[24]	RSSI and Bat Algorithm	RSSI scheme is used for distance estimation between anchor node and target node but the value of environment constant and Path loss component value is not mentioned.	Mean NL error, mean NL time.
[23]	BFOA	The trilateration method is used for distance computation but the value of environment constant and Path loss component value is not mentioned.	Mean NL, mean NL error and mean computation time
[35]	WOA	Covered only single objective function and multi-objective function is not	Average cost function

		dissuaded.	and standard deviation
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2.9.2. Related Work on Cluster-based Routing Optimization: B. Pitchaimanickam1 and colleagues [36] introduced HFAPSO, a hybrid approach of FFOA and PSO to determine the optimal CH for the LEACH-C algorithm. Through integrating PSO, this method enhances the global search capability of Firefly. This methodology is evaluated based on throughput, RE, and active node count. Findings indicate prolonged network longevity, leading to reduced energy usage and augmented active/alive node count (ALNs). A HGWCSOA-OCHS was proposed by P. Subramanian et al. [37]. By balancing the living and dead sensors in the network, the AEC of the network has been reduced and the lifespan of the network has been increased. Sengathir J. et al. [38] introduced a hybrid modified ABC algorithm aimed at securing the clustering process against issues like slow convergence and premature convergence and avoiding trapping the system at the optimal point. The outcomes of HMABCFA demonstrate significant enhancements compared to standard benchmarks, with network lifespan, energy stability, and network latency showing improvements of 23.21%, 22.88%, and 19.84%, respectively. Yogarajan et al. [39] introduced an Ant Lion algorithm tailored for CHS, aimed at prolonging network lifespan through optimization techniques. Furthermore, they utilized a discrete antlion optimization approach to identify the shortest path for mobile tanks. Leveraging Ant Lion's selective optimization methods, the mobile receiver efficiently gathers data by visiting chosen CH nodes. Simulation findings demonstrate that the suggested clustering technique enhances both network throughput and lifespan. Zongshan Wang et al. [40] presented a clustering approach for CHS employing a modified ABC algorithm. This modified ABC algorithm, derived from the original ABC algorithm, addresses the clustering challenges in WSNs by considering factors such as CH energy, density, and location. Initially, all nodes in the network possess identical energy levels, but the modified ABC method maximizes the disparity among CH groups. The authors introduced an energy-efficient routing strategy based on enhanced ant colony optimization for paths between a central storage center and a BS. To enhance energy efficiency and overall network performance, they proposed a polling control mechanism based on active/inactive nodes during intra-cluster communication in the continuous transmission phase. The efficacy of the proposed approach was evaluated across various conditions, with simulation results demonstrating its superiority over several comparable methods. Chuan Xu et al. [41]

introduced a novel EE area source routing protocol named ER-SR, drawing inspiration from approaches in the power distribution field. In this protocol, the source routing node strategically selects the optimal path for each shared node, allowing partial node involvement in routing while ensuring balanced energy consumption across sensor nodes. To mitigate data transmission energy consumption, the authors proposed an effective remote ant colony optimization technique to identify the most efficient transmission paths for each node. Simulation outcomes demonstrate that ER-SR outperforms alternative routing protocols in WSNs regarding network lifespan, packet delivery rate, and delivery delay, indicating a notable enhancement in energy efficiency. Wei Xiang et al. [42] introduced a routing approach tailored for energy efficiency in Software-Defined Wireless Sensor Networks (SDWSN). They proposed a scheme where control nodes are dynamically designated for various tasks. Addressing the NP-hard nature of selecting control nodes based on transmission distance and RE nodes, they put forth a strategy grounded in particle swarm optimization. Evaluation results demonstrate the superiority of their method over contemporary comparison techniques across various simulation scenarios. Amit Sarkar et al. [43] introduced Firefly contributions and Firefly Cyclic Randomization (FCR) within the context of the CHS in WSN. This approach employs three distribution functions – Gamma, Normal, and Uniform distributions – to derive randomly generated solutions. The Firefly Cyclic Grey Wolf Optimization (FCGWO) is then examined by altering random Grey Wolf Optimization vectors. Both FCR and FCGWO algorithms are utilized to identify the optimal CHs, aiming to minimize energy stability, delay, and inter-node distances. Evaluation is conducted for each distribution, focusing on energy efficiency, active node count, and network longevity. Melaku Tamene Mekonnen et al. [44] put forward clustering methodologies employing PSO and simulated annealing algorithms to identify the most efficient set of CHs in the network and enhance its longevity by optimizing the distance between the sink node, RE and the individual nodes. Toolboxes for both SA and PSO have been created in C++ and seamlessly incorporated into the OMNeT++ simulation environment to implement these clustering strategies. The simulation assesses the performance of the algorithms in terms of energy conservation, load distribution, and overall network lifespan. Amit Sarkar et al. [45] introduced a firefly-based cyclic randomized method for selecting the most efficient CH, aiming to minimize energy consumption, delay, and inter-node distances to enhance the network's longevity. The efficiency of CHS using Firefly contributions was compared against ABC, FABC, GA, GSO, and Firefly algorithms which is much better than

existing schemes considered for comparative analysis. Mojgan Rayenizadeh et al. [46] introduced the Swarm Intelligence-based Hesitant Fuzzy (SIHF) system. Utilizing hesitant fuzzy values, the FFOA determines the optimal weight of nodes, while hesitant fuzzy logic aids in CHS. The SIHF system underwent comparison with SIF, LEACH, MODLEACH, and M-GEAR protocols across various scenarios. Results demonstrated that the SIHF protocol exhibited a lower energy depletion rate compared to other protocols, consequently extending the network's lifespan. Amit Sarkar et al. [47] introduced FCGWO for selecting the optimal CH. This method prioritizes energy stabilization, delay minimization, and node distance reduction. The performance of the FCGWO-based CH selection (CHS) was compared against conventional techniques such as GWO-based CHS, FFOA), ABC, Half-Altered Artificial Bee Colony (FABC), Group Search Optimization (GSO), GA, and FFOA with Cyclic Randomization (FCR). Simulation results indicate that the proposed CHS approach is more effective in prolonging the network's lifecycle. B.N. Priyanka et al. [48] introduced a method for enhancing network longevity by implementing circular sectorization in WSN along with dynamic CHS using the WOA. Their proposed model suggests that achieving relatively balanced energy consumption is feasible in circular WSNs through sectorization. The effectiveness of this approach is evaluated by comparing it with the PSO and LEACH protocols. Deena Sivakumar et al. [49] utilized a Chaotic Gorilla Troops Optimization Algorithm (EACP-CGTOA) model to introduce an energy-conscious clustering technique characterized by high convergence rate and sensitivity. The EACP-CGTOA model incorporates three input parameters – energy ratio (ER), distance to BS, and distance to neighbor nodes – to formulate a fitness function. Numerous simulations were conducted to validate the improved performance of the EACP-CGTOA approach, with the outcomes analyzed from various perspectives. Experimental results demonstrated that the EACP-CGTOA model outperforms existing methods significantly in terms of energy efficiency and network longevity. Zongshan Wang et al. [50] introduced EECRAIFA, a cluster-based routing methodology. Initially, network nodes undergo clustering using a Self-Organizing Map neural network to determine optimal CHs. Subsequently, the FFOA is applied to optimize clustering by incorporating CH energy and average distance within clusters. FFOA defines the decision domain to further disperse CHs and create more suitable clusters. For inter-cluster routing, an advanced ACO is employed, incorporating the statistical variation coefficient in pheromone update and optimizing paths based on distance and energy. Moreover, a polling control strategy based on busy/idle nodes is integrated to enhance network throughput during

intra-cluster communication. Simulation experiments demonstrate that EECRAIFA effectively manages network energy consumption across various application scenarios, leading to increased throughput and extended network lifespan. Kathioli Panimalar et al. [51] introduced a solution to address the energy efficiency challenge in WSNs through CHS, combining a Differential Evolution algorithm with a hybrid Sparrow Search method. Node longevity is enhanced by leveraging the effective Sparrow Search Algorithm and the dynamic capability of Differential Evolution. This hybrid approach optimizes performance based on throughput, RE, and the quantity of active and inactive nodes. The proposed modified Sparrow search technique exhibits improvements in residual power and throughput compared to previous algorithms, utilizing the differential evolution model to identify the most suitable CHs. Within the framework of a WSN, Wang et al. [52] presented a cluster-based routing protocol and scrutinized the advantages and disadvantages of the LEACH protocol. The researchers juxtaposed the results with those of the existing LEACH methodology and proposed a refined iteration named LEACH-Impt. Enhanced performance in CHS, specialized node handling, and inter-cluster routing challenges are observed with LEACH-Impt compared to traditional LEACH. Sariga Arjunan et al. [53] enhanced network longevity through the proposal of an ACO-based routing scheme coupled with fuzzy logic-driven Cluster Head (CH) size adjustment. The endeavor encompasses cluster maintenance, inter-cluster routing, and CH selection. Employing a fuzzy-based technique, the network is partitioned into heterogeneous clusters, selecting CHs based on criteria such as node centrality, node degree, distance to BS, and distance to Cluster Members (CMs). Integration of ACO with suitable Forwarding Factors facilitates data transmission to the BS via inter-cluster routing. This method employs both proactive and reactive routing approaches, utilizing the shortest path to transmit data to the BS while maintaining load balance through threshold-based data transfer. Madhusudhanan Baskaran et al. [54] introduced a variant of FFOA termed synchronous FFOA to enhance network longevity. Simulation results reveal a 9.63% average reduction in packet loss ratio compared to EEHC and LEACH, indicating an improvement in network lifespan. Jin Duan et al. [55] introduced an enhanced version of the Population-based Optimization Algorithm (EPOA) for CHS (EPOA-CHS). The population initialization is carried out using the logistic-sine chaotic map, and a unique fitness function is adopted to facilitate suitable Cluster Head Selection (CHS), which is further hybridized with Levy flight for CH selection. The network's performance is evaluated based on metrics such as RE, network lifespan, and network throughput. Adumbabu et al. [56]

introduced an energy-efficient dynamic CHS and routing strategy employing ICOA and IJO-LF for CHS and routing, respectively. The performance of this proposed approach surpasses that of PEGASIS and TEEN concerning metrics such as energy consumption, ALNs, and dead nodes. Jing Li et al. [57] proposed a clustered routing technique named ODTD-LI. Comparative simulation results against EEICS, PEDAP, GIT, and LEACH illustrate superior performance in terms of network lifetime, average delay, and coverage rate with the suggested system. Uma Meena et al. [58] introduced a CHS method named EEYSGPO. This method considers parameters such as RE, communication quality, load, delay, and distance in CHS decisions. Simulation results indicate that EEYSGPO outperforms SSMOECHS, LEACH-PRO, EECHIGWO, and FGWSTERP in terms of throughput, number of dead nodes, and energy consumption.

Table 2.4 Summary of the Related Works on Cluster-based Routing Optimization

Reference	Algorithm (s)	Objective(s)	Performance Parameter(s)	Achievement(s)	Limitation(s)
[36]	FFOA with PSO and LEACH-C	To find the optimal CH using energy-efficient MHOA.	ANLs, RE, and throughput	Improvement in network life, ANLs, and reduced energy consumption.	LEACH-C is not a MHOA and compare with MHOAs.
[37]	HGWCSO A-OCHS	to enhance network life and reduce energy consumption.	RE, network life, ALNs, dead nodes.	The mean RE performs better than the other clustering methods.	Under different sink placements, the suggested HGWCSOA-OCHS-mean residual energy remains unaltered. The result is not verified.
[38]	HABC and FFOA	An energy-efficient approach to find the CH	ALNs, RE, FND, HND, and LND, network	Compared to the benchmarked techniques, the HMABCFA	Table 2 and 3 listed secure nodes but no description about

		using HABC and FFOA and improve the network life.	life, throughput.	improves energy stability by 19.84%, average network life by 23.21%, and reduces network latency by 22.88%.	the security is mentioned the paper.
[39]	ALOA and DALOA	Optimized CHS and routing	Lifetime of the nodes.	The network life is improved by 13% compared to existing.	Authors stated that the model is suitable for large scale network, but simulation is carried out with maximum 100 nodes.
[40]	Improved ABC	Design an optimal CHS using ABC and energy EE routing.	Network lifetime, average energy consumption, throughput, and network stabilization time.	Energy efficient CHS is implemented.	Limited scalability, and static environment assumption.
[41]	ER-SR	To select EE nodes using ER-SR algorithm for	Energy efficiency is higher in ER-SR.	According to simulation studies, ER-SR has greater energy efficiency.	In comparison to current routing systems, performance gains on the network lifetime,

					PDR, and delivery delay are moderate.
[42]	SDWSN	Routing	ALNs, FND.	Energy efficient	Area is 100x100 meters only and SNs are 300 to 600 which is not cost effective.
[43]	FCR and FCGWO	CHS	ALNs, AE, and network lifetime.	The FCGWO and FCR schemes had attained 59 and 58 ALNs out of 100 SNs respectively.	Area of the sensor field is not mentioned which is needed for better analysis.
[44]	Simulated Annealing and PSO	CHS	ALNs, Energy consumption.	Improve Network life and load balancing.	All node dead after 800 rounds of operations which is very less.
[45]	FCR	CHS and Routing	ALNs, Energy consumption, CHs, and network lifetime.	The proposed FCR scheme has outperformed the conventional CHS.	It is not clear from the simulation result that when last node is dead.
[46]	Hesitant fuzzy and FFOA	CHS	FND, LND, HND, and packets delivered to the BS.	Network life is improved using clustering method.	Fitness function is based on only FND, HND, and LND.
[47]	FFOA and GOA	Optimal CHS	Normalized network	The FCGWO method has better	The no of ANs in the proposed

			energy, alive node.	energy stabilization and run till 2000 rounds.	scheme is like other existing methods chosen.
[48]	WOA	CHS	RE and delay.	Energy efficient, dynamic CHS model is proposed.	An initial energy of WOA, PSO and LEACH are 50jules, 75 Jules and 100 Joules each over a coverage area of 600×600 meters which is too high energy for WSNs.
[49]	Chaotic gorilla troops optimization algorithm	CHS	ALNs, Average throughput, residual energy, and communication overheads.	Energy efficient CHS.	The sensor field is 400*400 square meters the total SNs are 1000 and node density is high and not cost effective.
[50]	FFOA AND ACO	Cluster based Routing to improve the network energy consumption, lifetime, and throughput.	RE, Network stability period, and throughput.	Energy efficient CHS and routing.	An initial energy of the nodes was considered 50 Jules which is high in case of WSNs.

[51]	Sparrow Search Algorithm	CHS	ALNs, RE, dead nodes, delay, and mean throughput.	CH stability is high.	The BS positions are (100,200) and (200,100) which are very similar.
[52]	LEACH_IMP	Comparative analysis of LEACH and LEACH-IMP in CHS and Routing.	Data transmission rate, energy consumption, and dead nodes.	LEACH-IMP is found much better than LEACH.	Simulated on static network.
[53]	Fuzzy and ACO	Fuzzy based CHS and ACO based routing.	ALNs, FND, LND, AEC, Total packets received by BS.	Improved network lifetime.	SNs and BS are static.
[54]	FFOA	CHS	Residual energy, alive node.	Improved network lifetime.	Only Residual energy, alive node are the performance parameters analyzed.
[55]	Enhanced POA	CHS	ALNs, Packet delivered to BS, and dead node.	Improve network life.	The fitness function includes only distance and energy parameters. Other parameters like node degree and centrality

					needed to be included to make the better FF.
[56]	ICOA and IJOA with Levy Flight (IJO-LF)	Energy efficient CHS and routing.	ALNs, AEC, and network life. PDR, throughput, and routing overhead.	The proposed method performs better than TEEN and PEGASIS.	Then BS is dynamic but movement is not defined.
[57]	ODTD-LI	Energy efficient CHS and routing.	Average delay, network lifetime, coverage rate, and network load balance.	The energy consumption is low in the ODTD-LI algorithm.	It is stated that the network contains no attack nodes but the mechanism used for protection is not mention in the proposed work.
[58]	<i>YSGA and POA</i>	CHS, and Energy efficient routing using POA.	network stability, dead node, throughput, and AEC.	Energy efficient CHS and Optimal route is selection is performed using POA.	The <i>FF</i> is designed based on the energy and distance between BS and CH. Other dependent factors like Node centrality and density are not considered for <i>FF</i> .

2.9.3. Related Work on Trust-aware Node Localization: The authors propose various trust-aware NL schemes for WSNs that considers trustworthy nodes to improve the NL accuracy

and reliability. The scheme uses a trust-based model on the behavior of nodes in the network and incorporates it into the localization algorithm. Po-Jen et al. [59] proposed a novel neural network-based NL strategy that improves both NL accuracy and success rates. By using correlated topology-trained data and online training, the novel technique has made the trained network model relevant to the topology, allowing for a more effective application of neural networks and more precise inter-node distance estimates. Pooyan et al. [60] proposed an RSSI-based Bayesian localization scheme for precision agriculture to solve the approximate inference issue. Bayesian and non-Bayesian distributed techniques suffer from the communication overhead and require a loop-free graph to reduce the overhead. proposed a new scheme to estimate only the local distance between nodes. The message is not broadcasted to all neighboring nodes and is passed the message to only a limited node. The computational complexity of the node at each iteration is low. Yuan et al. [61] proposed a unique lightweight Sybil-free APIT scheme based on RSSI to reduce the sybil attack in the node localization scheme. The Performance parameters are node localization accuracy, mean node localization error, and Sybil attack detection rate. The scheme is efficient for localization. But the limitation of the proposed schemes is only Sybil attack is considered during the localization and other attacks like badmouthing, on-off, wormhole, flooding, collusion, sinkhole, ballot-stuffing, and desynchronization attacks are possible in WSNs. Jingsha et al [62] proposed a reputation-based security model to enhance node localization's security and accuracy in hostile environments. Each anchor node's reputation is assessed using an assessment model so that TNs can obtain credible location information from highly trustworthy anchor nodes. Daojing et al [63] proposed a single and round-trip distance estimation algorithm and implemented an attack-resistant and efficient node localization scheme. The performance parameters are Node Localization and attacks. The work does not address the validation of the security of an attack-driven strategy constructed using Petri Net. Ning et al. [64] proposed a lightweight secure localization scheme is proposed. The ToA method is used to estimate the distance between the beacon node and the TNs. The proposed scheme reduces communication overheads and improves the security level. Both internal attacks and external attacks are addressed in the scheme. Although comparative analysis is done between communication overhead and anchor node localization accuracy is not mentioned. Jiang et al. [65] proposed an Efficient Distributed Trust Model (EDTM) algorithm. The direct and recommendation trusts are computed then communication trust, energy trust, and data trust. Furthermore, trust dependability and familiarity have been

defined to increase suggestion trust accuracy. The authors present some simulation results; however, they are confined to a small-scale network scenario and do not provide a comprehensive study of the model's performance under diverse network circumstances or attack scenarios. Even though the proposed trust model enhances security, the work lacks a full investigation of its security features and does not go through potential vulnerabilities, attack vectors, or defenses against malicious nodes in depth. The performance parameter area distributed trust model vs node behavioral strategies banding belief theory of the trust evaluation, detection rates, and energy consumption. Desai et al. [66] proposed a challenge-answer model that is used by a source node to determine the trustworthiness of a destination node by comparing the destination's response to the source's challenge. The self-scrutiny algorithm is used to maintain the integrity of the system memory in a node. The limitation of the proposed work is the use of read-only memory is a critical condition for the legitimacy of this work and homogenous OS is mandatory in the entire network. The performance parameters are the average energy consumed and the average time taken. Sina et al. [67] proposed ROA which exhibits exploration and exploitation characteristics. The ROA was inspired by the raccoon's propensity to evade predators while in quest of food. To improve the search process, the algorithm includes methods for exploration and exploitation. The authors compare ROA with several optimization techniques, including the artificial bee colony (ABC) algorithm, genetic algorithm (GA), and particle swarm optimization (PSO). then run tests on several benchmark functions, and then evaluate the outcomes based on the rate of convergence and the quality of the solutions. According to the experimental findings, the ROA surpasses the examined algorithms in terms of convergence speed and solution quality. Reddy et al. [68] designed an energy-efficient algorithm for NL. Krill Herd optimization (KHO) algorithm is used for the optimization of the NL. The crossover and mutation genetic operators are used to modify the optimization algorithm. The performance parameters are NL error, root mean square error, propagation error, and mean absolute error which are compared with the PSO algorithm. the performance of KHO is much better than PSO.

Table 2.5 Summary of the Related Work on Trust-aware Node Localization

Reference	Algorithm(s)/ Model(s)	Performance Parameter(s)	Limitation(s)
[60]	DV-hop-based localization against Sybil attack.	Mean localization error Vs anchor nodes, Mean localization error Vs Number of fake nodes.	The proposed scheme did not discuss about localization accuracy and error.
[61]	SF-APIT.	Mean localization error, Attack Detection Rate, Localization accuracy.	The number of target nodes used in the localization and error detection is not specified.
[69]	Trust based Localization Technique (TLB).	Attack Detection Rate, Throughput, Control overhead.	ECDSA cryptographic algorithm is used for key sharing which has more computation overhead.
[62]	Reputation-Based Secure Localization.	Localization error, Mean localization error vs computation time, Mean localization error vs anchor nodes.	RSSI based Localization is used but what value of environment constant is used is not discussed. The value of the constant varies between 2 to 5.
[64]	Secure ToA-based localization.	Probability of detecting attack, Communication overhead vs Anchor node, Communication overhead vs Time.	The proposed scheme did not discuss about localization accuracy and error.
[70]	RSSI and PSO-based secure localization against independent and Collusion attack.	Average Localization error Vs number of malicious nodes, localization rate Vs number of malicious node, Average Localization error Vs Noise intensity, Average Localization rate Vs Noise intensity.	RSSI based Localization is used but what value of environment constant is used is not discussed. The value of the constant varies between 2 to 5.

[71]	Wormhole attack aware localization using DV-hop.	Localization error vs anchor node density, infected anchor node detected, Localization error vs communication range.	The localization accuracy is an important performance parameter which is not discussed in the result analysis section.
[72]	Alternating direction method of multipliers (ADMM)	Root Mean Square Error Vs number of Anchor nodes, Probability of correct detection, Probability of False Detection.	The anchor nodes are just double of the malicious nodes but target node used in the proposed model is not mentioned.

The authors have developed mostly blockchains-based secure and reliable localization schemes which are not energy-efficient because of computational and communicational overheads. The main motive of the proposed work is to model a light-weight secure and reliable localization.

2.10. Research Gap: The extensive literature survey is carried out on node localization, Clustered-Routing Optimization, and Trust-aware Node Localization listed and summary is listed in the Table 2.3, 2.4, and 2.5. The research gaps identified are as follows:

Node Localization accuracy: The accuracy of the localization is still poor due to the path loss component and environment constant, which are not calibrated and whose values were chosen based on some assumptions. Authors have proposed numerous node-positing methods and meta-heuristic optimization schemes for accurate target node location. Appropriate path loss components and an environment constant are needed to enhance node localization. To further enhance NL, the meta-heuristic algorithm needs to be modified.

Energy-Efficient Clustered-Clustering: The extensive literature survey is carried out on cluster head selection and routing schemes employed in WSNs, and presenting a detailed summary of their limitations, features and functionalities listed in Table 2.4. Some protocols emphasize energy-efficient routing strategies, others emphasize load balancing and enhancing network stability. The various gaps are identified within the existing literature that our proposed protocol endeavors to address the issues. These gaps include areas such as comprehensive integration of energy-efficiency, load balancing, adaptation to dynamic network conditions, and effective handling of heterogeneous node environments. The proposed protocol seeks to bridge these gaps and offer advancements in cluster head selection and routing methodologies within WSNs.

Security Vulnerability: The malicious nodes are challenging in the hostile environment of node localization in WSNs. Authors have been used cryptographic algorithm for the security which have high computational and communicational overheads. Trust is rarely integrated in WSNs.

Lack of Multi-objective Optimization Models: The metaheuristic algorithms are problem dependent. The performance depends on a fitness function modeled and applied in the suitable optimization algorithm. The multi-objective optimization models require combining energy, node density, node centrality, distance between nodes which are challenging.

2.11. Research Objectives: In order to improve localization accuracy and network life, following objectives are set.

- To design an optimization scheme for node localization.
- To develop an optimized energy-aware routing for WSNs.
- To propose a trust management scheme for node localization in WSNs.

2.12. Summary: The extensive literature survey is carried out in the area of distributed localization. The role of the MHOA in localization is studied. The performance of any MHOA depends on how the objective function is modeled. An optimization scheme is modeled for the node localization. A modified SOA algorithm is used to improve the performance of the proposed scheme.

An extensive literature survey in the area of cluster-based routing is carried out to find the major challenges. The energy-efficient routing is still a big challenge in WSNs. An energy-efficient clustered-routing scheme is proposed to mitigate the issues.

Security is a major challenge in node localization. The finding of the literature survey shows that the cryptographic algorithm-based secure node localization suffers from the computation and communication overheads. A trust-based mechanism is proposed to perform a secure localization. For further enhancement of the localization error, a suitable MHOA is proposed.

CHAPTER-3

DESIGN AN OPTIMIZATION SCHEME FOR NODE LOCALIZATION

3.1. Node Localization Optimization: In this chapter, an optimization scheme for node localization in WSNs using the Received Signal Strength Indicator (RSSI)-based method and Seagal optimization algorithm (SOA) is modeled using a suitable fitness function. Chaotic and Lévy flight are used for randomization purposes to optimize the localization scheme. The precise localization of sensor nodes has a substantial impact on the functioning of WSNs. The process of determining the precise locations of the sensor nodes in WSNs is known as node localization. Despite being a very common positioning technology, GPS-enabled sensor nodes have a high energy consumption, making them unsuitable for NL in WSNs. The accuracy of NL is impacted by numerous variables; they are the network design, the density of anchor nodes, and the measuring area's geometric shape. The localization schemes can be broadly categorized into centralized and distributed. Range-free and range-based are the distributed localization schemes. The accuracy of the range-based localization is low as compared to range-free localization schemes. The position of the target nodes using range-based localization is estimated. Range-based schemes perform the localization using either distance or angle. The RSSI is the most widely used technique for estimating node position using node distance. Other location-aware strategies include triangulation, angle of arrival (AoA), time difference of arrival (TDoA), time of arrival (ToA), and maximum likelihood (ML). To improve the accuracy of localization, a meta-heuristic optimization algorithm is modelled using a suitable fitness function.

The following are the major contributions of the current article:

- The existing SOA algorithms are modified using a chaotic map and levy flight schemes. The modified metaheuristic algorithms, namely C-SOA and LF-SOA, have been used for NL optimization.
- In C-SOA, ten different chaotic maps have been chosen for the performance test. Out of these, the logistic map was found to be best suitable for exploration.
- In LF-SOA, exploration power is provided by the levy-flight distribution.

- Comparative analysis among SOA, C-SOA, and LF-SOA is performed.

3.2. SOA based-Proposed Model: The general architecture of the proposed model is shown in Fig. 3.1. The proposed model is the enhancement of the Seagull Optimization Algorithm using a suitable fitness function. The SOA has the drawbacks of a slow convergence rate, entrapment in local minima, and skipping real solutions throughout the optimization process. The standard SOA has been modified based on two mathematical techniques: Lévy flight and chaos theory. The chaotic map is used for the randomization of the sensor nodes. The local optima problem can be solved with the help of the Levy distributions. Infinite variance and changeable step size, which broadens the search process's scope and diversity.

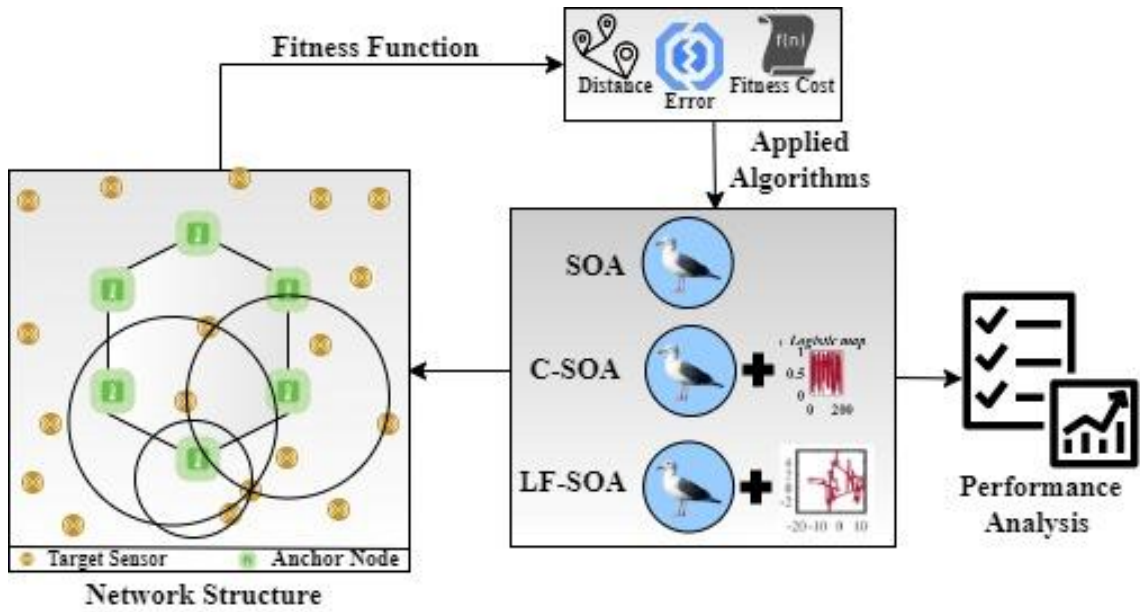


Fig. 3.1 Architecture of NL using SOA, C-SOA, and LF-SOA in WSNs

Metaheuristic optimization algorithms are problem-independent optimization algorithms. The SOA is a meta-heuristic algorithm shown in Algorithm 1. Seagulls live in colonies; the seagull's migration patterns and attacking behaviors serve as inspiration for the seagull optimization scheme. The migration and attacking behavior of the seagull is mathematically modeled with the exploration and exploitation phase. It has been accounted for in various research work that exploration is essential for addressing optimization issues. The migration and attacking behavior of seagull birds are modeled to estimate the target nodes. In the exploration phase, seagulls are moving and changing their position and finding the best position. In the exploitation phase, seagulls attack the prey. The existing SOA algorithm is based on a random number. Although SOA has a global exploration potential, it has drawbacks such as late convergence and a tendency

to get stuck in local optima. That is why SOA is modified using a chaotic map and levy flight. The comparative performance analysis among the SOA, C-SOA, and LF-SOA is performed, and according to experimental findings, the LF-SOA greatly outperforms the SOA and C-SOA in terms of NL accuracy, and NL time.

