

Enhancing network performance in IoT-WSNs through federated deep reinforcement learning-based intelligent routing

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ABSTRACT

By making it possible to collect and monitor data in real time, the installation of wireless sensor networks (WSNs) in the era of the internet of things (IoT) has brought about a transformation in a number of different industries. On the other hand, efficient data routing continues to be a significant challenge because of the dynamic nature of WSNs and the limitations of electronic devices connected to the IoT. This research presents an intelligent data routing technique that is based on federated deep reinforcement learning (FDRL), with the intention of optimizing data transmission in WSNs that are enabled by the IoT. In order to increase the efficiency of data routing, decrease latency, and extend the lifetime of the network, the model that has been recommended makes use of the collaborative learning skills of federated learning (FL) and the decision-making features of deep reinforcement learning (DRL). This is done in order to achieve these goals. It has been demonstrated through extensive simulations that the FDRL-based routing approach is superior to the methods that were previously utilized in terms of energy efficiency, the accuracy of data transfer, and the responsiveness to changes in the network. As a consequence of this, it is a solution that is conceivable for future applications including the IoT.

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1. INTRODUCTION

Internet of things (IoT)-enabled devices have led to the widespread use of wireless sensor networks (WSNs) in environmental monitoring, smart cities, and healthcare systems. Multiple sensor nodes collect, analyse, and send data to central servers in these networks. Due to sensor nodes' limited energy, processing, and bandwidth, and the network's dynamic topology, WSNs' data routing remains difficult [1], [2]. Traditional data routing systems sometimes struggle to address these issues, resulting in higher energy consumption, latency, and network lifespan. By enabling dynamic and adaptive routing tactics, advanced learning methods like deep reinforcement learning (DRL) can address these challenges. However, standard

DRL approaches' centralised structure may generate privacy and scalability difficulties, especially in large IoT networks [3], [4]. This paper proposes an innovative data routing strategy using federated deep reinforcement learning (FDRL) to overcome these limitations. Federated learning (FL) allows decentralised model training across nodes, protecting data privacy and enhancing scalability, while DRL provides the basis for dynamic routing strategy optimisation. This method addresses the main data routing challenges for WSNs and improves network performance [5], [6].

WSN data routing has been intensively explored, with many ways offered to address IoT-enabled network issues. Traditional routing protocols like AODV and DSDV use static or heuristic-based methods that do not account for WSNs' dynamic characteristics, resulting in suboptimal performance [7], [8]. Recent approaches emphasise machine learning to improve routing efficiency. Reinforcement learning (RL) has been used to construct adaptive routing protocols that learn best paths based on network conditions. These methods often require centralised training, which raises privacy and scalability concerns [9]. FL allows decentralised machine learning model training across devices, addressing these issues. Many studies have examined how FL and WSNs improve data routing efficiency and privacy. The integration of FL and DRL in WSNs is understudied [10]. An FDRL framework for IoT-enabled WSNs is presented in this study. FL's decentralisation and DRL's adaptability improve data routing in dynamic and resource-limited environments.

This study's network model for the IoT-enabled WSN represents these networks' standard characteristics and limitations while meeting the FDRL framework's requirements [11], [12]. Nodes monitor environmental conditions or collect data. Depending on the application, this data may include temperature, humidity, pressure, light intensity, and others. Local data processing at each node filters, aggregates, or preprocesses data before transmission. This reduces energy-intensive data transmission [13]. Sensor nodes communicate with each other to send data to the base station (BS) or gateway. The multi-hop communication model sends data to the BS via intermediary nodes. Battery-powered sensor nodes have limited energy. Energy conservation is crucial to network longevity because nodes must work efficiently [14]. Nodes can be distributed randomly or strategically in the target area. It depends on the application. Changes in node density and distribution can affect network connectivity and data routing. Mobile nodes may cause frequent network topology changes. Due to mobility, adaptive routing algorithms are needed to handle connectivity changes. Environmental factors like signal attenuation, interference, and noise can affect communication networks. The network operates in many settings. Due to these factors, routing decisions must be made [15], [16].

WSN nodes use multi-hop data transfer to send data to the BS. Data packets are routed through intermediary nodes before reaching the BS. Selecting intermediary nodes is crucial for latency reduction and energy efficiency. Distance, interference, and signal intensity affect node communication links. Link quality must be included in the routing plan to ensure data transmission reliability. Nodes can combine data from multiple sources before sending it. This reduces data volume and saves space and energy [17]. Given the short battery life of sensor nodes, energy efficiency is crucial to the network concept. Choose routes with less transmission power to save energy and reduce consumption. Implementing a routing load distribution system to prevent node failures and overload. Optimising energy use across all nodes is crucial to extend network lifetime [18].

