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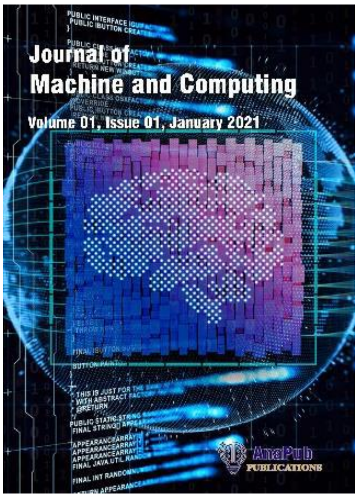

Shobana M, Udayakumar R, Vasanthi S and Nithya S

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Energy-Efficient Framework Clustering and Routing in WSN using Federated Deep Q-Network with Improved Fossa Optimization Algorithm

[1]M.Shobana, [2]R.Udayakumar, [3]S.Vasanthi, [4]Nithya S

[1]Associate Professor, Department of Computer Science and Engineering, SNS College of Technology, Coimbatore, Tamilnadu, India

[2]Professor, Kalinga University, India.

[3]Associate Professor, Department of Information Technology, Sona College of Technology, Salem, Tamilnadu, India

[4]Assistant Professor, Department of Computer Science and Engineering, Coimbatore Institute of Technology, Coimbatore, Tamil Nadu, India

shobanavsm@gmail.com, rsukumar2007@gmail.com , vasanthivedhamoorthy@gmail.com, nithya.s@cit.edu.in

Corresponding Author: M.Shobana

Abstract- Today's major goals in sensor network research are to extend the life of wireless sensor networks (WSNs) and reduce power consumption. IoT-based WSN are widely used in a range of applications, including military, healthcare, and industrial monitoring. WSN nodes often have limited battery capacities, making energy efficiency an important consideration for clustering and routing. Data is transferred from the source SNs to the destination SNs. These are likely to be completed in a secure manner and in less time. Energy-efficient data transmission is a significant challenge for WSNs coupled with IoT. This research provides an optimal clustering and routing paradigm for increasing network lifetime, reducing energy usage, and ensuring reliable data transfer. Cluster creation is carried out using a Trusted Energy-Efficient Fuzzy Logic-Based Clustering (TEEFLC) Algorithm, which takes into account node trustworthiness, residual energy, and network density. The Improved Fossa Optimization Algorithm (FOA) is used to choose the ideal Cluster Head (CH), maintaining balanced energy distribution and reducing the number of CH replacements. To provide efficient data transmission, a Federated Deep Q-Network (FDQN) based routing strategy is used, which optimizes next-hop selection based on energy efficiency and link quality. Simulation findings show that the proposed method outperforms standard clustering and routing protocols in terms of energy efficiency, packet delivery ratio, and network longevity, indicating that it is a viable solution for WSN-IoT applications.

Keywords: Wireless Sensor Networks (WSNs), Internet of Things (IoT), Cluster Head (CH), Fossa Optimization Algorithm (FOA), Federated Deep Q-Network (FDQN), trusted energy-efficient fuzzy logic-based clustering (TEEFLC).

1. Introduction

Wireless Sensor Networks (WSN) are integral to daily life, widely employed across diverse sectors including area monitoring, military surveillance, manufacturing and underwater detection, weather forecasting, industrial automation,agriculture, defense, healthcare, traffic management, and various commercial applications. However, the architecture of the routing protocol may be affected by factors like as real-time monitoring, node deployment tactics, security, and energy usage. This network comprises numerous sensor nodes (SN) for evaluating, acquiring, and detecting data distributed across the environment. Moreover, these sensor nodes demonstrate increased complexity and rely on a limited battery for power. Thus, the principal issue is the inadequate power sources leading to node malfunction. Clustering is an efficient approach for developing routing algorithms in WSNs, as it improves the network's longevity and scalability. The CH in a clustered WSN is crucial for data transfer. A substantial body of research has been undertaken on cluster-based routing. However, challenges arise from fault tolerance, uneven load distribution, and locally optimal solutions. This study aims to introduce a novel cluster-based routing method that improves routing efficiency and extends network longevity [1].

Efficient energy transmission is vital for WSN inside the IoT to improve network lifetime and guarantee dependable communication. Node trust, residual energy, and base station proximity determine clusters in the proposed paradigm using TEEFLC. FOA aids CH selection, increasing energy equity and reducing re-clustering activity. Multi-hop routing is improved by FDQNs adjusting to network conditions for data delivery. This fuzzy logic system considers network quality, residual energy, and traffic load to improve routing decisions. Deep reinforcement learning reduces energy footprint and packet loss with adaptive routing [2][3].

The IoT requires WSNs for real-time monitoring and data collecting, but energy constraints are a major issue. Clustering and routing methods often waste energy, re-elect CHs, and increase packet loss, shortening network lifespan. This research seeks an intelligent, energy-efficient, and adaptive data transport technique that reduces power consumption. This study uses fuzzy logic for clustering, FOA for CH selection, and FDQN for routing to reduce energy consumption, balance network load, and improve dependability. Scalable, self-adaptive, and durable WSN-IoT networks for environmental monitoring, smart agriculture, and industrial automation are needed [4-6].

Intelligent clustering and adaptive routing techniques are used in this research to improve WSN energy efficiency and reliability with the IoT. TEEFLC ensures optimal cluster formation, whereas FOA enhances CH selection for energy balance. Deep reinforcement learning improves data transfer in FDQN routing, reducing packet loss and network congestion. This study is relevant for smart cities, precision agriculture, industrial IoT, and environmental monitoring because it extends network longevity, improves data reliability, and reduces energy usage. This research overcomes WSN-IoT routing and clustering limitations to improve sensor network scalability, adaptability, and energy efficiency for practical deployment.

Opportunistic energy-efficient dynamic self-configuration routing (OEDSR) is used in the existing model for IoT applications. The residual energy and mobility factors of the SNs are used to identify the best path to the BS in a graph theory-based routing tree model. To decrease connections, dynamic cluster creation with hierarchical tree architecture creates an ideal path. To demonstrate the OEDSR protocol's efficacy, throughput, latency, and PDR are compared to peer routing systems [9]. The hybrid K-LionER scheme for WSN backed by the IoT was introduced in another model. K-LionER promises to improve network longevity and energy efficiency. K-means generates WSN clusters, with ant lion optimization selecting each CH. CHs aggregate cluster data and send it to the BS. K-LionER assigns the CH based on routing parameters, Remnant Energy (RE), CH-BS distance, and Intra-cluster Communication Cost. A detailed simulation is done with MATLAB 2017a. Compare K-LionER's success to LEACH, ECFU, and GADA-LEACH. The simulation findings show improvements in active nodes, stability duration, inactive nodes, and network longevity. K-LionER increases network lifespan by 10% to 48% compared to other routing methods [10].

The proposed WSN-IoT clustering and routing architecture prioritizes energy efficiency, network longevity, and data reliability. It uses fuzzy logic-based clustering, efficient CH selection, and deep reinforcement learning routing. A trustworthy energy-efficient fuzzy logic-based clustering algorithm first clusters SNs by residual energy, trustworthiness, and density. This ensures fair cluster formation, network stability, and energy savings. After clusters develop, the FOA evaluates energy levels, communication distances, and load distribution to find suitable CHs. FOA mimics fossa's predatory behavior to investigate and exploit suitable CH locations and reduce re-elections. After choosing the CH, an FDQN is used to run a multi-hop routing protocol. The fuzzy logic system evaluates residual energy, network quality, and traffic load to improve next-hop selection and adaptive routing. DRL in FDQN improves routing algorithms by examining historical data, energy efficiency, packet loss, and network performance. SNs collect data, CHs aggregate and transmit it using FDQN-based routing, and the deep reinforcement learning module optimizes transmission paths. In large WSN-IoT networks, the suggested solution improves energy efficiency, re-clustering costs, scalability, and data transmission.

The major contribution of the work are as follows:

- Introduces a reliable energy-efficient fuzzy logic-based clustering algorithm to improve cluster formation by accounting for residual energy, node trustworthiness, and density, hence improving network stability.
- Employs the FOA to identify energy-efficient CHs, hence assuring equitable energy utilization and minimizing the frequency of re-clustering.
- Implements a FDQN based routing system that dynamically selects the optimum paths based on residual energy, connection quality, and traffic load, decreasing packet loss and network congestion.
- Incorporates deep reinforcement learning (DRL) within FDQN to dynamically optimize routing patterns, improving energy efficiency and extending network longevity.
- Ensures scalability for extensive WSN-IoT networks by optimizing load allocation across nodes, minimizing communication overhead, and enhancing data transmission reliability.
- The suggested method markedly decreases energy consumption, enhances load balancing, and prolongs the lifespan of WSN-IoT networks in comparison to traditional clustering and routing methodologies.

The remaining parts of the work is organized as follows: Section 2 shows the survey of the existing models. Section 3 explains the working of proposed A Trust-Aware Energy-Efficient Framework for Intelligent Clustering and Routing in WSN-IoT model. Result and discussion part is represented in section 4. The work is concluded in section 5.

2. Literature Survey

Vijayendra K. H. Prasad et al. (2023) introduced an energy-efficient clustering-based routing methodology for WSNs, employing bioinspired optimization approaches for the selection of CHs and an adaptive routing strategy to reduce energy usage. The suggested model extends network longevity, minimizes energy expenditure, and enhances data transmission efficacy through the dynamic selection of appropriate CHs and paths. The methodology may encounter scaling challenges in ultra-large-scale WSN and may necessitate supplementary computational overhead for real-time reclustering and routing modifications [11].

