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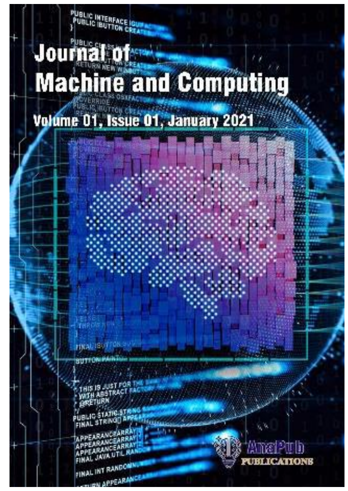

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EdgeAware-CHNet: A Federated Deep Learning Framework for Adaptive Cluster Head Selection in Scalable IoT-Enabled WSNs

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Abstract

The emergence of Internet of Things (IoT)-enabled Wireless Sensor Networks (WSNs) has revolutionized real-time monitoring in various domains, from environmental surveillance to industrial automation. Cluster head (CH) selection is also a complex process to perform efficiently and with low energy consumption, most particularly in a large-scale dynamic network. The paper presents EdgeAware-CHNet, a new fusion-decompose architecture, implemented by deep learning that allows adaptive and intelligent CH selection, information privacy, and minimal energy costs. The proposed system involves deployment of a MobileNetV2-Temporal Convolutional Network (TCN) hybrid model at edge devices; these devices learn the local patterns of data, using which they coordinate updates of data based on the Federated Averaging (FedAvg) algorithm without raw data sharing. Further, the strategies of CH selection are improved using a Deep Q-Network (DQN)-based reinforcement optimization module on the basis of energy efficiency, latency, and feedback on packet delivery. The soft-attention layers reinforce the spatial prioritization of CH candidates, which can make the system dynamic to the topology variances and a dynamic workload. Full simulation demonstrates the superiority of EdgeAware-CHNet in the important performance scales as compared to traditional and learning-based baselines. This model suggested a 96.45% degree of accuracy of CH selection, the network lifetime of 1820 rounds, and a PDR of 97.22, which is considerably higher than such models as LEACH, TEEN, and DQN-CH. Due to the synergistic integration of federated intelligence, reinforcement learning, and edge-aware optimization, EdgeAware-CHNet is a highly efficient and secure framework that can be used to address present-day WSN deployments.

Keywords: Federated Learning, Cluster Head Selection, IoT, Wireless Sensor Networks, Edge Computing, Deep Learning, DQN, Energy Efficiency, Packet Delivery Ratio, Attention Mechanism.

1. Introduction

The spread of the Internet of Things (IoT) has resulted in the multiplicative increase in connected devices, many of which are run in Wireless Sensor Networks (WSNs). Such networks include spatially dispersed sensor nodes sensing an environmental or physical condition including temperature, humidity, vibration, or motion and passing the data to a central sink node [1] [2] [3]. The field of autonomous operation as well as the possibility of functioning under extreme conditions or in remote areas allows WSNs to find widespread use in fields such as healthcare, agriculture, smart cities, industrial automation, and military surveillance. One of the basic issues within a WSN is energy management. Sensor node usually run off a limited battery supply and it is not always possible to recharge or replace the nodes. Therefore, methods of energy savings at the same time ensuring that there is no loss of communication delivery or high latency, are important to the sustainability of these networks. Cluster-based routing protocols are one of the energy-saving strategies which have drawn a lot of attention [4] [5] [6]. In such protocols, nodes are grouped to form clusters with a Cluster Head (CH) that collects and transmits data to the base station, thus decreasing unnecessary transmissions and energy [7].

Some clustering algorithms were proposed over the years. Conventional algorithms such as, LEACH (Low Energy Adaptive Clustering Hierarchy) TEEN (Threshold-sensitive Energy Efficient sensor Network protocol) and PEGASIS are probabilistic or threshold choosing CH. Albeit these techniques are computationally cheap, they are usually oblivious of contextual parameters like residual energy, link quality, and node centrality [8] [9]. They experience quick node depletion, imbalance in energy consumption, and poor routing of data. The most progress has been made in the recent entry of machine learning (ML) and deep learning (DL) processes into WSNs. Models including Random Forests, Support Vector Machines, Convolutional Neural Networks (CNNs) have been used both to increase CH selection accuracy as well as to predict network behavior [10] [11] [12]. Most ML/DL approaches are computationally centralized, which is problematic regarding privacy, particularly when the transmitted sensor information involves sensitive data: it might be sent to distant servers to undergo training. In addition, deep learning models are computationally demanding and are not well suited to run an edge device with a limited computing section [13] [14] [15]. Figure 1 illustrates the process of adaptive cluster head selection in a scalable IoT-enabled wireless sensor network.

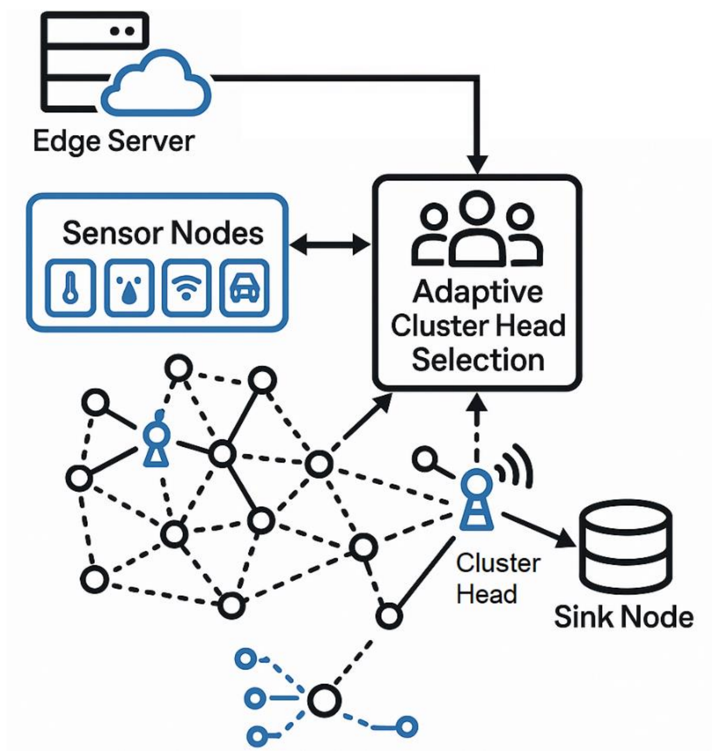

Figure 1. Adaptive Cluster Head Selection in IoT-Enabled WSNs

Federated learning (FL) has thus become a revolutionary tool in dealing with such issues. The use of FL allows training several models on edge nodes without exchanging raw data, which allows preserving privacy and minimizing communication difficulties. Currently, available FL-based CH selection schemes such as FL-CH and FL-BS are limited in terms of scalability, should not have dynamic feedback, and they never prioritize CH selection based on locations. Reinforcement learning incorporated in the selection of CHs has been promising. DQN Deep Q-Networks enable agents to perform an optimized learning algorithm with respect to CH policies that uses a set long-term rewards derived of networks states. These models are however time consuming with large amounts of training data and do not capture the temporal dependencies in the sensor behavior. In order to surpass the shortcomings of existing models, we suggest a highly flexible and realistic framework titled EdgeAware-CHNet. The framework presents a federated deep learning framework based on MobileNetV2 and Temporal Convolutional Networks (TCNs) to collect spatio-temporal features in an edge-level. FedAvg is used to aggregate these features to a global model that is used to make CH selection decisions. A reinforcement component based on the DQN approach is also introduced to update the CH selection policy according to the rewards provided by dynamic network. Attention mechanism is used to prioritize spatially significant nodes, to improve CH decision-making process further. This combination of FL, RL, and attention provides the resilience of CH selection strategy that is admirable and that consumes lower energy and is intelligent enough.