The proposed technique uses FL to train DRL models decentralised across the network. Each sensor node creates a local DRL model using data and network state. The local model learns to improve data transmission pathways by routing. Nodes periodically send locally trained model parameters to a server or BS [19]. The server consolidates these parameters to construct a global model that represents the collective learning of the network. Redistributing the global model to nodes allows them to improve their local models with network knowledge. Nodes can route more efficiently and intelligently. The FL framework protects privacy by keeping raw data in nodes. Sharing only model parameters reduces data breaches and ensures privacy [20]. The sensor nodes provide adequate network coverage with few dead zones. The network is constantly changing, yet the communication routes should remain stable enough for pattern training and data transfer. To keep the global model current, nodes will periodically synchronise with the BS to receive model modifications. These components create a robust and adaptable network model in the FDRL architecture. This model provides intelligent and efficient data routing in IoT-enabled WSNs [21].

Existing intelligent routing methods mainly rely on centralized RL models, which suffer from privacy concerns, communication overhead, and limited scalability in large IoT-enabled WSNs. The proposed FDRL framework addresses these limitations by combining decentralized FL with adaptive DRL-based routing. This integration enables privacy-preserving collaborative learning while improving routing efficiency, energy utilization, and network scalability. The proposed FDRL framework is designed for deployment in embedded IoT sensor nodes where routing intelligence can be executed locally with minimal computational overhead. The decentralized architecture enables adaptive firmware updates and supports reconfigurable embedded platforms operating under dynamic network environments.

2. METHOD

The coordinated FDRL model that has been suggested is intended to improve the routing of data in WSNs that are enabled by the IoT. In order to develop a routing strategy that is both clever and adaptable, this model makes use of the decentralized learning technique of FL and the decision-making capabilities of DRL [22]. In order to overcome the difficulties of dynamic topology, energy limits, and scalability in WSNs, the FDRL architecture involves the integration of FL with DRL. The framework functions in a coordinated manner, with several sensor nodes working together to train a global DRL model that may be utilized for improving the efficiency of data routing. The following are the primary elements that make up the FDRL framework: every single sensor node functions as a local DRL agent, and it trains its model by utilizing the observations and experiences that are specific to the area [23]. The local model acquires the ability to make routing decisions that improve network performance measures such as energy efficiency, latency, and the accuracy of data transfer. In a FL environment, the local models are synchronized with a central server (for example, the BS) on a regular basis. A global model is created by the server by aggregating the local models. This global model is then sent back to the sensor nodes for additional training and decision-making. It is necessary to design a system for coordination in order to guarantee that the local models are in accordance with the global model, while at the same time allowing for specific adjustments based on the conditions of the local environment [24]. The computational complexity mainly depends on local neural network inference and periodic parameter aggregation. Since only model parameters are exchanged, communication complexity is considerably lower than centralized learning approaches, making the framework scalable for dense IoT networks.

The coordinated FDRL approach that has been recommended for high-speed routing in IoT-enabled WSN makes an effort to make use of the capabilities of FDRL in order to maximize the effectiveness of routing decisions. As shown in Figure 1, this paradigm combines decentralized decision-making at individual sensor nodes with centralized coordination in order to produce routing methods that are both optimum and adaptive. There is a comprehensive framework for the cooperative FDRL routing model in IoT-enabled WSNs that is presented by this method. There is a possibility that the execution information and variations will change depending on the approaches that are used, as well as the specific requirements and characteristics of the communication network that is indicated in Figure 2.

Every single sensor node individually trains a local DRL model by making use of the observations it makes regarding the condition of the network. The following are the stages that are included in the training process: a collection of characteristics, including the amount of residual energy that is present in nodes, the quality of the link, the length of the data queue, and the distance to the BS are used to indicate the condition of the network at any instance. Because of these capabilities, the DRL agent is able to obtain the information that is required to make well-informed decisions on routing. The action space for each node is made up of the prospective nodes that could be the next hop for the transmission of data [25]. Given the present state of the network, the DRL agent will choose the next-hop node that is most suitable for the network. The purpose of the reward function is to provide an incentive for routing decisions that increase overall network performance, reduce latency, and boost energy efficiency. In order to establish the reward function, it is defined as a weighted sum of these objectives, with penalties for behaviors that contribute to the depletion of energy or high latency. A policy that creates a mapping between network states and routing actions is learned by the local DRL model. The agent iteratively improves its routing strategy depending on the rewards that it receives [26]. This policy is updated using RL algorithms such as Q-learning or deep Q-networks (DQN), which are examples of algorithmic approaches to RL.