Greeshma Arya et al. (2022) introduced an energy-efficient routing protocol for IoT-based WSN, incorporating reinforcement learning (RL) for clustering, MRFO for CH selection, and a Deep Belief Network (DBN) for optimum data transmission. The proposed paradigm extends network longevity, elevates PDR, diminishes energy usage, and augments node accessibility inside clusters. The method may incur computational overhead from deep learning-based routing decisions and may necessitate further optimization for real-time implementation in extensive networks [12].

Rajeswari A. R. et al. (2021) proposed a secure and energy-efficient cluster-based routing algorithm, the TEEFCA, which utilizes a fuzzy inference system for the optimal selection of cluster leaders and the formation of clusters based on residual energy, cluster density, and proximity to the base station. The proposed TEEFCA optimizes energy conservation, improves network stability, and prolongs network lifespan in comparison to current cluster-aware routing methodologies. The computational complexity of the fuzzy inference system may escalate with network size, necessitating additional optimization for real-time scalability in extensive WSN deployments [13].

Venkatesan Cherappa et al. (2023) introduced an energy-efficient clustering methodology utilizing the Adaptive Sailfish Optimization (ASFO) algorithm alongside K-medoids for optimal CH selection, and implemented an E-CERP to reduce network overhead and identify the shortest path. The suggested approach attains a PDR of 100%, a packet latency of 0.05 seconds, a throughput of 0.99 Mbps, a power consumption of 1.97 mJ, a network lifespan of 5908 cycles, and a PLR of 0.5% for 100 nodes, surpassing current methodologies. The methodology may incur computational overhead from ASFO-based clustering and may necessitate additional optimization for scalability in extensive WSN deployments [14].

N Nathiya et al. (2023) introduces an energy-efficient clustering and intrusion detection system for IoT-enabled WSN, employing the MapDiminution-based Training-Discovering Optimization method for optimal cluster routing and task scheduling, in conjunction with a hybrid Artificial Neural Network (ANN) and Simulated Annealing (SA) classifier for intrusion detection. The suggested framework attains an energy consumption of 0.01 J and an intrusion detection accuracy of 97.57%, surpassing current methods in energy efficiency and security. The computational complexity of the hybrid ANN-SA model may escalate with extensive deployments, and real-time processing efficiency may necessitate additional tuning [15].

Masood Ahmad et al. (2021) presented a Memetic Algorithm (MemA)-based clustering method for WSN-IoT aimed at addressing early convergence challenges in evolutionary algorithms, dynamically balancing cluster loads, and enhancing CH selection via local exploration techniques. The proposed method attains diminished control message overhead, optimized cluster quantity, decreased reaffiliation rate, and extended cluster longevity, surpassing established methods such as MobAC, EPSO-C, and PBC-CP. The computational complexity of MemA, attributed to local search and crossover mechanisms, may prolong processing time, necessitating additional optimization for real-time applications in extensive WSN-IoT [16].

Ahmad Saeedi et al. (2025) introduced a multi-objective binary whale optimization algorithm (BWOA) for the optimal selection of CH) in IoT-based WSN, integrated with a Mamdani-type fuzzy inference system (FIS) to facilitate energy-efficient cluster formation. A multi-hop shortest path routing mechanism is also employed to improve data transmission. The suggested methodology realizes a 4.5% enhancement in First Node Death (FND), a 7.8% improvement in Half Node Death (HND), and a 1.5% rise in Last Node Death (LND) relative to current methodologies, indicating superior network longevity and energy efficiency in IoT-based WSN. The computational complexity of BWOA and fuzzy-based clustering may elevate processing overhead, hence complicating real-time deployment in extensive IoT networks [17].

Nguyen Duy Tan et al. (2023) introduced an energy-efficient routing protocol employing grid cells (EEGT) to extend the lifespan of WSN-based IoT applications. The network is divided into virtual grid cells, and a CH Node (CHN) is selected depending on remaining energy and distance to the sink. In each cell, the Kruskal algorithm generates a minimum spanning tree (MST) to improve intra-cell communication, while the Ant Colony Algorithm (ACO) is employed to provide energy-efficient routes from CHNs to the sink. The proposed EEGT protocol exhibits enhanced energy efficiency and extended network lifespan relative to the LEACH-C, PEGASIS, and PEGCP routing protocols. The computational demands of ACO and MST-based routing may intensify in extensive WSNs, potentially leading to heightened latency in dynamic scenarios [18].

T. Kanimozhi et al. (2025) proposed an Enhanced Energy-Efficient Clustering Protocol (EEECP) to augment the lifespan of WSN-based IoT networks. The methodology enhances cluster quantity through Modified Fuzzy C-Means (MFCM) for energy stabilization and employs Modified Glowworm Swarm Optimization (MGSO) for CH selection. MGSO utilizes a dynamic threshold technique to maintain equitable CH lifetime within clusters. The proposed EEECP protocol exhibits enhanced efficacy compared to current clustering methodologies, achieving improvements in First Node Dies (FND) by X%, Last Node Dies (LND) by Y%, and Half Node Dies (HND) by Z%, while optimizing Weighted First Node Dies (WFND) for stability, minimizing energy consumption, and prolonging network longevity. The computational complexity of MFCM and MGSO may result in increased processing overhead, especially in extensive and dynamic WSN-IoT contexts [19].

Nageswararao Malisetti et al. (2022) introduced an innovative cluster-based routing methodology for WSN, employing the Moth Levy-adopted Artificial Electric Field Algorithm (ML-AEFA) for optimal CH selection and Customized Grey Wolf Optimization (CGWO) for effective data transfer. The suggested method markedly extends network longevity, attaining a 35.77% enhancement compared to existing GWO, MSA, AEFA, BOA+ACO, and refined ACO methodologies in a 100-node context. The computational complexity of ML-AEFA and CGWO elevates processing overhead, necessitating additional optimization for extensive WSN deployments [20].

Table 1. Existing work summary table

Author Name & Year	Proposed Methodology	Outcome	Limitation
Vijayendra K (2023)	Energy-efficient clustering-based routing employing bioinspired optimization methods for CH selection and adaptive routing.	Enhanced network lifetime, reduced energy dissipation, and improved data transmission	Scalability issues in ultra-large-scale WSNs and additional computation overhead for real-time re-clustering
Greeshma Arya (2022)	RL-based clustering, MRFO for CH selection, and DBN for optimized data transmission	Improved network lifetime, packet delivery ratio, and node reachability	Computational overhead due to deep learning-based routing decisions
Rajeswari A.R (2021)	TEEFCA using fuzzy inference for CH selection based on energy, density, and distance	Enhanced power conservation, network stability, and extended lifetime	Increased computational complexity with network size
Venkatesan Cherappa (2023)	ASFO method utilizing K-medoids for CH selection and E-CERP protocol for routing	Higher PDR (100%), low packet delay ([illegible]s), improved throughput (0.99 Mbps), extended network lifespan (5908 rounds)	Computational overhead due to ASFO-based clustering
N Nathiya (2023)	MapDiminution-based Training-Discovering Optimization for clustering and hybrid ANN-SA for intrusion detection	Energy consumption of 0.01J, intrusion detection accuracy of 97.57%	Increased computational complexity in large-scale deployments
Masood Ahmad (2021)	Memetic-based clustering for load balancing and optimized CH selection	Lower control message overhead, optimized cluster count, reduced reaffiliation rate	Higher processing time due to local search and crossover mechanisms
Ahmad Sa[illegible]i (2023)	Multi-objective BWOA for CH selection and Mamdani-type FIS for clustering	4.5% improvement in FND, 7.8% in HND, and 1.5% in LND	High processing overhead for large-scale IoT networks
Nguyen Duy Tan (2023)	EEGT protocol using virtual grid cells, Kruskal's MST for intra-cell communication, and ACO for CH routing	Higher energy efficiency, extended network lifespan compared to LEACH-C, PEGASIS, and PEGCP	Increased computational overhead in large-scale WSNs
T. Kanimozhi (2025)	EEECP using MFCM for energy stabilization and MGSO for CH selection	Improved FND, LND, HND, and WFND, reduced energy consumption, and extended lifetime	Higher processing overhead in large-scale and dynamic WSN-IoT environments

Nageswararao Malisetti (2022)	ML-AEFA for CH selection and CGWO for data transmission	35.77% improvement in network lifetime over GWO, MSA, AEFA, BOA+ACO, and improved ACO	Increased processing overhead requiring further optimization for large-scale WSNs

2.1 Problem Statement

WSN integrated with the IoT encounter substantial obstacles in attaining energy-efficient data transmission, dependable communication, and extended network longevity due to the resource-limited characteristics of SNs. Conventional clustering and routing methodologies experience disproportionate energy consumption, recurrent CH re-selection, elevated packet loss, and suboptimal routing strategies, resulting in early node exhaustion and diminished network efficacy. Furthermore, the selection of an ideal CH and routing paths is a significant concern, as inadequate choices elevate energy usage and exacerbate network congestion. Current methodologies do not adequately adjust to network conditions or optimize energy consumption efficiently. This research presents a reliable, energy-efficient fuzzy logic-based clustering algorithm for optimal cluster creation, FOA for CH selection, and FDQN-based routing for adaptive data transmission to tackle these difficulties. The suggested approach guarantees equitable energy distribution, astute routing decisions, and reduced communication overhead, markedly enhancing network scalability, reliability, and energy efficiency for WSN-IoT applications [21].