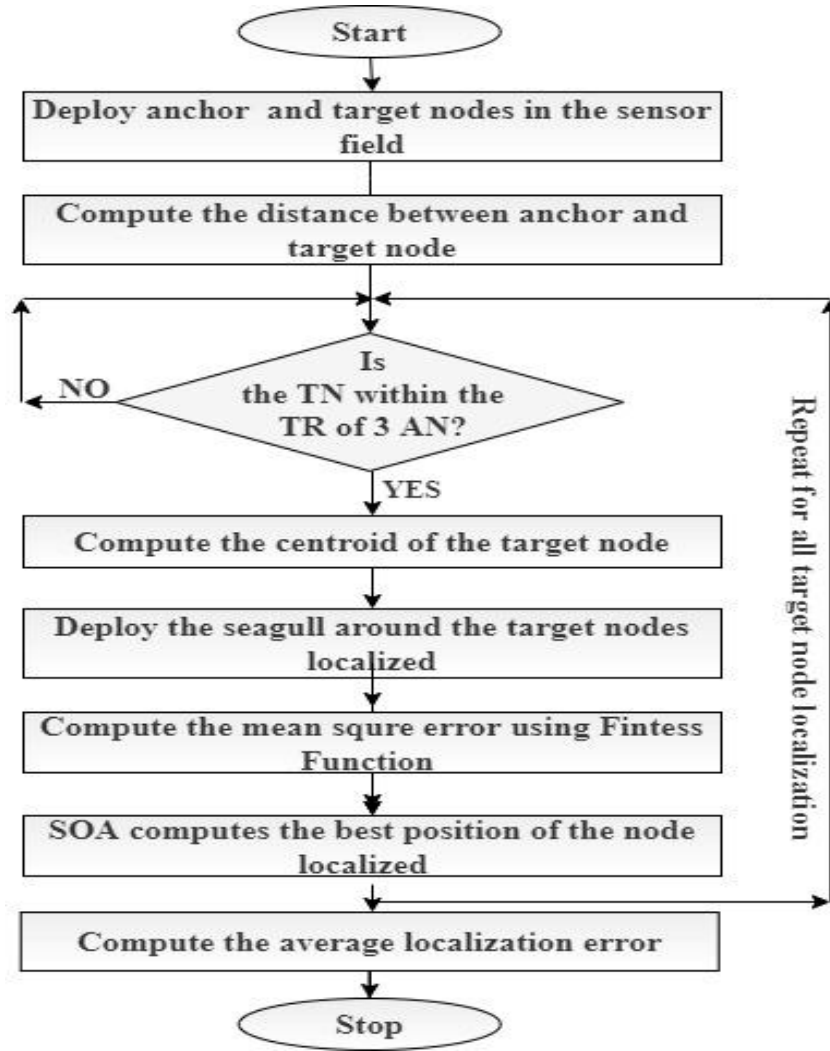


Fig. 3.2 Flowchart for Localization Using SOA in WSNs

3.2.1. Proposed Chaotic Map-based SOA(C-SOA): The target and anchor nodes are deployed in the environment using a chaotic pseudo-random number generation technique. The fitness value of each search agent (seagull) is estimated using the fitness function. Estimate the distance between the search agent and target node. Update the position of the seagull till the target node is not localized. Fig. 3.3 shows the pseudo-code of C-SOA.

Algorithm-3.1: Chaotic map-based Seagull Optimization Algorithm (C-SOA)

Input: Ps is the seagull population using chaotic pseudo-random number (c_r)

Output: p_{best} is the best position for the search agent (seagull)

1. Random initialization of $P(t)$, B , and Maximum_ iteration
2. Set the value of the $fc=2$, $u=1$, and $v=1$, $t=0$.
3. **While** ($t < \text{Maximum_Iteration}$)
4. { Compute the Fitness value (P_t) of each seagull to choose the current best
5. Generate the random number(rd)= $(0, 1)$
6. Generate the random number(θ)= $(0, 2\pi)$
7. Compute $r = u * e^{\theta v}$
8. Estimate the distance ($D(t)$)
9. Estimate the new position (p_{best})
10. Update the position of the optimal seagull along with c_r and fitness value
11. $t=t+1$;
12. } **End while**
13. **Output:** Best position (p_{best}) of the seagull and fitness value.

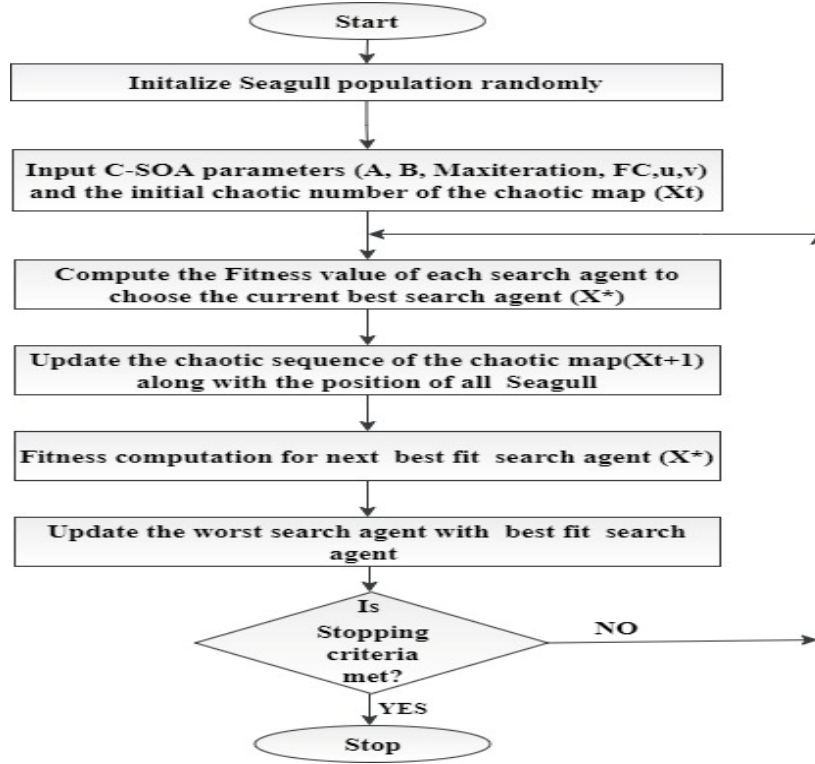


Fig.3.3: Flowchart for C-SOA-based Localization in WSNs

3.2.2. Proposed Levy flight for the SOA (LF-SOA): In Levy flight, there is a broad distribution of a single step of lengths, but each step is in the random direction, where the most extended single step of another random walk can dominate the random walk after many steps. Levy flight is a mathematical algorithm that mimics seagull hunting behavior. Lévy-flight distribution has been embedded with the seagull optimization algorithm. The most effective method to arbitrarily search for a target in an environment is represented by Lévy flights. The proposed algorithm name is LF-SOA, shown in Fig. 3.4.

Algorithm 3.2: Levy Flight-based Seagull Optimization Algorithm (LF-SOA)
Input: Ps is the seagull population deployed using levy flight. Output: Pbs is the best position for the search agent (seagull). Random initialization of $P(t)$, B, and Maximum_ Iteration Set the value of the $fc=2$, $u=1$, and $v=1$, $t=0$. While ($t < \text{Maximum_ Iteration}$) { Compute the Fitness value(P_t) of each seagull to choose the current best Generate the random number(rd)=$(0, 1)$

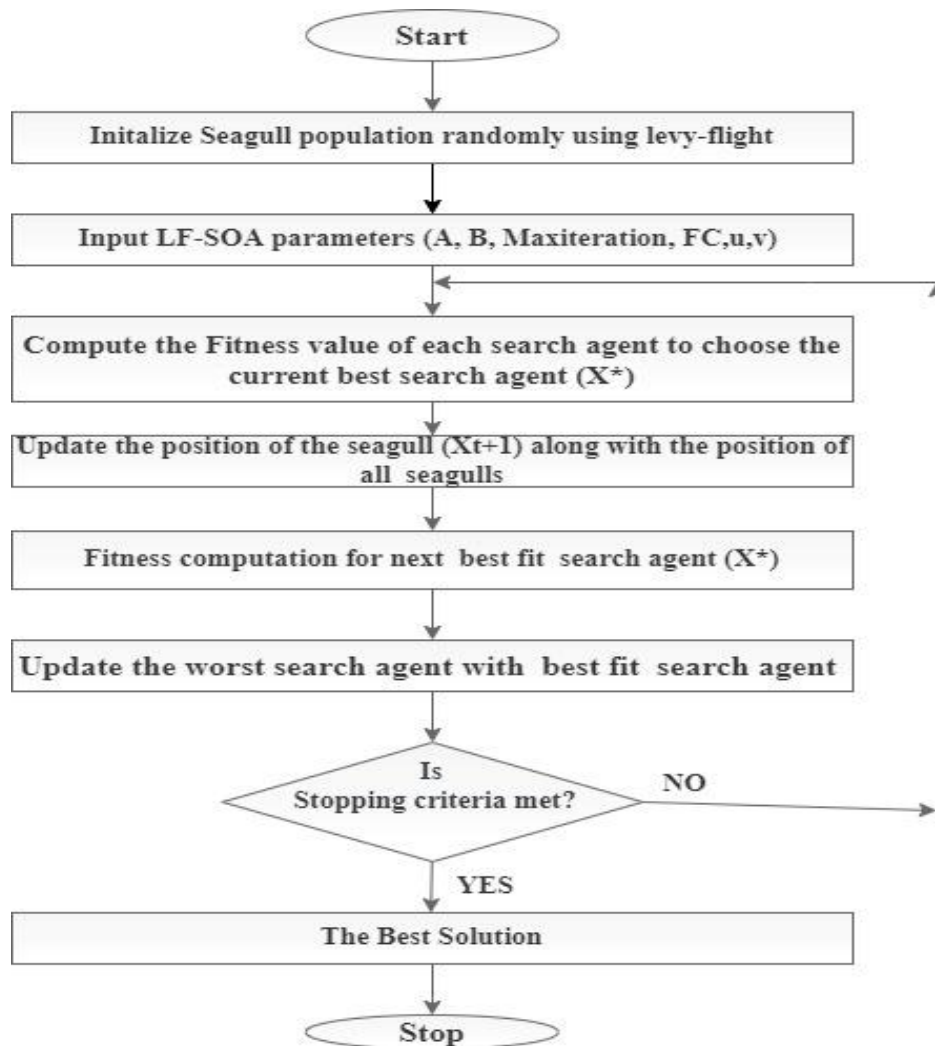
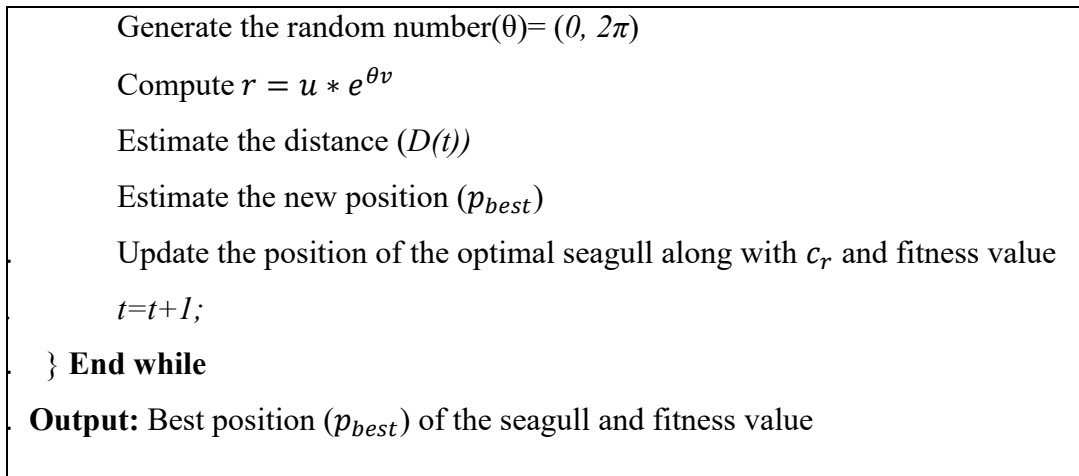


Fig. 3.4 Flowchart for LF-SOA-based Localization in WSNs

The Sensor nodes are deployed in the environment randomly. The fitness value of each search agent is estimated. Estimate the distance between the search agent and TN, and change the

position of the search agent till the nodes are not localized. Algorithm 3.2 shows the pseudo-code of the LF-SOA.

3.2.3. Methodology of Node Localization Optimization: The architecture of the NL is shown in Fig.3.3. The main objective is to find the location of the unknown nodes. There are two steps in range-based localization. the first step is estimating the distance between AN and TN and second step is estimating location of the unknown nodes/target node (TN). Each TN estimates its distance from the ANs using the RSSI value. Then, the location of the target nodes is estimated using the distance measured between the AN and the TN. It can be done using either a geometric approach or an optimization algorithm. Several metaheuristic methodologies have been introduced to address the NL problems. The following process is being used for the NL.

Step1. Anchor (AN) and target nodes (TNs) randomly deploy in the sensor field.

Step2. Estimate the distance between TN (x_t, y_t) and AN (x, y) using Euclidian distance measurement methods as follows.

$$d_{est} = \sqrt{(x - x_t)^2 + (y - y_t)^2} \quad (3.1)$$

The distance estimated between the nodes by RSSI contains some errors. The estimated distance (d_{est}) has been affected by the noise(n_i), which is in the range of $d_{est} \pm d_{est}(\frac{n_0}{100})$, where n_0 is the noise in the measured distance.

Step3. If the TN is placed within the communication range of three or more anchor nodes, the node is said to be localizable. The position of the TN is estimated using the trilateration method.

Step4. The SOA, C-SOA, and LF-SOA are used to find the optimal position of the TN. Seagull is the search agent in the NL scheme. All the search agents are initialized with centroids of the ANs available within the communication range. The centroid (x_{ck}, y_{ck}) of the ANs that exist within the communication range of the localizable node is as follows.

$$(x_{ck}, y_{ck}) = \left(\frac{1}{n} \sum_i^n x_i, \frac{1}{n} \sum_i^n y_i \right) \quad (3.2)$$

Step5. The actual positions of the sensor nodes in simulations are known, so it is possible to determine the actual distances($d_{act(i)}$) between nodes AN and TN. The objective function for the NL is the mean square distance between AN and TN, which is minimized using the SOA, C-SOA, and LF-SOA. The mean square distance between AN and TN is as follows.

$$f(x, y) = \frac{1}{n} \left(\sum_{i=1}^n d_{est(i)} - d_{act(i)} \right)^2, n \geq 3 \quad (3.4)$$

Step6. The SOA, C-SOA, and LF-SOA are used to minimize the objective function, which reduces the NL error, and the optimal value of TN is found.

Step7. Repeat the steps from step2 to step6 till all TNs are not localized.

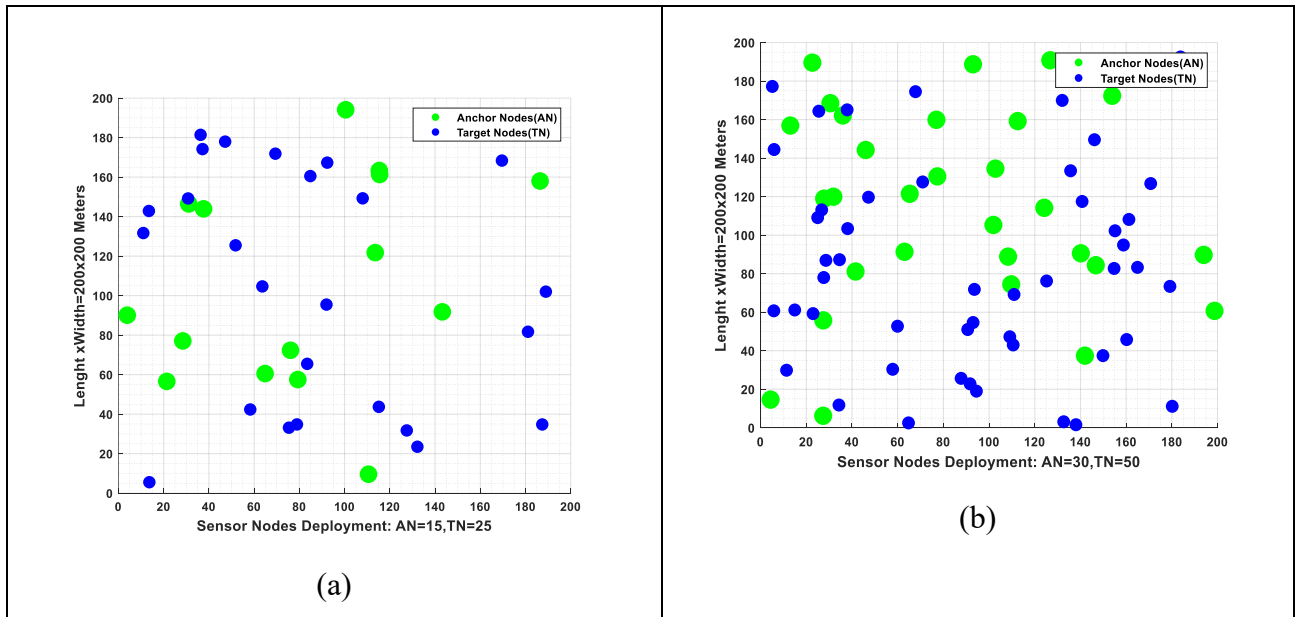
Step8. NL error (NL_E) is estimated after all target nodes are localized. NL_E between all ANs (x_i, y_i) and TN (X_i, Y_i) are as follows.

$$NL_E = \frac{1}{n} \sum_{i=1}^n \sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \quad (3.5)$$

The performance of the SOA, C-SOA, and LF-SOA is compared using average NL error (ANL_E), NL computation time (NL_T), and the number of TNs localized.

Localization optimization is shown in Fig.3.4. The AN & TN are deployed in an area of 200x200 meters. The distance between the AN and TN is estimated using the RSSI method, and the position of the TN is computed using three ANs. The fitness value of each search agent is computed, and the mean square error is estimated. Finally, the TNs are localized.

3.2.4. Performance Evaluation and Result Discussion: The simulation parameters required to simulate the proposed work is presented in Table 3.1. Performance metrics of SOA, C-SOA, and LF-SOA is presented in Table 3.2. The average value of the $NL_E(m)$, $NL_T(s)$, and NL_A is estimated and presented in Table 3.3.



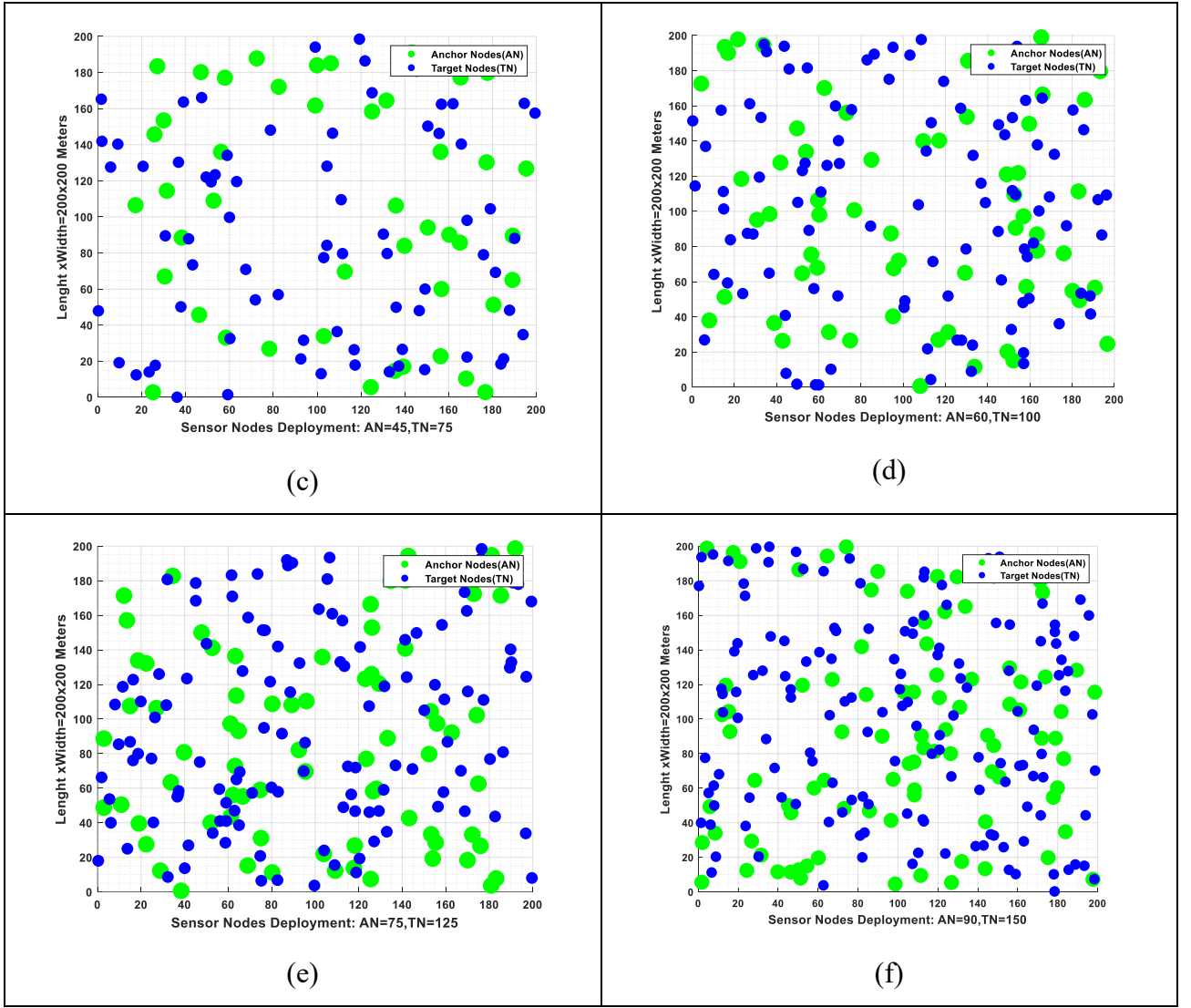


Fig 3.5: Six Scenarios of Random Deployment Sensor Node

All the sensor nodes deployed in the field are static throughout the simulations as shown in Fig. 3.5. The main task is to localize unknown sensor nodes in a 2-D environment. The environmental area for the simulation is 200x200 meters. A total of six cases are taken in which the size of anchor nodes are varies from 15 to 90, and target nodes are varies from 25 to 150.

Table 3.1: Simulation Parameters for SOA, C-SOA, and LF-SOA

Algorithm	Parameter	Value	Unit
	Target Nodes	25,50,75,100,125,150	
	Anchor Nodes	15, 30,45,60,75,90	
	Node Transmission Range (R)	30	m
	Deployment Area	200 x 200	m^2

	Total Iteration	20,40,60,80,100	
SOA	Frequency-controlled Parameter (f_c)	2	
C-SOA	Chaotic logistic map constant (μ)	4	
	Chaotic Index (β)	1.5	
LF-SOA	Correlation constant (u)	1	
	Correlation constant (v)	1	

Table 3.2: Performance Metrics of SOA, C-SOA, and LF-SOA

TN	AN	Iterations	SOA			C-SOA			LF-SOA		
			NL _E (m)	NL _T (s)	NL _A	NL _E (m)	NL _T (s)	NL _A	NL _E (m)	NL _T (s)	NL _A
25	15	20	0.718	0.38	13	0.628	0.32	15	0.421	0.35	18
		40	0.714	0.38	12	0.611	0.35	16	0.418	0.36	19
		60	0.706	0.40	14	0.602	0.39	16	0.409	0.30	20
		80	0.692	0.41	15	0.593	0.40	18	0.401	0.38	22
		100	0.652	0.40	16	0.583	0.40	19	0.401	0.38	23
50	30	20	0.662	0.47	40	0.543	0.45	40	0.398	0.41	44
		40	0.655	0.49	41	0.535	0.45	42	0.396	0.42	46
		60	0.649	0.49	43	0.527	0.42	45	0.396	0.42	47
		80	0.641	0.50	44	0.519	0.42	45	0.391	0.45	48
		100	0.641	0.51	44	0.510	0.40	46	0.386	0.45	48
75	45	20	0.589	0.66	58	0.502	0.57	66	0.387	0.48	70
		40	0.581	0.68	59	0.493	0.57	67	0.382	0.48	71
		60	0.577	0.68	59	0.489	0.51	67	0.382	0.51	71
		80	0.567	0.69	61	0.474	0.49	69	0.374	0.52	73
		100	0.566	0.70	62	0.474	0.48	72	0.369	0.52	74
100	60	20	0.538	0.74	85	0.449	0.56	93	0.361	0.56	94
		40	0.531	0.76	87	0.441	0.61	94	0.361	0.57	96
		60	0.527	0.77	87	0.433	0.61	94	0.350	0.57	97
		80	0.521	0.79	89	0.426	0.65	95	0.342	0.61	97
		100	0.511	0.79	92	0.426	0.66	96	0.337	0.62	99
125	75	20	0.501	0.83	110	0.417	0.68	118	0.320	0.72	121

		40	0.491	0.85	110	0.409	0.77	120	0.311	0.73	121
		60	0.487	0.86	113	0.399	0.79	121	0.309	0.73	123
		80	0.481	0.89	112	0.377	0.79	121	0.296	0.76	124
		100	0.473	0.93	115	0.377	0.81	122	0.296	0.77	124
	150	20	0.451	1.19	138	0.368	0.93	143	0.289	0.89	146
		40	0.447	1.27	139	0.351	0.93	143	0.289	0.89	146
		60	0.447	1.27	140	0.347	0.96	145	0.271	0.91	147
		80	0.427	1.30	141	0.336	0.98	145	0.264	0.93	148
		100	0.419	1.33	142	0.336	0.99	147	0.259	0.93	149

Table-3.3: Mean Value of Performance Metrics SOA, C-SOA, LF-SOA Estimated using Table 3.2

TN	AN	SOA			C-SOA			LF-SOA		
		ANL _E (m)	ANL _T (s)	ANL _A	ANL _E (m)	ANL _T (s)	ANL _A	ANL _E (m)	ANL _T (s)	ANL _A
25	15	0.696	0.39	16	0.603	0.37	17	0.410	0.35	21
50	30	0.649	0.49	43	0.526	0.42	44	0.393	0.43	47
75	45	0.567	0.68	64	0.486	0.52	69	0.378	0.55	72
100	60	0.525	0.77	88	0.435	0.61	95	0.350	0.67	97
125	75	0.486	0.87	116	0.395	0.76	121	0.306	0.81	123
150	90	0.438	1.27	143	0.347	0.95	145	0.274	0.91	148

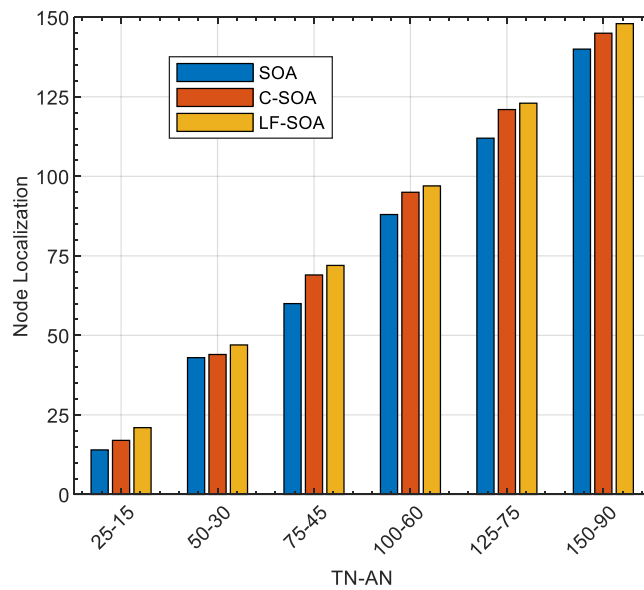


Fig. 3.6 Variation of Average Node Localization with TN-AN at different optimization algorithm

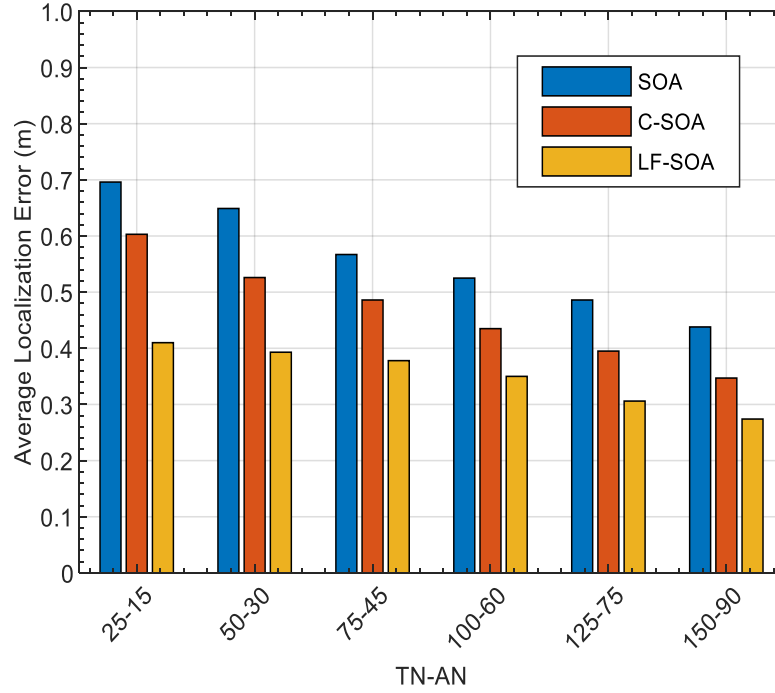


Fig. 3.7 Variation of Average Node Localization Error ($ANLE$) with TN-AN at Different Optimization Algorithm

Node Localization Accuracy: If there are not enough ANs, it is difficult to locate the position of the TNs. With an increase in anchor node density, NL accuracy increases. The NL accuracy depends on the number of anchor nodes used for NL in LF-SOA, C-SOA, and SOA, as shown in Fig.3.6.

Average Node Localization Error: The Fig.3.7 shows the comparative results among the SOA, C-SOA, and LF-SOA, and the average NL error is estimated. The simulation result shows that the average node localization error of LF-SOA is the least. When the size of AN and TN are 15 and 25, respectively, the average node localization error is 0.41. When the size of AN and TN are increased to 90 and 150, respectively, the average node localization error is reduced to 0.271, which is significantly less. Hence, the NL accuracy increases if the AN density is increased. The NL error decreases as the number of iterations increases. LF-SOA exhibits a greater drop in error than the SOA and C-SOA.

Computation Time: The average node localization time is another performance metric shown in Fig.3.8, and LF-SOA has faster node localization than the other two schemes. In contrast to SOA and C-SOA, the computation time for LF-SOA is extremely short.

