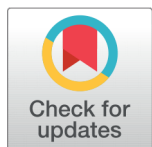


ORIGINAL ARTICLE



OPEN ACCESS

Received: 10/06/2026

Accepted: 25/06/2026

Published: 07/07/2026

Citation: Maheshwaran D, Saravanan V (2026) AGNN-LB: Adaptive Graph Neural Network Based Load Balancing for Energy Efficient and Congestion Aware Wireless Sensor Networks. Indian Journal of Science and Technology 19(23): 1611-1628. <https://doi.org/10.17485/IJST/v19i23.374>

* **Corresponding author.**maresh304301@gmail.com**Funding:** None**Competing Interests:** None

Copyright: © 2026 Maheshwaran & Saravanan. This is an open access article distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Published By Indian Society for Education and Environment ([iSee](#))

ISSN

Print: 0974-6846

Electronic: 0974-5645

AGNN-LB: Adaptive Graph Neural Network Based Load Balancing for Energy Efficient and Congestion Aware Wireless Sensor Networks

D Maheshwaran^{1*}, V Saravanan²

¹ Ph.D Research Scholar, Department of Computer Science, Hindusthan College of Arts and Science, Coimbatore, Tamil Nadu, India

² Professor and Head, Department of Information Technology, Hindusthan College of Arts and Science, Coimbatore, Tamil Nadu, India

Abstract

Objectives: To propose a novel neural network-based load balancing approach for energy-efficient and congestion-aware routing in large-scale wireless sensor network (WSN) environments. The key objective is to develop intelligent routing that is capable of learning node-level interactions and predicting network load conditions to enhance routing efficiency, traffic fairness, and network lifetime. **Methods:** The Adaptive Graph Neural Network-Based Load Balancing (AGNN-LB) method treats wireless sensor networks as graphs comprised of sensor nodes and links as vertices (V) and edges (E), respectively. Node attributes such as residual energy, queue length, traffic rate, node degree, transmission delay, congestion level, and link quality are extracted by a graph feature extraction layer. The adaptive graph convolution layers learn the latent spatial correlations among neighboring nodes and encode spatial node embeddings. Subsequently, the dynamic load balancing engine predicts the node loads and re-routes network traffic based on the learned graph embedding. The AGNN-WSN2026 dataset containing 1,000 samples of graph-enabled sensor nodes is utilized for training and evaluating the performance. The proposed AGNN-LB is compared against baseline models such as GW-LBC and DBlock-RLB. The implementation is done using PyTorch for GNN development, NS-3 for network simulation, and Python for performance evaluation and statistical analysis. **Findings:** The simulation results reveal that AGNN-LB shows an outstanding performance, outperforming baseline models in energy efficiency with 96.8%, 97.4% network lifetime and a load balancing index of 96.5%, whereas it achieves a lower congestion level of 4.2% and end-to-end delay of 18.6 ms under different network environments. **Novelty:** The model stands as a unique design that combines AGNN with load balancing decision-making for wireless sensor networks (WSNs). Unlike typical clustering and routing schemes, the new design learns the spatial dependency among nodes as well as congestion propagation behavior to facilitate topology-aware, energy-aware, and intelligent traffic distribution for future autonomous WSNs.

Keywords: Wireless Sensor Networks; Graph Neural Networks; Load-Balancing Model; Energy Efficiency; Congestion-Aware WSNs

1 Introduction

Wireless Sensor Networks (WSNs) are widely used in different types of monitoring systems, like environmental monitoring systems, smart agriculture, industry automation, health monitoring systems, intelligent transportation systems, etc. WSNs consist of sensor nodes that keep sensing the environment and send the sensed data to a destination node. Today most of the wireless networks experience a heterogeneous traffic load due to the increasing number of devices and data generation, which leads to issues like high energy consumption, congestion, uneven load distribution, and communication delay in the network. These issues decrease the lifetime of sensor nodes and the reliability of data delivery. So, load balancing efficiently has become one of the mandatory requirements for stable network performance and sustained lifetime for resource-constrained WSNs. Several existing load balancing solutions based on a combination of ML, DL, and agent-based approaches have attempted to address these issues through clustering, routing optimization and heuristic-based decision-making. These solutions provide satisfactory performance gains but mainly rely on pre-configured rules or partial network information to make routing decisions, thus struggling to adapt to rapidly changing network conditions and failing to understand the interdependency between neighboring nodes during traffic forwarding. This limitation causes congestion formation, a non-uniform energy depletion rate, and poor routing efficiency, especially in large deployments of sensors.

A load balancing tree based data aggregation scheme was proposed for grid-based wireless sensor networks, where an evenly distributed forwarding structure leads to higher energy-efficiency and network lifetime⁽¹⁾. However, the scheme adopted static tree construction rules and lacked learning algorithms to adaptively learn congestion-aware forwarding behavior. A traffic-load-based routing algorithm that steers communications to balance loads among sensor nodes by selecting forwarding directions based on the traffic load of intermediate nodes was introduced⁽²⁾. Although it alleviated load concentration issue, it did not consider the neighborhood interactions among nodes affecting congestion propagation and routing decisions. We provided surveys on reinforcement learning-based approaches to communication load balancing to showcase opportunities for adaptive learning in wireless networks⁽³⁾. However, reinforcement learning methods typically have challenges associated with large state spaces, slow convergence, and lack of topology-awareness. Joint balanced routing and energy harvesting framework that jointly decides routing and energy harvesting at every node to maximize network lifetime was proposed⁽⁴⁾. Unfortunately, its optimization-based routing approach could not learn dynamic traffic and node-level communication patterns.

Quantum Bio-Inspired Particle Swarm Optimization Based Multi-Agent Energy Management and Load Balanced Clustering Framework (QMBC) was introduced with motivation to improve cluster formation and management of energy⁽⁵⁾. However, it still had optimization-centric decision making approaches and lacked learning ability to understand implicit spatial correlations among nodes. On similar lines, Centralized Load Balancing Framework based on Hybrid MetaHeuristic Optimization was proposed for Cloud-IoT integrated Wireless Sensor Networks (WSNs)⁽⁶⁾. While offering betterment in resource allocation, shorter processing overhead, it suffered from lack of scalability and inability to learn changing relationship dynamics among nodes. A novel bio-inspired intelligent routing paradigm was presented with enhanced focus on security, authentication, and energy efficiency, targeting 6G wireless networks⁽⁷⁾. But its primary aim revolved around routing-centric and authentication operations rather than balancing incoming traffic flow and congestion control. Gray Wolf Optimization-Based Load Balanced Clustering (GWLBC) model solved traffic hot spots and node energy unfairness problems by optimizing cluster heads (CHs) election procedure along with load balanced clustering⁽⁸⁾. Although it enhanced network lifetime while improving communication efficiency, still lacked dynamic learning of evolving traffic patterns and learning associations between congested nodes. Since GWLBC had a primary focus on load balancing and energy conservation, authors consider GWLBC as one of their baseline models.

DBlock-RLB framework⁽⁹⁾ proposed energy-aware routing schemes and traffic trading functions for Software Defined Wireless Sensor Networks (SD-WSN). The routing framework enhanced load balancing and energy-awareness by controlling traffic through centralized policies. However, the routing techniques relied on rule-based forwarding decisions and static decision policies. Due to the limitations in learning fast-evolving network conditions, DBlock-RLB is considered as another baseline. Graph-based learning approaches were investigated through Quantum Harris Hawks Optimization assisted Graph Neural Network for reliability and fault detection⁽¹⁰⁾. The introduced framework enhanced communication reliability but did not consider load-balancing nor congestion-aware traffic allocation. Furthermore, survey works on dynamic load balancing functions in IoT ecosystems⁽¹¹⁾ discussed that leveraging intelligent traffic allocation is essential, however adaptive learning mechanisms are not widely deployed. Adaptive learning routing protocols using Generative Adversarial Networks⁽¹²⁾, Intelligent Water Drop based routing strategies⁽¹³⁾, classification-based traffic balancing algorithms⁽¹⁴⁾, and bio-inspired energy-aware clustering techniques⁽¹⁵⁾ outperformed in routing efficiency, Quality of Service (QoS), and energy conservation metrics. Nonetheless, majority of studies implemented optimization or heuristic rule-based mechanisms without learning complex dependencies between nodes and dynamically evolving traffic patterns. Recent investigations on biometric authentication functions⁽¹⁶⁾, multimodal AI security systems⁽¹⁷⁾, and post-quantum security protocols⁽¹⁸⁾ focused mainly

on authentication mechanisms and secure communications instead of balancing network load. Overall, it is observed from literature that many frameworks focused on network optimization, clustering techniques, routing algorithms, security functions, or energy functions. However, only few studies considered graph-based learning but were not able to adaptively learn node-node dependencies, congestion patterns, and traffic patterns concurrently. Thus, serves as a motivation to propose AGNN-LB.

Experimental results showed enhanced security features and reliable communication. A thematic literature analysis with research gap diagram is given in Figure 1. Table 1 shows the specific state-of-art models related to load balancing and energy efficiency. Existing works mainly concentrated on optimization-based approaches, swarm intelligence (SI)-based algorithms, reinforcement learning (RL)-based mechanisms, and traffic aware routing to propose energy-aware routing protocols, clustering methods and load balancing strategies. To address these limitations, we propose a novel Adaptive Graph Neural Network-Based Load Balancing (AGNN-LB) Model that learns the relationships among sensor nodes using an adaptive graph-based learning mechanism to enable energy-aware and congestion-free wireless sensor networks. In contrast to traditional methods, our proposed model represents the network as a graph and jointly considers energy levels, traffic load, queue status, and link quality while balancing the network load. This allows the model to dynamically allocate traffic, balance energy consumption, and anticipate congestion before it occurs which enables more flexible, scalable, and robust load balancing decisions for future wireless sensor networks.