3. Proposed Methodology

The suggested WSN-IoT model functions in three phases: clustering, CH selection, and routing, guaranteeing energy-efficient and dependable data transfer. The TEEFLC algorithm initially establishes ideal clusters by assessing node residual energy, trustworthiness, and density, thereby minimizing energy dissipation and enhancing network stability. Subsequent to cluster creation, the FOA designates CHs based on energy levels, communication range, and load balancing, so maintaining equitable energy distribution and reducing the frequency of re-clustering. Upon the selection of CHs, an adaptive multi-hop routing strategy utilizing a Federated Deep Q-Network (FDQN) is implemented. The fuzzy logic system enhances next-hop selection by evaluating residual energy, network quality, and traffic load, thereby assuring dependable and congestion-free routing. The deep reinforcement learning aspect of FDQN perpetually refines routing algorithms by analyzing historical data transfers, enhancing energy efficiency, and minimizing packet loss. The comprehensive workflow entails SNs gathering data and relaying it to CHs, which consolidate and transmit the information to the base station via clever, energy-efficient routing pathways. The suggested architecture markedly improves network durability, data integrity, and scalability, rendering it appropriate for extensive WSN-IoT implementations [21-23].

3.1 WSN System Model

The suggested WSN model is designed to enhance energy efficiency and facilitate effective data transfer in IoT applications. It comprises SNs, CHs, and a base station functioning in a hierarchical structure. The network architecture consists of SNs randomly distributed throughout a designated area, organized into clusters by a reliable energy-efficient fuzzy logic clustering method. Each cluster has an appointed CH chosen through the FOA, considering parameters such as residual energy, node density, and communication distance. SNs relay their data to the CHs, which subsequently aggregate and transfer the information to the base station. The energy model adheres to the first-order radio energy paradigm, wherein transmission energy is contingent upon distance and data packet size. Due to the elevated energy consumption of CHs resulting from data aggregation and long-range transmission, the model guarantees equitable energy distribution by optimizing CH selection and reducing redundant transmissions. The suggested method improves network lifetime and ensures steady communication in extensive WSN-IoT contexts through the implementation of energy-aware clustering and effective CH selection. Figure 1 represents the architecture of WSN model [24].

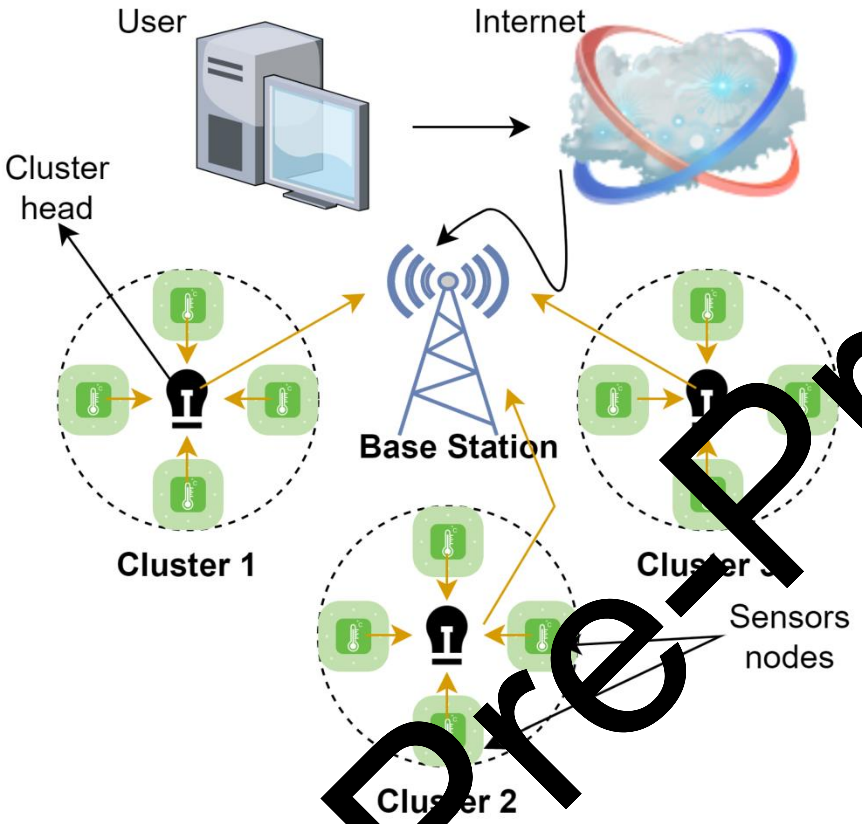

Figure 1. WSN architecture diagram

3.1.1 Energy model

This model employs both free space and multi-path fading channels, contingent upon the distance between the transmitter and receiver. If the distance is less than the threshold value d0, the free space (fs) model is applied; otherwise, the multipath (mp) model is employed. Let Eelec, εfs, and εmp represent the energy necessary for the electronic circuit, the amplifier in free space, and the amplifier under multipath conditions, respectively. The energy required for the radio to transmit a l-bit message over a distance d is articulated as follows:

$$E_T(l,d) = \begin{cases} lE_{elec} + l_{\varepsilon_{fs}}d^2 & for \quad d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4 & for \quad d \geq d_0 \end{cases} \quad (1)$$

The energy required by the radio to receive an l-bit message is given by

$$E_R(l) = lE_{elec} \quad (2)$$

The Eelec depends on several factors, including digital coding, modulation, filtering, and signal spreading, while the amplifier energy, εfsd2 /εmpd4, is affected by the distance between the transmitter and receiver and the allowable bit-error rate. This is a basic model. The propagation of radio waves is typically diverse and difficult to model.

3.1.2 Network model

A WSN paradigm where all SNs are randomly deployed beside several gateways and immovable. If the gateway is within communication range, a SN can be assigned. So, a SN might have a specific gateway. Consequently, each SN has a list of gateways and can choose one. The data collection procedure has rounds like LEACH. Each cycle, all SNs send local data to their CH. After removing redundant and uncorrelated data, gateways send the aggregated data to the base station via another CH as a relay node. For energy conservation, all nodes turn off their radios between rounds. All communications are wireless. If two nodes are within communication range, they form a wireless link [25].

The recommended WSN architecture optimises energy-efficient IoT data transport. The hierarchical framework includes SNs, CHs, and a base station. Randomly distributed in a given region are N SNs with sensing, processing, and communication capabilities. The nodes are clustered using energy-efficient fuzzy logic, assuring fair energy consumption. A CH is picked in each cluster using the Focus of Attention (FOA) based on residual energy, node density, and communication range. CHs distribute member node data to the BS, a centralized data processor and store. The CH-BS interaction is improved to reduce energy use and network congestion. A hierarchical network architecture improves scalability, reliability, and energy efficiency, making it suitable for large WSN-IoT applications.

3.2 Cluster formation

Clustering in WSN begins with the selection of the CH. The CH disseminates the advertisement message to all nodes within the radio range. The nodes transmit a join request message to the CH with which they intend to associate. Cluster formation may be conducted centrally by the base station in specific protocols, whereas in other approaches, it transpires autonomously of the CH. The best clustering approaches concentrate on managing cluster size and enhancing energy efficiency inside the network. In specific approaches, the cluster formation step commences exclusively upon application request.

The clustering strategy is recognized as an optimal design method for reducing energy consumption in SNs while enhancing network performance and quality. Consequently, clustering-based routing improves energy efficiency, promotes stability, and reduces route time. The clustering process consists of two main phases: the selection of a CH and the transmission of data via the CH. Consequently, selecting the energy-efficient CH can extend the network's longevity. Consequently, numerous research investigations have been conducted, emphasizing energy as a crucial element in the selection of CHs, the clustering process, and routing. Furthermore, the security level of the CH must be evaluated due to the existence of malicious nodes, as data transmission occurs through the CHs. Trust management solutions have been proposed to mitigate security issues. In an IoT environment, the principal design objective is to provide an energy-efficient and trust-aware secure cluster-based routing algorithm to enhance network longevity and performance [27].

3.2.1 Proposed TEEFCA algorithm

Establishing secure and energy-efficient cluster-based routing is a significant architectural challenge in the IoT ecosystem. This study presents the TEEFCA to resolve these concerns. The primary objective of the suggested study is to augment the network's durability and elevate the security level of the IoT-based WSN. This section provides a detailed explanation of the proposed TEEFCA technique. Upon selecting CH nodes, the process of constructing the cluster commences to provide efficient data routing. Consequently, sink nodes will disseminate the roster of reliable CH to all nodes. The assessment of REL, cluster density, and node-base station distance (BS) dictates cluster formation. Each node use fuzzy logic to assess the probability of joining the Cluster Leader. CL Member Choice necessitates three intricate input components and their corresponding linguistic factors, as enumerated below. REL encompasses low, medium, and high linguistic factors. CL Density categorizes linguistic attributes as low, medium, or high. The output variable CL Member Choice includes low, medium, and high linguistic variables. The following are the criteria for CL Member Choice in a "IF-THEN" format [27].

