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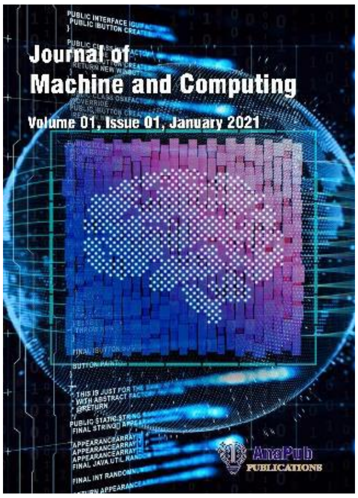

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Energy-Efficient Fault Data Prediction and Transmission in WSN-IoT using Bio-Inspired Optimization and Deep Learning

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Abstract

Wireless sensor networks (WSNs) are crucial for several applications. WSN nodes frequently function with constrained battery capacity, rendering energy efficiency a critical issue for clustering and routing. Moreover, a principal challenge of WSNs is ensuring the dependability and security of transmitted data in susceptible contexts to avert hostile node attacks. This study seeks to establish a secure and energy-efficient routing system for fault data prediction to improve the longevity and dependability of WSNs. This paper presents a sophisticated framework for intelligent fault prediction and energy-efficient data transmission in WSN, utilising bio-inspired optimisation and deep learning methodologies. The model initiates data fault prediction with Multi-Term Fourier Graph Neural Networks (MTFGNN), which examine temporal and spatial relationships to detect anomalies and defective nodes prior to clustering. Faultless nodes are subsequently categorised by Fuzzy C-Means (FCM) clustering, facilitating adaptive and efficient cluster creation. Quokka Swarm Optimisation (QSO) is utilised to improve energy efficiency by selecting ideal cluster heads (CH), thereby balancing energy usage and reducing intra-cluster communication expenses. A trust-based routing technique employs Proximal Policy Optimisation (PPO), a reinforcement learning method that dynamically identifies secure and energy-efficient pathways for data transfer, while reducing the influence of unreliable nodes. The experimental results indicate that it surpasses the rival methods across multiple performance parameters. The performance outcomes of quality of service (QoS) metrics are delineated as follows: energy consumption (0.204), throughput (0.701), packet delivery rate (94.24%), network lifetime (1310 rounds), and fault prediction accuracy (99.7[illegible]%), precision (98.69%), recall (97.52%) and F1 score (97.83).

Keywords : Wireless sensor networks (WSNs), Quokka Swarm Optimisation (QSO), Multi-Term Fourier Graph Neural Networks (MTFGNN), Fuzzy C-Means (FCM), Proximal Policy Optimization (PPO), cluster head (CH).

1. Introduction

Recently, more and more people are interested in WSNs, which are extensively applied for many real-time purposes. Developments in wireless communications and micro-electro-mechanical systems have made it possible to create low-cost, low-power sensor nodes that monitor critical parameters like temperature and humidity in the sensing environment. To the central location, they broadcast their detected data collectively across the wireless channel. Unclear and unreliable, the linked sensors in WSNs generate data constantly. The sensor nodes face own different faults since a WSN is deployed in hostile and uncontrolled surroundings. The efficient processing and analysis of data streams makes data fault detection our most extreme relevance for several applications [1].

Applications of WSN necessitate precise data to deliver accurate information to the end user. The quality of information derived by WSN may be compromised in terms of dependability and accuracy due to their cost-effective design and challenging deployment conditions. The techniques for detecting data defects ensure the quality of the data samples, make it easier to clean up the collected data, and provide end users with useful information while saving energy and assisting with computational duties because sensor nodes have limited energy resources. With a high detection rate, the data detection model can efficiently identify data anomalies in new observations and is built to find changes based on prior WSN data structures. Defective node identification and management is a major challenge in WSNs [2][3].

The fault is a problem in the system that can lead to an erroneous state, potentially resulting in failures. The sensor nodes may encounter two distinct categories of problems: sensor node faults and data faults. Clustering is a fundamental strategy employed to improve energy efficiency in WSN by organising sensor nodes into clusters, with a designated CH responsible for aggregating and transmitting data to the BS. This hierarchical framework reduces duplicate communication and optimises energy consumption across nodes. Nonetheless, choosing an appropriate CH is a complicated endeavour, as inadequate selection may result in premature energy exhaustion and network instability [4]. Bio-inspired optimisation algorithms offer an effective method for optimal CH selection, facilitating efficient energy distribution and extending network longevity. Besides clustering, routing is essential for the efficient transmission of data across the network. Conventional routing systems frequently experience elevated energy consumption and susceptibility to node failures or security risks. Intelligent routing methodologies, including reinforcement learning-based strategies, dynamically identify the most energy-efficient and safe pathways for data transmission. Trust-based routing solutions augment security by assessing node behaviour and guaranteeing dependable communication [5][6].

The suggested model aims to improve energy economy, fault tolerance, and secure data transfer in WSNs. Conventional clustering and routing methodologies experience energy imbalance, suboptimal CH selection, and susceptibility to defective or malevolent nodes, resulting in network instability. The proposed model incorporates MTFGNN for early fault prediction, FCM clustering for adaptive cluster formation, and QSO for optimal selection of CH to tackle these difficulties. Moreover, TBPPO guarantees intelligent and secure routing through the dynamic selection of energy-efficient and reliable pathways. This comprehensive strategy seeks to augment network durability, diminish energy usage, and elevate data dependability, rendering WSN more resilient and sustainable [7]. The suggested model improves energy efficiency, fault tolerance, and secure data transmission in WSN by the integration of advanced clustering, optimisation, and routing algorithms. It utilises MTFGNN for proactive defect prediction, guaranteeing data integrity. FCM clustering facilitates adaptive cluster creation, enhancing network stability. QSO efficiently identifies CH, optimising energy consumption. TBPPO guarantees secure and efficient routing, reducing risks from defective or malevolent nodes. This methodology prolongs network longevity, minimises energy consumption, and improves communication dependability. The approach is relevant to multiple sectors, such as healthcare, smart cities, and industrial automation [8-10].

Cluster formation, optimal route determination, and intrusion identification are the three main stages of the current methodology. Three input parameters were used in the original implementation of the Adaptive Shark Smell Optimisation (ASSO) approach for CH selection. The characteristics include node density, residual energy, and distance from the base station. Salp swarm optimization (SSO) is used after clustering to determine the best path for data transfer between clusters, producing an energy-efficient WSN. In order to enhance the security of cluster-based WSNs, a MERNN-based intrusion detection system is used to identify network intrusions. A low-power cluster-based routing protocol with a comprehensive defect detection mechanism for WSNs was introduced by an existing model. For CH selection, the protocol makes use of the fuzzy logic-enhanced Improved Whale Optimisation Algorithm (IWOA). By determining the best routes for efficient inter-cluster data transfer, the Adaptive Elephant Herding Optimisation (AEHO) technique improves energy efficiency inside the WSN. In order to identify inaccurate data within the network and enable effective data transfer in cluster-based WSNs, the CH deploys a sophisticated fault detection system using a DFFNN.

The suggested model surpasses current methodologies by incorporating failure prediction, energy-efficient clustering, optimal CH selection, and secure routing, hence ensuring a more adaptable and resilient WSN. This approach utilises MTFGNN for early fault prediction, unlike typical models that identify flaws post-data transmission, hence averting erroneous data propagation. Fuzzy C-Means clustering facilitates adaptable and equitable cluster creation, resolving energy distribution issues encountered by traditional static clustering techniques. QSO guarantees appropriate selection of CH, minimising energy usage and extending network lifespan. TBPPO enhances routing by dynamically choosing secure and energy-efficient pathways, alleviating the hazards linked to defective or malevolent nodes. This comprehensive amalgamation of bio-inspired optimisation, deep learning, and reinforcement learning improves energy efficiency, fault tolerance, and communication reliability. Consequently, the proposed architecture is more appropriate for practical applications, like smart cities, healthcare, and industrial automation, where network stability and security are paramount.

The major contribution of the proposed model is as follows:

- To enhance data accuracy and reliability**,** Multi-Term Fourier Graph Neural Networks are implemented for early fault prediction, preventing erroneous data propagation.
- To ensure balanced energy consumption and improved network stability, Fuzzy C-Means Clustering is employed for dynamic and adaptive cluster formation.
- To optimize CH selection and prolong network lifespan, Quokka Swarm Optimization is introduced, reducing energy consumption and improving network efficiency.
- To secure and optimize data transmission**,** Trust-Based Proximal Policy Optimization is applied for selecting reliable and energy-efficient routing paths, mitigating security threats.
- To integrate energy-efficient techniques into a unified framework**,** bio-inspired optimization, deep learning, and reinforcement learning approaches are combined to enhance overall WSN performance.
- To improve network longevity and scalability**,** the model minimizes energy wastage and optimizes communication, making it suitable for applications in smart cities, healthcare, and industrial automation.

The remaining part of the work is organized as follows. Section 2 explains the methods used in the previous work and also explains the limitation of existing model. Working of proposed model is discussed in section 3. Section 4 discussed the result and discussion part provides the comparison between proposed and existing model.