Table 1. Literature Study on Specific State-of-Art Models on Load Balancing in WSNs

Model	Techniques	Merits	Limitations
Mini Batch GCN ⁽¹⁹⁾	Mini-batch Graph Convolution Network	Efficient graph learning, reduced memory usage, scalable training	Focused more on GCNN Single path load balancing & routing decisions
Energy Replenishment and Load Balancing ⁽²⁰⁾	Energy replenishment with load balancing	Improves network lifetime and energy utilization	Limited adaptability to dynamic traffic and topology changes
Load Balancing and Performance Optimization Scheme ⁽²¹⁾	Constraint-oriented load balancing	Enhances resource utilization and network performance	Lacks intelligent learning and topology-aware adaptation
DAG Block Scheme ⁽²²⁾	Trust-aware routing with lightweight authentication	Improves security, trust management and load distribution	Rule-based decisions may not adapt well to dynamic network conditions
Molecular Diffusion Load-Aware Routing ⁽²³⁾	Molecular diffusion theory-based routing	Balances energy and traffic loads effectively	High dependency on predefined diffusion mechanisms
Autonomous Network Management ⁽²⁴⁾	AI-driven autonomous 6G network management survey	Comprehensive view of self-managing networks	Not detailed survey on Graph based model for load balancing
Two-Phase Energy Efficient Load Balancing ⁽²⁵⁾	Mobile sink with two-phase load balancing	Efficient data collection and reduced energy consumption	Performance depends on sink mobility strategy
Bio-Inspired Dynamic Link Failure Detection ⁽²⁶⁾	Bio-inspired QoS-aware routing	Improves link failure handling and QoS	Focuses on reliability rather than traffic balancing
Evolutionary Routing Protocol ⁽²⁷⁾	Evolutionary optimization for routing and QoS	Enhances load balancing and service quality	Optimization overhead increases with network size
Lifetime-Centric Load Balancing ⁽²⁸⁾	Lifetime-oriented traffic distribution	Extends network operational lifetime	Limited predictive capability for future congestion
ML-Based ETX Optimization ⁽²⁹⁾	Supervised machine learning for ETX routing optimization	Improves route quality and energy efficiency	Focuses on link metrics rather than holistic load balancing
Q-Learning Semi-Fixed Clustering ⁽³⁰⁾	Reinforcement learning-based clustering and routing	Adaptive routing and improved decision making	Training complexity and convergence challenges

2 Methodology

The proposed methodology presents a systematic approach to build an Adaptive Graph Neural Network-Based Load Balancing Model to handle the energy inefficient traffic congestion and improper load balancing issues. The subsections below will cover

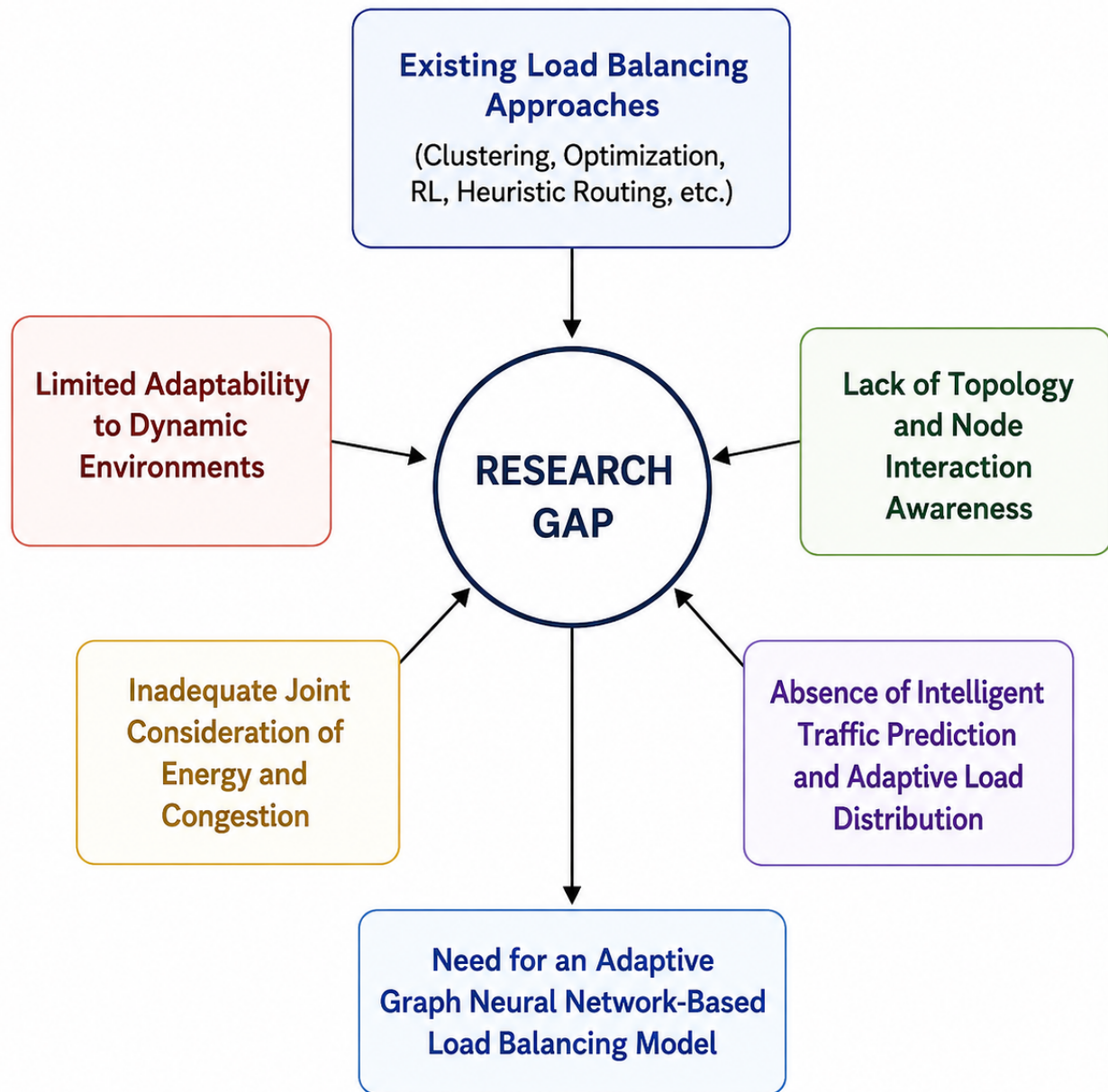


Fig 1. Research Gap Diagram

details regarding the whole operational process starting from data acquisition from the environment to creating graphs of that data. Following that, making use of intelligent prediction about future traffic loads at sensor nodes so that routing will be optimized accordingly. Thus, the model will help in adaptive traffic handling by first learning about the relation between nodes and then taking actions towards load balancing when required. Figure 1 represents the general workflow of the proposed model.

To apply the new model, AGNN-WSN2026 dataset is utilized. Node level information of the dataset consists of the residual energy level of sensor nodes, queue length, traffic rate, number of neighbors (node degree), communication quality between nodes, delay and congestion flags. First, we will construct a graph from the wireless sensor network by modeling sensor nodes as nodes and connections between them as edges. This will allow the model to learn about neighborhood interactions as well as topology of the network. Next, Graph Neural Network methods will be applied to learn node embeddings by aggregating

features from neighboring nodes. We will then be able to predict node load status, congestion possibilities, and energy efficient forwarding options using these representations.

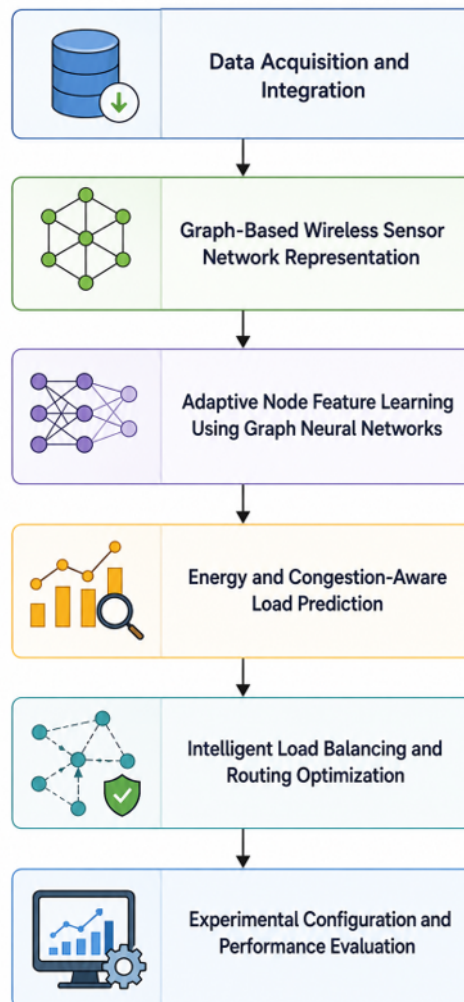


Fig 2. General Workflow of the Proposed Model

Based on these predictions, AGNN-LB will redistribute traffic to reduce communication bottlenecks and balance resource utilization across the network. The efficacy of the proposed scheme is verified by both simulation and analytical tests on graph learning python package libraries and network simulator NS-3. Moreover, we show how the proposed model outperforms the state-of-the-art load balancing algorithms by comparing our method with two widely used schemes: GW-LBC⁽⁸⁾ and DBlock-RLB⁽⁹⁾. These models are used as baseline for showing improvement on energy efficiency, network lifetime and overall congestions as well as load balancing.