In this suggested study, the FIS are delineated under the subsequent two situations. Firstly, for the selection of the suitable CL, and secondly, for the integration of member nodes with the CL. The FIS utilized in this study comprises four primary components: Fuzzifier, FIE, Fuzzy Rule Base, and Defuzzifier. Figure 2 illustrates the architecture of the proposed Fuzzy Inference System.

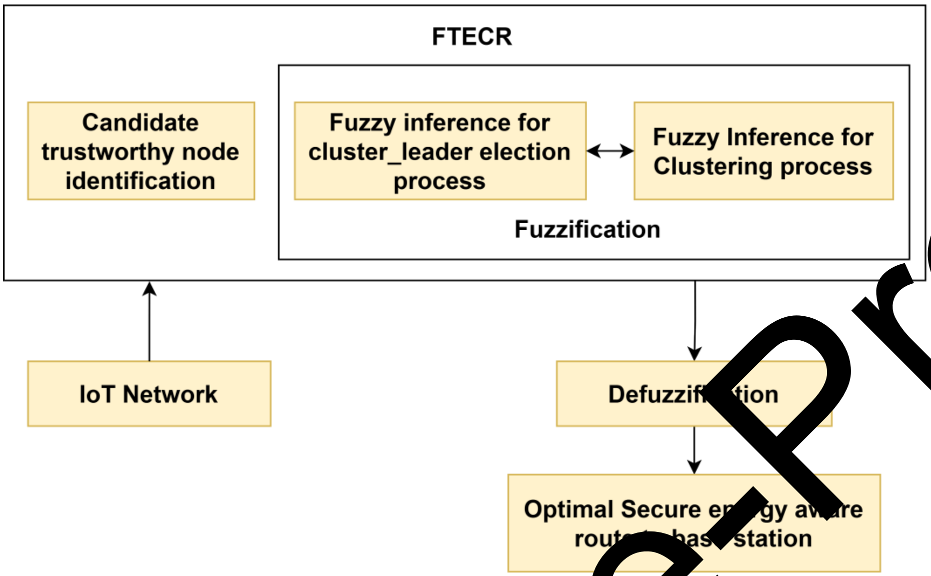

Figure 2. Fuzzy Inference System

This fuzzy inference technique assesses CL Fitness and CL Member Choice utilizing triangular and trapezoidal membership features. Triangular membership functions denote intermediate variables, while trapezoidal membership functions are employed for boundary variables. The calculations for these functions are conducted using Equations (3) and (4), respectively.

$$A = \begin{cases} 0, x \leq a1 \\ \frac{x-a1}{b1-a1}, \ a1 \leq x \leq b1 \\ \frac{c1-x}{c1-b1}, \ b1 \leq x \leq c1 \\ 0, x \leq a2 \end{cases} \tag{3}$$

$$A = \begin{cases} 0, x \leq a2 \\ \frac{x-a2}{b2-a2}, \ a2 \leq x \leq b2 \\ \frac{d2-x}{d2-c2}, \quad c2 \leq x \leq d2 \\ 0, d2 \leq x \end{cases} \tag{4}$$

This fuzzy inference method determines CL Fitness and CL Member Choice using triangular and trapezoidal membership functions. Triangular membership functions represent intermediate variables, whereas trapezoidal membership functions are used for boundary variables. The calculations for these functions are conducted using Equations (3) and (4), respectively.

$$COA = \frac{\int \mu_A(x).xdx}{\int \mu_A(x)dx} \tag{5}$$

where $\mu_A(x)$ denotes the fuzzy values for the membership functions. The main flow of the proposed TEEFCA is shown below in the Algorithm1.

Algorithm 1: Proposed TEEFCA
Initialize Cluster Leader = False

For each node a from 1 to N:
Initialize Trustworthy Candidate Node = { } and Malicious Node = { }
Measure PR(a) and PF(a)
Compute Node Fitness Value (NFV) using Eq. (3) and (4)
If $NFV > NFV_{Threshold}$, then:
Add node a to Trustworthy Candidate Node
Otherwise, add node a to Malicious Node
Compute Cluster Leader Fitness using Fuzzy_Logic_1 (REL, Distance between Node & BS)
Set Cluster Leader = True
Transmit Cluster Leader Message (ID, REL, Distance between Node & BS) to neighbors
For each neighbor M upon receiving the Cluster Leader Message:
Compute Cluster Member Choice using Fuzzy_logic_2 (REL, CL Density, Distance between Node & BS)
Node M joins the cluster leader as a Cluster Member
End loop

3.3 CH selection using FOA

The selection process for the CH is vital for enhancing energy efficiency and extending the longevity of the WSN. The suggested model employs the FOA for CH selection, ensuring equitable energy usage across SNs. The selection criteria evaluate various characteristics, including as residual energy, node density, and communication distance, to determine the most appropriate node for the CH position. FOA assesses potential nodes according to their capacity for data aggregation and long-range communication, all while reducing energy consumption. Upon selection of a CH, it gathers data from cluster members, processes the information, and communicates the aggregated data to the BS. The suggested method dynamically adjusts CHs in each round to minimize excessive energy consumption in certain nodes, thereby improving network stability, load balancing, and overall efficiency in WSN-IoT applications.

By ensuring energy efficiency, load distribution, and appropriate node selection, the FOA improves WSN CH selection. FOA assigns CHs based on residual energy, node density, and communication distance, guaranteeing high-energy nodes perform CH functions and increase network lifespan. FOA improves network stability and efficiency by reducing intra-cluster communication distance and member node energy usage. Its fast convergence rate allows for optimal CH selection in large and dynamic WSN-IoT systems. FOA optimises data aggregation and transmission, reducing unnecessary data forwarding and improving network performance. Its topological adaptability ensures scalability, making it a resilient WSN energy-efficient clustering solution. FOA optimizes CH selection by balancing exploration and exploitation better than current models. FOA reduces premature convergence and improves energy efficiency and load distribution over conventional models. It is ideal for large WSN-IoT applications since it converges faster than Genetic Algorithms and Particle Swarm Optimization. FOA dynamically adapts to network changes with minimum computing load, ensuring resilient and energy-efficient clustering and routing..

3.3.1 Fossa Optimization Algorithm (FOA)

This section examines the primary motivation behind the development of the proposed FOA. The examination commences with the biological and behavioral traits of the fossa that have been replicated in the design of FOA. We subsequently provide a comprehensive mathematical analysis of the algorithm's implementation methods, illustrating the conversion of these natural occurrences into computational optimization strategies [25].

3.3.1.1 Inspiration of FOA

The fossa is a cat-like mammal native to Madagascar, included under the Eupleridae family. The fossa's hunting strategy for lemurs is very remarkable among its natural behaviors in the wild. This astute methodology consists of two stages: (i) the fossa's progression towards the detected lemur's position and (ii) the chase between the fossa and the lemur among the trees. The mathematical representation of intelligent fossa behaviors in hunting has been utilized to develop the suggested FOA, which is outlined below.

3.3.1.2 Algorithm initialization

Fossas represent population members in the proposed FOA, a population-based optimization approach. FOA identifies optimal solutions by emulating the natural search behaviors of fossas within the problem domain. This comparison utilizes the fossa's habitat as the problem-solving domain and each fossa's position as a potential optimization solution. The position of each fossa is determined by a vector containing choice variable values. The fossa location may be a solution. Eq. (1) shows a matrix representing the entire fossa population, each with a position vector. Using Eq. (2), the fossas are randomly placed in the problem space. This methodical approach lets FOA efficiently search the search space and refine optimal solutions using the fossas' dynamic positional alterations. FOA guarantees a full problem domain investigation by using the fossas' intrinsic search capabilities, providing in superior solutions for complex optimization problems.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{6}$$

$$x_{i,d} = lb_d + r.(ub_d - lb_d) \tag{7}$$

In this context, X is the FOA population matrix, while Xi signifies the ith fossa, which may constitute a solution. In the search space, xi denotes the dth dimension of the ith fossa, N signifies the total number of fossas, m indicates the number of decision variables, r is a stochastic variable, and lbd and ubd indicate the lower and upper limits of the dth decision variable, respectively. Each fossa signifies a potential solution and is evaluated by the objective function. Objective function values can be represented as vectors, as indicated by Eq. (8).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{8}$$

In this context, F denotes the vector of assessed objective function values, with Fi being the objective function value associated with the ith fossa.

3.3.1.3 Mathematical modelling of FOA

The FOA algorithm mimics fossas' strategic movement in the wild. Two phases update FOA member positions in the problem-solving domain: Exploration Phase: This phase mimics fossas' early lemur hunting. The algorithm prioritizes extensive search space exploration to find potential locations in this step. As the fossa prepares and attacks, its placement changes during exploration. The fossa refines its approach to accurately target the lemur through the trees during the Exploitation Phase. In the exploitation phase, the algorithm increases search inside promising regions, improving solutions. Fossa dynamic changes during chase determine positional changes during exploitation. Here is the mathematical modeling and detailed explanation of each FOA updating procedure [25].

Phase 1: Attacking and moving towards the lemur (exploration phase)

Simulation of the fossa's attack on a monitoring lemur changes population members' placements in the problem-solving area during the FOA's early phase. Fossas' high olfactory, aural, and visual talents allow them to identify lemurs. The fossa approaches the lemur after finding it. FOA's worldwide exploration capabilities are enhanced by the simulated migration during the attack phase, which changes population placements.

