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Review

A Review on Congestion Mitigation Techniques in Ultra-Dense Wireless Sensor Networks: State-of-the-Art Future Emerging Artificial Intelligence-Based Solutions

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Abstract: The Internet of Things (IoT) and wireless sensor networks (WSNs) have evolved rapidly due to technological breakthroughs. WSNs generate high traffic due to the growing number of sensor nodes. Congestion is one of several problems caused by the huge amount of data in WSNs. When wireless network resources are limited and IoT devices require more and more resources, congestion occurs in extremely dense WSN-based IoT networks. Reduced throughput, reduced network capacity, and reduced energy efficiency within WSNs are all effects of congestion. These consequences eventually lead to network outages due to underutilized network resources, increased network operating costs, and significantly degraded quality of service (QoS). Therefore, it is critical to deal with congestion in WSN-based IoT networks. Researchers have developed a number of approaches to address this problem, with new solutions based on artificial intelligence (AI) standing out. This research examines how new AI-based algorithms contribute to congestion mitigation in WSN-based IoT networks and the various congestion mitigation strategies that have helped reduce congestion. This study also highlights the limitations of AI-based solutions, including where and why they are used in WSNs, and a comparative study of the current literature that makes this study novel. The study concludes with a discussion of its significance and potential future study topics. The topic of congestion reduction in ultra-dense WSN-based IoT networks, as well as the current state of the art and emerging future solutions, demonstrates their significant expertise in reducing WSN congestion. These solutions contribute to network optimization, throughput enhancement, quality of service improvement, network capacity expansion, and overall WSN efficiency improvement.

Keywords: WSNs; congestion mitigation; artificial intelligence; game theory; IoT; QoS

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1. Introduction

Wireless data traffic has increased due to exponential growth in the use of Internet of Things (IoT) devices. It is predicted that more than 29 billion IoT devices will be in use by 2030 [1]. The extremely high density of IoT device connectivity will bring several problems. Congestion is one of the major problems of IoT networks powered by wireless sensor networks (WSNs) [2–5].

The United States of America's (USA) military first proposed the idea of wireless sensor networks based on the Internet of Things (IoT) in 1950. The first program, called the Sound Surveillance System (SOSUS), was developed to use acoustic sensors to detect and track sound waves emanating from submarines in the Pacific and Atlantic oceans.

WSNs are interdisciplinary technologies that combine the comprehensive techniques of wireless communications, pervasive computing, networking, and signal processing [6]. WSNs have evolved continuously and incrementally since the 1960s [6]. However, the Defense Advanced Research Projects Agency (DARPA) launched a brand-new initiative called Distributed Sensor Networks (DSNs) in the 1970s [7]. The development of DSNs had a positive impact on academic study and scientific research. In the last 50 years, it has also attracted customers and researchers.

WSN-based IoT networks consist of widely distributed sensor nodes that allow us to track and respond to events and outcomes at a remote location [8,9]. The Internet of Things gained the attention of the scientific community in the late 20th century due to advances in a number of important areas, including communication technology, small hardware, security monitoring, etc. These technological developments made it possible to build low-cost, compact, and multifunctional WSN nodes [10]. Today, the wireless IoT network has evolved into an intelligent, self-healing, extremely dynamic, and distributed system [11]. Due to its efficiency and adaptability, the IoT is currently playing an important role in real-time monitoring and data acquisition.

In recent decades, IoT-based WSNs have been developed on a large scale, mainly for heavy industry and military applications. It is often referred to as the Internet of Everything (IoE) due to the widespread use of IoT devices. In this scenario, the IoE offers tremendous potential for the future of the smart world. However, the widespread use of wireless sensor devices will lead to wireless network congestion. When a large number of IoT devices attempt to access network resources that are bandwidth-constrained and lack network traffic management, congestion occurs in communication networks, especially WSNs. This negatively impacts the entire network by reducing network performance and quality of service (QoS), increasing the energy consumption, leading to packet loss and causing security concerns [12]. This study focuses on different WSN-based IoT network congestion strategies. The organizational structure of this study is shown in Figure 1.

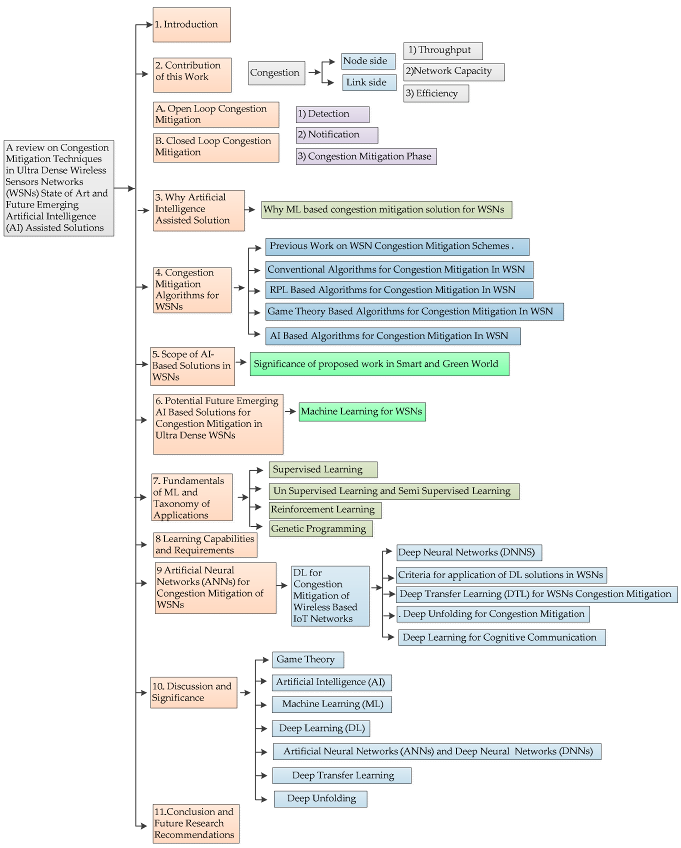

Figure 1. The pictorial overview of the survey.

2. Contribution of This Work

There are many published surveys on the topic of congestion mitigation in communication networks. This is one of the hot topics in communication. However, there is little work on congestion mitigation in WSNs. Specifically, a survey that provides an in-depth discussion on conventional as well as future emerging AI solutions in the context of WSN congestion mitigation is not available. In this survey, we present a review of state-of-the-art published work in the prospect of congestion mitigation in ultra-dense WSNs with futuristic AI solutions. The contributions of this work are as follows:

(1) This survey outlines the scope of AI-based future emerging solutions for the congestion mitigation of WSNs.
(2) WSN congestion mitigation solutions are divided into four major categories to support novice as well as expert readers' understanding by means of logical segregation of the state-of-the-art literature.
(3) This survey also provides criteria for integrating AI solutions into WSNs.
(4) Each section is comprehensively summarized with necessary figures and tables.
(5) Critical analysis of various types of AI solutions along with their applications in IoT is also an integral part of this study.
(6) This study highlights future recommendations for congestion mitigation in WSNs.

Congestion

Congestion is the overload of data produced by IoT devices as a result of a network failure. In this case, the rate of incoming data is greater than the transmission rate. Since the bandwidth of the channel is limited, the collision rate increases. Therefore, the increased rate of retransmission results in wasted energy, lower throughput, and shorter network lifetime [13]. Congestion can occur on both the node side and the link side.

Node side: When the arrival rate of packets exceeds the departure rate of packets on the specific node side.

Link side *congestion:* Here, the reason for congestion is contestation, bit error, and collision [14]. Link-level congestion is related to the sharing of channels between numerous nodes by the Media Access Control (MAC) layer contention-based protocols [15].

Congestion in WSNs is an important issue and affects throughput, energy efficiency, and network capacity. A detailed discussion on each is given in the following.

(1) Throughput

System throughput increases during acute congestion in extremely dense wireless IoT networks. As a result, network resources are not optimally utilized, and the backlog of IoT devices grows. The probability of network failure also increases with the duration of this situation. As a result, congestion occurs.

(2) Network Capacity

Network capacity is one of many network parameters being severely impacted by the increasing congestion of the Internet of Everything. Network capacity is decreasing, and performance is suffering as network congestion increases. One of the main causes of performance decline is network capacity.

(3) Efficiency

Energy efficiency is one of several factors affecting the operating cost of a network, and it is of great importance. The energy efficiency of the wireless network for the Internet of Things (IoT) is reduced in situations of extreme congestion, which increases the operating costs of the network and increases carbon emissions to the atmosphere.

A. Open Loop Congestion Mitigation

In this congestion control system, there is no feedback, which is known as open loop control. Moreover, it requires the use of a user-side or eNB-side congestion minimization mechanism. We could also refer to the above idea as a unilateral congestion mitigation technique to convey it differently. By intervening on either the source or the destination side, this strategy reduces congestion at an early stage. The open loop control system is characterized by its accessibility, ease of use, and slightly reduced precision.

B. Closed Loop Congestion Mitigation

Closed loop congestion control solutions involve creating a feedback system between the input and output sides. The input and output variables in this particular control system are interdependent, which means that any change in one variable will have a corresponding effect on the other. Compared to an open loop system, a closed loop system has higher accuracy. Clearly, there is a tradeoff between accuracy and cost. The goal of this control mechanism in the wireless Internet of Things (IoT) is to reduce overloads. In a closed loop system, congestion reduction is achieved by completing three separate processes [16].

(1) Detection

Monitoring and detecting deviations from normal in the immediate environment are the process of detection. In our example, the detection mechanism checks a number of constraints, including queue length and packet delay [17].

(2) Notification

A notification is a means of alerting the central control body to a deviation from the norm and triggering the implementation of the necessary countermeasures according to a predefined program. A combination of the above indicators is used by some notification approaches in IoT networks to detect congestion. According to reference [18] there is a limit on the length of the queue. When the buffer level exceeds the specified maximum value, congestion is detected, and a notification is sent.

(3) Congestion Mitigation Phase

The activation of the control center in response to the notification signals the completion of the closed loop process for congestion mitigation in IoT networks. The implementation of appropriate control measures to mitigate network congestion is the responsibility of the control center. In this phase, network traffic management considers the bandwidth of the network. Numerous strategies are used, including network resource optimization, traffic reduction, queue length adjustment, and packet and node scheduling.