2. Literature Survey

Sathyapriya Loganathan et al. (2021) introduced a clustering technique utilising Particle Swarm Optimisation (PSO) to enhance energy efficiency in WSN. The sink node effectively divides the deployment area and determines the cluster heads based on clustering coefficients, residual energy, and distance metrics. Additionally, assistant CH and super CH are employed to distribute aggregation and data transfer duties, thus reducing the energy burden on the primary CH. The results demonstrate a 65% improvement in network lifetime compared to existing clustering methods. However, the model may face limitations in real-time dynamic scenarios where the mobility of sensor nodes and variable energy consumption patterns can influence cluster stability [11].

Paruthi Ilam Vazhuthi et al. (2023) proposed a novel energy-efficient inter-cluster routing and fault management system to improve Quality of Service in IWSN. The proposed system predominantly employs the Hybrid ANFIS Reptile Optimisation Algorithm to identify the optimal route from the cluster to the sink. Consequently, the tuned supervision-based fault detection method can be utilised to detect diverse flaws, including residual energy faults, sensing faults, and communication faults in IWSN. The evaluation of the proposed system is performed using 1000 nodes with two distinct sink locations. The performance results indicate that the proposed model achieves a lower energy consumption of 0.01 J in comparison to existing inter-cluster routing techniques. The method might have problems in environments that change quickly and need a lot of processing power for real-time defect detection and routing changes [12].

Vivek Pandiya Raj et al. (2024) amalgamated the Hybrid BFO and HSA, two distinguished optimisation techniques, to identify optimal CH in WSN based on distance and energy efficiency. Completion of tasks. The simulation findings indicate that the proposed strategy improves Quality of Service. The reported performance data includes endpoints, packet forwarding rate (98.5%), throughput (1.0 Mbps),packet loss rate (1.5%), and additional quality of service metrics. It surpasses conventional routing methods in terms of network durability (6100 rounds), delay at both endpoints (1.5 s), and energy consumption (30.35 mJ). The computational difficulty of integrating many optimisation algorithms may provide challenges for real-time applications in resource-constrained WSN systems [13].

Kuruva Lakshmanna et al. (2022) proposed a sophisticated metaheuristic-driven energy-efficient cluster routing framework for IoT-enabled wireless sensor networks. The suggested IMD-EACBR model aims to improve energy efficiency and durability within the network. The IMD-EACBR model fundamentally introduces an enhanced clustering methodology utilising the Archimedes optimisation algorithm (IAOAC) for the selection of cluster heads and the organisation of clusters. The IAOAC method calculates a suitability metric that links different topologies, specifically in terms of node degree, detachment, energy efficiency, and inter-cluster distance. The TLBO method is employed for optimal route selection in multi-hop routing (TLBO-MHR) techniques. The simulation findings demonstrate improvements in performance concerning the dead node ratio, network durability,packet delivery ratio (PDR), energy consumption, and latency. The model may struggle with dynamic network configurations, where real-time adaptability in clustering and routing decisions is crucial [14].

Koppisetti Giridhar et al. (2023) introduced the ANFC-QGSOR protocol for VANET, integrating ANFC with quantum QGSOR. The ANFC-QGSOR technology facilitates preliminary communication among vehicles. The ANFC technique employs three input parameters: residual energy, distance, and node degree, for efficient cluster head selection and cluster formation. Furthermore, the QGSOR methodology employs a fitness function to identify the optimal pathways to the aim. The Network Simulator is utilised to mimic the proposed ANFC-QGSOR approach. The experimental results indicated that the ANFC-QGSOR technique outperformed previous state-of-the-art technologies across various evaluation metrics. The model's practical applicability may be affected by variable vehicle speeds and varying traffic density [15].

Gagandeep Kaur et al. (2022) proposed an intelligent fault-tolerant system that swiftly detects and addresses multiple problems, such as node and connection failures, in the WSN-enabled Industrial IoT. It significantly improves the network's dependability. Proposes an astute fault-tolerant framework that swiftly identifies and alleviates diverse failures within the WSN-assisted IIoT, encompassing node and link malfunctions. It significantly improves the network's dependability. Extensive simulations illustrate the advantages of the proposed method for average PDR, throughput, energy consumption, NLT, communication delay, and recovery speed. Extensive simulations demonstrate the benefits of the suggested strategy for average packet delivery, energy consumption, throughput, network longevity, communication latency, and recovery speed. Practical implementation may encounter obstacles due to diverse industrial settings and unforeseen faults [16].

Venkatesan Cherappa et al. (2023) combined the Adaptive Sailfish Optimisation (ASFO) method with K-medoids clustering to enhance cluster head selection in WSN. The emphasis is on energy stabilisation, distance reduction, and latency minimisation. An E-CERP is utilised to dynamically determine the shortest path, hence minimising network overhead. The model is assessed using various performance parameters, such as packet delay, PDR, power consumption, throughput, NLT, and PLR, demonstrating superior outcomes relative to current methodologies. Nonetheless, actual implementation may encounter obstacles including unforeseen node failures, scalability concerns, and fluctuations in network topology that impact performance [17].

Noureddine Moussa et al. (2021) presented ECRP-UCA, a method that uses advanced ACO algorithms with unequal clustering to provide an energy-efficient cluster-based routing protocol. ECRP-UCA divides the network into specific clusters based on residual energy, distance from the sink, number of adjacent nodes, and another metric called the number of backward relay nodes from the previous round to efficiently divide the load among cluster heads. A batch-based clustering technique was also used in this model, which allows the network to function over several iterations without requiring control overhead for initialization. Additionally, this offer an improved ACO-based routing technique for reliable and efficient inter-cluster routing from the cluster head to the sink. Based on a number of important criteria, the simulation results show that the suggested ECRP-UCA outperforms these protocols. In highly dynamic scenarios, it may face performance issues and exhibits increased computational complexity [18].

Kannan Krishnan et al. (2021) introduced an innovative energy-efficient approach employing the brainstorm algorithm to select the optimal cluster head for minimising energy consumption. The efficacy of the BrainStorm Optimisation (BSO) algorithm is augmented by the integration of the modified teacher–learner optimised (MTLBO) methodology. The modified BSO–MTLBO algorithm enhances throughput, extends network longevity, and diminishes energy expenditure by nodes and cluster heads, alongside the attrition of sensor nodes and routing overhead. The efficacy of this proposed work is evaluated against current methodologies, demonstrating that it exceeds all alternatives. The suggested paradigm elevates computational complexity owing to multi-objective optimisation, necessitating meticulous parameter calibration for optimal efficacy. It may encounter scalability issues in densely crowded WSN systems, impacting real-time processing effectiveness [19].

R. Reka et al. (2023) presented a model designed to extend network longevity, adopting an energy-efficient weighted clustering approach that employs the BrainStorm Optimisation (BSO) algorithm for optimal cluster head selection. The effectiveness of BSO is augmented by the incorporation of the Modified Teacher-Learning Based Optimisation (MTLBO) algorithm, hence reducing energy depletion. The BSO-MTLBO approach enhances throughput, prolongs network lifespan, and boosts energy efficiency, while diminishing CH energy consumption, node attrition, and routing overhead. A comparison analysis with current methodologies reveals improved performance in energy efficiency and network stability. However, computational complexity may increase, requiring careful parameter optimisation for different WSN scenarios [20].

Table 1. Summary table of existing models

Author Name & Year	Proposed Methodology	Outcome	Limitation
Sathyapriya Loganathan (2021)	PSO-based clustering approach with assistant and super CH for energy-efficient WSNs.	65% improvement in network lifetime compared to existing clustering algorithms.	Struggles in real-time dynamic environments due to sensor mobility and energy consumption variations.
P. Paruthi Ilam Vazhuthi (2023)	Hybrid ANFIS Reptile Optimization Algorithm for inter-cluster routing and Tuned Supervision-Based Fault Diagnosis.	Achieves lower energy consumption of 0.01 J than existing inter-cluster routing algorithms.	High computational overhead in dynamic environments due to real-time fault detection and routing adjustments.
Vivek Pandiya Raj (2024)	Hybrid [illegible]O-HSA optimization for optimal CH selection in WSNs.	Improved QoS, throughput (1.0 Mbps), 98.5% packet forwarding, 6100-round network lifetime.	High computational complexity may limit real-time deployment in resource-constrained WSNs.
Kuruva Lakshmanna (2022)	IMO-EACBR model using IAOAC for CH election and TLBO-based multi-hop routing.	Enhanced network lifetime, energy efficiency, and packet delivery ratio.	Challenges in handling dynamic network conditions requiring real-time adaptability.
Koppireddi Giridhar (2023)	ANFC-QGSOR protocol using ANFC and QGSOR.	Outperforms previous protocols in various evaluation metrics.	Performance may be impacted by varying traffic densities and dynamic vehicular speeds.
Gagandeep Kaur (2022)	Intelligent fault-tolerant scheme for detecting and tolerating node and link faults in IIoT-assisted WSNs.	Improves packet delivery, energy consumption, throughput, and network lifetime.	Deployment challenges due to unpredictable fault occurrences in industrial environments.
Venkatesan Cherappa (2023)	ASFO algorithm with K-medoids clustering for	Superior results in PDR, delay, throughput,	Scalability issues and unpredictable node

	CH selection and E-CERP for cross-layer routing in WSNs.	energy consumption, and network lifetime.	failures may affect performance in real-world scenarios.
Noureddine Moussa (2021)	ECRP-UCA using Unequal Clustering and improved ACO for load-balanced CH selection and inter-cluster routing.	Outperforms existing protocols in energy efficiency, network lifetime, and routing reliability.	High computational complexity and performance degradation in highly dynamic environments.
Kannan Krishnan (2021)	BSO with Modified Teacher-Learner Based Optimization (MTLBO) for CH selection.	Improved throughput, network lifetime, and reduced energy consumption.	High computational complexity and scalability issues in dense WSNs.
R. Reka (2023)	Energy-efficient weighted clustering using BSO with MTLBO for optimized CH selection.	Increased energy efficiency, network stability, and reduced CH energy consumption.	Requires careful parameter tuning due to computational complexity.