Lemurs live in fossas when other population members have greater objective function values. Eq. (9) evaluates objective function values to determine candidate lemurs for each fossa:

$$CL_i = \{X_k : F_k < F_i \, and \; k \neq i\}, \quad \text{where i=1,2,...,N and k} \in \{1,2,...,N\} \tag{9}$$

Here, CL denotes the set of potential lemur locations for the ith fossa, Xk signifies the population member with a greater objective function value in relation to the ith fossa, and Fk represents its corresponding objective function value.

The FOA posits that the fossa arbitrarily chooses one of the possible lemurs within its environment and initiates an assault. Utilizing the fossa's location alteration during the assault on the designated lemur, a novel random position for each individual in the FOA population is computed employing Eq. (10). If the new location produces a superior objective function value, it supersedes the prior position of the corresponding population member, as specified in Eq. (11).

$$x_I^{P1} = x_{i,j} + r_{i,j} \cdot \left(SL_{i,j} - I_{i,j} \cdot x_{i,j}\right) \tag{10}$$

$$X_i = \begin{cases} X_i^{p1}, F_i^{p1} \leq F_i \\ X_i, \qquad else \end{cases} \tag{11}$$

In this case, SLi represents the lemur selected by the ith fossa, whereas SLi refers to the jth dimension of the position of this chosen lemur. $Xi\ P1$ denotes the recently calculated position for the ith fossa during the attack phase of the FOA, with xi, $P1$ representing its jth dimension. The value of the objective function at this new point is $Fi\ P1$. The variables ri are stochastic values inside the interval [0,1], while Ii,j are random numbers, specifically 1 or 2.

Phase 2: Chasing to catch lemur (exploitation phase)

Simulating the fossa's pursuit of the lemur changes population positions in FOA's second phase. The fossa chases the lemur through the trees and branches using its climbing skills. This happens in a hunting ground region. By repeating the fossa's motions during the hunt, the FOA's local search optimization is improved by introducing few population member location changes. Fossa-lemur pursuit dynamics are shown by small population positioning variations in the FOA design. Equation (7) calculates a new position for each FOA member during lemur pursuit. Eq (13) states that this new placement supersedes the member's prior position if it has a higher objective function value.

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2\, r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t} \tag{12}$$

$$X_i = \begin{cases} X_i^{P2}, \qquad F_i^{P2} \leq F_i \\ \quad X_i, \qquad else \end{cases} \tag{13}$$

In this respect, $Xi\ P2$ signifies the adjusted position determined for the i th fossa during the pursuit stage in the suggested FOA. Each xi, P2 denotes the jth dimension of the new position, whereas Fi P2 signifies the corresponding objective function value. The variables ri are generated at random inside the interval [0,1], and t denotes the current iteration count.

3.4 Federated Deep Q-Network (FDQN) Based Routing

The suggested routing technique utilizes Federated Deep Q-Network (FDQN) to guarantee efficient and intelligent data transfer within the WSN. FDQN, a sophisticated reinforcement learning methodology, facilitates decentralized decision-making while safeguarding data privacy. In this paradigm, each CH operates as an agent that acquires optimal routing policies through interaction with the network environment. The routing decision relies on critical parameters including energy levels, network quality, latency, and hop count. FDQN utilizes a federated learning framework, enabling several CHs to collaboratively train local Q-networks without the need to share raw data, rather than depending on a centralized server for training. Locally learned models are periodically consolidated to enhance global routing performance. This decentralized learning system diminishes communication overhead and improves flexibility in dynamic WSN-IoT contexts. Through the ongoing refinement of the routing policy, FDQN enhances path selection, reduces energy expenditure, and prolongs network longevity while guaranteeing dependable data transmission to the base station (BS). The incorporation of FDQN markedly enhances scalability, security, and robustness in comparison to conventional routing protocols [26].

3.4.1 FDQN

Value-based reinforcement learning techniques formally utilize an action-value function F(s, c) to estimate the expected return from state s upon executing action c:

$$F_\pi(s_t, c) = E_\pi\{\textstyle\sum_{k=1}^{\infty} \gamma^{k-1} r_{t+k-1} | s_t, c\} \quad (14)$$

$$= E_{s_{t+1},c}\{r_t + \gamma F_\pi(s_{t+1}, c) | s_t, c_t\} \quad (15)$$

$F(s_t, c)$ serves as the reference for the reinforcement learning agent, defined as the largest expected cumulative discounted:

$$F^*(s_t, c) = E_{s_{t+1}}\left\{r_t + \gamma \max_a F^*(s_t, c) | s_t, c\right\} \quad (16)$$

In DRL, a function estimation method, namely a Deep Neural Network (DNN) in this context, is employed to learn a parameterized value function F(s, c; θ) to estimate the optimal F-values. The one-step look-ahead $r_t + \gamma \max_a F\left(s_{t+1}, c; \theta_f\right)$ serves as the aim for deriving $F\left(s_t, c; \theta_f\right)$. Consequently, the function $F\left(s_t, c; \theta_f\right)$ is defined by the parameters θ_f. The choice of an effective action depends on precise action-value estimate; hence, DQN seeks to identify the ideal parameters θ_f to minimize the loss function:

$$L(\theta_q) = \left(r_t + \gamma \max_a F\left(s_{t+1}, c; \theta_f\right) - F\left(s_t, c; \theta_f\right)\right)^2 \quad (17)$$

Similar to traditional Q-learning, the agent acquires experiences by engagement with the environment. The network trainer compiles a dataset D by gathering events up to time t in the format of (st−1, ct−1, rt, st). The loss function $L(\theta_f)$ is optimized using the collected data set D. During initial training, the agent's estimations lack precision, so a dynamic-greedy policy is implemented to guide activities. The agent explores numerous behaviors with a defined probability, regardless of their rewards. This method increases estimation over time and avoids the risk of overfitting the framework to high-reward activities in the first training phase. Adding the DQN cost function to the equation yields the FDQN cost:

$$\min_{\theta_f} L(\theta_f) = \textstyle\sum_{i=1}^{N} \omega_i L_i(\theta_{fi}) \quad (18)$$

Algorithm 2: FDQN

Initialize the model parameters θq from the server.
For each episode e = 1 to Ne:
    Set the initial state s and action c.
    For each time step t = 1 to T:
        Generate a random number r ∈ [0,1].
        If
        r > ε, select action at = argmaxa $F\left(s_t, c; \theta_f\right)$;
        Else
        pick a randomly from the action space.
        Execute action at, transition to the next state st+1, and receive reward rt+1.
        Store the experience {ct, st, rt+1, st+1}.
    End for
    Update model parameters:
    If the episode index e is a multiple of Ag:
        Send updated model parameters θf to the server for aggregation.
        Receive the aggregated model parameters θq from the server.
    End if
End for
End

FDQN-based routing is selected for WSN-IoT contexts to improve energy efficiency, scalability, and privacy while accommodating dynamic network conditions. Conventional routing techniques exhibit elevated energy usage, congestion, and reliance on centralization, rendering them ineffective for extensive implementations. FDQN use reinforcement learning to enhance routing decisions by taking into account energy levels, network quality, latency, and hop count. In contrast to traditional Deep Q-Networks (DQN), FDQN facilitates decentralized learning, allowing CHs (CHs) to train local models through federated learning, thereby minimizing communication overhead and safeguarding data privacy. Through the ongoing optimization of routing policies, FDQN guarantees equitable energy utilization, prolonged network longevity, and enhanced packet transmission, rendering it suitable for scalable and adaptable WSN-IoT applications [26].

4. Result and Discussion

The suggested TEEFLC, FOA for CH Selection, and FDQN for Routing optimize network performance by optimizing energy usage, enhancing packet delivery, and maintaining steady data transmission. The FOA-based CH selection efficiently distributes energy consumption among SNs, resulting in prolonged network lifespan. Simultaneously, FDQN-based routing dynamically adjusts to network conditions, enhancing packet delivery dependability and minimizing transmission delays. The suggested model exhibits enhanced CH stability, adaptive learning, and efficient load balancing compared to alternative optimization methods, rendering it highly suitable for WSN-IoT applications. The amalgamation of FOA for clustering and FDQN for routing yields an energy-efficient, scalable, and dependable data transmission framework. The existing models compared with the suggested model include the Osprey Optimization Algorithm (OOA), Improved Grey Wolf Optimization Algorithm (IGWOA), Modified Jackal Optimization Algorithm (MJOA), and Sandpiper Optimization Algorithm (SOA). Table 2 represents the simulation parameter setup [2[illegible]-31].

