Vol.67: e24231115, 2024
https://doi.org/10.1590/1678-4324-2024231115
ISSN 1678-4324 Online Edition

BABT
Brazilian Archives of Biology and Technology

Article - Engineering, Technology and Techniques

Modeling of Tuna Swarm Algorithm Based Unequal Clustering Approach on Internet of Things Assisted Networks

Balakrishnan Srinivasan[1]
https://orcid.org/0000-0002-3836-2926

Vinoth Kumar Kalimuthu[1*]
https://orcid.org/0000-0002-8920-4936

Thiruppathi Muthu[1]
https://orcid.org/0000-0001-9880-539X

Rajakani Velumani[2]
https://orcid.org/0009-0006-4767-0329

[1]Vivekanandha College of Engineering for Women, Department of ECE, Tiruchengode, India; [2]Anjalai Ammal Mahalingam Engineering College, Department of ECE, Thiruvarur, India.

Editor-in-Chief: Alexandre Rasi Aoki
Associate Editor: Fabio Alessandro Guerra

Received: 10-Nov-2023; Accepted: 26-Feb-2024

*Correspondence: vinodkumaran87@gmail.com; (V.K.K.)

HIGHLIGHTS

- The TSA-EEUCA method is used to robust synergy
- Challenge is suggested as the hotspot problem and is fixed by utilizing processes.
- Unequal clustering supports the distribution of the energy load more effectively.
- Binary variants of AOA to be suitable for the FS tasks.

Abstract: Internet of Things (IoT)-assisted Wireless Sensor Networks (WSNs) integrate traditional WSNs with the expansive ecosystem of IoT devices. This integration enables sensor nodes (SNs) to connect to the internet, facilitating seamless data exchange, remote monitoring, and real-time control of physical environments. IoT-assisted WSNs are crucial in various fields, including industrial automation, smart cities, healthcare, and environmental monitoring. In these networks, sensor nodes near the base station (BS) are responsible for relaying data to nearby nodes and the BS itself, a process that consumes significant energy. This issue, known as the "hotspot problem," arises when certain nodes deplete their energy faster than others. Unequal clustering techniques address this challenge by distributing the energy load more effectively, allowing nodes with higher energy reserves to take on more tasks while conserving the energy of nodes with lower reserves. This study introduces the Tuna Swarm Algorithm-based Energy Efficient Unequal Clustering Approach (TSA-EEUCA) to enhance the performance of IoT-assisted WSNs. The proposed method aims to improve energy efficiency and extend network lifetime by organizing nodes into clusters of unequal sizes.

The core of this approach is the Tuna Swarm Algorithm (TSA), inspired by the cooperative foraging behavior of tuna swarms. Unequal cluster formation and cluster head selection are determined by a fitness function that considers both energy levels and distance metrics. To validate the effectiveness of the proposed method, a series of simulations were conducted. The results showed that the proposed method outperforms existing techniques, offering a more efficient and longer-lasting solution for IoT-assisted WSNs.

Keywords: Internet of Things (IoT); Wireless Sensor Networks; Energy Enhancement; Network lifetime; Unequal clustering.

INTRODUCTION

A process of developing new technological characteristics that are intelligent retrieval, infrastructure-less wireless networks, on demand IT-services, self-reckoning, computerization, and the network of things are significantly changes and improved across various activities in our everyday lives. These exciting technologies have been applied in numerous areas, providing effective solutions for digital megacity water dispersal, self-acting transit, clever supervision, ecological observation, and inner city reliability.

The IoT comprises a vast network that interconnects a multitude of devices and smart objects. It is one of the most promising technologies, with rapid development potential and a significant impact on modern life. WSNs, considered a main component of IoT infrastructure, play a crucial role in this ecosystem. WSNs are the primary data-gathering tool used by IoT devices. A dense network of WSNs with IoT capabilities can support the development of a robust WSN-based IoT platform.

Although WSN-based IoT has demonstrated immense potential in various applications, it faces resource limitations such as limited processing power, slow communication, short battery life, and low memory capacity. Energy efficiency is critical for these nodes to perform effectively over extended periods, often years. Key activities such as communication, processing, data collection, and monitoring are heavily dependent on the energy available to sensor nodes (SNs). Due to limited battery power and energy loss, SNs are prone to energy depletion, potentially degrading network performance. Therefore, extending the network lifetime is a primary research goal in WSN-based IoT, especially when replacing batteries in hazardous or remote environments is challenging. The rate at which SNs consume energy is a fundamental factor in predicting the longevity of a WSN-based IoT. In wireless mesh network, group of nodes head, near the sink node can hurriedly deplete their energy, a problem known as the hotspot issue in WSNs. This issue can be mitigated by creating clusters of unequal sizes (UECs). Unequal clustering techniques help balance the energy load among CHs, reducing the size of clusters near the base station (BS) and increasing cluster size with distance from the BS. Clustering methods can be broadly categorized into meta-heuristic and standard techniques.

RELATED WORK

In [11], a new method called the Fire Hawk Optimizer-based Unequal Clustering Scheme for Hotspot Mitigation (FHOUCS-HSM) was introduced for IoT-enabled WSNs. The FHO method's innovative architecture targets UEC, and the FHOUCS-HSM approach uses a fitness function to optimize CH selection and UEC size. In [12], an energy-efficient fuzzy-based UEC with a sleep scheduling (EFUCSS) algorithm for IoT-enabled WSNs was developed. This algorithm enhances network longevity and reduces energy consumption through efficient data transmission, scheduling, and clustering. It employs Fuzzy C-Means (FCM) for UEC design to balance energy consumption by minimizing transmission distances, with CH selection based on fuzzy logic.