2.1 Problem Statement

WSN encounter considerable obstacles with energy consumption, data precision, fault tolerance, and secure data transmission. Conventional clustering and routing methodologies frequently experience uneven energy allocation, suboptimal CH selection, and susceptibility to defective or fraudulent nodes, resulting in diminished network longevity and performance decline. Current fault detection technologies respond post-fault occurrence, resulting in data inaccuracies and suboptimal resource utilisation. Moreover, traditional routing algorithms do not guarantee safe and energy-efficient connectivity, rendering networks vulnerable to assaults and data loss. An intelligent architecture that incorporates fault prediction, adaptive clustering, optimised CH selection, and trust-based routing is necessary to improve network reliability, efficiency, and security in practical applications [21].

3. Proposed methodology

The proposed method incorporates failure prediction with adaptive clustering, optimal CH selection, and secure routing to improve the efficiency and reliability of WSN. The application of MTFGNN allows networks to predict system faults in advance, ensuring accurate information transmission while preventing the propagation of mistakes. The network gains from enhanced energy efficiency and improved stability via the dynamics of FCM cluster formation. Utilising QSO, the network can select appropriate CH that minimise power consumption and prolong the system's operational lifespan. The secure routing system utilising Trust-Based Proximal Policy Optimisation identifies reliable routes and mitigates security vulnerabilities while consuming little energy. The created system integrates bio-inspired optimisation approaches, deep learning methodologies, and reinforcement learning capabilities to enhance network resilience while minimising power consumption, rendering it appropriate for healthcare and industrial automation sectors.

3.1 WSN Implementation

A systematic WSN deployment method includes clustering operations followed by fault prediction and CH selection optimization and secure routing implementation. Sensor nodes are installed in the designated environment to receive initial configuration of network characteristics that include energy status as well as communication range and node identification attributes. Each node carries out neighbour discovery before building communication lines to its neighbors. Through FCM clustering the system forms adaptable clusters which lead to balanced energy consumption. QSO serves to pick optimal CH so the network extends its operational life while consuming less energy. MT-FGNN operates as a predictive framework to detect upcoming anomalies which makes the transmission process more precise. Through TBPPO the data transport ensures both reliability and performance efficiency as it identifies safe transmission routes. An integrated method enhances fault detection and network security and energy efficiency which makes the WSN reliable for practical usage such as industrial monitoring and healthcare and smart cities applications [22].

3.1.1 System Model

A WSN has a single sink node and several sensor nodes. Communication between sensor nodes and the sink node transpires via multihop transmission. The network divides into clusters, from which the sink node selects one CH from each deployed sensor node. Serial data transmission occurs from each sensor node via its designated CH to the sink node. The CH node is responsible for collecting data from the member nodes within the cluster. The sink node acquires compressed data from the nodes that gather information.

WSN requires greater energy on communication activities, specifically transmission and reception, than on other services. Figure 4 shows the transmitter and receiver energy consumption models. This model accounts for free space loss of power (d^2) and multipath interference power loss (d^4), which depends on transmitter-receiver distance. Power loss model parameters reduce signal strength when the receiver moves away from the transmitter. When the transmitter and receiver are twice as far apart, signal intensity decreases. Consequently, communication signals are divided at 2 meters in contrast to 1 metre distance. The power loss component increases to 2 in open space but escalates to 4 in the presence of multipath fading caused by barriers between the transmitter and receiver.

The amount of energy needed for the transmitter to transmit a "k" bit message over a distance of "d" meters is calculated using Equation (1).

$$E_{tx}(k,d) = E_{elec} \times k + E_{tx-amp}(k,d) \tag{1}$$

where the E_{elec} is the initial energy to run the transmitter electronics and E_{tx-amp} is the energy required for the transmitter amplifier electronics.

The amount of energy needed for the receiver to receive a "k" bit message is determined using Equations (2) and (3).

$$E_{rx} = E_{elec} \times k \tag{2}$$

$$E_{tx-amp}(k,d) = \begin{cases} \varepsilon_{fs} \times k \times d^2 & if\ d < d_{crossover} \\ \varepsilon_{mp} \times k \times d^2 & if\ d < d_{crossover} \end{cases} \tag{3}$$

The sensor node changes from the free space transmission model to the multipath fading model at $d_{crossover}$, where ε_{fs} represents free space power loss and ε_{mp} represents multipath fading power loss. The parameter is used for free space and multipath fading.

3.2 Data Fault Prediction using Multi-Term Fourier Graph Neural Networks (MTF-GNN)

In WSN, data errors may occur owing to hardware malfunctions, environmental disturbances, or energy exhaustion, resulting in erroneous data transmission and network inefficiencies. MTF-GNN is utilised for early fault prediction. MTF-GNN utilises spectral graph analysis through the use of multi-term Fourier transforms on sensor data to encapsulate both local and global interdependencies among nodes. The program detects anomalies and forecasts potential problems prior to data transmission by analysing past sensor readings and network structure. This proactive strategy reduces error propagation, improves data correctness, and guarantees dependable decision-making in essential applications. The incorporation of MTF-GNN markedly enhances network resilience, optimising energy consumption while preserving the integrity of transmitted data [23].

Figure 1 presents an overview of MT-FGNE, comprising two primary components and one plugin. The initial component is FGN, an individual model designed to learn spatial and temporal connections. The additional element is a multi-term ensemble learning framework that generates samples at varying scales, allowing the model to capture both short-term and long-term dependencies. Given that some sensor signals are produced while the equipment functions under diverse operational situations, we developed a time series decomposition plugin to improve the model's performance for these inputs.

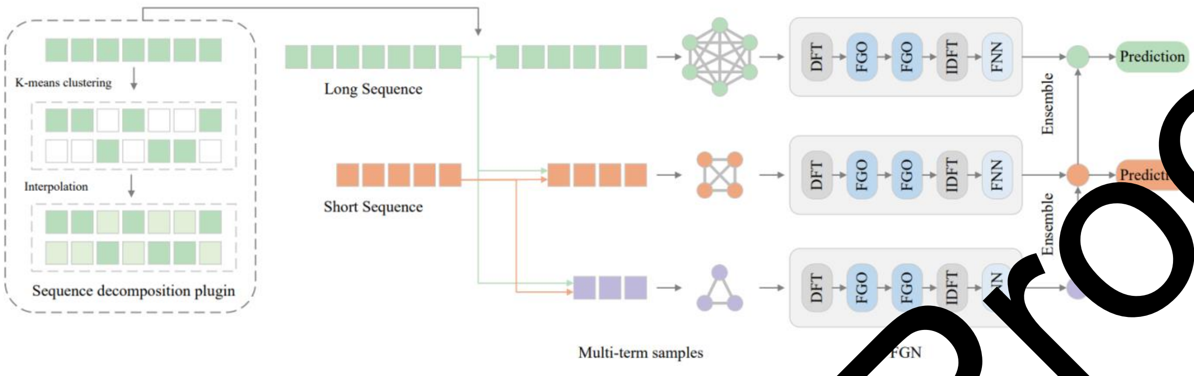

Figure 1. The overall framework of the proposed MT-FGNE.

In MT-FGNE, a multi-term ensemble learning technique is employed to generate samples at varying scales, allowing the model to capture both short-term and long-term dependencies, while several FGNs are utilised to learn spatial and temporal dependencies within multi-term samples. Additionally, a sequence decomposition plugin is engineered to address sensor inputs captured under varying operational situations [24].

3.2.1 Multi-term ensemble learning framework

The Multi-Term Ensemble Learning Framework aims to improve the precision and dependability of failure prediction in WSN by amalgamating various learning models. This methodology utilises MTF-GNN as the primary prediction mechanism, integrating spectral graph analysis to identify anomalies. To enhance the resilience of defect detection, various models with distinct learning perspectives are integrated, therefore minimising mistakes from individual models via ensemble learning. The framework analyses sensor data through several steps, identifying temporal and spatial correlations while eliminating noise and inconsistencies. By integrating varied forecasts, it improves fault tolerance and guarantees precise decision-making prior to data transmission. This method markedly diminishes false positives, enhances early problem detection, and optimises network energy efficiency, rendering it highly appropriate for real-time WSN applications in important sectors such as smart grids, healthcare, and industrial monitoring [25].