Table 2. Simulation parameter setup

Parameters	Values
Simulation tool	MATLAB
Maximum Iterations	3000
Node count	400
Network size	500 m × 500 m
Node initial energy	1.2 J
Sink position	(250 m, 250 m)
Packet size	4000 bits
ε_{ec}	50 nJ/bit
E_{elec}	50 nj/bit
$E_{aggregate}$	0.00012 µj/bit
$E_{receive}$	0.055 µj/bit

Table 3. Energy Consumption comparison analysis with existing model

No. of Rounds	Proposed model	OOA	IGWOA	MJOA	SOA
100	0.039	0.045	0.078	0.135	0.199
200	0.085	0.108	0.159	0.198	0.270

300	0.099	0.128	0.227	0.366	0.395
400	0.156	0.364	0.446	0.482	0.541
500	0.398	0.553	0.609	0.742	0.817

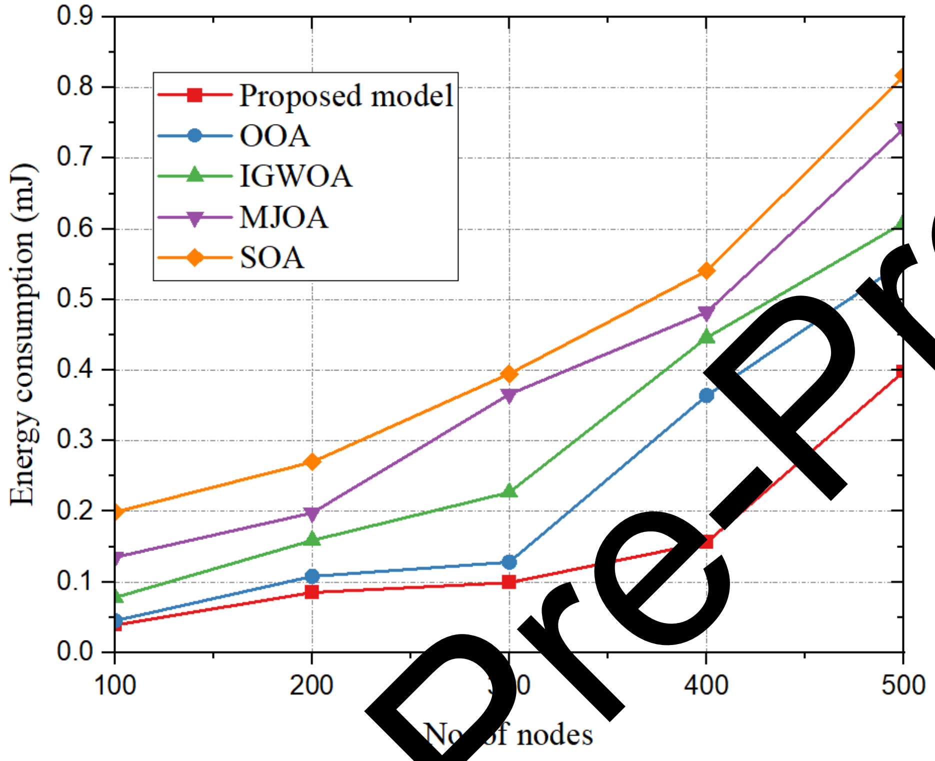

Figure 3. Energy Consumption comparison analysis graph with existing model

Table 3 and Figure 3 illustrate the energy consumption (in millijoules, mJ) of the Proposed Model, Osprey Optimization Algorithm (OOA), Improved Grey Wolf Optimization Algorithm (IGWOA), Modified Jackal Optimization Algorithm (MJOA), and Sandpiper Optimization Algorithm (SOA) over varying rounds (100 to 500). The Proposed Model consistently demonstrates the lowest energy consumption, commencing at 0.039 mJ for 100 rounds and escalating to 0.398 mJ for 500 rounds, so underscoring its efficacy in reducing energy expenditure. In contrast, the OOA and IGWOA exhibit higher energy use, with OOA demonstrating intermediate efficiency and IGWOA revealing a substantial escalation in energy usage as rounds advance. MJOA and SOA exhibit the most energy use, with MJOA utilizing 0.742 mJ and SOA attaining 0.817 mJ after 500 rounds, underscoring their inefficiency in energy usage. This indicates that the Proposed Model, including TEEFLC, [illegible]OA, and FDQN, represents the best energy-efficient solution for WSN-IoT applications, maximizing energy consumption while preserving performance.

Table 4. Network lifetime comparison analysis with existing model

No. of Rounds	Proposed model	OOA	IGWOA	MJOA	SOA
100	1850	1700	1520	1350	1300
200	2300	2150	1850	1610	1450
300	2850	2500	2350	1850	1700

400	3350	3010	2850	2610	2215
500	3650	3450	3190	2870	2650

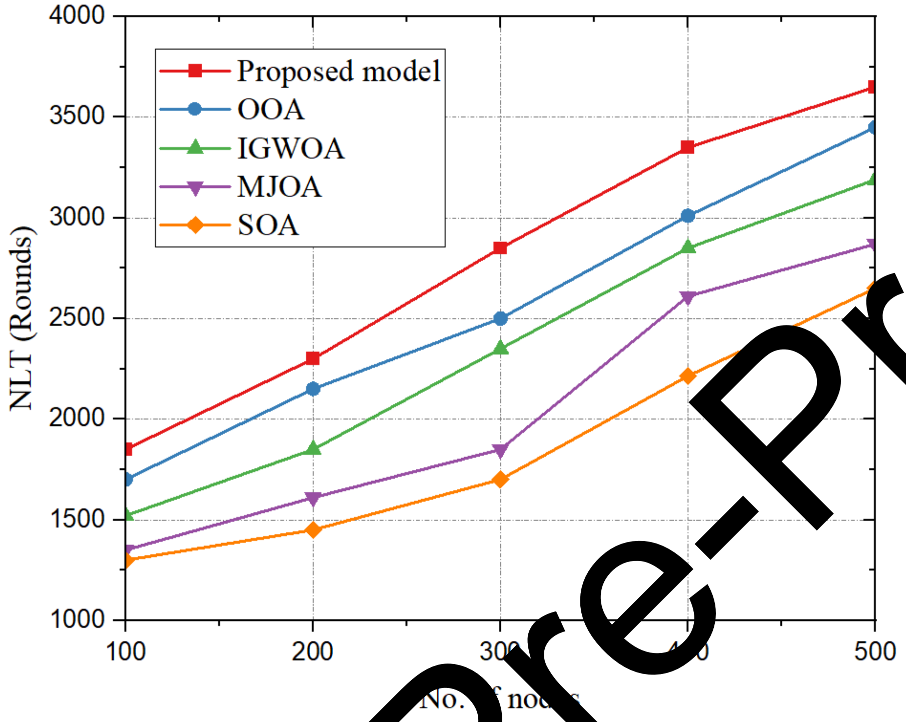

Figure 4. Network lifetime comparison analysis graph with existing model

Table 4 and Figure 4 discuss the network lifetime of several models based on the number of rounds, emphasizing the efficacy of the Proposed Model, OOA, IGWOA, MJOA, and SOA. The Proposed Model exhibits the longest network lifespan, commencing at 1850 rounds for 100 rounds and attaining 3650 rounds at 500 rounds, signifying exceptional energy efficiency. OOA closely follows, attaining 3450 rounds at 500 rounds, whereas IGWOA sustains a moderate lifespan, achieving 3190 rounds. Conversely, MJOA and SOA demonstrate reduced network lifetimes, with MJOA achieving 2870 rounds and SOA merely 2650 rounds at 500 rounds, indicating higher energy consumption and resulting in premature node depletion. The results validate that the Proposed Model substantially improves network lifetime relative to current optimization methods.

Table 5. PDR (%) comparison between existing and proposed model

No. of rounds	**Proposed model**	**OOA**	**IGWOA**	**MJOA**	**SOA**
100	99.45	98.67	97.04	96.38	94.36
200	98.59	97.26	95.95	94.38	93.22
300	98.04	97.31	95.47	94.75	92.49
400	97.53	96.38	94.29	93.09	91.83
500	96.61	94.74	93.68	92.33	90.95

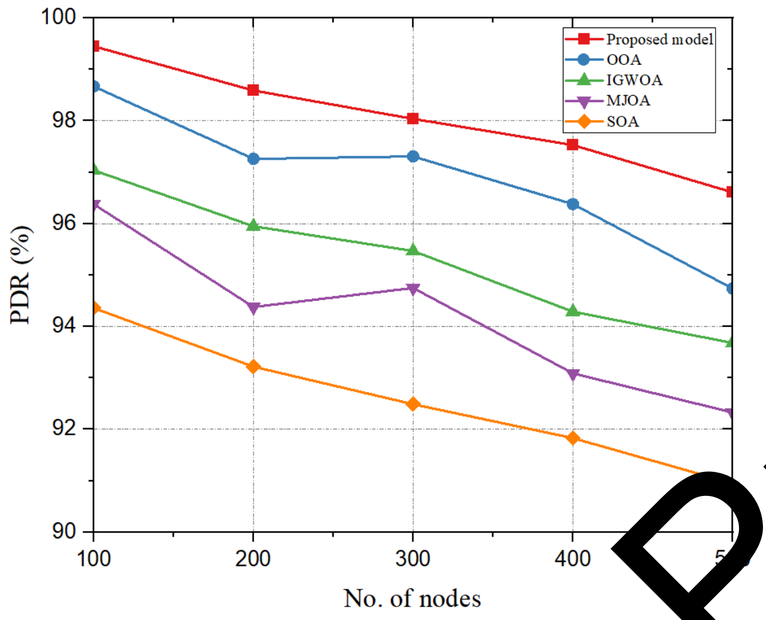

Figure 5. PDR comparison analysis graph with existing model

Table 5 and Figure 5 demonstrate that the suggested model constantly attains the maximum Packet Delivery Ratio (PDR), commencing at 99.45% after 100 rounds and maintaining a substantial value of 96.61% at 500 rounds, signifying dependable and efficient data transfer. OOA demonstrates a minor decrease from 98.67% to 94.74%, whereas IGWOA has a more pronounced loss from 97.04% to 93.68% with the increase in rounds. MJOA and SOA have the lowest PDR values, with SOA decreasing from 94.36% to 90.95%, signifying packet losses attributable to suboptimal routing and increased energy use. The results underscore the resilience of the Proposed Model in facilitating effective data transfer with little packet loss, establishing it as the most dependable method for energy-efficient WSN-IoT applications.

