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# Deep Learning-Based Route Optimization in Wireless Sensor Networks: Enhancing Energy Efficiency, Reliability, and Scalability

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**Abstract:** Wireless Sensor Networks (WSNs) are indispensable to a wide range of applications that demand cost-effective data gathering in harsh environments. An essential trade-off in WSN is the design of routing paths that reduce the energy cost and achieve the high transmission reliability. In this paper, we provide a unified view for solving the route optimization problem with deep learning approaches (deep reinforcement learning and graph neural networks). Through formulating the routing problem as a sequential decision-making problem, deep learning methods can learn adaptive policies that can choose dynamic energy-efficient and reliable communication paths using up-to-date network status (such as node residual energy, link quality and traffic load). The incorporation of graph neural networks additionally exploits the spatial distribution of sensor lay-out to describe local and global network fluctuations, which provides scalable and generalizable network decisions. The energy is consumed by means of transmission and reception costs and is also modelled in order to generate realistic optimization results. Simulation results also show that the deep learning-based routing has the advantages of extending network lifetime, less energy consumption, and better adapts to dynamic network environments against the conventional and heuristic protocols. The results demonstrate that deep learning has the potential to improve WSN both in terms of performance and sustainability. In future work,

we plan to investigate lightweight models for real-time execution, directly on sensor nodes, and hybrid policies that are able to mix learned and heuristic solutions.

**Keywords:** Wireless Sensor Networks, Route Optimization, Deep Reinforcement Learning, Graph Neural Networks

## I. Introduction

Wireless Sensor Networks (WSNs) have been playing a crucial role in huge variety of applications, including environmental monitoring, heathcare, military surveillance, and smart cities, to name a few, by collecting and transmitting information gathered from remote or hard to reach locations. However, WSNs also suffer from crucial issues such as energy constraint, dynamic topology, reliable data transmission, and latency that heavily impact network performance and lifetime. Perhaps the most import factors affecting the above three facts is route optimization, i.e., how to choose a minimum-energy data routing path between sensor nodes and the sink/base station. Conventional routing protocols for WSN, (e.g., LEACH, AODV, Directed Diffusion) are based on static processes or heuristics to reduce energy consumption or balance load across the covering area, with limited possibilities to adapt to dynamic conditions in practical environments, such as a node failure, variation in link quality, or mobility. In this regard, deep learning has been recognized as a promising technique to improve WSN route optimization through adaptive, data-driven, and intelligent routing decisions that outperform those based on traditional strategies. DL, as a branch of ML using artificial neural networks with multiple layers to model high-dimensional data to learn intricate and non-linear patterns, is well suitable for handling the intrinsic complexity and dynamics of the WSN routing problems. From what can be seen, few WSNs works on routing optimization with deep learning, and such works typically treat routing problems from the following three perspectives: supervised learning, reinforcement learning and graph learning according to the nature of the data available and the network architecture. Supervised learning methods provide a learning algorithm with labeled examples, such as network states, node attributes, link measurements, known high-quality routes, and/or near-optimal routes, and train a deep neural network to infer future high-quality paths over unseen network configurations. But how to easily collect the well-annotated data in real WSN settings [1]. Reinforcement learning, particularly the Deep Reinforcement Learning (DRL) paradigm, provides another alternative that rethinks routing from the perspective of solving a sequential decision-making problem in which an agent (i.e., a sensor node or centralised controller) learns optimal routing policies by interacting with the network environment in a trial-and error manner. As the agent hears feedback by means of rewards (long network lifetime, low energy consumption, low latency), it adapts its policy accordingly. Algorithms such as Deep Q-Networks (DQN), Policy Gradient methods, and Actor-Critic architectures have been successfully used to learn the best next-hop nodes or routes based on the current network state without the need of pre-labeled data. Another interesting direction is leveraging Graph Neural Networks (GNNs) which are well suited to the processing of graph-structured data, such as that of WSNs where nodes are sensors and edges represent communication links. It has been shown that the graph neural networks (GNNs) can generate representative node and edge representations by gathering neighborhood information in graph and thereby captures local/global graph statistical features. Such embeddings help to make better and less taxing routing decisions by predicting the best paths that are aware of energy, connectivity of nodes and reliability of links with an effective approach [2]. The application of GNNs in reinforcement learning can also facilitate the online optimization of routing in large-scale and dynamic WSNs. Developing deep learning-based route optimization in WSNs for data gathering can be decomposed into a number of actions, such as data collection (e.g. node residual energy, geographical location, link quality, RSSI or packet delivery ratio, traffic load, etc.). (Leskovec et al., 2014) The preprocessing of such data, to build input features that are suitable for modeling is an essential factor for the performance of the model. The choice of model architecture depends on the particulars of the problem: for spatial data, we can use CNNs; for sequential or time series data, we can use RNNs or LSTMs; for graph-structured network data, we can use GNNs. Learning can also be performed offline with simulation-generated data or online with the real network in a continual learning manner. Online training allows the model to dynamically adapt to unexpected changes in the network topology or environmental factors. Deployment approaches range from centralized control where deep learning models are hosted and routing instructions are broadcast and disseminated through a network, to a decentralized fashion where lightweight editions of the models are run by individual sensor nodes [3]. However, the latter method encounters challenges because of low-computation and energy resources as tropical countries, requiring model compression techniques or collaborating with edge intelligence. Simulations and empirical studies prove that deep learning-assisted routing can notably prolong the lifetime of WSNs in the sense of less energy waste, delay and more throughput compared to the classical routing protocols. In addition, deep learning NMs are also capable of tackling the scalability issue as the size and complexity of the network scale, by generalizing learned routing policies to never-seen network states [4]. However, many challenges still exist in this area, such as high computational cost for data collection and model training, interpretable and explainable routing decisions for trust and debugging, and robustness to adversarial attacks or sensor node compromise. Furthermore, combining domain knowledge with deep learning methods to supervise or regularize the learning process is also an active area of research to improve the speed and reliability of convergence. In summary, deep learning offers a revolutionary chance for optimizing routing in wireless sensor networks with the availability of adaptive, efficient, and intelligent routing schemes, which can react dynamically to the complicated and varying network scenarios. As many WSN applications are progressively becoming large-scale, diversified and complex, the application of deep learning is indispensable for mammoth, sustainable and reliable high-performance deployments of sensor networks [5].