Each sensor node performs local model training using its own observations without sharing raw data. After every communication round, locally updated model parameters are transmitted to the central server, where federated averaging (FedAvg) generates a global model. The updated global parameters are redistributed to all nodes, enabling collaborative learning while preserving data privacy.

The DRL agent employs a DQN architecture consisting of input, hidden, and output layers. The input state includes residual energy, link quality, queue length, neighbour availability, and distance to the BS. The action space represents the selection of the optimal next-hop node. The reward function maximizes packet delivery while minimizing latency, energy consumption, and routing overhead. The FL process is at the core of the FDRL system, which enables decentralized model training while simultaneously preserving a global perspective: the parameters of each sensor node's locally learned model, such as the weights of the neural network, are periodically communicated to a central server via the sensor nodes. For the purpose of reducing the amount of communication overhead, this sharing is carried out in a safe and effective manner. A number of methods, including FedAvg, are utilized by the central server in order to aggregate the local model parameters. An all-encompassing comprehension of the network is represented by the aggregated model, which incorporates the information from all of the nodes that are participating. Following this, the global model is sent back to the sensor nodes for distribution. The global parameters are incorporated into the local model of every node, which enables the node to take advantage of the collective learning that occurs

throughout the entire network. The frequency with which model changes are transmitted is decreased, and techniques such as model compression and selective parameter sharing are utilized [27]. This is done in order to reduce the amount of communication overhead. The FL mechanism significantly reduces communication overhead by exchanging model parameters instead of raw sensing data. Local DRL inference requires limited processing and memory resources, making the proposed framework suitable for low-power embedded IoT devices.

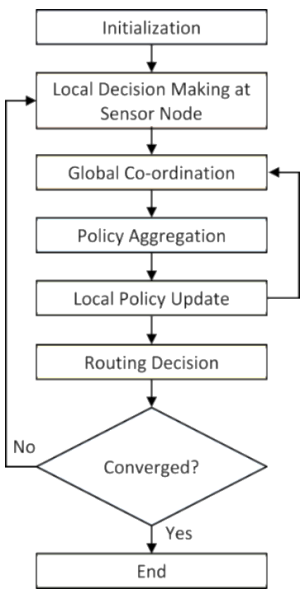


Figure 1. The flow diagram for the collaborated FDRL routing model

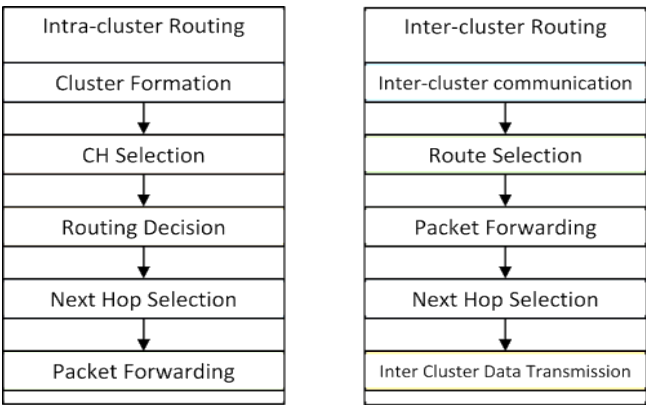


Figure 2. The flow illustration for intra-cluster and inter-cluster routing in collaborated FDRL

3. RESULTS AND DISCUSSION

Extensive simulations were conducted in a standard WSN simulation environment to evaluate the performance of the proposed FDRL-based routing strategy. The metrics considered include: the FDRL model demonstrates a significant reduction in energy consumption relative to conventional routing protocols, thereby contributing to an extended network lifetime. The adaptive characteristics of the FDRL model lead to reduced latency by routing data packets through the most efficient pathways. The model enhances data transmission accuracy by choosing routes characterized by superior link quality and reduced packet loss rates. The findings demonstrate that the FDRL-based routing strategy surpasses conventional methods, especially in contexts characterized by dynamic network conditions and strict energy limitations. The proposed framework was evaluated using multiple IoT-WSN scenarios with varying network sizes and traffic conditions. Performance was assessed using energy consumption, latency, packet delivery ratio, quality of service (QoS) probability, and network lifetime. The proposed FDRL was compared with multi-hop state-

