

A Review of Software-Defined Machine Learning-based Congestion Controls in Wireless Sensor Networks

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Abstract. The rapid proliferation of the Internet of Things (IoT) has made wireless sensor networks (WSNs) a cornerstone technology for modern applications, from smart cities to industrial automation. However, the inherent constraints of WSNs, such as limited energy, bandwidth, and computational power, make them highly susceptible to network congestion. This issue leads to packet loss, increased latency, reduced throughput, and significant degradation in quality of service (QoS). Although traditional congestion control mechanisms offer some relief, they often lack the adaptability required for the complex and dynamic nature of modern WSNs. This research examines the critical role of emerging technologies in mitigating congestion in WSNs, focusing on the integration of software-defined networking (SDN) and machine learning (ML). This study provides a review of this integration, often termed ML-SDWSN, analysing how centralised, programmable control of SDN can be enhanced by predictive and adaptive capabilities of ML to create more robust congestion control frameworks. It presents a comparative analysis of traditional methods against these novel SDN/ML-based strategies, highlighting performance improvements in throughput, energy efficiency, and network optimisation. Furthermore, this study identifies key limitations and open challenges, particularly the computational overhead of implementing ML algorithms in SDWSN environments for real-time control. By synthesising the current state of the art and outlining future research directions, this review underscores the significant potential of lightweight, hybrid artificial intelligence (AI)-driven solutions to alleviate congestion, thereby enhancing network capacity, ensuring QoS, and improving the overall efficiency and longevity of these networks.

Keywords: Internet of Things, Congestion, Software-Defined Networks, Machine Learning, Wireless Sensor Networks.

1 Introduction

In recent years, the emergence of small, more affordable and intelligent sensors has facilitated the development of self-organising wirelessly communicating networks known as wireless sensor networks (WSNs). These networks play an important role in numerous applications, from environmental monitoring to industrial automation [1].

They are used in smart homes, factories, healthcare facilities, traffic lights, and other applications. Furthermore, WSNs consist of distributed devices known as sensor nodes equipped with sensing, processing, and communication abilities. This enables WSNs to collect and transmit data efficiently in real time [2, 3] across large areas with minimal energy consumption and cost. These tiny devices are responsible for beaming data wirelessly. They have small batteries, low-power processors, and result in restricted bandwidth. Now, when data volume exceeds bandwidth capacity, it results in network overload, leading to packet loss and congestion.

The battery-powered sensor nodes suffer severe energy constraints, making energy efficiency a critical concern for network longevity, while the complexity of managing the increasing number of sensor nodes limits the scalability of WSNs. The research in [4] identified key WSNs challenges such as limited energy, restricted computational power, and dynamic topologies as the primary factors leading to network congestion. These challenges ultimately hinder the operational effectiveness of these networks. According to [5], congestion causes communication failures, high energy consumption, increased latency, and compromised data integrity.

Although traditional congestion control approaches can achieve better energy consumption and throughput [6], they often lack the adaptability required for the dynamic nature of WSNs. This is due to their reliance on static thresholds and manual configuration [7]. In other words, traditional approaches have focused on energy savings and data efficiency by adjusting rates based on priorities or managing buffers. To address these limitations, software-defined networking (SDN) was introduced into WSNs creating a new paradigm often referred to as software-defined WSNs (SDWSNs) [7]. The aim is to offload the complex routing logic from the nodes to a more powerful controller. This paradigm enables centralised control and programmable resource management. The decoupling of the control and data planes allows for more efficient handling of large-scale sensor data. Despite its advantage, the centralised model could introduce new challenges in traffic routing control, particularly under high traffic intensity, and often conflict with the many-to-one traffic patterns of WSNs [8]. Consequently, congestion remains a significant challenge in SDWSNs, leading to packet loss, higher latency, and performance degradation [9].

As shown in Fig. 1, Jurado-Lasso et al. [10] proposed the integration of machine learning (ML) with SDWSNs, termed ML-SDWSNs. This framework embeds ML modules in the application and control planes. The data plane consists of sensor nodes that generate network data, which is collected, processed, and stored in a database. The ML module handles training, testing, tuning, and deployment of models to support intelligent decision-making in the SDWSN controller. The controller manages flow tables, routing algorithms, and network operations dynamically, enabling intelligent traffic management, adaptive routing, anomaly detection, and predictive network optimisation. Consequently, the framework improves network efficiency, reduces latency and congestion, improves energy utilisation, supports real-time decision-making, and increases the scalability and reliability of WSNs through automated data-driven control. However, such frameworks must address critical concerns regarding computational complexity, resource constraints, and scalability. Prasanth and Uma [11] concurred that

a hybrid approach integrating ML with traditional methods is a promising direction for optimising congestion management in SDWSNs.