1.1. Main Contribution of the Work

- An original federated deep learning framework of CH selection in IoT based WSNs is proposed through MobileNetV2 and TCN.
- Deep Q-Network-based reinforcement feedback module integration to dynamically optimize CH strategies.
- Use of an attention mechanism to give priority to the spatially central and energy-rich nodes in selection of CHs.
- The use of lightweight and resource-starved models at the edge to make decisions in real-time, without giving up energy.
- Design of an energy-friendly load balancing and opportunistic routing scheme to reduce the latency and to extend the lifetime of the networks.

Section 2 provides a survey of related studies, highlighting limitations in traditional and learning-based CH selection methods. Section 3 details the proposed EdgeAware-CHNet methodology, including sensor deployment, federated training, and adaptive optimization. Section 4 describes the results and discussion, including comparative performance metrics across ten models. Finally, Section 5 concludes the paper and outlines future directions for extending the framework in real-world WSN deployments.

2. Related Work

The ability of the Internet of Things (IoT) to send and receive data between devices means that it is essential in smart infrastructure, as well disaster response. In order to deal with energy efficiency in smart cities, this article proposes a hybrid genetic algorithm (GA)-based protocol that consists of greedy mutation strategy over IoT based heterogeneous wireless sensor networks (WSNs) [16]. The method uses weighted fitness criterion on the node density, remaining and average energy, as well as distance. Even more, the performance is boosted by a 3-tier node heterogeneity model and energy-efficient deployment strategy. The suggested approach increases network life by up to 31.41% more than the current GA-based algorithms, representing its sustainability of smart city systems.

The Internet of Things (IoT) has been changing the face of agriculture, empowering it with real-time control over different factors influencing the environment such as temperature, humidity, and soil moisture, improving the process of crop management and yield. Nevertheless, sensor data is very huge, which poses cumbersome processing and communication problems [17]. An efficient clustering algorithm was presented with the modification of the fuzzy logic to determine cluster heads (CH) and an improved Crow swarm optimization algorithm (ECSO) in order to find the best data delivery path. Simulation output of a smart agricultural system indicates that this strategy yields better performance values-68 Mbps throughput and a 90.9% packet delivery indicator than the current approaches perform in terms of energy consumption and delay as well as communication integrity, thereby enhancing productivity and profitability.

Wireless Sensor Networks (WSNs) and the Internet of Things (IoT) are revolutionary technologies that are redefining industries such as agriculture, healthcare, environment monitoring among others. IoT-based WSNs in agriculture comprise the application of a sensor in soil moisture monitoring, crop health, irrigation, and temperature that help make intelligent decisions and enhance yields. The performance however is hampered by the energy and memory constraints of sensors, especially on large scale deployments [18]. A solution to this is what we call EEDC, an Energy Efficient Data Communication with Region based hierarchical Clustering towards Efficient Routing (RHCER). The multi-tier structure also with the use of tier subdivision employs a multi-criteria decision to choose the head in the cluster for a balanced load distribution and multi-hop communication which is energy efficient. Through simulations, the energy saved by simulation is 31% and the drop ratio of packets increases to 38%.

The Internet of Things (IoT) has revolutionized agriculture since it allows real-time tracking of environmental conditions such as temperature, moisture, humidity, and crop development. Although this enhances better decision-making and grain production, the large amount of data that is collected is a challenge to handle [19]. That the use of modified fuzzy logic to select the cluster head (CH) and the use of Enhanced Crow Swarm Optimization (ECSO) as a means of optimal routing assisted by the Whale Optimization Algorithm (WOA). Throughput (68 Mbps), packet delivery ratio (90.9%), delay and energy efficiency have shown a improvement in simulation results of a smart agriculture scenario which outsmarts competitors when it comes to agricultural productivity and profitability.

The major constraint in the IoT-enabled Wireless Sensor Networks (WSNs) is energy dissipation, and thus optimum utilization of energy is crucial to enhancing the lifespan of the network. Clustering is a suitable approach of load balancing and scalability. A scheme involving Genetic Algorithm (GA) proposed to overcome energy waste [20]. Stochastic Cluster Head Selection Model (SCHSM) uses the factors such as node energy, node distance, node density, node capacity in the fitness formula. Optimized in such a way as to be used on networks of multiple sink nodes that move, the protocol not only enhances the distribution of energy, but also reduces communication holes through some sort of sink location. There is also conformation on simulation results which show that the protocol improves network performance.

3. Methodology

EdgeAware-CHNet uses WSN nodes that are deployed in a dynamic environment using IoT facilities. Environmental and connectivity data are gathered at each node, and preprocessed locally. Each edge device is trained with a MobileNetV2-TCN model to have the ability to extract spatiotemporal features and weights on the model will be averaged with FedAvg. The global model is used to compute CH probabilities and attention weighting is also used. A Deep Q-Network improves on these choices according to rewards of the network such as latency and energy efficiency. The final CH list entails edge-aware routing and workload scheduling to get optimal WSN performance. Figure 2 shows the architecture of proposed model.