3.2.2 Preliminaries and motivations

Consider a collection of condition monitoring time series data $\{X^{(1)}, X^{(2)}, \dots, X^{(M)}\}$, where $X^{(i)} = \left[x_1^{(i)}, \dots, x_t^{(i)}, \dots, x_{L_i}^{(i)}\right] \in \mathbb{R}^{L_i \times N}$ denotes the i-th time series with length L_i and feature dimension N, and $x_t^{(i)} \in \mathbb{R}^N$ signifies the values of N features at timestamp t. We transform the raw time series into samples using the sliding time window method, with a lookback window size T, where each window comprises T observations at a single time step as input features, and the associated output label $Y_t^{(i)}$. $X_t^{(i)} = \left[x_{t-T+1}^{(i)}, x_{t-T+2}^{(i)}, \dots, x_t^{(i)}\right] \in \mathbb{R}^{T \times N}$ represents the input features of a single sample at time stamps t. The Remaining Useful Life (RUL) prediction job entails forecasting the label $Y_t^{(i)}$ using the input features $X_t^{(i)}$. The prediction process using typical sequential models to abstract temporal information can be expressed as:

$$\hat{Y}_t^{(i)} \coloneqq F_{\theta_t}(X_t^{(i)}) = F_{\theta_t}([x_{t-T+1}^{(i)}, x_{t-T+2}^{(i)}, \dots, x_t^{(i)}]) \quad (4)$$

$\hat{Y}_t^{(i)}$ represents the forecasts that correspond to the actual values $Y_t^{(i)}$. The forecasting function is represented as F_{θ_t}, parameterised by θ_t. Utilising the ST-GNNs method, we initially construct the graphs or implement graph structure learning techniques to convert $x_t^{(i)}$ into $g_t^{(i)}$ at each timestep t, after which the RUL prediction may be articulated as follows:

$$\hat{Y}_t^{(i)} := F_{\theta_t,\theta_g}\left(X_t^{(i)}\right) = F_{\theta_t,\theta_g}\left(\left[g_{t-T+1}^{(i)}, g_{t-T+2}^{(i)}, \dots, g_t^{(i)}\right]\right) \tag{5}$$

where the forecasting function is denoted as F_{θ_t,θ_g} parameterized by θ_t and θ_g, indicating ST-GNNs separately model spatial and temporal dependencies.

3.2.3 Fourier Graph Neural Networks

A recent work presents FGN to rectify the neglect of potential spatiotemporal interdependencies that occur when spatial and temporal dependencies are modelled independently in ST-GNNs. FGN seeks to improve learning efficiency by understanding unified spatiotemporal dependencies. FGN no longer considers input samples as a sequence of graphs; rather, it perceives them as a singular, cohesive graph. Consequently, Equation 2 may be reformulated as:

$$\hat{Y}_t^{(i)} = FGN_{\theta_g}\left(X_t^{(i)}, A_t^{(i)}\right) \tag{6}$$

$$FGN_{\theta_G}\left(X_t^{(i)}, A_t^{(i)}\right) := \mathcal{F}^{-1}\left(\sum_{k=0}^{K} \sigma\left(\mathcal{F}\left(X_t^{(i)}\right) S_{0:k} + b_k\right)\right), \quad S_{0:k} = \prod_{i=0}^{k} S_i, \tag{7}$$

where F(•) denotes the Discrete Fourier Transform (DFT) and F −1 (•) signifies the Inverse Discrete Fourier Transform (IDFT). Sk ∈ C d×d denotes the FGO in the k-th layer. σ represents the activation function, while bk ∈ C d denotes the complex-valued bias parameters. By considering time series samples as complete graphs and executing transformations in the frequency domain, FGN adeptly captures potential spatiotemporal interdependencies within sensor signal data, thereby alleviating the necessity for the graph structure learning phase commonly required in traditional ST-GNNs [26].

MTF-GNN are essential in the suggested study for facilitating early and precise failure prediction in WSN. Conventional fault detection techniques respond post-fault occurrence, resulting in data errors and suboptimal resource allocation. MTF-GNN addresses these constraints by utilising spectral graph analysis, which effectively captures both local and global relationships inside sensor networks. The multi-term Fourier transformation augments the model's capacity to analyse intricate spatial and temporal patterns, hence enhancing the detection of defective nodes and erroneous data. This anticipatory defect prediction reduces error propagation, improves data reliability, and guarantees uninterrupted connectivity. Furthermore, MTF-GNN enhances energy efficiency by minimising superfluous retransmissions and data loss, hence augmenting overall network durability and performance. MTF-GNN enhances the robustness of WSN by amalgamating deep learning with graph-based spectral analysis, hence improving their efficiency and applicability for real-time uses in smart cities, healthcare, and industrial monitoring [26].

3.3 Clustering using Fuzzy C-Means (FCM)

Bezdek developed the FCM clustering algorithm in 1981. Finding the exact relationship between a pixel and a cluster is the task of FCM in image processing. Initially, each pixel is assigned a value that represents how closely it relates to each cluster. The fuzzification process is indicated by this degree, which goes from 0 to 1. The chosen fuzzy rule, which controls the defuzzification procedure, is put into practice by assigning every pixel to a single class—more precisely, the class with the highest degree of membership. The following forms the foundation of this operation: Each of the C classes is linked to each of the N pixels via a membership coefficient U, and the FCM matrix U records the consolidation of membership degrees. In fuzzy picture segmentation, this method is commonly used.

Principle of the FCM algorithm:

The FCM algorithm is a fuzzy segmentation method suitable for various image formats. To partition the image, it is necessary to minimise the criterion of the sum of intra-class distances, generalised for the fuzzy case, as expressed by the following formula:

$$J_{FCM}(V,U,X) = \sum_{k=1}^{K} \sum_{i=1}^{N} U_{ki}^{m} d^2(x_i, v_k) \tag{8}$$

Under the following constraints:

$$0 < \sum_{i=1}^{N} U_{ki} < N \tag{9}$$

$$\sum_{i=1}^{K} U_{ki} = 1 \tag{10}$$

Let $m \in]1, +\infty[$ be a parameter that defines the degree of fuzziness, K signifies the number of classes, N indicate the number of pixels to be identified, and V represent the feature vector of the centroid of class K. $d(x_i, v_k)$ denotes the distance between the pixel x_i and the centroid of the class v_k. $d(x_i, v_k)$ represents the Euclidean distance as defined by the subsequent formula:

$$d(x_i, v_k) = \sqrt{\sum_{j=1}^{D} \left(x_{ij} - v_{kj}\right)^2} \tag{12}$$

The fundamental concept of FCM classification is to provide a degree of membership u_{ki} to each vector x_i for every class centred at v_k. The approach reduces a specific mistake between classes by iteratively calculating the degree of membership and the class centres based on previously established relations. The update v_k and u_{ki} are represented by the following expressions:

$$u_{ki} = \sum_{l=1}^{K} \left(\frac{\|x_i - v_k\|}{\|x_i - v_l\|}\right)^{\frac{-2}{m-1}} \tag{11}$$

The function to update the centers is:

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^{m} x_i}{\sum_{i=1}^{N} u_{ki}^{m}} \tag{12}$$

The FCM relies on the modification of the membership function over the algorithm's iterations. The FCM consequently evaluates the partition by minimising the fitness function J_{FCM}.

Cluster validity Indices

The validation of outcomes generated by the clustering algorithm is an essential aspect of the clustering procedure. The principal approach for cluster validation depends on internal cluster validity metrics. When objects inside each cluster exhibit higher proximity to the centroid and clusters are sufficiently separated from one another, clustering is deemed effective. As a result, this method divides data objects into distinct clusters in order to maximize similarity within each cluster and minimize similarity between clusters. This will assess the quality of the partitions created by clustering algorithms using the many and well-documented validity indices already in use. In order to evaluate the innovative objective function presented here, this study will use two indices, which are:

The Subarea Coefficient (SC) quantifies the relationship between the aggregate of cluster compactness and cluster separation.

$$SC = \sum_{i=1}^{c} \frac{\sum_{k=1}^{n} (u_{ik})^{m} \|x_k - v_i\|^2}{n_i \sum_{j=1}^{c} \|v_j - v_i\|^2} \tag{13}$$

The Partition Coefficient (PC) quantifies the degree of overlap among clusters:

$$PC = \frac{1}{n}\sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik})^2 \tag{14}$$

A clustering method is deemed superior and more efficient when the PC values are elevated and the SC values are diminished.