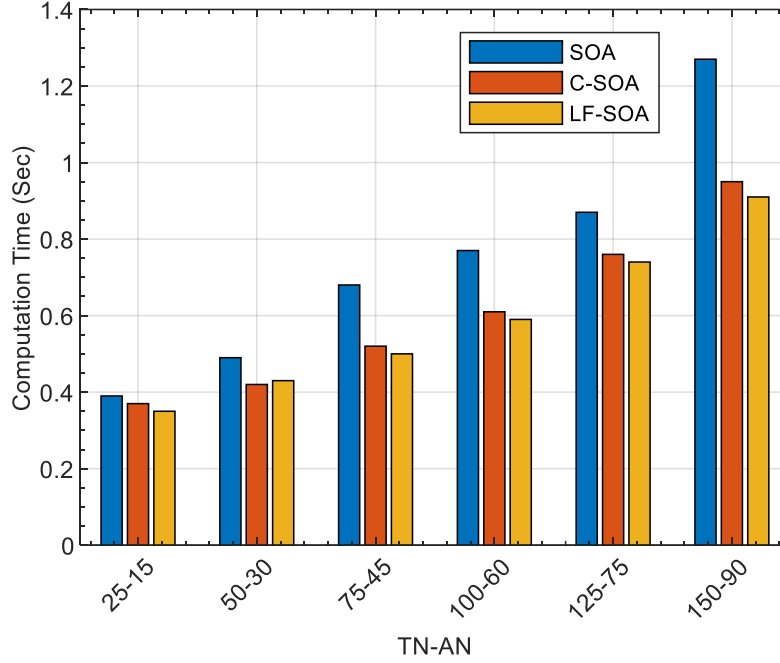


Fig. 3.8 Variation of Computation Time with TN-AN at Different Optimization Algorithm

3.3. Summary

The modified SOA is proposed for NL in the present article. The primary goal of this optimization is to reduce the localization error, minimize the computation time, and enhance the accuracy of NL. The conventional SOA is modified using the fitness function and simulation is carried out on the modified SOA. Modified SOA is further modified using the chaotic map mentioned above known as C-SOA and simulation is carried out with the proposed fitness function. Modified SOA used Levy-flight for randomization and simulation is carried out again with the proposed fitness function. The comparative analysis among SOA, C-SOA, and LF-SOA is performed using the proposed simulation condition. The outcomes of the simulations demonstrate how well the suggested method refines NL. Regarding error and computation time, the C-SOA and LF-SOA do far better than the SOA, and the performance of the LF-SOA is better than the C-SOA. The proposed C-SOA and LF-SOA are applied to a range-based NL scheme.

The future work will investigate the range-free NL scheme to minimize NL error, minimization of computation time, and optimization of NL accuracy. Further, SOA can be hybridized with another meta-heuristic algorithm to optimize the above performance parameters.

CHAPTER-4

DEVELOP AN OPTIMIZED ENERGY-AWARE ROUTING FOR WSNs

In this chapter, an optimized energy-aware routing model is developed for WSNs. POA is a meta-heuristic algorithm modelled using five fitness functions for clustering and three fitness function for routing to send data to the base station efficiently.

4.1. Clustering in WSNs: Wireless Sensor Networks (WSNs) are made up of small, low-power, distributed sensor nodes that connect wirelessly to collect data from their surroundings. Sensors, microcontrollers, and wireless transceivers are all found in these nodes. This data is collected and processed by a central base station (BS). WSNs are utilized in a variety of applications, including environmental monitoring, healthcare, automation, smart home, and smart cities. Because battery-powered nodes necessitate data aggregation and efficient communication, energy efficiency is a critical challenge. Security methods safeguard against threats. Energy management, scalability, reliability, and maintenance are all challenges. Despite these obstacles, WSNs are critical for real-time data collecting and monitoring in a variety of applications ranging from weather forecasting to precision farming.

Clustering [73-74] is one of the most basic methods for extending the lifespan and increasing the usefulness of WSNs. However, selecting CHs [75-76] for energy stabilization to increase network life expectancy is still a significant problem in WSNs. Nodes self-organize [77-79] into clusters are called cluster formation [80]. Several techniques, like DD, PEGASIS, HEED, and GPSR can be employed for cluster formation. A CH gathering and transmitting data from each cluster to the BS. Energy level, distance to the BS, or a combination of these parameters are frequently considered while choosing the CH. Data fusion and transmission are typically handled by CHs by reducing the quantity of data delivered to the BS, data aggregation helps conserve bandwidth and energy. The scalability is improved by clustering. As the network expands, adding more nodes or clusters becomes relatively simple because CHs administer their clusters, which reduces the complexity of network management. The load can be distributed uniformly among CHs with the aid of clustering, preventing certain nodes from using up their energy resources more quickly than others. This might prolong the life of the network. Clustering can offer some fault tolerance if a CH fails or a sensor node becomes inaccessible. To preserve network

operation, other cluster nodes can choose a new CH or change their responsibilities. Nodes may periodically reorganize themselves during dynamic clustering [81-83] in response to variables like energy levels, network architecture changes, or data traffic patterns.

4.2. Energy-efficient (EE) Routing in WSNs: The EE routing [84-85] algorithms are essential in WSNs to optimize energy consumption and extend the network's lifespan. WSNs are made up of many small, resource-constrained SNs that work together to collect, process, and transmit data to a centralized sink or gateway. Given these nodes' limited energy resources, it is critical to create routing protocols that minimize energy usage while preserving data delivery. Many EE routing techniques have been modeled for WSNs, each with its own strategy for preserving energy and prolonging network life. These protocols are following. LEACH [86] is one of the most extensively used EE CHS and routing [87-88] techniques for WSNs. It uses a clustering strategy, in which nodes are arranged into clusters, with one node serving as the cluster leader known as cluster head (CH). The CH combines and transmits data from cluster members (CMs) [89] to the BS. To balance energy [90] consumption across the network, nodes take turns acting as CHs but LEACH has some significant disadvantages like unequal cluster formation, communication overhead due to periodic advertising of their candidacy, static sensor networks, inadequate handling of node failures, and no direct address to data aggregation.

Many authors have proposed two optimization algorithms, one for cluster head formation which aggregate data from the cluster members and other for routing to send data to the BS which are not energy-efficient due to computation overheads and communication overheads. This work proposed a model which required single MHOA for cluster head formation and routing as well. The main contributions of the research are as follows:

- The clustering and routing are NP-hard problems, and five FFs for CHS and three FFs for routing are used with the original POA to solve the problems.
- POA is used to select the optimal CH, and the selection of the optimal CH depends on the five FFs. The performance parameters of the FFs are node degree, distance to the neighbor's nodes, distance to the BS, node centrality, and RE.
- POA is also used to select the optimal path between CHs and BS and the selection of the optimal path between CHs and BS depends on the three FFs. The performance parameters of the FFs are node degree, distance, and RE.

- The energy-efficient CHS and the optimal path selection for data transfer to the BS and prolong the life of the network. Furthermore, the total number of packets received by the BS is increased by decreasing the energy consumption of the nodes during data packet transfers.

4.3. Network Model for Clustered-Routing: A high-level diagram of the proposed WSN model is shown in Fig. 4.1. The following things are considered when developing the network model.

- All SNs are homogenous in their property.
- All SNs are deployed randomly in the sensor field of area 200*200 square meters except sink node.
- Six scenarios have been considered to deploy the base station (sink node) and sensor nodes as shown in the Fig.4.2 and Fig. 4.3. In the first, second, and third scenarios, the base station is deployed at the center (100,100) of the sensor field (200x200 square meters), and in the fourth, fifth, and sixth scenarios, the base station is deployed outside of the sensor deployment field at (100,250).
- All sensors have the same transmission radius.
- The sensors' position is static after the deployment.
- Every sensor is aware of its neighbor sensors.
- Each sensor has 0.5 Jules initial energy.
- All sensor nodes are non-GPS sensor nodes) that is why the locations of the nodes are unknown. A unique number is assigned to each node.
- The distance between the SNs is estimated using the RSSI method.
- The sensors deployed in the environment send the node ID and position to the BS. The BS executes the CHs selection algorithm to select the CHs, and CMs are assigned to the suitable CH. Afterwards, the POA-based routing is executed to choose the optimal path from CHs to BS.

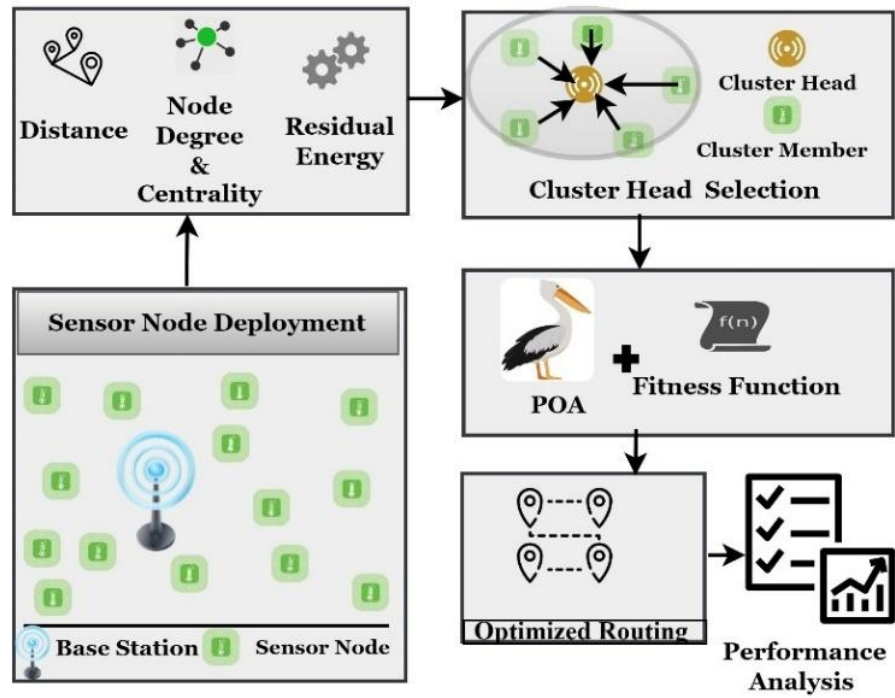


Fig 4.1: Proposed Model for Optimized Energy-Aware Routing in WSNs

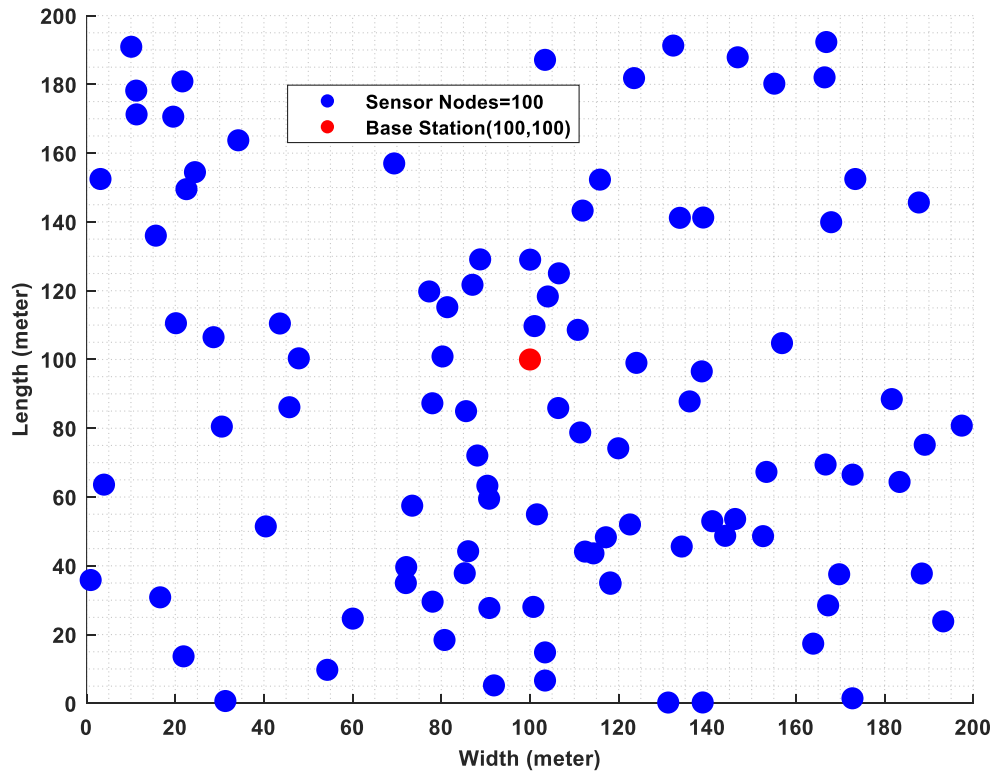


Fig. 4.2(a): SNs=100 and BS (100,100) Deployment for Clustering and Routing in WSNs

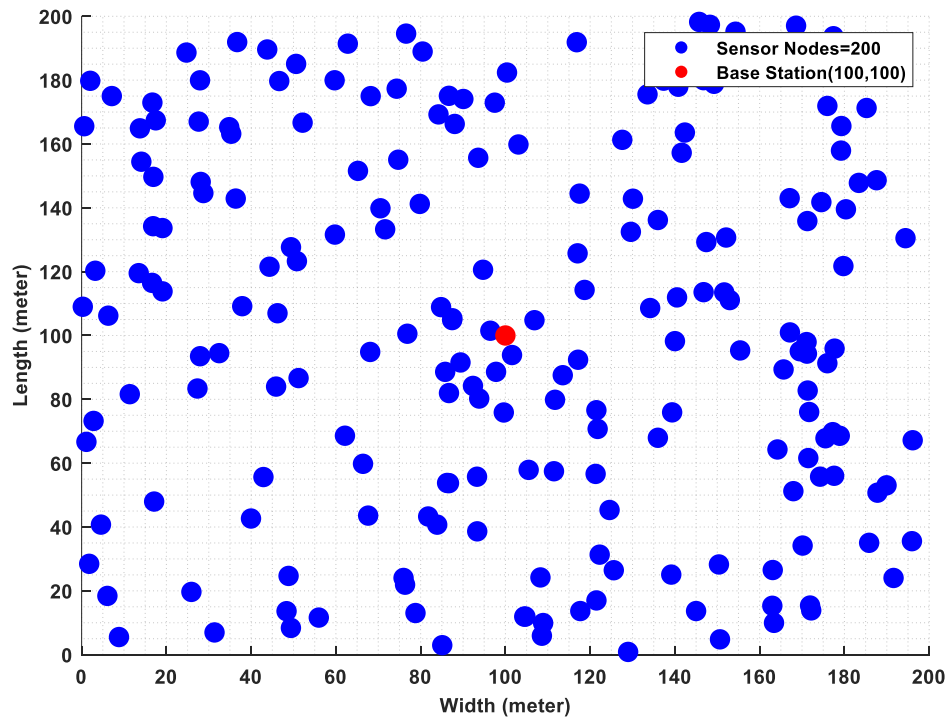


Fig. 4.2(b): SNs=200 and BS (100,100) Deployment for Clustering and Routing in WSNs

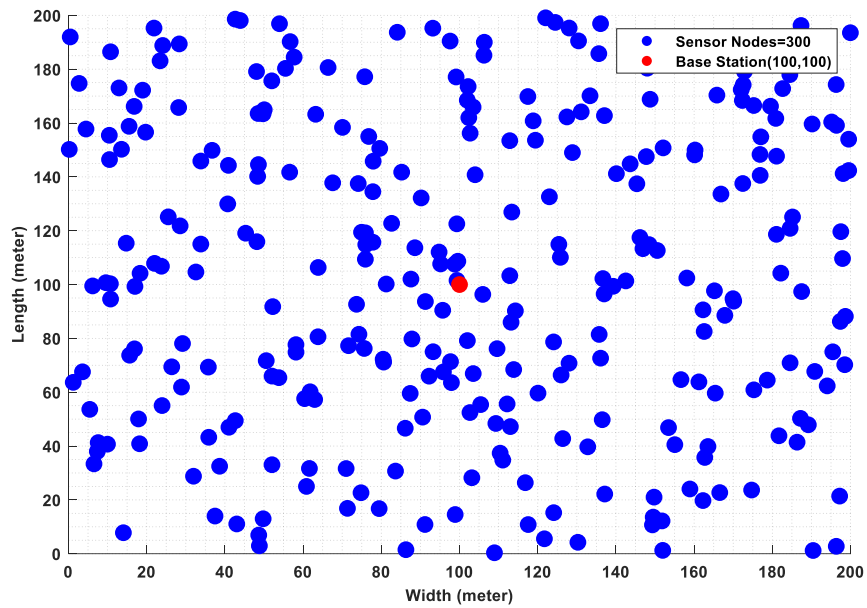


Fig. 4.2(c): SNs=300 and BS (100,100) deployment for Clustering and Routing in WSNs

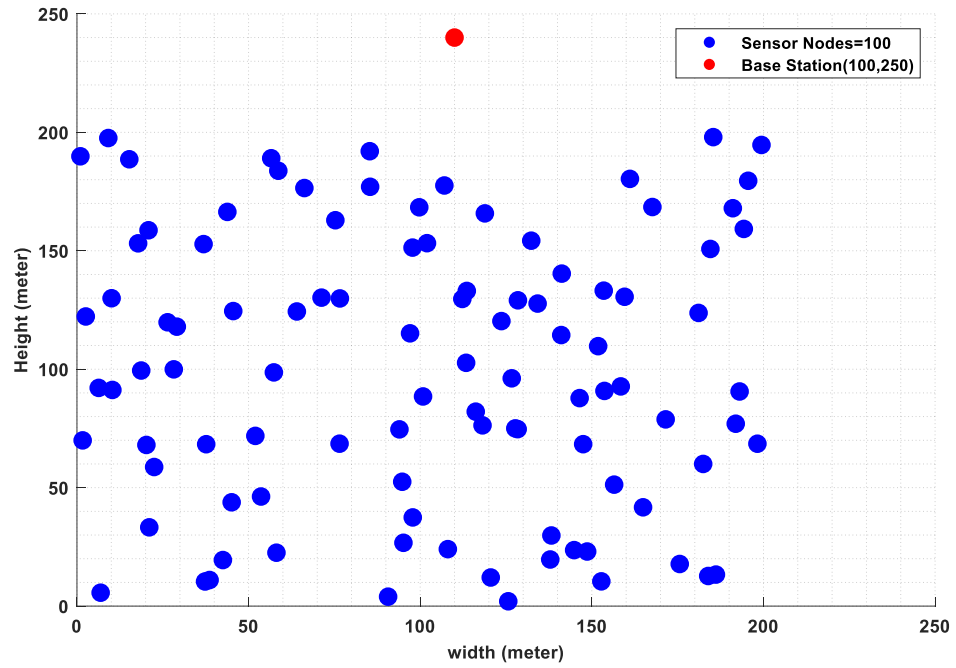


Fig. 4.3(a): SNs=100 and BS (100,250) deployment for Clustering and Routing in WSNs

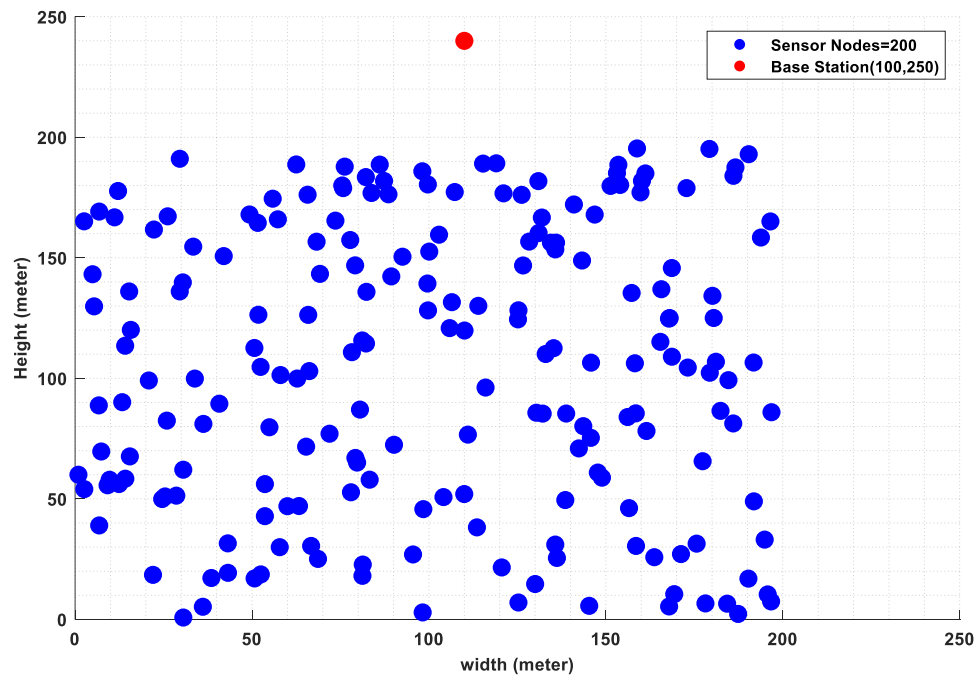


Fig. 4.3(b): SNs=200 and BS (100,250) deployment for Clustering and Routing in WSNs

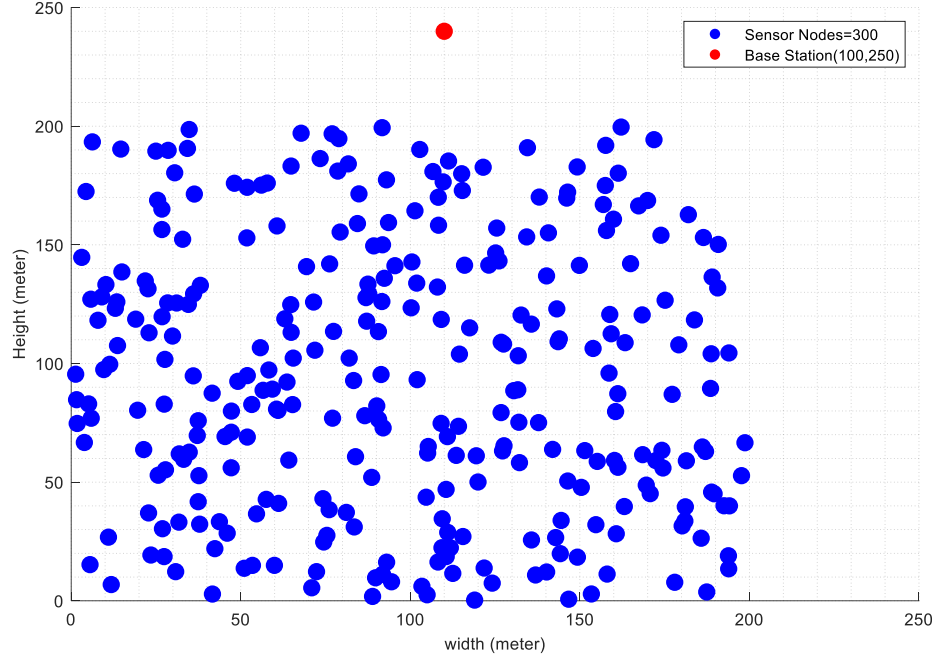


Fig. 4.3(c) SNs=300 and BS (100,250) deployment for Clustering and Routing in WSNs

The choice of algorithm is determined by the WSN's unique requirements and characteristics, including the application, energy limitations, and network size. POA is chosen and modified using the suitable fitness function to achieve the proposed objectives.

4.4. Energy Model for Clustered-Routing: The sensor nodes have limited energy, but they can aggregate data to make efficient use of that energy. The amount of energy needed to transport data depends on the distance between nodes and the number of bits being sent. The amount of energy needed for receiving is also influenced by how many bits are being received. The energy required for the direct transmission between the transmitter and receiver is as follows:

$$E_{trans}(l, d) = \begin{cases} E_{edtr} * w + E_{afs} * w * d_{tr}^2, & \text{if } d_{tr} < d_{th} \\ E_{edtr} * w + E_{amp} * w * d_{tr}^4, & \text{if } d_{tr} > d_{th} \end{cases}, d_{th} = \sqrt{\frac{E_{afs}}{E_{amp}}} \quad (4.1)$$

$$E_{receiv}(w, d) = E_{edtr} * w \quad (4.2)$$

The energy lost to operate the transmitter is E_{trans} , the transmission amplifier's energy dissipation is E_{receiv} , w is the message's length in bits, and d_{tr} is a distance between the transmitter and receiver. E_{edtr} is an energy dissipated at transmitter receiver. E_{edta} is an energy dissipated in amplification. Threshold distance is d_{th} .

In the multi-hop scenario, the energy needed to transfer data from the source to the destination node will be half that of direct transmission as follows:

$$E_{trans} = E_{edtr} * w + E_{edta} * w * \left(\frac{d_{tr}}{2}\right)^2 \quad (4.3)$$

4.5. Pelican Optimization Algorithm: POA [91] is a nature-inspired stochastic optimization algorithms developed by Pavel Trojovský in 2021. In POA, pelicans are the search agents that hunt prey. The Pelican defines a set of SNs from which to choose CHs from a network's sensors. The CHs are used to send data to the BS.

4.6. Proposed Model: The proposed work aims to transfer data from CHs to BS in such a way that the energy consumed by the nodes are least. The proposed work can be divided into two phases. The phase one is cluster formation, algorithm-1 represents the CH selection scheme using POA, and phase-2 is routing optimization to select the optimal route from sources (CHs) to the BS.

Algorithm 4.1. POA for CH Selection	
1.Input:	Parameter initialization: Pelican population= N_p
	2. Maximum no of Iteration= T_{max}
	3. Estimate the fitness value (ff_{CH}) using equ. (4.8)
	4. for $i = 1: T_{max}$
	4. Random initialization of the prey using equ. (4.11)
	5. for $j = 1: N_p$
	6. Exploration phase: Movement of SA towards the prey
	7. For $p = 1:m$
	8. Estimate the new status of the CH using equ. (4.14)
	9. End for
	10. Update the i^{th} pelican position using equ. (4.15)
	11. Exploitation phase: To attack on prey
	12. For $p = 1:m$
	14. Estimate the new position of the CH using equ. (4.16)
	15. End.
	16. Update the i^{th} SA using equ. (4.17)
	17. End.
	18. Update the solution for the best candidate
	19. End.
20. Output:	CH is the best candidate solution attained by POA-Proposed

4.7. Fitness Function of POA: A class of optimization methods called MHOA is intended to identify the best solutions to complex problems. In the optimization process, the objective function also referred to as the fitness or cost function [92] acts as a criterion to assess a solution's quality. Fitness evaluation, search guidance, convergence rate, adaption and learning, and problem-specific information are the main tasks of the FF in MHOA.

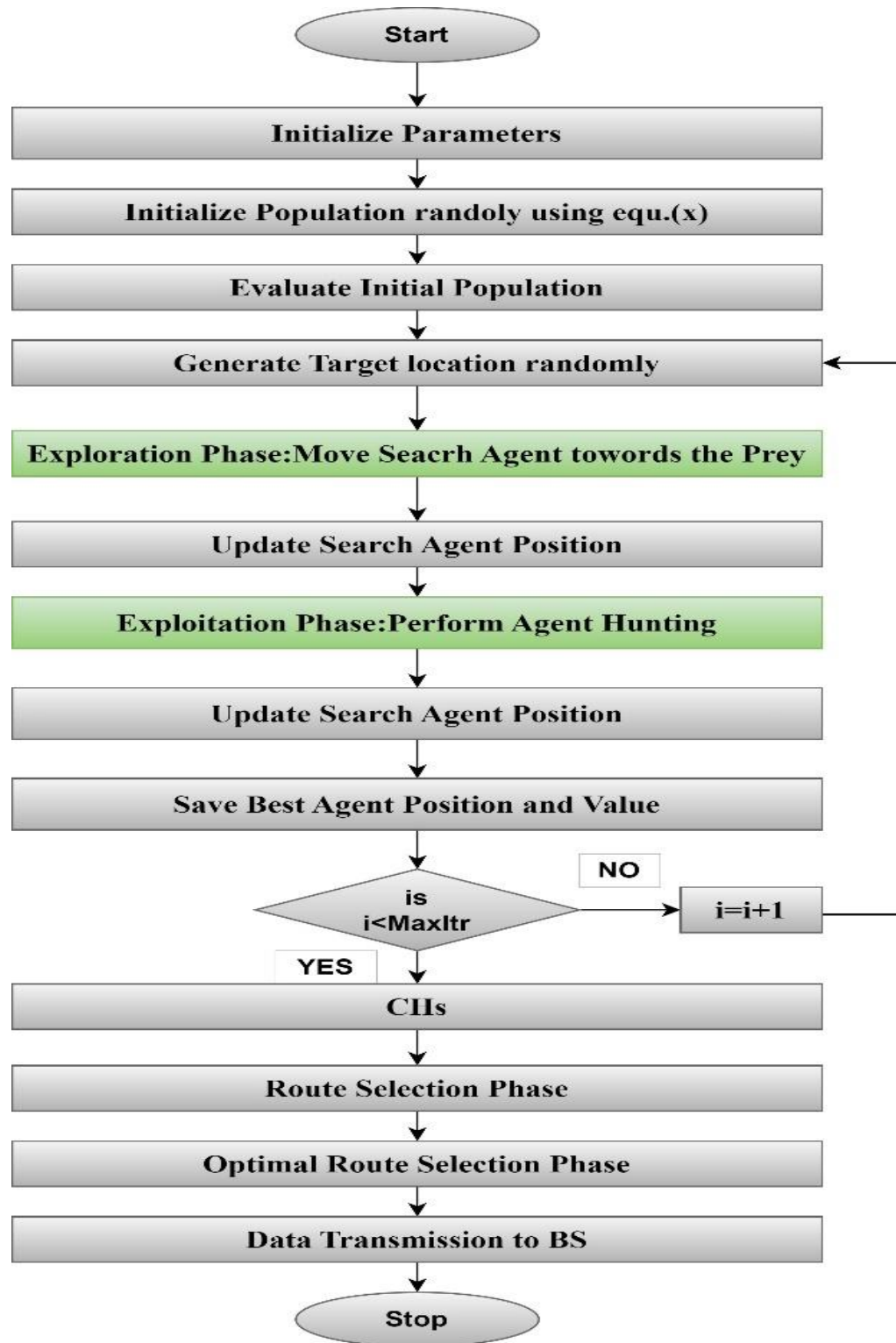


Fig. 4.4: Flowchart of the Proposed Work for the Clustering and Routing

4.7.1. Distance among the CHs and BS: It specifies a distance between CH and BS. The length of the transmission channel determines how much energy the node uses. For data transmission, the node that is closer to the BS is preferred because the BS requires more energy if it is located

far away from the CH. So, more energy consumption could be the cause of the abrupt decline in CH. The FF of the distance between CHs and BS is expressed in equ. (4) as follows:

$$ff_1 = \sum_{i=1}^{N_{CH_j}} (dist(CH_i, BS)) \quad (4.4)$$

4.7.2. Distance Among CMs and CH: When the distance between the CH and the CMs increases, the energy consumed by the nodes also increases. This is because the nodes may need to use more energy to transmit data over longer distances to reach the CH. Hence, The CM located at a shorter distance will be preferred as a CH for data transfer to the BS. It uses less energy. The FF for the distance between CH and CM is expressed in equ. (4.5) as follows:

$$ff_2 = \sum_{j=1}^{M_{CH}} \left(\sum_{i=1}^{N_{CH_j}} (dist(CM_i, CH_i) / N_{CH_j}) \right) \quad (4.5)$$

4.7.3. Residual Energy of the CH: To gather information from the CMs and forward it to the BS, CH performs several operations. The node with more RE is preferred to be a CH since the CH needs higher levels of energy to complete the task. The FF of the RE is presented in equ. (4.6) as follows:

$$ff_3 = \sum_{j=1}^{N_{CH}} \frac{1}{E_{CH_j}} \quad (4.6)$$

Where N_{CH} is the size of the CH in the network and E_{CH_j} is the RE of the j^{th} CH.

