



Review

Comprehensive review on congestion detection, alleviation, and control for IoT networks

Anitha P.^a, H.S. Vimala^a, Shreyas J.^{b,*}^a Department of Computer Science and Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bengaluru, India^b Department of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka, 576104, India

ARTICLE INFO

Keywords:

IoT
Congestion
Routing protocol
6LoWPAN
IoT simulators
Learning-based congestion control

ABSTRACT

Context: The Internet of Things (IoT) comprises various computing devices that operate on a non-standard platform and can connect to wireless networks to transmit data. These devices typically have limited storage capacity, restricted network bandwidth, and a lower level of computing power, which can cause congestion in the network. Hence, it is crucial to have a congestion control mechanism in place to facilitate efficient data transfer in IoT networks.

Objective: To address congestion in the IoT, this research attempts to offer an overview of several congestion detections, avoidance, and control-based routing protocol techniques.

Method: A systematic mapping study was carried out to pinpoint relevant literature. From this process, 102 publications were identified as the most relevant studies of congestion detection, congestion avoidance, congestion control, routing protocol, congestion control in 6LoWPAN, and learning-based congestion control.

Results: Most relevant articles are clustered based on congestion detection (10%), congestion avoidance (12%), congestion control (23%), avoiding congestion through routing protocol (14%), congestion control in 6LoWPAN (19%), and controlling the congestion through learning based methods (24%).

Conclusion: Congestion control is necessary for IoT to maintain network stability, reliability, and performance. It helps to ensure that critical applications can operate seamlessly and that IoT devices can communicate efficiently without overwhelming the network. Congestion control algorithms ensure that the network operates within its capacity, preventing network overload and maintaining network performance.

1. Introduction

The Concept of the IoT was proposed in the year 1999 by Kevin Ashton, he described IoT as uniquely identifiable interoperable connected objects with Radio-Frequency Identification (RFID) technology (Madakam et al., 2015) (Wang et al., 2015) (da Cruz et al., 2018).

IoT systems allow users to automate, analyze, and integrate the system (Al-Fuqaha et al., 2015).

IoT has applications across all industries and markets. Some of the applications of IoT are in manufacturing/industries, transportation/mobility, energy sector, retail, municipal, health care, supply chain, agriculture, building, and other (Hossein Motlagh et al., 2020a; Andersen et al., 2018). The smart home has received significant attention, because of the prevalence of online game (Guo et al., 2021), video streaming (Aliyu et al., 2018), home audio (Shah et al., 2018), home video security system (Hoque and Davidson, 2019; Hamdan et al.,

2019; Ghafoor et al., 2020), smart-meter (Gupta et al., 2021), smart power grid (Risteska Stojkoska and Trivodaliev, 2017) etc.

The provided graph Fig. 1 indicates a significant transition from conventional devices to IoT devices during the past decade. It is projected that by the year 2030, around 75% of all devices would be IoT-based resulting in a considerable rise in data traffic on networks (Anon, 2022). It is evident that the proliferation of IoT devices is set to have a substantial impact on data transmission and management in the future.

Controlling congestion is a significant challenge in managing cyberspace traffic (Waheed et al., 2021). According to recent research, the number of devices connected to the network has increased significantly. The IoT market is expected to grow 500 billion by 2030. A wide range of objects around us, such as thermostats, fitness trackers, water pumps, cars, street lights, electric meters, elevators, and even gym vests, are now interconnected. However, as the number of nodes increases, several challenges arise, such as lack of security, energy

* Corresponding author.

E-mail address: shreyas.j@manipal.edu (Shreyas J.).<https://doi.org/10.1016/j.jnca.2023.103749>

Received 4 March 2023; Received in revised form 29 August 2023; Accepted 21 September 2023

Available online 4 October 2023

1084-8045/© 2023 Elsevier Ltd. All rights reserved.