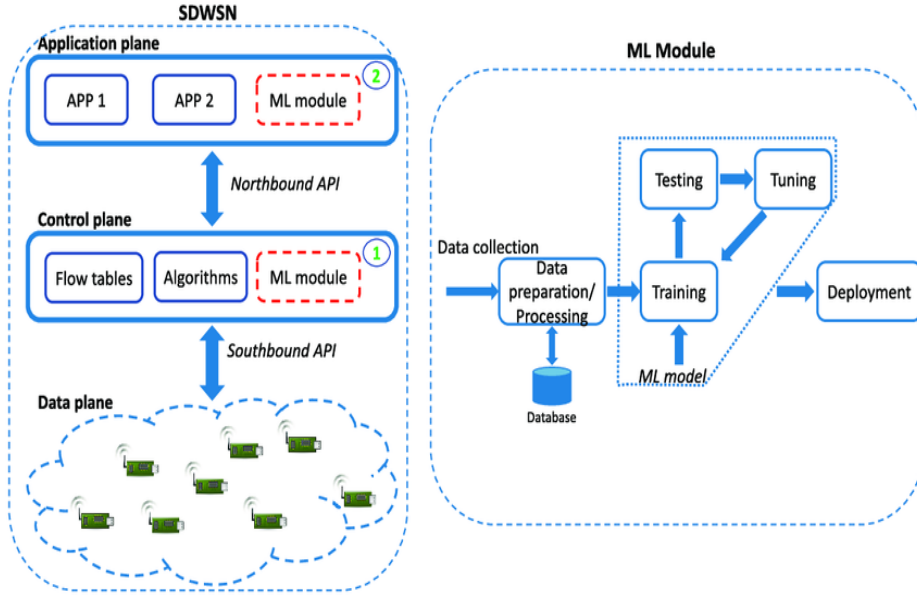


Fig. 1. A simple representation of an ML-SDWSN architecture [10].

Therefore, this study examines the evolution of congestion control mechanisms in WSNs, with a particular emphasis on SDN and ML approaches. It analyses current methodologies, compares traditional and emerging solutions, and identifies research gaps in the field. The aim is to explore how SDN, ML, and traditional approaches can enhance congestion control in WSNs. The contributions of the study can be discussed as follows:

- It provides a review of the convergence between SDN architectures and ML-based solutions for congestion control in WSNs.
- It presents a comparative analysis between traditional congestion mitigation techniques and those that take advantage of the SDN and ML paradigm, demonstrating performance improvements that are possible through this integration.
- It identifies the challenges in implementing ML algorithms within the constraints of SDN controllers for real-time congestion management in resource-limited WSN environments.
- It highlights open challenges and future directions in the development of light-weight hybrid algorithms.

This paper proceeds as follows. Section 2 discusses the background and fundamentals. Section 3 presents SDN and ML congestion control solutions. Section 4 reviews related surveys. Section 5 provides a comparative analysis of existing studies. Section

6 discusses open issues and suggests future directions. Section 7 presents the discussion and findings. Section 8 concludes this review.

2 Background and Fundamentals

WSNs have become a foundational technology by enabling the autonomous, real-time collection of data from the physical world without relying on human intervention or existing infrastructure. This capability is critical in military surveillance, remote patient healthcare monitoring, precision environmental tracking, and industrial automation systems. From the Great Barrier Reef [12] to the smart factories of Germany [13], WSNs provide the critical data link between the environment and digital systems. These developments are driven by advances in embedded systems and wireless communication technologies, which facilitate real-time data collection and processing across various sectors [14]. However, the constraints of sensor nodes, including limited processing capabilities, storage, communication bandwidth, and energy resources, pose significant challenges to the efficient operation and management of WSNs. These limitations necessitate energy-efficient solutions, adaptable communication protocols, and optimal deployment strategies to improve network performance [15]. This has led to the integration of SDN and ML solutions. This section presents a literature review of the challenges associated with these solutions.