3. Why Use an Artificial Intelligence-Assisted Solution?

The development of artificial intelligence is often considered essential to the development of engineering and technology. In the wireless communication network of the near future based on the Internet of Things, artificial intelligence will play an essential role in meeting the requirements of the communication system. Smart infrastructures, including smart grids, smart homes, smart cities, smart meters, and a globally interconnected smart grid, will proliferate in the coming era. Internet of Everything (IoE) communications technology will be used to make the concept of a smart world a reality. To realize a smart society, a wireless network based on the IoE must also be built. It is critical to make communication systems and other key components intelligent to improve their functionality. It is crucial to find an artificial intelligence (AI)-based solution to meet the future needs of a technologically advanced and environmentally friendly society [19]. The list of Nomenclature is shown in Table 1.

Table 1. Nomenclature in the survey.

Acronyms	Definition
IOT	Internet of Things
IP	Internet Protocol
6LoWPAN	IPv6 over Low-Power Wireless Personal Area Network
QoS	Quality of Service
I-IOT	Intelligent Internet of Things
RACH	Random Access Channel
ROC	Receiver Operating characteristic
SGNANs	Smart Grid Neighborhood Area Networks
SoNCF	Self-organizing network coordination framework
TCP/IP	Transmission Control Protocol IP
TARA	Topology Aware Resource Adaptation (TARA)
LTE-A	Long-Term Evolution-Advanced
LSTM	Long Short-Term Memory
ML	Machine Learning
M2M	Machine to Machine
MAC	Media Access Control
CAT-M	Machine type category
mMTC	Massive Machine Type Communication
MADM	Multi-Attribute Decision Making
CAT-N	Narrowband IoT Category
OS	Operating system
OHCA	Optimization-based Hybrid Congestion Alleviation
PB-ALOHA	Pseudo Bayesian ALOHA
PRA	Prioritized Random Access
PSO	Particle Swarm Optimization
RPL	Routing Protocol low-power and lossy networks
SOSUS	Sound Surveillance System
SDN-IoT	Software-Defined Networking based on IoT
SDRs	Software-Defined Routers
TR	Technical Report
UDP	User Datagram Protocol
USA	United States of America
WSNs	Wireless Sensor Networks

Why Use an ML-Based Congestion Mitigation Solution for WSNs?

A subfield of artificial intelligence (AI) called machine learning (ML) is concerned with using machine learning algorithms to help computers acquire new information and skills. These algorithms make it easier for a computer to evolve into an intelligent being. We will explore the many types of machine learning and their associated algorithms in later sections. It is predicted that advanced systems will emerge in the near future that have the ability to self-heal, be highly dynamic, and be self-preserving. In thesae systems, machine learning is of critical importance. Future wireless networks will be intelligent enoaugh to meet the above requirements, with DL and ML algorithms playing a crucial role [19,20]. It is expected that resource management in the extremely dense IoT network will be significantly affected by deep learning (DL) and machine learning (ML) [21]. A comparison of the contributions made by researchers in the field of IoT network congestion mitigation is shown in Table 2. The utilization of deep neural networks (DNNs) in WSN devices facilitates the capability of these IoT devices to perform intricate sensing tasks and foster collaboration between the environment and humans [22].

Table 2. Comparison of the survey with contribution related to congestion mitigation in IoT.

Main Domain	Ref	Type	Year	Contribution	Scope of the Work Congestion	IoT	AI
Game theory application security prospect	[23]	Survey	2008	Survey on Game theory to solve challenges relevant to energy efficiency and security	X	✓	✓
Role of LTE-A in Emerging Machine Type Category (CAT-M) and Narrowband IoT Category (CAT-N).	[24]	Survey	2017	Up-to-date and comprehensive survey on (CAT-M) and (CAT-N).	✓	✓	X
Machine learning applications in the IoT domain	[25]	Survey	2018	Comprehensive Survey on ML techniques and applications in IoT	X	✓	✓
Routing Protocol low-power and lossy networks (RPL) by contiki operating system (OS)	[26]	Survey	2018	First Survey that categories RPL via contiki OS	✓	✓	X
Deep Transfer Learning	[27]	Survey	2018	Review latest work on transfer learning via DNNs as well as their application.	X	X	✓
Application Deep reinforcement learning (DRL) in IoT and UAV	[27]	Survey	2019	Review on Deep reinforcement learning in network different prospects.	X	✓	✓
WSN recourses allocation by DL and ML.	[28]	Survey	2020	This work comprehends the DL and ML based techniques for resource allocation in WSN in Heterogeneous Networks (HetNets), NOMA, D2D communication prospective.	X	✓	✓
Various congestion mitigation algorithms are reviewed.	[29]	Survey	2020	This review is based on different techniques to control congestion as well a novel taxonomy has been proposed.	✓	X	✓
Transfer Learning	[30]	Survey	2021	Transfer learning and different machine learning techniques relationships.	X	✓	X
Congestion mitigation AI algorithms in nature	[24]	Survey	2023	Reviewed AI algorithms exist in nature.	✓	X	✓
AI based algorithms review to solve congestion in WSN.	This work	Survey	2023	The novel review on congestion mitigation based on AI based solution in WSN.	✓	✓	✓

4. Congestion Mitigation Algorithms for WSNs

Considering the significance of the topic, the research community has proposed many congestion control techniques. In this study, we focused on congestion mitigation techniques for WSNs, as discussed below.

4.1. Previous Work on WSN Congestion Mitigation Schemes

Previous work in the domain of WSN congestion mitigation can be divided into four main categories, as shown in Figure 2. We will explain these one by one in the following.

Figure 2. An overview of congestion mitigation AI algorithms in the literature for WSN.

4.1.1. Conventional Algorithms for Congestion Mitigation in WSN

A method for optimizing the use of network resources was proposed in a paper by Manal El Tanab [31]. The proposed method facilitates the allocation of time-constrained uplink resources with contention. Achieving maximum resource utilization leads to a reduction in congestion, energy consumption, access latency, and blocking probability. This study also examines the variables that cause the degradation of IoT devices with a backlog in WSN. Compared with the strategy of the dynamic banning of access classes, the proposed method performs better and is more effective. The results of the previous work, where a binary integer programming scenario was created, show that the proposed strategy achieves a desirable access delay value. Back-off (BO) and distributed queuing (DQ) are two commonly used computer network techniques.

Collision-Free Full-Duplex Communication for MAC (CFFD-MAC) is a proposal discussed by R. Rukaiya et al. in [32] that attempts to increase the throughput of IoT networks by leveraging full-duplex transmission in existing wireless sensor networks (WSNs). The proposed strategy uses a slotted-time contention protocol within the MAC architecture to achieve the desired purpose. With minimal control overhead, this protocol allows devices to randomly access the communication channel. Devices use a queue for efficient use and send data in contention-free time slots with non-colliding neighboring nodes to achieve the lowest number of hops possible.

Huasen Wu and Chenxi Zhu in [33] introduced Fast Adaptive Slotted ALOHA (FASA) to manage random access IoT devices when traffic is bumpy. Observing the data of consecutive colliding and unused slots is critical to optimize the S-ALOHA. The estimated active number of IoT devices under FASA quickly converges towards the true number thanks to the drift analysis-based architecture. Moreover, the authors showed that the proposed system is stable until the average arrival rate is less than e(-1) by studying the drift of the slots. The simulation results show that the proposed system outperforms more established methods such as Pseudo Bayesian ALOHA (PB-ALOHA) and achieves near-ideal performance in reducing access delay. In addition, FASA performs better in delay and is robust to bursty traffic.

In [34], Golnaz Farhadi and Akira Ito proposed a novel group-based paging for wireless IoT base networks to reduce congestion. Group-based paging allows the eNodeB to coordinate with the network, and this system manages congestion RACH. The proposed technique differs from traditional paging methods in that it does not require each IoT device to attempt to establish a network connection. However, the proposed paging strategy gives the selected IoT device, referred to as a group, authority over the RACH procedure of IoT devices in the form of an access group. The authors also proposed signaling techniques that facilitate resource allocation at the access group level for data messages directly and group-based connectivity through group delegation. Numerical results show that the group access technique achieves significantly lower access delay compared to the standard access scheme. It also supports signaling protocols based on the number of group delegates rather than the number of IoT devices, where the signaling overhead is proportional to the number of group delegates. The proposed system can increase the number of IoT devices that can be offloaded simultaneously without incurring congestion management, overhead, and access latency. It also promotes resource reuse by effectively utilizing data transfer resources.

The channel resource usage, in an efficient manner, depends on the reassignment of the channel. Software-Defined Networking based on IoT (SDN-IoT) is a promising methodology for channel reassignment. Moreover, it also facilitates Software Defined

Routers (SDRs) go via the SDN controller for traffic load scheduling, helping to meet the better usage of network resources as well as the mitigation of congestion WSNs. Reinforcement learning has the ability to take hard decision capability; hence, in [35], Tong Wu and Pan Zhou proposed one of the novel resource allocation mechanisms by utilizing deep reinforcement learning for optimizing the reassignment of multi-channel on controlling the traffic in SDN-IoT (core backbone network). The authors developed a multi-channel reassignment for the optimization of the objective function through a traffic control and multi-channel reassignment (TCCA) algorithm and Multi-Agent Deep Deterministic Policy Gradient (MADDPG) called (TCCA-MADDPG). To handle the backbone network complexity of the network and dynamics, the authors employed IoT traffic prediction results, making the information part of the channel state. At the same time, the TCCA-MADDPG algorithm alleviated the environment with multi-agent instability by partly observing the state through the multiple agents' cooperation. To ensure better time utilization continuity states in the channel, a Long Short-Term Memory (LSTM) layer is added to the neural network. The simulated results reveal that the proposed mechanisms outperform the existing schemes and converge quickly.

Smart cities with wireless IoT networks will include massive machine-based communications (mMTCs) over the cellular network. However, the dynamic characteristics, including quality of service requirements, transmission frequency, payload size, and energy efficiency, pose significant obstacles to the development of IoT applications based on the wireless communications of the future. The major obstacles in WSNs are congestion mitigation and effective energy management during periods of high traffic. Massive random access attempts cause severe degradation in WSN performance, as they result in a sharp increase in the probability of preamble collisions and congestion to manage the enormous access that is the root cause of many problems in the wireless IoT network.