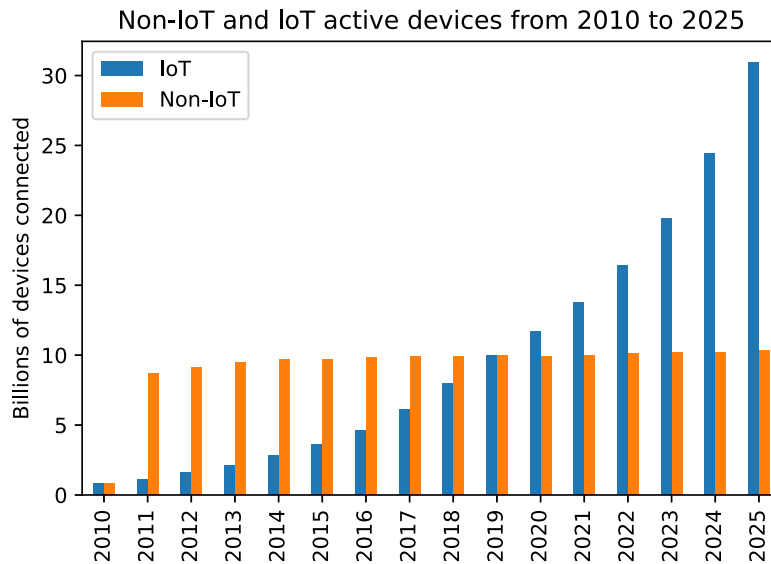


Fig. 1. Comparison of Increase in IoT Devices Versus Non-IoT Devices from 2010 to 2025.

conservation, reliability, network routing, quality of service, scalability, resource sharing, and network congestion (Imran et al., 2020).

A 6LoWPAN network is a wireless network made up of compact, low-power devices that converse using the IPv6 protocol. It is described in RFC 4944 and RFC 6282. These gadgets are generally utilized in IoT applications, where they can be combined with sensors, actuators, smart objects, or other embedded systems (Montenegro et al., 2007a).

Congestion on the internet also rises as the number of devices rises. During the data transmission for various applications in IoT and in the 6LoWPAN network, many problems may occur. If selected protocols/techniques are unable to handle congestion, then the following issues within the network can arise. They are as follows:

- **Increase in packet loss:** packets are transmitted from source to destination, if one or more packets fail to reach their destination, due to network load, then this scenario is called packet loss or packet drop (Huq et al., 2015).
- **Increase in the delay:** Time taken for a packet to reach its destination is delayed. If there is a long delay, then network congestion might be one of the reasons. In these circumstances, it is better to select the best path to reach its destination. Therefore, Routing protocol plays a vital role in avoiding congestion (Al-Kaseem et al., 2019).
- **Load balancing:** Effectively distributing the packets among different paths in the network, such that they reach their destination without any problem is analyzed as load balancing. If the proper decision on selecting the path without a load in the network is not considered during the transmission of packets, then congestion occurs (Tseng, 2016).
- **Throughput:** It plays an important role in avoiding congestion, as throughput is the number of packets transmitted successfully from source to destination in a stimulated period, proper techniques have to be implemented to control the congestion (Mishra et al., 2018a).
- **Energy Efficiency:** Continuous data transmission among IoT devices keeps networking devices active all the time, that results in the drainage of energy continuously. Hence, to improve the energy of devices, congestion has to be controlled (Hossein Motlagh et al., 2020b).

In addition to these problems, network service quality is affected by network lifespan, connection quality, control overhead, end-to-end delay, and heterogeneous devices in the network. Since the IoT is thought to be a component of the future internet, that will span all

types of domains, resource sharing will be a barrier to the development of the IoT in the future if the congestion network problem is not solved.

The essential part of IoT is considered as a 6LoWPAN network. As, a consequence of memory, power, and processing resources limitation, bandwidth, and load balancing in 6LoWPAN the network causes congestion that reduces the performance of the network and QoS. To tackle these problems — congestion detection, avoidance, and control mechanisms are necessary. Apart from huge efforts from standardization bodies, industries, alliances, research, and others, network congestion still exists. Hence, high priority should be given to controlling the congestion in the network and facilitating efficient spectrum utilization. The important terminologies of this paper is given in (see Table 1) for better understanding.

1.1. Related surveys

This study offers an overview and review of recent research projects and several strategies for avoiding congestion problems in the IoT and 6LoWPAN networks. Several surveys are conducted to review congestion in IoT networks, summarized in Table 2.