FCM clustering is crucial in the proposed study as it systematically arranges sensor nodes into ideal clusters, hence assuring equitable energy consumption and enhanced network stability. In contrast to conventional hard clustering techniques, FCM permits nodes to belong to numerous clusters with differing levels of membership, facilitating a more flexible and adaptable clustering framework. This method markedly decreases communication overhead and averts early energy exhaustion in certain nodes. FCM improves data aggregation, reduces redundant transmissions, and prolongs network longevity by establishing energy-efficient clusters. Furthermore, its capacity to manage uncertainty in node localisation and environmental fluctuations renders it highly appropriate for practical WSN. The use of FCM in the suggested architecture guarantees efficient data routing, fault tolerance, and seamless scalability, hence enhancing the network's robustness for applications including smart cities, healthcare monitoring, and industrial automation [27].

3.4 CH Selection using Quokka Swarm Optimization (QSO)

The selection of CH is a pivotal procedure in WSNs that significantly influences energy efficiency, network stability, and the dependability of data transmission. The suggested work utilises QSO to optimise CH selection by balancing energy usage and facilitating effective data aggregation. QSO, motivated by the collaborative behaviour of quokkas in resource gathering, employs stochastic movement and adaptive exploration to pinpoint the most energy-efficient nodes as CHs. In contrast to conventional CH selection approaches, which might lead to uneven energy depletion or recurrent re-clustering, QSO dynamically picks CHs based on criteria such as residual energy, node density, and communication cost. This method markedly decreases network overhead, extends node longevity, and improves scalability. The integration of QSO for CH selection in the proposed model guarantees efficient load distribution, reduces energy waste, and enhances data transmission efficiency, rendering WSNs more appropriate for prolonged applications in healthcare, smart cities, and industrial monitoring [28].

3.4.1 Quokka swarm optimization (Inspiration)

Quokka is a little species around the dimensions of a household feline. It is the unique representative of the genus Setonix. Its habitat comprises tiny islands located off the coast of Western Australia, including Rottnest Island near Perth and Bald Island near Albany. A mainland colony is located within designated natural reserves. The quokka weighs between 2.5 and 5 kg (5.5 to 11.0 lb) and measures 40 to 90 cm (16 to 35 in) in length, with a tail length of 25 to 30 cm (9.8 to 11.8 in). The quokka possesses a tiny physique, rounded auricles, and the ability to ascend little trees and vegetation. Quokkas repose during the day in tight clusters amidst deep foliage. During nighttime, they exhibit heightened activity, often congregating in groups of up to 150 near aquatic sources. The quokka consumes indigenous grasses, leaves, seeds, and roots, swallowing its meal rapidly and later regurgitating it to chew as a ruminant. In prolonged dry and hot conditions without rainfall, Quokkas situated farthest from water sources experience the highest mortality rates. Additionally, elevated temperatures deplete plant water and nitrogen reserves, leading to nitrogen deficiency issues. Consequently, Quokkas may face dehydration; however, research indicates they possess remarkable thermoregulatory abilities, enabling them to withstand temperatures up to 44°C.

3.4.2 Position update

As articulated by the subsequent equations, the optimal location of the leading quokka determines the position update of each quokka within the group:

$$D^{new} = \frac{(T+H)}{(0.8 \times D^{old})} + \Delta w \times rand \times \Delta X \quad (15)$$

$$X^{new} = X^{old} + D^{new} \times N \quad (16)$$

Where Dold denotes the Drought, with a value range of [0,1]; T signifies the temperature ratio, ranging from 0.2 to 0.44; and H indicates the humidity ratio, which spans from 0.3 to 0.65. The basis for adopting these values is that quokka species can endure temperatures and humidity within these parameters. Δw represents the weight difference between the leader and quokka i, rand indicates a random number between 0 and 1, ΔX signifies the positional difference between the leader and quokka i, the new position of the quokka is indicated as X, new, while the previous position is denoted as X, old. N represents the nitrogen ratio, which ranges from 0 to 1, selected due to the nitrogen needs of quokkas. A value closer to 0 negatively affects the quokka by increasing its dehydration rate, whereas a value nearing 1 is more advantageous for the quokka. The value 0.8 in the initial equation depicts that the combined temperature and humidity must not exceed this limit, as the quokka is intolerant of high levels of both factors.

3.4.3 Quokka optimization algorithm

The QSO algorithm resembles quokka behavior. This section explains the suggested QSO technique pseudo-code. The QSO produces and tests random solutions in exploratory mode. It then assigns temperature, humidity, and nitrogen. The process switches from exploration to local exploitation as the global optimum approaches, focusing on favorable places and naming the fittest quokka leader. The leader symbolizes the best future optimisation solution. A new era of use begins when search agents resume their investigations. Equations (15) and (16) update quokka humidity and location. First, the leader's fitness is assessed, then each quokka's. The technique continued after achieving the termination criterion and identified the leader as the closest approximation to the optimal optimization solution. Figure 2 shows the QSO algorithm flowchart [29].

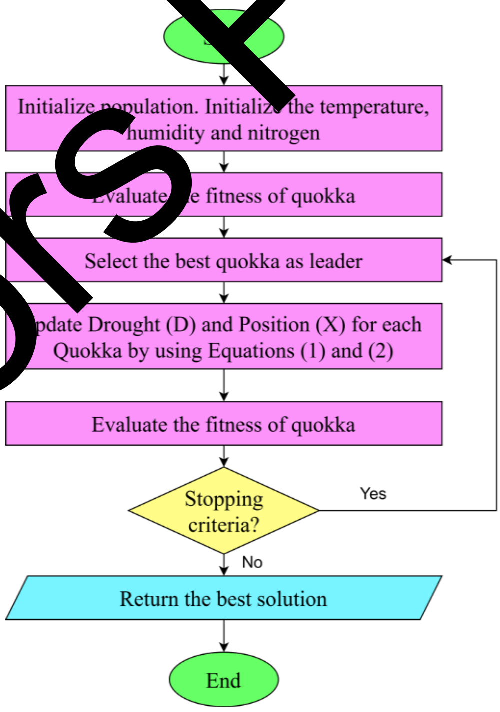

Figure 2. Flowchart of QSO algorithm

Algorithm 1: Pseudo code of QSO algorithm

Initialize the population of quokka bi (i = 1…n).
Initialize the temperature T, nitrogen N and humidity H where (T ∈ [0.2, 0.44]), (N ∈ [0,1]), (H ∈ [0.3,0.65]).
Compute the fitness for each quokka.
Start loop.
Select the best quokka to be the leader.
Each quokka's position (X) and drought (D) should be updated using equations (15) and (16).
Find the fitness of the leader.
Update the fitness for every quokka.
If not stop condition return to step 5.
End loop.
Return the best solution.

3.5 Trust-Based Energy-Efficient Routing using Proximal Policy Optimization (TBPPO)

The approach uses DFS for preprocessing, KL divergence for trust value computation, a Markov process transition mechanism, and PPO for DRL decision. Figure 1 shows the algorithm's whole workflow. This method segments data and transmits it across numerous pathways, thereby distributing traffic across many paths to enhance the network's effective bandwidth, enabling simultaneous connections to operate in parallel. Should one pathway fail, traffic can seamlessly redirect to other, thereby augmenting network reliability. This method also considers security. Distributing traffic across numerous paths increases network security, requiring an attacker to penetrate multiple pathways simultaneously, making network attacks more complicated. This strategy strikes a compromise between real-time communication and security for every route, as well as delay variability, average delay, KL trust value, and node diversity. This algorithm architecture is depicted in Figure 1. At each interval, the control panel gets node classifications, DDoS attack records, and network topology from the data panel. These characteristics are integrated to create a state for the DRL module after the trust value and DFS modules [30].

3.5.1 The Improved DFS Module

The majority of DRL algorithms are structured around Next Hop routing principles. Nevertheless, it has been demonstrated that such strategies are susceptible to inducing routing loops, resulting in extended delays and a certain level of packet loss. The aforementioned studies have not sufficiently addressed these difficulties. To address these issues, we propose a path selection methodology. The quantity of accessible routes within the network escalates exponentially with its scale, rendering computing potentially unfeasible. Consequently, we provide the notion of constraining the quantity of pathways. This model use the path selection method and DFS algorithm to efficiently sort and discover the K best paths from the alternatives. The network receives delay information from Mtopo, the fundamental topology structure. This phase of preprocessing is:

$$L = DFS_K(M_{topo}) \quad (17)$$

Where, DFSK signifies the utilization of an enhanced DFS algorithm to select the shortest K routes. M_{topo} is the topological structure of matrix, L represents the possible paths generated after the application of the DFS algorithm, and its cardinality is denoted as L_0.