In [36] M. S. Ali, E. and Hossain proposed a unique random access-based collision resolution model for heavy IoT traffic. The basic preamble collisions are resolved by the proposed solution. The simulation results show how S-ALOHA models have affected the success rate of RA. With excellent reliability and efficiency, this model can coexist with a

Long-Term Evolution-Advanced (LTE-A) Media Access Control (MAC) layer protocol and network access.

Congestion on RACHs in LTE-A can result from WSNs accessing the channel simultaneously. The Extended Access Barrier (EAB) strategy is the basic choice of 3GPP to reduce RACH congestion by blocking low-priority devices. Various EAB-based strategies are proposed to restructure the arrival of IoTs; nevertheless, these mechanisms provide erratic performance. In [21], R. G. Cheng et al. provided an analytical model to study the effectiveness of the EAB algorithm in LTE-A networks. Simulations show the accuracy of the analysis. The analytical model theme targeting the QoS constraint could achieve the best values for the repetition period for system information block type 14 (SIB14).

To prevent congestion before it occurs, A. Ndikumana, S. Ullah, and K. Thar developed the Novel Co-operative and Fully Distributed Congestion Control (NCFCC) strategy for CCN in [37]. CMTB is one of the hybrid congestion management techniques and combines Dynamic Token Bucket and Receiver-Based Congestion Management (FDCC), which is a modified version of additive increase or multiplicative decrease. The proposed plan operates in two phases. The second phase is initiated when the CMTB asks the FDCC to reduce traffic after trying all the middle nodes but without success. PSR messages are used to turn on the FDCC. By changing the data transmission rate of the intelligent consumer nodes, the FDCC takes control. The simulation results show that the proposed mechanism, which has been evaluated in several simulation scenarios, achieves remarkable throughput gains compared to current ideas in the literature. The congestion mitigation strategies used in WSN are categorized by type and strategy in Table 3.

Table 3. Categories of congestion mitigation based on IoT type and technique.

Reference	RPL	Smart Grid	6LowPAN	Game Theory	WSN	Health Care IoT	Industrial IoT	AI	I-IoT	Optimization
[38,39]	✓	X	✓		✓	X	X	X	X	X
[40]	X	✓	X		✓	X	X	X	X	X
[41,42]		X	✓	✓	✓	X	X	X	X	X
[43,44]	✓				✓	✓				
[44–47]	✓	X	X	X	✓	X	X	X	X	X
[48]	X	X	X	X	X	X	✓	✓		
[49]	✓	X	X	X	✓	X		✓	X	X
[50]	X	X	X	✓	✓	X				
[51]	X	X	X	X	✓	X	✓		✓	✓
[52]	X	X	X	X	✓			✓		✓
This work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

One of the main problems in the literature is the congestion of the radio access network (RAN) in LTE-A. Prioritized Random Access (PRA) is a mechanism proposed by J. P. Cheng and C. H. Lee to solve the RAN congestion problem in LTE-A networks based on 3GPP. These mechanisms utilize the various WSN traffic RACH resource allocation techniques based on bakeoff with a priority basis to meet the quality of service requirements. The dynamic access blocking algorithm is proposed to address the worst RAN congestion. Simulation results show that PRA has shorter delay and higher reliability for smart meters and emergencies compared to EAB. Moreover, PRA can maintain the quality of H2H communication while differentiating priorities for different traffic types.

In [53], S. Y. Jung, S. H. Lee, and J. Kim proposed an RA framework for reliability management in WSNs to reduce the failure rate. This framework includes an algorithm to estimate the number of active WSN devices in a cell using the uudecoded preamble counts and the preamble loss probability. In addition, it has an algorithm that modifies transmissions of the number preamble to determine the failure probability of RA. In addition, an algorithm called adaptive ACB factor decision is used to modify the ACB factor based on state information. A simulator is used to evaluate the performance of the proposed framework.

To reduce congestion in IoT networks, R Hassan et al. presented a unique adaptive technique in [54]. The adaptive nature of the mechanism, which can respond to the transmitted traffic and the changing conditions of the network, makes this technology highly novel. However, it does not yet provide a division of IoT traffic into multiple classes based on priorities. When the buffer's threshold is reached, the downstream node is notified. When a notification is received, the downstream node changes the traffic rate. Repeating this process leads to a reduction in network congestion.

To reduce congestion in IoT networks, Sharma et al. in [55] proposed the Bidirectional Reliable and Congestion Control Transport Protocol (BRCCTP). These techniques use the rate adaptation method to control congestion within WSN. It supports bidirectional reliability in data transmission. The ratio between the average packet delay and the average packet arrival time is used to determine the degree of congestion of the nodes. Since all data sources have the same priority index, congestion can be reduced. As soon as the WSN is detected as overloaded, the latencies during data transmission increase significantly.

To relieve WSN congestion, Zhuang et al. introduced the "Congestion-Adaptive Data Collection scheme (CADC)" in [56]. In addition, a technique based on lossy compression was developed to reduce congestion. Weighted CADC techniques are also used to reduce congestion in cyber-physical applications. In this technique, chunks of data are defined according to different priorities.

SoNCF, a framework for self-organizing network coordination, was proposed in [57] In this algorithm, a pulse-coupled oscillator model is used for dynamic time partitioning. The problems with exposed and hidden nodes are solved using the proposed algorithm. Moreover, the relief from traffic congestion is to be distributed. Priorities for data packets were not considered in the study.

WSNs play an important role in the IoT [58]. The Internet integrates 6LoWPANs and WSNs. However, an Internet Protocol (IP) stack designed for wired networks is used to implement the sensor nodes [59]. However, the use of the Transmission Control Protocol IP (TCP/IP) standard in 6LoWPAN networks and WSNs presents a number of issues and challenges, including buffer and energy resources and bandwidth limitations. In addition, User Datagram Protocol (UDP) lacks a congestion control mechanism at the end of data transmission, while TCP requires additional resources for connection establishment and termination.

4.1.2. RPL-Based Algorithms for Congestion Mitigation in WSN

A plan to reduce IoT congestion was presented in [60] by GP Sunitha and colleagues. IoT traffic congests the nodes on the sink side. The proposed routing protocol is based on a three-phase balanced zone to solve this problem. In the first phase, the network is divided into clusters of equal size. In the second phase, a zone leader is selected for each zone with the least IoT traffic. For this zone, this leader is responsible for routing. In the third stage, the zones are divided according to the degree of congestion. This research can be used to reduce congestion at both the inter-cluster and intra-cluster levels.

Misra et al. in [45] proposed a Reliable and Energy Efficient Protocol (REEP), a reliable data routing protocol with congestion mitigation for IoT networks. This routing technology is data-centric and demand-driven. The routing stage is determined by local communication. However, this technique incurs significant transmission cost and message overhead in WSNs.

To reduce congestion in WSN, Farsi et al. in [49] developed the Congestion-Aware Clustering and Routing (CCR) protocol. This protocol increases the number of packets sent and the lifetime of the WSN while satisfying the QoS requirements. Bandwidth allocation is an effective solution in a network congestion scenario where other applications interfere with high-priority traffic.

Tang et al. proposed an RPL-based multipath routing mechanism for congestion avoidance called CA-RPL in [61]. They also developed the DELAY ROOT RPL routing method that reduces the average delay of the root node. CA-RPL reduces network congestion by distributing large amounts of traffic among numerous channels. The proposed methods also include three additional metrics: the rank of ETX (Anticipated Transmission Count), the selection of the parent using multiple packets, and DELAY ROOT.

A unique RPL-based objective function called "congestion-aware objective function (CA-OF)" was proposed by Al-Kashoash et al. in [62]. This method works well for high traffic volumes. This formula combines two measurements. The packet is forwarded to the sink node via less congested nodes: 1) buffer occupancy and 2) ETX. Algorithms to reduce congestion in wireless IoT networks are summarized in Table 3.

A congestion-aware routing protocol to minimize congestion was proposed in [43], and it is based on the survivable path routing protocol. The target of the method is a high-traffic WSN (IoT in healthcare). The signal to interference and noise ratio of the link are used to determine the routing path. The ratio between the minimum remaining energy of the nodes on the path and the total energy consumed on the potential communication path is used to determine the survivability of the path.

RPL is proposed for limited IoT devices and WSNs [63]. Numerous studies have been conducted to apply RPL in different contexts, including node mobility [38,64], different traffic patterns [65], forwarding, and multi-casting. The RPL network still provides unusual work that solves the congestion problem [66]. This study extends the web-based CoAP/6LoWPAN protocol stacks by integrating congestion mitigation functionalities. The congestion mitigation mechanism was proposed in [67]. The Cooja simulator and Contiki OS have not yet been tested with the above work [68].

4.1.3. Game Theory-Based Algorithms for Congestion Mitigation in WSN

S. Chowdhury and C. Giri proposed a congestion control algorithm for a tree-based network in [69] using non cooperative game theory. In this technique, the data transmission rate of each leaf node is optimized. The main objective of this work is to identify a unique Nash equilibrium point for the best data transfer rate of each leaf node, which prevents congestion at the parent destination until the service rate for the destination node remains the same. The throughput of the entire network is, thus, optimized. The author of this paper believes that the main causes of packet loss are channel congestion and buffer overflow. NGTCC (Non-cooperative Game Theory-based Congestion Control) is the name of the proposed work to reduce traffic. The simulation results of the proposed work show that it performs better than the alternatives in terms of throughput and data transfer rate.

The optimization-based hybrid congestion mitigation (OHCA) strategy for 6LoWPAN was proposed in [66]. It uses both resource management and traffic control strategies. When congestion occurs, OHCA uses Gray Relational Analysis (GRA) [65] to find another route that is not congested. In the absence of an alternate route, OHCA implements a traffic management strategy using a "game theory-based congestion control framework (GTCCF)" [70] and modifies the transmit data rates of the associated leaf nodes.

However, the currently proposed congestion mitigation strategy ignores the above problem and instead emphasizes only network throughput or delay. Non-cooperative Gaming for Energy-efficient Congestion Control (NGECC), a unique approach, was proposed in [71].