## 1.1Deep Learning and WSN

In Wireless Sensor Networks (WSNs), complex and dynamic environments make it difficult for the conventional routing mechanisms to efficiently handle data delivery. These traditional algorithms work based on pre-defined heuristics, or rule-based strategies that might not always well adapt to the dynamics of network conditions like a failure of nodes, fluctuation in the quality of links, and energy level variations. Deep learning provides a disruptive alternative since it can serve as adaptive, intelligent and data-driven techniques that are good at dealing with the complexity and uncertainty in WSNs. Deep learning models, especially multilayer artificial neural networks, are incredibly adept to learn complicated patterns and complex non-linear associations in vast amounts of high-dimensional data. In WSNs this property enables these models to capture intricate relationships among node energies, network topologies, traffic distributions and link qualities that may be neglected by conventional routing algorithms. The use of deep learning techniques at this level can potentially allow the network to make more subtle and effective routing decisions that have the abil ity to optimize the most imp ortant performance indices of the network including energy, network lifetime, latency, and thro ughput [6]. An important aspect of deep learning is that it can learn and continue learning. Routing policies can be learned, and update constantly, by using techniques such as deep reinforcement learning in response to the feedback they receive from the network environment in real time. This enables the system to adapt in a robust and timely manner with no explicit reprogramming or manual intervention. This adaptability is particularly useful in WSNs being used in hostile or dynamic environments. Furthermore, newer architectures such as Graph Neural Networks (GNNs) are well-suited for WSNs since they inherently treat the network as a graph, and as a result, learn to generate rich representations that take into account both the local node relationship, and the structure and topology of the entire network. This enables energy-efficient and robust and scalable routing policies [7].

## 1.2 Deep Learning Approaches in WSN Routing

### Reinforcement Learning (RL) & Deep RL

Tasking routing as sequential decision-making formulates routing in WSNs as a sequence of decisions taken one step at a time, where the actions taken at each stage influence the network state in the future and consequently the end-to-end performance. Within this framework, an entity (i.e., sensor nodes or a centralized controller) senses the current network situation, e.g., the energy of the nodes, the quality of the links, or the topology, and makes a decision regarding where to forward data at the next hop. Every choice we make affects the next route and leads to a set of successive choices. This naturally adapts to reinforcement learning (RL) where the agent learns an optimal routing policy by interacting with the network environment and getting feedback through reward. Rewards are intended to promote energy conservation, decreasing latency, or extending the network lifetime. Gradually, the agent learns to choose the best actions to maximize the cumulative rewards, and adapts to varied environments without hard-coded rule sets. Treating routing as a sequence of decisions for optimization enables dynamic, context-aware routing to achieve both short-term and long-term network objectives [8].

Wireless Sensor Networks, where nodes (or central agents) learn best routing policies through experimentation and reinforcement learning. Through experimenting with various route paths and seeing how well the network performs (energy consumption, delay, and packet reception), they get feedback in terms of reward and punishment. This allows the learning agent to learn to make better routing decisions that rewards routes that maximize network battery life and throughput. After enough probing and learning, the agent develops its own policy that can change as the environment and network topology change, without the need for hard-coded logic, thus enabling 'smarter', more robust routing in complex, dynamic environments [9].

The deep reinforcement learning model DQN has been applied to jointly solve the linear sum assignment problem and the routing problem to get an effective routing solution in infrastructure mode Wireless Sensor Networks (WSNs). In this approach, routing is cast as a Markov Decision Process whereby the agent has access to network status, including node energy, links quality and the topology, and, as the agent explores the environment, it learns how to make the best decisions that maximize a source-destination path life-span. The goal of DQN is to approximate the optimal action-value function that calculates the expected cumulative reward for making a particular next-hop node have been taken according to the current network state. The agent makes use of the function to select a next-hop node that maximizes the long-term objectives (e.g., energy and load balance). The agent interacts with the network and receives rewards based on the outcomes such as lower energy consumption or prolonging the network lifetime and updates the rewards and the DQN. By doing exploration and learning continuously, the DQN automatically updates the routing policies dynamically with time, to respond to varying networks without human intervention [10].