aware routing strategy based on traffic flow forecasting (MHSA-TFF), cooperative deep reinforcement learning (CDRL), reinforcement learning-based routing schemes combined with multi-optimality routing criteria (RLR-M), and decentralized partially observable Markov decision process (Dec-POMDP) under identical simulation settings. The proposed routing framework is suitable for smart city, industrial IoT, environmental monitoring, and healthcare applications requiring reliable and energy-efficient communication. The decentralized learning strategy ensures robust operation under dynamic network conditions.

Figure 3 presents an evaluation of the proposed and existing approaches by calculating the average energy consumption per node for intra-cluster routing across 10 pairs of clusters. The energy consumption values for each cluster pair are presented in millijoules (mJ). The FDRL approach exhibits enhanced energy efficiency, characterized by the lowest average energy consumption per node within the samples analyzed. The energy consumption metrics for each approach reflect the degree of energy efficiency achieved in conducting intra-cluster routing tasks across the 10 cluster pairings. The probability of satisfaction of the QoS criteria for inter-cluster routing is illustrated in Figure 4, which illustrates 10 different combinations of clusters. For each pair of clusters, the probability values for QoS are shown in the form of percentages. The FDRL approach that was proposed displays the highest likelihood of QoS, which corresponds to the largest median proportion of effective QoS fulfillment that was seen in inter-cluster routing samples. The QoS probability values provides an indication of how well each strategy performed in meeting the QoS requirements for inter-cluster communication among the ten different cluster pairs. Throughout all of the samples for inter-cluster routing, the FDRL technique that was suggested had the lowest average energy consumption per node, which indicates that it had the highest energy efficiency. This is demonstrated in Figure 5. According to Figure 6, the suggested FDRL has the highest average percentage of successful QoS fulfillment across samples and the best QoS probability when it comes to intra-cluster routing. This is demonstrated by the fact that it has the suggested FDRL.