In this work, the energy parameter of the 6LoWPAN network is considered for the first time. Moreover, the real-time simulator Cooja and the operating system Contiki are used to test this work.

In IoT, WSNs play an important role [58]. The Internet integrates 6LoWPANs and WSNs. An Internet Protocol (IP) stack is used to implement the sensor nodes, but it is designed for wired networks [59] However, using the Transmission Control Protocol IP (TCP/IP) standard in 6LoWPAN networks and WSNs presents a number of issues and challenges, including buffer and energy resources and bandwidth limitations. In addition, TCP requires additional resources for connection establishment and termination, while User Datagram Protocol (UDP) has no congestion control mechanism at the end of data transmission.

In [72] Michopoulos et al. developed the Duty Cycle-Aware Congestion Control (DCCC6) method to reduce congestion in 6LoWPAN networks. This method determines the radio duty cycle and changes the operation as needed. It uses a modified "Additive-Increase Multiplicative-Decrease AIMD" method to reduce network congestion and dynamic buffer allocation for congestion detection.

Fuse, Gripping, and Deaf are three different congestion avoidance strategies that were developed by Castellani et al. in [42]. They are used in CoAP/6LoWPAN networks to regulate both unidirectional and bidirectional data flows. The basic ideas behind these proposed algorithms are distributed backpressure. The missing acknowledgment packet and buffer occupancy strategies both use griping. In the AIMD scheme, Fuse and Deaf are used for both congestion detection and congestion mitigation. Congestion mitigation reduces incoming packets by adjusting the transmission rate.

For CoAP/6LoWPAN networks, Hellaoui and Koudi [41] presented a technique for congestion mitigation. The concept of flocking birds serves as the basis for this algorithm. To avoid congested paths, this concept is implemented by routing packets through congestion-free zones. Moreover, the proposed method uses the buffer occupancy technique to identify congested nodes and manage resources by selecting the least congested paths to reduce congestion. An RPL-based algorithm called "Queue Utilization Based RPL (QU-RPL)" was proposed by Kim et al. in [35]. This algorithm makes use of the queue. For selecting the parent for traffic load balancing, the aforementioned technique uses a queue utilization factor [73].

The authors in [41] proposed the mechanism for congestion control for 6LoWPAN networks, called Game Theory Congestion Control (GTCC). This algorithm senses congestion via the flow rate of the packet, also called a packet generation rate, deducted from the service rate of the packet. When any parent node senses congestion by the Data Information Object (DIO) control packet, it transmits the message of congestion to all affiliated children. After receiving the DIO message all affiliated children start changing their parents. In this method, the nodes utilize game theory for deciding whether to change the parent or not. When the parent change is completed, the new DIO message is transmitted to inform the other nodes about the update.

In [66], the hybrid congestion mitigation mechanism was proposed for 6LoWPAN, named Optimization-based Hybrid Congestion Alleviation (OHCA). This employs both resource control and traffic regulation approaches. During congestion, OHCA utilizes Grey Relational Analysis (GRA) [65] to find a congestion-free alternate path. If an alternate path is not available, then OHCA applies a traffic reduction mechanism via a game theory-based congestion control framework (GTCCF)"[38] and the adjustment of sending data rates of the related leaf nodes is carried out.

Game theory-based algorithms control the traffic [23]. For solving the congestion issue, the work in [42] and the algorithms employed in [41] overlap. They used game theory for routing the proposed algorithm to be aware of application priorities as well as node priorities, although, game theory based on no cooperation supports a framework for analysis and characterizing the decisions and interactions among various players having a conflict of interest [74].

In [67], the authors proposed a congestion mitigation mechanism based on game theory through resource control and traffic control strategies. However, this mechanism does not consider the parameter of energy. This method also does not consider the environment of the 6LoWPAN network and has not been tested on Cooja. One of the major concerns is energy consumption. Hence, the efficiency of energy is the prima facie benchmark in limited-resource networks and in energy like WSNs [75].

Yet, the currently proposed solution for congestion mitigation only emphasizes the delay or network throughput and does not consider the aforementioned issue [76]. In [77], the authors proposed a novel algorithm, Non-cooperative Gaming for Energy-efficient Congestion Control (NGECC). This work was the first time the energy parameter was considered for the 6LoWPAN network. Moreover, this work was tested on the real-time Cooja simulator and Contiki operating system.

4.1.4. AI-Based Algorithms for Congestion Mitigation in WSN

In [78], to deal with the extremely dense congestion in IoT networks, Naeem Faisal created a novel model-free and adaptive fuzzy neural network (NN) based on a deep reinforcement learning mechanism. These techniques utilize the MPTCP protocol, the multi-path transport control protocol. To deal with states with highly dynamic IoT traffic dimensions, this unique model is proposed that approximates the value of state action function and actor function (action). In addition, this model dynamically modifies the congestion subflow window size to account for the changing environmental conditions. The simulation results show that the proposed approach outperforms the Deep Quantum Learning (DQN) and Software Defined Network (SDN)-based MPTCP in terms of good performance. The proposed approach requires time-consuming training and execution, which leads to delays in the IoT network.

A recent decoupled learning optimization procedure was presented by Nan Jiang in [79]. This scheme involves the optimization of several features, including average access delay, successful device access, and average energy consumption. In addition, this algorithm jointly optimizes other RACH techniques, such as DQ, BO, and Access Class Barring (ACB). This tactic separates traffic configuration from spoilage. The Gated Recurrent Unite Recurrent Neural Network (GRU-RNN) model was previously used to predict real-time values of IoT real-time traffic. Due to the random nature of IoT real-time traffic, these values exhibit short-term correlation. The task of the target controller is to use various Deep Reinforcement Learning (DRL) agents to configure the system parameters for the RACH scheme. In addition, the goal of DQN is to manage the unique action selection of BO and the Distributed Queuing (DQ) scheme. Deterministic Policy Gradient (DDPG) is used to regulate the ongoing action selection of ACB mechanisms. The numerical results of the proposed system show that the cooperative model and the decoupled learning scheme outperform traditional learning schemes in terms of training efficiency. Moreover, cooperative learning can successfully adapt the RACH schemes, resulting in the highest performance for each RACH scheme. This shows how the training effectiveness and convergence can be improved by using projected IoT traffic data in conjunction with a learning procedure. These techniques can also be used in the 5G New Radio Network (NR) to optimize RACH schemes and can be extended to optimize solutions to dynamic challenges.

A congestion avoidance strategy for Smart Grid Neighborhood Area Networks (SG-NANs) based on ML techniques was proposed by N. K. Pratas and H. Thomsen in [80]. In this approach, the source node decides whether to transmit data based on the current traffic in the network. This decision is made based on the packets currently in the buffer and the channel utilization factor. All broadcasts and network nodes are used to measure the parameters. Additionally, based on the usefulness of data applications, the division of traffic into different categories is considered. To train the model, the approaches from ML require data sets. The proper techniques to generate data sets are the first contribution of this work. Using this data, we can better define the network behavior and the influence of the different categories. It also helps in separating the traffic categories. So, this separation leads to improved performance at the expense of the original complexity of the system. On the other hand, sometimes, feature selection is carried out to reduce the complexity. An evaluation and use of the two-classification algorithm is made. One has a low computational cost and is based on decision trees. To evaluate its performance in the first phase, the receiver operating characteristic curve (ROC) is used, which has the highest accuracy value. Moreover, at the level of the tested SG NAN settings, better improvements were obtained in terms of network delay, throughput, and PDR. The behavior of the system is tested at a higher level in different traffic categories, and QoS is observed. To clarify the results, the compliant throughput and the compliance factor are introduced at this level. In the last level, the categorization is performed using neural networks. Better simulation results were obtained for all these categories, albeit at a cost due to computational complexity.

In [41], H Hellaoui et al. proposed a congestion solution in IoT networks for Constrained Application Protocol (CoAP), IPv6 over Low-Power Wireless Personal Area Network (6LoWPAN) networks. The proposed algorithm applies the swarm intelligence notion procedure for forwarding the packets of data via routes free from traffic and avoiding congested routes. In [81], S. J., H. Singh proposed a congestion-aware algorithm using fuzzy logic (CAUF) for finding the routing path that will be optimal to prevent congestion from picking the best parent from the tree structure of WSN. The model of parent selection is added to a multi-attribute decision making (MADM) by using a fuzzy weighted sum model.

In [44], Prasenjit Chanak proposed a congestion mitigation three-step scheme. Each step uses one algorithm to achieve the purpose. (1) Level Detection Algorithm, step one, named setup phase. (2) Request Distribution Algorithm, named request distribution phase. (3) Event Distribution Algorithm, named data routing and event occurrence report phase. In fact, in medical WSN, various sensors have different priorities. This scheme senses the various sensors with different priorities towards the gateway. Before the transmission of packets, priority is set by source nodes based on the data's importance.

Huang et al. [82] proposed a Fairness-Aware Congestion control scheme (FACC). In this scheme, a congestion-aware rate-based fairness control was reported. In this method, all intermediate WSN sensor nodes are divided into near-sink and near-source nodes. The congestion is detected by the loss of packets at the sink node. In [83], Kang et al. proposed a Topology-Aware Resource Adaptation (TARA) solution to minimize congestion in IoT networks. The focus of this scheme is an additional resource adaptation for congestion alleviation in WSNs. This is achieved by activating a peculiar sleeping sensor node to establish the new topology. This new topology manages heavy network traffic.

To reduce congestion in WSNs, Sergiou et al. in [44] offered the Hierarchical Tree Alternative Route (HTAP) method. To find all promising paths leading to the sink, a tree is built based on the source. For the purpose of forwarding the additional packets, HTAP chooses the node with the smallest buffer. However, this plan results in a significant time delay and message overhead.

Guo et al. proposed a Convolutional Neural Network (CNN) in [48] to increase the bandwidth of Mukherjee et al.'s contribution by inserting additional layers. The concept of a multilayer deep learning Neural Network in an industrial WSN with a clustering-based method to optimize the transmission power was proposed by Mukher-jee et al. in [50]. The application of CNN deep learning algorithms was found to improve the QoS and optimize the security aspects of WSN. Recurrent feedback increased the strength and efficiency of the CNN structure.