4.7.4. Cluster Head Degree: The degree of CH specifies how many sensor nodes are a part of the specific CH. The CHs with fewer sensors are chosen because the CHs with more CMs consume energy more quickly. The FF of the CH degree is presented in equ. (4.7) as follows:

$$ff_4 = \sum_{j=1}^{N_{CM}} CH_j \quad (4.7)$$

Where N_{CM} is the total number of CM associated with CH_j .

4.7.5. Node Centrality: Node centrality is a measure of how centrally positioned a node is about its neighbors. The FF of the node centrality is presented in equ. (4.8) as follows:

$$ff_5 = \sum_{i=1}^{N_{CM}} \frac{\sqrt{\sum_{j \in N_{CH}} dist^2(i, j) / N_{CM}}}{network_{dim}} \quad (4.8)$$

Where N_{CM} is total number of CM of the CH_j. These five objective functions have a weight value assigned to it. The many objectives in this instance are reduced to a single FF.

To prevent node failure when acting as a CH, priority is given to ω_1 to elevate the importance of RE. Subsequently, ω_2 and ω_3 are prioritized next to identify the CH from the BS with the shortest distance, thereby reducing energy consumption. The fourth priority, assigned to node degree (ω_4), aids in selecting the CH with the least node connections. Lastly, node centrality (ω_5) is considered the least priority, serving to enhance the connection between CMs and the CH. The transformed FF from five objective functions is shown in the equ. (4.9).

$$ff_{CH} = \sum_{i=1}^5 \omega_i * ff_i \quad (4.9)$$

Where $\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1$.

4.7.6. Cluster Formation: The CHs are chosen by the POA. The potential function mentioned in equ. (10) is the basis of becoming the CH of any CMs. The potential of the any sensor is more if the sensor node has higher RE and are closer to the CMs. If the two CHs are at the same distance from the SN, then the SN becomes the CM of the CH which has higher RE.

$$P_{SN} = \frac{\kappa * E_{CH_j}}{dist(SN_i, CH_j)} \quad (4.10)$$

Where κ is the proportionality constant, E_{CH_j} is the RE of the CH_j, and $dist(SN_i, CH_j)$ is the distance between the SN_i and CH_j.

4.8. Routing using POA: Communicating directly between BS and CHs is not feasible due to the limited communication range and battery of the SNs. That is why multi-hop routing is the requirement of the proposed work. Fig. 4.5 depicting the general routing scenario. POA is chosen for optimized routing. In the routing phase, dimension(m) of each pelican is equal to the size of CHs. Each Pelican is a search agent (SA) and SA is candidate solution of the problem. The SAs are randomly deployed in the search space using equ. (11). In the search field, the prey's position is generated randomly.

$$P_i: P_{i,j} = lb_j - rand * (ub_j - lb_j), i = 1 \text{ to } N, j = 1 \text{ to } m \quad (4.11)$$

Where P_i is the location of i^{th} pelican in the search area. The value of the j^{th} decision variable is $P_{i,j}$. Where N is the search agent and j . The lower and upper bounds of the j^{th} decision variables are lb_j and ub_j respectively. The population matrix of a pelican is mathematically represented by matrix P as follows.

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix} = \begin{bmatrix} P_{1,1} & \dots & P_{1,j} & \dots & P_{1,m} \\ \vdots & & \vdots & & \vdots \\ P_{i,1} & & P_{i,j} & & P_{i,m} \\ \vdots & & \vdots & & \vdots \\ P_{N,1} & & P_{N,j} & & P_{N,m} \end{bmatrix}_{N \times m} \quad (4.12)$$

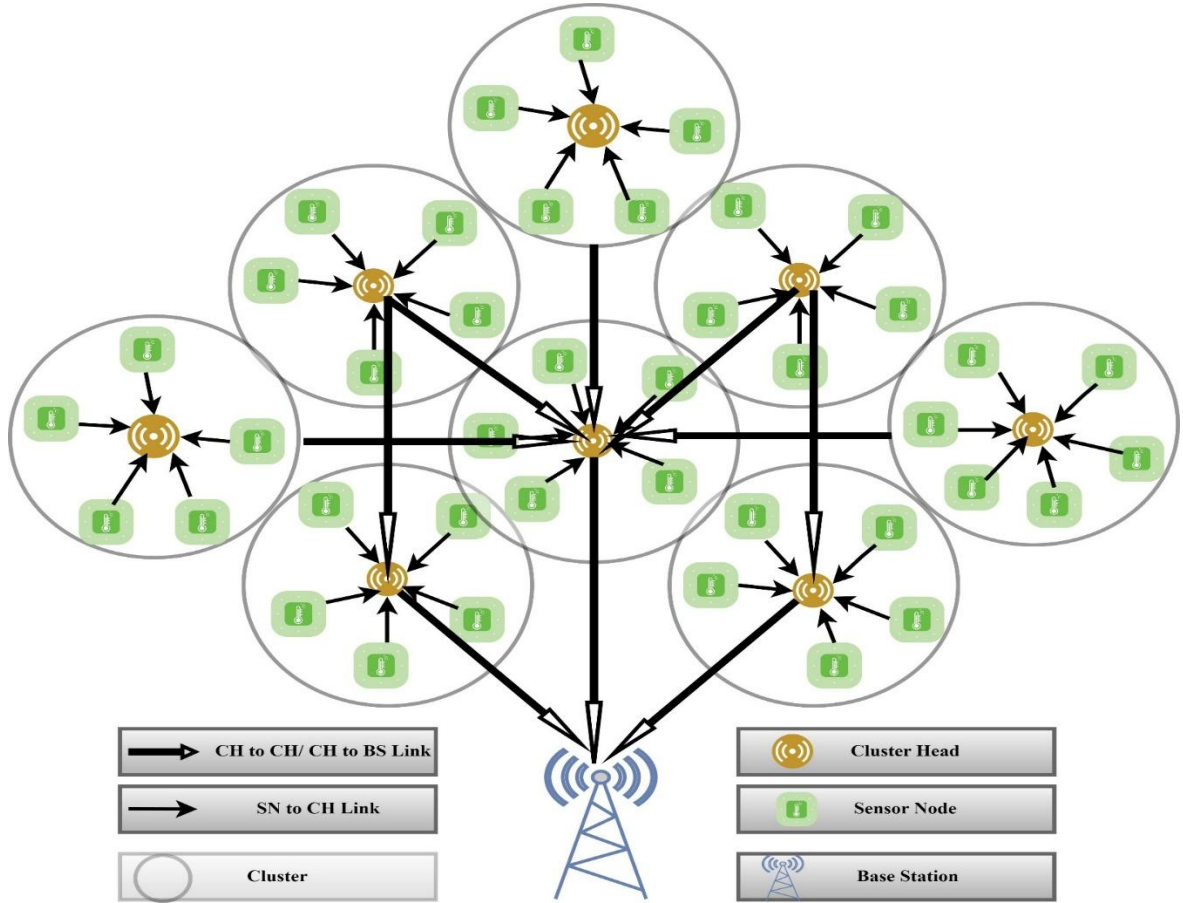


Fig. 4.5: Proposed Clustering Model for Routing in WSNs

The objective function (ff) vector, as illustrated in equ. (4.13), is used to derive the values obtained for the FFs. The goal of routing is to find the optimal route from CHs to the BS. To do this, RE, distance, and node degree are combined to create a fitness function (ff_R). The ff_R of the

distance, RE, and node degree are expressed in the equ. (4.5), equ. (4.6), and equ. (4.7) respectively. The total fitness value for the routing optimization is as follows:

$$ff_R = \sum_{i=1}^3 \varphi_i * ff_i \quad (4.13)$$

Where, $\varphi_1 + \varphi_2 + \varphi_3 = 1$ and the weighted values (φ_i) are 0.5, 0.3 and 0.2 for the φ_1 , φ_2 and φ_3 respectively. To update the candidate position for optimal solutions, the proposed POA mimics the behavior of pelican. The two main phases of the simulation are exploration and exploitation. In the exploration phase, SA moves toward the prey shown in equ. (4.14).

$$P_i(x_{i,j})^{exploration} = \begin{cases} x_{i,j} + rand. (position_{prey,j} - I.x_{i,j}), & \text{if } ff_{prey} < ff_{sa} \\ x_{i,j} + rand. (x_{i,j} - position_{prey,j}), & \text{otherwise} \end{cases} \quad (4.14)$$

Where $P_i(x_{i,j})$ is the current position of the i^{th} SA in the exploration phase. Random number(I) has the value 1 or 2 which is chosen randomly. ff_{prey} is the current FF value of the prey and ff_{sa} is the current FF value of the SA. The SA position is updated if the current FF value of the SA (ff_p) is better than the SA as shown in equ. (15).

$$x_i = \begin{cases} x_i^{SA}, & ff_{new} < ff_{old} \\ x_i, & \text{otherwise} \end{cases} \quad (4.15)$$

The new position of the SA in the exploitation phase, is shown in equ. (16).

$$P_i(x_{i,j})^{exploitation} = x_{i,j} + 0.2 \left(1 - \frac{t}{itr_{max}}\right) * \left(1 - \frac{t}{itr_{max}}\right) * x_{i,j} \quad (4.16)$$

Where $x_{i,j}$ is the older location of the SA, t is the current iteration, itr_{max} is the total number of iterations. Finally, equ.(4.17) models the new pelican position, which is subject to acceptance or rejection based on effective updating.

$$X_i = \begin{cases} P_i(x_{i,j})^{exploitation}, & P_i(x_{i,j})^{exploitation} < ff_i \\ X_i, & \text{otherwise} \end{cases} \quad (4.17)$$

This model employs a dynamic clustering mechanism that periodically selects CHs based on them RE and proximity to sensor nodes.

4.9. Performance Analysis: The performance analysis is carried out for the FND, LND, AEC, and total no of byte received at the base station.

Table 4.1 Simulation parameters for LEACH, DEEC, BOAACO, and POA_Proposed

Parameters	Value
WSNs network area Case1-1	200x200 Square meter
WSNs network area Case1-2	250x250 Square meter
Sensor Nodes (SNs)	100,200,300

Initial energy of the SNs	0.50 Jules
Energy dissipated at receiver and transmitter	50 nj/bit
Packet size	4000 bits
Message size (w)	500 bits
Sensor communication range	100 meters
$\omega_1, \omega_2, \omega_3, \omega_4, \omega_5$	0.35, 0.25, 0.2, 0.2, 0.1
$\varphi_1, \varphi_2, \varphi_3$	0.5, 0.3, 0.2
BS coordinates	BS ₁ (100,100) and BS ₂ (100,250)

4.10. Performance Parameters: Several performance metrics, such as network lifetime, energy consumption, ALNs, and the total number of packets received by the base station, were used to assess the suggested model. Two scenarios have been well-thought-out in the simulation. In the scenario one, the BS is positioned inside the environment field at the center (100,100) and in scenario 2, the BS is positioned outside of the environment field at (100,250). A total of three cases (100, 200, and 300 nodes) have been chosen for the SN deployments.

Alive Node (ALN): ALN usually refer to sensor nodes that are now in use and functioning as part of the network. When the network contains many active nodes, performance is enhanced.

Average Energy Consumption (AEC): The total energy consumed by the node throughout each iteration.

Total Packets Received by BS: The total number of packets that BS receives depends on the RE and distance between CHs and BS.

First Node Dead (FND): Nodes that have failed or run out of energy are referred to as dead nodes. When the first sensor node in a network break or stops functioning, it is referred to as the FND.

Last Node Dead (LND): When the final sensor node in a network break or stops functioning, it is referred to as LND.

Table 4.2 ALNs of LEACH, DEEC, BOAACO, and POA_Proposed

No of Rounds	LEACH	DEEC	BOAACO	POA_Proposed
ALNs Vs No of Rounds when BS positioned at (100,100) and SN=100				
400	100	100	100	100
800	100	100	100	100
1200	70	80	90	100

1600	50	70	85	100
2000	20	50	70	100
2400	10	30	55	90
2800	0	10	45	50
3200	0	0	30	45
3600	0	0	0	30
4000	0	0	0	10
4400	0	0	0	0
ALNs Vs No of Rounds when BS positioned at (100,100) and SN=200				
600	200	200	200	200
1200	190	200	200	200
1800	140	160	180	200
2400	110	130	170	200
3000	80	100	150	200
3600	50	70	130	190
4200	10	40	90	150
4800	0	30	60	140
5400	0	0	10	110
6000	0	0	0	50
6600	0	0	0	0
ALNs Vs No of Rounds when BS positioned at (100,100) and SN=300				
1000	300	300	300	300
2000	300	300	300	300
3000	240	260	280	300
4000	200	260	270	300
5000	180	210	250	300
6000	10	90	230	290
7000	0	30	190	250
8000	0	20	160	240
9000	0	0	0	185

10000	0	0	0	100
11000	0	0	0	0
ALNs Vs No of Rounds when BS positioned at (100,250) and SN=100				
200	100	100	100	100
400	100,	100	100	100
600	90	100	100	100
800	70	90	100	100
1200	50	80	90	100
1500	30	60	50	90
1800	0	30	40	70
2100	0	0	30	50
2400	0	0	0	35
2700	0	0	0	20
3000	0	0	0	0
ALNs Vs No of Rounds when BS positioned at (100,250) and SN=200				
400	200	200	200	200
800	200	200	200	200
1200	140	160	200	200
1600	110	120	180	200
2000	80	90	150	200
2400	30	70	130	190
2800	0	40	90	170
3200	0	0	70	150
3600	0	0	0	125
4000	0	0	0	100
4400	0	0	0	0
ALNs Vs No of Rounds when BS positioned at (100,250) and SN=300				
500	300	300	300	300
1000	300	300	300	300
1500	240	260	300	300
2000	200	230	270	300
2500	80	100	250	300
3000	20	70	240	290

3500	0	30	190	260
4000	0	0	180	250
4500	0	0	0	165
5000	0	0	0	100
5500	0	0	0	0

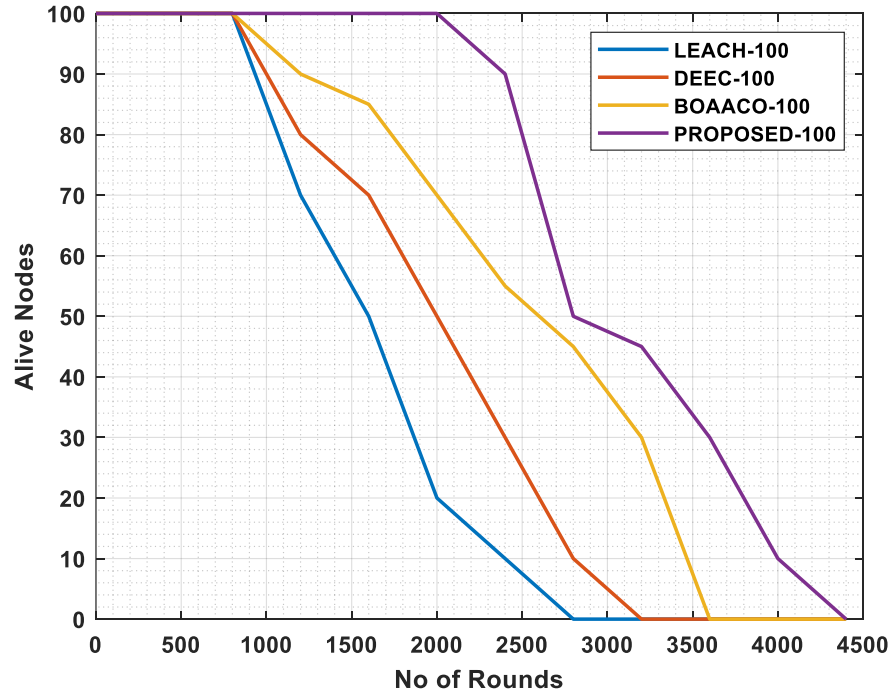


Fig.4.6: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=100

4.10.1 Case study 1: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=100: In the proposed work, the first node is dead after 800 rounds of operations and all nodes are dead after 4400 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 800 rounds but the last node is dead after 2800,3200, and 3600 rounds of operations as shown in Fig. 4.6 and in Table 4.2.

4.10.2 Case study 2: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=200: In the proposed scheme, the first node is dead after 3000 rounds of operations and all nodes are dead after 6600 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 800,1200, and 1200 rounds respectively but

the last node is dead after 2800,3200, and 3600 rounds of operations respectively as shown in Fig.4.7 and in Table 4.2.

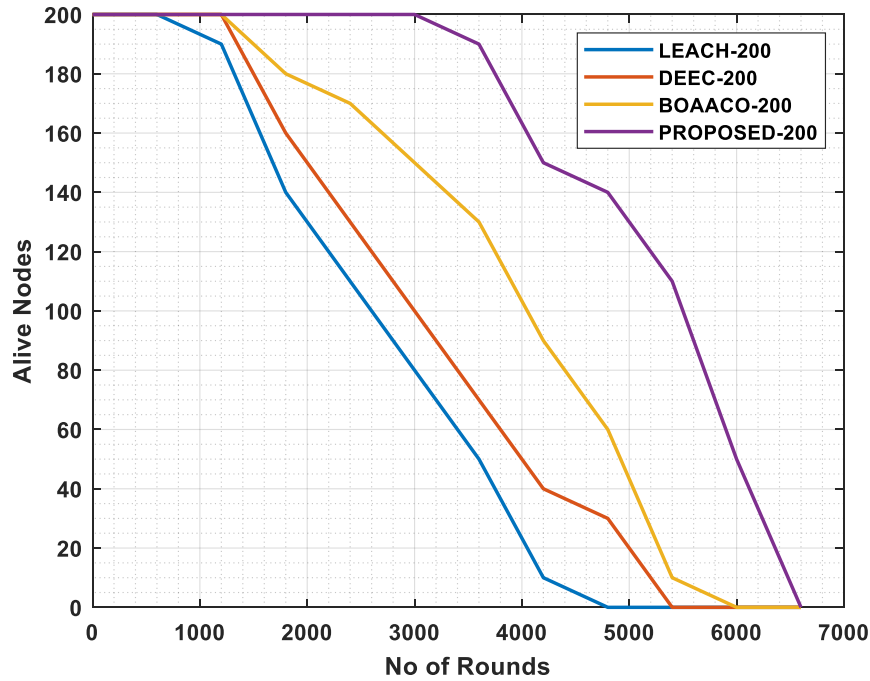


Fig.4.7: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=200

4.10.3 Case study 3: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=300: In the proposed scheme, the first node is dead after 5000 rounds of operations and all nodes are dead after 11000 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 2000 rounds respectively but the last node is dead after 7000,8000, and 9000 rounds of operations respectively as shown in Fig.4.8 and in Table 4.2.

4.10.4 Case study 4: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=100: In the proposed scheme, the first node is dead after 1300 rounds of operations and all nodes are dead after 3000 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 400,600, and 800 respectively but the last node is dead after 1800,2100, and 2400 rounds of operations respectively as shown in Fig.4.9 and in Table 4.2.

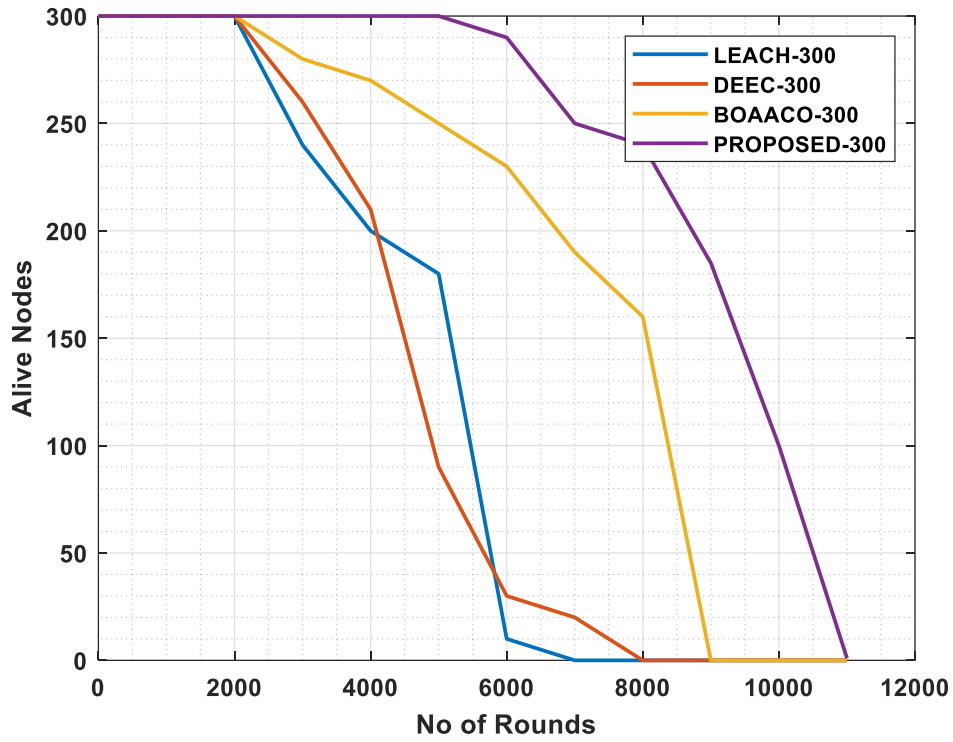


Fig. 4.8: ALNs Vs No of Rounds when BS positioned at (100,100) and SN=300

4.10.5 Case study 5: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=200: In the proposed scheme, the first node is dead after 2000 rounds of operations and all nodes are dead after 4400 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 800,800, and 1200 respectively but the last node is dead after 2800,3200, and 3600 rounds of operations respectively as shown in Fig.4.10 and in Table 4.2.

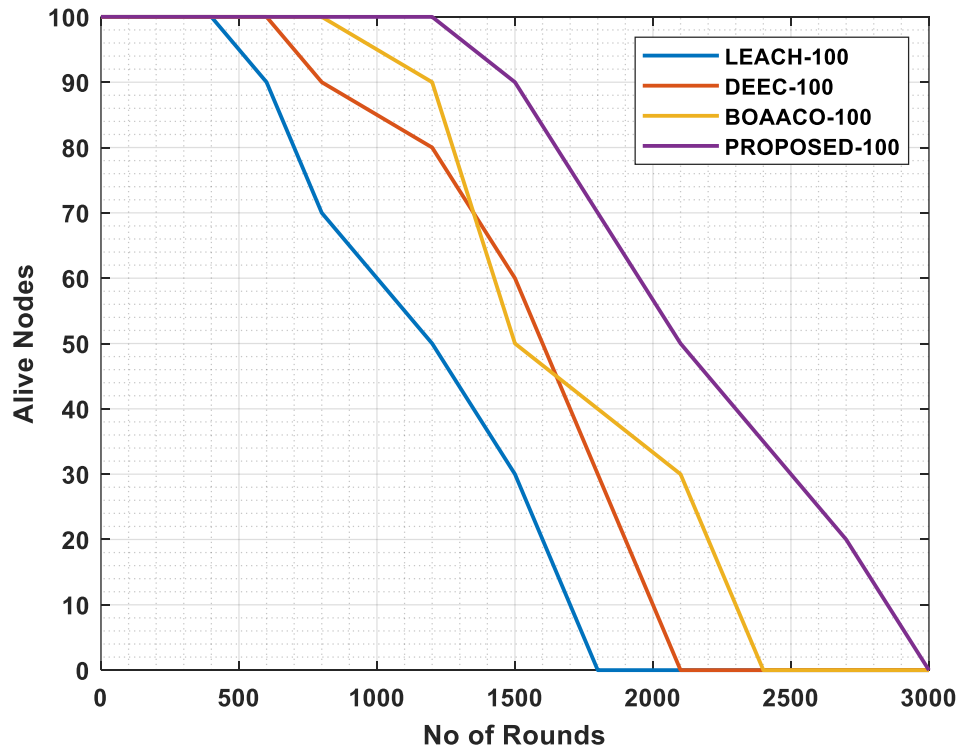


Fig. 4.9: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=100

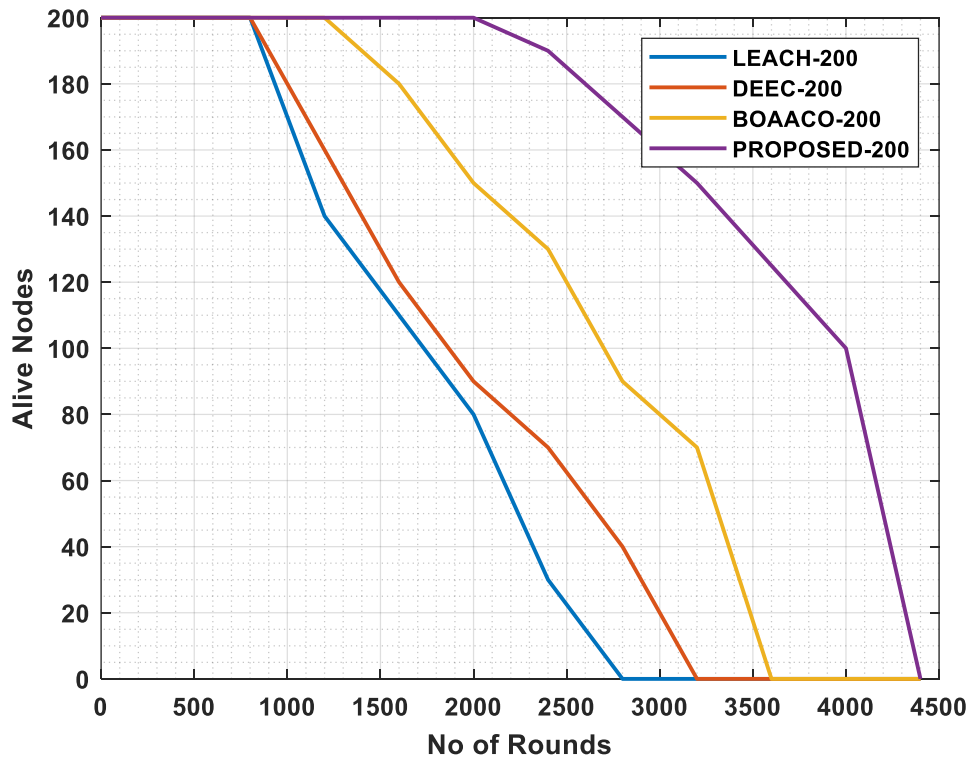


Fig. 4.10: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=200

4.10.6 Case study 6: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=300: In the proposed scheme, the first node is dead after 2500 rounds of operations and all nodes are dead after 5500 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the first node is dead after 1000,1000, and 1500 respectively but the last node is dead after 3400,4000, and 4500 rounds of operations respectively as shown in Fig.4.11 and in Table 4.2. The LEACH, DEEC and BOAACO show a gradual decrease in ANL as the number of rounds increases, indicating a decline in network lifetime with time. The result analysis shows that the POA_Proposed model offers superior performance in terms of network lifetime extension compared to LEACH, DEEC, and BOAACO in the given simulation scenario-1.

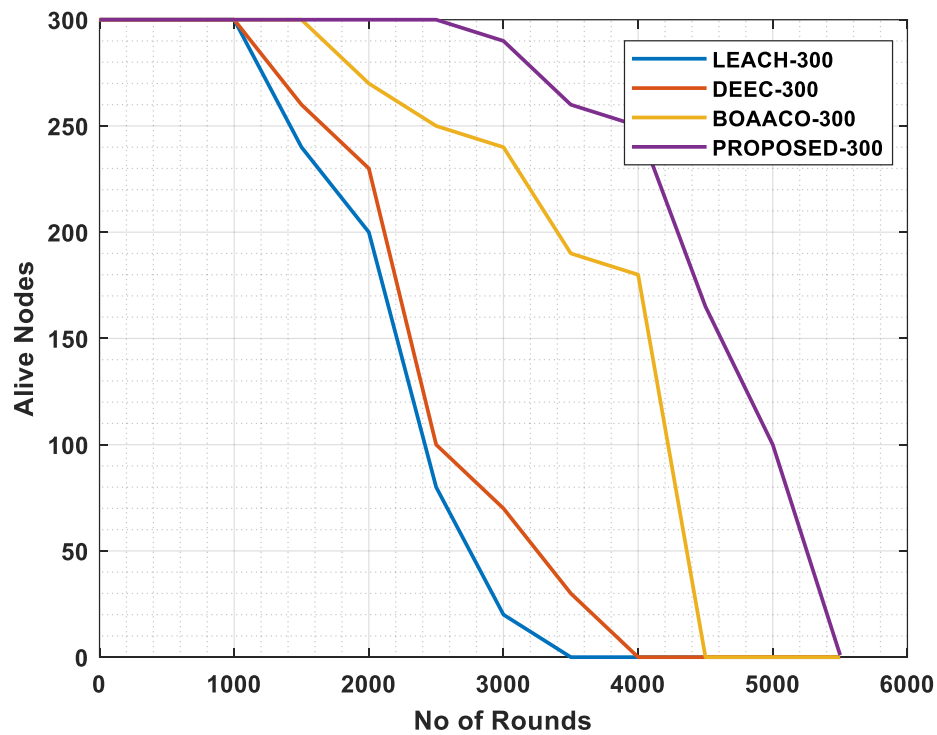


Fig. 4.11: ALNs Vs No of Rounds when BS positioned at (100,250) and SN=300

4.10.7 Case study 7: AEC Vs No of Rounds when BS positioned at (100,100) and SN=100: It can be observed that the AEC of the proposed scheme was less compared to LEACH, DEEC, and BOAACO. The residual energy of the proposed model is much better than the other three existing schemes. The AEC is zero after 4400 rounds of operations as shown in Fig. 4.12 and in Table 4.2. In case of LEACH, DEEC, and BOAACO, the AEC is zero after 2000, 2800, and 3600 rounds of operations.