The survey in Lim (2019) explains congestion detection, avoidance, and mitigation with protocols but does not consider the congestion control in 6LoWPAN and simulators used. In Jain et al. (2022a) and Maheshwari and Yadav (2020) authors described only congestion mitigation, whereas in Haka et al. (2020) describe only congestion techniques in 6LoWPAN. Tariq et al. (2020) explains congestion mitigation and detection, Alvi et al. (2021) describes congestion mitigation, Ojie and Pereira (2017) gives details about IoT simulators, and binti Wan Abdullah et al. (2016) suggested only congestion mitigation. In Kharrufa et al. (2019) suggested routing protocols and congestion control in 6LoWPAN. Mishra et al. (2018b) explains only congestion avoidance and mitigation. It introduces categories of congestion analysis, routing protocols, congestion control in 6LoWPAN, different types of IoT simulators, evaluation metrics, and learning-based congestion control.

1.2. Purpose of the research methodology

This research aims to provide an overview of various congestion detection, congestion avoidance, and congestion control techniques in IoT networks and explains how routing protocol techniques avoid congestion. It also provides a general overview of avoiding congestion that occurs in the 6LoWPAN network. The survey also highlights several metrics for evaluating congestion control. Furthermore, a quick overview of several IoT simulator types is provided.

Table 1
Definitions of important terminology.

Terminology	Definitions
Congestion Detection	It is the process of lessening network congestion in order to boost service quality in the IoT network and in the 6LoWPAN network.
Congestion Avoidance	These are methods that assist a network in staying clear of a congested state in the IoT network and in the 6LoWPAN network.
Implicit Notification	Inferring network congestion based on observed network behavior is known as implicit congestion notification.
Explicit Notification	Explicit congestion notification involve routers or other devices explicitly signaling that there is congestion.
Congestion Mitigation	It tries to reduce the impact of congestion on network efficiency by performing various procedures after congestion is detected.
Congestion Control	These methods aid in a networks ability to recover from a congested state in the IoT network and in the 6LoWPAN network.
Traffic Control	Deals with regulating the flow and movement of data traffic throughout the network.
Resource Control	Resource Control manages and distributes network resources. The efficient management of resource availability and allocation across the network includes techniques and procedures for identifying, reducing, and preventing congestion.
Hybrid Control	Refers to the utilization of various congestion control mechanisms and strategies. It combines reactive and proactive methods to deal with congestion-related issues and enhance network performance.
Routing Protocol for Low-Power and Lossy Networks (LLN)	It is a routing protocol that uses less power and is frequently prone to packet loss for wireless networks.
Adaptive Routing algorithm	A dynamic routing algorithm is a distinct term for an adaptive routing algorithm. This algorithm focuses its routing choices on network topology and traffic.
Non-Adaptive Routing Algorithm	A static routing algorithm is a distinct term for non-adaptive routing algorithm. It does not rely on its routing choices on network topology and traffic.
Storing Mode	The complete RPL domain routing table is present in every mode. Any node can communicate directly with any other node.
Non-Storing Mode	The whole routing table is only present in the border routers of the RPL domain.
Route-Over Routing	The route-over approach makes a routing choice in the network layer.
Mesh-Under Routing	The mesh-under routing method makes the decision in the adaption layer.
Reactive Method	A reactive approach is one in which network devices or nodes only interact or perform actions in response to a specified event.
Proactive Method	Entails devices communicating and sharing data with one another or with a central system on a regular basis, regardless of whether an event has occurred.
6LoWPAN	It is a standard that specifies the transmission of IPv6 packets over low-power wireless networks with a focus on devices with constrained resources and low data rates.

1.3. Motivation

IoT is a concept that describes the objects interconnected to each other (Deguchi et al., 2020). IoT sensors are integrated with smart home devices, emergency response, industrial automation, autonomous vehicles, public safety, and the Internet of Medical Things (IoMT) (Mirela Catalina et al., 2020). These devices use sensors that transmit data to software, allowing them to perform the task. Due to their utility towards society and automation, the number of devices connected has increased. Routing the data should satisfy a set of Quality of Service (QoS) parameters that becomes an immense challenge. These characteristics motivate us to analyze congestion detection, avoidance, control, and different routing protocols that avoid congestion.