### Supervised Learning

Learning-based approaches are used in Wireless Sensor Networks (WSNs) to predict the most promising paths where a neural network is trained with annotated datasets, including properties such as route quality, energy levels of the nodes, link stability, etc. The network learns how to map these inputs to ideal routing choices with loss terms based on mispredictions to be small for known BoP routes. This supervised framework allows the model to learn general behavior from training examples and infer efficient routes for new network states. However, capturing complete and correctly labeled datasets can be difficult in practice. Once trained, the network can easily infer the optimal paths, leading to better energy efficiency and network performance over conventional approaches.

For the deep learning model with regard to WSN route optimization, the training process requires data with accurate network status shown and the antithesis of optimal or near optimal paths. Such data sets may comprise node energy, positions, link quality metrics, traffic e.g load as well as best routing decisions in order to minimize the energy used or to minimize latency, for example. Collecting such labeled data might be challenging – especially in real world settings where the ideal route may not be known, or computational expensive to obtain. Usually, we get these datasets from some kind simulations or heuristic algorithms. The quality and variety of data are crucial for the model's generalization over different network conditions and predicting routing accurately [11-13].

**Unsupervised Learning**

ORIENTATION Clustering nodes or learning network topology representations assists in enhancing routing decisions in WSN by structuring network in manageable clusters or extracting salient structural features. Clustering has been employed to reduce the routing complexity by using the data aggregation and localized communication in the clusters that saves a lot of energy and makes the network scale-able. Or learning topology representations, such as graph embedding, and capturing the links and node relationships, for making the models to comprehend connecting patterns of the network. These methods help routing algorithms make better decisions by combining both plots Attribute and network Structure for the local node condition and global network constructions and reach at more efficient, balanced, and robust data transmitting path in WSN [14].

**1.3WSN Route Optimization Using Deep Learning**

**Data collection:** Data collection serves as an important initial stage in order to optimize routing in WSNs based on deep learning. It consists of collecting a fine-grained query about the network, such as nodes' attributes (e.g., residual energy, geographical position, and buffer status) and link qualities (e.g., signal strength, packet delivery ratio, and delay). A traffic matrix and snapshots of the network topology are also observed to obtain a complete state view. This data is used as the input to train and validate deep learning models, that learn useful patterns and take informed routing decisions. The efficiency of the routing optimization process is directly related with accuracy and recency of data collection [15].

**Model Design:** Model Design is an important stage in the process of deep learning application on WSN route optimization. This is to identify the suitable neural network structure that can process the input data well and make routing decision with high accuracy. Different model are adopted based on the nature of data and routing task, CNNs is good for spatial data [16], they can capture the local node features and environmental context; RNNs or LSTM is proper for sequential or time series data, they can learn the temporal pattern in network traffic or energy consumption [17]; GNNs is well suited to WSNs, since the WSNs can be naturally modeled as a graph, it can capture the complex node relationships and topology information [14]. Generally, the model's output is the best next-hop node, or the optimal routing path. The design needs to carefully consider the number of layers, the type of activation functions, and the training objective in order to achieve the right trade-off between prediction accuracy, computational cost, and robustness to varying network conditions [16].

**Learning Network:** Learning deep network model to optimize route in WSN means, we take a captured network data and then iteratively tune node parameters of the model to minimize the error of prediction. The training can be supervised - the model learns from labled datasets which describe some optimal (or near-opitmal) routing decision, or it can be reinforcement based - learning decisions on fly in interaction with the network and receiving reward feedback related to energy, latency or time of network operation. For training, data is normally divided into training, validation, and test datasets to prevent the model from overfitting to the dataset. Offline training, based on simulation-generated data, or online training which allows for continuous adaptation to real-time changes in the network. Some important choices to be made during the training process are loss functions, hyperparameters like learning rate and batch size, and avoiding overfitting with dropout or regularization. Under such network conditions an efficient routing decision can be accurately predicted by a well-trained model [17].