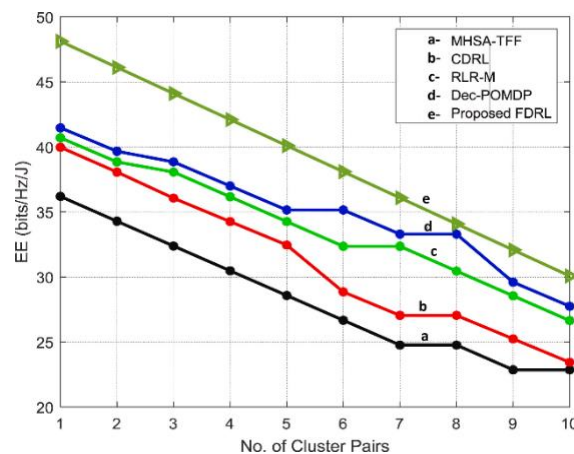


Figure 3. Precision of the evaluated classification methods

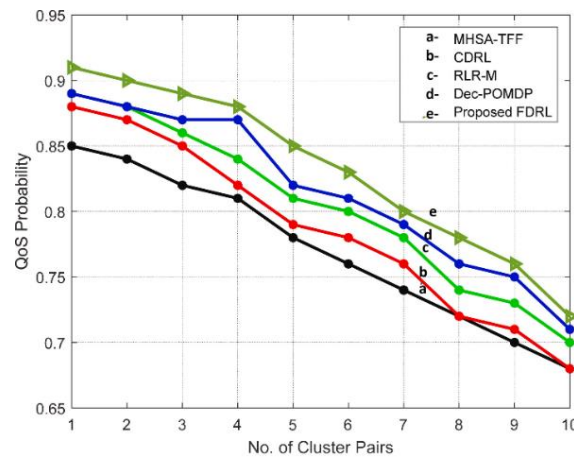


Figure 4. Accuracy of the evaluated classification methods

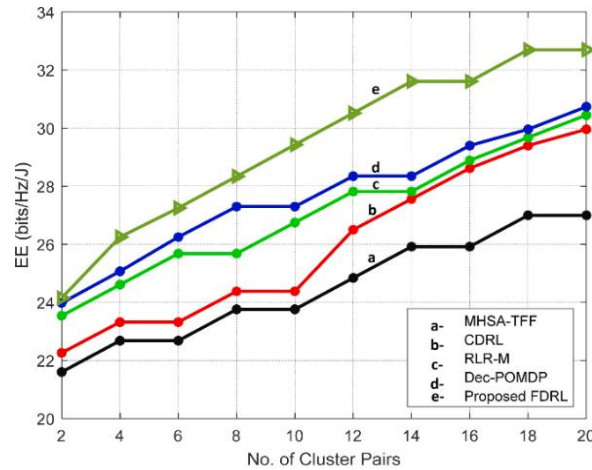


Figure 5. The energies efficiency of inter-cluster routing in an IoT-enabled WSN for 20 cluster pairings using MSHA-TFF, CDRL, RLR-M, Dec-POMDP, and the suggested FDRL

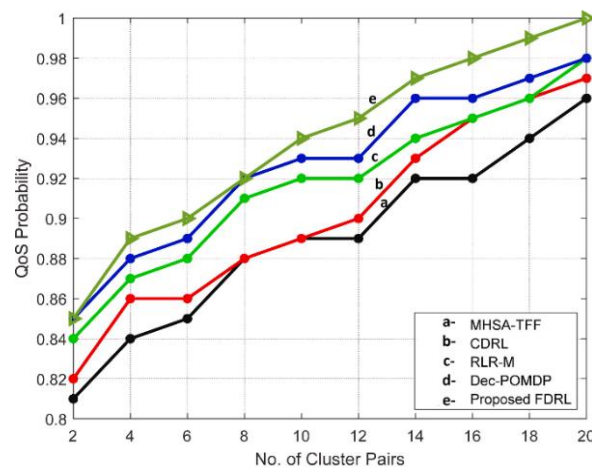


Figure 6. Inter-cluster routing quality-of-service probabilities for 20 cluster pairs in an IoT-enabled WSN using MSHA-TFF, CDRL, RLR-M, Dec-POMDP, and the proposed FDRL

Figure 7 contains four subplots representing the performance metrics of the proposed intelligent data routing strategy for IoT-enabled WSNs based on FDRL. Here's a detailed explanation of each graph: Figure 7(a) demonstrates that energy consumption decreases as the number of network nodes increases. This indicates that the proposed strategy effectively optimizes energy use, likely due to efficient routing and load distribution among nodes, and Figure 7(b) shows a decreasing trend in latency as the network size grows. The FL model likely reduces decision-making delays, enabling faster data transmission even in larger networks. Figure 7(c) shows the packet delivery ratio increases with the number of nodes, indicating that the proposed routing strategy ensures reliable data delivery. This is a positive outcome, reflecting robust handling of network traffic and minimizing packet loss. Figure 7(d) shows the network lifetime improves as the number of nodes increases. This suggests that the energy-efficient design of the routing strategy extends the operational life of the entire network, particularly in resource-constrained IoT systems.

These results collectively validate the effectiveness of the proposed framework in achieving better energy efficiency, reduced latency, improved delivery ratio, and extended network lifetime as the network size scales. An intelligent data routing strategy that is based on FDRL for IoT-enabled WSNs has been proposed as a solution to the challenges that arise when attempting to route data in environments that are both dynamic and resource-constrained. The incorporation of intelligent decision-making, cluster-based routing, and DRL strategies results in a significant improvement in the reliability threshold, maximum sum rate, energy efficiency, and QoS likelihood.