1.4. Study approaches and contribution

This article concentrated on: identifying, avoiding, and managing the congestion in IoT. Implementing a routing protocol to control congestion. Control methods are employed in the 6LoWPAN network to prevent congestion. A description of several simulator types, performance indicators, and learning-based congestion control methods is explained in this article.

The study can be classified into 5 layers of IoT Protocol architecture followed by various congestion detection in IoT thereafter with congestion avoidance in IoT using different techniques, and then with different congestion control techniques used in IoT. The next section discusses variant routing protocols in IoT networks. The next section highlights congestion control techniques used in the 6LoWPAN network. It highlights different types of simulators used for IoT. Finally, at the end of the survey, learning-based congestion control techniques are highlighted. The contributions of this study are:

1. This study summarizes various indications of congestion metrics used in detecting congestion in IoT networks.
2. It gives an overview of different techniques and epitome of proposed work used to avoid congestion.
3. This survey mentions various congestion occurrences, congestion notification, and congestion control techniques.
4. This study gives an overall idea of the different types of routing techniques, routing metrics, routing modes, and schemes to control congestion.
5. This study consolidates congestion detection, avoidance, and congestion control in the 6LoWPAN network.
6. This survey also provides a brief introduction to all the IoT simulator tools used to implement the algorithm.
7. This study also provides a brief introduction to learning-based congestion control.

1.5. Organization of paper

The rest of the paper is organized as follows. The organization of this survey is represented in Fig. 2. Section 3 gives an overview of IoT protocol architecture. Congestion analysis in IoT has been interpreted in Section 4. The comprehensive overview of routing the packet in the network regarding controlling the congestion is explained in Section 5. Section 6 explains controlling the congestion in the 6LoWPAN network. The extensive overview of simulator tools used for detecting, avoiding, and controlling congestion is explained in Section 7. In Section 8 the list of evaluation metrics is used for avoiding congestion. In Section 9, learning-based techniques are used to avoid congestion, and Section 10 gives the details of the survey outcome. Finally, the survey is concluded in Section 11 with future directions.

Table 2

Summary of existing surveys on congestion in IoT network.

Ref.No	Congestion Detection	Congestion Avoidance	Congestion mitigation	Routing protocol in IoT	Congestion control in 6LoWPAN	IoT Simulators	Learning based congestion control	Main Characteristics considered for survey
Lim (2019)	YES	YES	YES	YES				Very little explanation regarding avoidance and mitigation of the congestion
Jain et al. (2022a)			YES					Explanation about rate adaption and traffic engineering schemes
Maheshwari and Yadav (2020)			YES					Focus of different techniques to achieve congestion control within an IoT network
Haka et al. (2020)					YES			Used the concept Prioritization
Tariq et al. (2020)	YES		YES					This survey highlights short come of CoAP
Alvi et al. (2021)			YES					Discussed few metrics that shows the results for congestion
binti Wan Abdullah et al. (2016)			YES					Congestion control was performed on health monitoring system
Kharrufa et al. (2019)				YES	YES			Detail explanation about RPL and its routing metrics
Mishra et al. (2018b)		YES	YES					Various congestion techniques used at transport layer
Kumar and Raubal (2021)							YES	Using Deep Learning Congestion detection, prediction, and alleviation are explained
Kanellopoulos and Sharma (2022)							YES	It only uses Load balancing techniques to avoid congestion
Al-Kashoash et al. (2019)	YES	YES	YES		YES	YES		Congestion detection, avoidance, and control in WSN and in 6LoWPAN networks are explained.
Ojie and Pereira (2017)						YES		Simulation tools to aid researchers and developers in selecting the right tool for their experiments when working with IoT applications
Tafa and Milutinovic (2021)						Yes		This research analyzes a few machine-learning-based approaches to CC and offers a roadmap for their integration into computer systems.
Our Survey	YES	YES	YES	YES	YES	YES	YES	All mentioned categories are described.