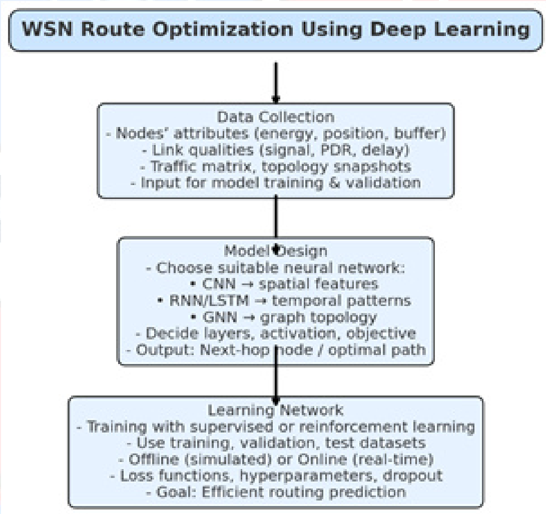


*Fig 1: WSN Route Optimization Using Deep Learning*

## 2. Reviews

**Priyadarshi (2024)** had explored the transformative impact of the rise of Internet of Things (IoT)-based Wireless Sensor Networks (WSNs), which was said to have triggered an industry-wide paradigm shift and underscored the need for reliable, efficient routing techniques. The paper was claimed to have presented a general survey about how ML methods could solve routing problems in WSNs. It was observed, first, that the paper presented a summary about traditional routing protocols and its drawback were stressed there. As a next step, the implementation of ML approaches — both reinforcement learning (RL), supervised learning (SL), and unsupervised learning (UL) — to improve the routing performance was investigated. Another source noted that the paper also delved into the primary obstacle to ML-based routing, including data quality, energy consumption, scaling issues, or security issues. Examples of applications and case studies from the real-world were also provided to demonstrate the actual applications and to derive some practical experiences. Furthermore, simulations and experimental performance comparisons between ML-based and formal techniques were also reported. In the forward, the article explains that it intends to describe recent trends and note outstanding issues as “a guidepost for future studies”. It was thought that the conclusion should have listed the main findings and stressed the disruptive impact of ML on WSN routing technologies.

**Kooshari et al. (2024)** examined wireless sensor networks (WSNs), highlighting the issue of limited energy resources in sensor nodes and the necessity of optimal routing protocols to enhance network longevity and efficiency. The study was claimed to have introduced an optimal routing approach that lowers the energy consumption in WSNs. In the preliminary stage, authors have clustered the sensor nodes using Water Strider Algorithm (WSA) and elected the cluster heads for routing. and the cluster heads transmitted packets to the base station with the assistance of the Ant Colony Optimization (ACO) algorithm, in order to decrease traveling distance, in the form of mobile sink. The work was claimed to propose a discrete version of WSA for cluster head selection and a multi-objective function comprising error rate, energy consumptions, PDR and Euclidean distance. In addition, these authors modelled CH traversal as TSP and use ACO instead to minimize it. The objective was to reduce the energy, packet transmission error, and network lifetime. The simulations performed through the MATLAB, at different motion models, it is claimed to be achieved that the proposed approach clearly minimized the consumed energy, and the packets are received probability increases, and the fewer numbers of dropped packets, but a number of active nodes. Comparative results, said to demonstrate that the proposed method performed better than PSO, GWO, IC-WSNs, and CBR in terms of energy consumption, PDR (success reported at 97.3%), and shorter routing delay 25.97%, 5.78% and 17.98% lower by respect of HHO, WOA and GWO are 25.97%, 5.78% e 17.98% respectively.

**Shutnan et al. (2023, July)** had discussed that wireless sensor networks (WSNs) were composed of sensor nodes and played a vital role in collecting data across various applications with minimal human intervention, even in challenging environments. The article had highlighted the efficient routing was a major challenging in achieving reliable and delay communications while transferring sensed data from sensor nodes to the central sink, where WSNs faced various routing challenges because of their inherent requirements and limited properties. The existing routing protocols, scenarios of the features and the advantages and limitations had been reviewed and researched by the authors. By this sort of extensive poll, I have offered readers some guide of what the merits and demerits of the different routing systems were. It was the objective of the study to support scientists and engineers in their endeavour to find efficient and robust solutions for such routing problems, thus underlining the importance of WSN within the scope of modern technologies.

**Del-Valle-Soto et al. (2023)** had reviewed the growing number of clustering routing protocols proposed for Wireless Sensor Networks

(WSNs), which had driven the need for survey studies offering concise and insightful overviews of current methodologies. The review had focused on the recent clustering routing approaches which are metaheuristic-based addressing a gap in the literature as there were few publications that reported a comprehensive survey in this field. Their goal was to do a comprehensive study of the metaheuristic-based approaches, particularly with attention to optimal cluster head selection. The authors were hoping to bring some new protocol structures for low energy protocols in WSNs. In their work, the authors had undergone an analysis of the metaheuristic methodology and features of each protocol, while they had also provided a performance comparison in terms of search characteristics, network attributes, network structure, iterative algorithmic techniques, search options, measurement metrics and results.

**Raja Basha (2022)** had reviewed the key challenges in developing and implementing wireless sensor networks (WSNs), which were described as networks consisting of devices capable of sensing, processing, storing, and communicating wirelessly. It was also stated that several sensors could be included in each network terminal, to observe changes in physical quantities such as temperature, humidity, illuminance, and vibration. The survey discussed different routing algorithms which include geographic routing, energy-aware routing, delay-aware routing, QoS-aware routing, secure-aware routing, and hierarchical-aware routing to solve these issues. The author had also intended to examine which elements of WSNs facilitated the automatic interference and behavior. The selection of the WSN applications had been based, as mentioned, on the basic characteristics, operations and conditions managing for particular applications. The research was structured in a systematic way based on a protocol for systematic literature review. Finally, the performance of existing routing algorithm was analyzed in terms of energy, delay, packet delivery ratio, throughput, false ratio, packet loss ratio, and network overhead.