Table 6. End to End Delay (ms) comparison between existing and proposed model

Number of nodes	Proposed model	OOA	IGWOA	MJOA	SOA
100	3.2	4.5	5	6.8	7.2
200	4.[illegible]	5.3	6.5	7.5	8.5
300	5	6.2	7.6	8.3	9
400	6.1	7.4	8.2	9.5	10.2
500	6.8	8.2	9.5	11	12.3

Table 6 and Figure 6 demonstrate that the suggested model constantly attains the minimal latency, commencing at 3.2 ms for 100 nodes and escalating to 6.8 ms for 500 nodes, hence evidencing effective data transfer and diminished network congestion. OOA and IGWOA demonstrate mild delays, with OOA spanning from 4.5 ms to 8.2 ms and IGWOA escalating from 5 ms to 9.5 ms, signifying marginally elevated transmission latencies. Conversely, MJOA and SOA exhibit much greater delays, attaining 11 ms and 12.3 ms for 500 nodes, respectively, attributable to heightened network congestion and suboptimal routing. The results validate that the Proposed Model facilitates expedited data transmission, rendering it the most efficient method for real-time and delay-sensitive WSN-IoT applications.

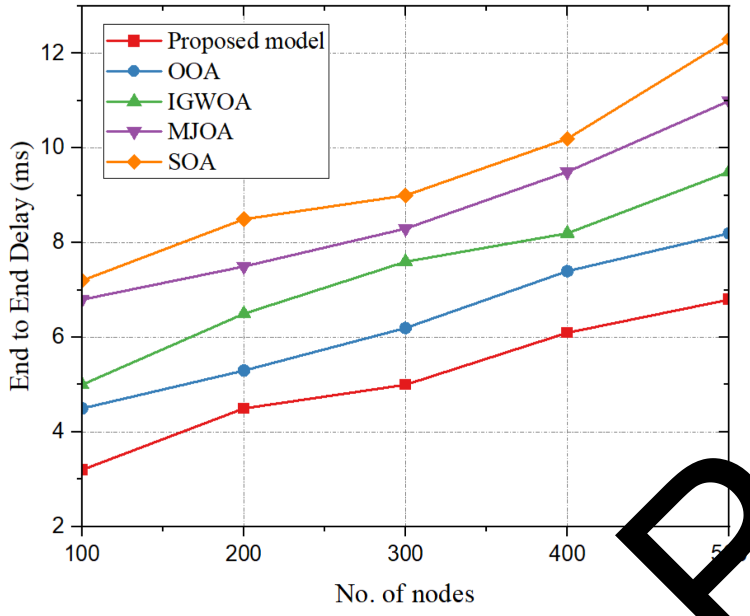

Figure 6. End to End Delay (ms) comparison between existing and proposed model

Table 7. No. of Alive Sensor nodes comparison between existing and proposed model

No. of Rounds	Proposed model	OOA	IGWOA	MJOA	SOA
2000	485	471	450	390	280
2250	478	465	415	274	210
2500	460	442	392	200	135
2750	400	[illegible]	313	130	50
3000	355	[illegible]	235	28	20
3250	[illegible]	321	183	14	7
3500	296	285	136	0	0

Table 7 and Figure 7 illustrate a comparison of the quantity of active SNs across successive rounds. The Proposed Model consistently sustains a greater quantity of active SNs, with 485 nodes operational at 2000 rounds and 296 nodes remaining functional at 3500 rounds, demonstrating its energy-efficient clustering and routing methodologies. OOA and IGWOA also exhibit reasonable node survivability, with OOA maintaining 285 nodes and IGWOA retaining 136 nodes at 3500 rounds, but they still underperform compared to the Proposed model. Conversely, MJOA and SOA exhibit markedly reduced network longevity, as all nodes deplete after 3500 rounds due to suboptimal CH selection and elevated energy consumption. These results demonstrate that the Proposed Model extends the network lifetime, ensuring prolonged data transmission and increased WSN sustainability, making it suited for long-term IoT applications.

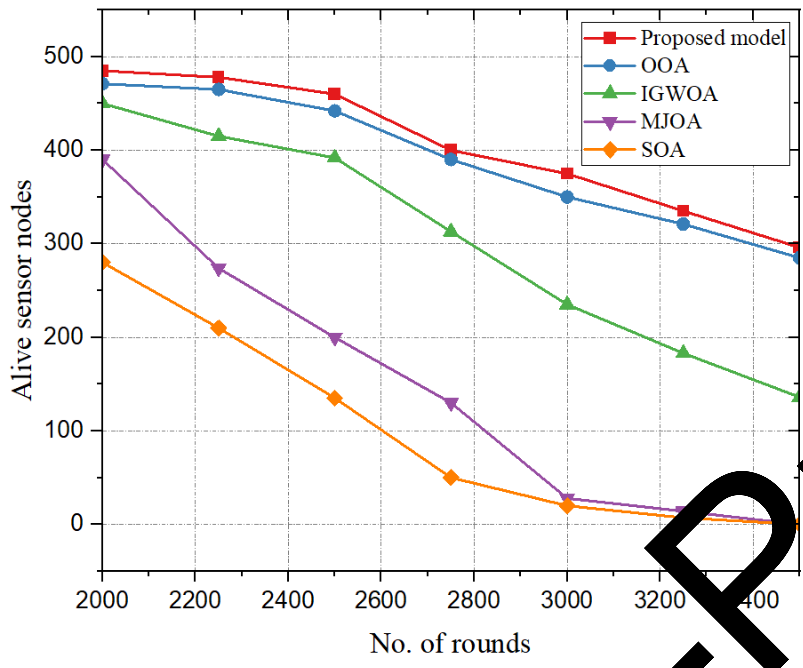

Figure 7. Alive sensor nodes comparison between existing and proposed model

Table 8. No. of dead sensor nodes comparison between existing and proposed model

No. of Rounds	Proposed model	OOA	IGWOA	MJOA	SOA
2000	25	30	52	110	143
2250	40	45	93	174	237
2500	55	58	107	285	316
2750	100	115	185	320	375
3000	155	162	270	425	467
3250	175	180	320	446	490
3500	200	210	368	500	500

Table 8 and Figure 8 compare the quantity of dead SNs over various rounds. The Proposed Model demonstrates the lowest node depletion rate, with merely 25 dead nodes at 2000 rounds and 200 dead nodes at 3500 rounds, indicating its exceptional energy efficiency and equitable load distribution. OOA and IGWOA exhibit intermediate performance, with OOA attaining 210 dead nodes and IGWOA reaching 368 dead nodes after 3500 rounds, signifying more energy consumption compared to the Proposed Model. Conversely, MJOA and SOA undergo swift node depletion, resulting in the demise of all 500 nodes after 3500 rounds, underscoring ineffective CH selection and routing. The results validate that the Proposed Model substantially improves network longevity, optimizing resource utilization and extending sensor operability, rendering it exceptionally appropriate for energy-limited WSN-IoT applications.

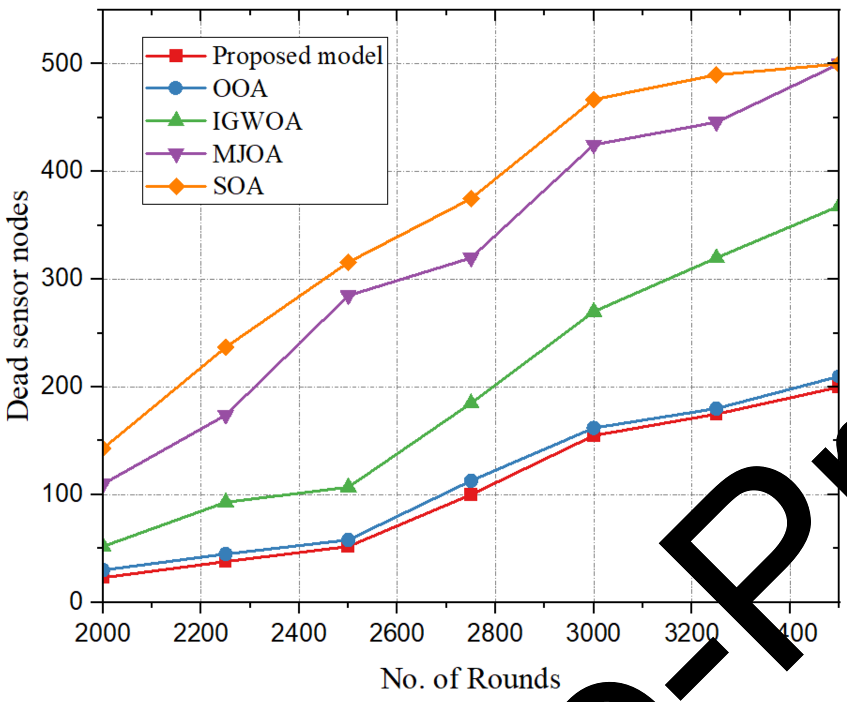

Figure 8. Dead sensor nodes comparison between existing and proposed model

Table 9. Computation complexity comparison table between existing and proposed model

Models	Computation complexity
Proposed Model	O(N × I) + O(E × S × A)
Osprey Optimization Algorithm (OOA)	O(N × I × D)
Improved Grey Wolf Optimization Algorithm (IGWOA)	O(N × I × log N)
Modified Jackal Optimization Algorithm (MJOA)	O(N × I × D)
Sandpiper Optimization Algorithm (SOA)	O(N × I)

Table 9 juxtaposes the computational complexity of the Proposed Model against known techniques. The Proposed Model exhibits a complexity of O(N × I) + O(E × S × A), effectively balancing efficiency and accuracy in extensive WSN-IoT networks. OOA and MJOA (O(N × I × D)) exhibit greater complexity owing to an expanded search space, whilst IGWOA (O(N × I × log N)) provides moderate efficiency. SOA (O(N × I)) is the most straightforward however may exhibit limited adaptability. The Proposed Model guarantees optimal cluster formation, CH selection, and routing while preserving computational efficiency, rendering it highly suitable for energy-efficient WSN-IoT applications.