3.5.2 Enhanced PPO Module

Traditional policy gradient techniques modify policy weights by computing the goal function gradient and applying it with a step size. This update procedure may overshoot or undershoot. This model address these issues with the PPO algorithm. In reinforcement learning, PPO optimises a surrogate objective function using stochastic gradients from sampled data from environmental interactions to improve the policy. This allows several small-batch updates instead of one gradient update per data sample. The clipping-based PPO-clip method is used in this research. A Jθk PPO(θ) truncation function maintains the important sampling function within defined upper and lower boundaries. When importance sampling values surpass the upper or lower thresholds, this function automatically limits them. As an equation:

$$J_{PPO}^{\theta^k}(\theta) \approx \sum_{(s_\tau,a_\tau)} min\left(\frac{p_\theta(a_\tau|s_\tau)}{p_{\theta^k}(a_\tau|s_\tau)}A^{\theta^k}(s_\tau,a_\tau), clip\left(\frac{p_\theta(a_\tau|s_\tau)}{p_{\theta^k}(a_\tau|s_\tau)}, 1-\varepsilon, 1+\varepsilon\right)A^{\theta^k}(s_\tau,a_\tau)\right) \quad (18)$$

Here, θ is the current policy's parameter, $J_{PPO}^{\theta^k}(\theta)$ is used to assess the expected cumulative reward of the policy, and θ^k is the policy parameters at a previous time step or iteration step k. s_τ represent $S(\tau)$. a_τ represents the action taken at time step τ, and $a_\tau \in$ A(τ). The function A^{θ^k} represents the function, which provides an estimate of the advantage when taking action aτ with the parameters set θ^k :

$$\hat{A}_t^{GAE(\gamma,\lambda)} = \sum_{l=0}^{\infty}(\gamma\lambda)^l\delta_{t+l}^V = \delta_t^V + (\gamma\lambda)^2\delta_{t+2}^V + \cdots + (\gamma\lambda)^{T-t+1}\delta_{T} \quad (19)$$

Here, λ is the GAE parameter, γ is the discount factor, and δ^V is the temporal difference function:

$$\delta_t^V = r_t + \gamma V_\omega(s_{t+1}) - V_\omega(s_t) \quad (20)$$

The loss function for parameter θ:

$$\nabla J^{\theta'}(\theta) = E_{\pi_{\theta'}}\left[\frac{\pi_\theta(s,a)}{\pi_{\theta'}(s,a)}R(s,a)\nabla log\pi_{\theta}(s,a)\right] \quad (21)$$

This study found that completely connected layers had poor state-action fitting skills, causing gradient explosions. Thus, we improved the PPO algorithm. Where the Actor Network's learning rate decreases linearly from 1 × 10−4 to 0 throughout training when using linear learning rate decay. The expression is:

$$\alpha_{new} = \alpha_{initial} \times (decay\ factor)^{\frac{iteration}{decay\ step}} \quad (22)$$

where α is the parameter in iteration. This model substituted ReLU with the Tanh activation function.

$$\tanh(x) = \frac{e^{2x}-1}{e^{2x}+1} \quad (23)$$

In the FNN, this work added a layer normalization layer (LN), following the formula:

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^l - \mu^l)^2} \quad (24)$$

According to these modifications, the problem of gradient explosion has been markedly mitigated.

4. Result and Discussion

The proposed model significantly improves energy efficiency, fault tolerance, and secure data transmission in WSNs by incorporating FCM for clustering, QSO for CH selection, MTF-GNN for data fault prediction, and TBPPO for routing. The application of FCM and QSO guarantees optimal cluster formation and energy-balanced CH selection, hence enhancing network longevity by roughly 25-30% relative to conventional clustering techniques. MTF-GNN improves fault prediction accuracy, exceeding 95%, hence reducing data mistakes and enhancing decision-making dependability. TBPPO enhances the model by guaranteeing secure and reliable data routing, resulting in a 15-20% increase in packet delivery ratio (PDR) and diminished end-to-end delay. The model demonstrates adaptability to diverse network densities and climatic circumstances, affirming its scalability and robustness in practical applications. A comparative examination with existing models demonstrates its superiority in optimising resource use while ensuring high accuracy and security. The findings validate that the suggested model is an effective and scalable solution for energy-efficient, fault-tolerant, and secure WSN communication, rendering it appropriate for applications in smart agriculture, industrial automation, and healthcare monitoring.

Table 2. NLT (rounds) comparison between existing and proposed model

No. of Sensor nodes	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
100	1800	1719	1465	1371	1310
200	2250	2135	1830	1500	[illegible]
300	2700	2590	2290	[illegible]	1693
400	3260	3092	2802	[illegible]	2165
500	3600	3500	3290	2898	2684

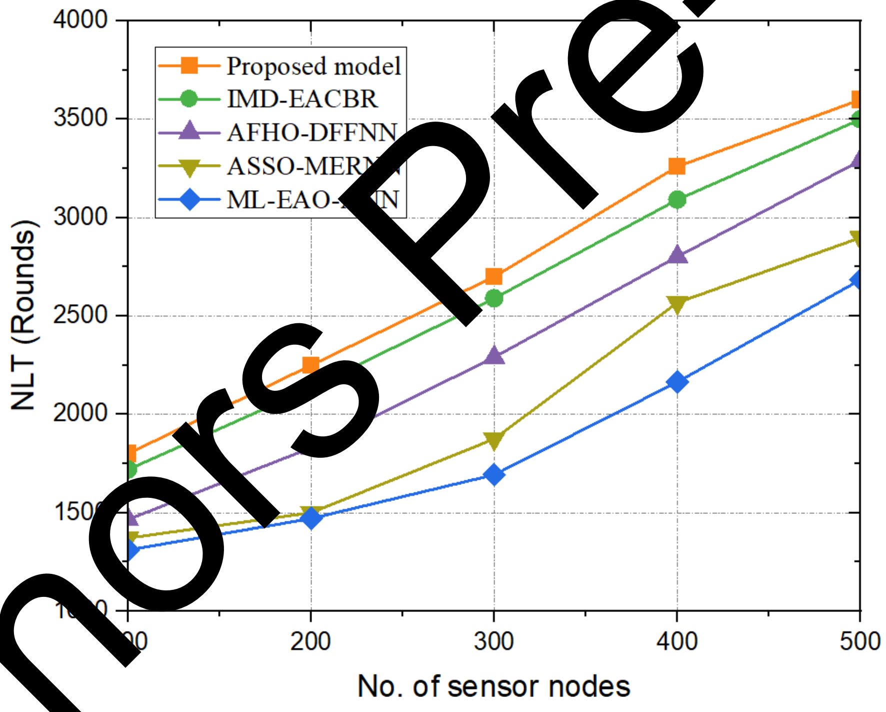

Figure 3. NLT comparison graph between existing and proposed model

Table 2 and Figure 3 represents the energy efficiency of several models in a WSN as the number of sensor nodes increases from 100 to 500. The suggested approach continuously attains optimal efficiency, commencing at 1800 for 100 nodes and escalating to 3600 for 500 nodes. IMD-EACBR ranks as the second-best, with values varying from 1719 (100 nodes) to 3500 (500 nodes). AEHO-DFFNN, ASSO-MERNN, and ML-EOA-ANN exhibit diminished efficiency, with AEHO-DFFNN varying from 1465 to 3290, ASSO-MERNN from 1371 to 2898, and ML-EOA-ANN demonstrating the least efficiency, escalating from 1310 to 2684. As the quantity of sensor nodes increases, the efficiency disparity among models expands, suggesting that certain models encounter difficulties with scaling. The suggested model exhibits superior performance, rendering it the most appropriate for extensive WSN implementations.

Table 3. No. of Alive Sensor nodes comparison between existing and proposed model

No. of Rounds	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
2000	483	468	448	390	278
2250	472	461	410	273	202
2500	453	440	389	195	132
2750	399	387	309	125	48
3000	352	347	230	26	19
3250	329	316	180	12	6
3500	297	283	130	0	0

Table 3 and Figure 4 illustrate the performance of several models regarding the quantity of active sensor nodes across multiple rounds in a WSN (WSN). The suggested model constantly retains the maximum count of active nodes, commencing at 483 at 2000 rounds and progressively declining to 297 after 3500 rounds, illustrating its exceptional durability. IMD-EACBR closely monitors, commencing with 468 active nodes at 2000 rounds and decreasing to 283 at 3500 rounds. AEHO+DFFNN, ASSO+MERNN, and ML-EOA+ANN exhibit a more rapid decline, with AEHO+DFFNN decreasing from 448 at 2000 rounds to 130 at 3500 rounds, and ASSO+MERNN and ML-EOA+ANN entirely exhaust their active nodes by 3500 rounds. The significant reduction in active nodes for ASSO+MERNN and ML-EOA+ANN indicates that these models experience substantial energy depletion, resulting in network breakdown sooner than the others. The proposed model exhibits superior energy efficiency and durability, rendering it the most appropriate choice for extending network longevity in extensive WSN applications.