**Ghawy et al. (2022)** had explored the enhancement of wireless communication and artificial intelligence technologies through the Internet of Things (IoT) paradigm, which was noted to contribute to the development of various applications. However, the authors were aware that the booming proliferation of smartphones and IoT devices in wireless sensor networks (WSNs) had raised some new challenges, such as worsening QoS (in terms of increasing end-to-end latency, energy consumption, and packet loss). To overcome the difficulties, a study had introduced an improved routing protocol called Multipath Particle Swarm Optimization Routing Protocol (MPSORP) based on Particle Swarm Optimization (PSO) algorithm. This procedure was developed to tackle heavy congestion and network flow disparities in WSN-mediated IoT applications. The researchers had simulated MPSORP through NS-2 under different scenarios and against AODV and DSDV protocols. The results show that MPSORP out-perform the other schemes in terms of energy efficiency, end-toend (ETE) delay, packet delivery ratio and higher throughput and less normalized load.

**Arya et al. (2022)** reviewed the recent advancements in Internet of

Things (IoT)-based constrained Wireless Sensor Networks (WSNs), highlighting the growing interest and significant developments aimed at achieving efficient resource utilization and improved service delivery. They also emphasized the need for powerful communication networks for IoT systems and strategically deployed energy-conscious WSNs. They indicated that WSN node deployment with respect to clustering mechanisms were important for the improvement of network lifetime and they also noted the significance of the correct choice of cluster head (CH) for an effective data transmission and better node reachability. In their architecture, they claimed to have made an energy-efficient Deep Belief Network (DBN) routing protocol for which PDR was enhanced. the network was first clustered by an RL algorithm which incentivized nodes in a cluster and the CH selection with the Mantaray Foraging Optimization (MRFO) algorithm. The sink nodes received data from the selected CH through deep learning. The performance of proposed protocol is evaluated in terms of the network lifetime, energy consumption, number of alive nodes and packet delivery ratio, and compared with the existing algorithms in which the results show that the proposed DBN routing protocol achieves better network lifetime.

**Zagrouba and Kardi (2021)** surveyed energy-efficient routing protocols in wireless sensor networks (WSNs), offering a classification and comparison based on a newly proposed taxonomy that distinguished nine categories of protocols, including latency-awareness, next-hop selection, network architecture, and others. They decomposed the categories -and proposed some routing protocols for each one- taking into account features, implementation, pros and cons, as well as sought out a general comparison between protocols in the categories, per set of factors present in each of them. Their simulation results (using NS3 simulator on protocols like LEACH, Mod-LEACH, iLEACH, E-DEEC, multichain-PEGASIS and M-GEAR) revealed that routing function should use variety of intelligent methods to extend the network lifetime and also to have better sensing area coverage.

**Nabavi et al. (2021)** were reported to have highlighted the growing popularity of wireless sensor networks (WSNs) due to the widespread use of communication networks and the ease of information transmission and collection. They observed that the flexibility of WSNs to operate in any environment with minimum amount of observation or engineering effort lead to their widespread deployment applications in different fields. The authors indicated that one of routing information from sensor nodes to the sink in WSNs was considered as major problem which must be solved to consume a uniform energy and to live in longer the network. Because most wireless networks did not have infrastructure and sensor nodes were power-constrained, they pointed out that an early energy depletion in nodes would result in a failure of the network. In their work, a method was proposed to search the best path in WSNs via a multiobjective greedy algorithm for a near-optimal routing. The model suggested nearest neighbor sensor nodes with nodes beginning with nearly equal energy and then along with the transmission of data diminishing the same at a slow pace. They explained that nodes based its choice on the value of combining more than one factors to decide the next hop. Simulation results indicated that the energy consumption was symmetrical, the network lifetime is reduced gradually reflecting that the energy was effectively used and the packet delay of less than 450 ms for 15 nodes in a network with 650 connections, with an increased throughput of about 97%. Previous algorithms were also outperformed in several performance evaluations criteria.

**Younus et al. (2021)** were reported to have discussed software-defined networking (SDN) as an emerging flexible architecture widely applied in various fields, particularly anticipated to play a crucial role in enabling the Internet of Things (IoTs). SDN divides the network into two, the control plane and the data plane and it's the controller that manages the entire network. Their work emphasized the application of SDN technology in wireless sensor networks (WSNs), for the purpose of routing, as the current routing algorithms do not have enough power to find the best paths. To this end, they recommended using reinforcement learning (RL) for routing optimisation in software based wireless sensor networks (SDWSN). They proposed a reward function considering energy efficiency and Quality-of-Service (QoS) metrics, while the RL agent adjusted routing decisions by leveraging the received rewards and historical knowledge. Network control was also established in a Web control fashion. Their RL-approach to SDWSN was evaluated against the conventional SDN, EASDN, QR-SDN, TIDE, as well as non-SDN techniques, such as Q-learning and RL-based routing (RLBR). Results were reported to have achieved better performance of RL-based method with life extension of network ranging 8%–33% and packets delivery ratio (PDR) enhancement 2%–24. % They believed their results could help engineers to improve the performance of WSN through better routing approaches.