To minimize congestion in WSNs, N. A. S. Al-Jamali in [51] proposed an I-IoT-based modified element-wise attention gate using a Convolutional Recurrent Neural Network (EG-CRNN) deep learning algorithm. The proposed system was used to predict the number of packets in the WSN and to help manage the cluster heads of the WSN. This plan takes advantage of self-feedback, which improves both short-term and long-term memory. To update the weights of the EG-CRNN, the above approach also proposed a deep learning training algorithm. Moreover, it accelerates the process training required to achieve the error target.

To reduce the overload in WSNs, the authors of [52] presented a unique approach called collaborative distributed Q-learning. The authors used the Bellman equation for the Q-learning process in the proposed solution. Moreover, this approach allows IoT devices to gradually learn the exclusive RA slots for data transmission. As a result, there are fewer concurrent transmissions in the WSN access network. The autonomous Q-learning process is different from this approach. It uses a collaborative method. Moreover, the congestion level of the learning process is used for RA slots. In terms of throughput, convergence time, and collision probability, the numerical results show that collaborative Q-learning has better performance. The previous congestion mitigation efforts consist of two parts.

(1) Congestion mitigation based on RPL rare work is conducted with this type of methodology.
(2) Congestion mitigation based on non-RPL methodologies did not consider the stack protocol of 6LoWPAN. One rare research work has been conducted on congestion mitigation mechanisms in RPL networks. We will explain these mechanisms in the following paragraphs.

The Dynamic Alternative Path Selection Scheme (DAlPaS), described in [46], is a phase-based resource regulation mechanism based on congestion mitigation without RPL. The first stage of congestion mitigation deals with light congestion, while the second stage deals with heavy congestion. The load balancing technique is used as the primary application, which controls the topology technique to prevent overloads in intermediate nodes. If the aforementioned method is unsuccessful, a hard stage is used to control the data flow and determine alternative routing paths.

To reduce congestion, two methods, Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO), were presented in [84]. To determine the ideal data rate of PSOGSA for each child, a multi-objective search is used with the above technique. The optimization function considers both the energy parameters of the nodes and the priority of the transmitted data packets.

In [85], the authors proposed a novel solution for congestion mitigation based on packet-priority intimation (PPI). In this method, the PPI part in the packet is used to indicate its priority. This method exploits the routing protocol of the Ad hoc On-Demand Distance Vector (AODV), making it a congestion-aware mechanism. In [86], several situations of congestion in the WSN communication channel were presented. The evaluation is based on the transmitter output power level, time intervals of transmission, and generation rate of the packet.

Anurag Gautam and Ibraheem in [24] investigated a wide range of natural AI mitigation solutions for deregulated power systems (DPSs). In addition to providing concepts and pseudocodes for optimization algorithms, such as Grey Wolf Optimization (GWO), Teaching Learning-Based Optimization (TLBO), JAYA Algorithm (JAYA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), inspired by natural processes, the authors also studied conventional and non-conventional algorithms. The authors also investigated methods of system-wide congestion mitigation.

This research was conducted by the authors in the context of reducing DPS traffic congestion caused by renewable energy sources. Potentially, these methods could be used to optimize wireless sensor networks (WSNs) for effective spectrum, energy, and WSN resource management. These algorithms should be used for resource management on the tower side.

The following section of the review focuses on recently developed AI-based WSN congestion mitigation techniques. Before proceeding, it is important to understand the limitations that AI algorithms face.

5. Scope of AI-Based Solutions in WSNs

What limitations might be encountered when using AI-based algorithms to reduce congestion in WSN? This is a crucial question. In answering this question, we must consider the limitations of wireless sensors and IoT devices. Resources, such as memory, power, and processing speed, are scarce on the IoT side, while they are more readily available on the tower side. The likelihood of deploying certain AI-based solutions on both sides depends on the resource allocation. Deep learning (DL), deep reinforcement learning (DRL), and other approaches that require more resources can be deployed on the tower side, where resources, such as memory, processing power, and bandwidth, are abundant. In contrast, due to resource constraints, only AI algorithms with lower power and bandwidth requirements can be used on the IoT side; examples include Reinforcement Learning (RL) and Federated Learning (FL). It is possible to use RL and FL on both the tower and IoT sides. Figure 3 illustrates the range of AI methods available to reduce congestion in WSNs.

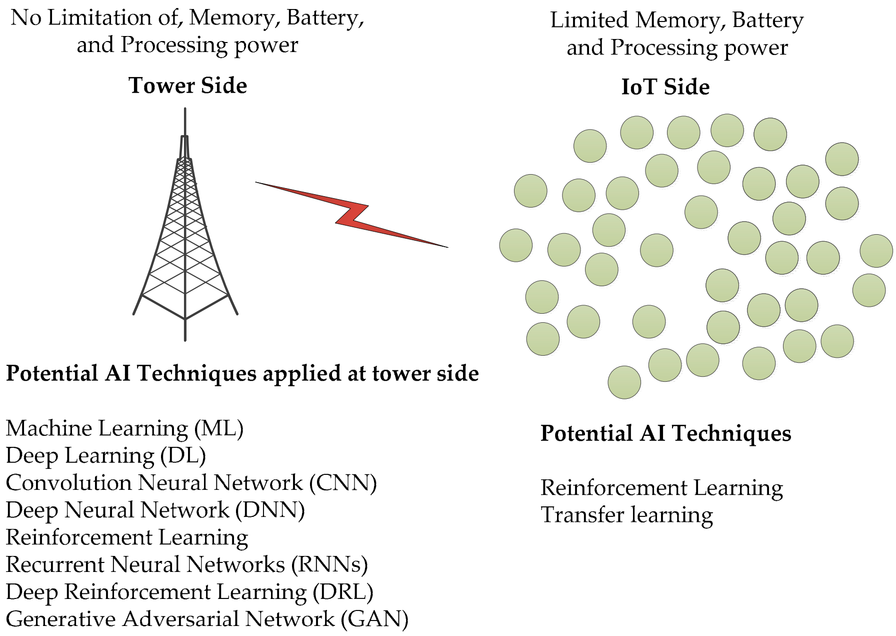

Figure 3. Scope of various AI techniques in congestion mitigation in WSNs.

Significance of Proposed Work in Smart and Green World

Another crucial question is where this work can be practically applied. This research is useful wherever we use wireless networks for IoT. Smart homes, smart grids, smart cities, and even the broader idea of a "smart and green world" are all scenarios we can consider. The use of IoT and AI-based technologies to control our homes, communities, power grids, and, ultimately, the entire planet is referred to as "smart" technology. The term "green", in turn, refers to the commitment to a sustainable environment achieved by minimizing carbon emissions, reducing energy consumption, and effectively managing resources.

The futuristic "smart and green world" will certainly include the integration of IoT and artificial intelligence. The proposed efforts have the potential to contribute significantly to the realization of this dream [87].

6. Potential Future Emerging AI-Based Solutions for Congestion Mitigation in Ultra-Dense WSNs

In this section, we will shed light on a potential future emerging solution based on AI for congestion mitigation in ultra-dense IoT wireless networks, such as machine learning (ML), deep learning (DL), Artificial Neural Networks (ANNs), etc.

Machine Learning (ML) for WSNs

Traditionally, it has been assumed that machine learning (ML) can be used to solve problems only when a large amount of training data is available, no precise mathematical model for the system is available, and only numerical analysis over time is acceptable. Modern solutions based on ML are widely used to solve a variety of problems in both WSNs and modern communication systems. Due to adaptive communication networks that are self-healing, self-maintaining, highly dynamic, self-learning, and highly intelligent for the evolution of IoE network communication, there is a huge potential for reducing congestion in WSNs through ML-based solutions. Moreover, the algorithms of ML have a very high potential to replace the current approaches to congestion in WSNs and other problems. In this paper, we explain the basics of ML as well as the scope of ML in IoT networks and congestion avoidance in IoT networks [88]. The algorithms discussed in this paper are compared in Table 4.

Table 4. Summary of algorithms in congestion mitigation for IoT existing techniques.

Algo.	Ref.	Solution Technique				Packet Loss Type		Limitation
		Traffic Control	Resource Control	6LoWPAN	WSN	Buffer Loss	Channel Loss	
Back pressure	[67]	✓	X	✓	X	✓	X	Simulation not verified in real WSN simulators like cooja
GTCCF	[38]	✓	X	✓	X	✓	X	High energy consumption, low throughput
OHCA	[66]	✓	✓	✓	X	✓	X	High energy consumption, low throughput
NCGEE	[77]	✓	✓	✓	X	✓	✓	-
Game Theory	[23, 75]	✓	X	✓	X	✓	X	-
DCCC6	[89]	X	✓	✓	X	✓	X	-
GTCC	[41],	✓	X	✓	X	✓	X	-
RPL	[39]	✓	X	✓	X	✓	X	-
This work	-	✓	✓	✓	✓	✓	✓	-

7. Fundamentals of ML and Taxonomy of Applications

In this section, we will describe the ML types, such as supervised, unsupervised, and reinforcement learning, and their applications as well as emerging potential challenges that are also indicated in IoT wireless-based networks in congestion mitigation [90]. Figure 4 shows the taxonomy of ML and DL algorithms.