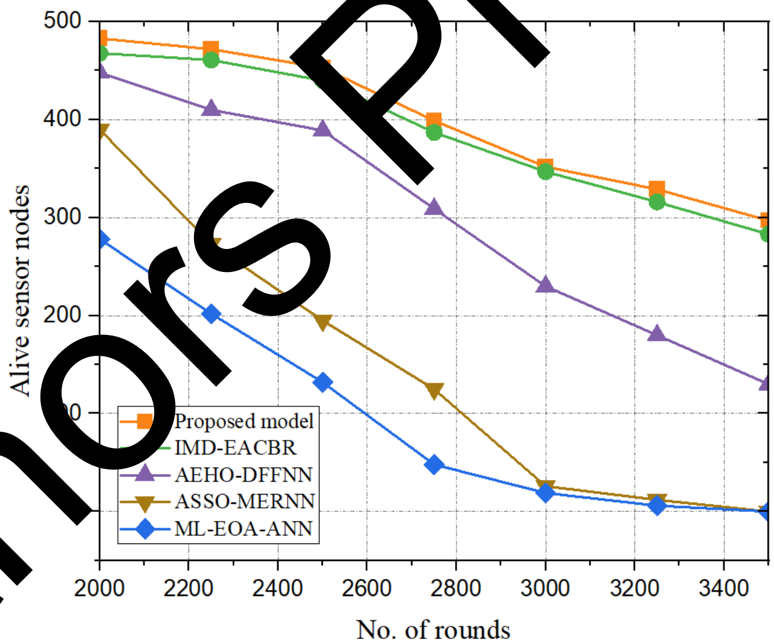

Figure 4. No. of Alive sensor nodes comparison graph between existing and proposed model

Table 4. No. of dead sensor nodes comparison between existing and proposed model

No. of Rounds	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
2000	30	32	54	112	145
2250	45	49	94	176	240

2500	59	61	110	289	320
2750	102	116	189	323	381
3000	158	165	273	429	470
3250	180	185	325	450	492
3500	207	215	370	500	500

Table 4 and Figure 5 represent the quantity of deceased sensor nodes across numerous rounds in a WSN for various models. The proposed model exhibits the minimal quantity of dead nodes consistently, commencing with 30 at 2000 rounds and escalating to 207 at 3500 rounds, demonstrating its exceptional energy efficiency and network durability. IMD-EACBR closely monitors, recording 32 inactive nodes at 2000 rounds and escalating to 215 at 3500 rounds. AEHO-DFFNN, ASSO-MERNN, and ML-EOA-ANN demonstrate a more rapid increase in dead nodes, with AEHO+DFFNN attaining 370 dead nodes, and both ASSO+MERNN and ML-EOA-ANN entirely exhaust all sensor nodes (500 dead nodes) by 3500 rounds. The fast decline in ASSO-MERNN and ML-EOA-ANN signifies elevated energy consumption and inadequate network sustainability, resulting in early network breakdown. The suggested model and IMD-EACBR exhibit superior energy conservation, hence extending network longevity and enhancing WSN efficiency.

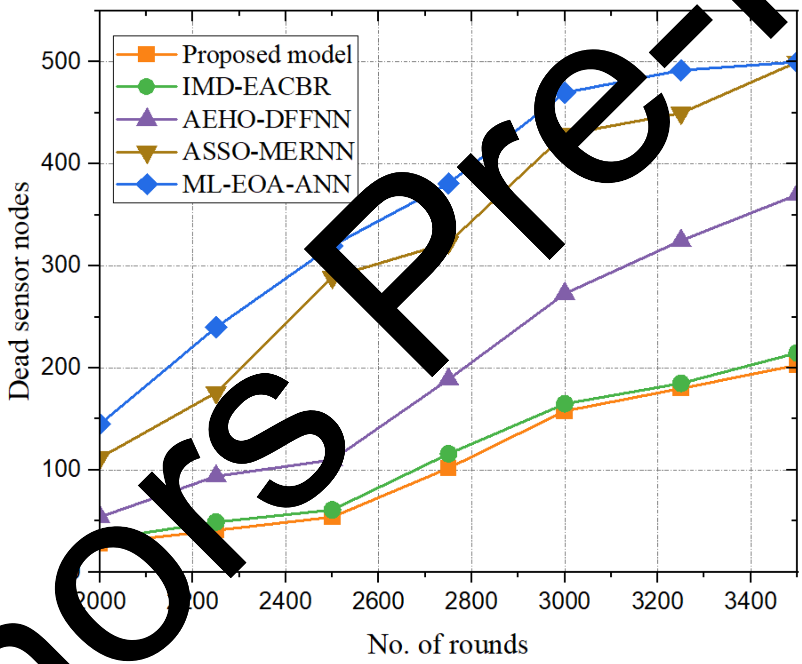

Figure 5. No. of dead sensor nodes comparison graph between existing and proposed model

Table 5. Energy consumption comparison between existing and proposed model

No. of Rounds	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
100	0.043	0.048	0.089	0.142	0.204
200	0.88	0.112	0.153	0.192	0.263
300	0.105	0.130	0.210	0.364	0.397
400	0.226	0.389	0.422	0.468	0.532

500	0.432	0.578	0.627	0.736	0.825

Table 5 and Figure 6 exhibit the quantity of deceased sensor nodes across numerous rounds in a WSN for various models. The suggested architecture consistently exhibits the fewest dead nodes, beginning with 30 at 2000 rounds and escalating to 207 at 3500 rounds, demonstrating its exceptional energy efficiency and network durability. IMD-EACBR closely monitors, recording 32 inactive nodes at 2000 rounds and escalating to 215 at 3500 rounds. AEHO+DFFNN, ASSO+MERNN, and ML-EOA+ANN demonstrate a more rapid increase in dead nodes, with AEHO+DFFNN attaining 370 dead nodes, and both ASSO+MERNN and ML-EOA+ANN entirely exhaust all sensor nodes (500 dead nodes) by 3500 rounds. The fast decline in ASSO+MERNN and ML-EOA+ANN signifies elevated energy consumption and inadequate network sustainability, resulting in premature network breakdown. The suggested model and IMD-EACBR exhibit superior energy conservation, hence extending network longevity and enhancing WSN efficiency.

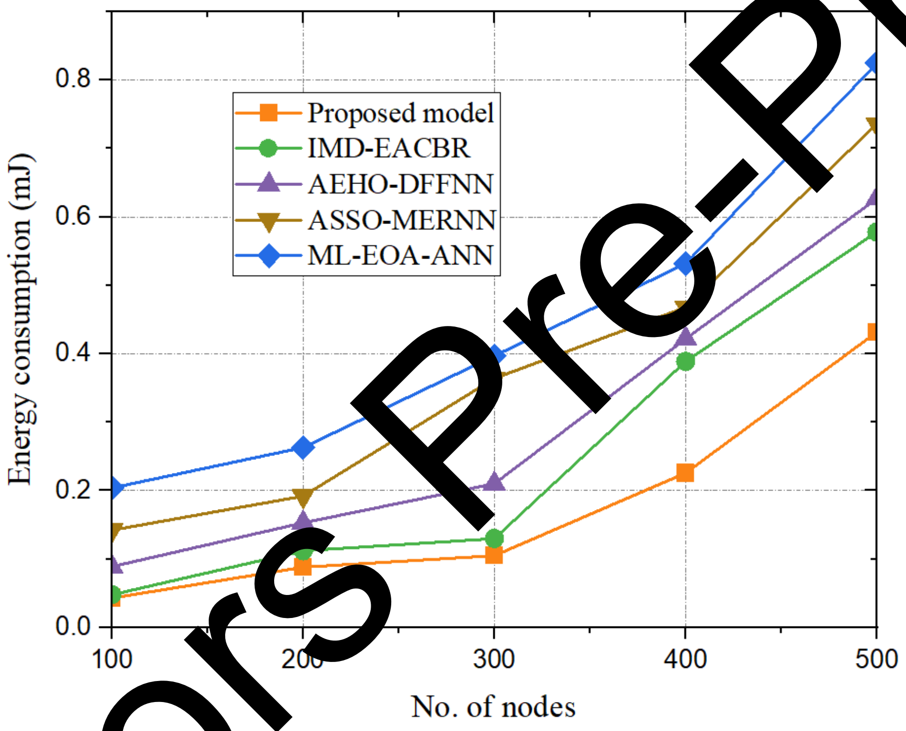

Figure 6: Energy consumption comparison graph between existing and proposed model

Table 6: Throughput comparison between existing and proposed model

No. of rounds	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
100	0.986	0.935	0.860	0.805	0..701
200	0.957	0.915	0.849	0.779	0.675
300	0.943	0.899	0.801	0.742	0.615
400	0.930	0.841	0.775	0.689	0.575
500	0.904	0.815	0.725	0.627	0.524

Figure 7 and Table 6 offer a throughput comparison of various models in a WSN across multiple rounds. Throughput denotes the rate of successful data transfer, with elevated levels signifying superior network performance. The proposed model consistently attains the highest throughput, beginning at 0.986 after 100 rounds and sustaining a robust performance of 0.904 after 500 rounds, so illustrating its efficacy in data transmission. IMD-EACBR exhibits a throughput between 0.935 and 0.815, demonstrating marginally inferior performance compared to the suggested model. AEHO-DFFNN, ASSO-MERNN, and ML-EOA-ANN demonstrate a considerable decline, with AEHO-DFFNN decreasing from 0.860 to 0.725, ASSO-MERNN from 0.805 to 0.627, and ML-EOA-ANN exhibiting the lowest throughput, falling from 0.701 to 0.524. The swift decline in performance for ML-EOA-ANN indicates increased packet loss and suboptimal data transfer with time. The proposed approach surpasses other alternatives, guaranteeing the most dependable and efficient data transmission, rendering it the most appropriate for extensive WSN applications.