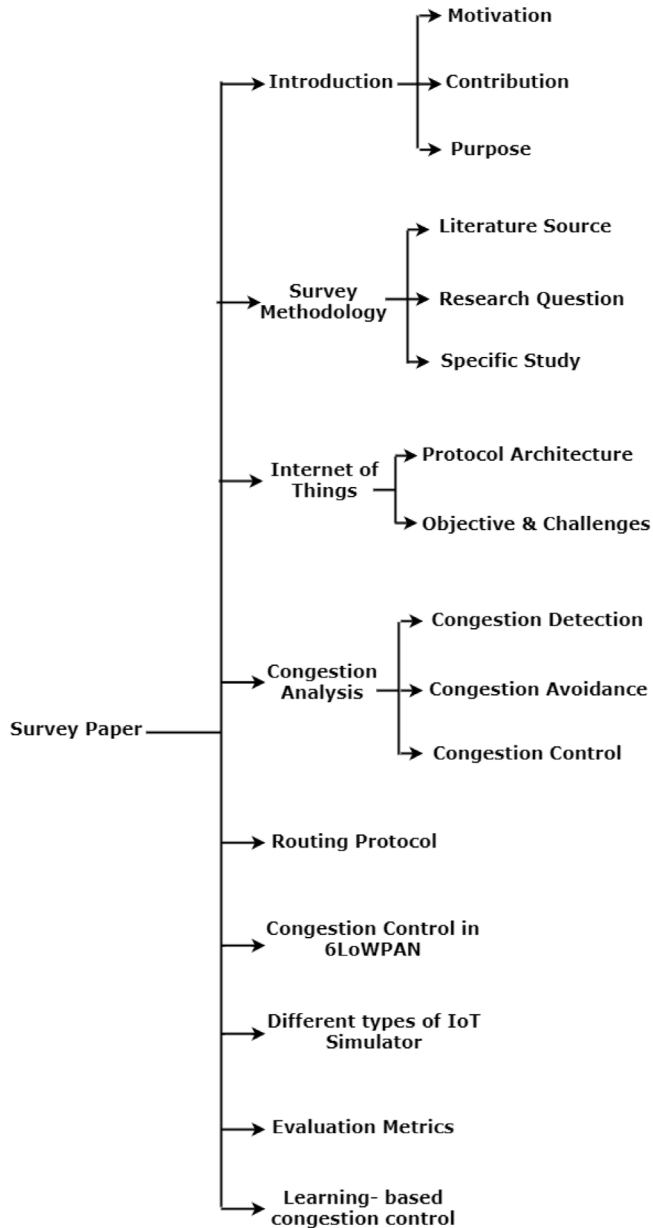


Fig. 2. Organization of the survey.

2. Survey methodology

To carry out this comprehensive review, we used the systematic mapping methodology proposed by Abdelmaboud et al. (2015), which provides a detailed systematic review of a specific topic.

2.1. Systematic reviews and mappings: Research questions

This study intends to present an overview of current research and challenges in congestion control, that provides a better path for further research about congestion control techniques in IoT. The objective of the study is to be defined by the following research questions:

RQ1: How are the publications related to congestion-aware techniques distributed over the years?

RQ2: In which forums have researched congestion-aware techniques, and which forums have published more articles?

RQ3: What are the different IoT simulators used for congestion-aware techniques?

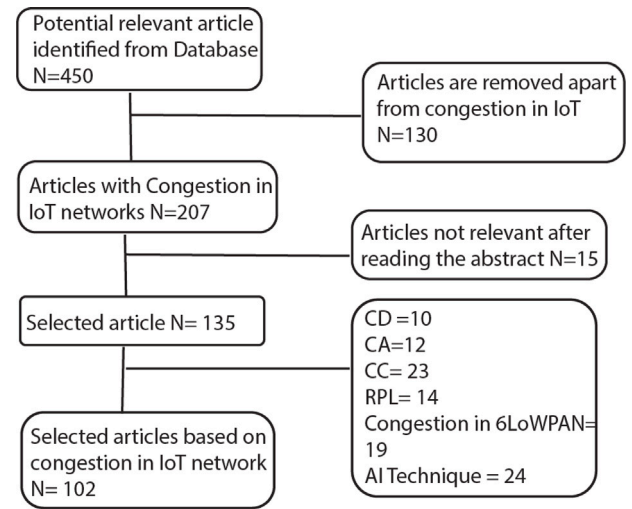


Fig. 3. Flowchart of the search method.