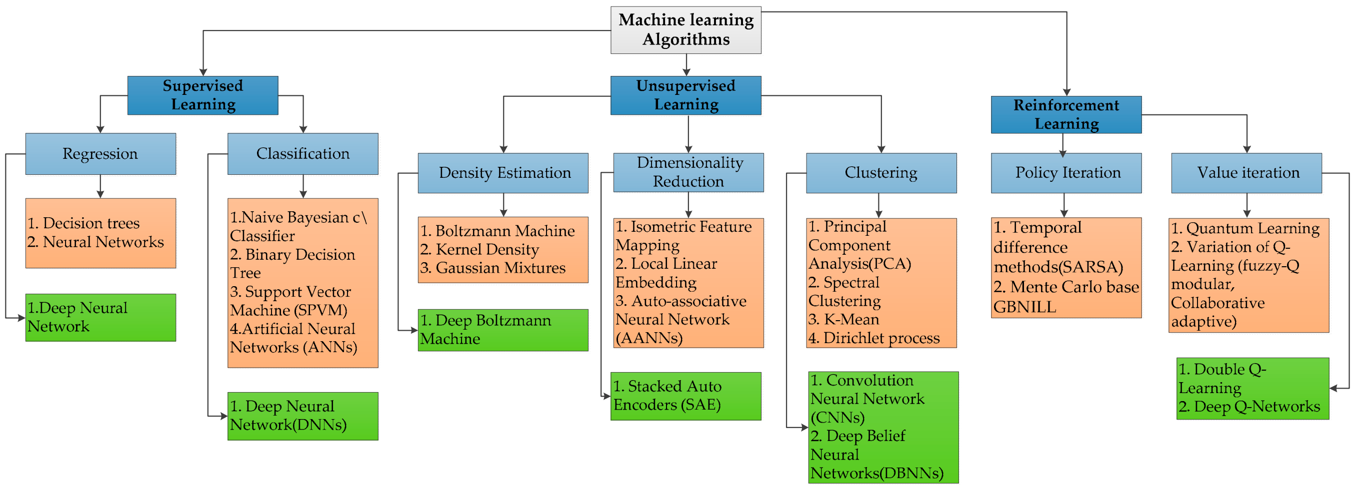

Figure 4. Overview of ML and DL algorithms green boxes for DL algorithms.

7.1. *Supervised Learning*

In this learning method, the function or model is learned using paired, labeled data sets, representing known inputs, outputs, and targets. The website ML uses examples from training data as well as expertise to perform the necessary operations and learn the required behavior. Figure 5 shows the supervised learning process. The ideal example of supervised machine learning is when the parameters for the inputs and outputs in a joint distribution are known and the inputs and outputs can be retrieved from the previous experience of the domain [91]. However, in situations such as body area networks (BANs), where a real distribution or mathematical model is not available, there is no suitable model of channel propagation. In these general learning problems, learning is used to approximate the distribution of the different classes, such as discriminative or generative models, using prior data. The typical applications of supervised learning are classification and regression tasks. Support vector machine (SVM) and k-nearest neighbor (kNN), on the other hand, are typical supervised learning algorithms [92]. The authors in [93] proposed a hybrid learning system that helps in dynamic channel tracking and channel estimation. This learning method can be used in downlink communication at the physical layer to eliminate interference and distribute power efficiently. To reduce congestion in the IoT, interference elimination and power distribution are critical. Latency reduction and caching are two of the most commonly used strategies to reduce congestion in wireless WSNs. Intelligent caching, which reduces latency and is used in satellite communications, is one of the most widely used applications of ML [94]. We can use intelligent caching in IoT networks to reduce latency, which reduces congestion in wireless IoT communication networks. Determining the membership of WSNs to the eNB based on content demand is another new case where the monitored ML can be crucial.

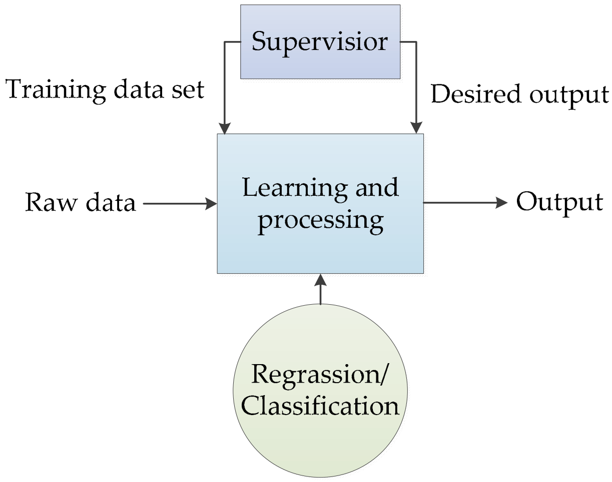

Figure 5. Demonstration of supervised learning principle.

7.2. *Unsupervised Learning and Semi-Supervised Learning*

While in semi-supervised learning, only a tiny fraction of the data is labeled, in supervised learning, there is no need for labeled training data. Figure 6 illustrates how unsupervised learning works. Unsupervised learning and semi-supervised learning are commonly used for classification and clustering tasks. Popular algorithms for these learning strategies include maximum likelihood learning, PCA, k-means clustering (kMC), etc. Unsupervised learning can be used for a variety of tasks, including distribution estimation, feature categorization, distribution-specific sampling, point clustering, and feature extraction, in the extremely dynamic physical layer of the IoT-based wireless network.

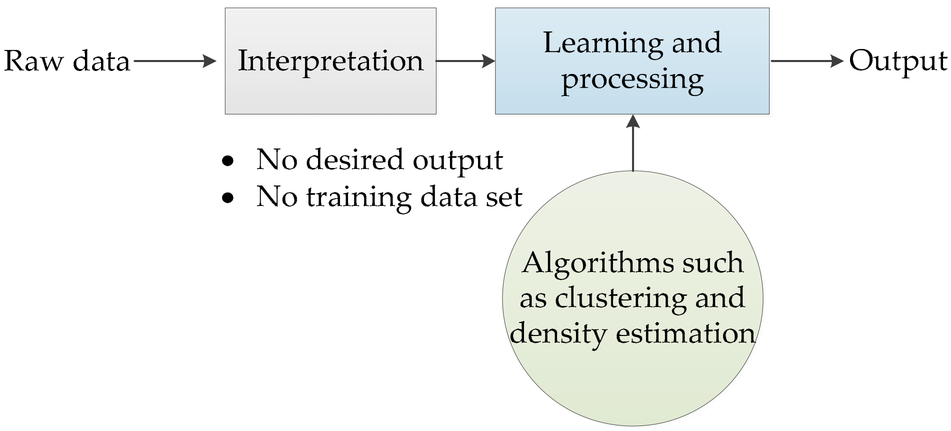

Figure 6. Demonstration of unsupervised learning principle.

Unsupervised and semi-supervised learning can be potentially used for the equalization of the channel. The pre-coding/encoding scheme selection for the optimization of performance is one of the potential areas of unsupervised learning. There are many potential areas of semi-supervised and unsupervised learning, like clustering/grouping/pairing of nodes/points for optimal allocation of radio resources management and for the optimal allocation of network resources [95]. In [52], S. K. Sharma proposed a novel solution named "novel collaborative distributed Q-learning scheme" to mitigate the congestion of Random-Access Channels in WSN. This scheme allows the WSN to gradually learn the unique slots for data transmission. Hence, the WSN with concurrent transmissions is minimized. The numerical analysis proved better performance in collision probability, throughput, and convergence time.

In [96], I. Idrissi presented a generative adversarial network (GAN), a unique unsupervised learning technique that uses ANNs to detect intruders. Any anomaly in a WSN is immediately detected by these algorithms. These ML/DL algorithms have great potential to reduce WSN congestion, so researchers should pay close attention to them. More information can be found in [97]. The above potential sectors have both more problems and the potential to reduce congestion in IoT networks [98]. Table 5 compares the advantages and disadvantages of supervised learning, unsupervised learning, and deep learning and their deployment in wireless IoT networks.

Table 5. Pros. and cons. of supervised learning, unsupervised learning, and deep learning with their application in IoT networks.

Learning Algo	Advantages	Disadvantages	Application in IoT
Supervised Learning	(a) Fully integrated control of data analysis. (b) Output of the model is in advance known. (c) Suited to learning challenges with labeled input data.	(a) Labeled data are required (b) Data sets for training needed in large numbers. (c) High capacity for computation is required.	(a) Learning based on an instance, reasoning based on the case, Bayesian networks, support vector machines, ANNs, K-nearest neighbor, decision Trees, case-based reasoning, and ensembles of classifiers [91]. (b) In constrained resources environments and distributed environments such as IoE face difficulties in implementing Supervised Learning.
Unsupervised Learning	(a) labeled data not needed (b) In unlabeled data attempts to sort hidden structure. (c) Human error is minimized arises in Supervised Learning) (d) Feasible for complex and large models where labeled is not available.	(a) Only the data sets at input are needed and no previous information about data sets as well as output is required. (b) The objectives of learning are subjective compared with the Supervised Learning (c) No much control of data analysts over data.	(a) The major application of Unsupervised learning in the prospect *includes ANNs, clustering, and association rule learning* [99]. (b) This learning scheme is utilized in the application of IoE that requires hidden layer extraction, and faster results in the ultra-dense IoE networks.
Reinforcement Learning	(a) No labeled data set as well as the desired output (b) Computational complexity is less in comparison to Supervised Learning and Unsupervised learning. (c) Easily implemented in a distributed framework like IoT. (d) Trade-off between exploitation and exploration. (e) Suitable for real-time environment learning	(a) No previous information about the environment is needed. (b) Take more time for steady-state convergence. (c) The learning depends on the agent's actions, and observations. (d) Learning depends on the reward and plenty. Learning may be affected when the distribution of plenty and reward in a distributed environment.	(a) Distributed implementation and operation simplicity make it a favorite for IoE environments. (b) The dynamic wireless IoE environment is feasible for continuous, interaction with the environment, continuous learning and reward actionable feedback with the environment. (c) The RL's main application in IoE is Q-learning.
Deep Learning	(a) Reduce the feature extraction part that wastes time used in classical ML. (b) Highly flexible and configurable than the classical ML. (c) May achieve learning accuracies higher than the classical ML (d) When the data amount is large performance is much better in compassion with the classical ML.	(a) Involvement of many parameters and slower learning process. (b) Sensitive to the size of data and data structure. (c) The topology determination, parameter, and the topology training method lacking theoretical tools. (d) DL algorithms require more time and a high GPU framework. (e) It is more difficult to interpret the DL models.	(a) In the existing literature DL algorithms applications include LSTM, deep Recurrent Neural Networks (RNNs), deep belief networks, CNNs networks, and Boltzmann machine [97]. (b) Easy to extract the accurate information, accurate information from the complex as well as the raw WSNs data system. (c) The need for huge battery, memory, and energy resources it challenging to deploy the DL in distributed devices with constraint recourses devices [100].