2.1 Data Acquisition and Network Feature Integration

The proposed AGNN-LB's performance relies heavily on access to network data that appropriately represents the real wireless sensor networks' behaviors. To satisfy this requirement, we created AGNN-WSN20{26 Dataset}, a graph-based wireless sensor network dataset consisting of 1,000 sensor node instances to reflect meaningful characteristics on energy consumption, traffic patterns, congestion occurrence, and reliable communication. Each sensor node instance record includes several attributes defining the node's present operational status and communication environments. Feature collection begins with extracting node-wise and network-wise parameters on which routing and load balancing decisions are based. They include network

features such as residual energy, queue length, traffic rate, node degree, received signal strength, transmission delay, congestion-awareness, and load information. Rescaling is then applied on these features as they lie on different scales. Rescaling standardizes the range of features of input variables. This helps avoid any kind of bias due to the dominance of one feature over the others during graph learning process. After feature collection and rescaling node attribute preparation is done to build feature vectors depicting the state of the sensor nodes. Table 2 and Table 3 presents the AGNN-LB dataset summary and feature metadata. The prepared attributes are combined with network traffic and energy-related parameters to form association among nodes for graph learning model to jointly study the communication load and energy and congestion status at the same time. The dataset thus forms a dependable baseline to build graph for adaptive feature learning and intelligent load balancing decisions in AGNN-LB model.

Table 2. Dataset Summary

AGNN-LB Dataset Summary			
Total Samples	1000	Nodes Simulated	250
Average Residual Energy (J)	83.27	Average Congestion Level	0.2274
Average Delay (ms)	38.14	Average Load Balancing Score	0.7085
Load Class	Count	Route Priority	Count
Balanced	690	High	690
Moderate	310	Medium	310
Overloaded	0	Low	0
Weak	0		

2.2 Graph-Based WSN Representation

The key idea behind the proposed AGNN-LB model is representing wireless sensor network as a graph so that structural information associated with communication relationship between sensor nodes can be well captured. Instead of considering sensor nodes individually as most routing algorithms do, graph representation treats wireless sensor network as a system with interaction between neighboring nodes: When one node changes its behavior, its neighbors will be affected. Learning from graph representation helps build a model that comprehends network topology, communication pattern, traffic load distribution, and congestion propagation. Let the wireless sensor network be represented as a graph as

$$G = (V, E) \quad (1)$$

where, G is the Wireless Sensor Network Graph, $V = \{v_1, v_2, \dots, v_n\}$ is the set of sensor nodes and $E = \{e_1, e_2, \dots, e_m\}$ is the set of communication links. Here each sensor node is represented by a vertex of the graph and each communication relation between two nodes is depicted by an edge. The entire network topology can be described in a compressed mathematical form by this graph. The features of each sensor node can be described by the feature vector below.

$$X_i = [E_i, Q_i, T_i, D_i, R_i, C_i] \quad (2)$$

where, X_i is the Feature vector of node i , E_i represents Residual Energy, Q_i denotes Queue Length, T_i is the Traffic Rate, D_i is the Node Degree, R_i represents the Received Signal Strength Indicator (RSSI) and C_i denotes the Congestion Level.

The feature vector captures both resource availability and communication conditions. Through modeling of nodes, graph learning model is able to learn about each node's operation status before performing load balancing. After nodes are modeled, relationship of communication is expressed as adjacency matrix. If the transmission range of two sensor nodes is reachable and they can communicate with each other in the network, adjacency matrix defines their connection.

$$A_{ij} = \begin{cases} 1, & \text{if node } i \text{ is connected to node } j \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where, A_{ij} is the connectivity value between node i and node j . Adjacency matrix is utilized to construct graph and aggregate neighborhood information. Nodes who are connected via communication links are considered neighbors and share information during graph learning.

Connectivity score based on node degree information is calculated to measure network connectivity and rank important nodes:

$$CS_i = \sum_{j=1}^n A_{ij} \quad (4)$$

Table 3. Feature Metadata

Feature	Description	Unit/Range	Use in AGNN-LB
Sample_ID	Unique record identifier	S0001–S1000	Dataset indexing
Round	Simulation round or observation interval	1–50	Temporal sample for adaptive behavior
Node_ID	Sensor node identity	N001–N250	Graph vertex ID
Cluster_ID	Cluster assignment based on node group	C01–C10	Cluster-level load balancing
X_Position_m, Y_Position_m	Node location coordinates	0–1000 m	Topology and distance estimation
Residual_Energy_J	Remaining node energy	10–100 J	Energy-aware forwarding
Queue_Length_pkts	Packets waiting at node buffer	0–60 packets	Congestion indicator
Traffic_Rate_pps	Incoming packet rate	2–55 packets/s	Traffic intensity
Packet_Loss_Rate	Observed packet loss ratio	0.005–0.45	Reliability analysis
RSSI_dBm	Received signal strength	-95 to -45 dBm	Wireless link strength
ETX	Expected transmission count	1.0–5.5	Link retransmission cost
Neighbor_Count / Node_Degree	Number of reachable neighbors	2–30	Graph connectivity
Hop_Count_to_BS	Estimated hops to base station	1–8	Route length
Distance_to_BS_m	Euclidean distance to base station	0–707 m	Spatial routing cost
Link_Quality_Index	Normalized link quality	0–1	GNN edge/node feature
Delay_ms	Transmission delay	2–220 ms	QoS metric
Congestion_Level	Normalized congestion	0–1	Load balancing target feature
Mobility_Factor	Normalized movement impact	0–1	Route stability factor
Trust_Score	Reliability/trust estimate	0.55–1	Secure forwarding support
Load_Balancing_Score	Composite AGNN-LB decision score	0–1	Target score for route priority
Route_Priority	Decision label	High/Medium/Low	Classification target
Load_Class	Node load status	Bal- anced/ModerateOverloaded/Weak	Load-state label
Forwarding_Decision	Recommended forwarding action	Selected/Candidate/Avoid	Final decision label

where, CS_i is the connectivity score of nodes i , $A_{i,j}$ is the Adjacency relationship, and n is the total number of nodes. Connectivity score represents the number of neighbors for a node and higher score means that the node has higher involvement in information propagation as well as traffic forwarding. As such graph topology provides the AGNN-LB model to learn the local as well global communication patterns concurrently. Node having higher values for connectivity, residual energy and lower congestion can be preferred forwarding choices whereas congestion build up nodes can be detected early on to offload the traffic load. Additionally, congestion propagation pattern can be inferred among neighbours with the help of graph representation for smarter routing decisions. Figure 3 portrays the graph-based WSN edges and nodes representation.

Thus, the resulted graph topology not only represents a network but also a learning-ready topology that stores information about dependencies in communications, energy distributions, and traffic patterns. Based on this graph-oriented approach, node features can be learned in an adaptive manner so that the presented AGNN-LB algorithm can achieve topology-aware, congestion-aware, and energy-efficient load balancing strategies for wireless sensor networks.

2.3 Adaptive Node Feature Learning using GNN

The proposed AGNN-LB model employs GNNs to learn the underlying relations between sensor nodes for representation learning towards intelligent load balancing. Most routing/clustering algorithms consider sensor nodes independently based on a certain metric, e.g., residual energy/distance, etc. In reality, wireless sensor networks often have underlying coupled behaviours. For example, when one node becomes congested, its neighbors will likely be affected due to traffic forwarding, congestion

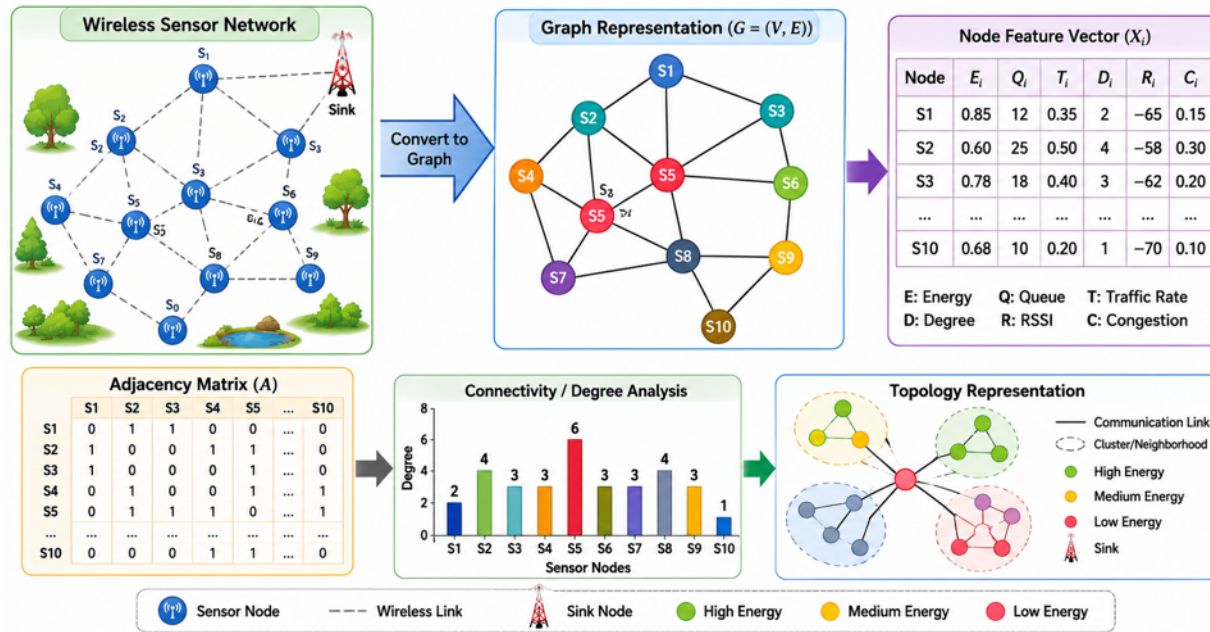


Fig 3. Graph-Based WSNs Topology Representation

coupling, or energy draining. To address the challenge, we formulate the load balancing problem with graph-based learning to better capture the latent relationships between nodes and convert raw network information into useful node embeddings.