Chauhan and Soni [13] proposed an energy-aware UEC algorithm (EAUCA) to address energy holes and extend network lifespan. EAUCA creates unequal-sized clusters, making clusters near the BS smaller. The division of the network into UECs is based on nodes' distances from and residual energy to the BS. Jasim and colleagues [14] developed an energy-efficient UEC method based on a balanced energy technique (EEUCB), utilizing varying distances to minimize energy loss. EEUCB employs a high-capacity energy node and a binary CH approach with a sleep-awake mechanism. It also introduces a clustering rotation methodology with two different clusters and involving two or more clusters systems, considering remoteness thresholds, BS coverage node averages, and median liveliness thresholds.

Sivakumar [15] introduced the Balanced-Imbalanced Cluster Algorithm (B-IBCA) with a Stabilized Boltzmann Approach (SBA) to balance energy consumption across UECs in WSNs. B-IBCA uses stabilization logic to ensure consistent energy usage among SNs and the Boltzmann evaluation technique to assign appropriate radii between SNs.In [16], the Energy-efficient Multihop Routing with UEC method (EMUC) was developed to create clusters of different sizes based on the distance between the BS and SNs. This method aims to balance energy consumption among CHs by implementing multi-hop communication for data transmission to the BS. Ali and coauthors [17] presented a novel two-phase UEC lightweight technique based on a BS-determined threshold, considering the distance from the BS and the residual energy of SNs. They also introduced a re-clustering method where CHs are locally replaced within each cluster level.

THE PROPOSED MODEL

In this dissertation, propose a newest TSA-EEUCA scheme designed to address the SSIDs problem in IoT-aid WSNs. The primary goal of the TSA-EEUCA move toward to organize nodes into group together of varying range to enhance liveliness efficacy and extend network's lifetime. Figure 1 illustrates the overall course of action of the TSA-EEUCA scheme.

Scheme Model

The set of connections comprises NSNs with similar capabilities deployed randomly within an X*Y sensor field [18]. Nodes and the sink are stationary, with the sink centrally located and known to all deployed nodes. Symmetric wireless connections are used for data transmission and control messages. The radio model calculates energy consumption by nodes. The free space (fs) model is used for distances less than a threshold (d_0); otherwise, the multi-path model is applied. In the TSA-EEUCA technique, inspired by the cooperative foraging behavior of tuna swarms, the Tuna Swarm Algorithm (TSA) is central. Tunas, being top predators in the ocean, employ cooperative strategies like parabolic and spiral foraging to capture prey efficiently [19]. The TSA algorithm integrates these foraging tactics to optimize cluster formation and cluster head (CH) selection in WSNs.

During parabolic foraging, the TSA mimics the tunas' strategy of encircling prey in a parabolic path to optimize cluster formation. In spiral foraging, tunas form a spiral shape to explore and capture prey in shallow waters. This strategy is adapted in the TSA-EEUCA algorithm to optimize CH selection and cluster formation. For asymmetrical cluster structure and CH selection, the TSA-EEUCA technique evaluates suitability based on energy and distance criterion [20, 21]. The fitness function determines optimal CH candidates (CHCs) based on their energy levels and proximity to other nodes and the base station (BS). Nodes with higher residual energy and favorable distances are more likely to be selected as CHCs.

The CH selection process involves determining the competition radius (R_c) and rejection radius (R_j) for each node, ensuring balanced energy consumption and efficient data aggregation. Nodes evaluate their candidacy as CHs based on these radii and compete to become CHs based on their fitness scores. This approach ensures that CHs are strategically placed to minimize energy consumption and maximize network lifetime. Figure 2 outlines the iterative steps involved in the TSA algorithm.

$$E_{Tx}(l, d)=E_{Tx\text{-}elec}(l)+E_{Tx\text{-}amp}(l, d)=\begin{cases} l*E_{elec}+l*\varepsilon_{fs}*d^2 \text{if } d<d_0 \\ l*E_{elec}+1*\varepsilon_{mp}*d^4 \text{if } d\geq d_0 \end{cases} \quad (1)$$

The energy necessary for the radio to receive a k-bits message can beexpressed as:

$$E_{RX}(k)=E_{elec}*k \quad (2)$$

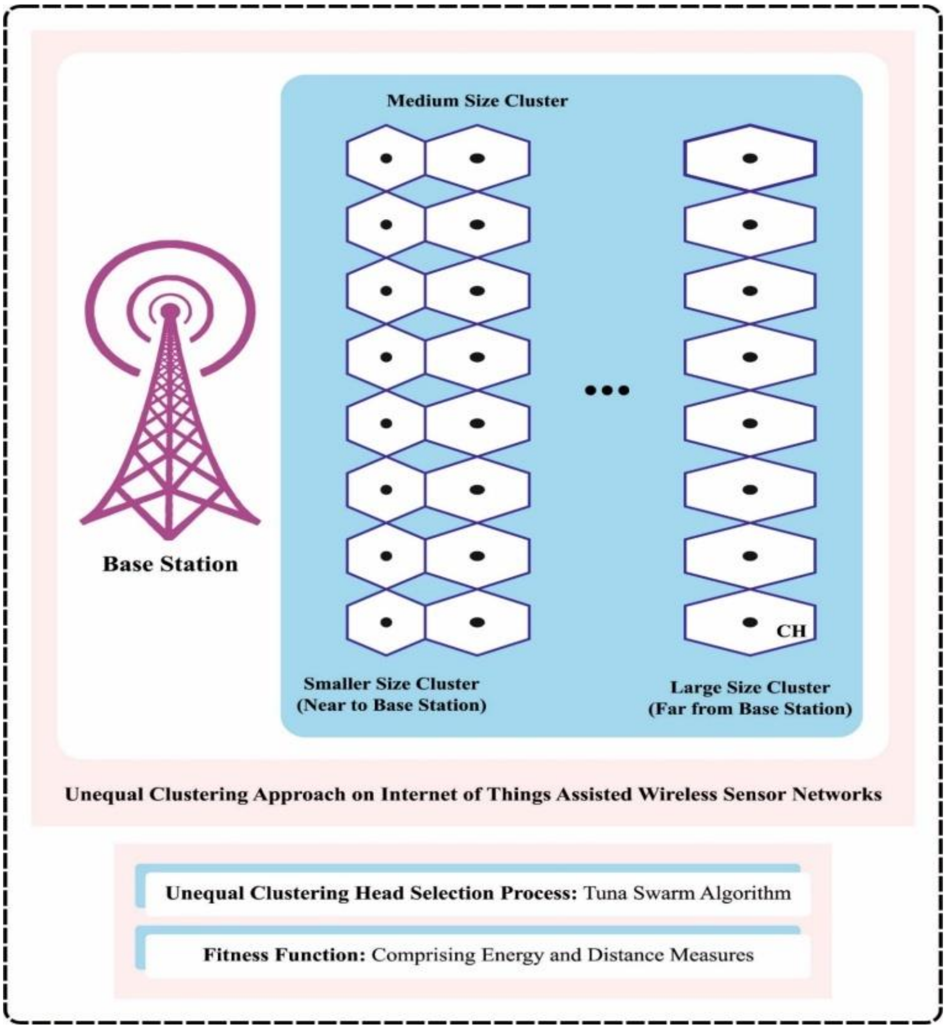

Figure 1. Proposed method process diagram

The mathematical model for initializing the tuna individual is as follows:

$$X_i^{int}=rand\cdot(ub-lb)+lb=\begin{matrix}[x_i^1 x_i^2 \,.\,.\,.x_i^j] \\ \begin{cases} i=1,2,\ \ldots,\ NP \\ j=1,2,\ \ldots,\ Dim \end{cases}\end{matrix} \tag{3}$$

TS can be mathematically modelled as follows:

$$X_i^{t+1}=\begin{cases} X_{best}^t+rand\cdot(X_{best}^t-X_i^t)+TF\cdot p^2\cdot(X_{best}^t-X_i^t), & \text{if rand} <0.5 \\ TP\cdot p^2\cdot X_i^t, & \text{if rand} \geq 0.5 \end{cases} \tag{4}$$

$$p=\left(1-\frac{t}{t_{max}}\right)^{t\left(\frac{t}{i\ max}\right)} \tag{5}$$

The spiral foraging approach is mathematically modeled as follows:

$$X_i^{t+1}=\begin{cases}\alpha_1\cdot(X_{rand}^t+\tau\cdot|X_{rand}^t-X_i^t|+\alpha_2\cdot X_i^t), & \\ \quad i=1 & \text{if rand} <\frac{t}{t_{max}} \\ \alpha_1\cdot(X_{rand}^t+\tau\cdot|X_{rand}^t-X_i^t|+\alpha_2\cdot X_{i-1}^t), & \\ \quad i=2,3,\ \dots,NP & \\ \alpha_1\cdot(X_{best}^t+\tau\cdot|X_{best}^t-X_i^t|+\alpha_2\cdot X_i^t) & \\ \quad i=1 & \text{if rand}\geq\frac{t}{t_{max}} \\ \alpha_1\cdot(X_{besi}^t+\tau\cdot|X_{best}^t-X_i^t|+\alpha_2\cdot X_{i-1}^t) & \\ \quad i=2,3,\ \dots,\ NP & \end{cases} \quad (6)$$

The computation process is given as:

$$\alpha_1=a+(1-a)\cdot\frac{t}{t_{max}}) \quad (7)$$

$$\alpha_2=(1-a)-(1-a)\cdot\frac{t}{t_{max}} \quad (8)$$

$$\tau=e^{bl}\cdot\ \cos\ (2\pi b) \quad (9)$$

$$l=e^{3\ \cos\ (((t_{max}+1/t)-1)\pi)} \quad (10)$$

The Figure 2 presents proposed method steps.