2.1 Traditional Congestion Control in WSN

Traditional congestion control in WSNs relies on rate adjustment, priority-based scheduling, and buffer management. Although effective in certain scenarios, these methods often lack the adaptability required for dynamic network conditions encountered in WSNs [7]. Traditional controls can be classified into three types, namely traffic control protocols, source control protocols, and hybrid mechanisms, while Bohloulzadeh and Rajaei [9] presented four different types of controls, namely traffic control protocols, source control protocols, priority-aware approaches, and queue-assist mechanisms. The aim of traditional congestion controls is to reduce traffic load, find alternative paths, prioritise critical data, or manage buffer queues to prevent and alleviate network overload [9].

Traffic Control Protocols: These protocols manage congestion by reducing the transmission rate at the source node and limiting the number of packets injected into the network. They often employ techniques such as additive increase multiplicative decrease (AIMD) or rate-based methods. AIMD adjusts the rates based on successful transmissions or congestion detection, whereas rate-based methods calculate available bandwidth based on previous rates.

Source Control Protocols: These protocols address congestion by increasing network resources or using idle or alternative routes to transfer data to the sink. They aim to

divert traffic from congested points. Examples include topology-aware resource adaptation (TARA), adaptive duty cycle-based congestion control (ADCC), and other protocols that construct multiple paths from source to sink [16].

Priority-Aware Approaches: In scenarios where data importance varies, such as healthcare applications, these methods prioritise access to the channel for accumulated nodes or higher priority packets. They adjust channel allocation policies to favour critical data. According to Kumar and Kumar [17], protocols such as priority-based congestion control protocol (PCCP), dynamic predictive congestion control (DPCC), prioritised heterogeneous traffic-oriented congestion control protocol (PHTCCP), class-based optimised congestion management protocol (COCM), congestion control based on reliable transmission (CCRT), and priority-based application-specific congestion control clustering (PASCCC) fall into this category, often classifying packets and assigning them to different priority queues.

Queue Assistant Mechanisms: Queue assistant mechanisms focus on managing node queues to keep their lengths low, typically using simple rate-adaptation techniques such as AIMD. This is because congestion detection often relies on buffer occupancy or queue length. Examples include buffer-based congestion avoidance schemes such as interference-aware fair rate control (IFRC), queue-based congestion control protocol with priority support (QCCP-PS), and methods that adjust transmission rates dynamically based on buffer levels [17].

2.2 SDN in WSNs and its Applications

The integration of SDN with traditional WSNs represents a significant technological advancement. The aim is to overcome the inherent limitations of conventional WSNs, including high hardware and deployment costs, excessive energy consumption, and challenges related to standardisation and scalability. The core concept of SDWSNs is to take advantage of the programmable network management of SDN to enhance the functionality, efficiency, and flexibility of a network. This is achieved by decoupling the control logic of the network from its data-transmitting functions, creating a more adaptable and manageable architecture [18].

Benefits of SDWSNs: SDWSN offers benefits that address the shortcomings of WSN. This is due to the capacity of the SDN to simplify network management and configuration through increased network programmability and abstraction, enabling dynamic and flexible network control, and contributing to cost reduction [19]. The separation of the control and data planes centralises network intelligence in a programmable controller, simplifying the network, and enhancing scalability. This architecture enables optimised energy management. Zare Soltani et al. [20] state that SDN controllers can re-route traffic dynamically to reduce energy consumption by up to 40%. SDWSNs improve network reliability through a global network view, adaptive routing mechanisms

that respond to changing conditions, and simplified network management owing to centralised control. This benefit provides greater architectural flexibility for future developments.

Applications of SDWSNs: In Industry 4.0 and the Industrial Internet of Things (IIoT), SDWSNs manage data routing for automation and machine health monitoring. Their scalable nature makes them ideal for traffic management and infrastructure monitoring. Furthermore, SDWSNs are well suited for environmental monitoring, for coordinating patient sensors in healthcare systems, and for precision agriculture to manage crop and soil sensors. Despite this promising potential, SDWSNs still face ongoing challenges in achieving optimal energy consumption, ensuring robust security, and implementing effective distributed control mechanisms for various use cases [21].

3 SDN and ML Congestion Control Solutions

This section explores the interaction between SDN and ML as a powerful approach to tackle network congestion. It delves into how ML-driven congestion control solutions can enhance the adaptability and intelligence of SDN-based architecture.