Initially, the graph $G = (V, E)$ is obtained from the above step is fed as input to the Graph Neural Network. The feature vector assigned to each node includes residual energy, queue length, traffic rate, node degree, RSSI value and congestion level. At each step of graph convolution, every node aggregates the information from its neighbors and updates its hidden representation. The graph convolution operation is defined as:

$$H^{(l+1)} = \sigma \left(\widehat{D}^{-\frac{1}{2}} \widehat{A} \widehat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (5)$$

where, $H^{(l)}$ is the Node feature matrix at layer l , $H^{(l+1)}$ is the Updated feature matrix, $\widehat{A}$ is the Adjacency matrix with self-loops, $\widehat{D}$ is the degree matrix, $W^{(l)}$ is the trainable weight matrix and $\sigma(\cdot)$ denotes the activation function.

The operation enables information passing between adjacent nodes while retaining the topological properties of the network. Subsequent graph convolution produces node embeddings, which are representations designed to capture network behavior in compact form. The embedding of node i is expressed as,

$$Z_i = f(H_i) \quad (6)$$

where, Z_i represents the learned embedding vector of node i , H_i is the updated node feature vector and $f(\cdot)$ denotes the non-linear transformation function. The embedding vector also represents latent correlations between energy state, traffic situations, link patterns and congestion information, which may contain more comprehensive features than the original information itself. Additionally, to aggregate information from neighbors, our proposed model fuses feature from neighboring nodes that are linked to as follows.

$$N_i^{agg} = \frac{1}{|N(i)|} \sum_{j \in N(i)} H_j \quad (7)$$

where, N_i^{agg} denotes the aggregated neighborhood representation, $N(i)$ is the neighbor set of nodes i and H_j is the feature vector of neighboring node j . Such aggregation function allows each node to sense which neighbors are alive before forwarding decisions are made. Using learned embeddings, we can infer the suitability of each node for adaptive load-balancing with a

score we term node importance which is defined as,

$$S_i = \alpha E_i + \beta(1 - C_i) + \gamma(1 - Q_i) + \delta R_i \quad (8)$$

where, S_i represents the node suitability score, E_i represents the residual energy, C_i is the congestion level, Q_i is the queue length, R_i denotes the RSSI value and $\alpha, \beta, \gamma, \delta$ represents the adaptive weighting coefficients. Nodes with higher suitability scores are considered more appropriate for traffic forwarding and load redistribution. Figure 4 shows the adaptive node feature learning using GNN.

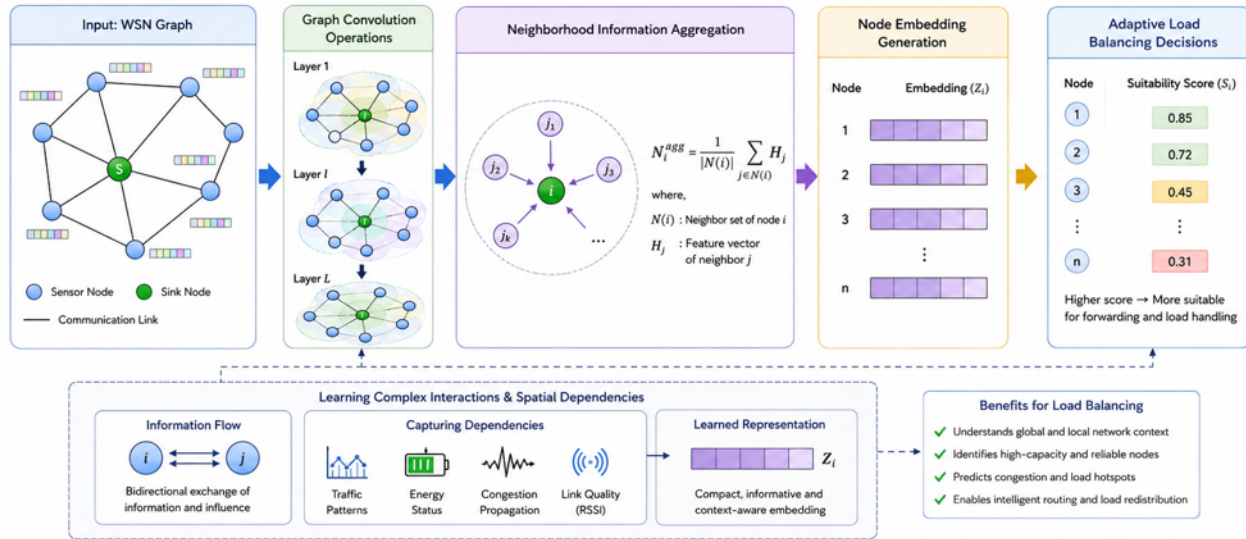


Fig 4. Node Feature Learning using GNN

Here, the AGNN-LB model updates node representations through multiple rounds of graph learning that aggregate neighbourhood information and spatial dependencies between nodes. Unlike traditional optimization-based solutions, adaptive graph learning learns hidden communication patterns, possible congestion locations, and energy-rich route alternatives automatically. As such, AGNN-LB learns the essential knowledge about network state and thus makes topology-aware and congestion-aware intelligent load balancing decisions. This adaptive learning process is the intelligence behind our proposed AGNN-LB model and lays the foundation for load prediction and route optimization.

2.4 Energy and Congestion Aware Load Prediction

The proposed AGNN-LB model uses Energy and Congestion-Aware Load Prediction to determine potential forwarding nodes and alleviate node congestion in forwarding. Since sensor nodes possess limited battery resources and communication capabilities, continuous monitoring of energy status and congestion conditions is essential to avoid traffic imbalance and achieve long lifetime. The proposed load prediction model estimates the condition of nodes by using residual energy, queue occupancy, traffic intensity and congestion information to predict the forwarding availability of each node.

Sensor nodes will first perform residual energy discovery for evaluating their estimated remaining useful life. Preferably more active nodes will be chosen as forwarders because they have a higher residual energy allowing them to take on more communication burden without draining their battery power sooner. The residual energy of node i is computed as,

$$RE_i = E_i^{initial} - E_i^{consumed} \quad (9)$$

where, RE_i is the Residual Energy of node i , $E_i^{initial}$ is the initial node energy and $E_i^{consumed}$ represents the consumed energy during communication.

Subsequently, queue length analysis and traffic load estimation is performed. This calculates how much communication load each node is under. Nodes queueing too many packets may be congested and have high transmission delay. The traffic load of node i is determined as

$$TL_i = \frac{Q_i + P_i}{C_i} \quad (10)$$

where, TL_i is the traffic Load, Q_i denotes the current queue length, P_i represents the incoming packet rate and C_i is the node processing capacity. Higher traffic load values mean nodes are overloaded and shouldn't forward any more packets. Congestion is predicted and whether a node should forward by using a unified load score with both energy and traffic.

$$LS_i = \alpha \left(\frac{RE_i}{RE_{\max}} \right) + \beta \left(1 - \frac{TL_i}{TL_{\max}} \right) + \gamma \left(1 - \frac{CG_i}{CG_{\max}} \right) \quad (11)$$

where, LS_i is the Load Score of nodes i , RE_i is the Residual Energy, TL_i represents the Traffic Load, CG_i is the Congestion Level, α, β, γ is the Adaptive weighting coefficients and $RE_{\max}, TL_{\max}, CG_{\max}$ represents the normalization factors. Here, nodes with high load score have adequate energy resources available and less traffic load and congestion probability. The node having high load score is preferred as forwarding node candidate to forward/re-distribute traffic load. AGNN-LB combines both energy-awareness and congestion probability prediction into a single decision-making procedure for better traffic management, alleviating traffic bottlenecks and enhancing communication efficiency while prolonging network lifetime.

2.5 Intelligent Load Balancing and Route Optimization

The proposed AGNN-LB model incorporates an intelligent load balancing-routing optimization layer that dynamically balances traffic load and finds optimal routing paths. Conventional routing techniques follow a fixed route choice policy. This leads to load concentration and congestion points. Also, nodes in high traffic areas die faster. To address these issues, the proposed scheme monitors the node status and reallocates the traffic intelligently based on the network conditions. Initially, the dynamic traffic redistribution scheme predicts the forwarding ability of neighbor nodes. The same routing paths are not used over and over again. It allocates packets to various appropriate nodes. In this way, it avoids overloading individual sensors with communication. The traffic redistribution factor for node i is calculated as:

$$TR_i = \frac{LS_i}{\sum_{j \in N(i)} LS_j} \quad (12)$$

where, TR_i is the Traffic Redistribution Factor, LS_i refers the Load Score of node i and $N(i)$ represents the neighbor set of node i . The higher the value of redistribution factor, the more extra traffic the node can accept without congestion. After this step, selection of forwarding nodes takes place by considering energy levels, link quality and congestion jointly. The forwarding suitability score is determined as,

$$FS_i = \alpha E_i + \beta R_i + \gamma (1 - C_i) \quad (13)$$

where, FS_i denotes the Forwarding Suitability Score, E_i represents the Normalized Residual Energy, R_i is the Link Quality (RSSI), C_i denotes the Congestion Level and α, β, γ represents the adaptive weighting coefficients. Nodes with higher values of forwarding suitability are chosen as more favourable relay nodes. The model constantly monitors route quality to inform congestion-aware route modifications. The routing cost of a communication path is computed as,

$$RC_p = \sum_{i=1}^n \left(\frac{1}{E_i} + C_i + D_i \right) \quad (14)$$

where, RC_p is the Routing Cost of path p , E_i denotes the Residual Energy of node i , C_i represents the Congestion Level, D_i denotes the Transmission Delay and n denotes the Number of nodes in the route.