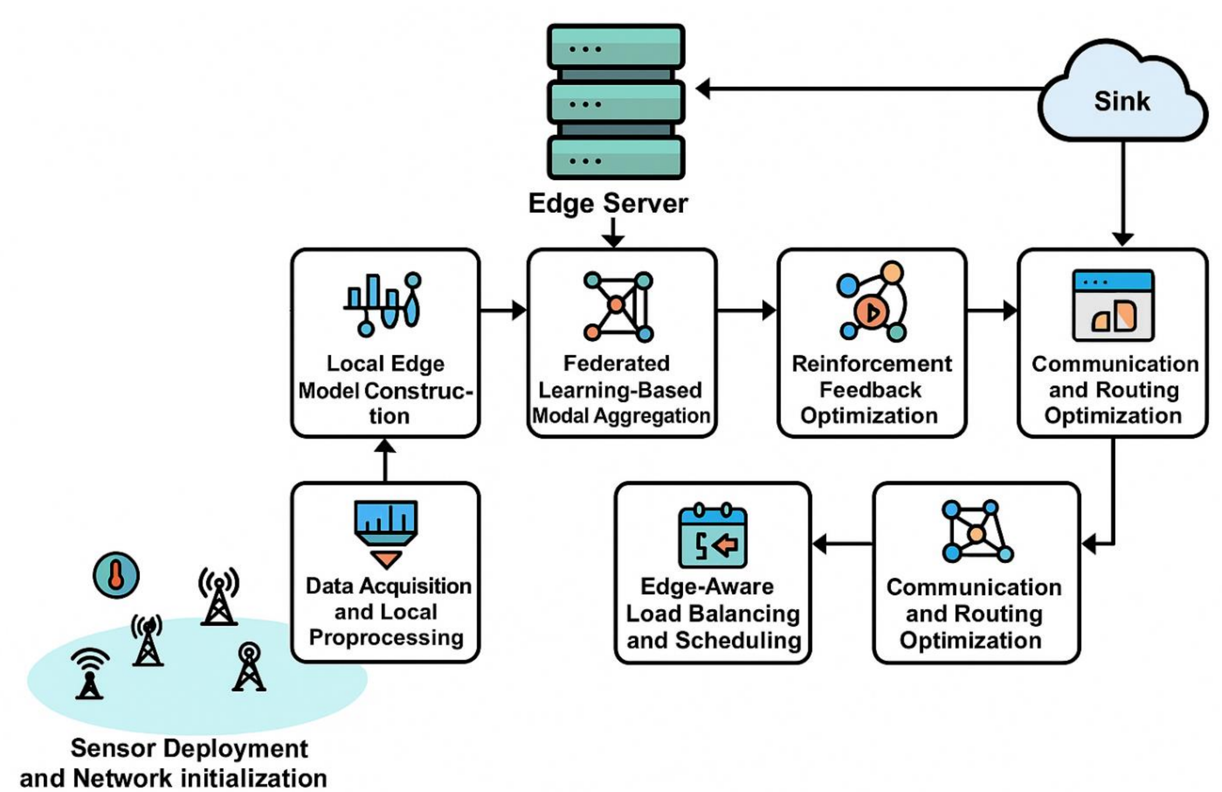

Figure 2. Architecture of Proposed Model

3.1. Sensor Deployment and Network Initialization

EdgeAware-CHNet remains anchored on the strategic positioning of heterogeneous wireless sensor network (WSN) nodes that are IoT-enabled. These sensor nodes are dispersed across an area of varying sizes of monitoring, which is often modeled as a 500m width by 500m length since most applications use this size of the field, however, to suit the applications need the framework can be scaled to a larger or smaller area. The deployment assumes different densities of the nodes, such as from sparse to ultra-dense nodes, to present realistic scenarios of the scalability challenges. Nodes have a special sensing system that is custom to the environmental monitors like a temperature, humidity, vibration, or motion sensor. A given identifier is introduced to each node, and it is set at a few geographic coordinates randomly or with the help of a grid structure that enables a proper spatial distribution. Besides a geographical position, nodes will be initialized with remaining batteries at different levels, namely between 0.5 and 1.0 J, simulating different battery levels. To emulate the short-range transmission body seen in energy-constrained WSNs, their range of communication is normally limited to 50 meters. There is also disparity in hard ware features i.e. CPU speed, memory size, sensing interval in the sensor nodes. The system distinguishes common nodes and gateway nodes or edge servers that are intermediaries between the WSN and the cloud. These edge servers are more computationally and storage-sufficient, and they become very vital in both the federated learning process and cluster administration. The parameter initialization of node mobility in mobile sensor setup and assignment of neighbor lists in accordance with their vicinity and link quality is also part of initialization procedure.

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \qquad (1)$$

Where d_{ij} is the Euclidean distance between nodes i and j and $(x_i, y_i), \left(x_j, y_j\right)$ are coordinates of nodes i and j.

3.2. Data Acquisition and Local Preprocessing

After the integration and initialization of the nodes, monitoring and data acquisition becomes constant. Every node in the network measures environmental factors e.g. temperature, humidity, sound, or gas, at a regular time interval depending on the nature of sensor. At the same time, it collects metadata that is essential in handling the network, such as Received Signal Strength Indicator (RSSI), Signal-to-Noise Ratio (SNR), link quality, battery level and mobility index (of mobile nodes). These data points are not only necessary when performing analysis specific to application, but they are also significant in sustaining health and structure of the network. Raw sensor data however are typically prone to noise following physical interference, hardware inaccuracies, and environmental influence. Thus, the nodes will perform lightweight local preprocessing to enhance the integrity of data prior to training the models.

$$z = \frac{x - \mu}{\sigma} \qquad (2)$$

Where x is the raw input value, μ is the mean of the feature, σ is the standard deviation of the feature and z is the normalized output. The preprocessing pipeline starts with anomaly detection which is performed with a filter based on moving average to remove temporary upward and downward fluctuations in data values. Outliers outside of a particular threshold of standard deviations are removed or smoothed according to local heuristics. Then the data is filtered and afterward, Z-score normalization is performed in order to make the data standard, so that features like RSSI or battery levels have a zero mean and unit variance. This avoids the feature dominance, and the local training convergence is faster. Location updates in mobile WSN are also normalized around prior movement centroid in order to maintain context that is consistent. Timestamps are synced with the lightweight protocols to make time-series consistencies of edge model inputs. The locally preprocessed information is next inserted into a temporary sliding buffer having a fixed window size, so that this information is accessible in training the local model and also said information is not unnecessarily duplicated in the memory.

3.3. Local Edge Model Construction

In order to facilitate the decentralized intelligence in WSNs, a lightweight model can be located in each edge node, and the model can learn and make decisions in the local level. In contrast to the CNN-BiLSTM models and variants, that, despite being efficient, might require a lot of processing resources, EdgeAware-CHNet has a more cost-efficient architecture, the MobileNetV2-Temporal Convolution Network (TCN) hybrid. MobileNetV2 is the ladder to extracting feature/characteristics-rich and spatial representations of structured sensor data. It also utilizes depth wise separable convolutions which help to decrease the number of parameters and computational requirements thus, it is well-suited to resource-constrained environments at the edge.

$$y(t) = \sum_{k=0}^{K-1} x(t - r \cdot k) \cdot w(k) \tag{2}$$

Where $y(t)$ is the output at time t, x is the input signal, $w(k)$ is the kernel weights, r is the dilation rate and K is the Kernel size. The Temporal Convolution Network (TCN) on top of MobileNetV2 exploits the time-based dependencies encountered in sequential data like RSSI or battery level trends. TCNs also employ the causal convolution and dilation to conserve temporality and long-term memory, but unlike LSTMs and GRUs do not employ recurrent connections. This architecture thereby, lowers the latency and heightens parallelism throughout training and inference. The end-product of the hybrid model is an output of low-dimensional feature vector containing the spatial features of the local surrounding and the temporal features of node. They are computed as the quality scores assigned to nodes these feature vectors are used to determine whether the node will be selected as a Cluster Head (CH) or not. In order to avoid over fitting as well as to avoid overloading the local node, early stop conditions and drop out regularization are used. The data are not exchanged, as a part of the trained model parameters are transferred to the edge server in the case of federated aggregation.

3.4. Federated Learning-Based Model Aggregation

EdgeAware-CHNet incorporates a Federated Learning (FL) in order to optimize the global model globally to reduce overhead in data transmission and maintain privacy. Unlike uploading the raw sensitive data to a central storage or server, every node would train the MobileNetV2-TCN model independently on their local data. Once the local model training of a specified epochs has been performed, the nodes transmit the current weight of this model into a subsequent aggregator, which is, in most cases, using a more powerful edge server or gateway node.

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^{(k)} \tag{3}$$

Where w_{t+1} is the aggregated model weights at round $t + 1, w_t^{(k)}$ is the model weights from client k at round t, n_k is the number of samples at client k and $n = \sum_{k=1}^{K} n_k$ is the total number of samples across clients. These updates are aggregated into a single global model by the server via the Federated Averaging (FedAvg) algorithm. FedAvg takes an average of the parameters of the local model which are weighted by the number of the samples each node in training used. This approach guarantees that models of more active nodes will have a relatively bigger impact on the worldwide update. This model is subsequently redistributed to the nodes, so the network performs the same throughout. In addition to ensure additional security, lightweight homomorphic encryption can optionally be used to encrypt model updates. This federated paradigm is able to guarantee that sensitive sensor data in the node would not be available outside the node but still support collective intelligence so that CH can be better predicted and systems are more responsive. The global model hence progressively optimizes on several rounds, including various patterns of node behavior and environmental situations in the network.

3.5. Adaptive Cluster Head (CH) Probability Estimation

The selection of Cluster Head (CH) plays an important role in the energy efficiency and performance of WSN. With the global trained federated model, a probability of being chosen as a CH is computed on every node by means of several variables such as the remaining energy, degree of connectivity, mean link quality, and node centrality within its surrounding area. The MobileNetV2-TCN network produces a node quality score, normalized across the cluster, to obtain CH probability.

$$P_{CH}^{(i)} = \frac{\alpha E_i + \beta D_i + \gamma C_i}{\sum_{j=1}^{N} \left(\alpha E_j + \beta D_j + \gamma C_j\right)} \tag{4}$$

Where $P_{CH}^{(i)}$ is the probability of node i being selected as CH, E_i is the residual energy of node i, D_i is the degree centrality of node i, C_i is the connectivity strength, α, β, γ are weighting factors, and N is the total number of nodes. A soft attention mechanism is incorporated into the edge server in order to develop spatial awareness and dynamic adaptability. Such a layer is interested in the spatial elements that play the role in CH selection e.g., nodes close to the cluster centroid or stable link structure. The attention mechanism uses the weights on each feature dimension, depending on how well the prior selection outcomes of CH were attained by the feature dimension. These weights are dynamically adjusted at every federated training round making the system to concentrate on features of more relevance to the prevailing network situations (e.g. high mobility vs. stationary deployment). Cluster Heads in each specific round are defined as nodes in a cluster with the highest probability of CH, but with the constraint of enabling nodes with remarkable performance not to be chosen early due to the rotation scheme.

$$\tilde{f}_i = \sum_{j=1}^{n} softmax\left(q_i^T k_j\right) \cdot v_j \qquad (5)$$

Where $\tilde{f}_i$ is the attention-enhanced feature representation for node i and q_i, k_j, v_j are query, key and value vectors and n is the total number of features.