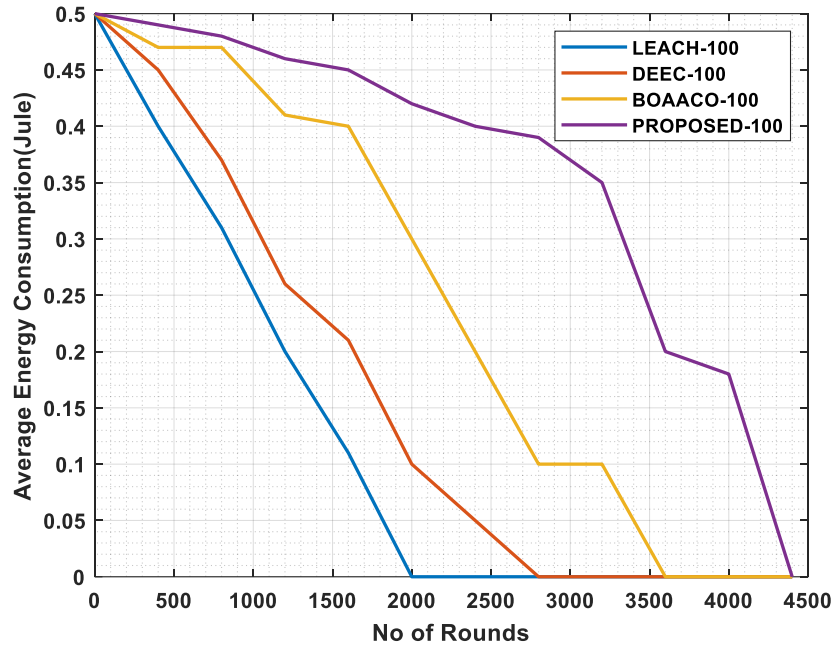


Fig. 4.12: AEC Vs No of Rounds when BS positioned at (100,100) and SN=100

Table 4.3 Residual Energy of LEACH, DEEC, BOAACO, and POA_Proposed

No of Rounds	LEACH	DEEC	BOAACO	POA_Proposed
AEC Vs No of Rounds when BS positioned at (100,100) and SN=100				
400	0.401	0.449	0.479	0.491
800	0.311	0.372	0.466	0.482
1200	0.202	0.261	0.410	0.462
1600	0.111	0.211	0.400	0.451
2000	0.0	0.101	0.300	0.420
2400	0.0	0.051	0.201	0.402
2800	0.0	0.0	0.10	0.391
3200	0.0	0.0	0.10	0.349
3600	0.0	0.0	0.0	0.200
4000	0.0	0.0	0.0	0.181
4400	0.0	0.0	0.0	0.0
AEC Vs No of Rounds when BS positioned at (100,100) and SN=200				
600	0.400	0.450	0.48	0.491

1200	0.310	0.368	0.459	0.477
1800	0.201	0.261	0.411	0.472
2400	0.110	0.210	0.401	0.451
3000	0.0	0.100	0.300	0.430
3600	0.0	0.050	0.200	0.421
4200	0.0	0.0	0.100	0.400
4800	0.0	0.0	0.10	0.369
5400	0.0	0.0	0.0	0.219
6000	0.0	0.0	0.0	0.181
6600	0.0	0.0	0.0	0.0
AEC Vs No of Rounds when BS positioned at (100,100) and SN=300				
1000	0.440	0.468	0.48	0.49
2000	0.311	0.441	0.458	0.479
3000	0.220	0.360	0.440	0.470
4000	0.140	0.310	0.400	0.450
5000	0.0	0.200	0.360	0.430
6000	0.0	0.151	0.290	0.410
7000	0.0	0.0	0.190	0.400
8000	0.0	0.0	0.100	0.350
9000	0.0	0.0	0.0	0.280
10000	0.0	0.0	0.0	0.180
11000	0.0	0.0	0.0	0.0
AEC Vs No of Rounds when BS positioned at (100,250) and SN=100				
200	0.410	0.460	0.470	0.49
400	0.311	0.351	0.411	0.468
600	0.220	0.230	0.380	0.452
800	0.100	0.200	0.300	0.441
1200	0.0	0.150	0.280	0.400
1500	0.0	0.100	0.180	0.360
1800	0.0	0.0	0.050	0.320

2100	0.0	0.0	0.0	0.300
2400	0.0	0.0	0.0	0.240
2700	0.0	0.0	0.0	0.170
3000	0.0	0.0	0.0	0.00
AEC Vs No of Rounds when BS positioned at (100,250) and SN=200				
400	0.411	0.420	0.470	0.49
800	0.320	0.352	0.460	0.478
1200	0.220	0.230	0.412	0.450
1600	0.100	0.200	0.390	0.420
2000	0.0	0.100	0.320	0.370
2400	0.0	0.0	0.180	0.360
2800	0.0	0.0	0.150	0.320
3200	0.0	0.0	0.0	0.260
3600	0.0	0.0	0.0	0.190
4000	0.0	0.0	0.0	0.160
4400	0.0	0.0	0.0	0.0
AEC Vs No of Rounds when BS positioned at (100,250) and SN=300				
500	0.411	0.421	0.470	0.490
1000	0.321	0.350	0.423	0.479
1500	0.220	0.230	0.380	0.470
2000	0.100	0.200	0.300	0.450
2500	0.0	0.100	0.281	0.420
3000	0.0	0.0	0.180	0.370
3500	0.0	0.0	0.050	0.320
4000	0.0	0.0	0.0	0.261
4500	0.0	0.0	0.0	0.240
5000	0.0	0.0	0.0	0.190
5500	0.0	0.0	0.0	0.0

4.10.8 Case study 8: AEC Vs No of Rounds when BS positioned at (100,100) and SN=200: The simulation results as shown in Fig.4.13 and Table 4.3 represent that the AEC of the proposed scheme was less compared to LEACH, DEEC, and BOAACO and performed better when the number of sensor nodes increase to 200. The residual energy of the proposed model is much better than the other three existing schemes. The AEC is zero after 4400 rounds of operations. In case of LEACH, DEEC, and BOAACO, the AEC is zero after 3000, 4200, and 5400 rounds of operations.

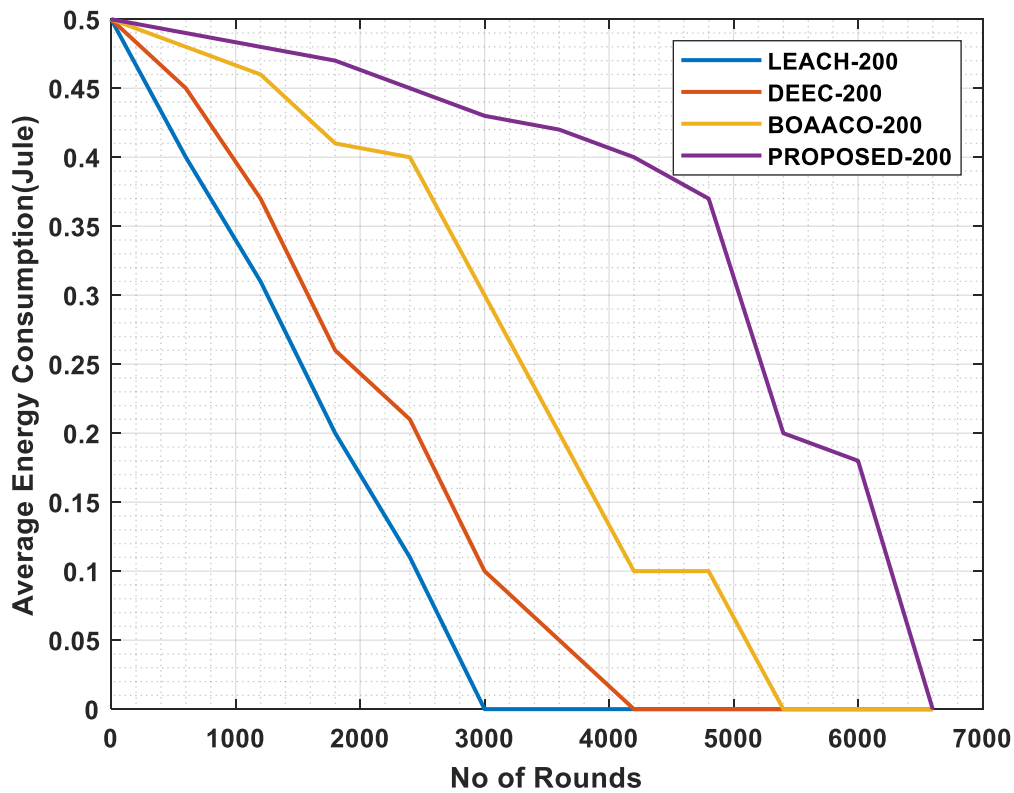


Fig. 4.13: AEC Vs No of Rounds when BS positioned at (100,100) and SN=200

4.10.9 Case study 9: AEC Vs No of Rounds when BS positioned at (100,100) and SN=300: The simulation results as shown in Fig.4.14 and Table 4.3 represent that the AEC of the proposed scheme was less compared to LEACH, DEEC, and BOAACO and performed better than case study-7, 8 when the number of sensor nodes increase to 300. The residual energy of the proposed model is much better than the other three existing schemes. The AEC is zero after 11000 rounds of operations. In case of LEACH, DEEC, and BOAACO, the AEC is zero after 2000, 2800, and 3600 rounds of operations.

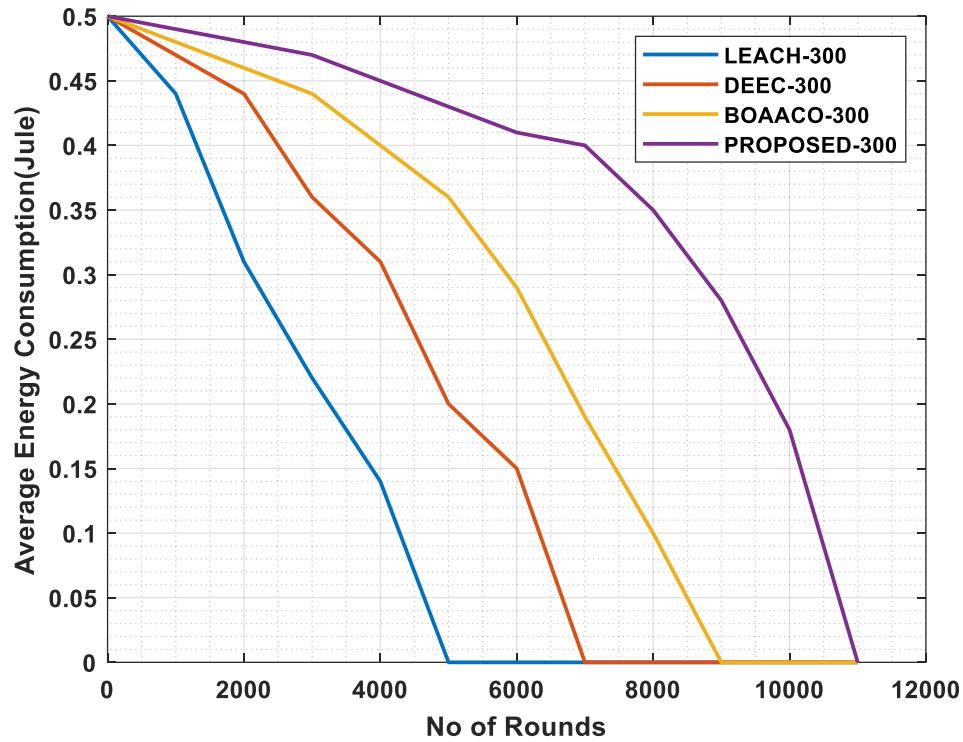


Fig.4.14: AEC Vs No of Rounds when BS positioned at (100,100) and SN=300

4.10.10 Case study 10: AEC Vs No of Rounds when BS positioned at (100,250) and SN=100: It can be observed from Fig. 4.15 and Table 4.3 that the AEC is more when BS is positioned outside of the environment field but the AEC of the proposed scheme was less compared to LEACH, DEEC, and BOAACO. The AEC is zero after 3000 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the AEC is zero after 1200, 1800, and 2100 rounds of operations.

4.10.11 Case study 11: AEC Vs No of Rounds when BS positioned at (100,250) and SN=200: The simulation results as shown in Fig.4.16 and Table 4.3 represent that the AEC is zero after 4400 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the AEC is zero after 2000, 2400, and 3200 rounds of operations and the performance is better when SNs incases to 200.

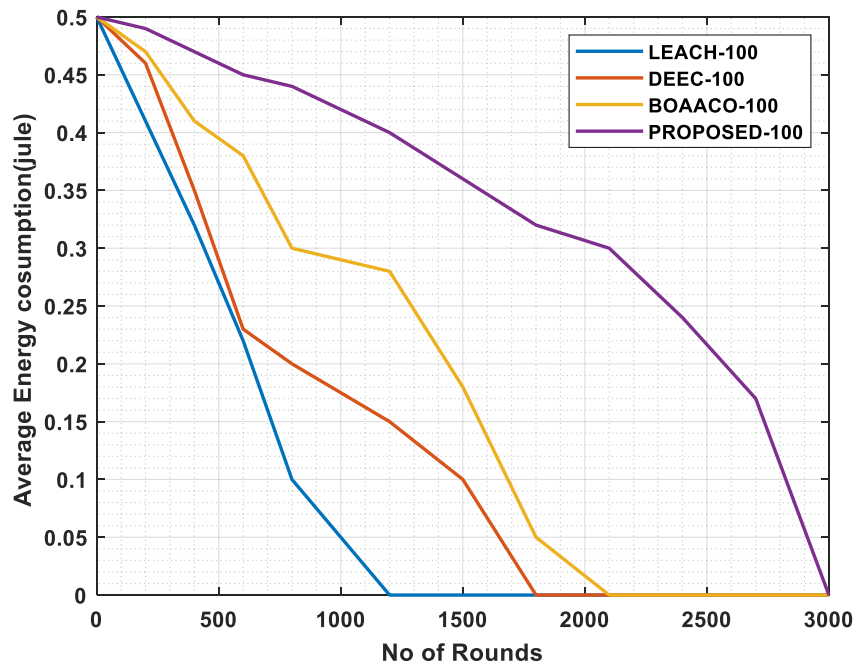


Fig. 4.15: AEC Vs No of Rounds when BS positioned at (100,250) and SN=100

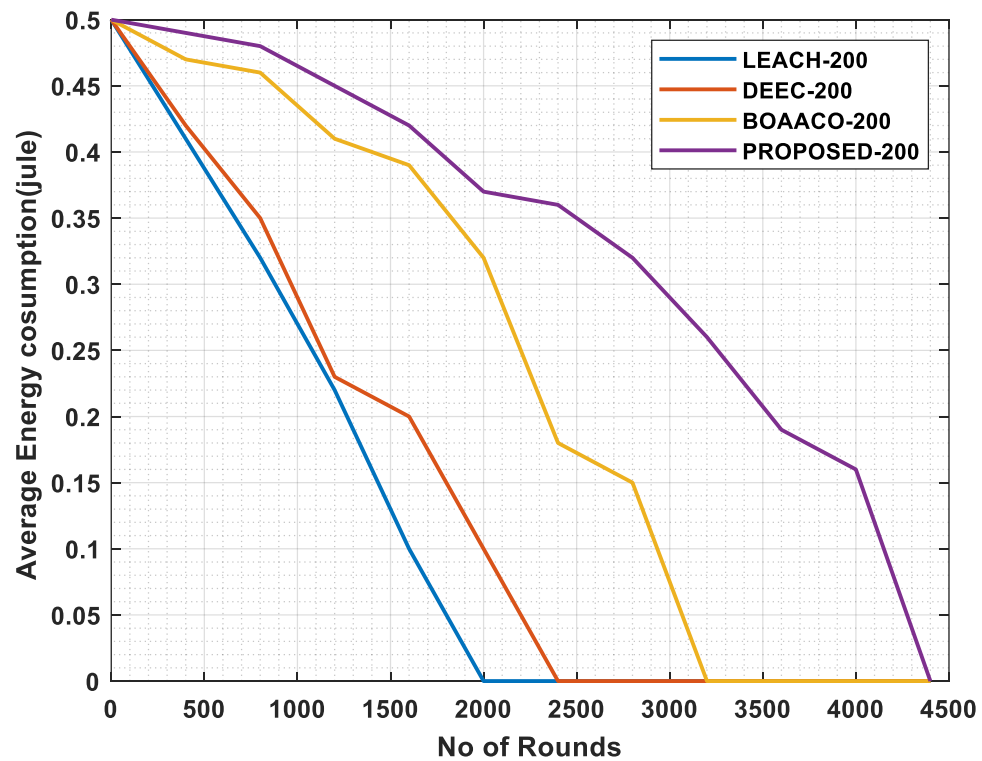


Fig. 4.16: AEC Vs No of Rounds when BS positioned at (100,250) and SN=200

Table 4.4 Packets Received at BS using LEACH, DEEC, BOAACO, and POA_Proposed

No of Rounds	LEACH	DEEC	BOAACO	POA_Proposed
Packets Received (Bytes) by BS when BS positioned at (100,100) and SN=100				
3000	19998	59989	89879	119986
Packets Received (Bytes) by BS when BS positioned at (100,100) and SN=200				
3000	49996	149989	169987	239993
Packets Received (Bytes) by BS when BS positioned at (100,100) and SN=300				
3000	99989	169995	199989	289987
Packets Received (Bytes) by BS when BS positioned at (100,250) and SN=100				
3000	13997	49989	69988	109993
Packets Received (Bytes) by BS when BS positioned at (100,250) and SN=200				
3000	29997	109995	139996	199994
Packets Received (Bytes) by BS when BS positioned at (100,250) and SN=300				
3000	79992	129994	149993	229989

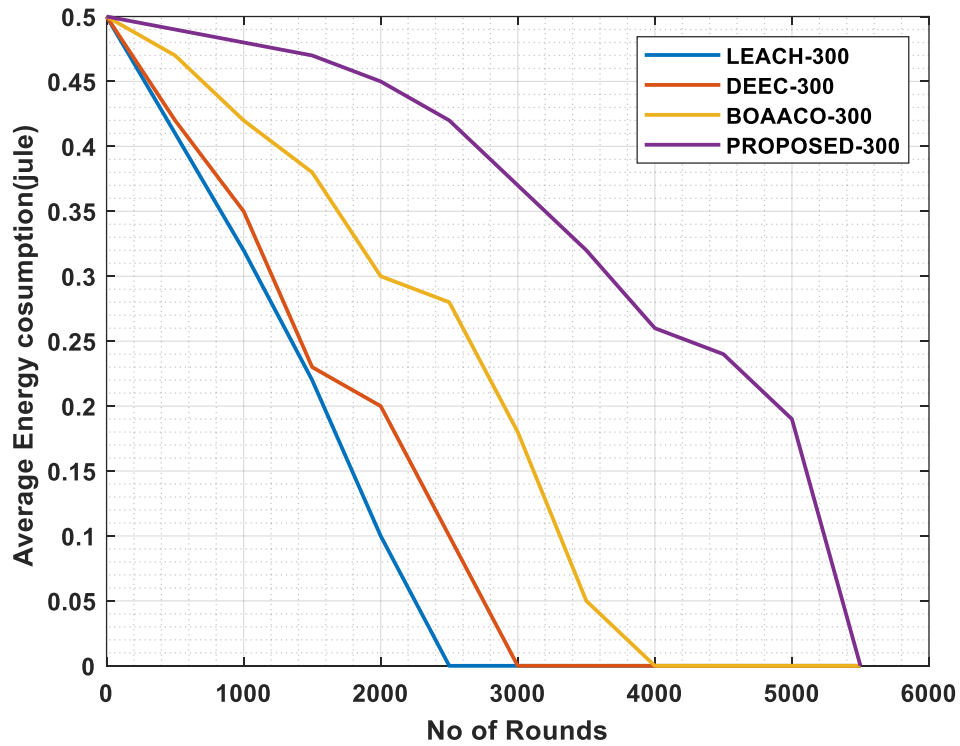


Fig. 4.17: AEC Vs No of Rounds when BS Positioned at (100,250) and SN=300

4.10.12 Case study 12: AEC Vs No of Rounds when BS positioned at (100,250) and SN=200: The simulation results as shown in Fig.4.17 and Table 4.3 represent that the AEC is zero after 5500 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the AEC is zero after 2500, 3000, and 4000 rounds of operations and the performance is better the case study-10,11 when SNs incases to 300. Overall, the simulation results shows that the POA_Proposed performs the best in terms of energy efficiency, consistently exhibiting the lowest AEC values across all rounds. LEACH, on the other hand, consistently consumes the highest amount of energy.

4.10.13 Case study 13: No of packets Received by BS when BS positioned at (100,100): The obtained results of LEACH, DEEC, BOAACO, and the proposed scheme in terms of total data packets received by the BS are shown in Fig.4.18 and Table 4.4. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 19998, 59989, 89879, and 119986 bytes when SNs deployed inside of the environment field are 100. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 49996, 149989, 169987, and 239993 when SNs deployed are 200. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme

are 99989, 169995, 199989, and 289987 Bytes when SNs deployed are 300. The simulation result shows that the total packet received by the BS is high when SN density is increases.

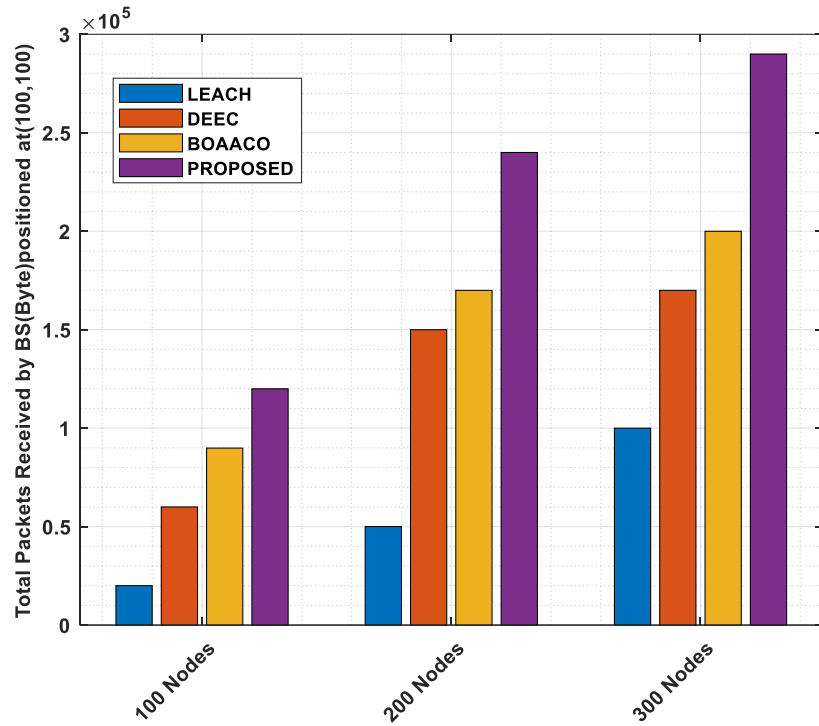


Fig. 4.18: No of packets Received by BS when BS ositioned at (100,100)

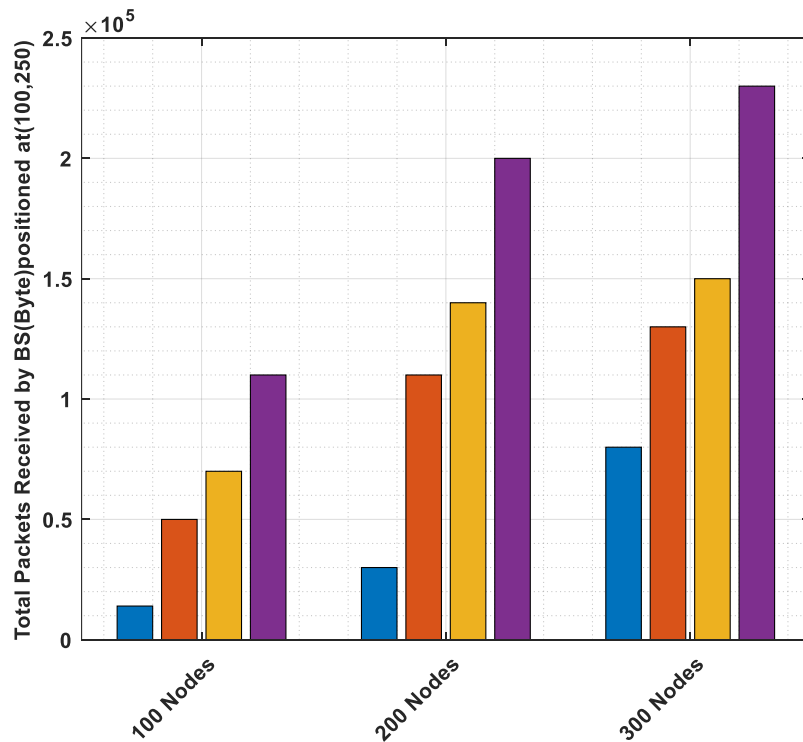


Fig. 4.19: No of packets Received by BS when BS Positioned at (100,250)

4.10.14 Case study 14: AEC Vs No of Rounds when BS positioned at (100,250) and SN=200: The simulation results as shown in Fig.4.17 and Table 4.3 represent that the AEC is zero after 5500 rounds of operations. In the case of LEACH, DEEC, and BOAACO, the AEC is zero after 2500, 3000, and 4000 rounds of operations and the performance is better the case study-10,11 when SNs incases to 300. Overall, the simulation results shows that the POA_Proposed performs the best in terms of energy efficiency, consistently exhibiting the lowest AEC values across all rounds. LEACH, on the other hand, consistently consumes the highest amount of energy.

4.10.15 Case study 15: No of packets Received by BS when BS positioned at (100,100): The obtained results of LEACH, DEEC, BOAACO, and the proposed scheme in terms of total data packets received by the BS are shown in Fig.4.18 and Table 4.4. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 19998, 59989, 89879, and 119986 bytes when SNs deployed inside of the environment field are 100. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 49996, 149989, 169987, and 239993 when SNs deployed are 200. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 99989, 169995, 199989, and 289987 Bytes when SNs deployed are 300. The simulation result shows that the total packet received by the BS is high when SN density is increases.

4.10.16 Case study 16: No of packets Received by BS when BS positioned at (100,250): The obtained results of LEACH, DEEC, BOAACO, and the proposed scheme in terms of total data packets received by the BS are shown in Fig. 4.19 and in Table 4.4. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 13997, 49989, 69988, and 109993 bytes when SNs deployed outside of the environment field at the center (100,250) and total SNs deployed are 100. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 29997, 109995, 139996, and 199994 bytes when SNs deployed are 200. The total data packets received by BS in the case of LEACH, DEEC, BOAACO, and the proposed scheme are 79992, 129994, 149993, and 229989 bytes when SNs deployed are 300. As the number of SNs increases the performance of the proposed scheme and exiting algorithm are increased. In both cases when BS is deployed at center or outside of the environment field the total packets received by the BS in increased and performance is always better when BS is situated at the center of the environment field.

The results demonstrate that proposed model outperforms existing routing protocols in terms of energy efficiency and network lifetime extension. The impact of the modified POA is discussed on energy efficiency and how it outperforms traditional clustering and routing methods. Analyze the scalability of the proposed scheme in terms of network density, highlighting its adaptability to different deployment scenarios.

4.11. Summary

In proposed work is an energy-efficient optimized cluster-based routing protocol for WSNs. The proposed scheme leverages a modified POA(POA_Proposed) to optimize cluster formation, data routing, and energy consumption. The POA is modeled using five fitness functions for cluster heads selection. The fitness functions are residual energy, distance between cluster member and cluster head, distance between cluster head and base station, node degree, and node centrality. The selected cluster heads are the suitable node for the optimal route selection to send data to the base station. For the optimal route selection, three fitness functions are modeled using POA. The fitness functions are residual energy, distance between cluster head and base station, and node degree. The proposed work ensuring the longevity of the proposed network. The findings show that the suggested model performs better than current routing protocols in terms of network lifetime extension and energy efficiency. The impact of the modified POA on energy efficiency and how it outperforms traditional clustering and routing methods is discussed. Analyze the scalability of the proposed scheme in terms of network density, highlighting its adaptability to different deployment scenarios.

CHAPTER-5

PROPOSE A TRUST MANAGEMENT SCHEME FOR NODE LOCALIZATION IN WSNS

In this chapter, a trust management scheme is proposed for node localization to ensure localization accuracy and security against the malicious nodes. Trust-aware localization improves the security of WSNs by guaranteeing the precise estimation of unknown nodes, even when there are malicious nodes present. Incorporating trust management into localization ensures the prevention of network integrity and operation.

5.1. Trust Aware Localization: WSNs have a self-organizing structure where several sensor nodes (SNs) are randomly deployed in the environment to sense surrounding data. Anchor nodes [ANs] and unknown nodes, or target nodes [TNs], are two types of nodes that participate in the node localization (NL) process. The NL [93-98] is a popular and cost-effective approach in a variety of fields, including smart homes, meteorology, tracking, health care, reducing pollution, industrial automation, surveillance, and the military. A hostile node could interfere with the NL [99] process and broadcast false information in the WSNs, posing a major security risk. Thus, only legitimate nodes should participate in the NL process [100-102]. Only legitimate ANs will send the information to the neighbor nodes to carry out secure NL, which requires the implementation of trust management methods [103-105]. The mechanisms and methods employed to assess and establish confidence among the participating nodes in the network are referred to as trust management [106-115] in WSNs. As a result of the distributed and autonomous nature of WSNs, trust management is essential. It is challenging to ensure the security and dependability of WSNs since they typically operate in a hostile and unpredictable environment. Consequently, the goal of trust management is to create a relationship of trust between nodes to offer secure and reliable communication between nodes. Numerous techniques and protocols are used to evaluate a node's trustworthiness based on its interactions and behavior with other nodes. These methods and protocols assess a node's trustworthiness using a variety of parameters, including its energy level, routing behavior, and communication patterns. The management of trust in WSNs can be done in several ways, including reputation-based, behavior-based, and hybrid methods. Reputation-based trust management assesses a node's trustworthiness

based on its previous actions. In contrast, behavior-based trust management assesses the nodes' trustworthiness in real time based on their behavior and interactions with other nodes. Hybrid approaches create a more robust and dependable trust management system by combining both reputation-based and behavior-based trust management techniques. According to the method used to find the position of the target node, the node localization algorithms can be roughly divided into two categories: RFNL and RBNL. The goal of RFNL [116-117] is to estimate SNs position without using direct distance measurements. It instead focuses on connection and relative relationships between network nodes. Anchor nodes or comprehensive signal propagation characteristics are not required for range-free approaches. Commonly used range-free localization methods include centroid localization, DV-Hop [118-121], and APIT [122]. RBNL entails establishing the geographic placements of SNs inside a network based on distance or communication range measurements between nodes. This method is based on the premise that if the distance between a node and many reference nodes (commonly referred to as anchor nodes) is known, the position of the node can be calculated using techniques such as trilateration or multi-lateration. The RBNL [123] uses a variety of methods, including the TDoA, RSSI [124-125], ToA, and AoA, to determine the location of TNs based on distances or angles between AN and TN. The RBNL methods provide a more precise node position compared to RFNL. All RBNLs require specialized hardware for node localization, which makes the process costly except RSSI. As a result of their affordability and simplicity of implementation, the RSSI technique is the most suitable. The performance of the NL can be significantly impacted by errors that can be generated by hostile or non-malicious nodes. The objective of the paper is to address the challenge of accurately locating nodes in WSNs while ensuring the trustworthiness of the ANs. Metaheuristic optimization [126] is a type of optimization algorithm used to address complicated optimization problems when traditional methods are inefficient or impossible. These methods are intended to identify approximate solutions to optimization problems by intelligently and heuristically exploring the search space, frequently inspired by natural phenomena. The MHOAs [127-128] are used for further enhancement of the localization performance. The PSO, BOA, and COA are the algorithms used for the enhancement.