3.1 SDN Congestion Controls

Khan et al. [22] proposed a graph-theoretic approach using a centralised SDN controller to construct a conflict graph that identifies overlapping paths. It uses centrality measures such as eigenvector and degree to select non-overlapping paths and to minimise queueing delay. The aim is to satisfy quality of service (QoS) requirements, such as end-to-end delay, for multiple applications sharing the same WSN while avoiding congestion through global network visibility. However, its performance degrades in networks with low path diversity. Furthermore, it is not suitable for high-mobility environments owing to frequent topology changes. In addition, its centralised computation may be time-consuming for large-scale networks.

Almuntasheri and Alenazi [21] proposed an SDN-based routing protocol that selects paths based on node energy levels rather than the shortest path. The controller switches paths dynamically to avoid draining critical nodes. The aim is to prolong the lifespan of the network, prevent node failures, and avoid battery replacements in IIoT environments. However, it increases end-to-end delay because longer and more energy-efficient paths are selected. Furthermore, it is limited to static or low-mobility scenarios and requires frequent energy updates, thereby increasing control overhead.

Sasirekha et al. [23] proposed a hybrid control architecture with local and global controllers. Local controllers handle dynamic events such as congestion, while the global controller manages topology and resource allocation. The aim is to balance responsiveness and optimality, improve scalability, and handle both static and dynamic network conditions efficiently. However, its complex hierarchical control structure may introduce significant coordination overhead. Furthermore, its evaluation is based on

simulation, leaving its real-world performance uncertain. In addition, it has not been tested thoroughly under conditions of high interference or mobility.

3.2 ML Congestion Controls

Alqaraghuli and Karan [24] used deep reinforcement learning (DRL) with the 2-dimensional convolutional neural network (2DCNN) and the 3-dimensional convolutional neural network (3DCNN) to optimise energy-efficient routing in SDWSNs. The controller predicts rewards for routing decisions to maximise network lifespan. The aim is to address energy constraints in WSNs and extend network lifespan through intelligent, adaptive routing mechanisms. However, the 3DCNN architecture introduces high computational complexity. Furthermore, this approach requires extensive training data and relies heavily on simulation for validation. In addition, it does not handle real-time dynamic network changes or QoS metrics such as latency explicitly.

Younus et al. [25] combined RL with SDN to optimise routing using four reward functions based on energy, distance, and hop count. The model employs tree-spanning protocols to ensure loop-free paths. The aim is to improve the lifespan and convergence speed of the network through centralised control and adaptive reward-based learning. However, it relies on predefined reward functions, which may not be generalised effectively under diverse or dynamic network conditions. Furthermore, this approach was tested on a small-scale testbed consisting of only 14 nodes, raising scalability concerns. In addition, it does not address explicitly the challenges posed by heterogeneous traffic patterns or real-time QoS requirements.

4 Related Surveys

In recent years, numerous surveys have been conducted on congestion control and the application of ML in wireless networks. However, there is a shortage of reviews that examine the integration of SDN and ML for congestion control in WSNs. Existing studies have focused on ML-based congestion mitigation and load-balancing routing in SDN environments. This review bridges this gap by providing an in-depth analysis of their combined potential.

Babayigit et al. [26] analysed surveys and review studies to establish a systematic taxonomy for SDN research. This aimed to map the dominant themes and to identify critical gaps in the field. The findings revealed that the dominant themes were security, IoT, network functions virtualisation (NFV), and AI. The identified research gaps included security, 5G/6 G integration, and load balance. They proposed future work on hybrid environments, adaptive security, ML-based management, scalability, and interoperability.

Jurado-Lasso et al. [10] conducted a comprehensive survey on SDWSNs to review their current status and significant challenges. This was aimed at identifying the dominant research themes and critical gaps in the field. The findings revealed that the dominant themes were energy efficiency, control overhead, security, and reliability. The identified research gaps included the need for standardisation, scalable solutions, and

adaptive ML techniques. They proposed future work on hybrid architectures, real-world testbeds, integration with 6 G and edge computing, security, interoperability, and resource management.

Kumar et al. [27] analysed state-of-the-art traffic engineering (TE) techniques for SDWSN-based IoT networks. This aimed to examine methods for flow management, fault tolerance, and traffic analysis, and to identify key challenges. The findings highlighted the advantages of SDN, including centralised control and programmability. The identified research gaps included scalability, security, energy efficiency, and autonomous management. They proposed future work on optimised TE solutions, hybrid architectures, real-world deployments, and integration with 5G/6 G, edge computing, and AI-driven optimisation.