3.6. Reinforcement Feedback Optimization

A Deep Q-Network (DQN) complement (a reinforcement learning module) is integrated to enhance the process of CH selection further and make it time-sensitive appropriate to real-time network performance requirements. This module runs at server end and constantly reviews the performance of previous CHs. The state vector given to the DQN framework contains an aggregate of performance indicators like energy consumption, packet delivery ratio, communication delay, and CH rotation frequency. The action space will have strategies of selection such as retain current CHs, rotate CHs or merge neighboring clusters.

$$R_t = \lambda_1 \cdot \Delta E + \lambda_2 \cdot PDR_t - \lambda_3 \cdot L_t \qquad (6)$$

Where R_t is the reward at time $t, \Delta E$ is the energy savings compared to previous round, PDR_t is the packet delivery ratio at time t, L_t is the latency at time t, and $\lambda_1, \lambda_2, \lambda_3$ are tunable weights. A reward function computes the effects on the performance of the system when an action is carried out. As the example, when energy consumption is reduced to the minimum and delivery ratio is maximized, high reward is assigned. The DQN adjusts its Q-values so that it can use them to decide on the CH to choose in the future. This reinforcement loop works parallel to federated training and offers a second round of optimization, so that the network can learn autonomously to find the most effective cluster formation strategies on its own based on the changing conditions in the environment or operating circumstances.

3.7. Edge-Aware Load Balancing and Scheduling

In order to avoid overloading some CHs, as well as provide fair distribution of energy, the edge server has a load balancing and scheduling mechanism. The edge server will reassign nodes such that no CH is overloaded based on node quality scores, traffic patterns and approximate predicted workload. The time-based workload trend is also considered by this scheduling engine: the time-series forecasting methods (e.g., Prophet or ARIMA) are used to predict the high communication periods.

$$L_i = \sum_{j \in C_i} \frac{R_j}{R_i} \qquad (7)$$

Where L_i is the load on CH i, C_i is the set of member nodes in cluster i, R_j is the data rate of node j, and R_i is the data capacity of CH i. To alleviate the load during high-load occasions, temporary micro-clusters can be created under secondary CHs to transfer the traffic offloaded by overloaded areas. Additionally, the scheduling engine contains sleep-wake where non-critical sensor nodes go in to suffer a sleep mode in off-peak time. The system monitors the feedback of the DQN module and local edge models to dynamically optimise distribution of load, communications, and use of resources.

3.8. Communication and Routing Optimization

The last stage of EdgeAware-CHNet is to provide secure and low-power consuming connections among Cluster Heads and central sink node. Custom routing protocol is utilized and designed based on a hybrid cost function, which integrates Euclidean distance, residual energy, and link stability. Every CH considers the potential routing paths, and chooses the one that requires the least amount of total cost to the sink.

$$Cost_{ij} = \alpha \cdot d_{ij} + \beta \cdot \left(\frac{1}{E_i}\right) \qquad (8)$$

Where $Cost_{ij}$ is the communication cost between nodes i and j, d_{ij} is the distance, E_i is the residual energy of sender node and α, β are tunable weighting parameters. In order to improve the fault tolerance and reduce the latency, the concept of opportunistic forwarding is also proposed, which means back up CHs will be selected to relieve the forwarding role during communication breakdown. The system also runs multipath routing when the traffic is high to overcome traffic congestion and loss of data. The dynamic updates of routing tables are performed on the basis of periodical health-check and node status broadcast packets. A TTL (Time-To-Live) counter is incorporated in packet headers to detect routing loops and delay so as to avoid them, and the input to the reinforcement module can be used to impose a penalty on unstable paths. The advantages of this communication strategy are high reliability and low latency of data transfer combined with energy conservation which is essential in long term WSN sustainability.

$$P_{tx} = P_0 + \eta \cdot d^{\gamma} \qquad (9)$$

Where P_{tz} is the transmission power, P_0 is the base power consumption, η is the medium-specific constant, d is the distance to receiver and γ is the path loss exponent.

3.9. Novelty of the Work

The EdgeAware-CHNet is the first to combine the federated deep learning, reinforcement feedback optimization, and spatial attention mechanism in an adaptive Cluster Head (CH) selection scheme in scalable Internet of Things (IoT)-enabled WSNs. In comparison to the currently existing models that utilize fixed thresholds or centralized training, EdgeAware-CHNet allows achieving privacy-preserving distributed intelligence through the training of MobileNetV2-TCN models at the edge and aggregation with FedAvg. This makes it possible to learn in the real-time without exposing raw data to various environments. The framework specially employs a Deep Q-Network (DQN) to be able to constantly optimize CH selection policies according to development in network conditions including energy, latency and PDR values. Another feature is a soft-attention architecture that introduces the priority of spatially important nodes, improving CH selection context and fairness. Its edge-optimized design makes it deployable even in nodes that have few resources. Such amalgamation of federated learning, reinforcement adaptation, and spatial intelligence is an original, scalable, and safe method of intelligent WSN management.

Algorithm: EdgeAware-CHNet – Federated Adaptive Cluster Head Selection

Input: $N = \{n_1, n_2, \dots, n_K\}$: Set of WSN nodes, D_k is the local dataset at node n_k.

E_k, C_k, D_k are residual energy, connectivity, and centrality of node n_k.

T is the number of federated training rounds.

Output: $P_{CH} = \left\{P_{CH}^{(1)}, P_{CH}^{(2)}, \dots, P_{CH}^{(K)}\right\}$ is the CH selection probabilities

$CH \subseteq N$ is the set of selected Cluster Heads

Initialization

For each $n_k \in N$

Assign initial energy $E_k \in [0.5,1.0]$, location (x_k, y_k), and transmission range R

$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ // Calculate pairwise distance

Data Acquisition and Preprocessing

Each node n_k acquires RSSI, SNR, battery level, and connectivity metrics from D_k

$z = \frac{x-\mu}{\sigma}$ // Normalize using Z-score

Local Model Training (MobileNetV2-TCN)

Train local MobileNetV2-TCN model M_k on D_k using causal convolution:

$y(t) = \sum_{k=0}^{K-1} x(t - r \cdot i) \cdot w(i)$

Federated Aggregation (FedAvg)

Transmit $w_k \leftarrow weights$ from M_k to aggregator.

$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^{(k)}$ // Aggregate global model

Broadcast updated weights w_{t+1} to all nodes.

CH Probability Estimation

For each node compute CH selection score:

$P_{CH}^{(i)} = \frac{\alpha E_k + \beta D_k + \gamma C_k}{\sum_{j=1}^{N}(\alpha E_j + \beta D_j + \gamma C_j)}$

$\tilde{f}_i = \sum_{j=1}^{n} softmax(q_i^T k_j) \cdot v_j$ // Enhance with attention

Reinforcement Optimization (DQN-based)

Initialize Q-table with state s_t as network status and action $a_t \in \{rotate, retain, merge\}$

$R_t = \lambda_1 \cdot \Delta E + \lambda_2 \cdot PDR_t - \lambda_3 \cdot L_t$ // Compute reward

Update Q-values using Bellman equation.