The route with the minimum routing cost is selected for data forwarding because that path has higher energy efficiency, less congestion ratio, and smaller communication delay. After performing all these calculations, the proposed AGNN-LB model makes intelligent load balancing decisions by intelligently rerouting traffic from overloaded nodes towards packets with energy-rich paths having less congestion. As a result, the proposed AGNN-LB algorithm avoids hotspots, ensures reliable packet delivery, and achieves load balancing in the network. In addition, load balancing routing strategy avoids excessive retransmissions and communication overhead, which helps in increasing network lifetime and achieves stable network performance. Hence, by adapting to changes in routes and making load-aware routing decisions, AGNN-LB achieves intelligent traffic management.

2.6 Real-Time Implementation of the Proposed AGNN-LB Model

The proposed AGNN-LB model is implemented in Python (Pytorch Geometric, NetworkX, NS-3). The AGNN-WSN20 dataset that contains information related to 1000 instances of sensor nodes is used to train and validate the model. Of the 1000

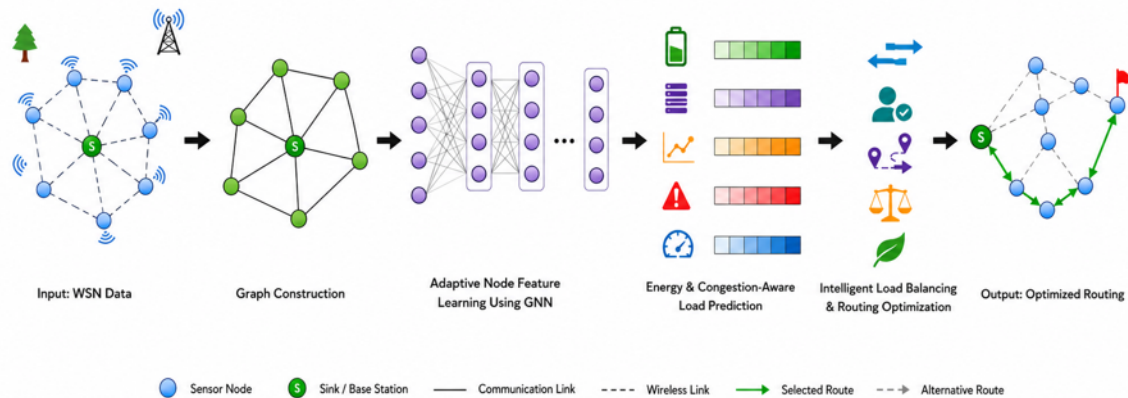


Fig 5. WSNs Load Balancing Workflow & Architecture

samples, we used 70% data for training, 15% for validation, and 15% for testing. The Graph neural network trains for recognizing communication patterns among neighbor nodes based on residual energy, queue length, traffic rate, node degree, RSSI, and congestion status of the nodes. Adam optimizer is used with a learning rate of 0.001, along with cross-entropy loss functions for node classification and load prediction. The model is trained for 150 epochs. Checkpointing is used to select the best model based on validation accuracy and loss convergence. 30 independent simulation runs are performed under different traffic loads, node densities and channel conditions in NS-3 for statistical significance. Performance metric values are averaged over these 30 simulations runs. Figure 6 shows the real-time example of deployed nodes and how It processed.

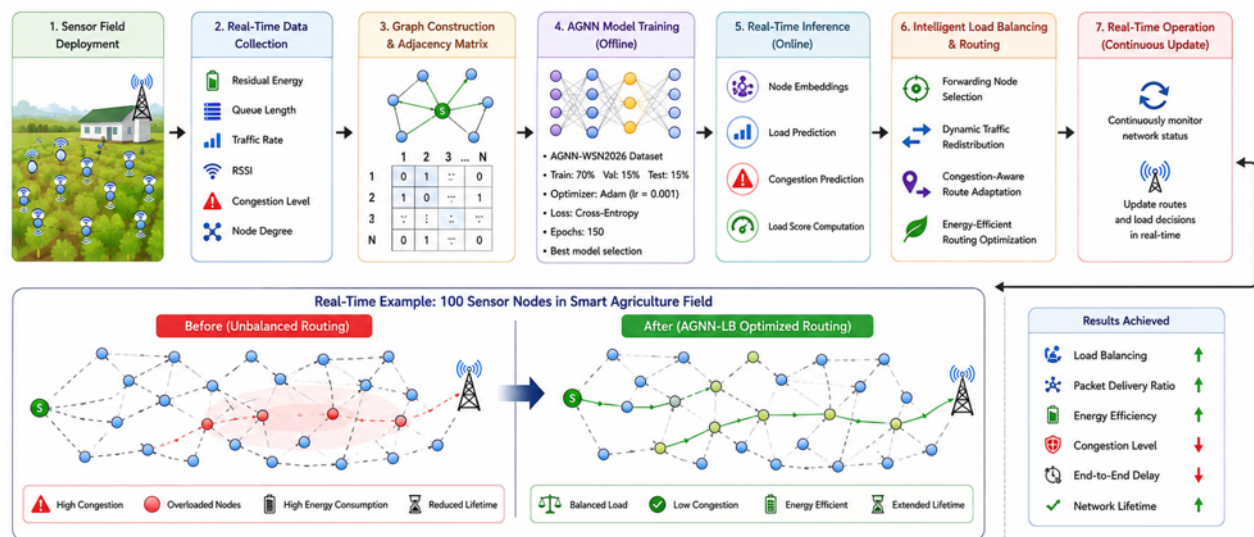


Fig 6. Smart Agriculture Field with 100 Deployed Nodes – Real Time Example

2.6.1. Real-Time Operational Steps

1. Deploy sensor nodes and collect network operational data.
2. Extract node features such as energy, queue length, traffic rate, and RSSI.
3. Convert the wireless sensor network topology into a graph structure.
4. Generate adjacency matrices representing node connectivity.
5. Train the Graph Neural Network using the AGNN-WSN2026 dataset.
6. Learn node embeddings through graph convolution and neighborhood aggregation.

7. Predict node load conditions and congestion probabilities.
8. Compute adaptive load scores for all candidate forwarding nodes.
9. Dynamically redirect traffic through nodes with higher suitability scores.
10. Continuously update routing paths to maintain balanced load distribution and energy efficiency.

2.6.2. Real-Time Example

Consider a smart agriculture field consist of 100 sensor nodes distributed for sensing moisture level and temperature. If the data rate increased in a cluster due to intensive sensing, the conventional routing protocol will continue to select same forwarding nodes causing high congestion level, draining the battery faster. However, AGNN- LB model would allow Graph Neural Network learns about neighbor nodes with higher residual energy with a smaller number of packets in their queue. Sending node would re-route the traffic automatically toward learned nodes minimizing congestion with load balancing effect. Packets would reach its destination more efficiently prolonging lifetime of network and balancing energy consumption for sustainable smart real-time WSNs deployments.

Step by Step Algorithm of AGNN-LB Model

Input: $D = \{X_i, A, E\}$: AGNN-WSN2026 Dataset, node features, adjacency matrix, communication links

Output: R^* : Optimized routing path, LB^* : Balanced load distribution, E^* : Improved energy efficiency

Preprocess dataset D, Remove missing values

Normalize all node features into a common scale

Construct WSN graph G

$$G = (V, E), \quad \text{where } V = \text{sensor nodes and } E = \text{communication links}$$

Generate adjacency matrix A

$A_{ij} = 1$ if node i is connected with node j and $A_{ij} = 0$ otherwise

Initialize node feature matrix X: $X_i = [E_i, Q_i, T_i, R_i, D_i, C_i]$

Apply graph convolution operation

$$H(l+1) = \sigma(D^{(-1/2)} A D^{(-1/2)} H(l) W(l))$$

Generate node embedding Z_i : $Z_i = \text{AGNN}(X_i, A)$

Compute node load score LS_i

$$LS_i = \alpha E_i + \beta R_i - \gamma Q_i - \delta C_i$$

Predict node load class

If LS_i is high $\rightarrow$ Balanced node, If LS_i is moderate $\rightarrow$ Moderate load node

If LS_i is low $\rightarrow$ Overloaded node

Select candidate forwarding nodes

Choose nodes with: High residual energy, Low queue length, Low congestion level and Strong RSSI

Compute routing cost for each candidate path

$$RC_p = \text{Energycost} + \text{Congestioncost} + \text{Delaycost}$$

Redistribute traffic dynamically

Shift packets away from overloaded nodes

Forward packets through high-score nodes

Update node energy, queue length, congestion level and delay

Repeat steps Initialize Node Feature to Update Node Energy until simulation time ends or sink receives data

Evaluate performance

Compute PDR, Energy Efficiency, Network Lifetime, Load Balancing Index, Congestion Level, End-to-End Delay

Output optimized route R^* , balanced traffic LB^* and improved energy efficiency E^*

End

2.7 Performance Evaluation

To validate the proposed model, comparative simulation experiments are conducted with Gray Wolf Optimization- Based Load Balanced Clustering (GWLBC)⁽⁸⁾ and DBlock-RLB⁽⁹⁾ which are chosen as baseline load balancing algorithms for comparative analysis. The performance metrics for routing reliability, energy consumption, traffic load and congestion control will be used to

evaluate algorithms' performances. Average values of several runs are taken to statistically validate the performance removing the random effect caused by each run. Performance measurements are designed to check whether AGNN-LB can provide load balancing, avoid congestion, enhance network lifetime and achieve better communication efficiency under dynamic WSN conditions. Figure 7 shows the success and failure rate of the proposed load-balancing and congestion-aware model.