5.2. Research Contributions: Trust-aware NL has been proposed as a solution to the problems with existing localization. The following are the main contributions of the proposed scheme:

- To assign a unique ID to each anchor node to prove the legitimacy of the anchor node for secure NL.

- To address the challenges proposed by a trust-aware node localization scheme, the scheme uses a reputation-based trust evaluation model to estimate the trust of the nodes being malicious or compromised and incorporates this information into the localization process to improve accuracy.
- The position of TN is estimated using information from the most reliable ANs.
- To provide a solution that can improve the accuracy and reliability of NL in WSNs, even in the presence of malicious attacks.
- To apply the MHOAs for further enhancement of the performance parameters.
- The comparative analysis of the proposed scheme with the existing scheme.

The rest of the work is organized as follows: Section 5.4 presents the three MHOAs. Section-5.5 presents the proposed model which illustrates the trust evaluation scheme and secure and optimized NL process. Section-5.6 presents the result evaluation and comparative analysis among the COA, BOA, and PSO. Section-5.7 presents the conclusion and future work.

5.3. MHOA for Secure Localization Optimization: MHOA is a effective and versatile problem-solving strategies that have gained attention in a variety of domains, including engineering, computer science, finance, and biology. These algorithms provide a reliable fast way for discovering near-optimal solutions to complicated optimization problems, particularly when standard methods fail. The main characteristic of MHOA is that it does not guarantee to find the global optimum but aims to provide an approximate solution in a reasonable amount of time.

5.3.1. Particle Swarm Optimization (PSO): PSO [129-132] PSO has a straightforward but powerful notion. To discover the best answer, individual particles (representing potential solutions) travel through a multi-dimensional search space, mimicking the behavior of a flock of birds or a school of fish. It was proposed by J. Kennedy and R Eberhart in 1995. Each particle acts as a search agent that moves through the search space in quest of the best solution. The position of the search agent corresponds to a potential solution, and the speed and direction of motion are represented by the velocity. Within the search space, particles are initially initialized at random. After that, each particle assesses its fitness using a fitness function. The fitness function specifies the optimization goal, which may be either minimizing or maximizing a particular criterion. Particles communicate with one another by sharing information about their best position, called as "personal best" (p^{Best}), and the best location found by any particle in the

swarm, called as "global best" (g^{Best}). Particles communicate with one another by sharing information about their best position, called "personal best" (p^{Best}), and the best location found by any particle in the swarm, called "global best" (g^{Best}). Particles change their velocity and position based on their individual experiences (p^{Best}) and swarm knowledge (g^{Best}). The algorithm's two basic stages are exploration and exploitation. Exploration is the process of searching various areas of the search space for potentially superior solutions, whereas exploitation is the process of refining the current best solution identified. Numerous optimization issues, such as those involving neural network training, engineering design, function optimization, image processing, and others have been solved using PSO. It is well-known for its ease of use, efficiency, and ability to find good solutions in a short period. However, depending on the issue features and parameter settings, it may experience early convergence or become stranded in local optima. The steps of PSO are as follows:

- **Population Initialization:** Initialize the position(x_i) and velocity(v_i) of each particle randomly. Each particle's position and speed are as follows:

$$position: x_i = \{x_{i1}, x_{i2}, x_{i3}, x_{i3} \dots \dots \dots x_{iN}\} \quad (5.1)$$

$$velocity: v_i = \{v_{i1}, v_{i2}, v_{i3}, v_{i3} \dots \dots \dots v_{iN}\} \quad (5.2)$$

Calculate the fitness value using the fitness function of each search agent's current position. For the updations of p^{Best} and g^{Best} , compare each search agent's current fitness value to the fitness of its previously discovered best value (p^{Best}). If the present position of a search agent leads to a better solution update p^{Best} . Update p^{Best} if the current value of a search agent leads to a better solution.

- **Update the position and velocity:** Particle best position and swam best position are as follows:

$$v^{new} = w * v^{old} + (C_c * rand() * (p^{Best} - x_{current})) + (S_c * rand() * (g^{Best} - x_{current})) \quad (5.3)$$

Where w , C_c and S_c are the inertia, cognitive and social components respectively, the swarm moves in the groups is called inertial parameter(w) which controls the direction of the search agent movement. C_c is used to quantify the local performance (p^{Best}) compare to previous performance. Compute the new position of the search agent based on its new velocity. S_c is used to quantify the g^{Best} .

$$x_{current} = x_{current-1} + v^{new} \quad (5.4)$$

The algorithm ends once the target degree of accuracy is attained.

5.3.2. Butterfly Optimization Algorithm (BOA): Sankalop Arora and Satvir Singh presented the BOA [133], a swarm-based metaheuristic algorithm, in 2018. The way that butterflies seek out food is the inspiration for it. The cooperative migration of butterflies in the direction of the food source can be used to characterize their behavior. To locate a food source or mate, butterflies detect and analyze the fragrance in the air. BOA imitates this behavior to locate the best solution available within the search space. BOA uses butterflies as search agents (SAs) to carry out optimization. The intensity of fragrance produced by a butterfly relates to its fitness function. Every butterfly releases a scent to entice one another. Each butterfly will either fly in the direction of the one that is releasing more scent or at random. A butterfly's fitness will change as it travels from one place to another. The fragrance will propagate long distances and be sensed by other butterflies, allowing them to communicate personal information and build a network of shared social knowledge. When a butterfly detects another butterfly's fragrance, it will travel toward it, a process known as global search. In another scenario, if a butterfly cannot detect fragrance in its surroundings, it would travel randomly, which is known as local search. The stimulus intensity of a butterfly is affected the fitness function. BOA contains three phases: initialization, iteration, and finalization. In each BOA run, the initialization is completed first, followed by iterative searching, and ultimately, the algorithm is terminated when the optimal solution is found. All butterflies are deployed in the search space randomly. The fitness value of each butterfly is estimated. The algorithm goes through several iterations. All butterflies in the solution space are moved to new places and their fitness values are calculated in each iteration. The fragrance of the butterfly is estimated using the three essential parameters which are stimulus intensity (I_b), modality(m), and power exponent(p). I_b of a butterfly is associated with fitness function. The natural phenomena of butterflies include I_b variation and f_b formulation. Steven's power law differentiates smell from an 's'. BOA generates fragrance dependent on the intensity of the stimulation as follows:

$$f_{bi} = s * I_{bi}^p, i = 1 \text{ to } N \quad (5.5)$$

Where f_{bi} is the magnitudes of the fragrance perceived by the butterfly b_i , N is the butterfly population. The value of the stimulus intensity depends on s and p . The values of s and p are lie between 0 and 1. When the value of the power exponent(p) is 1, a butterfly's smell spreads universally without absorption, making it simple to achieve a single global optimum because all butterflies experience it equally. this is an ideal case. However, if $p = 0$, other butterflies cannot

detect the smell, preventing optimization. This is impractical. So, the power exponent is a very essential component and the value of p should lie between 0 and 1. Where p is set to a value between 0 and 1. Every butterfly in the environment moves to new locations after every iteration, after which their fitness values are evaluated. The algorithm begins by estimating the fitness values for all butterflies at different locations across the solution space. These butterflies will emit scent wherever they are which is mimicked using equ.(5.6) The approach involves two fundamental phases: the global and local search phase. During the global search phase, the butterfly approaches the butterfly that is the fittest; equ.(5.6) represents the fittest butterfly.

$$x_{bi}^{t+1} = x_{bi}^t + (rand^2 * g_{bi}^{Best} - x_{bi}^t) * f_{bi} \quad (5.6)$$

The solution vector of the i^{th} butterfly is x_{bi}^t . g_{bi}^{Best} is the global best solution of the current iteration, and random number ($rand$) lies between 0 and 1. The butterfly moves randomly (p_{bi}^{Best}) during the local search phase; this butterfly is represented by equ.(5.7).

$$x_{bi}^{t+1} = x_{bi}^t + (rand^2 * x_{bj}^t - x_{bk}^t) * f_{bi} \quad (5.7)$$

Where x_{bj}^t and x_{bk}^t are the butterflies in the solution space.

5.3.3. Coati Optimization Algorithm (COA): COA is a novel MHOA designed in 2022 by Mohammad Dehghani, Zeinab Montazeri, and Pavel Trajkovski to simulate the actions of coatis in their natural habitat. Coati is a species of mammal called a coati. Coatis are raccoon family members that are indigenous to Central and South America. They are distinguished by their long tails, slim bodies, and unusual facial masks. Because of their extreme adaptability, coatis can be found in a variety of habitats, including woods, grasslands, and even cities. They are omnivorous and mostly active during the day, eating a variety of foods such as fruits, insects, small vertebrates, and eggs. These socially adept critters frequently live in bands and are renowned for their intelligence. Coati bands are normally led by a dominant male, and members work together to do activities including hunting, grooming, and protecting one another. The COA[101] is a novel meta-heuristic optimization technique, is intended to simulate coati behavior in WSNs. The coatis' strategy for attacking and escaping predators are both highly intelligent actions. Attacking and hunting coatis as well as the way that coatis flee from predators are some of COA's primary sources of inspiration. Mathematical models of the COA use the exploration and exploitation phases. The principal goal of the proposed COA method is to mimic the behaviors of the coati.

- **Population Initialization:** COA is a meta-heuristic optimization algorithm (MHOA). Each coati is a member of the population which is the candidate solution to the problem. The position of each coati is randomly initialized in the search space using the equ.(5.8) as follows.

$$C_i: c_{i,j} = lb_j - rand * (ub_j - lb_j) \quad (5.8)$$

Where C_i is the location of i^{th} coati in search filed. The value of the j^{th} decision variable is $c_{i,j}$. The total number of decision variables is N , lb_j , and ub_j are the lower and upper bound of the j^{th} decision variables. Matrix C as follows represents the coati's population matrix.

$$C = \begin{bmatrix} C_1 \\ \vdots \\ C_i \\ \vdots \\ C_N \end{bmatrix} = \begin{bmatrix} C_{1,1} & \dots & C_{1,j} & \dots & C_{1,m} \\ \vdots & & \vdots & & \vdots \\ C_{i,1} & \dots & C_{i,j} & \dots & C_{i,m} \\ \vdots & & \vdots & & \vdots \\ C_{N,1} & \dots & C_{N,j} & \dots & C_{N,m} \end{bmatrix}_{N \times m} \quad (5.9)$$

- **Mathematical model of COA:** A COA is a novel MHOA that mimics behavior of coati in the nature. Two natural behaviors are modelled in the process of moving the coatis around in the algorithm. Exploration and exploitation of coatis, which attack and flee from predators, respectively. The coati population is divided into two groups. Group one is involved in exploitation phase and other group involved in exploration phase. The position of the best population member is assumed as the location of the prey in the optimization process. The location of the coatis involved in the exploitation is mathematically simulated using the equ. (5.10), equ.(5.11), and equ.(5.12) as follows:

$$C_i: c_{i,j} = c_{i,j} - rand * (prey_j - I \cdot c_{i,j}), \quad for \ i = 1 \ to \frac{N}{2}, j = 1 \ to \ m \quad (5.10)$$

In phase 1, the new position of the prey and coati area as fallows.

$$prey: prey_j = lb_j - rand \cdot (ub_j - lb_j) \quad (5.11)$$

$$C_i: c_{i,j} = \begin{cases} c_{i,j} - rand * (prey_j - I \cdot c_{i,j}) & for \ F_{prey} < F_i \\ c_{i,j} - rand * (c_{i,j} - prey_j) & otherwise \end{cases} \quad (5.13) \quad for \ i = \frac{\lfloor N \rfloor}{2} + k \ to \ N \quad (5.12)$$

Where $k = 1 \ to \ \frac{\lfloor N \rfloor}{2} + 1$. Where $c_{i,j}$ is the new location of the coati. I is set of integers chosen randomly and $I = \{1, 2\}$. The floor function is $\lfloor . \rfloor$. The new location is updated if the fitness value is presented using equ.(5.14) as follows.

$$C_i = \begin{cases} C_i^{new} & F_i < F_{th} \\ C_i & Otherwise \end{cases} \quad (5.14)$$

Where C_i^{new} is the new location of the i^{th} SA. F_i is the objective function. F_{th} is the threshold value of the objective function. In the second phase, the process of updating coatis'(ie SA)

positions in the search field is formulated based on coatis' behavioral patterns when confronted with predators and escaping from predators. A coati flees from its place when a predator attacks it. To simulate the behavior of coati, the position is generated in the search space randomly as follows.

$$lb_j^{new} = \frac{lb_j}{l} \text{ and } ub_j^{new} = \frac{ub_j}{l} \quad l = 1, 2, 3, 4, \dots \dots \dots L \quad (5.15)$$

$$C_i^{new}: C_{i,j}^{new} = c_{i,j} + 1 - 2r). lb_j^{new} + r. (ub_j^{new} - lb_j^{new}), \quad i = 1 \text{ to } N/2 \text{ and } j = 1 \text{ to } m \quad (16)$$

Now update the location of the SA according to the objective function value is presented in equ.(5.17) as follows:

$$C_i = \begin{cases} C_i^{new} & F_i^{new} < F_{th} \\ C_i & \text{Otherwise} \end{cases} \quad (5.17)$$

Where C_i^{new} is the new position of the coati. lb_j^{new} is the local lower bound and ub_j^{new} is a local upper bound in the 2nd phase of the searching prey.

5.4. Proposed Model for Secure Localization: Here the sensor nodes' environments, functions, and capacities are described by the network model. The Fig.5.1 is a high-level diagram representing the proposed model. The unique ID is assigned to each AN. The trust values of all ANs are computed, and only the trustworthy nodes participate in the localization process. The term "trust is dynamic" refers to the fact that the level of trust assigned to a node change based on the behavior of that node. Trust is an asymmetric relationship, meaning that it is not mutual or equal between the two individuals. Additionally, trust is not transferable, meaning that if node A trusts node B and node B trusts node C, it does not necessarily mean that node A trusts node C.

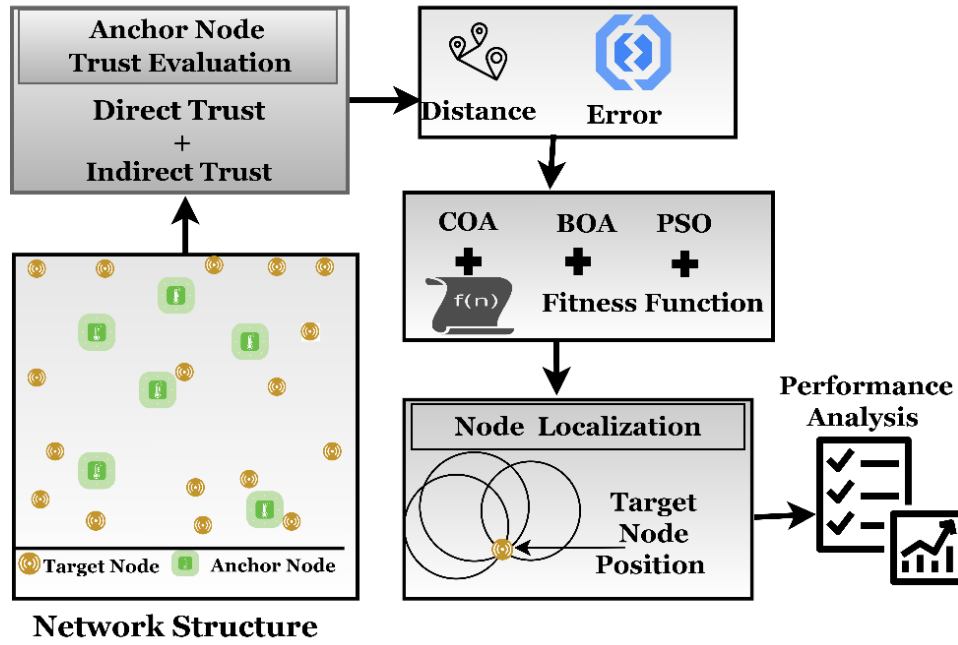


Fig.5.1: Network Structure for Secure Localization in WSNs

5.4.1. Network Scenario and Assumption: The proposed algorithm comprises three types of sensor nodes. The nodes are anchor nodes, non-gps sensor nodes also known as TN, and malicious nodes (MN) that are randomly deployed in two-dimensional (2D) environments. Not all TNs have precise position data. All sensors are uniform in their technological attributes, especially the transmission range within their respective categories. A node localization technique can be completed by all sensors with sufficient energy. The sensors must therefore make all choices independently of a central controller. The assessment of the nodes' behaviors is important to identify whether the node is legitimate or malicious. The cryptographic-based and trust-based are the two main security mechanisms to assess the trust behaviors of the node in WSNs. The cryptographic-based security mechanism is static and the trust-based security mechanism is dynamic which mitigates internal attacks in the distributed environment.

5.4.2. Direct Trust: It is a technique can be used for secure node localization [134] in WSNs. It is based on the idea that the nodes closest to a target node are more likely to have accurate information about its location. Direct Trust is a distributed algorithm that allows the nodes to cooperate to determine their location accurately. The Direct Trust technique uses a trust metric to determine the reliability of the distance measurement between two nodes. The trust metric is calculated based on the direct observations made by a node about its neighbors. Each node maintains a list of its neighbors, and the distance between them is measured using a suitable

technique such as time of flight, received signal strength, or angle of arrival. Direct Trust assumes that nodes that have a more direct line of sight to a target node are more reliable for localization. Nodes closer to the target node are assigned higher trust values, and the nodes farther away are assigned lower trust values. The trustworthy nodes are used to calculate the position of the target node. The Direct Trust technique has several advantages over other localization techniques in WSNs. First, it is a distributed algorithm that does not require any central coordination or communication. Second, it is robust to noise and errors in distance measurements. Third, it is scalable to large-scale networks. This involves assigning a trust value to all nodes in the network based on its behavior and the recommendations of other nodes. This can be done using various techniques, such as reputation-based systems or Bayesian networks. The nodes A, B, C, P, and Q are the anchor nodes in the simulation environment, as shown in Fig.5.2. Node C is a common neighbor node to nodes A and B. $R_A^B(t)$ is the recommendation credibility of node B estimated at anchor node A at time t is as follows:

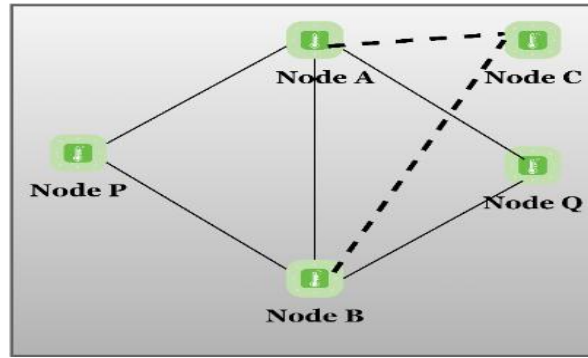


Fig. 5.2: Network Scenario for Trust Evaluation in WSNs

The direct trust ($D_A^B(t)$) of node B estimated at node A is presented using equ.(5.18) and equ.(5.19) as follows:

$$D_A^B(t) = \frac{\sqrt{\sum_{x \in X} \left((DT_A^C(t)) - (DT_B^C(t)) \right)^2}}{[C_{AB}]} \quad (5.18)$$

$$R_A^B(t) = (1 - D_A^B(t)) * \frac{\sum_{i \in C_{XY}} (x_i \wedge y_i)}{n} \quad (5.19)$$

Where X is a set of direct trust, Y is a set of recommendation sent by any neighbor(B), $x_i \in X$, $y_i \in Y$, $(x_i \wedge y_i) = 0$ if set X and Y shows different behavior and $(x_i \wedge y_i) = 1$ if set X and Y shows similar behavior. C_{AB} is the common neighbors of nodes A and B.

5.4.3. Indirect Trust: Indirect Trust Management (ITM) in WSNs refers to a mechanism for assessing the trustworthiness of a node in the network based on the recommendations of other

trusted nodes, rather than directly observing its behavior. In ITM, nodes in the network do not rely solely on their own observations of the behavior of other nodes to determine whether they can be trusted. Instead, they also consider the opinions of other nodes that they trust. This approach can be especially useful in large-scale networks, where it may not be practical for every node to directly observe the behavior of every other node. The Indirect Trust ($IT_P^Q(t)$) on node Q estimated by node P at time t is presented using equ. (5.20) as follows:

$$IT_P^Q(t) = \frac{\sum_{NN-\{Q\}}(R_P^C(t) * D_C^Q(t))}{\sum_{NN-\{Q\}}(R_P^C(t))} \quad (5.20)$$

Similarly, $IT_A^B(t)$ is estimated. Now, the total node trust $NT_A^B(t) = w \cdot D_A^B(t) + (1 - w) * IT_A^B(t)$, where w is the weight of the direct trust. Once the trust values are calculated, they are propagated throughout the network to allow each node to make decisions based on the trust values of other nodes. This can be achieved using various communication protocols, such as gossip-based protocols or routing protocols.

5.4.4. Reputation-based Trust Model: In the Reputation-based Trust Model, each node in the network has a reputation value that reflects its reliability and trustworthiness. The reputation value is calculated based on the feedback received from other nodes in the network about the node's performance in terms of NL accuracy, power consumption, and communication reliability. The feedback can be obtained through direct observation or indirect inference, depending on the network architecture and available resources. Nodes with high reputation values are considered more reliable and trustworthy, and their localization estimates are given more weight in the calculation of the overall localization result. Nodes with low reputation values, on the other hand, are considered less reliable and their localization estimates are given less weight or ignored altogether. The Reputation-based Trust Model has several advantages over other localization methods. First, it is robust against malicious attacks and node failures because it relies on the collective feedback of multiple nodes, rather than the behavior of individual nodes. Second, it is adaptable to changing network conditions because the reputation values can be updated dynamically based on the feedback received. Finally, it is scalable to large networks because the reputation values can be computed in a distributed manner using algorithms. The received power level is affected by the path-loss. Friis' transmission equation is used to express the received power at a distance d from the transmitter is presented using equ. (5.21) as follows:

$$P_r(d) = P_t \frac{G_t G_r \lambda^2}{(4\pi)^2 (D_{AN_{ij}}^{Estimated})^n L} \quad (5.21)$$

Where G_t and G_r are the power gain of the transmitter, and receiver respectively. λ is the wavelength of the signal. L denotes various losses that are not related to the propagation loss. The parameter L may comprise system losses such as antenna loss, transmission line attenuation, loss at various filters, and so on. When there are no such system losses, the factor L is frequently greater than or equal to one. In this simulation the value of L is assumed to be 1. The value of the path loss exponent(n) is assumed to be 2 for the free space without any obstacle. The estimated distance between anchor nodes i and j is computed using the equ. (5.3) as follows.

$$D_{ANij}^{Estimated} = \frac{K}{\sqrt{P_r(d)}} \quad (5.22)$$

Where $k = \sqrt{\frac{G_t G_r P_t}{(4\pi L) P_r(d)}} * \lambda$

The trust factor γ is as follows:

$$\gamma = \frac{|D_{ANij}^{actual} - D_{ANij}^{estimated}|}{D_{ANij}^{actual} + D_{ANij}^{estimated}} \quad (5.23)$$

and the reputation of the anchor node i computed by node j at the $t+1$ is as follows:

$$R_{ANij}^{t+1} = (1 - \gamma) + \gamma R_{ANij}^t \quad (5.24)$$

5.4.5. Trust-aware Node Localization: The trust-aware RSSI-based NL scheme is implemented for estimating the coordinates of TNs. NL aims to compute the coordinates of TNs by the minimization of the value of the fitness function. Localization of the TN is an NP-hard problem. The POA MHOAs are used to solve the NP-hard localization issue of WSNs. The fundamental precept of localization techniques is that deployed ANs with known coordinates (GPS-equipped sensors) transmit beacons with those coordinates to assist other nodes in locating themselves. Trust is a belief or confidence shared by a node or object based on the protocols specified. The positions of unknown nodes using the trilateration [135] method are estimated using the highly trustworthy beacon node deployed randomly as shown in Fig.5.3.

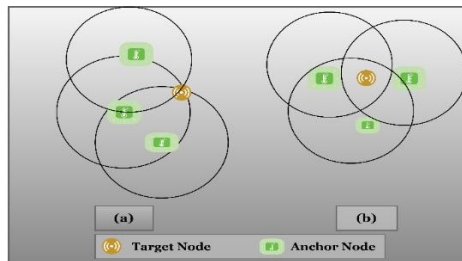


Fig.5.3: Possible Node Location using Tri-lateralation Method

There are a trustworthy AN and TN are deployed randomly in 200x200 square meters area. The equ. (5.25) represents the coordinates of the trustworthy beacon nodes are as follows:

$$P_{AN}: x_{i,j} = \{x_{1,1}, x_{2,2}, x_{3,3}, \dots \dots \dots x_{An,An}, \} \quad (5.25)$$

The position of the randomly deployed unknown nodes which will be discovered by trustworthy beacon nodes is presented using equ.(5.26) as follows:

$$P_{TN}: x_{i,j} = \{x_{1,1}, x_{2,2}, x_{3,3}, \dots \dots \dots x_{Tn,Tn}\} \quad (5.26)$$

RSSI-based localization is a technique used in WSNs to estimate the positions of TN based on the RSSI measurements. RSSI represents the received signal power at the TN and can be used to estimate the distance from the distant transmitter (AN). The signal strength attenuates as it travels through space, and this attenuation can be used to estimate the distance between the transmitting node (AN) and the receiving node (TN). The steps of NL are as follows:

- **Signal Propagation Model:** To estimate distances, Free Space Path Loss (FSPL) model is used which state that the signal power attenuates with the square of the distance between the transmitter and receiver is represented using equ.(5.27) as follows:

$$RSSI_d = RSSI_0 - 10 * n * \log_{10}(D_{t,r}^{Estimated}) \quad (5.27)$$

Where $D_{t,r}^{Estimated}$ is the distance between AN and TN, $RSSI_d$ is signal received at distance $D_{t,r}^{Estimated}$, $RSSI_0$ is signal strength at reference distance which is measured during calibration as shown in the Fig.5.4. The path loss component(n) is varying between 2 to 5 depends on environment.

Calibration Phase: The correct value of the path loss component (n) and the reference value of $RSSI_0$ are essential for localization. The ANs transmit signals to TN, and TN records the RSSI value received along with corresponding distances. The value of n and $RSSI_0$ can be estimated using the set of distances and $RSSI_0$ can be estimated using the set of distances and $RSSI_d$ values recorded.

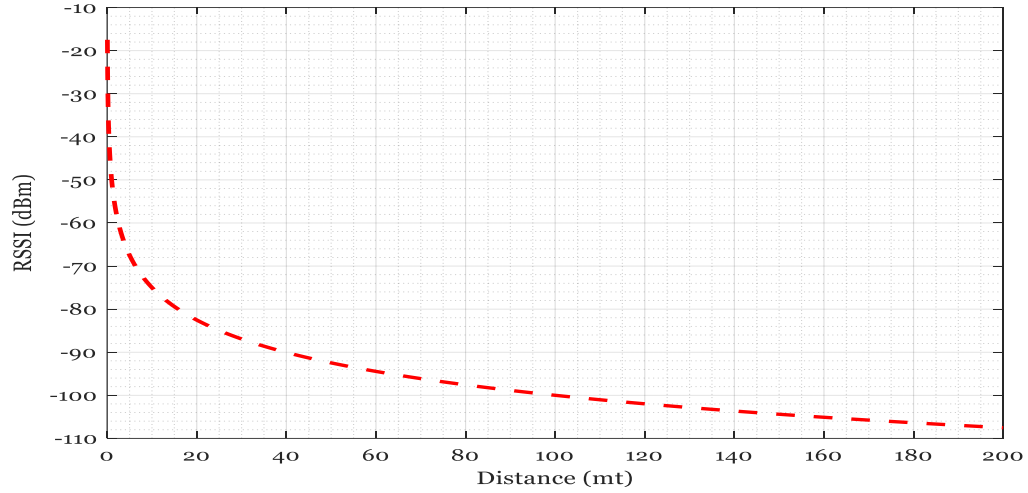


Fig.5.4: Calibration of RSSI Vs Distance Relationship

Distance Estimation: The TN send signals to ANs deployed in the environment. The ANs receive the signals and send their RSSI values to the TN. The unknown node estimates the distances using equ.(5.27) to each AN using the calibrated value of the $RSSI_0$ and path-loss component(n).

Position Estimation: To estimate the position of the TN, the trilateration approach is used when the distances from at least three ANs are known. If the coordinates of the three non-collinear AN are (x_{AN1}, y_{AN1}) , (x_{AN2}, y_{AN2}) , (x_{AN3}, y_{AN3}) , and the coordinate of the target node (TN) is (x_{TN}, y_{TN}) , then Euclidian distance from TN to other AN is presented using equ. (5.28) as follows:

$$\begin{cases} (x_{AN1} - x_{TN})^2 + (y_{AN1} - y_{TN})^2 = r_1^2 \\ (x_{AN2} - x_{TN})^2 + (y_{AN2} - y_{TN})^2 = r_2^2 \\ (x_{AN3} - x_{TN})^2 + (y_{AN3} - y_{TN})^2 = r_3^2 \end{cases} \quad (5.28)$$

After applying substitution { 3rd equation of set (5.28) -1st equation of set (5.28) and similarly

$$\begin{cases} 2(x_{AN1} - x_{AN3})x_{TN} + 2(y_{AN1} - y_{AN3})y_{TN} + x_{AN3}^2 - x_{AN1}^2 + y_{AN3}^2 - y_{AN1}^2 = r_3^2 - r_1^2 \\ 2(x_{AN2} - x_{AN3})x_{TN} + 2(y_{AN2} - y_{AN3})y_{TN} + y_{AN3}^2 - y_{AN2}^2 + y_{AN3}^2 - y_{AN2}^2 = r_3^2 - r_2^2 \end{cases} \quad (5.29)$$

The equ.(5.29) is equivalent to $A.X=B$, where

$$A = \begin{bmatrix} 2(x_{AN1} - x_{AN3}) & 2(y_{AN1} - y_{AN3}) \\ 2(x_{AN2} - x_{AN3}) & 2(y_{AN2} - y_{AN3}) \end{bmatrix},$$

$$X = \begin{bmatrix} x_{TN} \\ y_{TN} \end{bmatrix}, \text{ and}$$

$$B = \begin{bmatrix} r_3^2 - r_1^2 + x_{AN3}^2 - x_{AN1}^2 + y_{AN3}^2 - y_{AN1}^2 \\ r_3^2 - r_2^2 + x_{AN3}^2 - x_{AN2}^2 + y_{AN3}^2 - y_{AN2}^2 \end{bmatrix}$$

The position of the TN ($X(x_{TN}, y_{TN})$) is presented using equ.(5.30) as follows:

$$A.X = B, \text{ then } \Rightarrow A^T A.X = A^T . B \Rightarrow \text{Then } X = (A^T . A)^{-1} . A^T . B \quad 5.30$$

The main aim of the optimization is to minimize the localization error. The fitness function is a crucial aspect of optimization. They provide a quantifiable evaluation of how well different solutions might work to address an issue and guide the search algorithm to find the best or nearly the best solutions. The creation and application of an appropriate fitness function is essential to the efficiency of optimization algorithms. The difference between the actual distance and the estimated distance calculated for the TN localization serves as the fitness function in the proposed model as shown in equ.(5.31). When all TNs are localized, then an overall localization error is defined. It is stated as a mean square of the distance between the estimated node (X_{est}, Y_{est}) and actual node (X_{act}, Y_{act}). The mean square error is presented using the equ.(5.31) which is formulated using the Obj_Fun ($F_i(x)$) as follows:

$$Fitness_i = F_i: F_i(x, y) = \frac{\sqrt{\sum_{i=1}^N ((X_{act} - X_{est})^2 + (Y_{act} - Y_{est})^2)}}{N} \quad (5.31)$$

Where N is the number of TN. This fitness function is used in the following MHOA to enhance the performance.