Load Balancing and Scheduling

$L_k = \sum_{j \in C_i} \frac{R_j}{R_k}$ // Estimate load

If $L_k > \tau$ (threshold)

Reassign members to balance load

Communication and Routing Optimization

$Cost_{ij} = \alpha \cdot d_{ij} + \beta \cdot \left(\frac{1}{E_i}\right)$ // Compute route cost

Determine minimal-cost route from CH to sink node using Dijkstra's or ACO-based heuristic.

Return: Selected Cluster Heads CH, and their selection probabilities P_{CH}

End Algorithm

4. Results and Discussions

EdgeAware-CHNet is a privacy preserving, scalable and adaptable framework that performs adaptive selection of cluster heads (CH) in IoT-enabled Wireless Sensor Network (WSNs). The essence of it is the combination of federated deep learning and edge-aware optimization to contribute to the network lifespan, energy efficiency, and well-balanced communication in dynamically varying sensor systems. The first step consists of heterogeneous sensor nodes that are distributed over a geographical area and which are initialized with the available energy, start position, and transmission capacity. These nodes constantly keep track of environmental or application specific parameters as well as gathering crucial metadata including signal strength, down to battery state and neighbor connections. Local preprocessing is done using features such as anomaly filtering, normalization to obtain clean and uniform data to feed the models. Figure 3 illustrates the spatial distribution of sensor nodes, with selected Cluster Heads (CHs) highlighted in red based on probabilistic criteria.

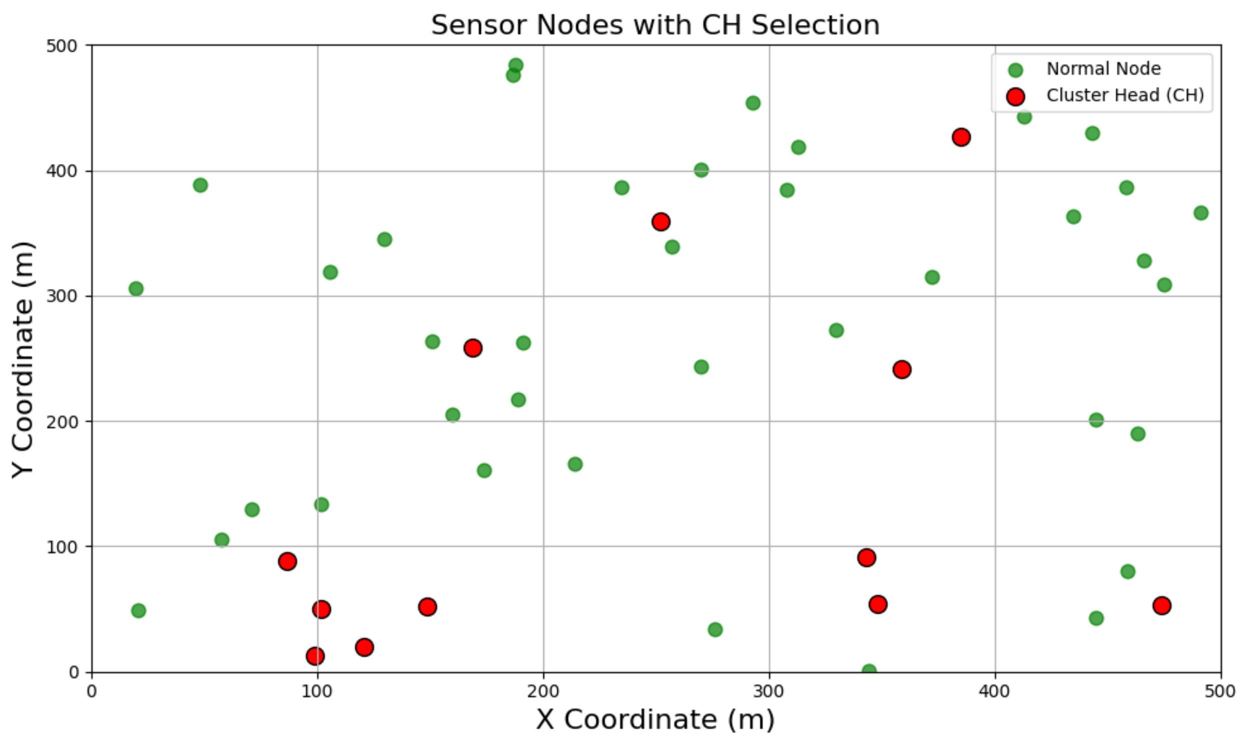

Figure 3. Cluster Head (CH) Selection among Deployed Sensor Nodes

Lightweight MobileNetV2-TCN model is trained by each edge node on locally gathered information. According to temporal and spatial attributes, these models learn to develop patterns which determine how well CH is suited, and thus optimal. The trained model weights can be transferred, say on a regular basis, to a capable edge server and simply averaged by using the Federated Averaging algorithm without sharing raw data. This is privacy-saving and overhead communicating factor can be considerably decreased. The attention mechanisms augment the global model, which computes the CH probability on every node. Deep Q-Network (DQN) reinforcement module will also define the best strategy of CH selection depending on the rewards such as energy efficiency, successful delivery, and latency. The system also forecasts communication loads and that makes the scheduling and routing balanced. Lastly, a hybrid cost-based routing framework is formed that is interpretive, low latency, and can support the forwarding of data efficiently and lengthens network lifetime. EdgeAware-CHNet thereby facilitates intelligent, adaptive and sustainable operations of the current IoT-WSNs.

Table 1: CH Selection Accuracy Comparison

Model	Accuracy (%)
EdgeAware-CHNet	96.45

LEACH	82.34
SEP	84.21
TEEN	85.76
PEGASIS	81.33
DEEC	86.45
HEED	83.29
PSO-CHS	90.67
FL-CH	92.14
DQN-CH	91.55

Table 1 and Figure 4 shows the CH selection accuracy of edgeAware-CHNet to the nine benchmark protocols. The proposed model demonstrates the maximum accuracy of 96.45%, which beats such conventional schemes as LEACH (82.34%) and PEGASIS (81.33%), which are based on the use of the fixed thresholds and do not follow the intelligent learning process. Other models that are slightly better because of the underlying consideration of residual energy like some as SEP, TEEN, and HEED though are not dynamically well adjusted to choosing the next suitable path in a varying networks. The learning-based methods, PSO-CHS, FL-CH, and DQN-CH, are more accurate, with results of up to 92.14%, but such methods do not meet the privacy-predicting training characteristics of federated learning.