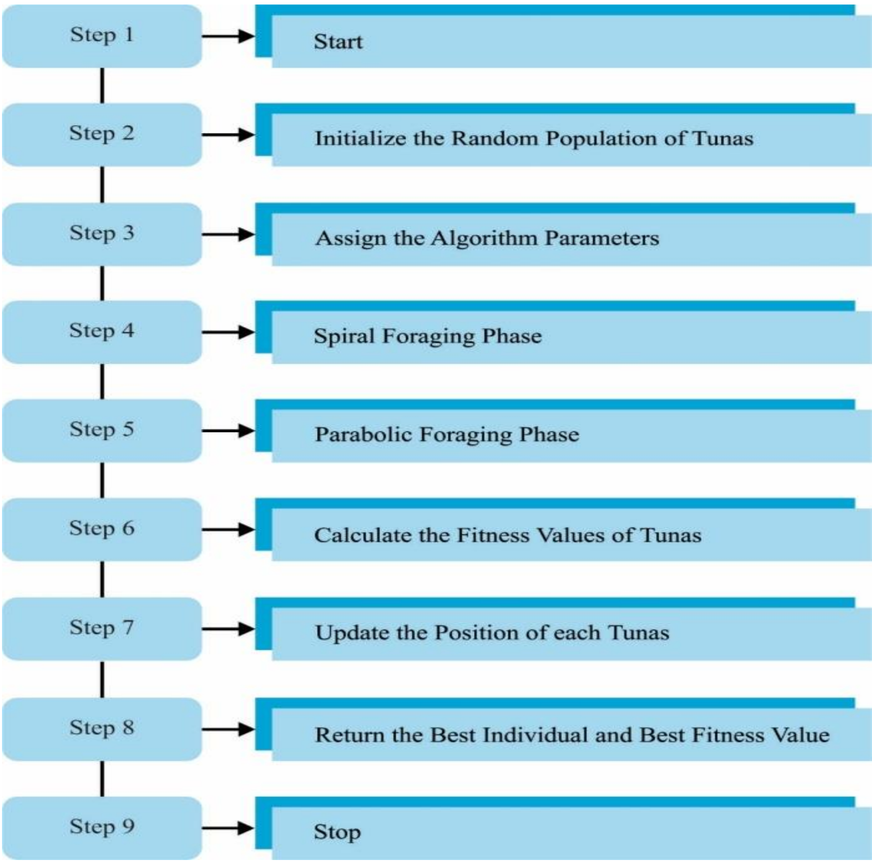

Figure 2. Proposed method flow diagram

The equation is represented as follows:

$$R_t=\left(1-0.3\times\frac{d_{max}-d(i,\ BS)}{d_{max}-d_{nin}}\right)\times R_{max} \quad (11)$$

$$R_j=\alpha\times\beta\times R_c \quad (12)$$

$$\alpha = \begin{cases} \max\left[\frac{1}{2}, \left(1 + \frac{E_{ave}\text{-}E_i}{E_{ave}}\right)\right], E_i \geq E_{ave} \\ \min\left[\frac{3}{2}, \left(1 + \frac{E_{ave}\text{-}E_i}{E_{ave}}\right)\right], E_i < E_{ave} \end{cases} \tag{13}$$

$$\beta = \begin{cases} \max\left[\frac{1}{2}, \left(1 + \frac{N_{ave}\text{-}N_i}{E_{ave}}\right)\right], N_i \geq N_{ave} \\ \min\left[\frac{3}{2}, \left(1 + \frac{N_{ave}\text{-}N_i}{N_{ave}}\right)\right], N_i < N_{ave} \end{cases} \tag{14}$$

$$N_{ave} = \frac{\pi \times N \times R_c^2}{S^2} \tag{15}$$

$$t_i = \frac{d(i, \cdot RN_s)}{R_s} \times t_0 \tag{16}$$

RESULTS AND DISCUSSION

In this revision, the presentation of the planned technique is analyzed underneath different node calculate (NC). Table 1 shows an evaluation of the proposed algorithm in terms of energy consumption (ECM), network lifetime (NLT), and throughput (THRO).

Table 1. Proposed Method analysis of ECM, NLT, and THRO

Nodes	Proposed	Bi-HCLR	FEECIIR	NFEPO	FR-LDG	HEED
Power utilization (millijoules)						
100	5	30	45	63	69	136
200	14	40	75	89	112	160
300	22	49	104	113	145	181
400	31	63	120	142	162	214
500	40	79	148	170	188	255
Life Span of Network (Rounds)						
100	5900	5500	5500	5000	4802	4299
200	5475	5347	5210	4787	4604	4007
300	5471	5358	5018	4692	4375	3835
400	5434	5227	4910	4326	4104	3420
500	5392	5236	4703	4095	3898	3099
Throughput (Mbps)						
100	99.80	98.79	94.98	91.17	80.52	75.92
200	98.18	96.57	82.51	77.71	69.47	71.09
300	97.85	95.19	73.49	69.46	60.44	63.04
400	96.58	92.95	66.66	60.04	54.21	52.21
500	95.92	92.16	63.23	53.80	45.39	47.99

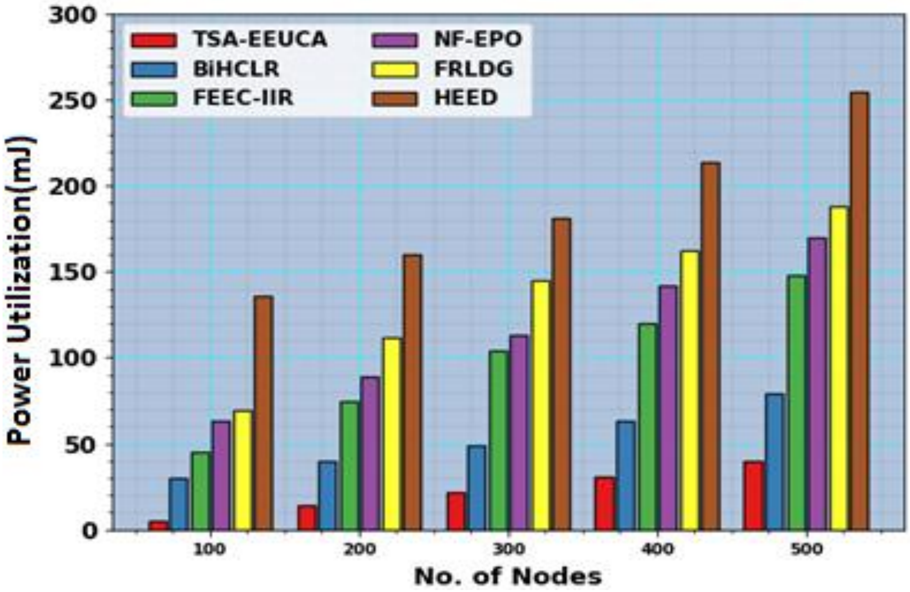

Figure 3. Proposed method ECM outcome

In Figure 4, the LSN results of the proposed technique are presented. The results highlight the improved LSN values of the proposed technique.