**Khan et al. (2021)** discussed wireless sensor networks (WSNs) as systems consisting of spatially distributed autonomous sensors designed to monitor various physical or environmental conditions, such as temperature, sound, and pressure, and to transmit the collected data cooperatively through the network infrastructure. SDN divides the network into two, the control plane and the data plane and it's the controller that manages the entire network. Their work emphasized the application of SDN technology in wireless sensor networks (WSNs), for the purpose of routing, as the current routing algorithms do not have enough power to find the best paths. To this end, they recommended using reinforcement learning (RL) for routing optimisation in software based wireless sensor networks (SDWSN). They proposed a reward function considering energy efficiency and Quality-of-Service (QoS) metrics, while the RL agent adjusted routing decisions by leveraging the received rewards and historical knowledge. Network control was also established in a Web control fashion. Their RL-approach to SDWSN was evaluated against the conventional SDN, EASDN, QR-SDN, TIDE, as well as non-SDN techniques, such as Q-learning and RL-based routing (RLBR). Results were reported to have achieved better performance of RL-based method with life extension of network ranging 8%–33% and packets delivery ratio (PDR) enhancement 2%–24. % They believed their results could help engineers to improve the performance of WSN through better routing approaches.

**Al Aghbari et al. (2020)** were reported to have reviewed the advancements in wireless communication, focusing on low-cost and limited-power devices known as wireless sensor networks (WSNs). They also pointed out that sensor nodes (which are sodata forwardg COPs) suffering from scarce energy which is consumed during data transmission, ergo the energy consumption and the network's lifetime are the major problems of the WSNs. It is mentioned in [11] that a lot of studies have been done to find sufficient routing algorithm to conserve energy. But, they indicated that it was still a hard problem to design routing algorithms to optimize energy consumption and prolong network lifetime efficiently. It was explained that the article explored different optimization methods applied to routing path decision-making and present an extensive review of research during 2010-2019. Their results were claimed to provide insights for future work that would try to bridge the gap and investigate new trends in the WSN field.

**Khan, Hassan, and Jung (2020)** had emphasized the crucial role of underwater sensor networks (UWSNs) in ocean exploration and monitoring through data collection and transmission to ground stations. They reasoned that efficient routing protocols must be designed for robust and reliable data delivery from source to destination nodes. They also reported obstacles encountered in design of routing protocols in consequence of the influence of the underwater environment, the mobility of acoustic channels, rude noise environment of radio channels, as well as the dynamic characteristics of optical channels. The literature also made a survey on challenges faced in routing protocol design and then gave a brief introduction to representative protocols for UWSNs, classifying protocols into localization-based, localization-free and cooperative schemes. They have been compared according to energy consumption, network lifetime, delay, reliability and communication overhead. Finally, Khan et al. focusing on research directions into the future to improve the routing protocol in UWSN.

**Sharma et al. (2019)** were reported to have described wireless sensor networks (WSNs) as resource-constrained systems characterized by limited battery power, computational capacity, and communication abilities at the sensor node level. They focused on the long-time challenge that how to minimize power to prolong the lifetime of wireless sensor networks intensively for reliability and quality. Their work emphasized that energy-aware routing protocols have been extensively investigated in order to enhance the performance of WSNs, but sensor nodes are usually considered homogeneous. But as the real situations were just the same with the fast development of the Internet of Things, they had to take into consideration node heterogeneity, which actually could be utilized positively in routing algorithm. They surveyed different types of heterogeneous WSNs including energy, computation and link heterogeneity and the resultant routing algorithms for performance improvement. Their paper was reported to be focused on routing strategies in diverse heterogeneous WSN scenarios, with much space given to clustering-based routing schemes. They also addressed the implications of interactions and impact of heterogeneities on the routing decisions and provided research direction insights for future work in this area.

**Guleria and Verma (2019)** discussed the significant role wireless sensor networks (WSNs) had played in recent years for applications such as tracking and monitoring in remote environments. They also emphasized that the development of energy-efficient routing protocols was still a critical issue due to WSN’s dynamic topology and distribution characteristics. Their paper was intended to compare hierarchical routing protocols to enhance energy capabilities and prolong lifetime of network. They presented a comparative analysis on hierarchical energy efficient routing protocols which includes traditional and swarm intelligence algorithms. The protocols were classified according to such dimensions as energy efficiency, data aggregation, location awareness, QoS, scalability, load distribution, fault tolerance, query-based processing, and multipath forwarding. A systematic literature review on protocols published between 2012 and 2017 has been performed to provide technical support to improve on protocols in the future. Ultimately, gaps were revealed in the existing methodologies by the authors and potential lines of further investigation were also discussed.