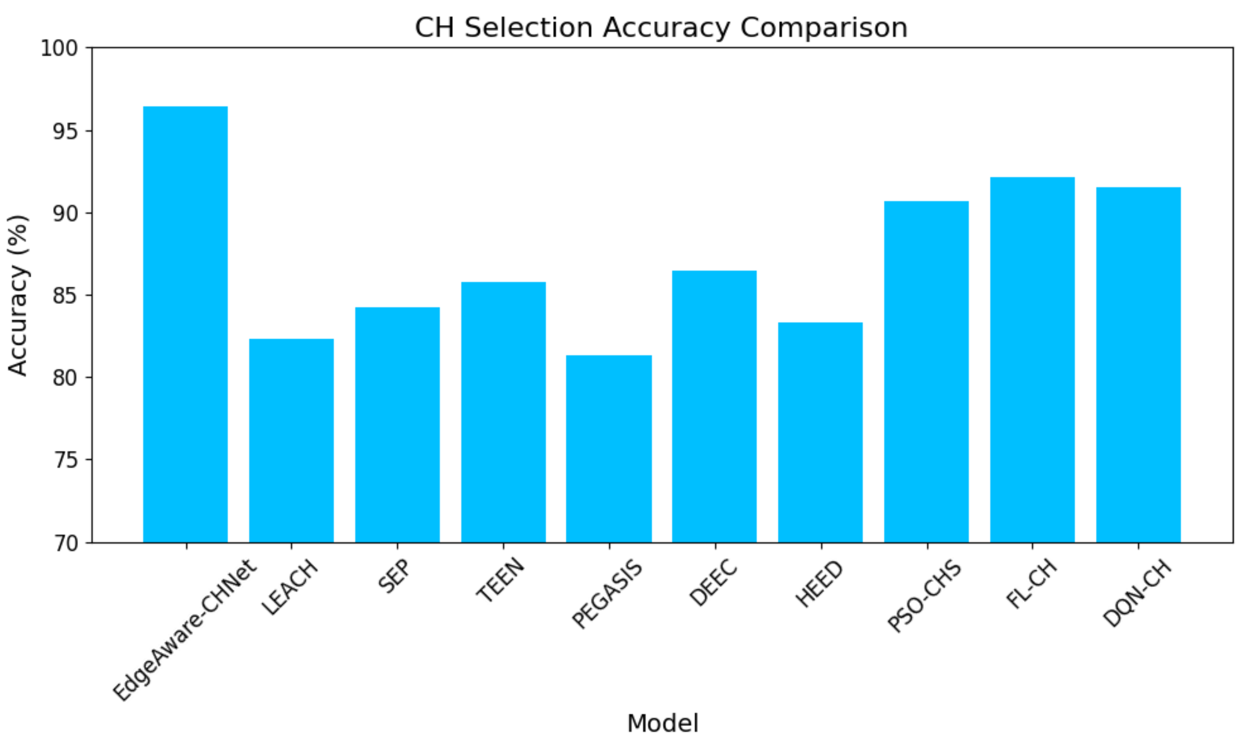

Figure 4. CH Selection Accuracy Comparison

Our superior performance can be explained by the high quality of EdgeAware-CHNet, which depends on the use of federated deep learning as well as the soft attention-based feature selection and probability refinement using the DQN. Such a high accuracy guarantees the best node selection, which has a direct bearing on the longevity of the network, energy balance, and quality of communications, and thus the system is sound when it comes to real-life applications of IoT-WSN even in different confinements.

Table 2: Network Lifetime Comparison (Rounds Until First Node Dies)

Model	Network Lifetime (Rounds)
EdgeAware-CHNet	1820
LEACH	1203
SEP	1267
TEEN	1298
PEGASIS	1155
DEEC	1344
HEED	1229
PSO-CHS	1603
FL-CH	1708
DQN-CH	1664

Table 2 and Figure 5 measures the lifetime of the network as number of rounds until death of the first node. EdgeAware-CHNet holds the most rounds (1820) comparatively to LEACH (1203) and SEP (1267). These traditional procedures have the tendency of overwhelming certain nodes leading to early exhaustion of energy. Both DEEC and TEEN have an improved performance (12981344 rounds) because of the energy-awareness of CH choice. Among the models based on learning, PSO-CHS, FL-CH, and DQN-CH only have decent lifetimes (1603-1708 rounds) inferior to EdgeAware-CHNet.

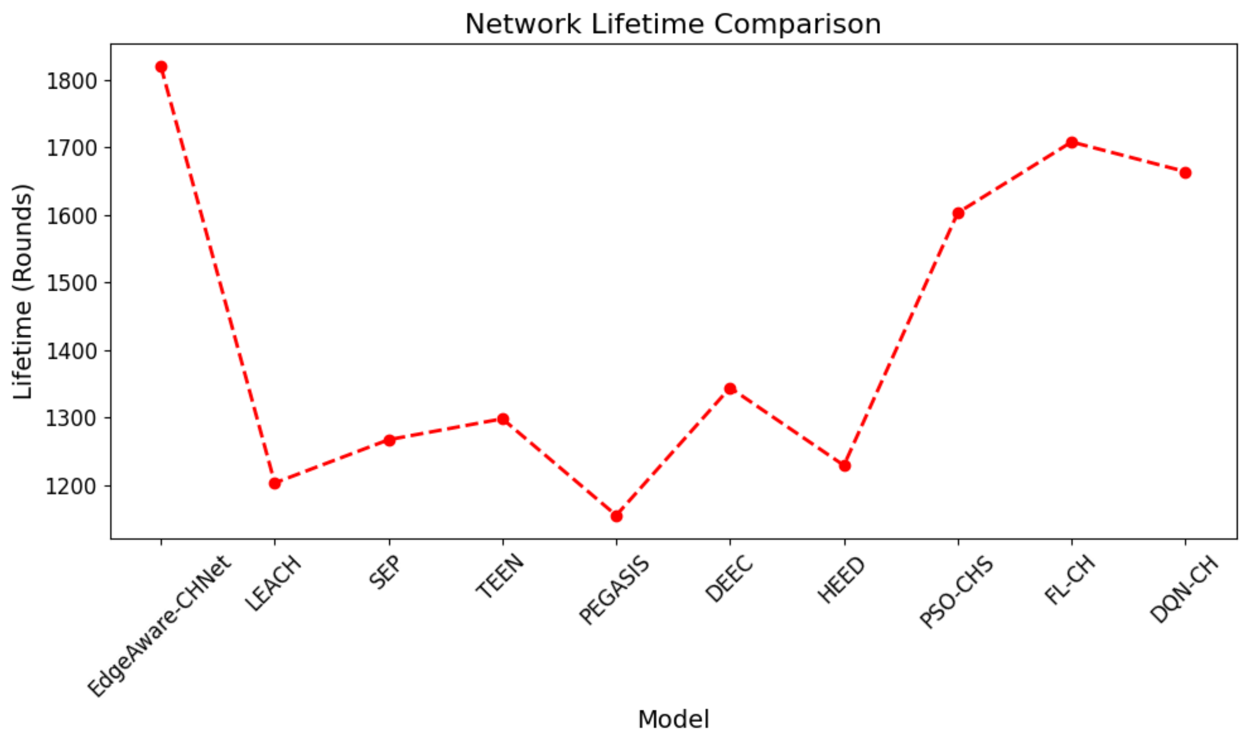

Figure 5. Network Lifetime Comparison

The most impactful one is the reinforcement learning-backed feedback loop with which EdgeAware-CHNet is continuously training the CH selection strategy according to the current real-time levels of energy efficiency as well as network latency and/or throughput. Also, federated model updates save on communication overhead, which further helps to make the nodes last long. The significant increase of network lifetime shows that the proposed model is useful to deliver the energy load in a balanced manner and prevent some nodes to be overloaded, hence increases the energy sustainability of the whole networks used in critical monitoring systems.

Table 3: Average Energy Consumption

Model	Avg. Energy Consumption (J)
EdgeAware-CHNet	0.31
LEACH	0.56
SEP	0.52
TEEN	0.49
PEGASIS	0.61
DEEC	0.47
HEED	0.53
PSO-CHS	0.38
FL-CH	0.33
DQN-CH	0.35

Table 3 and Figure 6 performs an analysis of average energy consumed by each protocol in the operation. The average energy consumption of the EdgeAware-CHNet is the lowest (0.31 J) compared to the traditional approach like LEACH (energy=0.56 J) and PEGASIS (energy=0.61 J) where frequent re-clustering or long routes are involved. Although the protocols such as DEEC and TEEN consume relatively little energy (with values of about 0.47-0.49 J), they do not adapt to dynamic workloads in real time. Such models as FL-CH and DQN-CH also show satisfactory performance (0.3310.35 J), but they are much slower than the EdgeAware-CHNet. This enhancement is credible to intelligent selection of CH considering node centrality, link stability and estimated load thus being able to minimize retransmission and localized communication.