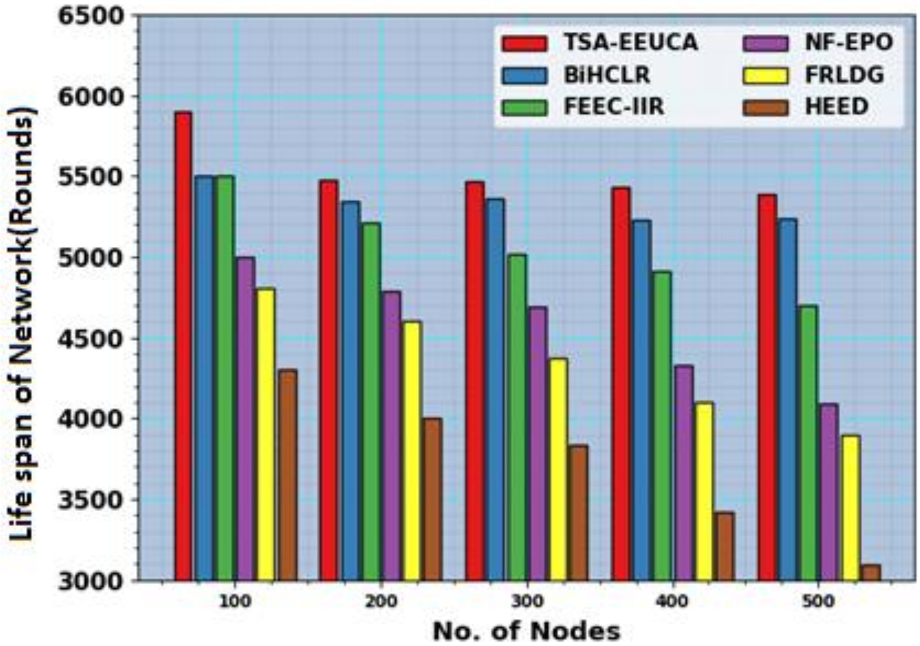

Figure 4. Proposed method LSN outcome

Figure 5 illustrates the comparative THRO results of the proposed method. The outcomes show that the TSA-EEUCA system has higher THRO values.

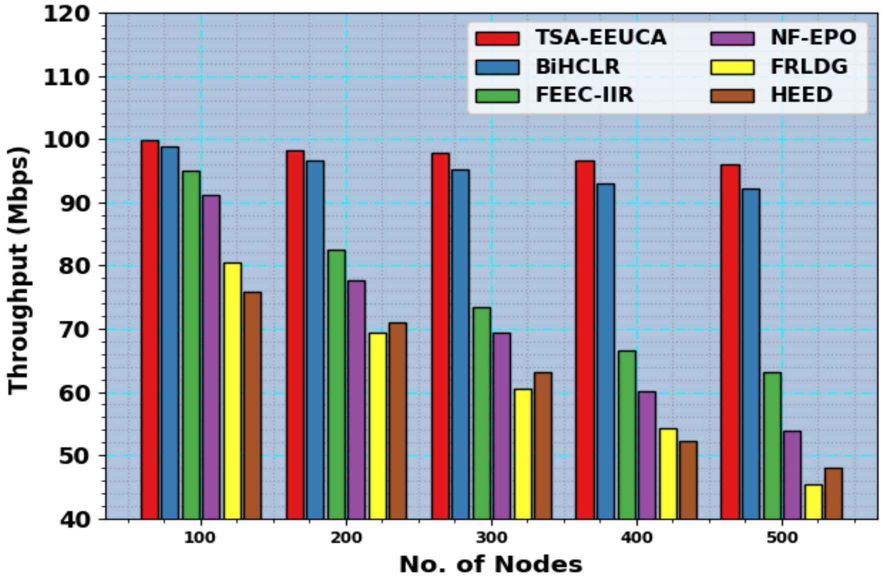

Figure 5. Proposed method Throughput outcome

Figure 6 depicts the DDR outcomes of the proposed algorithm. The results show that the TSA-EEUCA method achieves higher DDR values.

Table 2 presents the evaluation results of the datagram distribution ratio (DDR), packet failure ratio (PFR), and boundary-to-boundary latency (BTBL) with newest TSA-EEUCA.

Table 2. Proposed Method analysis of DDR, PFR, and BTBL

Nodes	Proposed	Bi-HCLR	FEECIIR	NFEPO	FR-LDG	HEED
Datagram Distribution Ratio (%)						
100	100.00	100.00	99.23	98.23	97.19	95.24
200	99.89	99.14	98.22	97.28	96.19	94.13
300	99.16	98.28	97.23	96.22	94.27	92.20
400	98.14	97.11	96.25	95.25	93.25	90.14
500	97.64	96.24	95.15	94.24	92.21	88.23
Datagram Loss Ratio (PFR) (%)						
100	0.00	0.00	1.10	2.07	3.13	5.09
200	0.46	1.21	2.12	3.05	4.12	6.20
300	1.18	2.05	3.09	4.12	6.07	8.12
400	2.20	3.22	4.07	5.09	7.08	10.19
500	2.70	4.07	5.20	6.07	8.12	12.10
Boundary-to- Boundary Latency (sec)						
100	2.11	3.26	4.08	4.29	4.78	5.91
200	2.01	3.57	4.15	5.04	5.71	6.62
300	2.39	4.12	5.00	6.18	6.66	7.42
400	3.02	4.12	5.78	7.84	8.26	8.63
500	3.13	4.77	6.37	8.92	9.37	9.64