**Mohamed et al. (2018)** were reported to have described wireless sensor networks (WSNs) as collections of small, power-constrained nodes designed to sense data and transmit it to a base station (BS), covering large regions of interest for various applications. They further emphasized that the WSNs’ primary concern was to ensure that the ROI is covered in the best manner possible and also to assure efficient transmission of the surveillance data to the BS. Although deployment consumes a lot of energy and there may be problems with energy fairness in dynamic routing topologies, the high network performance in terms of coverage and connectivity was proven to be an achievable goal in their research. The authors classified WSN applications according to various criteria in order to deduce the major protocol design issues and investigated the energy efficiency of several proactive routing protocols from different viewpoints. Their investigation paid particular attention to the energy overhead and fairness of the protocols under study, and compared the most energy efficient routing protocol between themselves in homogeneous proactive networks. The results showed that energy overhead and routing decision were the most important factors affecting NS frame’s life and NS rationality, indicating the remaining challenges in NS research.

**Bhushan and Sahoo (2018)** highlighted that due to the dynamic topology, resource constraints, and distributed nature of wireless sensor networks (WSNs), routing protocols must meet several critical requirements. WSNs are defined as networks that consist of large numbers of distributed, low-power and autonomous smart sensors with one or more base stations, that cooperatively observe environmental or physical conditions, such as pressure, temperature, sound and motion. The authors stressed that in WSNs, routing protocols efficiency depend on both network lifetime and energy conservation. They further emphasized that Quality of Service (QoS) differentiated support has been a major challenging issue and there has been a greater deal of focus on the QoS-aware routing protocols in these last few years. In their paper, they initially reviewed the several challenging aspects and challenges of WSN-based routing protocols design. Bhushan and Sahoo have subsequently classified these protocols into three main groups and theyare: (1) flat network routing protocols, (2) hierarchical network routing protocols and (3) QoS-aware routingprotocols. They also investigated the flat network protocols and categorized them into three types, namely reactive, proactive and hybrid, while hierarchical protocols were divided into chain-based, gridbased, tree-based and area-based protocols. The paper also conducted a survey of various QoS routing protocols and finally discussed the open research problems with respect to the design of routing protocols for WSNs.

**Sun et al. (2017)** discussed the challenge of achieving efficient data routing in energy-constrained wireless sensor networks (WSNs). They introduced a new routing algorithm for obtaining an optimal data transmission path in WSNs, which is based on ant colony optimization. Enhancing the heuristic function and taking the communication distance between the nodes, transmission direction and the remaining energy of the node, their approach sought to discover an efficient path from source to destination. As a result, it has been claimed to decrease the network energy consumption and prolong network lifetime. Simulation results claimed that the ant colony algorithm achieved low energy consumption of nodes and prolonged the functioning time of the network.

**Shabbir and Hassan (2017)** discussed routing as a significant topic in wireless sensor networks (WSNs) that had attracted considerable attention from the research community over the previous decade. Ten routing techniques which are ant colony optimization (ACO) based were found to have rich feature. Even there had been several survey studies on the routing protocols comparing them by different dimensions, it was noted that a systematic survey of ACO-based routing schemes was still missing. Theirs is said to have been the first study to address this point by conducting a detailed survey of the ACO-based routing protocols in WSNs. They also categorized these routing algorithms, documented and qualitatively compared the most important ACO-based protocols, and presented some of the remaining open issues in WSN design.

## III. Mathematical Formulation for Optimization

### 3.1 WSN Routing Optimization Problem Formulation

Objective: Minimize total energy consumption while ensuring reliable data transmission from source nodes to sink.

Let

- N = total number of sensor nodes
- Ei = residual energy of node iii
- $P_{ij}$ = transmission power cost for sending data from node I to node j.
- $x_{ij}$”{0,1} = routing decision variable; 1 if data is forwarded from node i to j, 0 otherwise

- $L_{ij}$ = link quality metric (e.g., packet delivery ratio or link reliability) between nodes i and j.

**Constraints**

**Flow conservation at each node iii (except sink)**

$$\sum_{j=1}^{N} x_{ji} = \sum_{k=1}^{N} x_{ik} + s_i$$

where si=1 if i is a source node (generates data), else 0.

**Energy constraint**

$$\sum_{j=1}^{N} P_{ij} x_{ij} \leq E_i$$

**Binary routing decision**

$$x_{ij} \in \{0,1\}$$

Objective function (minimize total energy consumption weighted by link quality)

$$\min_{x_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{P_{ij}}{L_{ij}} \cdot x_{ij}$$

### 3.2 Deep Reinforcement Learning (DRL) Formulation for Routing

In DRL, routing is formulated as a Markov Decision Process (MDP) with

- State $s_t$: Network status at time t, e.g., residual energies, node connectivity, link qualities.
- Action $a_t$ : Routing decision (e.g., select next hop node).
- Reward $r_t$: Feedback signal, e.g., negative energy cost or successful packet delivery.

**Goal**

**Maximize expected cumulative reward**

$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right]$$

where $\pi$ is the routing policy, ã” [0,1] is the discount factor.

**Deep Q-Network (DQN) Update Rule**

The Q-function estimates expected reward of taking action a in state s:

$$Q(s,a;\theta) \approx \mathbb{E}[r + \gamma \max_{a'} Q(s',a';\theta) | s,a]$$

where $\theta$ are network weights.