Table 3

Literature sources.

Literature Source	Percentage
IEEE Xplore	32%
Springer	15%
ACM	14%
MDPI	10%
Science Direct	9%
IETF	6%
Elsevier	5%
RFC	3%
Other	6%

RQ4: What are the main performance metrics used to evaluate the congestion in the IoT network?

RQ5: How machine learning can be used to control the congestion in the network?

RQ6: How many articles are looking at congestion detection, congestion avoidance, congestion control, routing protocols, and congestion control in 6LoWPAN?

RQ7: How are articles distributed in congestion at different node levels?

RQ8: How are articles distributed in terms of the occurrence of congestion notification methods and congestion levels?

RQ9: Which are the most prevalent simulators used to evaluate the congestion-aware techniques?

RQ10: How are articles related to congestion-aware techniques distributed in terms of evaluation and simulators used?

RQ11: Finally, What are the potential future directions for research in this area?

In summary, this study aims to provide insights into the current state of research on congestion control in IoT networks and identify potential avenues for future research in this area.

2.2. Literature source and search techniques

The survey follows a holistic research methodology to provide an overview of different methods for detecting, avoiding, and controlling congestion in IoT networks. Fig. 3 represents out of 450 reviewed articles, the study covers 102 papers that present various methods and techniques to avoid congestion. The research articles are collected from 2015 to 2023 from different peer-reviewed journals and international conferences that are listed in Table 3.

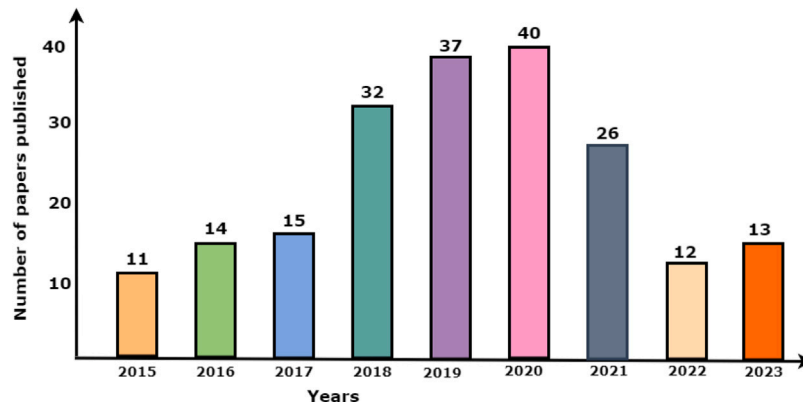


Fig. 4. Year-wise distribution of retained papers for survey.

2.3. Specific study selection

In order to select the most relevant and important articles, **Inclusion** and **Exclusion** criteria were developed. Based on the criteria, the primary studies were selected by reading the title, abstract, and full text of the articles in order to ensure that the results were related to the research area under study. In order to limit the scope of this research, the studies exclude the security and dependability approaches.

Concerning **RQ1**, Fig. 4 shows the statistics of year-wise publications on the congestion of IoT networks considered in our survey.

Regarding **RQ2**, the publication forums of the retained papers are identified. The summary of the publication forum of the retained paper is listed in Table 4. More articles are published in IEEE publications.

2.3.1. Inclusion criteria

1. The articles related to congestion detection, avoidance, and control in IoT networks.
2. The article related to implicit or explicit notification occurrence of congestion in IoT networks.
3. The articles related to traffic, resource, and hybrid congestion control in IoT networks.
4. The articles related to different routing techniques and metrics to avoid congestion in IoT networks.
5. The articles related to controlling the congestion through routing protocol and algorithm that occur in the 6LoWPAN network
6. The articles reporting on the Request for Comments (RFC) standard published by the Internet Engineering Task Force (IETF) and simulators are considered beyond 2015.
7. The articles related to different IoT Simulators for congestion control in IoT.
8. The article related to Artificial Intelligence techniques used to control congestion.