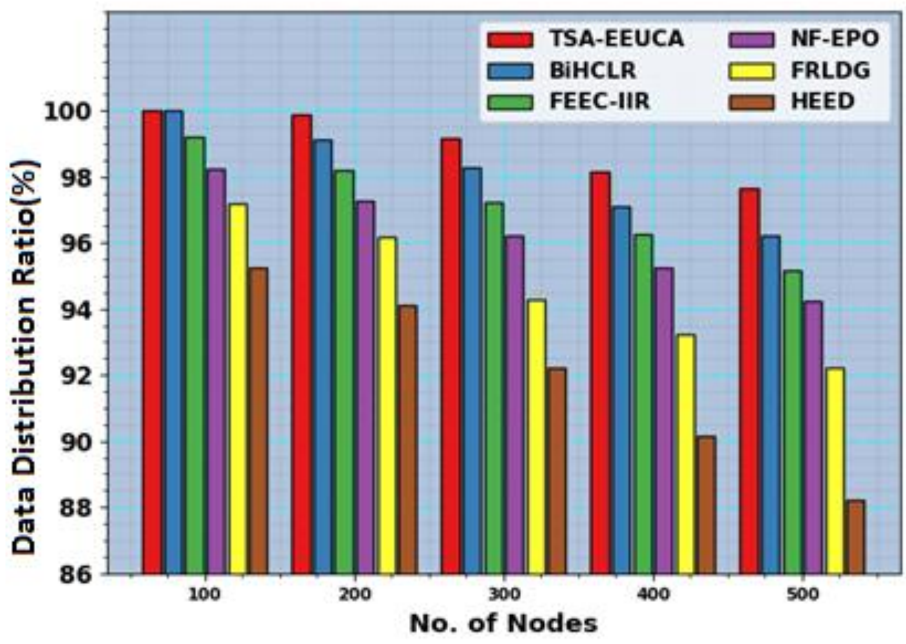

Figure 6. Proposed method DDR outcome

Figure 7 examines the PFR results of the proposed method compared to recent systems. The results indicate that the HEED algorithm has the highest PFR outcomes.

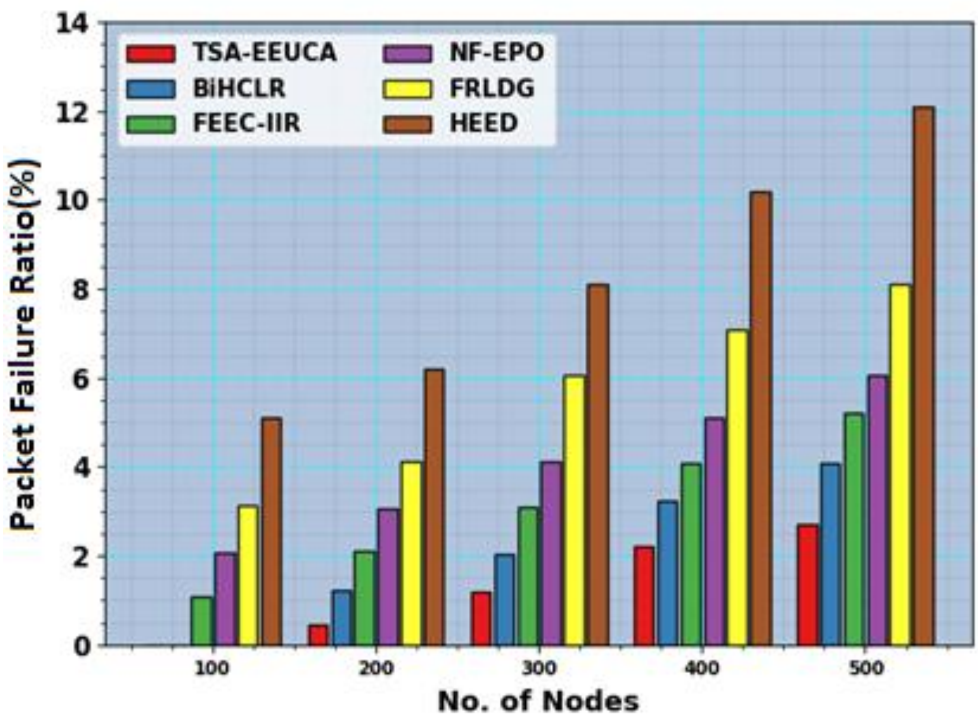

Figure 7. Proposed method PFR outcome

Figure 8 shows the BTBD outcomes of the proposed system compared to recent approaches.