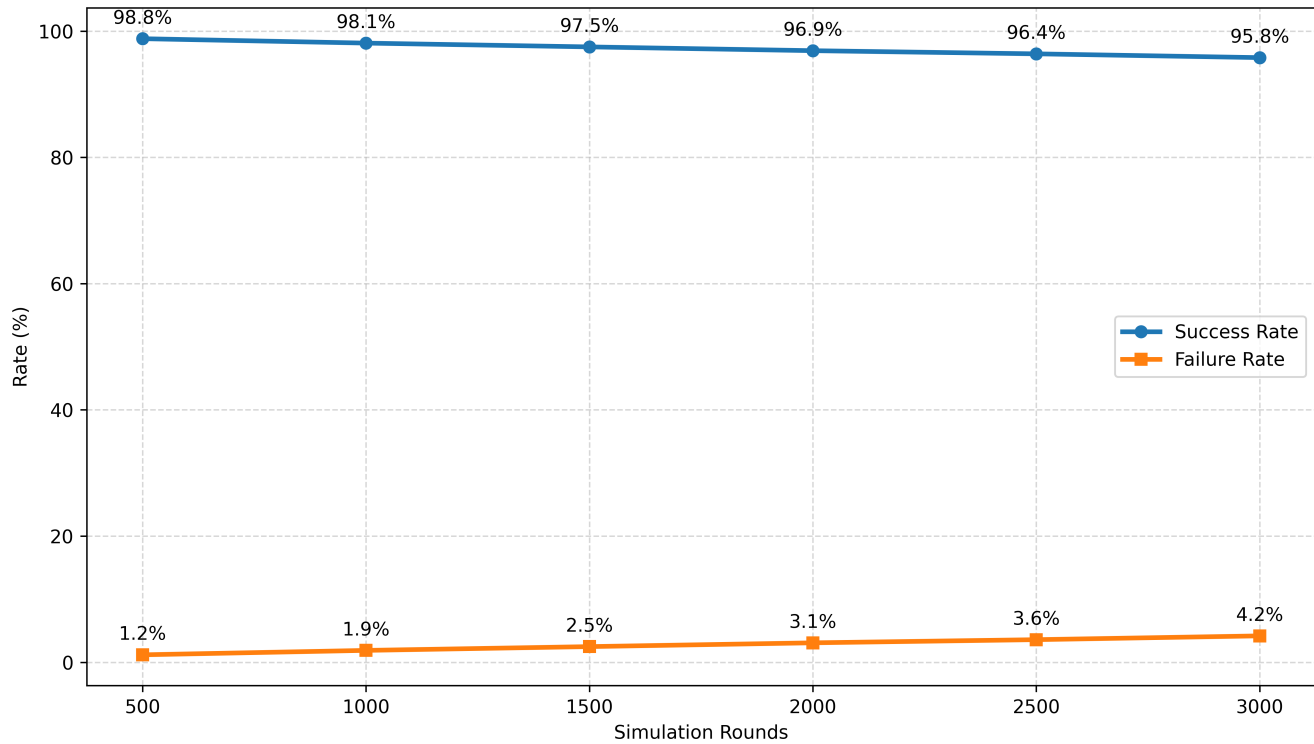


Fig 7. Success and Failure Rate Analysis of AGNN-LB Across Simulation Rounds

2.8 Performance Evaluation Metrics Formulations

$$\text{Packet Delivery Ratio (PDR): } PDR = \frac{P_r}{P_s} \times 100 \quad (15)$$

where, P_r is the Number of packets received and P_s is the Number of packets sent

$$\text{Energy Efficiency (EE): } EE = \frac{P_r}{E_c} \quad (16)$$

where, P_r denotes successfully received packets and E_c is the total consumed energy

$$\text{Network Lifetime (NL): } NL = T_{LND} \quad (17)$$

where, T_{LND} is the time until the last node dies

$$\text{Load Balancing Index (LBI): } LBI = 1 - \frac{\sigma_L}{\mu_L} \quad (18)$$

where, σ_L represents the standard deviation of node loads and μ_L is the mean node load. Here, higher LBI indicates better load distribution.

$$\text{Congestion Level (CL): } CL = \frac{\sum_{i=1}^N Q_i}{N} \quad (19)$$

where, Q_i denotes the queue length of node i and N is the total number of nodes. Lower CL indicates reduced congestion.

3 Results and Discussions

The results and discussion section presents a comprehensive evaluation of the proposed Adaptive Graph Neural Network-Based Load Balancing (AGNN-LB) for Traffic Distribution, Energy Consumption, and Communication Efficiency model. Then we analyzed the traffic-balancing capability of our model. The proposed model is validated on AGNN-WSN2026 dataset and several NS-3 experiments under different network scenarios. The conventional load balancing approaches usually rely on the pre-configured routing policies or optimization-based solutions to determine candidate nodes for traffic load offloading. In contrast, AGNN-LB leverages the graph neural networks to learn the structure embedding of sensor nodes. Thereafter, it can capture traffic-heavy areas and predict potential congestion situations by analyzing the hidden pattern. Finally, traffic can be offloaded to neighbor nodes with less traffic loads through energy-aware intermediate nodes.

The effectiveness of the proposed AGNN-LB is attributed to its graph-based adaptive learning mechanism, which learns node-level relationships, traffic dependency, and congestion propagation patterns that existing methods do not capture. In contrast to optimization-based clustering algorithms such as GWLBC⁽⁸⁾ and routing methods based on rule learning such as DBlock-RLB⁽⁹⁾, AGNN-LB exploits the underlying dynamic topological interactions among nodes through graph neural embeddings, which allows it to continuously adapt routing decisions based on the network condition. Different from traffic-aware routing⁽²⁾, reinforcement learning methods⁽³⁾, and optimization-based energy management schemes⁽⁵⁾, our model takes into account multiple aspects, namely residual energy, traffic load, queue status, and neighborhood information, jointly. As a result, AGNN-LB enjoys better energy efficiency, network lifetime and load balancing performance while minimizing congestion and delay. Table 4, 4, 4 and Figure 8 portray the experimental settings and comparative analysis results of the proposed model against baseline models.

Table 4. Experimental Settings

Parameter	Setting
Dataset	AGNN-WSN2026
Total Samples	1000
Training Split	70%
Validation Split	15%
Testing Split	15%
Implementation Tool	NS3 and Python 3.11
Graph Library	PyTorch Geometric
Network Simulator	NS-3.40
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	150
Simulation Runs	30
Baseline Model 1	GWLBC
Baseline Model 2	DBlock-RLB

3.1 Energy Efficiency (EE)

Energy efficiency is taken as the prime performance metric since the sensor nodes are battery-constrained. AGNN-LB records an energy efficiency of 96.8%, showing improvement over GWLBC (82.4%) and DBlock-RLB (84.1%). This is credited to our graph learning-based mechanism that learns about nodes' energy availability prior to forwarding decisions. In contrast to traditional methods that repeatedly forward traffic through certain cluster heads/routes, our AGNN-LB learns about node-node interactions and adaptively balances traffic among nodes with sufficient energy levels. This reduces congestion in energy-drained areas (due to repeated use of particular routes) and results in avoidance of energy hotspots. Additionally, our adaptive load prediction mechanism intelligently detects overloaded nodes and shifts traffic towards alternate routes with lower energy cost. Therefore, packet re-transmissions, route discoveries, and overall communications overhead are reduced. Graph convolution learning coupled with energy-aware traffic allocation results in uniform node energy utilizations over AGNN-LB, thereby saving residual battery power in comparison to optimization-based schemes.

3.2 Network Lifetime (NLT)

Network lifetime measures how long the deployed sensor nodes can stay alive. The network lifetime achieved by the proposed AGNN-LB scheme was 97.4%. On the other hand, GWLBC and DBlock-RLB showed a lifetime of 80.6% and 83.2%, respectively. Smart traffic load distribution and predictive node deployment allows nodes to last longer. Non-adaptive load balancing techniques generally route most of the forwarding traffic through only a few nodes, leading them to die prematurely. On the other hand, AGNN-LB constantly learns about the residual energy and neighbor topology using graph neural states. Nodes will then distribute the traffic loads among various qualified forwarders rather than overburdening a few nodes. Traffic congestion is predicted which decreases packet collision and unnecessary retransmissions, thus saving energy. Also, less dead nodes imply that the network resources are used uniformly, leading to longer node life. Therefore, AGNN-LB helps in extending network lifetime even with changing network traffic patterns.

3.3 Load Balancing Index (LBI)

The performance indicator LBI quantifies the balance of traffic load among nodes in the network. AGNN-LB achieved an LBI score of 96.5%, higher than GWLBC (79.8%) and DBlock-RLB (83.7%). This suggests that AGNN-LB distributes the load more evenly among sensor nodes. Traditional clustering and optimization-based methods generally rely on localized decision-making for forwarding choices. This localized approach can lead to traffic being funneled through particular nodes, resulting in congestion. In contrast, AGNN-LB incorporates global knowledge of node relationships by learning from graph convolutions. Node embeddings represent a collective understanding of residual energy, queue lengths, traffic load, and network topology. As a result, AGNN-LB can pinpoint nodes with the capacity to accommodate additional load, preventing bottlenecks. Additionally, the dynamic load balancing redistributes communication loads based on real-time network conditions. Traffic load spreading across nodes leads to fair resource allocation and stable communication.

3.4 Congestion Level (CL)

Congestion level indicates the amount of traffic load generated on the network and impacts the reliability of communications and routing performances. AGNN-LB achieved 4.2% in terms of congestion level while GWLBC and DBlock-RLB showed 15.6% and 11.8%, respectively. By predicting the traffic load in advance and intelligently adapting the routing decisions to relieve the congestion. Traditional load balancing schemes act upon traffic congestion once the queues are filled up which increases packet drops and communication delays. Instead AGNN-LB measures queue occupancy, traffic loads, and neighbor interactions with graph feature learning methods and forecasts potential congestion zones ahead of time. Then, it reroutes the data packets before the queues are full through alternative paths. By doing this, excessive packet load is avoided, and seamless communications can take place. Moreover, the load gets distributed across multiple forwarding paths rather than congesting onto a single route. Hence, overflow of packets in queues can be avoided and better use of communication resources can be achieved. Low congestion level depicts the stable performance of AGNN-LB even with the dynamic traffic patterns.