2.3.2. Exclusion criteria

1. The article reports on congestion detection, avoidance, and control techniques that do not apply to IoT networks.
2. The article reports on simulators that do not belong to IoT network simulators.

3. Internet of Things

Connecting everyday things embedded with electronics, software, and sensors to the internet enables them to collect and exchange data on the same platform the IoT (Gillis, 2021). These devices sense and collect data for aggregating and analyzing better decision-making that will prove advantageous to applications. The benefits of IoT are efficient resource utilization, minimizing human efforts, saving time, development of AI through IoT, improved security, etc. There are three

Table 4

Publication forums of retained papers.

Publication Source	No
Transactions	
Transactions on Sustainable Computing	3
Transactions on Mobile Computing	2
Transactions on Network and Service Management	2
Transactions on communication	1
Transactions on ACM	1
Transaction on Industrial Information	1
Transactions on Wireless communication	1
Journals	
IoT journal	9
IEEE Access	8
International Symposium on Wireless Communication	5
International Symposium on Computing and Networking	5
IEEE Journal on selected area in communication	5
ACM	5
Electronics Sensors MDPI	5
Electronics	4
Wireless Personal Communication	4
Wireless network	3
IETF	2
Journal of Reliable Intelligent	2
Ad hoc network journal	2
International Journal of Computer Science and Engineering	2
International Journal of Future Generation Communication	2
International Journal of Distributed Sensor Network	1
Elsevier Material Today	1
Journal of Advanced Simulator	1
IEEE System Journal	1
Elsevier Sustainable Cities and Society Journal	1
Conferences Proceeding	
International Conferences on communication	4
International Conference on Advanced Computing	3
International Conference on Distributed Computing in Sensor Systems	2
International Conference on Protection	2
Computer Science review	2
International Conference on IoT	1
Other International Conferences	9
Total	102

aspects of things to show how it works; the first is to connect, ensure that the internet is accessed by all of the gadgets, then analyze where all the data is connected, and then it has to be analyzed to build a business-intelligent solution, finally is to improves the system (Sharma and Gondhi, 2018).

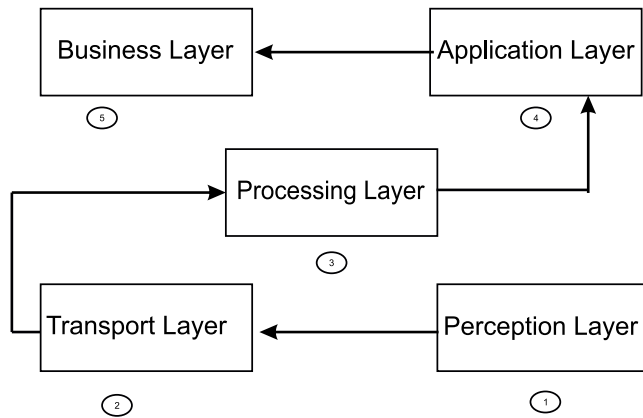


Fig. 5. IoT architecture.

3.1. IoT architecture

The IoT protocol stack that fully confirms the effectiveness of the wireless communication stack is taken as a subject of this survey. There is no single architecture for IoT, different researchers proposed various IoT architectures (Shreyas and Kumar, 2020). 5 layers of the architecture are depicted in Fig. 5.

- **Perception Layer:** This layer is also called the physical layer, which has a sensor for gathering information about everything around us by sensing the objects, it also identifies other objects around the environment.
- **Transport Layer:** The sensor data is been transferred from the physical layer to the processing layer through a network layer such as wireless, LAN, etc. The issue related to this layer is congestion, which is eliminated in the proposed technique that uses congestion detection, avoidance, and control.
- **Processing Layer:** This layer is also known as a middle layer. It stores analyzes and processes the information, that comes from the transport layer. It includes many technologies such as databases, cloud computing, and big data. It has the capacity to handle a number of services to its lower layer.
- **Application Layer:** This layer provides application services to its user for instance smart home, smart cities (Li et al., 2018a), smart parking (Khanna and Anand, 2016) and smart health (Catarinucci et al., 2015).
- **Business Layer:** This layer handles the entire IoT system. Apart from delivering the required data, this layer will also present their data in an expressive way. It involves flowcharts, graphs, analysis of data, etc. (Sethi and Sarangi, 2017).