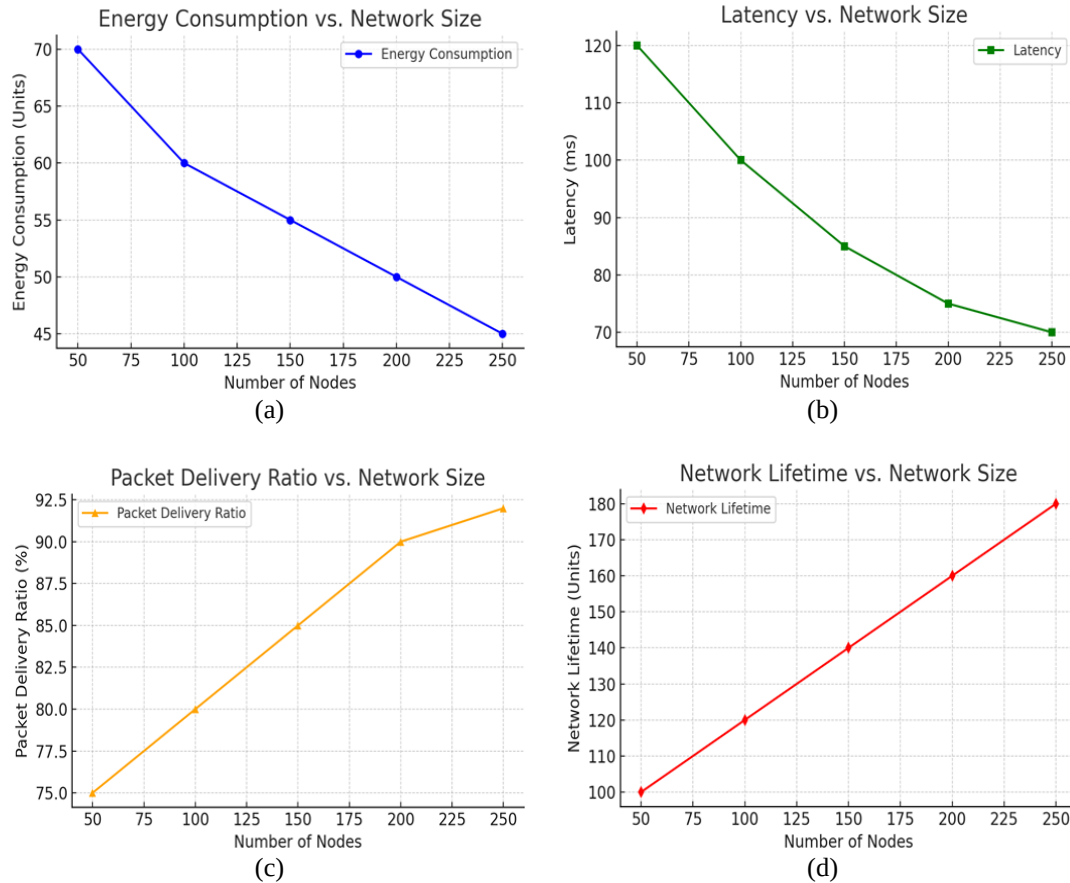


Figure 7. Performance curves of the proposed FDRL; (a) energy consumption, (b) latency, (c) packet delivery ratio, and (d) network lifetime with respect to network size

4. CONCLUSION

The expanding realm of IoT-enabled WSNs necessitates creative approaches to address the fundamental challenges of data routing, including dynamic topology, energy limitations, and the requirement for scalable and adaptive strategies. This paper introduces an innovative data routing strategy utilizing FDRL to effectively tackle these challenges. The proposed coordinated FDRL model integrates the decentralized learning features of FL with the adaptive decision-making advantages of DRL. This integration facilitates the creation of a routing strategy that is both efficient and scalable, dynamically adjusting to network conditions, optimizing energy use, and guaranteeing reliable data transmission throughout the network. This approach presents a distinctive framework in which individual sensor nodes function as local agents, developing their models from local observations and periodically synchronizing with a central server via the FL process. This decentralized training approach effectively safeguards data privacy while simultaneously improving the system's scalability by reducing reliance on centralized data collection. The proposed model underwent thorough simulations, showcasing notable enhancements in essential performance metrics including energy efficiency, latency, data transmission accuracy, and network longevity. The findings demonstrate that the FDRL-based routing strategy surpasses conventional approaches, especially in situations characterized by fluctuating network conditions and strict energy limitations. The coordinated FDRL model offers a compelling approach for intelligent data routing in IoT-enabled WSNs. By tackling the essential issues of energy efficiency, adaptability, and scalability, the suggested approach could greatly improve the performance and reliability of upcoming IoT applications. The proposed routing framework can be extended to application-specific integrated circuit (ASIC) and very-large-scale integration (VLSI) implementations through dedicated hardware accelerators for neural network inference and federated aggregation. Such implementations can further reduce latency and energy consumption in large-scale IoT deployments. Future work will investigate field-programmable gate array (FPGA)-assisted DRL acceleration, lightweight embedded FL modules, and adaptive routing implementations for next-generation reconfigurable IoT platforms.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Sravanam Sreeja	✓		✓	✓			✓			✓	✓		✓	✓
Koneti Varalakshmi	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Zarapala Sunitha Bai		✓				✓		✓	✓	✓	✓	✓		
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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding this study.

DATA AVAILABILITY

The data supporting this study are available from the corresponding author upon reasonable request.

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