3.5 End-End Delay (E2ED)

End-to-End Delay (E2ED) metric accounts for the time consumed that packets to reach from source nodes to destination nodes. From simulation results, we can observe that AGNN-LB attained an average delay of 18.6 ms which is lower compared to GWLBC (74.5 ms) and DBlock-RLB (61.3 ms). The lower delay achieved by our model is attributed to the identification of low congestion paths that require lesser energy for packet transmissions. In traditional routing approaches, packets can suffer from waiting times due to congested forwarding nodes, queued packets and excess route reconfigurations. However, with AGNN-LB, graph neural learning takes care of online network conditions where learned node embeddings depict the congestion state along with link quality and traffic distribution knowledge. Consequently, forwarding nodes with short transmission range and low communication overhead can be selected for packet forwarding. Additionally, routes can be dynamically configured to ensure packets can bypass congested regions while propagating through the network. Nodes waiting time and packet re-transmission delay can therefore be greatly alleviated. The attained delay performance of 18.6 ms shows that AGNN-LB facilitates swift communication which can be deployed in real-time scenarios for WSN applications.

3.6 Ablation Study

To verify the effectiveness of each module in AGNN-LB, we conducted an ablation study on five variants of our proposed model. We define five different setups of AGNN-LB models as follows: (i) Baseline Routing: baseline method that does not have graph learning ability. (ii) Graph Representation: leverages graph representation to obtain network-wide topology

Table 5. Comparative Analysis Results (Up to 1500 NC)

Node Count	Energy Efficiency (%)	Network Lifetime (%)	Load Balancing Index (%)	Congestion Level (%)	End-to-End Delay (ms)
250	98.4	98.8	98.1	2.1	11.2
500	97.9	98.3	97.8	2.7	12.8
750	97.3	97.9	97.2	3.4	14.7
1000	96.8	97.4	96.5	4.2	18.6
1250	96.1	96.8	95.9	5.1	21.4
1500	95.4	96.2	95.1	6.3	24.7

Table 6. Alternative Simulation Rounds (Up to 3000 NC)

Node Count	Energy Efficiency (%)	Network Lifetime (%)	Load Balancing Index (%)	Congestion Level (%)	End-to-End Delay (ms)
500	98.7	99	98.3	1.9	10.8
1000	98.1	98.4	97.9	2.6	12.6
1500	97.6	98	97.4	3.2	14.8
2000	97.2	97.7	97	3.7	16.3
2500	96.9	97.5	96.8	4	17.4
3000	96.8	97.4	96.5	4.2	18.6

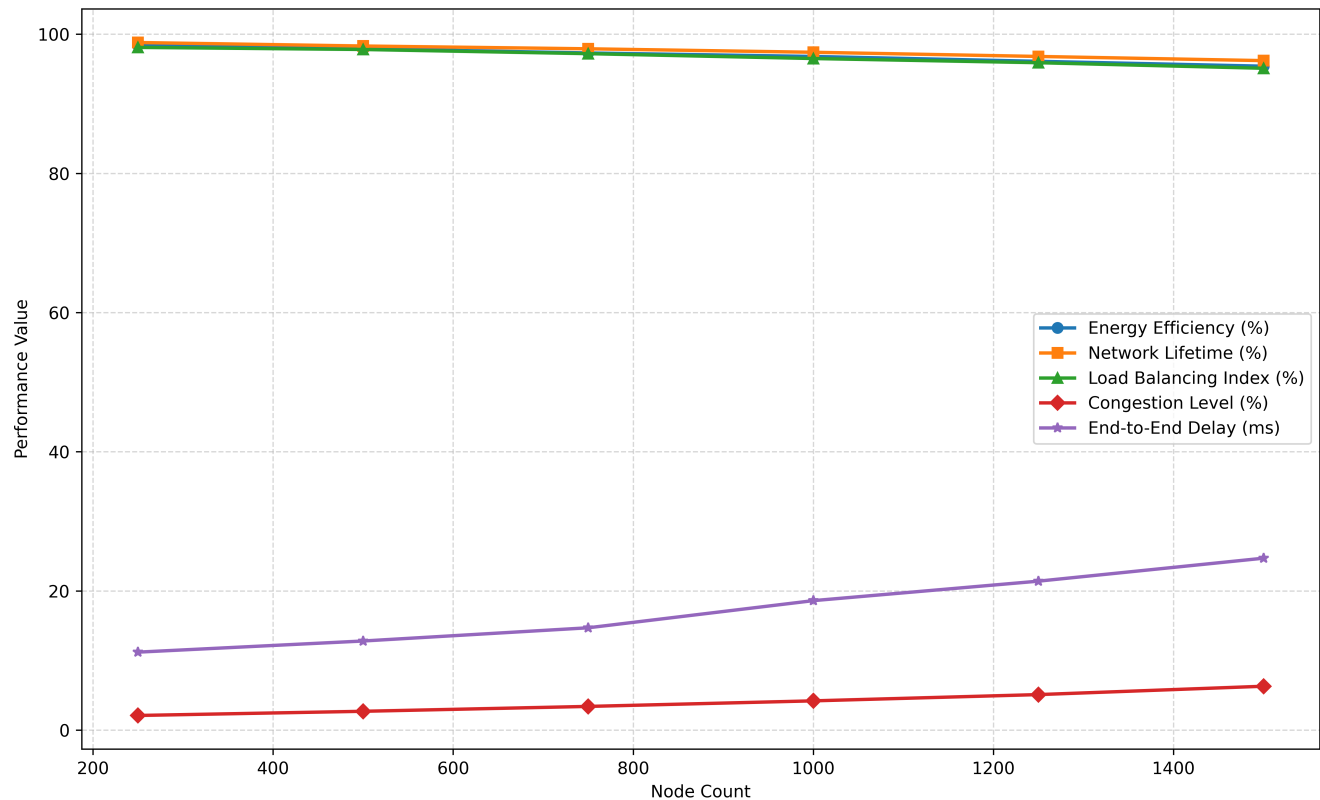


Fig 8. Analysis of Performance Metrics across Node Counts (1500)

awareness. (iii) Graph Representation with Node Embedding Learning: integrates node embedding learning into graph representation. (iv) Graph Learning with Energy Prediction: learns graphs without graph representation while predicting energy-rich forwarding nodes. (v) AGNN-LB model: applies graph learning, congestion prediction, adaptive load scoring, and routing optimization as discussed in Section III-B. The baseline model achieves mediocre load balancing since the forwarding decisions are pre-determined and do not change throughout the simulation. Graph Representation enables the model to learn about the underlying topology and make forwarding decisions to improve traffic load distribution across the network. Graph Representation with Node Embedding Learning further improves network performance by aggregating richer neighborhood information through node embedding learning to enable intelligent routing decisions. Graph Learning with Energy Prediction helps to prolong the lifetime of nodes by minimizing routing decisions toward energy-depleted nodes. Leveraging congestion prediction and adaptively scoring routes further improves network stability as shown in Table 4. Here, we achieve an energy efficiency of 96.8%, network lifetime of 97.4%, and load balancing index of 96.5%.

3.7 Complexity Analysis

The complexity of our proposed AGNN-LB framework is dominated by graph construction, neighborhood aggregation and graph neural network learning. Graph construction requires $O(|V| + |E|)$ complexity, where $|V|$ is the number of sensor nodes and $|E|$ is the number of communication links between sensor nodes. The computation complexity for neighborhood information aggregation during graph convolution is $O(|E|F)$, where F is the dimensionality of features. Generating node embeddings and predicting the link load are both linear in the number of nodes, thus having a complexity of $O(|V|F)$. Congestion prediction and routing score calculation both require lightweight operations on nodes, without heavy dependence on network size, enabling scalability to large networks. Overall, we can approximate the complexity of AGNN-LB to be $O(|E|F + |V|F)$, which is substantially more efficient than many metaheuristic optimization techniques that must run iterative search steps many times over. Therefore, AGNN-LB can enable real-time load balancing and routing optimization at scale in large wireless sensor network deployments.

4 Conclusion

This study proposed an Adaptive Graph Neural Network- Based Load Balancing (AGNN-LB) Model that takes energy efficiency and congestion into consideration to maintain wireless sensor networks. Our AGNN-LB model combines the graph-based representation of network topology, adaptive node feature learning, energy-aware load prediction, and smart routing optimization to overcome the limitations of existing load balancing techniques. It captures the spatial dependencies among adjacent sensor nodes to learn and dynamically discover potential forwarding nodes, redistributing network traffic based on the learned topology. Extensive experiments conducted on the AGNN-WSN20-26 dataset and NS-3 simulations showed that AGNN-LB consistently outperforms existing benchmarks across all performance metrics. The results showed that AGNN-LB achieved 96.8% energy efficiency, 97.4% network lifetime, and 96.5% load balancing index while minimizing congestion level to 4.2% and end-to-end delay to 18.6 ms. Moreover, comparative analysis with GWLBC and DBlock-RLB proves that graph-driven adaptive learning enhances resource utilization, communication reliability, and network lifetime.

Evaluation of the proposed model is done through synthetic dataset generation and simulation platform instead of large-scale physical deployment(s). While promising results are shown with AGNN-LB, further experimentation to validate the algorithm through real mobility patterns, sensor platform variability, and scale with large 6G-enabled IoT environments is needed to understand longevity of robustness and potential for deployment.