Algorithm-5.1: Pseudocode of Trust-Aware NL using COA
1. <i>Obj_Fun</i> $F(x)$, $x=(x_1, x_2, x_3, \dots, x_{dim})$ 2. Initialize population of N Coati(x_i), $i=1, 2, 3, \dots, N$ 3. Total No of iteration($itrMax$) 4. Begin: for loop1 5. for $i=1: itrMax$ 6. update prey position with the best member of the population 7. Exploration phase: 8. Begin: for loop2 9. for $i=1:N/2$ 10. Estimate the position of new SA(coati) using equ.(5.10) 11. update the position of the coati using equ.(5.13) 12. End: for loop2 13. Begin: for loop3 14. for $i=(N/2+1):N$ 15. Estimate the position of the prey using equ.(5.11) 16. Estimate the new position of the SA using equ.(5.12) 17. Update the position of the SA using equ.(5.14)

```

18. End: for loop3
19. Exploitation Phase:
20. Calculate lower and upper bound using equ.(5.15)
21. Begin: for loop4
22. for  $i=1:N$ 
23. Estimate the new position of the  $i^{th}$  SAt using equ.(5.16)
24. Update the position of the  $i^{th}$  SA using equ.(5.17)
25. End: for loop4
26.  $F_i(x)$  is best solution
27. End: for loop1
28. return  $F_i(x)$ 
29. Output: the localized node locations

```

5.4.6. Trust Aware Node Localization using BOA: Each localized node (TN) runs BOA independently using the fitness function to determine the TN's optimal location. The starting value of the modality (c) is set to 0.01, while the initial value of the power exponent (a) is set to 0.1. Algorithm-2 shows the pseudocode of trust-aware NL using BOA.

Algorithm-5.2: Pseudocode of Trust-Aware NL using BOA

```

1. Obj_Fun  $F(x)$ ,  $x=(x_1, x_2, x_3, \dots, x_{dim})$ 
2. Parameters Initialization:
3. Initialize the Butterfly population( $x_i$ )
4. Total No of iteration( $itrMax$ )
5. Deployed Butterfly randomly
6. Initialize each Butterfly with an initial trust value (0.5)
7. Begin: for loop1
8.   for  $i=1: itrMax$ 
9.     Begin for loop 2
10.      for  $i=1: N$     //  $N=No$  of Butterfly
11.        Compute the fitness value of butterflies using equ.(5.31)
12.      End for loop 2
13.      Compute the  $p_{bi}^{Best}$  of the butterflies using equ.(5.7)
14.      Compute the trust of each Butterfly using equ.(5.24)

```

```

15.   Begin for loop 3:
16.        $r = \text{rand} ();$ 
17.       if ( $r < 0.5$ ) Begin: for loop1
18.           Compute  $g_{bi}^{Best}$  using equ.(5.6)
19.       Else
20.           Compute  $p_{bi}^{Best}$  using equ.(5.7)
21.       Update trust values
22.   End: for loop3
23. End: for loop1
24. Record the localized node positions from the global butterfly
    positions.
25. Output: the localized node locations

```

5.4.7. Trust Aware Node Localization using PSO: The PSO runs independently to minimize the fitness function and the initial values of inertial weight(w) is set to 0.7 and the values of C_c and S_c are set to 1.494 which were recommended for better convergence rate [42,43]. Algorithm-3 shows the pseudocode of trust-aware NL using PSO.

Algorithm-5.3: Pseudocode of Trust-Aware NL using PSO

```

1: Obj_Fun  $F(x)$ ,  $x = (x_1, x_2, x_3, \dots, x_{dim})$ 
2. Parameters Initialization:
2. Initialize  $w$ ,  $C_c$  and  $S_c$ 
3: Deploy  $N$  particles randomly in the search space
4: Total No of iteration( $itrMax$ )
5. Initialize each particle with an initial trust value (0.5)
6: Begin: for loop1
7:   for  $i = 1: itrMax$ 
8.   Begin: for loop2
9:     for  $i = 1: N$  //  $N = \text{No of Particle}$ 
11:    Compute the fitness value( $p^{Best}$ ) of particles using equ.(5.31)
12:  End for loop 2
13.  Compute the  $p^{Best}$  of the butterflies using equ.(5.3)
12:  Compute the trust of each Particle using equ.(5.24)
13.  Choose the  $g^{Best}$  among the  $p^{Best}$ 

```

13. **Begin for loop 3:**
16. *Compute the particle velocity using equ.(5.3)*
- 12: *Update particle position using equ.(5.4)*
19. *Update trust values using equ.(5.24)*
20. **End: for loop3**
21. **End: for loop1**
22. *Record the localized node positions from the global particle positions.*
23. **Output:** *the localized node locations*

Performance Metric: Three performance metrics are proposed for performance evaluation and analysis as follows:

Average Node localization Errors (ANL_E): The ANL_E is the mean distance error between the position (X_{est}, Y_{est}) estimated and the actual position (X_{ac}, Y_{ac}) of the TN.

$$ANL_E(\%) = \frac{\sqrt{\sum_{i=1}^N ((X_i^{est} - X_i^{act})^2 + (Y_i^{est} - Y_i^{act})^2)}}{N} \quad (5.32)$$

Average Computation Time (ANL_t(s)): The mean NL time also known as average computation time of NL. The time take by the NL process is as follows:

$$ANL_t(s) = \frac{\sum_{i=1}^N NL_t(s)}{N} \quad (5.33)$$

Where N is the total nodes (AN+TN+MN) deployed in the sensor filed.

Average Node Localization (ATNL): ATNL is the average of the TNL of N_p of trails(pass).

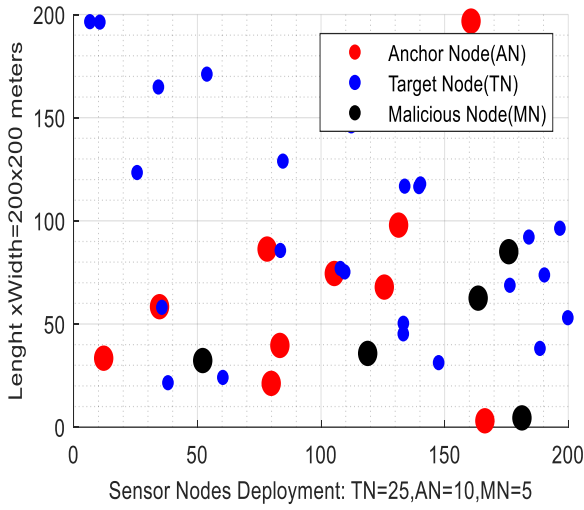
$$ATNL = \frac{\sum_{i=1}^N TNL_t}{N_p} \quad (5.34)$$

5.5. Simulation and Result Analysis: The proposed NL-based COA scheme was executed 30 times with different sets of AN, TN, and MN to obtain average localization, error, and computation time of NL. All simulations are carried out on 11th Gen Intel(R) Core (TM) i7-1165G7 @ 2.80GHz, 16.0 GB RAM, 64-bit OS, x64-based CPU; ASUS LAPTOP-U8PJ5GVA. The simulation parameters used for NL that influence the characteristics of a wireless network simulation are outlined in Table-5.1. A total of six different scenarios have been taken for the simulation of AN, TN, and MN in the sensor field and all scenarios of the node's deployment are

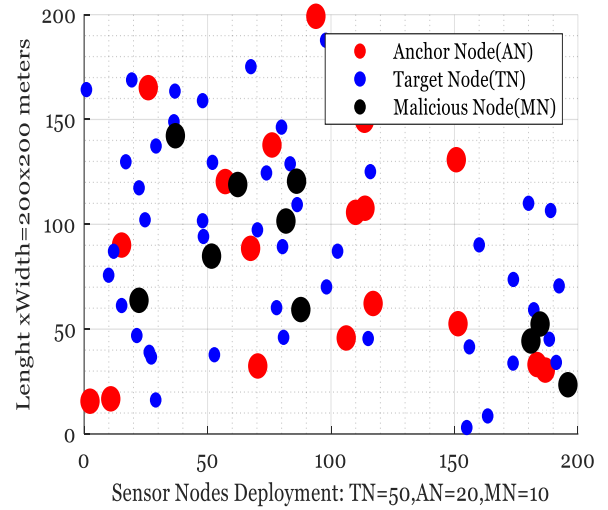
shown in Fig.5. The simulation is being carried out on a 200x200 meter space. In a wireless network simulation, this area represents the place where nodes will be deployed and communicate. These could be regular wireless network nodes that are the subject of the simulation's investigation or evaluation. Three types of sensor nodes are deployed. ANs are positioned randomly in a wireless network for the positioning of other nodes. For the six different cases, the malicious nodes are introduced in the sensor field. These nodes have been purposefully compromised or are acting maliciously, which could indicate security issues or weaknesses in the wireless network. The transmission range of nodes in the simulation ranges from 10 to 30 meters. This signifies that a node within this range can communicate directly with other nodes. The total Number of Iterations is set at 200 iterations. Each iteration is a single simulation run or cycle in which various parameters and conditions can be changed to examine how the wireless network performs. The simulation includes a defined deployment area, varying numbers of the target, anchor, and malicious nodes, a communication range, and a total number of iterations for observing the network's behavior under various scenarios.

Table-5.1: Simulation Parameters for Secure Localization in WSNs

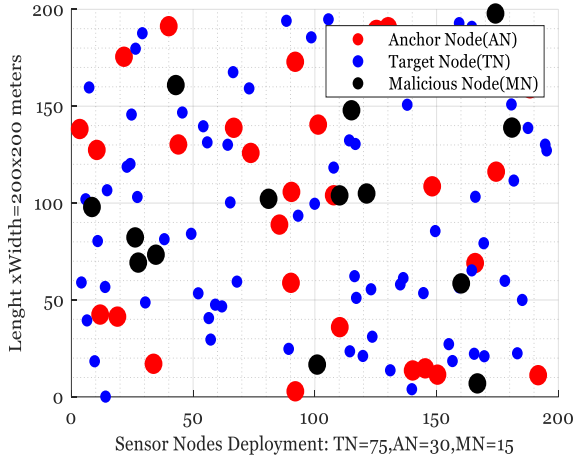
Deployment Area	200x200 Meters
Target Node (TN)	25,50,75,100,125,150
Anchor Node (AN)	10,20,30,40,50
Malicious Node (MN)	5,10,165,20,25,30
Transmission Range	10 to 30 Meters
Total no of iteration	200
Total no of Pass (Trails)	10



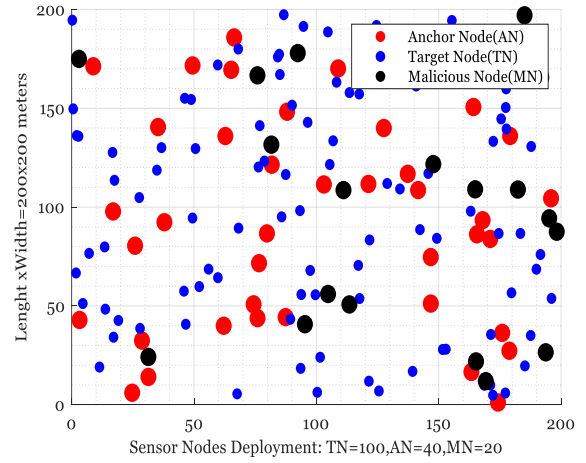
(a)



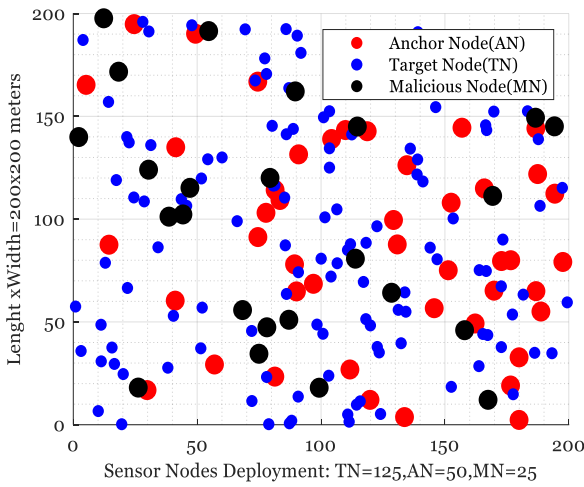
(b)



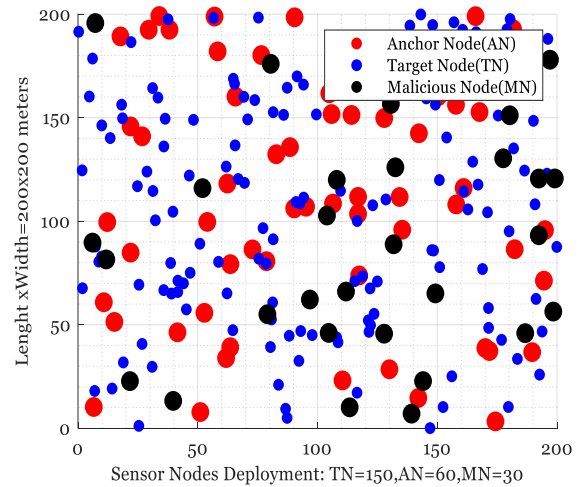
(c)



(d)



(e)



(f)

Fig.5.5: Scenarios of Sensor Nodes (AN, TN, MN) Deployment for Trust-Aware NL in WSNs

Table-5.2: Simulation Results of COA_Proposed, PSO, and BOA

T N	A N	M N	Trail Pass	PSO			BOA			COA_Proposed		
				NL _e (mt)	NL _t (s)	TN _L	NL _e (mt)	NL _t (s)	TN L	NL _e (mt)	NL _t (s)	TN L
25	10	5	1	40.25	0.34	15	28.50	0.27	18	24.25	0.23	19
			2	38.50	0.35	17	27.25	0.26	18	23.75	0.24	19
			3	34.80	0.34	16	26.80	0.28	16	22.85	0.21	18
			4	32.50	0.34	17	32.20	0.28	17	20.00	0.22	20
			5	37.70	0.35	15	28.25	0.29	17	21.85	0.22	21
			6	36.50	0.36	16	28.00	0.27	18	24.00	0.23	19
			7	34.80	0.35	16	27.75	0.28	15	23.85	0.24	20
			8	32.40	0.35	17	28.00	0.27	18	23.20	0.23	19
			9	35.55	0.35	17	29.50	0.29	19	23.25	0.24	20
			10	36.30	0.34	16	29.25	0.28	18	24.11	0.23	19
50	20	10	1	32.25	0.43	34	26.80	0.38	37	20.15	0.26	40
			2	31.50	0.44	36	25.20	0.36	35	21.75	0.25	39
			3	30.50	0.43	35	26.55	0.38	36	22.25	0.27	38
			4	31.75	0.44	35	28.45	0.37	36	23.60	0.25	41
			5	32.25	0.43	34	25.20	0.35	37	22.40	0.27	41
			6	30.50	0.44	33	26.50	0.37	34	23.55	0.24	39
			7	30.60	0.45	35	24.20	0.36	38	22.85	0.27	41
			8	32.20	0.44	34	26.50	0.37	37	20.00	0.27	40
			9	28.50	0.43	36	28.40	0.35	36	20.01	0.26	40
			10	30.60	0.45	35	24.25	0.38	38	22.01	0.25	39

75	30	15	1	28.80	0.62	54	22.80	0.41	58	18.69	0.37	61
			2	25.60	0.61	53	21.75	0.39	59	16.95	0.35	60
			3	27.75	0.63	55	24.25	0.36	57	17.77	0.36	62
			4	27.25	0.64	53	22.68	0.38	54	18.99	0.35	61
			5	25.80	0.61	54	23.71	0.41	55	19.95	0.34	60
			6	26.80	0.63	54	22.75	0.39	59	18.87	0.37	63
			7	25.20	0.64	55	22.75	0.37	58	17.39	0.33	62
			8	25.30	0.61	55	24.25	0.34	57	17.39	0.36	62
			9	30.50	0.63	53	22.68	0.41	58	18.69	0.36	61
			10	28.50	0.64	54	22.71	0.40	58	17.40	0.37	62
100	40	20	1	24.20	0.71	76	21.50	0.52	79	16.35	0.44	84
			2	24.55	0.72	73	22.30	0.55	81	15.87	0.42	83
			3	23.55	0.70	75	21.70	0.53	78	16.77	0.43	83
			4	23.50	0.71	76	21.30	0.52	79	17.79	0.45	85
			5	24.80	0.72	74	20.50	0.53	78	16.98	0.44	82
			6	23.50	0.73	77	22.80	0.54	79	15.89	0.42	84
			7	24.40	0.72	76	22.50	0.54	78	15.21	0.45	85
			8	23.50	0.70	77	21.90	0.53	80	14.41	0.43	85
			9	23.20	0.72	77	21.85	0.52	79	15.61	0.44	85
			10	22.30	0.73	78	20.85	0.53	80	16.33	0.42	84
125	50	25	1	19.55	0.79	101	17.60	0.70	103	11.27	0.55	111
			2	19.25	0.78	102	17.95	0.74	101	11.99	0.54	110
			3	20.50	0.76	103	16.55	0.73	104	12.11	0.57	112
			4	19.25	0.77	104	17.70	0.72	102	10.97	0.55	113

			5	20.40	0.78	102	17.60	0.70	102	10.89	0.57	112
			6	19.25	0.80	103	17.45	0.71	105	11.37	0.55	110
			7	19.40	0.81	101	16.85	0.70	104	11.28	0.56	111
			8	20.20	0.80	100	17.60	0.72	103	10.49	0.56	112
			9	18.40	0.81	102	17.60	0.72	103	11.27	0.57	111
			10	19.25	0.80	101	17.60	0.71	103	10.48	0.57	112
			1	18.75	1.15	122	16.80	0.86	126	09.73	0.68	146
			2	19.45	1.17	123	15.85	0.85	125	08.45	0.66	147
			3	18.70	1.14	120	15.95	0.84	124	07.47	0.64	147
			4	19.40	1.19	121	15.75	0.87	127	06.68	0.67	145
150	60	30	5	18.70	1.15	119	16.55	0.85	123	06.64	0.66	144
			6	19.40	1.17	119	15.25	0.83	125	08.43	0.64	148
			7	19.40	1.18	121	15.65	0.87	127	08.41	0.67	145
			8	18.75	1.14	122	15.45	0.84	127	07.44	0.67	145
			9	18.75	1.16	122	15.35	0.86	126	06.69	0.66	146
			10	18.50	1.18	123	16.55	0.88	126	06.68	0.69	146

Table-5.3: Mean Values of Simulation Results of COA_Proposed, PSO, and BOA

T N	A N	M N	PSO			BOA			COA_Proposed		
			ANLe (m)	ANL _t (s)	ATNL (%)	ANLe (m)	ANL _t (s)	ATNL (%)	ANLe (m)	ANL _t (s)	ATNL (%)
25	10	5	35.93 0	0.34 7	64.80	28.550	0.277	69.60	23.111	0.229	77.60
50	20	10	31.02 0	0.43 8	69.40	26.205	0.367	72.80	21.857	0.259	79.60
75	30	15	27.15 0	0.62 6	72.00	23.033	0.386	76.40	18.209	0.356	81.40

100	40	20	23.75 0	0.71 6	75.90	21.720	0.531	79.10	16.121	0.434	84.00
125	50	25	19.55 0	0.79 0	81.52	17.450	0.715	82.40	11.212	0.559	89.12
150	60	30	18.98 0	1.16 3	80.80	15.915	0.855	83.73	7.662	0.664	97.27

This section presents simulation results using the fitness function mentioned in the equ.(5.32). The MHOAs mentioned in the preliminaries section run independently using the objective function. A comparative analysis of COA(COA_Proposed), PSO, and BOA is illustrated. The simulation results of COA_Proposed, BOA, and PSO are listed in Table-5.2. The mean values of NL, NL error and Computation time obtained from the MHOAs are presented in Table-5.3.

5.5.1. The average node localization (ATNL): Fig.5.6 shows that the value of ATNL increases as the number of ANs, TNs, and MNs increases from 25 to 150, 10 to 60, and 5 to 30 respectively, and the ATNL value of PSO, BOA, and COA increases from 64.8% to 80.80%, 69.60 to 83.73%, and 77.60% to 97.27% respectively. The localization accuracy of COA_Proposed is always better than the BOA, and PSO.

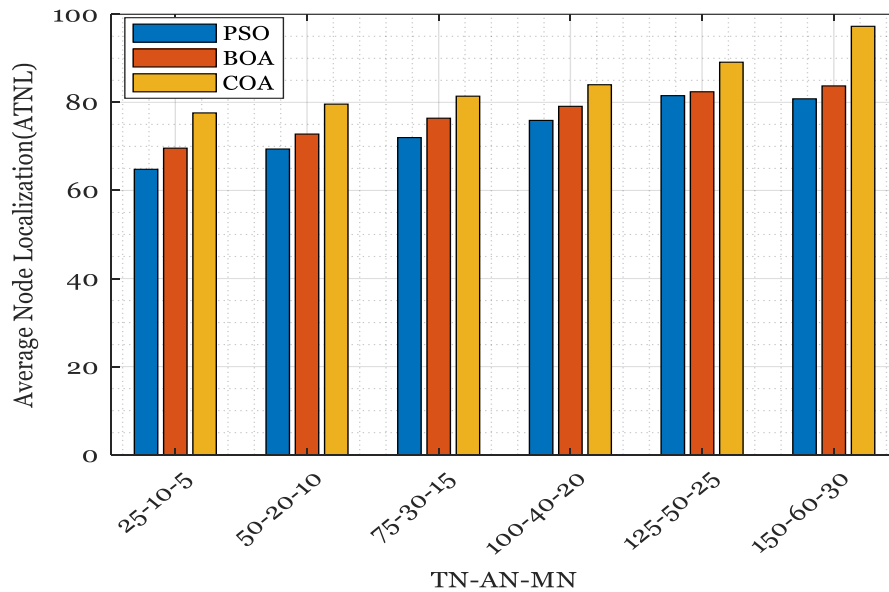


Fig.5.6: Variation of Average Node Localization at Different TN-AN-MN

5.5.2. The average node localization (ANL_e): Fig.5.7 shows that the value of ANL_e decreases as the number of ANs, TNs, and MNs increases from 25 to 150, 10 to 60, and 5 to 30 respectively, and the ANL_e value of PSO, BOA, and COA_Proposed decreases from 35.93 to 18.98, 28.55 to 15.915, and 23.111 to 7.662 meters respectively. The localization error of COA_Proposed, is always less than the BOA, and PSO.

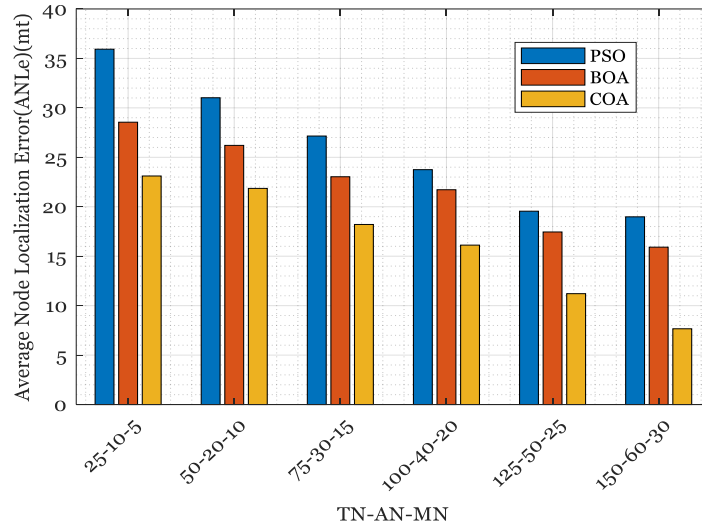


Fig.5.7: Variation of Average Node Localization Error at Different TN-AN-MN

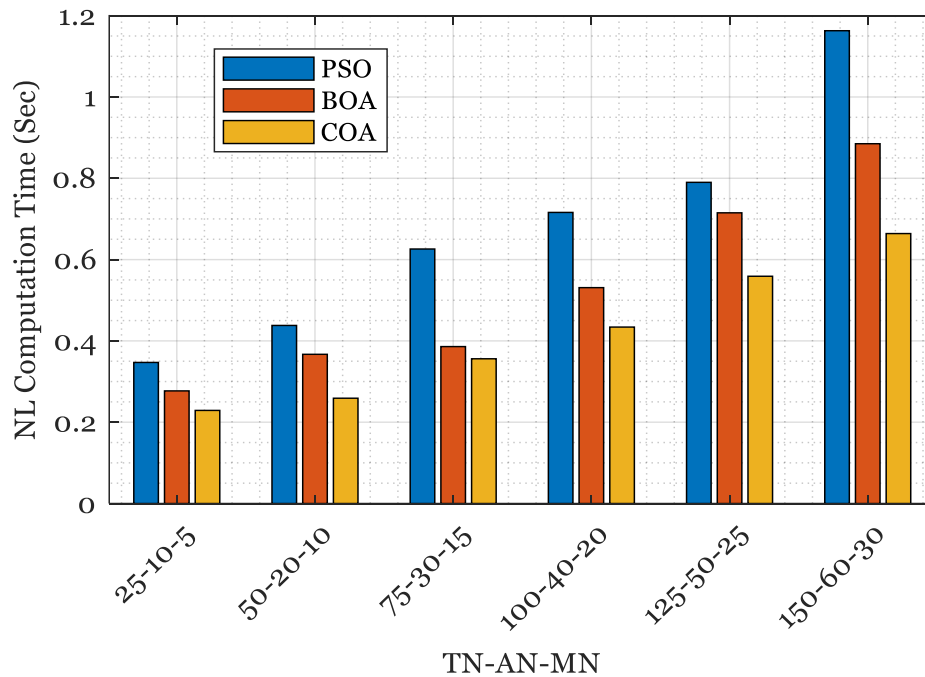


Fig.5.8: Variation of Average Computation Time at Different TN-AN-MN

5.5.3. Average NL Computation Time: Fig.5.8 shows that the value of ANL_t increases as the number of ANs, TNs, and MNs increases from 25 to 150, 10 to 60, and 5 to 30 respectively, and the ANL_t value of PSO, BOA, and COA_Proposed increases from 0.347 to 1.163, 0.227 to 0.855, and 0.229 to 0.664 seconds respectively. The results demonstrate that the localization computation time of COA_Proposed is always less than the BOA, and PSO.

5.6. Summary: The proposed work successfully executes the trust evaluation scheme in the decentralized localization of WSNs. Only trustworthy nodes are participated in the localization process. The localization process is incorporated with COA_Proposed. The proposed model is simulated for localization accuracy, localization error, and localization computation time. Throughout the simulations, the ratio of AN to TN remains consistent at 2.5. The simulation results show how well NL is refined by the proposed strategy. The COA_Proposed perform significantly better than the BOA, and PSO in terms of NL error, localization accuracy, and NL estimation time.

CHAPTER-6

CONCLUSION AND FUTURE WORK

6.1. Conclusion

The proposed work addressed three research objectives related to WSNs in heterogeneous environments: to design an optimization scheme for node localization, to develop an optimized energy-aware routing for WSNs, and to propose a trust management scheme for node localization in WSNs.

Firstly, the target nodes are localized using the RSSI and trilateration method. The extensive simulation is carried out using six different scenarios, and the localization accuracy, localization error, and localization computation time are estimated. The localization error is the fitness function for the SOA, C-SOA, and LF-SOA algorithms. The localization error is minimized using these three metaheuristic algorithms. The performance of C-SOA and LF-SOA is always better than the conventional SOA algorithm.

Secondly, the proposed work developed an optimized energy-aware routing for WSNs. The POA is modeled using five fitness functions for cluster head selection. The cluster heads are eligible nodes for routing the data packets to the base station. The POA is further modeled using three fitness functions for the routing. The proposed clustering and routing schemes enhance the life of the network. The comparative performance analysis is carried out. The performance of the POA_Proposed is better than the LEACH, DEEC, and BOAACO schemes.

Lastly, a trust management scheme is formulated and applied to anchor nodes. Only trustworthy, legitimate nodes are involved in the localization process to ensure the security and reliability. The localization error is the fitness function for the COA_Proposed heuristic algorithm. The localization accuracy, error, and computation time of the COA_Proposed is always better than BOA and PSO.

6.2. Future Work

- To improve localization performance, the proposed scheme can be hybridized with another meta-heuristic algorithm, and it is essential to emphasize that RSSI-based localization faces several challenges and restrictions, including signal jitter, interference, and environmental influences. To enhance the accuracy and robustness of the localization, additional techniques, including signal averaging, outlier rejection, and filtering, may be used.

- The proposed scheme (POA_Proposed) does not consider environmental factors like path loss components and delays in forwarding the data from CHs to the BS. Future work aims to include path loss and delay and design better WSNs.
- The range-based localization methods are used for the localization. The range-free localization method can be used for the localization process.
- Energy-efficient clustered routing is performed in the work. Security is a big challenge that can be mitigated using a suitable lightweight security algorithm.
- A more lightweight trust management can be designed to reduce the computation overhead.