Akpakwu et al. [28] analysed congestion control mechanisms in the Constrained Application Protocol (CoAP) for IoT networks. They aimed to review state-of-the-art approaches and identify key challenges. The findings revealed significant challenges, such as dynamic traffic patterns, energy efficiency, and interoperability issues. The identified research gaps included limitations of traditional TCP and the need for solutions tailored to constrained environments. They proposed future work on a three-state Markov model for congestion classification, adaptive control based on ML, and integration with 5G/6 G and edge computing.

5 Comparative Analysis

Table 1 presents ML-based models for congestion control in WSNs, highlighting their strengths in intelligent and data-driven adaptation for SDWSN. Godfrey et al. [29] developed DOS-RL, which improves PDR by 10%–20 % and energy efficiency over OSPF and SDN-Q, though facing slow learning and reward design issues. Alqaraghuli and Karan [24] used a DQN with 3DCNN to extend lifespan by 17% (~678 252 seconds), maintain 85.07% PDR, and reduce hops to 9.81. Younus et al. [25] developed an RL-based SDWSN that enhances network lifespan by 23%–30% and reduces delays and jitter but has convergence and overhead limitations. Consequently, these models optimise dynamic metrics like lifespan and energy efficiency through continuous learning, yet incur high computational costs and complex implementation, limiting deployment on resource-constrained WSNs.

Table 1. Comparison of ML-based Solutions for SDWSNs.

Reference	Methods	Setup	Metrics	Strengths
[24]	Deep Q-Network (DQN) with 2D/3D CNN architectures.	Simulation with 100 random WSNs (8–32 nodes); Python/TensorFlow.	Network lifespan, packet delivery rate (PDR), and prediction time.	3DCNN outperforms 2DCNN; 18% longer network lifespan.

[25]	Q-learning with reward functions based on energy, distance, and hops.	Real testbed with Raspberry Pi (14 nodes); Python-based.	Network lifespan, convergence rate.	23%–30% longer network lifespan than RL-based WSN; faster convergence.
[29]	Q-learning with dynamic objective selection (DOS) and reward shaping.	NS-3 simulation with 30–60 nodes; integrated with PyTorch/TensorFlow via ns3-ai.	PDR, end-to-end delay, and energy efficiency.	Adapts to dynamic changes; balances multiple objectives; outperforms OSPF and SDN-Q.

Table 2 presents SDN-based models for congestion control in WSNs, highlighting their strengths in centralised control, graph-theoretic optimisation, and energy-aware routing. Khan et al. [22] developed a congestion avoidance model using graph-theoretic algorithms to select node-disjoint paths, achieving up to 34% better performance than existing works and up to 14% worse than the optimal solution, but assumes low mobility. Almunasher and Alenazi [21] proposed an SDN-based energy-aware routing protocol where the Ryu controller shifts traffic to energy-preserving paths when nodes reach low energy thresholds, doubling transmission lifetime but increasing end-to-end delay. Sasirekha et al. [23] introduced SDSense, using k-edge-disjoint topologies and local congestion detection (60% queue occupancy) to trigger centralised rate reallocation, improving reliability. However, these models face challenges including control overhead, dependency on controller reachability, and limited path diversity. Consequently, ML solutions are better suited for long-term autonomous optimisation in dynamic environments, although SDN-based solutions are ideal for programmable infrastructures, with advanced systems integrating both paradigms.

Table 2. Comparison of SDN-based Solutions for SDWSNs.

Reference	Method	Setup	Metrics	Strengths
[22]	Graph-theoretic path selection using a conflict graph and centrality measures	Simulation in Java using Watts-Strogatz graph models (35–50 nodes). Compared to the optimal brute-force method and OF-ANM.	Average queue length, end-to-end delay, and algorithm execution time.	Up to 34% better performance than existing works (OF-ANM) in delay reduction. Provides a global view for multi-application QoS.

[21]	SDN controller	Simulation using Mininet-Wi-Fi and the Ryu controller (5-node topology). Compared to shortest path routing.	Node energy consumption, transmission time, node failure rate, and end-to-end delay.	Doubles the transmission time compared to shortest path routing. Prevents node failure and avoids costly battery replacements.
[23]	Hybrid hierarchical SDN architecture with local and global controllers	Simulation-based analysis that focuses on topology construction, scheduling (TDMA), and congestion control.	Topology stability, packet delivery under congestion, flow setup time, and resource allocation efficiency.	Improved scalability and fault tolerance. Responsive to dynamic network conditions via local control.