7.3. Reinforcement Learning

Reward, punishment, and feedback are the foundations of reinforcement learning [101]. The reward and punishment are based on the activities performed in a real-time environment. The reward is updated when a step is taken in the desired direction; otherwise, plenty is updated in the equation. The algorithm adaptively converges and maximizes the output (reward) once it reaches the desired location [102]. Figure 7 illustrates the basics of reinforcement learning, a learning method that is halfway between supervised and unsupervised learning [103]. This algorithm is applied when no data are available for training sessions. In this area, a distributed model-free reinforcement learning algorithm was proposed for performance assignment [104], and several well-known algorithms refer to this process as a Markov decision process. In [105], Lawal Mohammed Bello proposed to model RACH using QL-mathematics.

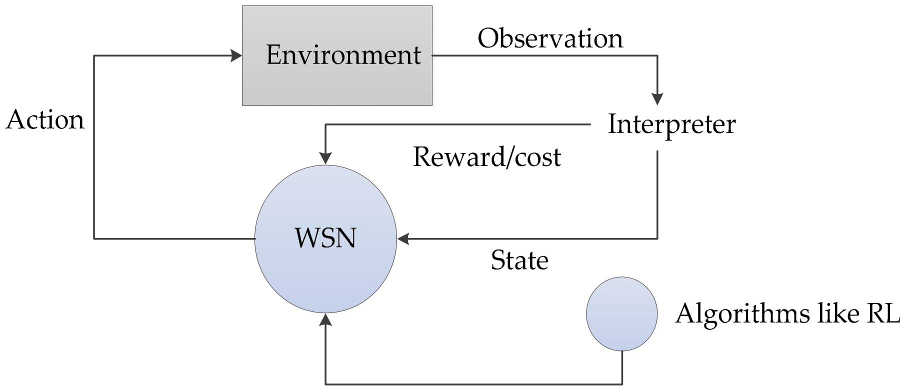

Figure 7. Demonstration of RL principle.

In [106], Mohammad Gheshlaghi proposed a novel technique for rapid learning. In [52], Shree Krishna Sharma proposed the collaborative QL algorithm reward with many variables. This aforementioned QL algorithm needs the attention of researchers to explore in the context of congestion mitigation in IoT networks.

7.4. Genetic Programming

The inspiration of genetic programming is biological evolution; it works on limitations and constraints, evaluates the objective fitness, and finds the optimal solution to the subject problem. Genetic programming techniques are employed for the solution of many estimation and optimization problems in the various layers of IoT-based wireless communication systems.

8. Learning Capabilities and Requirements

The ML learning models for ML learning algorithms are based on the nature and size of the data for training. The algorithms based on batch learning are applied in the application and have large amounts of prior available data in for training. The batch learning algorithm works on the assumption of unlimited computing time availability and searches all available data. These offline learning schemes normally face issues in practical applications in terms of the limited amount of data. Hence, an algorithm based on batch learning is not suitable for processing real-time data. For the real-time training of data, online training/learning is a feasible solution for data applications with streaming data.

The constraint is fixed and there is time availability for each sample. Channel tracking and intelligent caching are the most common applications for online learning and batch learning (offline) in wireless WSNs to reduce congestion.

Model-based learning has high computational efficiency and uses well-known objective functions to maximize performance indices. In contrast, data-only learning uses all available data samples to extrapolate or/and interpolate the samples, which requires more time and memory. The overload of the IoT can be significantly reduced by model-based learning and learning based on samples. These two learning strategies can be used for symbol decoding and content demand, respectively. In [107], the capabilities of different algorithms of ML and the learning requirements for communication are discussed. Table 5 categorizes supervised learning, unsupervised learning, and deep learning methods according to the advantages and disadvantages of their use in Internet of Things networks.

9. Artificial Neural Networks (ANNs) for Congestion Mitigation of WSNs

The biological processing of data in the human brain served as the basis for ANN, which aims to understand the many operations performed on observed data. The common application of ANN is the recognition of various patterns in data provided as input after they have passed through numerous ANN layers.

The ANN has three main layers of neurons; these are input layer, a hidden layer/s, and output layer. Where each neural layer performs a specific operation on given/input data to applications of ANNs, the hidden layers of neural networks are quickly increasing. There are a few well-known structures termed as Neural Turing Machine (NTM), Convolutional Neural Networks (CNN), Echo State Network (ESN), Multi-Layer Perceptron (MLP), Feed-Forward Network (FFN), Generative Adversarial Network (GAN), Hopfield Network (HN) Recurrent Neural Network (RNN), etc.

The above Neural Network (NN) topologies describe the direction of data flow in NN, with RNN neurons connecting from the output of the feedback layer to the preceding layers and FFN neurons connecting from the input layer to the output layer [107,108].

The process by which the connection weights between the other neurons are learned is called ANN training. The supervised learning technique is used for this purpose. Various techniques, such as Levenberg–Marquardt, Mean Square Error (MSE), Newton method, Quasi-Newton, conjugate gradient, and gradient descent, among others, are used for error reduction in the learning process. In calculating the error in each layer and correcting according to the learned/remembered weights, error reduction is an iterative process that propagates backward from the output layer to the input layer. One of the future strategies to reduce the overload of WSNs that studies need to focus on is ANN [95].

9.1. DL for Congestion Mitigation of Wireless-Based IoT Networks

A branch of ML is called DL. The deep layer of the neural network is where the input data are propagated to create the intelligent system [109]. To compute the output, the deep layers perform many different mathematical operations, including thresholding/limitation and combination [110]. A system based on DL automatically learns to map or model the already accessible data sets through significant feature extraction, either through unsupervised or/and supervised learning approaches [111]. In [112], the application of the DNN technique in wireless network-based communication was studied. The applications of DL are strongly encouraged for use in the upcoming wireless communication networks [113].

DL offers tremendous promise for wireless communications and for reducing congestion in WSNs that manage, deploy, schedule, maintain, and control resources (radio, channels, energy), among others [114]. DL in [115] and [94] was proposed as an optimization approach for downlink beamforming. The above proposal needs to be studied in the context of reducing congestion in WSN networks, as it could provide excellent results. These also offer tremendous potential for IoT congestion in the areas of data loading and caching, traffic routing, power control, resource sharing, traffic routing, dynamic spectrum access, etc. The authors of [116] give an overview of various DL applications in wireless networks. In [100], dynamic/intelligent allocation of radio resources was highlighted in a survey of wireless communication networks at the physical layer. In [117], a plan for channel characteristics for BSs with multiple antennas was presented. With only a few adjustments, this method can be used to reduce congestion in IoT networks. Due to the growth of IoT communications in the near future, ANNs have significant potential for estimation, job preservation, control, scheduling, tracking, and optimization to reduce congestion in wireless IoT networks. ANNs are important enablers in the deep learning process, as shown in Figure 8 [112]. Important aspects of data from DL as well as distribution have been learned automatically.

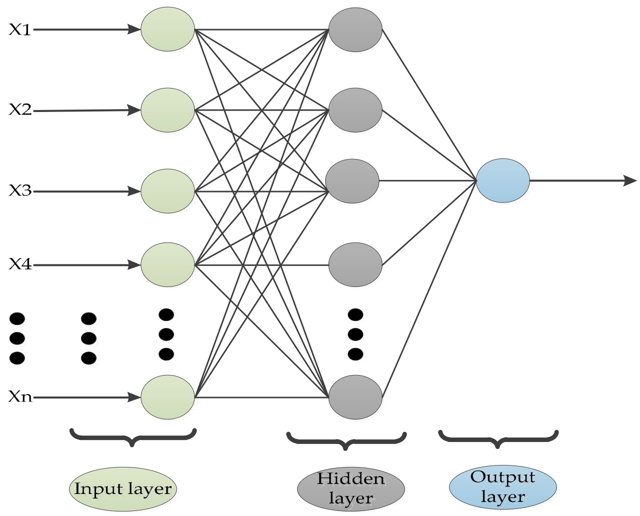

Figure 8. Working principle of ANNs.

9.1.1. Deep Neural Networks (DNNs)

The practical implementation of ANNs, despite the potential answers offered by ANNs, encounters challenges related to the computing power required for training. These problems are partially solved by modern computer technology. The graphical processing units of modern graphics processing units (GPUs) speed up the training process by performing numerous weight calculations at once, which reduces the training time. In addition, fast GPUs open up the possibility of using ANNs with many hidden layers. DNNs are the classic example of DLs and have a large number of intermediate layers of neurons as well as more complicated connections between them. Although these applications are critically delayed, recent advances in DNNs enable their use in daily life. This is achieved by first training DNNs offline and then performing operations (optimization, tracking, etc.) online.

Beam forming is one of the time-critical applications on the physical layer. The repetitive processes used here by conventional networks to introduce latency into the communication network will become obsolete in later communication networks. DNNs also face the biggest training challenge in a very long time. Quantum-based algorithms for DNN training could provide effective remedies. The architecture for training DDNs is still under development, although much has been achieved. The communication system, which is based on end-to-end communication, also uses auto encoders that employ DNNs [30]. The optimization of the peak-to-average power ratio (PAPR) and bit error rate (BER) of a DNN-based auto encoder in an OFDM system was presented in [118]. Researchers should pay close attention to the work in [119] to investigate the possibility of congestion mitigation in an IOE-based network. In addition, a localization-based architecture for symbol detection in MIMO systems was proposed in [120]. For M-MIMO systems, this approach uses fingerprinting and channel estimation. The aforementioned method is used in both physical layer resource allocation and congestion avoidance. Power optimization and control are two common DNN applications at the physical layer of communication networks [121]. To reduce congestion in wireless IoE networks, power optimization and control are essential. One of the most important solutions to reduce congestion in high-density wireless IoT networks could be the one proposed in [5].

9.1.2. Criteria for Application of DL Solutions in WSNs

Where can we use DL-evolving AI algorithms, like ANNs and DNNs, in WSNs, and where can we not use them? This is the crucial question. Figure 9 shows extremely congested WSNs with full buffers that leave arriving packets in the queue. To reduce congestion in WSNs, ANNs and DNNs are used. Since ANNs and DNNs require more processing power, memory, and bandwidth, we can deploy them on the tower side. Several materials are accessible on the tower side. On the IoT side of WSNs, since resources are limited in terms of memory, power, and bandwidth, we cannot use these types of algorithms there.