REFERENCES

- [1] Kulkarni, Raghavendra V., and Ganesh Kumar Venayagamoorthy. "Particle swarm optimization in wireless-sensor networks: A brief survey." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 41, no. 2 (2010): 262-267.
- [2] Ismail, Mohd Ismifaizul Mohd, Rudzidatul Akmam Dzauddin, Shafiq Samsul, Nur Aisyah Azmi, Yoshihide Yamada, Mohd Fitri Mohd Yakub, and Noor Azurati Binti Ahmad Salleh. "An RSSI-based wireless sensor node localisation using trilateration and multilateration methods for outdoor environment." *arXiv preprint arXiv:1912.07801* (2019).
- [3] Zafari, Faheem, Athanasios Gkelias, and Kin K. Leung. "A survey of indoor localization systems and technologies." *IEEE Communications Surveys & Tutorials* 21, no. 3 (2019): 2568-2599.
- [4] Al Shayokh, Md, and Soo Young Shin. "Bio inspired distributed WSN localization based on chicken swarm optimization." *Wireless Personal Communications* 97, no. 4 (2017): 5691-5706.
- [5] Arora, Sankalap, and Ranjit Kaur. "Nature inspired range based wireless sensor node localization algorithms." (2017).
- [6] Wang, Wei, Xuming Liu, Maozhen Li, Zhaoba Wang, and Cunhua Wang. "Optimizing node localization in wireless sensor networks based on received signal strength indicator." *IEEE Access* 7 (2019): 73880-73889.
- [7] Lalama, Zahia, Samra Boulfekhar, and FouziSemechedine. "Localization Optimization in WSNs Using Meta-Heuristics Optimization Algorithms: A Survey." *Wireless Personal Communications* 122, no. 2 (2022): 1197-1220.
- [8] Phoemphon, Songyut, Chakchai So-In, and Nutthanon Leelathakul. "Improved distance estimation with node selection localization and particle swarm optimization for obstacle-aware wireless sensor networks." *Expert Systems with Applications* 175 (2021): 114773.
- [9] Mihoubi, Miloud, Abdellatif Rahmoun, Pascal Lorenz, and Nouredine Lasla. "An effective Bat algorithm for node localization in distributed wireless sensor network." *Security and Privacy* 1, no. 1 (2018): e7.
- [10] Strumberger, Ivana, Miroslav Minovic, Milan Tuba, and Nebojsa Bacanin. "Performance of elephant herding optimization and tree growth algorithm adapted for node localization in wireless sensor networks." *Sensors* 19, no. 11 (2019): 2515.
- [11] Sharma, Neha, and Vishal Gupta. "Meta-heuristic-based optimization of WSNs Localization Problem-a Survey." *Procedia Computer Science* 173 (2020): 36-45.
- [12] Lee, Meonghun, and Hyun Yoe. "WiBiA: Wireless sensor networks based on biomimicry algorithms." *International Journal of Computational Intelligence Systems* 12, no. 2 (2019): 1212-1220.
- [13] Dhiman, Gaurav, and Vijay Kumar. "Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems." *Knowledge-based systems* 165 (2019): 169-196.

- [14] Arora, Sankalap, and Priyanka Anand. "Chaotic grasshopper optimization algorithm for global optimization." *Neural Computing and Applications* 31, no. 8 (2019): 4385-4405.
- [15] Kaur, Gaganpreet, and Sankalap Arora. "Chaotic whale optimization algorithm." *Journal of Computational Design and Engineering* 5, no. 3 (2018): 275-284.
- [16] Tavazoei, Mohammad Saleh, and Mohammad Haeri. "Comparison of different one-dimensional maps as chaotic search pattern in chaos optimization algorithms." *Applied Mathematics and Computation* 187, no. 2 (2007): 1076-1085.
- [17] Alwan, Nuha AS, and Zahir M. Hussain. "Compressive sensing with chaotic sequences: an application to localization in wireless sensor networks." *Wireless Personal Communications* 105, no. 3 (2019): 941-950.
- [18] Cheng, Mangmang, Tao Qin, and Jing Yang. "Node Localization Algorithm Based on Modified Archimedes Optimization Algorithm in Wireless Sensor Networks." *Journal of Sensors* 2022 (2022).
- [19] Mihoubi, Miloud, Abdelatif Rahmoun, and Pascal Lorenz. "Metaheuristic RSSI based for node localization in distributed wireless sensor network." In *2017 Global Information Infrastructure and Networking Symposium (GIIS)*, pp. 64-70. IEEE, 2017.
- [20] Kulkarni, Raghavendra V., and Ganesh Kumar Venayagamoorthy. "Particle swarm optimization in wireless-sensor networks: A brief survey." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 41, no. 2 (2010): 262-267.
- [21] Xu, Yaming, Jianguo Zhou, and Peng Zhang. "RSS-based source localization when path-loss model parameters are unknown." *IEEE communications letters* 18, no. 6 (2014): 1055-1058.
- [22] Sun, Ziwen, Li Tao, Xinyu Wang, and Zhiping Zhou. "Localization algorithm in wireless sensor networks based on multi-objective particle swarm optimization." *International Journal of Distributed Sensor Networks* 11, no. 8 (2015): 716291.
- [23] Arora, Sankalap, and Satvir Singh. "Node localization in wireless sensor networks using butterfly optimization algorithm." *Arabian Journal for Science and Engineering* 42, no. 8 (2017): 3325-3335.
- [24] Mihoubi, Miloud, Abdelatif Rahmoun, and Pascal Lorenz. "Metaheuristic RSSI based for node localization in distributed wireless sensor network." In *2017 Global Information Infrastructure and Networking Symposium (GIIS)*, pp. 64-70. IEEE, 2017.
- [25] Rajakumar, R., J. Amudhavel, P. Dhavachelvan, and T. Vengattaraman. "GWO-LPWSN: Grey wolf optimization algorithm for node localization problem in wireless sensor networks." *Journal of computer networks and communications* 2017 (2017).
- [26] Li, Tu, Wang Yan, Li Ping, and Peng Fang. "A WSN positioning algorithm based on 3D discrete chaotic mapping." *EURASIP Journal on Wireless Communications and Networking* 2019, no. 1 (2019): 1-13.
- [27] Kanosh, Huthaifa M., Essam Halim Houssein, and Mazen M. Selim. "Salp swarm algorithm for node localization in wireless sensor networks." *Journal of Computer Networks and*

Communications 2019 (2019).

- [28] Wu, Hua, Ju Liu, Zheng Dong, and Yang Liu. "A hybrid mobile node localization algorithm based on adaptive MCB-PSO approach in wireless sensor networks." *Wireless communications and mobile computing* 2020 (2020).
- [29] Song, Ling, Xiaoyu Jiang, Liying Wang, and Xiaochun Hu. "Monte Carlo node localization based on improved QUARTE optimization." *Journal of Sensors* 2021 (2021).
- [30] Arafat, Muhammad Yeasir, and Sangman Moh. "Bio-inspired approaches for energy-efficient localization and clustering in UAV networks for monitoring wildfires in remote areas." *IEEE Access* 9 (2021): 18649-18669.
- [31] Chuku, Ndubueze, and Asis Nasipuri. "RSSI-Based localization schemes for wireless sensor networks using outlier detection." *Journal of Sensor and Actuator Networks* 10, no. 1 (2021): 10.
- [32] Sekhar, Pudi, E. Laxmi Lydia, Mohamed Elhoseny, Marwan Al-Akaidi, Mahmoud M. Selim, and K. Shankar. "An effective metaheuristic-based node localization technique for wireless sensor networks enabled indoor communication." *Physical Communication* 48 (2021): 101411.
- [33] Cheng, Mangmang, Tao Qin, and Jing Yang. "Node Localization Algorithm Based on Modified Archimedes Optimization Algorithm in Wireless Sensor Networks." *Journal of Sensors* 2022 (2022).
- [34] Rani, Shalli, Himanshi Babbar, Pardeep Kaur, Mohammad Dahman Alshehri, and Syed Hassan Ahmed Shah. "An optimized approach of dynamic target nodes in wireless sensor network using bio inspired algorithms for maritime rescue." *IEEE Transactions on Intelligent Transportation Systems* (2022).
- [35] Mirjalili, Seyedali, and Andrew Lewis. "The whale optimization algorithm." *Advances in engineering software* 95 (2016): 51-67.
- [36] Pitchaimanickam, B., and G. Murugaboopathi. "A hybrid firefly algorithm with particle swarm optimization for energy efficient optimal cluster head selection in wireless sensor networks." *Neural Computing and Applications* 32 (2020): 7709-7723.
- [37] Subramanian, P., J. Martin Sahayaraj, S. Senthilkumar, and D. Stalin Alex. "A hybrid grey wolf and crow search optimization algorithm-based optimal cluster head selection scheme for wireless sensor networks." *Wireless Personal Communications* 113 (2020): 905-925.
- [38] Sengathir, J., A. Rajesh, Gaurav Dhiman, S. Vimal, C. A. Yogaraja, and Wattana Viriyasitavat. "A novel cluster head selection using Hybrid Artificial Bee Colony and Firefly Algorithm for network lifetime and stability in WSNs." *Connection Science* 34, no. 1 (2022): 387-408.
- [39] Yogarajan, Gunasekaran, and T. Revathi. "Improved cluster-based data gathering using ant lion optimization in wireless sensor networks." *Wireless Personal Communications* 98 (2018): 2711-2731.
- [40] Wang, Zongshan, Hongwei Ding, Bo Li, Liyong Bao, and Zhijun Yang. "An energy efficient routing protocol based on improved artificial bee colony algorithm for wireless sensor networks." *IEEE Access* 8 (2020): 133577-133596.

- [41] Xu, Chuan, Zhengying Xiong, Guofeng Zhao, and Shui Yu. "An energy-efficient region source routing protocol for lifetime maximization in WSN." *IEEE Access* 7 (2019): 135277-135289.
- [42] Xiang, Wei, Ning Wang, and Yuan Zhou. "An energy-efficient routing algorithm for software-defined wireless sensor networks." *IEEE Sensors Journal* 16, no. 20 (2016): 7393-7400.
- [43] Sarkar, Amit, and T. Senthil Murugan. "Analysis on dual algorithms for optimal cluster head selection in wireless sensor network." *Evolutionary Intelligence* 15, no. 2 (2022): 1471-1485.
- [44] Mekonnen, Melaku Tamene, and Kuda Nageswara Rao. "Cluster optimization based on metaheuristic algorithms in wireless sensor networks." *Wireless Personal Communications* 97 (2017): 2633-2647.
- [45] Sarkar, Amit, and T. Senthil Murugan. "Cluster head selection for energy efficient and delay-less routing in wireless sensor network." *Wireless Networks* 25 (2019): 303-320.
- [46] Rayenizadeh, Mojgan, Marjan Kuchaki Rafsanjani, and Arsham Borumand Saeid. "Cluster head selection using hesitant fuzzy and firefly algorithm in wireless sensor networks." *Evolving Systems* (2022): 1-20.
- [47] Murugan, T. Senthil, and Amit Sarkar. "Optimal cluster head selection by hybridization of firefly and grey wolf optimization." *International Journal of Wireless and Mobile Computing* 14, no. 3 (2018): 296-305.
- [48] Priyanka, B. N., R. Jayaparvathy, and D. DivyaBharathi. "Efficient and dynamic cluster head selection for improving network lifetime in WSN using whale optimization algorithm." *Wireless Personal Communications* 123, no. 2 (2022): 1467-1481.
- [49] Sivakumar, Deena, S. Suganthi Devi, and T. Nalini. "Energy aware clustering protocol using chaotic gorilla troops optimization algorithm for Wireless Sensor Networks." *Multimedia Tools and Applications* (2023): 1-19.
- [50] Wang, Z., Ding, H., Li, B. et al. Energy Efficient Cluster Based Routing Protocol for WSN Using Firefly Algorithm and Ant Colony Optimization. *Wireless Pers Communication* 125, 2167–2200 (2022). <https://doi.org/10.1007/s11277-022-09651-9>.
- [51] Kathirolu, Panimalar, and Kanmani Selvadurai. "Energy efficient cluster head selection using improved Sparrow Search Algorithm in Wireless Sensor Networks." *Journal of King Saud University-Computer and Information Sciences* 34, no. 10 (2022): 8564-8575.
- [52] Wang, Zhong-xun, Min Zhang, Xinglong Gao, Wenqi Wang, and Xiaolin Li. "A clustering WSN routing protocol based on node energy and multipath." *Cluster Computing* 22 (2019): 5811-5823.
- [53] Arjunan, Sariga, and Pothula Sujatha. "Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol." *Applied Intelligence* 48 (2018): 2229-2246.
- [54] Baskaran, Madhusudhanan, and Chitra Sadagopan. "Synchronous firefly algorithm for cluster head selection in WSN." *The Scientific World Journal* 2015 (2015).
- [55] Wang, Zhen, Jin Duan, Haobo Xu, Xue Song, and Yang Yang. "Enhanced pelican optimization algorithm for cluster head selection in heterogeneous wireless sensor networks." *Sensors* 23, no.

18 (2023): 7711.

- [56] Adumbabu, I., and K. Selvakumar. "Energy Efficient Routing and Dynamic Cluster Head Selection Using Enhanced Optimization Algorithms for Wireless Sensor Networks." *Energies* 15, no. 21 (2022): 8016.
- [57] Wu, Shuiyan, Xiaofei Min, and Jing Li. "Optimal data transmission for wsns with data-location integration." *Symmetry* 13, no. 8 (2021): 1499.
- [58] Shalika, Shalika, Uma Meena, and Ajay Agarwal. "Optimized Routing Protocol Using Metaheuristic Techniques for Improving Energy Efficiency in WSN." (2023).
- [59] Chuang, Po-Jen, and Yi-Jun Jiang. "Effective neural network-based node localization scheme for wireless sensor networks." *IET Wireless Sensor Systems* 4, no. 2 (2014): 97-103.
- [60] Abouzar, Pooyan, David G. Michelson, and Maziyar Hamdi. "RSSI-based distributed self-localization for wireless sensor networks used in precision agriculture." *IEEE Transactions on Wireless Communications* 15, no. 10 (2016): 6638-6650.
- [61] Yuan, Yali, Liuwei Huo, Zhixiao Wang, and Dieter Hogrefe. "Secure APIT localization scheme against sybil attacks in distributed wireless sensor networks." *IEEE Access* 6 (2018): 27629-27636.
- [62] He, Jingsha, Jing Xu, Xingye Zhu, Yuqiang Zhang, Ting Zhang, and Wanqing Fu. "Reputation-based secure sensor localization in wireless sensor networks." *The Scientific World Journal* 2014 (2014).
- [63] He, Daojing, Lin Cui, Hejiao Huang, and Maode Ma. "Design and verification of enhanced secure localization scheme in wireless sensor networks." *IEEE transactions on Parallel and Distributed Systems* 20, no. 7 (2008): 1050-1058.
- [64] Xie, Ning, Yicong Chen, Zhuoyuan Li, and Dapeng Oliver Wu. "Lightweight secure localization approach in wireless sensor networks." *IEEE Transactions on Communications* 69, no. 10 (2021): 6879-6893.
- [65] Jiang, Jinfang, Guangjie Han, Feng Wang, Lei Shu, and Mohsen Guizani. "An efficient distributed trust model for wireless sensor networks." *IEEE transactions on parallel and distributed systems* 26, no. 5 (2014): 1228-1237.
- [66] Desai, S. Sundeep, and Manisha J. Nene. "Node-level trust evaluation in wireless sensor networks." *IEEE Transactions on Information Forensics and Security* 14, no. 8 (2019): 2139-2152.
- [67] Koohi, Sina Zangbari, Nor Asilah Wati Abdul Hamid, Mohamed Othman, and Gafurjan Ibragimov. "Raccoon optimization algorithm." *IEEE Access* 7 (2018): 5383-5399.
- [68] Sabbella, Veerraghava Reddy, Damodar Reddy Edla, Amruta Lipare, and Saidi Reddy Parne. "An efficient localization approach in wireless sensor networks using krill herd optimization algorithm." *IEEE Systems Journal* 15, no. 2 (2020): 2432-2442.
- [69] Rani, T. P., J. Aruna Jasmine, and S. Susila Sakthy. "Trust Based Localization Technique." *Ilkogretim Online* 19, no. 4 (2020): 6638-6657.

- [70] Nguyen, Tu N., Vinh V. Le, Shao-I. Chu, Bing-Hong Liu, and Yao-Chuan Hsu. "Secure localization algorithms against localization attacks in wireless sensor networks." *Wireless Personal Communications* (2021): 1-26.
- [71] Zheng, Tianshuai, Jinglei Tan, Xuesong Wu, Ruiqin Hu, Qifang Chen, Zhiquan Liu, and Ye Du. "SARM: A network State-Aware Adaptive Routing Mutation method for power IoT." *Computer Networks* 255 (2024): 110889.
- [72] Labraoui, Nabila, Mourad Gueroui, and Makhoul Aliouat. "Secure DV-Hop localization scheme against wormhole attacks in wireless sensor networks." *Transactions on Emerging Telecommunications Technologies* 23, no. 4 (2012): 303-316.
- [73] Zachariah, Ushus Elizebeth, and Lakshmanan Kuppusamy. "A hybrid approach to energy efficient clustering and routing in wireless sensor networks." *Evolutionary Intelligence* (2022): 1-13.
- [74] Maheshwari, Prachi, Ajay K. Sharma, and Karan Verma. "Energy efficient cluster-based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization." *Ad Hoc Networks* 110 (2021): 102317.
- [75] Lalwani, Praveen, Sagnik Das, Haider Banka, and Chiranjeev Kumar. "CRHS: clustering and routing in wireless sensor networks using harmony search algorithm." *Neural Computing and Applications* 30 (2018): 639-659.
- [76] Singh, Santar Pal, and Subhash Chander Sharma. "A survey on cluster-based routing protocols in wireless sensor networks." *Procedia computer science* 45 (2015): 687-695.
- [77] Lalwani, Praveen, Haider Banka, and Chiranjeev Kumar. "BERA: a biogeography-based energy saving routing architecture for wireless sensor networks." *Soft Computing* 22 (2018): 1651-1667.
- [78] Krishnan, Kannan, B. Yamini, Wael Mohammad Alenazy, and M. Nalini. "Energy-efficient cluster-based routing protocol for wsn based on hybrid bso-tlbo optimization model." *The Computer Journal* 64, no. 10 (2021): 1477-1493.
- [79] Agarwal, Vaibhav, Shashikala Tapaswi, and Prasenjit Chanak. "Energy-efficient mobile sink-based intelligent data routing scheme for wireless sensor networks." *IEEE Sensors Journal* 22, no. 10 (2022): 9881-9891.
- [80] Rambabu, Bandi, A. Venugopal Reddy, and Sengathir Janakiraman. "Hybrid artificial bee colony and monarchy butterfly optimization algorithm (HABC-MBOA)-based cluster head selection for WSNs." *Journal of King Saud University-Computer and Information Sciences* 34, no. 5 (2022): 1895-1905.
- [81] Bongale, Anupkumar M., C. R. Nirmala, and Arunkumar M. Bongale. "Hybrid cluster head election for WSN based on firefly and harmony search algorithms." *Wireless Personal Communications* 106 (2019): 275-306.
- [82] Nagarajan, Lavanya, and Shankar Thangavelu. "Hybrid grey wolf sunflower optimization algorithm for energy-efficient cluster head selection in wireless sensor networks for lifetime enhancement." *Iet Communications* 15, no. 3 (2021): 384-396.

- [83] Gupta, Suneet K., and Prasanta K. Jana. "Energy efficient clustering and routing algorithms for wireless sensor networks: GA based approach." *Wireless Personal Communications* 83 (2015): 2403-2423.
- [84] Chauhan, Vinith, and Surender Soni. "Mobile sink-based energy efficient cluster head selection strategy for wireless sensor networks." *Journal of Ambient Intelligence and Humanized Computing* 11 (2020): 4453-4466.
- [85] Chaurasia, Soni, and Kamal Kumar. "MOORP: Metaheuristic based optimized opportunistic routing protocol for wireless sensor network." *Wireless Personal Communications* 132, no. 2 (2023): 1241-1272.
- [86] Chaurasia, Soni, Kamal Kumar, and Neeraj Kumar. "Mocraw: A meta-heuristic optimized cluster head selection-based routing algorithm for wsns." *Ad Hoc Networks* 141 (2023): 103079.
- [87] Almasri, Marwah Mohammad, and Abrar Mohammed Alajlan. "Modified Optimization for Efficient Cluster-based Routing Protocol in Wireless Sensor Network." *INTELLIGENT AUTOMATION AND SOFT COMPUTING* 33, no. 3 (2022): 1687-1710.
- [88] Kumar, Rajeev, and Dilip Kumar. "Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network." *Wireless Networks* 22 (2016): 1461-1474.
- [89] Mosavvar, Islam, and Ali Ghaffari. "Data aggregation in wireless sensor networks using firefly algorithm." *Wireless Personal Communications* 104 (2019): 307-324.
- [90] Al-Kaseem, Bilal R., Zahraa K. Taha, Sarah W. Abdulmajeed, and Hamed S. Al-Raweshidy. "Optimized energy-efficient path planning strategy in WSN with multiple Mobile sinks." *IEEE Access* 9 (2021): 82833-82847.
- [91] Trojovský, Pavel, and Mohammad Dehghani. "Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications." *Sensors* 22, no. 3 (2022): 855.
- [92] Praveen Kumar, R., Jennifer S. Raj, and S. Smys. "Performance analysis of hybrid optimization algorithm for virtual head selection in wireless sensor networks." *Wireless Personal Communications* (2021): 1-16.
- [93] Liu, Xingcheng, Shaohua Su, Feng Han, Yitong Liu, and Zhihong Pan. "A range-based secure localization algorithm for wireless sensor networks." *IEEE Sensors Journal* 19, no. 2 (2018): 785-796.
- [94] Han, Guangjie, Jinfang Jiang, Lei Shu, Mohsen Guizani, and Shojiro Nishio. "A two-step secure localization for wireless sensor networks." *The Computer Journal* 56, no. 10 (2013): 1154-1166.
- [95] Yu, Ning, Lirui Zhang, and Yongji Ren. "A novel D-S based secure localization algorithm for wireless sensor networks." *Security and Communication Networks* 7, no. 11 (2014): 1945-1954.
- [96] Biswas, Rathindra Nath, Swarup Kumar Mitra, and Mrinal Kanti Naskar. "Wireless node localization under hostile radio environment using smart antenna." *Wireless Personal Communications* 116 (2021): 1815-1836.
- [97] Ahmed, Ayam Tawfeek, Ahmed Noori Rashid, and Khalid Shaker. "Localization in Wireless

Sensor Network." *Webology* 19, no. 1 (2022): 692-704.

- [98] Farooq-i-Azam, Muhammad, and Muhammad Naeem Ayyaz. "Location and position estimation in wireless sensor networks." *Wireless sensor networks: Current status and future trends* (2016): 179-214.
- [99] Dong, Shi, Xin-gang Zhang, and Wen-gang Zhou. "A security localization algorithm based on DV-hop against Sybil attack in wireless sensor networks." *Journal of Electrical Engineering & Technology* 15 (2020): 919-926.
- [100] Han, Guangjie, Jinfang Jiang, Lei Shu, Jianwei Niu, and Han-Chieh Chao. "Management and applications of trust in Wireless Sensor Networks: A survey." *Journal of Computer and System Sciences* 80, no. 3 (2014): 602-617.
- [101] Dehghani, Mohammad, Zeinab Montazeri, Eva Trojovská, and Pavel Trojovský. "Coati Optimization Algorithm: A new bio-inspired metaheuristic algorithm for solving optimization problems." *Knowledge-Based Systems* 259 (2023): 110011.
- [102] Ishmanov, Farruh, Aamir Saeed Malik, Sung Won Kim, and Bahodir Begalov. "Trust management system in wireless sensor networks: design considerations and research challenges." *Transactions on Emerging Telecommunications Technologies* 26, no. 2 (2015): 107-130.
- [103] Han, Guangjie, Li Liu, Jinfang Jiang, Lei Shu, and Joel JPC Rodrigues. "A collaborative secure localization algorithm based on trust model in underwater wireless sensor networks." *Sensors* 16, no. 2 (2016): 229.
- [104] Dohare, Indu, and Karan Singh. "Lightweight Trust Evaluation in IoT: Bio-Inspired Metaheuristic Approach." In *Cloud IoT*, pp. 243-255. Chapman and Hall/CRC, 2022.
- [105] Khedr, Ahmed M., S. Sheeja Rani, and Mohamed Saad. "Hybridized Dragonfly and Jaya algorithm for optimal sensor node location identification in mobile wireless sensor networks." *The Journal of Supercomputing* (2023): 1-23.
- [106] Desai, S. Sundeep, and Manisha J. Nene. "Multihop trust evaluation using memory integrity in wireless sensor networks." *IEEE Transactions on Information Forensics and Security* 16 (2021): 4092-4100.
- [107] Zhao, Jin, Jifeng Huang, and Naixue Xiong. "An effective exponential-based trust and reputation evaluation system in wireless sensor networks." *IEEE Access* 7 (2019): 33859-33869.
- [108] Javaid, Nadeem. "A secure and efficient trust model for wireless sensor IoTs using blockchain." *IEEE Access* 10 (2022): 4568-4579.
- [109] Desai, S. Sundeep, and Manisha J. Nene. "Node-level trust evaluation in wireless sensor networks." *IEEE Transactions on Information Forensics and Security* 14, no. 8 (2019): 2139-2152.
- [110] Feng, Renjian, Xiaofeng Xu, Xiang Zhou, and Jiangwen Wan. "A trust evaluation algorithm for wireless sensor networks based on node behaviors and ds evidence theory." *Sensors* 11, no. 2 (2011): 1345-1360.

- [111] Jiang, Jinfang, Guangjie Han, Feng Wang, Lei Shu, and Mohsen Guizani. "An efficient distributed trust model for wireless sensor networks." *IEEE transactions on parallel and distributed systems* 26, no. 5 (2014): 1228-1237.
- [112] Kumar, Anand, Karan Singh, Tayyab Khan, Ali Ahmadian, Mohamad Hanif Md Saad, and Manisha Manjul. "ETAS: an efficient trust assessment scheme for BANs." *IEEE Access* 9 (2021): 83214-83233.
- [113] Reddy, Vijender Busi, Sarma Venkataraman, and Atul Negi. "Communication and data trust for wireless sensor networks using D-S theory." *IEEE Sensors Journal* 17, no. 12 (2017): 3921-3929.
- [114] Kim, Tai-Hoon, Rekha Goyat, Mritunjay Kumar Rai, Gulshan Kumar, William J. Buchanan, Rahul Saha, and Reji Thomas. "A novel trust evaluation process for secure localization using a decentralized blockchain in wireless sensor networks." *IEEE access* 7 (2019): 184133-184144.
- [115] Kumar, Rakesh, Sunil K. Singh, and D. K. Lobiyal. "UPSRVNet: Ultralightweight, Privacy preserved, and Secure RFID-based authentication protocol for VIoT Networks." *The Journal of Supercomputing* (2023): 1-28.
- [116] Kumar, Gulshan, Mritunjay Kumar Rai, and Rahul Saha. "Securing range free localization against wormhole attack using distance estimation and maximum likelihood estimation in wireless sensor networks." *Journal of Network and Computer Applications* 99 (2017): 10-16.
- [117] Sun, Haibin, and Meng Tian. "Improved range-free localization algorithm based on reliable node optimization and enhanced sand cat optimization algorithm." *The Journal of Supercomputing* (2023): 1-35.
- [118] Chen, Honglong, Wei Lou, Zhi Wang, Junfeng Wu, Zhibo Wang, and Aihua Xia. "Securing DV-Hop localization against wormhole attacks in wireless sensor networks." *Pervasive and Mobile Computing* 16 (2015): 22-35.
- [119] Li, Xiaoyin, Lianshan Yan, Wei Pan, and Bin Luo. "Secure and robust DV-Hop localization based on the vector refinement feedback method for wireless sensor networks." (2017): 810-821.
- [120] Wang, Hongbin, Liping Feng, Rong Li, and YiChi Zhang. "The Secure Localization Algorithm of SDV-HOP in Wireless Sensor Networks." *Telkomnika* 14 (2016).
- [121] Mohamed, Enas, Hatem Zakaria, and Mohamed B. Abdelhalim. "An improved DV-hop localization algorithm." In *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2016 2*, pp. 332-341. Springer International Publishing, 2017.
- [122] Li, Mao, Feng Jiang, and Cong Pei. "Improvement of triangle centroid localization algorithm based on PIT criterion (ITCL-PIT) for WSNs." *EURASIP Journal on Wireless Communications and Networking* 2022, no. 1 (2022): 1-16.
- [123] Misra, Sudip, and Tamoghna Ojha. "SecRET: Secure range-based localization with evidence theory for underwater sensor networks." *ACM Transactions on Autonomous and Adaptive Systems (TAAS)* 15, no. 1 (2021): 1-26.
- [124] Abouzar, Pooyan, David G. Michelson, and Maziyar Hamdi. "RSSI-based distributed self-localization for wireless sensor networks used in precision agriculture." *IEEE Transactions on*

Wireless Communications 15, no. 10 (2016): 6638-6650.

- [125] Shilpi, Prateek Raj Gautam, Sunil Kumar, and Arvind Kumar. "An optimized sensor node localization approach for wireless sensor networks using RSSI." *The Journal of Supercomputing* 79, no. 7 (2023): 7692-7716.
- [126] Dohare, Indu, and Karan Singh. "Green communication in sensor enabled IoT: integrated physics inspired meta-heuristic optimization-based approach." *Wireless Networks* 26 (2020): 3331-3348.
- [127] Mohan, Y., Yadav, R.K. & Manjul, M. Seagull optimization algorithm for node localization in wireless sensor networks. *Multimed Tools Appl* (2024). <https://doi.org/10.1007/s11042-024-18331-8>.
- [128] Y. Mohan, R. K. Yadav and M. Manjul, "PANLS: Performance Analysis of Node Localization Scheme in WSNs," 2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2023, pp. 950-956, doi: 10.1109/ICTACS59847.2023.10390138.
- [129] Kennedy, James, and Russell Eberhart. "Particle swarm optimization." In *Proceedings of ICNN'95-international conference on neural networks*, vol. 4, pp. 1942-1948. IEEE, 1995.
- [130] Eberhart, Russell C., and Yuhui Shi. "Tracking and optimizing dynamic systems with particle swarms." In *Proceedings of the 2001 congress on evolutionary computation (IEEE Cat. No. 01TH8546)*, vol. 1, pp. 94-100. IEEE, 2001.
- [131] Shi, Yuhui. "Particle swarm optimization: developments, applications and resources." In *Proceedings of the 2001 congress on evolutionary computation (IEEE Cat. No. 01TH8546)*, vol. 1, pp. 81-86. IEEE, 2001.
- [132] Shen, Shu, Lijuan Sun, Yibo Dang, Zhiqiang Zou, and Ruchuan Wang. "Node localization based on improved PSO and mobile nodes for environmental monitoring WSNs." *International Journal of Wireless Information Networks* 25 (2018): 470-479.
- [133] Sharma, Tarun K. "Enhanced butterfly optimization algorithm for reliability optimization problems." *Journal of Ambient Intelligence and Humanized Computing* 12, no. 7 (2021): 7595-7619.
- [134] Garg, R., Gulati, T. & Kumar, S. Range free localization in WSN against wormhole attack using Farkas' Lemma. *Wireless Netw* 29, 2029–2043 (2023). <https://doi.org/10.1007/s11276-023-03279-8>
- [135] Shenbagharaman, A., and B. Paramasivan. "Trilateration method-based node localization and energy efficient routing using rsa for under water wireless sensor network." *Sustainable Computing: Informatics and Systems* 41 (2024): 100952.