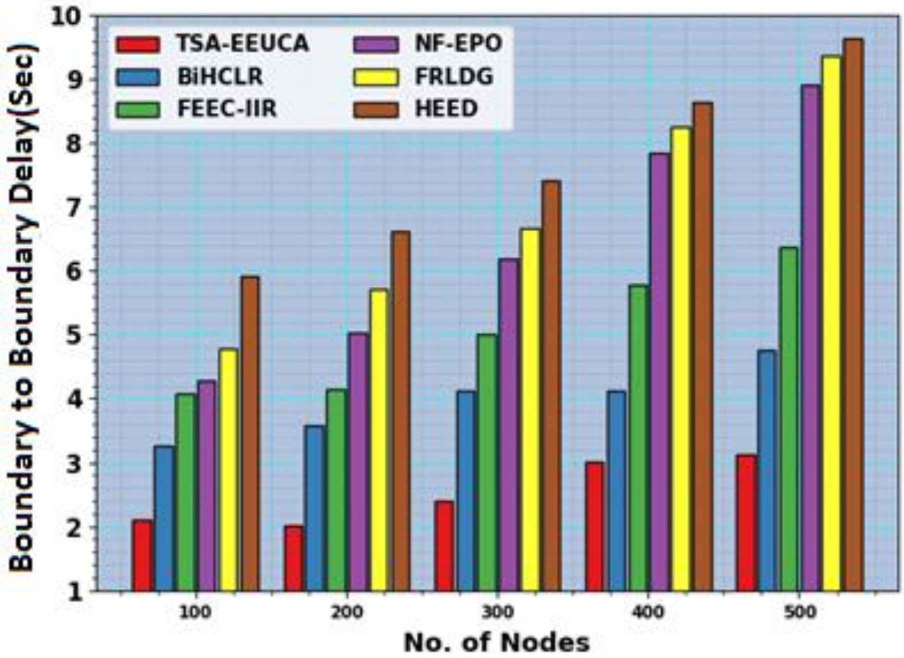

Figure 8. Proposed method BTBD outcome

Table 3 and Figure 9 present the bit error rate (BER) outcomes of the proposed algorithm compared to recent approaches.

Table 3. Bit Error Rate Analysis

	Bit Error Rate (%)					
Nodes	Proposed	Bi-HCLR	FEECIIR	NFEPO	FR-LDG	HEED
110	1.63	2.96	6.25	7.96	9.23	9.90
220	0.58	3.25	7.26	10.36	12.36	13.65
330	2.96	5.96	10.96	12.68	15.78	17.91
440	4.35	9.25	12.95	16.87	18.89	20.39
550	5.25	9.35	16.89	20.84	25.96	26.01

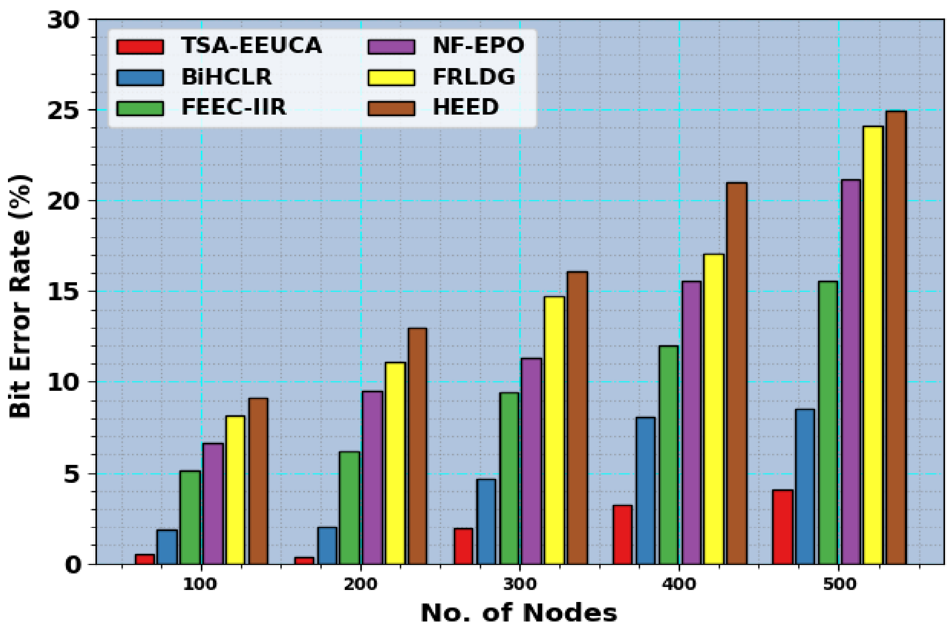

Figure 9. Proposed method BER analysis with Existing method

CONCLUSION

We introduce TSA-EEUCA, a novel approach designed to mitigate energy hotspots in IoT-assisted Wireless Sensor Networks (WSNs). This method aims to optimize energy efficiency and extend network lifespan by organizing nodes into clusters of varying sizes. Inspired by the cooperative foraging behavior observed in tuna swarms, TSA-EEUCA leverages the Tuna Swarm Algorithm (TSA). This algorithm is instrumental in creating unequal clusters and selecting cluster heads (CHs) using a fitness function that integrates energy levels and distance metrics. In the proposed method, nodes near the base station (BS) are responsible for transmitting data to adjacent nodes and the BS itself, which can deplete their energy unevenly, leading to the hotspot problem. Unequal clustering addresses this challenge by distributing the energy load more effectively. Nodes with higher energy reserves undertake more tasks while those with lower reserves conserve energy, thereby enhancing overall network efficiency. To validate the effectiveness of proposed method, extensive simulations were conducted. The results demonstrate significant improvements over existing techniques, showcasing proposed method capability to provide a superior solution for managing energy hotspots in IoT-assisted WSNs. By leveraging TSA's ability to mimic natural swarm behaviors, our approach not only optimizes energy consumption but also prolongs the operational lifespan of WSNs, crucial for applications in industrial automation, smart cities, healthcare, and environmental monitoring. This novel approach contributes to advancing the field of IoT-assisted WSNs by addressing critical energy efficiency challenges, thereby supporting sustainable and reliable operation across diverse application domains.

Funding: The authors declare they have no funding applied.
Conflicts of Interest: The authors declare they have no conflicts of interest to report regarding the present study.