6 Open Issues and Future Directions

The increasing scale and complexity of modern networks, especially WSNs and the IoT, have brought significant challenges to maintaining reliability and managing congestion. Although AI/ML promise optimisation, several open issues persist, necessitating a clear direction for future research.

6.1 Open Issues

Based on the existing literature, several issues or challenges hinder the effective implementation of ML-driven congestion control. These can be summarised as follows:

Complexity of ML Model Deployment: Despite the promise of ML models for real-time adjustments, significant challenges remain in tuning parameters precisely and in the computational complexity of processing real-time network data. WSNs typically have limited computational power, memory and energy resources, making it challenging to deploy these sophisticated models [6, 8].

Network Heterogeneity and Interoperability: Studies consistently highlight unresolved issues related to interoperability, adaptive security, and the lack of standardised solutions across heterogeneous networks. Despite proposed advances, such as ML-based traffic engineering and Constrained Application Protocol (CoAP) optimisations for congestion control, practical frameworks for large-scale deployments are still largely underexplored [9].

Dynamic Network Environments: Dynamic traffic patterns, energy constraints inherent in many IoT devices, and the diversity of IoT protocols further complicate the implementation of effective congestion control.

Lack of Real-World Evaluation: A significant gap in current research is the lack of long-term evaluations of SDN solutions in real-world settings, particularly in emerging domains such as WSNs, edge computing and vehicular networks [9]. These issues underscore the critical need to develop robust congestion control mechanisms.

Network Expansion: As the network scales, issues like reliability and congestion become more pronounced, while traditional SDWSNs rely on centralised control, large-scale expansion often necessitates distributed or hierarchical control systems [30]. However, latency and inefficiency in dynamic environments underscore the need for distributed and adaptive congestion control mechanisms that complement the centralised SDN approach. Achieving this balance is crucial for optimising performance and ensuring reliable data transmission in WSNs [9].

6.2 Future Directions

To address the identified challenges and improve network performance, future research should focus on the following:

Advanced ML Integration for Anomaly Detection: The integration of ML models for anomaly detection in SDWSNs can enhance congestion detection significantly by identifying unusual traffic patterns. Specifically, recurrent neural networks (RNNs), particularly those employing long short-term memory (LSTM) units, have demonstrated a high accuracy of 87% in detecting anomalies in sensor behaviour. This capability is crucial for identifying congestion points effectively [9].

Adaptive and Context-Aware Management: More studies are needed on adaptive ML techniques that can adapt dynamically to changing network conditions and traffic patterns. Studies should also explore cross-layer optimisation strategies that consider interactions between network layers to achieve more holistic congestion management. Furthermore, the development of context-aware systems that take advantage of real-time environmental and network conditions to make informed decisions about congestion control is also important.

7 Discussion and Findings

The major issue is that data packets pile up and cause congestion. Preventing this is critical for maintaining network functionality and reliable data delivery. The proposed

hybrid control systems address this through rapid on-the-spot decisions by local controllers when congestion is imminent, while the global controller manages long-term resource allocation to optimise network capacity. Although ML methods have proven effective in adaptive routing simulations, a significant gap remains in their real-world deployment owing to the limited processing power, energy, and data availability of tiny sensor devices not designed for high-performance computing.

To address these issues, the SDN architecture offers a robust framework for offloading complex tasks, managing data paths, and aiding congestion avoidance. However, a major discussion point remains the validation gap. Although simulations and small testbeds have shown improvements, there is a distinct lack of testing in real large-scale networks.

8 Conclusions

This paper has explored how SDN and ML can enhance congestion control in WSNs, which are inherently prone to congestion owing to their limited energy, bandwidth, and computational resources. Research suggests that effective solutions require hybrid approaches that combine local and global control for fast decision-making and strategic management. It suggests further the development of lightweight algorithms suitable for resource-constrained sensor nodes and greater emphasis on real-world evaluations to validate theoretical improvements. However, the study acknowledges that congestion, resource limitations, and the need for adaptability remain significant challenges in these networks. Furthermore, a critical oversight identified is the impact of random object interference, such as an object that triggers a sensor and causes network congestion during a scientific experiment.

In future work, developing robust mechanisms to detect and mitigate unpredictable physical interferences, alongside continued efforts in hybrid, lightweight ML-driven SDN solutions, will be crucial to ensuring the reliability and efficiency of WSNs.

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