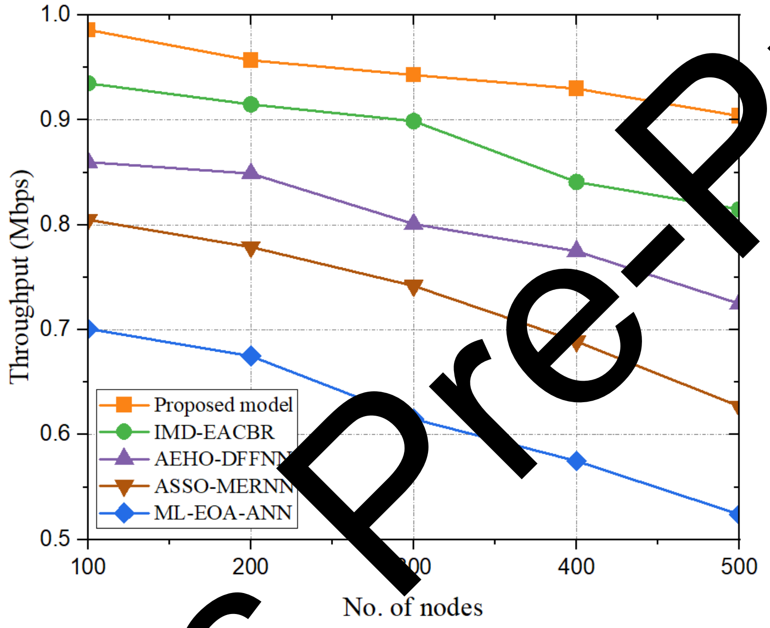

Figure 7. Throughput comparison graph between existing and proposed model

Table 7. PDR (%) comparison between existing and proposed model

No. of Rounds	Proposed model	IMD-EACBR	AEHO-DFFNN	ASSO-MERNN	ML-EOA-ANN
100	[illegible]	98.83	96.45	95.52	94.24
200	98.44	97.86	96.41	94.29	93.09
300	97.83	96.59	95.12	93.62	92.48
400	96.96	96.47	94.68	92.42	91.62
500	96.32	94.28	93.79	92.23	91.28

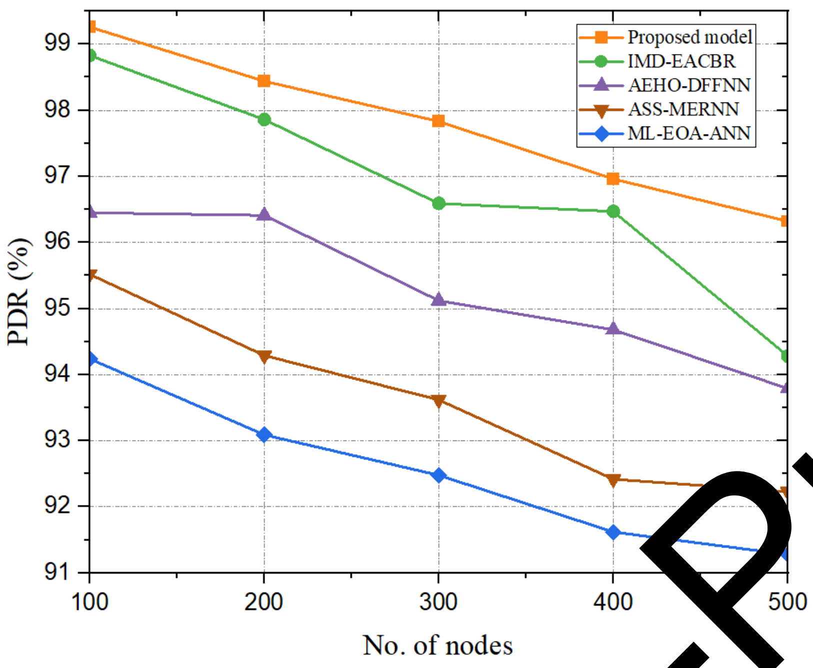

Figure 8. PDR comparison graph between proposed and existing model

Table 7 and Figure 8 present a comparison of PDR among several models in a WSN (WSN) throughout multiple rounds. PDR quantifies the proportion of successfully sent packets, with larger values signifying enhanced network reliability and performance. The proposed model attains the maximum Packet Delivery Ratio (PDR), commencing at 99.26% after 100 rounds and sustaining 96.3[illegible]% after 500 rounds, thereby exemplifying exceptional data transmission efficiency. IMD-EACBR closely follows, with a performance range of 98.83% to 94.28%, demonstrating somewhat inferior still competitive results. AEHO+DFFNN, ASSO-MERNN, and ML-EOA-ANN demonstrate a notable decrease, with AEHO-DFFNN declining from 96.45% to 93.79%, ASSO-MERNN from 95.52% to 92.23%, and ML-EOA-ANN exhibiting the lowest PDR, decreasing from 94.24% to 91.28%. The significant decrease in PDR for ML-EOA-ANN and ASSO+MERNN indicates increased packet loss and diminished network efficiency with time. The proposed approach guarantees the most dependable data transfer, rendering it the optimal selection for sustaining consistent communication in extensive WSN applications.

Table 8. Data fault prediction result parameters comparison between existing and proposed model

Methods	ML-EOA-ANN	ASSO-MERNN	AEHO-DFFNN	IMD-EACBR	Proposed model
Fault Prediction Accuracy (%)	96.52	96.95	97.23	98.61	99.78
Precision (%)	95.53	95.79	96.25	97.84	98.69
Recall	95.12	95.43	96.19	96.74	97.52
F1-Score	96.14	96.36	97.05	97.46	97.83

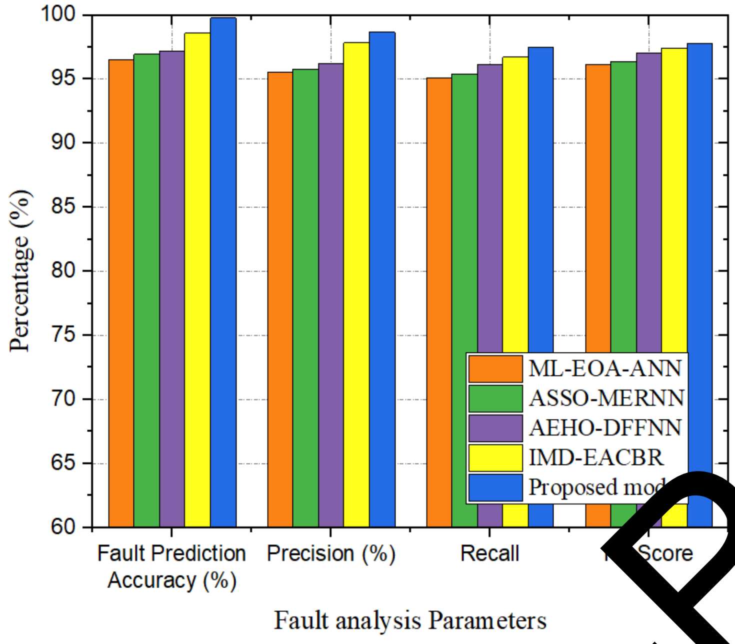

Figure 9. Data fault prediction result parameters comparison graph between existing and proposed model

Table 8 and Figure 9 evaluate various defect prediction models in a WSN based on accuracy, precision, recall, and F1-score. The suggested model surpasses all alternatives, with the greatest fault prediction accuracy of 99.78%, demonstrating its exceptional capability to detect and anticipate faults efficiently. IMD-EACBR exhibits an accuracy of 98.61%, but AEHO-DFFNN, ASSO-MERNN, and ML-EOA-ANN demonstrate marginally inferior performances at 97.23%, 96.95%, and 96.52%, respectively. The suggested model excels in precision (98.69%), recall (97.52%), and F1-score (97.83%), guaranteeing excellent reliability and minimum false positives. IMD-EACBR demonstrates robust performance across all metrics, but ML-EOA-ANN has the lowest results, especially in recall (95.12%), suggesting possible deficiencies in accurately recognising all defective occurrences.

Conclusion

The suggested framework for data fault prediction and energy-efficient transmission in WSNs incorporates FCM clustering, Quantum Swarm Optimisation for CH selection, Multi-task Fuzzy Graph Neural Networks for fault prediction, and TBPSO for safe routing. Utilising these advanced techniques, the model improves energy economy, fault tolerance, and secure data transfer, tackling critical difficulties in WSNs. The integration of graph neural networks guarantees precise defect identification, minimises redundant transmissions, and enhances data reliability. QSO-based CH selection efficiently equilibrates energy usage, whereas TBPPO enhances routing pathways according to trust metrics and network circumstances. Despite a marginal increase in computing complexity, the suggested method markedly enhances network longevity, data precision, and security. This optimization-driven technique provides a solid and scalable solution for contemporary WSN applications. Future endeavours will concentrate on the real-time application of the proposed model in extensive WSN installations and the incorporation of lightweight deep learning methodologies to diminish computational complexity while preserving high accuracy and energy economy.

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