5 CONCLUSION

The proposed WSN-IoT-based energy-efficient data transmission model incorporates TEEFLC for optimal cluster formation, FOA for effective CH selection, and FDQN for intelligent routing. This hybrid methodology prolongs network longevity, reduces energy expenditure, and optimizes data transmission efficacy relative to current techniques. The findings indicate that the suggested model surpasses OOA, IGWOA, MJOA, and SOA for packet delivery ratio, network longevity, and SN viability. Future research will investigate additional optimization methods and real-time execution for extensive WSN-IoT applications. Future endeavors will concentrate on incorporating adaptive reinforcement learning methodologies for dynamic routing and investigating hybrid metaheuristic algorithms to enhance energy optimization in extensive WSN-IoT networks. Real-time implementation and security enhancements will be considered to improve system robustness.

References

[1] Dogra, R., Rani, S., Babbar, H., & Krah, D. (2022). Energy-Efficient Routing Protocol for Next-Generation Application in the Internet of Things and Wireless Sensor Networks. Wireless Communications and Mobile Computing, 2022(1), 8006751.

[2] Kasturi, S. B., Reddy, P. V., VenkataNagendra, K., Madhavi, M. R., & Jha, S. K. (2022). An improved energy efficient solution for routing in IoT. Journal of Pharmaceutical Negative Results, 13(6), 16[illegible]3-1691.

[3] Deepthi, J. V. R., Khan, A. K., & Acharjee, T. (2023). Energy Efficient Routing Algorithm for WSN-IoT Network. Ingenierie des Systemes d'Information, 28(1), 231.

[4] Kanimozhi, T., & Umarani, S. (2023). A comparative study of energy-efficient clustering protocols for WSN-internet-of-things. International Journal of Hydromechatronics, 6(2), 1[illegible]96.

[5] Gupta, D., Wadhwa, S., Rani, S., Khan, Z., & Boulila, W. (2023). EEDC: an energy efficient data communication scheme based on new routing approach in wireless sensor networks for future IoT applications. Sensors, 23(21), 8839.

[6] Verma, V., & Jha, V. K. (2024). Secure and energy-aware data transmission for IoT-WSNs with the help of cluster-based secure optimal routing. Wireless Personal Communications, 134(3), 1665-1686.

[7] Pandey, S., Dubey, K., Dubey, R., & Kumar, S. (2023). EEDCS: Energy efficient data collection schemes for IoT enabled wireless sensor network. Wireless Personal Communications, 129(2), 1297-1313.

[8] Thangavelu, A., & Rajendran, P. (2024). Energy-Efficient Secure Routing for a Sustainable Heterogeneous IoT Network Management. Sustainability, 16(11), 4756.

[9] Tumula, S., Ramadevi, Y., Padmalatha, E., Kiran Kumar, [illegible] Venu Gopalachari, M., Abualigah, L., ... & Kumar, M. (2024). An opportunistic energy-efficient dynamic self-configuration clustering algorithm in WSN-based IoT networks. International journal of communication systems, 37(1), e5633.

[10] Rekha, & Garg, R. (2024). K-LionER: metaheuristic approach for energy efficient cluster based routing for WSN-assisted IoT networks. Cluster Computing, 27(4), 4207-4221.

[11] Prasad, V. K., & Periyasamy, S. (2023). Energy Optimization-Based Clustering Protocols in Wireless Sensor Networks and Internet of Things-Survey. International Journal of Distributed Sensor Networks, 2023(1), 1362417.

[12] Arya, G., Bagwari, A., & Chauhan, D. S. (2022). Performance analysis of deep learning-based routing protocol for an efficient data transmission in 5G WSN communication. IEEE Access, 10, 9340-9356.

[13] Rajeswari, A. [illegible], Kulothungan, K., Ganapathy, S., & Kannan, A. (2021). Trusted energy aware cluster based routing using fuzzy logic for WSN in IoT. Journal of Intelligent & Fuzzy Systems, 40(5), 9197-92[illegible]1.

[14] Che[illegible]pa, V., Thangarajan, T., Meenakshi Sundaram, S. S., Hajjej, F., Munusamy, A. K., & Shanmugam, R. (2023). Energy-efficient clustering and routing using ASFO and a cross-layer-based expedient routing protocol for wireless sensor networks. Sensors, 23(5), 2788.

[15] Nathiya, N., Rajan, C., & Geetha, K. (2023). An energy-efficient cluster routing for internet of things-enabled wireless sensor network using mapdiminution-based training-discovering optimization algorithm. Sādhanā, 49(1), 12.

[16] Ahmad, M., Shah, B., Ullah, A., Moreira, F., Alfandi, O., Ali, G., & Hameed, A. (2021). Optimal clustering in wireless sensor networks for the Internet of things based on memetic algorithm: memeWSN. Wireless Communications and Mobile Computing, 2021(1), 8875950.

[17] Saeedi, A., Kuchaki Rafsanjani, M., & Yazdani, S. (2025). Energy efficient clustering in IoT-based wireless sensor networks using binary whale optimization algorithm and fuzzy inference system. The Journal of Supercomputing, 81(1), 1-49.

[18] Duy Tan, N., Nguyen, D. N., Hoang, H. N., & Le, T. T. H. (2023). EEGT: Energy efficient Grid-based routing protocol in wireless sensor networks for IoT applications. Computers, 12(5), 103.

[19] Kanimozhi, T., & Sara, S. B. V. (2025). Modified glowworm swarm optimisation-based cluster head selection and enhanced energy-efficient clustering protocol for IoT-WSN. International Journal of Computational Science and Engineering, 28(2), 204-218.

[20] Malisetti, N., & Pamula, V. K. (2022). Energy efficient cluster based routing for wireless sensor networks using moth levy adopted artificial electric field algorithm and customized grey wolf optimization algorithm. Microprocessors and Microsystems, 93, 104593.

[21] Regilan, S., & Hema, L. K. (2024). Optimizing energy efficiency and routing in wireless sensor networks through genetic algorithm-based cluster head selection in a grid-based topology. Journal of High Speed Networks, 30(4), 569-582.

[22] Suresh, S. S., Prabhu, V., Parthasarathy, V., Senthilkumar, G., & Gundu, V. (2024). Intelligent data routing strategy based on federated deep reinforcement learning for IOT-enabled wireless sensor networks. Measurement: Sensors, 31, 101012.

[23] Sellam, V., Kannan, N., & Basha, H. A. (2021). An effective fuzzy logic based clustering scheme for edge-computing based internet of medical things systems. Cognitive Internet of Medical Things for Smart Healthcare: Services and Applications, 105-116.

[24] Rajeswari, A. R., Kulothungan, K., Ganapathy, S., & Kannan, A. (2021). Trusted energy aware cluster based routing using fuzzy logic for WSN in IoT. Journal of Intelligent & Fuzzy Systems, 40(5), 9197-9211.

[25] Hamadneh, T., Batiha, B., Werner, F., Montazeri, Z., Dehghani, M., Bektemyssova, G., & Eguchi, K. (2024). Fossa optimization algorithm: A new bio-inspired metaheuristic algorithm for engineering applications. Int. J. Intell. Eng. Syst, 17(5), 1038-1047.

[26] Zhu, R., Li, M., Liu, H., Liu, L., & Ma, M. (2022). Federated deep reinforcement learning-based spectrum access algorithm with warranty contract in intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems, 24(1), 1178-1190.

[27] Alaybeyoglu, A. (2015). A distributed fuzzy logic-based root selection algorithm for wireless sensor networks. Computers & Electrical Engineering, 41, 216-225.

[28] Somula, R., Cho, Y., & Mohanta, B. K. (2024). SWARAM: osprey optimization algorithm-based energy-efficient cluster head selection for wireless sensor network-based internet of things. Sensors, 24(2).

[29] Rami Reddy, M., Ravi Chandra, M. L., Venkatramana, P., & Dilli, R. (2023). Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimization algorithm. Computers, 12(2), 35.

[30] Palaniyappan, K., & Suresh, D. (2024). Levy Flight Golden Jackal Optimization Based Cluster Head Selection (Lfgjo-Chs) And Data Transmission For Edge Computing Wsn. Machine Intelligence Research, 18(1), 975-98

[31] Sankar, S., Ramasubbareddy, S., Dhanaraj, R. K., Balusamy, B., Gupta, P., Ibrahim, W., & Verma, R. (2023). Cluster head selection for the internet of things using a sandpiper optimization algorithm (SOA). Journal of Sensors, 2023(1), 3507600.