The loss function minimized during training is:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\right)^2\right]$$

where
• D is experience replay buffer,
• è" are weights of target network.

### 3.3 Graph Neural Network (GNN) Layer Propagation

For node i at layer l

$$h_i^{(l)} = \sigma\left(\sum_{j\in\mathcal{N}(i)} \frac{1}{c_{ij}} W^{(l)} h_j^{(l-1)} + W_0^{(l)} h_i^{(l-1)}\right)$$

Where:

- hi = embedding of node iii at layer l,
- N(i) = neighbours of node i,
- cij = normalization constant (e.g., degree-based),
- $W^{(l)}$, $W0^{(l)}$ = learnable weight matrices,
- $\sigma$ = activation function (e.g., ReLU).

Final output embeddings $hi^{(L)}$ can be used to predict routing decisions for node i.

### 3.4 Energy Model for Transmission

Energy consumed to transmit k bits over distance d

$$E_{tx}(k,d) = E_{elec} \times k + E_{amp} \times k \times d^{\alpha}$$

• $E_{elec}$: energy per bit for transmitter electronics,
• $E_{amp}$: energy per bit per $m^{á}$ for amplifier,
• á: path loss exponent (usually 2 to 4).

Energy for receiving

$$E_{rx}(k) = E_{elec} \times k$$

WSN route optimization is basically related to choosing data transmission routes which afford less overall energy consumption and at the same time ensure a successful communication between sensor nodes and Bs. This problem is formulated mathematically using decision variables that indicate the choice of links connecting the nodes; each link is assigned an energy cost and reliability value. The aim is to obtain a minimum of the total weighted energy usage on the entire network, summing over the energy costs of sending packets to nodes divided by the quality of the communication link, taking into account that the Favourenergy efficiency as well as high link reliability [18]. This optimization is under a variety of constraints such as flow conservation (i.e., the amount of data entering a node is the same as that leaving the node, except from source or sink nodes) and demand for residual energy at each node to avoid nodes from dying out before their time. Deep learning methods, and DL-oriented acquisition, such as deep reinforcement learning (DRL), represent this routing problem as a decision process over time, such as state transition process, in which network states in terms of node energy, connectivity, demand load etc are taken as inputs, and its action is finding the next hop relay node in a sequence. The deep neural network model-learning a policy for maximal long-term-rewards of successful data transfer and saving energy. This is stochastically modeled with the Q-function, which estimates the accumulated expected reward provided by transfer routing actions and is iteratively updated to learn better decisions. Besides, graph neural networks can take advantage of the space structure of sensor networks by processing the features of nodes and neighbourhood through layers of transformations into node embeddings. These embeddings inform the routing decisions in order to consider both the local and global network dynamics. Routing optimization is backed by the energy consumption model which determines the power required for data packet transmission and reception as a function of data size and the inter-node distance, including the electronics-amplifier energy costs. Through combining these two mathematical models, we propose a holistic structure, DCGCN-runtime, which allows deep learning models to optimize routing efficiently in the context of the limited and dynamic WSN environment [19].

## IV. Findings of Study

**Enhancement in Energy Consumption:** Deep learning, particularly deep reinforcement learning and graph neural networks, properly learn routing strategies that achieve more energy efficiency in overall energy consumption of WSN compared to conventional heuristic routing algorithms.

**Adaptive Routing:** Deep learning in routing process, especially in edge routing, can help networks ruler and rerouser themselves on the fly to adapt to the dynamic changes, such as energy consumption of nodes, link qualities, and traffic demands, and can become fault-tolerant without human intervention.

**Long Network Lifetime:** The deep learning-enhanced routing can effectively balance load and select energy-efficient routes, leading to a long lifetime of the sensor nodes and network, and thus can reduce node failure events.

**Multiple Objective Optimization:** The deep learning framework is capable of optimizing multiple routing objectives (e.g., energy consumption, latency, and packet delivery success, etc) at the same time by learning policies that effectively negotiate these objectives.

**Generalization and Scalability:** With the use of graph neural networks for example, the model can learn routing policies for different topologies and size of the network which provides scalability in large deployments of WSN.

**Computational Limitations:** Despite the potential for deep learning to make superior routing decisions, directly deploying the models on energy-constrained sensor nodes is still a significant challenge; inference is frequently outsourced toward more powerful edge or base stations.

## V. Conclusion

Deep learning-based approaches offer a powerful and flexible means to solve the challenging route optimization problem for WSNs. By representing routing as sequential decision making, deep reinforcement-learning agents can learn policies that reduce the usage of energy while guaranteeing the communications reliability. Graph neural networks take this further by exploiting the spatial relationships of sensor deployments, which in turn enables adaptive and scalable routing decisions. In conjunction with the accurate modeling of energy consumption, they significantly increase network lifetime and enhance performance compared to classical routing protocols. Future systems will seek to design lightweight deep learning models that are capable of real-time adoption on sensor nodes and hybrid frameworks that fuse heuristic with learned routing strategies providing improved efficiency and robustness.

## Author's Declaration:

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