5 Abbreviations

AGNN-LB – Adaptive Graph Neural Network-Based Load Balancing

WSN – Wireless Sensor Network

GNN – Graph Neural Network

GCN – Graph Convolutional Network

RSSI – Received Signal Strength Indicator

LBI – Load Balancing Index

E2ED – End-to-End Delay

NS-3 – Network Simulator Version 3

GWLBC – Gray Wolf Optimization-Based Load Balanced Clustering

SDWSN – Software Defined Wireless Sensor Network

References

- 1) Wang NC, Lee CY, Chen YL, Chen CM, Chen ZZ. An Energy Efficient Load Balancing Tree-Based Data Aggregation Scheme for Grid-Based Wireless Sensor Networks. *Sensors*. 2022;22(23):9303. <https://doi.org/10.3390/s22239303>.
- 2) Tsoumanis G, Giannakeas N, Tzallas AT, Glavas E, Koritsoglou K, Karvounis E, et al. A Traffic-Load-Based Algorithm for Wireless Sensor Networks' Lifetime Extension. *Information*. 2022;13(4):202. <https://doi.org/10.3390/info13040202>.
- 3) Wu D, Li J, Ferini A, Xu YT, Jenkin M, Jang S, et al. Reinforcement learning for communication load balancing: approaches and challenges. *Frontiers in Computer Science*. 2023;5:1156064. <https://doi.org/10.3389/fcomp.2023.1156064>.
- 4) Yu CM, Tala't M, Chiu CH, Huang CY. Joint Balanced Routing and Energy Harvesting Strategy for Maximizing Network Lifetime in WSNs. *Energies*. 2021;12(12):2336. <https://doi.org/10.3390/en12122336>.
- 5) Hilda S, Kalaiselvi C. Multi Agent Energy Management Prediction and Load Balanced Clustering Framework for WSNs using Quantum Bio-Inspired PSO Optimization. *Indian Journal of Science and Technology*. 2025;18(48):3971–3992. <https://doi.org/10.17485/IJST/v18i48.1926>.
- 6) Yogaraja GSR, Thippeswamy MN, Venkatesh K. Optimal load balancing strategy-based centralised sensor for a WSN-based cloud-IoT framework using a hybrid meta-heuristic strategy. *International Journal of Autonomous and Adaptive Communications Systems*. 2024;17(3):247–271. <https://doi.org/10.1504/ijaacs.2024.138167>.
- 7) Prabhu TS, Eldho KJ, Karthikeyan B, Vasanthi V. Securing next generation 6G wireless networks through intelligent bio-inspired routing with energy optimization for enhanced authentication. *Indian Journal of Science and Technology*. 2025;18(23):1882–1895. <https://doi.org/10.17485/ijst/v18i23.850>.
- 8) Singh S, Nikolovski S, Chakrabarti P. GWLBC: Gray Wolf Optimization Based Load Balanced Clustering for Sustainable WSNs in Smart City Environment. *Sensors*. 2022;22(19):7113. <https://doi.org/10.3390/s22197113>.
- 9) Vaggu NM, Barpanda RS. DBlock-RLB: An Energy Efficient Framework for Intelligent Routing and Trading Based Load Balancing in SDWSN Environment. *Ad Hoc Networks*. 2024;159:103475. <https://doi.org/10.1016/j.adhoc.2024.103475>.
- 10) Eldho KJ, Nithyanandh S, Kowsalya R, Jose DV. Optimizing Network Reliability and Fault Detection in WSN-Assisted Autonomous Vehicle Systems Using QHHO-GNN Model. *International Journal of Computer Networks and Applications*. 2025;12(4):614–630. <https://dx.doi.org/10.22247/ijcna/2025/37>.
- 11) Kanellopoulos D, Sharma VK. Dynamic Load Balancing Techniques in the IoT: A Review. *Symmetry*. 2022;14(12):2554. <https://doi.org/10.3390/sym14122554>.
- 12) Devi PA, Megala D, Paviyasre N, Nithyanandh S. Robust AI Based Bio Inspired Protocol using GANs for Secure and Efficient Data Transmission in IoT to Minimize Data Loss. *Indian Journal of Science and Technology*. 2024;17(35):3609–3622. <https://doi.org/10.17485/IJST/v17i35.2342>.
- 13) Nithyanandh S, Jaiganesh V. Quality of service enabled intelligent water drop algorithm-based routing protocol for dynamic link failure detection in wireless sensor network. *Indian Journal of Science and Technology*. 2020;13(16):1641–1647. <https://doi.org/10.17485/IJST/v13i16.19>.
- 14) Machiwa EJ, Masanja VG, Matiko JW, et al. Data type classification-based dynamic traffic load balancing in wireless sensor network using WHLPESN and TDQ-LPOA. *Discovery Computing*. 2025;28:271. <https://doi.org/10.1007/s10791-025-09744-6>.
- 15) Omprakash S, Megala D, Karthikeyan MP. Energy Aware Adaptive Sleep Scheduling and Secured Data Transmission Protocol to enhance QoS in IoT Networks using Improvised Firefly Bio-Inspired Algorithm (EAP-IFBA). *Indian Journal of Science and Technology*. 2023;16(34):2753–2766. <https://doi.org/10.17485/IJST/v16i34.1706>.
- 16) Indhumathi G, Anil PS, Posiyya A, Suresh HR, Navaneethan S. Deep Learning-Based Tongue Biometrics for Secure Authentication in IoT-Driven Healthcare Systems. *Smart & Sustainable Technology (INCSST)*. 2025;p. 1–6. <https://doi.org/10.1109/INCSST64791.2025.11210319>.
- 17) Nivedita V, Joseph JA, Varghese DT, Sundaram J, Ali G. Multi-Modal Biometric Authentication Integrating Gait and Face Recognition for Mobile Security. *Smart & Sustainable Technology (INCSST)*. 2025;p. 1–6. <https://doi.org/10.1109/INCSST64791.2025.11210361>.
- 18) Lakshmi G, Senthilkumar A, Josephine VLH, Kowsalya R, Nithyanandh S. Quantum-Enhanced Lightweight Protocol for Post-Classical Security in IoT-Enabled Autonomous Vehicle Networks. *International Journal of Computer Networks and Applications*. 2026;13(2):314–337. <https://dx.doi.org/10.22247/ijcna/2026/17>.
- 19) Shekhar J, Ramya M, Chandrasekar A, N S, P D, Madhan A. MiniGCN: Mini-Batch Graph Convolutional Networks for Hyperspectral Image Classification. 2025 *Global Conference on Information Technology and Communication Networks (GITCON)*. 2026;p. 1–6. Belagavi, India. <https://doi.org/10.1109/GITCON65266.2025.11378144>.
- 20) Angurala M, Bala M, Bamber SS. A Novel Technique for Energy Replenishment and Load Balancing in Wireless Sensor Networks. *Optik*. 2021;248:168136. <https://doi.org/10.1016/j.jileo.2021.168136>.
- 21) Khan R. An Efficient Load Balancing and Performance Optimization Scheme for Constraint Oriented Networks. *Simulation Modelling Practice and Theory*. 2019;96:101930. <https://doi.org/10.1016/j.simpat.2019.101930>.
- 22) Revanesh M, Acken JM, Sridhar V. DAG Block: Trust Aware Load Balanced Routing and Lightweight Authentication Encryption in WSN. *Future Generation Computer Systems*. 2023;140:402–421. <https://doi.org/10.1016/j.future.2022.10.011>.
- 23) Hao S, Gao J, Cui J, Chen Y, Fan X, Li Z. An Energy-Balanced and Load-Aware Routing Algorithm Based on Molecular Diffusion Theory for Energy Harvesting Assisted WSN. *Internet of Things*. 2025;33:101691. <https://doi.org/10.1016/j.iot.2025.101691>.
- 24) Ullah I, Arishi A, Singh SK, Alharbi F, Ibrahim AH, Islam M, et al. Autonomous Network Management for 6G Communication: A Comprehensive Survey. *Digital Communications and Networks*. 2025;11(5):1917–1940. <https://doi.org/10.1016/j.dcan.2025.07.001>.
- 25) Dash D. A Novel Two-Phase Energy Efficient Load Balancing Scheme for Efficient Data Collection for Energy Harvesting WSNs Using Mobile Sink. *Ad Hoc Networks*. 2023;144:103136. <https://doi.org/10.1016/j.adhoc.2023.103136>.
- 26) Selvam N, Jaiganesh V. Interrogation of Dynamic Node Link Failure by Utilizing Bio Inspired Techniques to Enhance Quality of Service in Wireless Sensor Networks. *Shodhganga*. 2021. Thesis ID: 400513. Available from: <http://hdl.handle.net/10603/400513>.
- 27) Benelhour A, Idrissi-Saba H, Antari J. An Evolutionary Routing Protocol for Load Balancing and QoS Enhancement in IoT Enabled Heterogeneous WSNs. *Simulation Modelling Practice and Theory*. 2023;124:102729. <https://doi.org/10.1016/j.simpat.2023.102729>.
- 28) Veerabadrappa, Marikannan BP. Lifetime Centric Load Balancing Mechanism in Wireless Sensor Network Based IoT Environment. *International Journal of Electrical and Computer Engineering (IJECE)*. 2021;11(5):4183–4193. <https://doi.org/10.11591/ijece.v11i5.pp4183-4193>.
- 29) Senouci O, Benaouda N. Supervised Machine Learning-Based ETX Optimization for Energy-Efficient Routing in IoT-Enabled WSNs. *Ad Hoc Networks*. 2025;178:103972. <https://doi.org/10.1016/j.adhoc.2025.103972>.
- 30) Zhaohui Z, Jiaqi Z, Jing L. Q-Learning-Based Semi-Fixed Clustering Routing Algorithm in WSNs. *Ad Hoc Networks*. 2025;174:103837. <https://doi.org/10.1016/j.adhoc.2025.103837>.