REFERENCES

1. Kumar KV, Rajakani V. Modeling of Intrusion Detection System using Double Adaptive Weighting Arithmetic Optimization Algorithm with Deep Learning on Internet of Things Environment. Braz Arch Biol Technol. 2024;67. doi:10.1590/1678-4324-2024231010.
2. Jain A. Unequal clustering protocols for wireless sensor networks—taxonomy, comparison and simulation. Wireless Pers Commun. 2022;124(8):517-71. https://doi.org/10.1007/s11277-021-09372-5.
3. Mehra PS, Jain K, Chawla D, Dagur A, Singh S, Sharma J. GWO-EFUCA: Grey Wolf Optimisation and Fuzzy Logic based Unequal Clustering and Routing protocol for sustainable WSN-based Internet of Things. 2022. https://doi.org/10.21203/rs.3.rs-2151630/v1.
4. Arikumar KS, Natarajan V, Satapathy SC. EELTM: an energy efficient LifeTime maximization approach for WSN by PSO and fuzzy-based unequal clustering. Arab J Sci Eng. 2020;45(12):10245-60. https://doi.org/10.1007/s13369-020-04616-1.
5. Kumar KV, Thiruppathi M. Oppositional Coyote Optimization based Feature Selection with Deep Learning Model for Intrusion Detection in Fog Assisted Wireless Sensor Network. Acta Montan Slovaca. 2023;28(2). doi:10.46544/AMS.v28i2.18.
6. Naderloo A, Fatemi Aghda SA, Mirfakhraei M. Fuzzy-based cluster routing in wireless sensor network. Soft Comput. 2023;27(10):6151-8. https://doi.org/10.1007/s00500-023-07976-6.
7. Wohwe Sambo D, Yenke BO, Förster A, Dayang P. Optimized clustering algorithms for large wireless sensor networks: a review. Sensors (Basel). 2019;19(2):322. https://doi.org/10.3390/s19020322.
8. Muthulakshmi K, Balaji SP, Stephe S, Vijayalakshmi J. Adaptive Wind Driven Optimization based Energy Aware Clustering Scheme for Wireless Sensor Networks. Tech Vjesn. 2024;31(2):466-73. doi:10.17559/TV-20230610000715.
9. Han G, Guan H, Wu J, Chan S, Shu L, Zhang W. An uneven cluster-based mobile charging algorithm for wireless rechargeable sensor networks. IEEE Syst J. 2018;13(4):3747-58. https://doi.org/10.1109/JSYST.2018.2879084.
10. Kumar KV, Balakrishnan S. Multi-objective Sand Piper Optimization Based Clustering with Multihop Routing Technique for IoT Assisted WSN. Braz Arch Biol Technol. 2023;66. doi:10.1590/1678-4324-2023220866.
11. Gupta IK, Mishra AK, Diwan TD, Srivastava S. Unequal clustering scheme for hotspot mitigation in IoT-enabled wireless sensor networks based on fire hawk optimization. Comput Electr Eng. 2023;107:108615. https://doi.org/10.1016/j.compeleceng.2023.108615.
12. Thiruvenkatasamy S, Sivaraj R, Vijayakumar M. Blockchain Assisted Fireworks Optimization with Machine Learning based Intrusion Detection System (IDS). Tech Vjesn. 2024;31(2):596-603. doi:10.17559/TV-20230712000798.
13. Jacob SS, Karthikeyan B, Johnpeter T, Jayamala R. Deployment with Location Knowledge by Multi Area Approach for Detecting Replica Nodes in Wireless Sensor Network. Tech Vjesn. 2024;31(1):254-61. doi:10.17559/TV-20230508000613.

14. Jayamala R, Oliver AS, Jayanthi J, Nithya N. Enhanced Secured and Real-Time Data Transmissions in Wireless Sensor Networks using SFRT Routing Protocol. Tech Vjesn. 2024;31(2):420-5. doi:10.17559/TV-20230617000742.
15. Jasim AA, Idris MYI, Razalli Bin Azzuhri S, Issa NR, Rahman MT, Khyasudeen MFB. Energy-efficient wireless sensor network with an unequal clustering protocol based on a balanced energy method (EEUCB). Sensors (Basel). 2021;21(3):784. https://doi.org/10.3390/s21030784.
16. Balakrishnan S, Kumar KV. Hybrid Sine-Cosine Black Widow Spider Optimization based Route Selection Protocol for Multihop Communication in IoT Assisted WSN. Tech Vjesn. 2023;30(4). doi:10.17559/TV-20211216115635.
17. El Assari Y. Energy-efficient multi-hop routing with unequal clustering approach for wireless sensor networks. Int J Comput Netw Commun (IJCNC). 2020;12(3):57-75. https://doi.org/10.5121/ijcnc.2020.12304.
18. Rajakani V, Kumar KV. Barnacles Mating Optimizer with Hopfield Neural Network Based Intrusion Detection in Internet of Things Environment. Tech Vjesn. 2023;30(6). doi:10.17559/TV-20211216115635.
19. Agrawal D, Pandey S. Load balanced fuzzy-based unequal clustering for wireless sensor networks assisted Internet of Things. Eng Rep. 2020;2(6). https://doi.org/10.1002/eng2.12130.
20. Thiruppathi M, Kumar KV. Seagull Optimization-based Feature Selection with Optimal Extreme Learning Machine for Intrusion Detection in Fog Assisted WSN. Tech Vjesn. 2023;30(5). doi:10.17559/TV-20211216115635.
21. Alsolai H, Maashi M, Saeed MK, Mohamed A, Assiri M, Abdelbagi S, et al. Leveraging metaheuristic unequal clustering for hotspot elimination in energy-aware wireless sensor networks. Sensors (Basel). 2023;23(5):2636. https://doi.org/10.3390/s23052636.