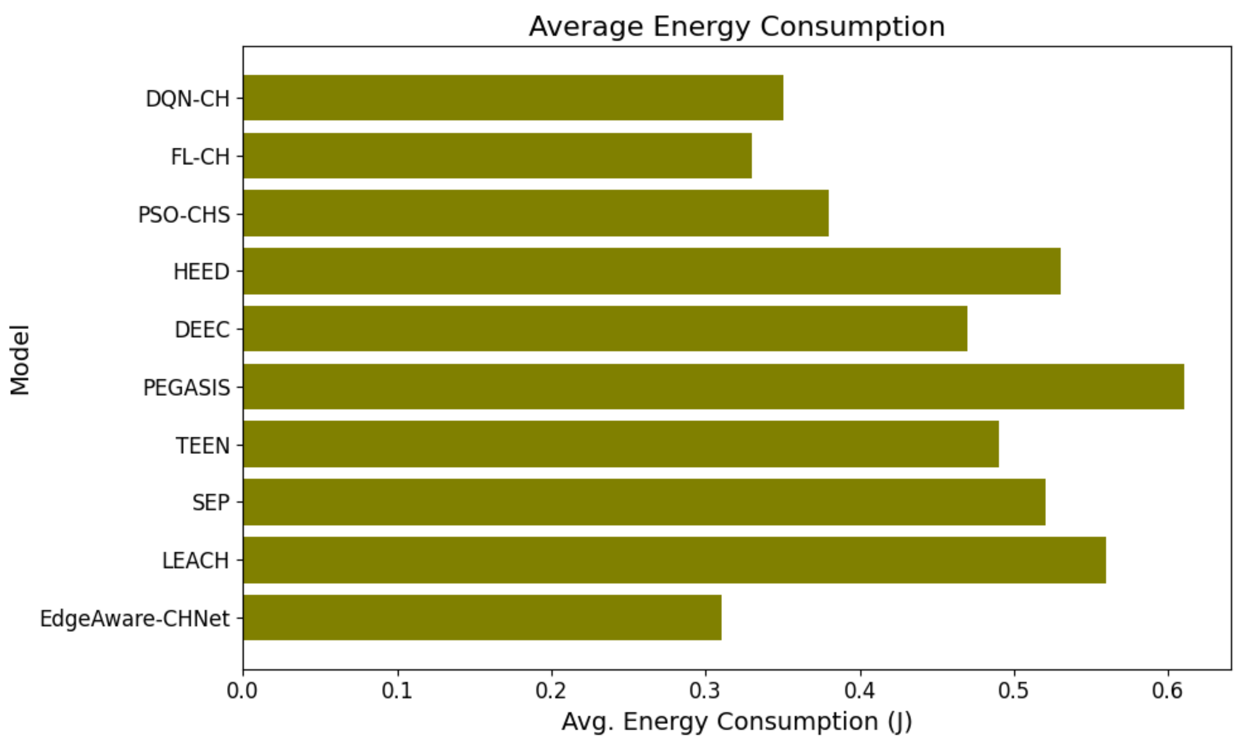

Figure 6. Average Energy Consumption

Federated learning paradigm does not involve transmitting raw data to centralized servers, which eliminates energy depletion in forwarding data. Energy minimisation of the model demonstrates that it is well suited to a resource constrained setting, e.g. remote sensing, or industry Internet of Things, where recharging a battery is impractical.

Table 4: Packet Delivery Ratio (PDR%)

Model	PDR (%)
EdgeAware-CHNet	97.22
LEACH	81.65
SEP	83.4
TEEN	84.35
PEGASIS	80.12
DEEC	85.67
HEED	82.39
PSO-CHS	91.44
FL-CH	94.32
DQN-CH	93.12

In Table 4 and Figure 7, the Packet Delivery Ratio (PDR), which defines the quality of the data sent is shown. The PDR delivered by EdgeAware-CHNet is the highest of all 97.22%, which is superior to that of traditional schemes, such as PEGASIS (80.12%) and LEACH (81.65%), whose performance can be easily reduced as more packets may be dropped because of path selection in cases of inefficiencies or node energy depletion. Such models as DEEC, SEP, and HEED increase the transmission rate slightly (up to 85.67%) by choosing the nodes using the energy level or density of the neighborhood.

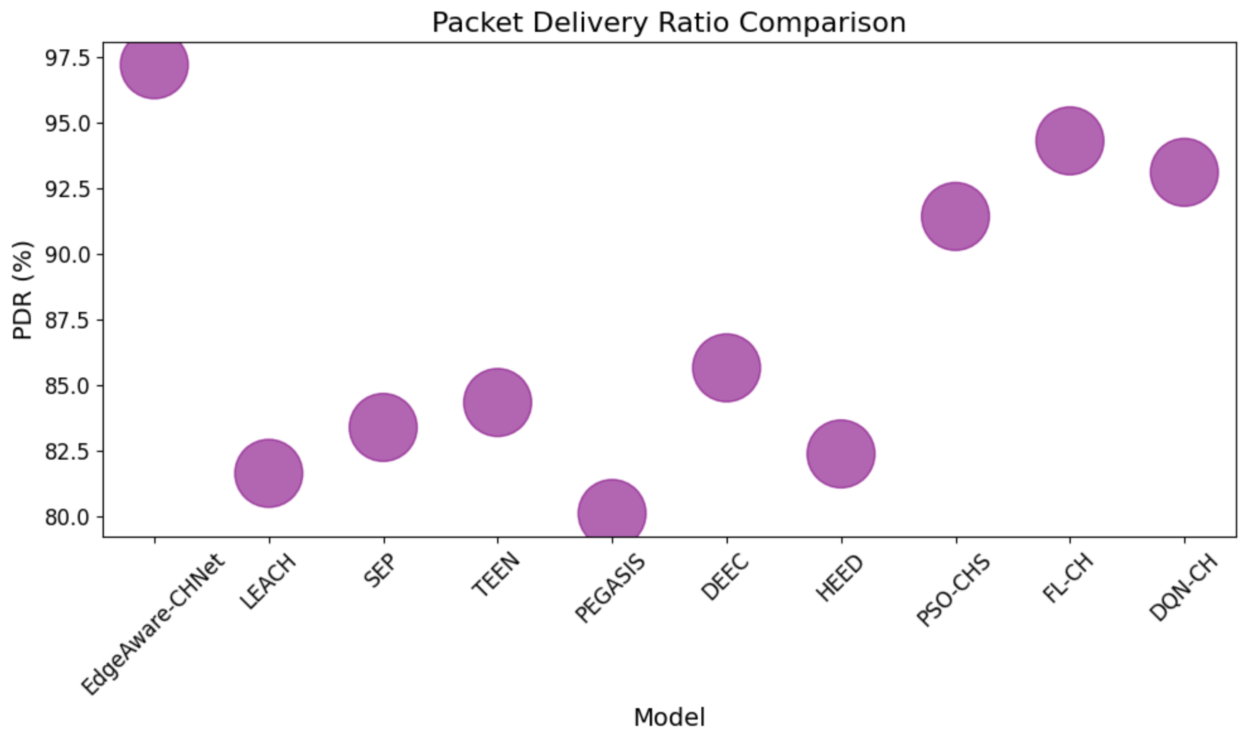

Figure 7. Packet Delivery Ratio Comparison

The most successful ones belong to the PSO-CHS, FL-CH, and DQN-CH with the PDR values of 91-94%, which make use of clever tricks but are deprived of the ability to adjust routing in real-time conditions. The outstanding PDR of EdgeAware-CHNet is because of the hybrid routing algorithm it supports which has a cost-priority-aware routing algorithm and a multi path routing capability, which will avoid faulty or congested nodes. Besides, there is link stability as attention-based CH prediction module minimizes packet retransmissions. A combination of these mechanisms leads to a high reliability state, and the suggested model is perfectly suited to such mission-critical systems as smart health care, industrial automation, or environmental monitoring.

Table 5: Latency Comparison

Model	Latency (ms)
EdgeAware-CHNet	39.6
LEACH	61.4
SEP	58.2
TEEN	55.3
PEGASIS	64.7
DEEC	53.5
HEED	57.9
PSO-CHS	45.1
FL-CH	42.3
DQN-CH	44.7

Table 5 and Figure 8 reveals that EdgeAware-CHNet has the shortest latency and is lower by more than 20 ms, compared to traditional models, which include PEGASIS (64.7 ms), LEACH (61.4 ms), and SEP (58.2 ms). The major problems of these models are long transmission paths or over-head in the control. Hierarchical architectures also cause TEEN and DEEC to have small reductions in latency but show latency around 53 to 55 ms. Among the techniques developed in the recent years, FL-CH and DQN-CH delay decreases to 42.3 ms and 44.7 in comparison to EdgeAware-CHNet, respectively.