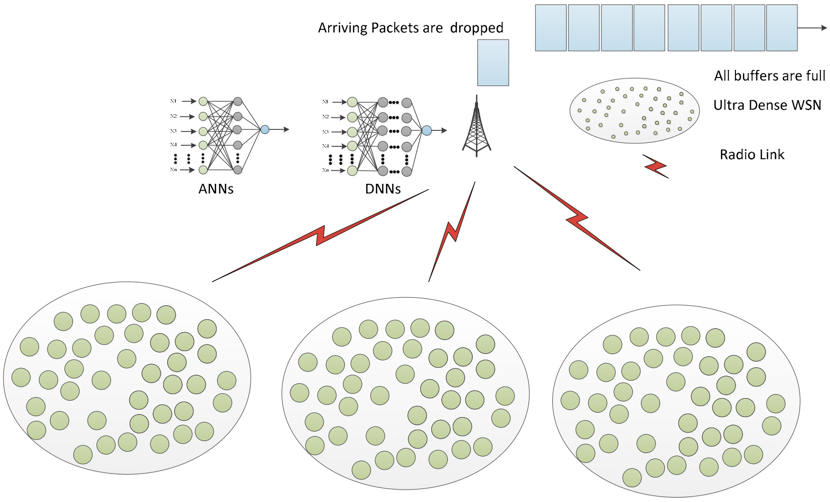

Figure 9. ANN and DNN schematics to mitigate congestion in WSN.

9.1.3. Deep Transfer Learning (DTL) for WSN Congestion Mitigation

This is another novel research direction for reductions in large data requirements for the learning process. Transfer learning is defined as the transfer of the learned knowledge from the existing data in the specific context in the novel situation, but the related situation is termed transfer learning. Furthermore, transfer learning provides an edge over other learning techniques via data size reduction for the learning process, reduction in time, memory, energy, and other related parameters. In addition, it reduces the training data sets conditions to be independent and identically distributed (IID) by the data. In this context, in [10], a survey was conducted for various methods for transfer learning. Transfer learning could play a future emerging important role in Congestion Mitigation of Ultra-Dense wireless IoE networks.

In [122], the authors reviewed different transfer learning methods. In this study, DTL techniques are divided into two groups: instance-mapping networks and adversarial-based networks. The instances of the source domain are used in the classification of adversarial-based and instance-mapping networks along with the instances with high similarity from both domains. A pre-trained network is partially reused in the source domain, while features are found that can be transferred separately in each domain via an adversarial scheme. To study DTL from the perspective of WSNs, researchers need to pay close attention to the above features of DTL.

9.1.4. Deep Unfolding for Congestion Mitigation

Each iteration of the iterative neural network method is unfolded, converted into a structure with layers, and then combined to create ANN's ideal design using the unfolding concept. This architecture is easily trainable. The architecture of the detector, which uses a computation based on the iterative deconvolution of ANN layers, was proposed in [22] for decoding MIMO and forward relay channels. But, in general, determining the best ANN size (number of layers and neurons) for the considered difficulty (dimensions known) is an unsolved research problem. Nowadays, smart and intelligent relay settings are increasingly used in current wireless communication systems/networks [112]. The question of how and when to integrate deep deconvolution into the communication network DL is one of the key issues.

9.1.5. Deep Learning for Cognitive Communication

A radio-based system, referred to as a "cognitive radio", has the ability to learn, understand its environment, and change its behavior as needed [29]. User sensing requirements, radio spectrum sensing, and environment sensing are three categories into which the concepts of adoption, learning, and sensing can be classified. There are numerous studies on this topic, one of which is [123], in which Akyildiz and Lee give a concise introduction to Cognitive Radio (CR) and outline the design of the next-generation wireless network CR. Next-generation advanced network features, such as spectrum management, mobility, sharing, and congestion mitigation, are also addressed in this study. The study of congestion mitigation in wireless sensor networks (WSNs) is now limited to this particular congestion mitigation. S. K. Sharma and T. E. Bogale in [124] evaluated Cognitive Radio (CR) techniques and noted the drawbacks under real-world conditions. Exploring a framework or technique that can be used in a variety of situations has been referred to as an open challenge by other authors. According to the above viewpoint, there is enormous potential for a framework or approach that can be used for a variety of WSN congestion scenarios.

The study of [125] proposed machine learning (ML)-based unsupervised and supervised learning methods for spectrum sensing in Cognitive Radio networks. To control the performance, a reinforcement-based deep learning system for spectrum sensing in cognitive radio networks was presented in [126]. Since secondary users can access an unused spectrum, thanks to dynamic spectrum sharing, the spectrum utilization efficiency is increased. This spectrum sensing technique mentioned above underutilizes the IoE spectrum, so a spectrum-sharing-based DL algorithm has a greater chance of reducing the congestion of the wireless IoE network.

10. Discussion and Significance

In this section, we provide concluding remarks on the reviews, addressing a broad spectrum of topics.

10.1. Game Theory

Game theoretic models offer the possibility of maintaining a balance between the various WSN actors, such as cell towers and wireless sensors, within the network. These models enable the optimal allocation of WSN resources, such as spectrum sharing, by allowing the understanding of incentives and scenarios for different participants.

10.2. Artificial Intelligence (AI)

Resource allocation systems can be efficiently and adaptively managed using artificial intelligence techniques, such as optimization strategies and reinforcement learning. Artificial intelligence prediction algorithms are very good at correctly predicting congestion patterns in wireless sensor networks and then applying appropriate congestion mitigation methods based on the expected data. The aforementioned designs include the application of efficient routing techniques, frequency allocation, and power resource allocation. The effectiveness of AI is based on its ability to efficiently reduce congestion in extremely dense wireless sensor networks through the prediction, optimization, and dynamic allocation of network resources.

10.3. Machine Learning (ML)

By detecting congested locations in dense WSNs, the ML approaches enable the proactive activation of congestion mitigation solutions in the future. Tactics used by the ML algorithms include adjusting coverage, finding alternate routes, and improving cell load distribution.

10.4. Deep Learning (DL)

Large amounts of data are processed by DL to evaluate the behavior of IoT devices in WSNs and provide accurate predictions about channel quality, congestion, and other factors. As a result, DL algorithms improve the accuracy of congestion prediction and help make congestion mitigation measures more effective.

10.5. Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs)

Modeling complicated connections in extremely dense WSNs is useful to improve traffic prediction and reduce congestion. These networks maximize WSN resources and allocate them intelligently by carefully evaluating data sources, such as network topology, user mobility, and application types [127,128].

10.6. Deep Transfer Learning

The Deep Transfer Learning (DTL)-distributed algorithm can be used on both the IoT and eNB sides. It uses the experience of one website to improve the functionality of another relevant website. DTL enables the transfer of learning experiences from one WSN site to another in the context of congestion mitigation [118].

10.7. Deep Unfolding

Recursive congestion avoidance techniques are transformed into deep neural networks by deep unfolding. By using DL architectures to optimize tasks, such as frequency allocation, power allocation, interference cancelation, and channel allocation, this method improves the efficiency in extremely dense WSNs.

11. Conclusions and Future Research Recommendations

The problem of wireless network congestion is a major obstacle for wireless communication networks. Wireless sensor networks (WSNs) are gradually becoming congested as Internet of Things (IoT) devices proliferate in networks. When the data demand of Internet of Things (IoT) devices exceeds the capacity of the network, wireless sensor networks (WSNs) become congested. This leads to inefficient use of resources and risks network outages. Therefore, researchers continue to develop effective algorithms that can reduce congestion. The data requirements of devices on wireless networks have led to a number of solutions. However, the introduction of state-of-the-art artificial intelligence (AI) solutions offers a potentially promising future. In wireless sensor networks (WSNs), many artificial intelligence techniques have been recognized for their potential use in managing congestion for data-intensive Internet of Things (IoT) devices, both at the wireless node and tower infrastructure levels. Additionally, the scope and implementation criteria are identified. By using various techniques, including congestion prediction, network infrastructure optimization, resource allocation optimization, and interference control, the aforementioned methods are able to successfully reduce the problems caused by congestion in wireless sensor networks (WSNs). The application of machine learning (ML), deep learning (DL), artificial intelligence (AI), artificial neural networks (ANNs), deep neural networks (DNNs), and game theoretic approaches can reduce congestion, increase throughput, improving quality of service (QoS), improving overall performance, enhancing user experience, and increasing capacity in densely populated wireless sensor networks (WSNs) based on the Internet of Things (IoT). In the quest for better congestion minimization in WSNs, there are several research directions, some of which include:

1. In extremely dense WSNs, dynamic wireless nodes with changing topologies and placements predominate. The development of congestion mitigation algorithms must take this dynamic nature into account. These network requirements should be addressed through efficient congestion mitigation techniques.
2. Numerous wireless sensor nodes with different capabilities, data requirements, and communication protocols form extremely dense wireless IoT sensor networks. Managing traffic congestion in a highly complex environment is a challenging topic for scientists and is, therefore, a well-known research area.
3. There are often constraints on the power, memory, and bandwidth of wireless nodes. These limitations must be prioritized in newly developed congestion mitigation methods used in IoT.
4. IoT devices that process sensitive data are found in highly populated WSNs. These devices face security and privacy threats due to congestion. In addition, these devices

need to collect sensitive and personal information in order to use new approaches for congestion mitigation. When using congestion mitigation approaches, it becomes increasingly important to ensure the security and privacy of IoT-sensitive data. In this situation, the distributed learning approach known as federated learning can protect sensitive data.

5. WSNs must be able to process data and make decisions for many IoT devices in real time. Giving these high-priority devices an immediate reprieve requires innovative approaches to eliminate congestion. Striking a balance between reducing latency and successfully managing congestion is a difficult task. Congestion reduction in WSNs presents a great opportunity for hybrid AI algorithms that combine established conventional and AI-based emergent algorithms. Combining two or more AI techniques, such as prediction and learning or optimization and learning, leads to a variety of hybrid algorithms. This area should be further explored [129,130].

While there are many potential future opportunities to reduce congestion in WSNs, only a few have been highlighted above. In addition, it is expected that this review will inspire new research approaches that are essential for reducing congestion in WSNs.

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