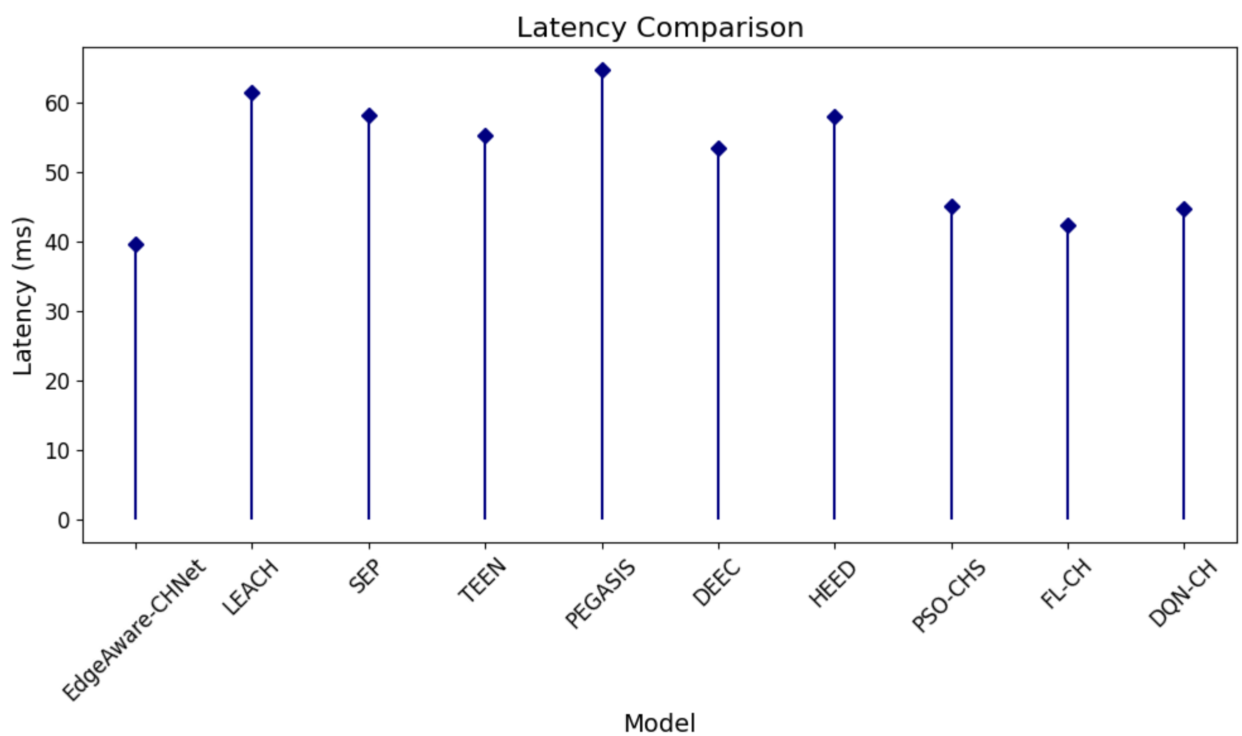

Figure 8. Latency Comparison

The enhanced latency performance is attributed to dynamic CH scheduling, in that, the nodes are balanced according to the workload that is predicted, and the hybrid routing makes the hop count minimal. Additionally, the federated architecture will decentralize computation; hence, it evades unwarranted central delays. Queuing is further reduced by the data forwarding which is based on opportunity. Streamlined latency has been the key to real-time use cases such as smart surveillance, industrial control or disaster responses, and this finding anchors EdgeAware-CHNet in time-sensitive IoT-WSN applications.

4.1. Discussion

The performance of EdgeAware-CHNet demonstrated the benefits of its EdgeAware design over traditional and state-of-the-art models on all major performance metrics using simulation results. The most significant one is CH selection accuracy of 96.45% that is much faster compared to LEACH (82.34%), SEP (84.21%), and even state-of-the-art models such as DQN-CH (91.55%). The improved accuracy is accredited both to the MobileNetV2-TCN hybrid that attains fine-grained spatiotemporal variations of sensor data, and the federated strategy which guarantees that the learning is extracted within various and heterogeneous node conditions. EdgeAware-CHNet manages up to 1820 before the first node failure, as compared with 1203 (LEACH), 1298 (TEEN), and 1664 (DQN-CH) as far as network lifetime is concerned. That shows that the program can spare nodes to absorb energy evenly and does not involve overwhelming specific CHs. The role of attention mechanism is crucial in this way because its priority is assigned to nodes that have enough residual energy and central locales thus leading to balanced rotation of CH.

The mean energy consumption is powerfully low of 0.31 J, which indicates that the framework is precise as well as resource-saving. Competing models are much more energy hungry (e.g. PEGASIS at 0.61 J) mostly because of inefficient routing and re-clustering. The DQN feedback loop also increases the energy efficiency of EdgeAware-CHNet by learning to avoid actions that eat into battery reserves and costs the network dearly. Moreover, the EdgeAware-CHNet Packet Delivery Ratio (PDR) is logged at 97.22, the value among all the tested models. It is especially important in such mission-critical areas as healthcare or disaster monitoring where data integrity is not a compromise. The values achieved by models such as HEED, PEGASIS are lower because of network fragmentation and instability of paths, whereas, EdgeAware-CHNet practically optimizes the routing paths based on the quality of links and their workload forecasts.

The second important metric is latency, and once more, EdgeAware-CHNet leads with the average delay of 39.6 ms. With opportunity forwarding and proactive edge-aware load scheduling, opportunism tends to reduce queuing delay and congestions. This is in sharp contrast to 64.7ms delay experienced in PEGASIS which employs sequential forwarding based on chains, and hence producing greater variability in delay. Such findings confirm the fundamental notion of this study: finding an adaptive, federated, and edge-aware system of selecting CHs can considerably lie structure the performance of WSN, both in terms of accuracy, efficiency, and scale. All these components, including federated deep learning, DQN-based optimization, and more, synergistically lead to this performance gain. The simulations also confirm that EdgeAware-CHNet retains its overall advantage over different densities of nodes and mobility patterns, demonstrating robustness and scalability.

5. Conclusion and Future Work

The proposed study presented EdgeAware-CHNet as a novel federated deep learning architecture that would optimize cluster head (CH) selection in scalable IoT-enabled Wireless Sensor Networks. Designed based on combining MobileNetV2-TCN as a local spatiotemporal feature, federated aggregation with FedAvg, attention-guided prioritizing, and reinforcement learning feedback by DQN, the model shows a significant improvement in performance. This is confirmed by simulation outcomes, wherein the CH selection accuracy gains 96.45%, the network lifetime growths to 1820 rounds, and the packet delivery ratio is 97.22%, and evidently surpasses other representative models such as LEACH, FL CH, and DQN CH. Among the best moments about EdgeAware-CHNet could be privacy-preserving federated composition, which qualifies it as a good solution to a sensitive data-wise application like healthcare or military WSNs. Moreover, it is edge-aware and has a low computational burden, which makes it implementable in the real-time on nodes with limited resources. Subsequent research will be aimed at practical implementation in terms of hardware realizations of the model (for example, sacrificing Raspberry Pi and ES32-based sensors), in order to test the model efficacy on such physical limitations. Furthermore, it will be desirable to examine how adversarial robustness can be applied to protection against spoofing or Byzantine nodes in federated systems, as well as how to use the model with heterogeneous sensor modalities (e.g., vision, sound, motion). Overall, EdgeAware-CHNet is a privacy preserving, smart, and scalable platform of the future generation of IoT-WSNs, and such combination of performance, adaptability, and sustainability is hard to beat.

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