4. Congestion analysis in IoT

The congestion in a network is defined as the state where a node or link carries so much data that may affect network service quality. Due to this, the long delay in the queue, packet loss, blockage of connection, decrease in response time, and less throughput can occur (Akhtar et al., 2019). Hence, this section gives a brief analysis of congestion in IoT networks. The general implementation step for controlling the congestion is explained in Fig. 6. The taxonomy of network congestion in IoT is shown in Fig. 7.

4.1. Congestion detection

Congestion detection is a procedure or technique that identifies abnormality in normal traffic. Here, the abnormality is referred to as a packet that has not been transferred from the source node to the

destination node (Ahmed and Paulus, 2017). This section provides an analysis of the recent existing research works correlated to congestion detection in IoT. In an IoT network, a huge data is generated by the sensor which leads to congestion at the parent node during communication. To resolve this problem Congestion-Aware Routing (CoAR) protocol is proposed. This protocol detects congestion based on queue occupancy of present and past traffic. Whenever a large number of packets are exhibited in the network and occupy the buffer space, CoAR uses a queue management mechanism that implements an adaptive buffer threshold technique. If the queue occupancy of each node traverses 50% of the total queue size, then the size of the parent queue will increase else it decreases (Bhandari et al., 2018; MR and HS, 2023).

The algorithm Constraint Application Protocol-Rate (CoAP-R) provides the solution during heavy traffic in the network and it improves the performance of CoAP. CoAP-R uses present and past channel load conditions and current buffer occupancy to detect congestion. If the source sending rate is greater than the allotted rate, CoAP-R decreases the sending rate of the packets to their destination and avoids congestion in the IoT network. CoAP-R uses the max-min fair allocation principle to identify the sending rate. The CoAP-R algorithm is simulated in static and dynamic scenarios (Ancillotti et al., 2018).

The high traffic rate in IoT networks causes congestion at the node level and packets are discarded due to buffer occupancy. To avoid this, the Time Synchronized Channel Hopping (TSCH) algorithm is considered, and that is an effective method to detect and control congestion in IoT. A backlog is nothing but a packet that is in the output queue. Based on the estimated backlog factor, the node decides to change the parent node and avoids congestion. Detecting the congestion is done through continuous monitoring of the queue backlog level of all nodes (Farg et al., 2020).

In IoT-based applications, one of the major tasks is to detect and monitor the object continuously. The localization and detection of the object continuously result in congestion that causes packet loss and extensive usage of energy. So, to overcome this problem the Consistent Data Collection and Assortment in the Progression of Continuous Objects (CDCAPC) algorithm is scheduled that applies a Preliminary Congestion Control Scheme (PCCS) to control traffic. The receiver node accepts the packets based on their priority, if there is no high-priority packet then the threshold value of the packet will be accepted. If the overloading of the packet still exists, the CDCAPC implements the Representative Boundary Nodes Identification and Congestion Control (RBNACC) algorithm that creates a cluster and boundary node that changes the parent node. The benefit of this algorithm is that it selects a few nodes for data transmission in the hotspot. By implementing this, it can increase network lifetime by reducing energy consumption (Rahman et al., 2018).

A single platform connects heterogeneous devices in an IoT network over the Internet. Congestion in the network rises along with the number of connected devices. The route maintains track of each line by calculating the number of packets and the size of each packet in order to determine the load of a certain link. Congestion may be avoided by altering the transmission rate in accordance with the state of the network. To swiftly adjust the transmission rate when the bandwidth and delay control change, the author offers a novel congestion control strategy with a delay-based variation (Verma et al., 2019). The proposed method is appropriate for the lightly weighted device (Verma and Kumar, 2020).

The Naive Bayesian model is developed for the heterogeneous network, which frequently triggers congestion and indirectly affects the application of IoT. The proposed algorithm NB-TCP captures the packet loss state and different types of wireless or wired networks. The receiver calculates the lost packet pattern by making the packet a high and low priority. When there is a heavy load in a network the low-priority packets are discarded. In case there are no low-priority packets the high-priority packets are discarded. If any of the packet sequences

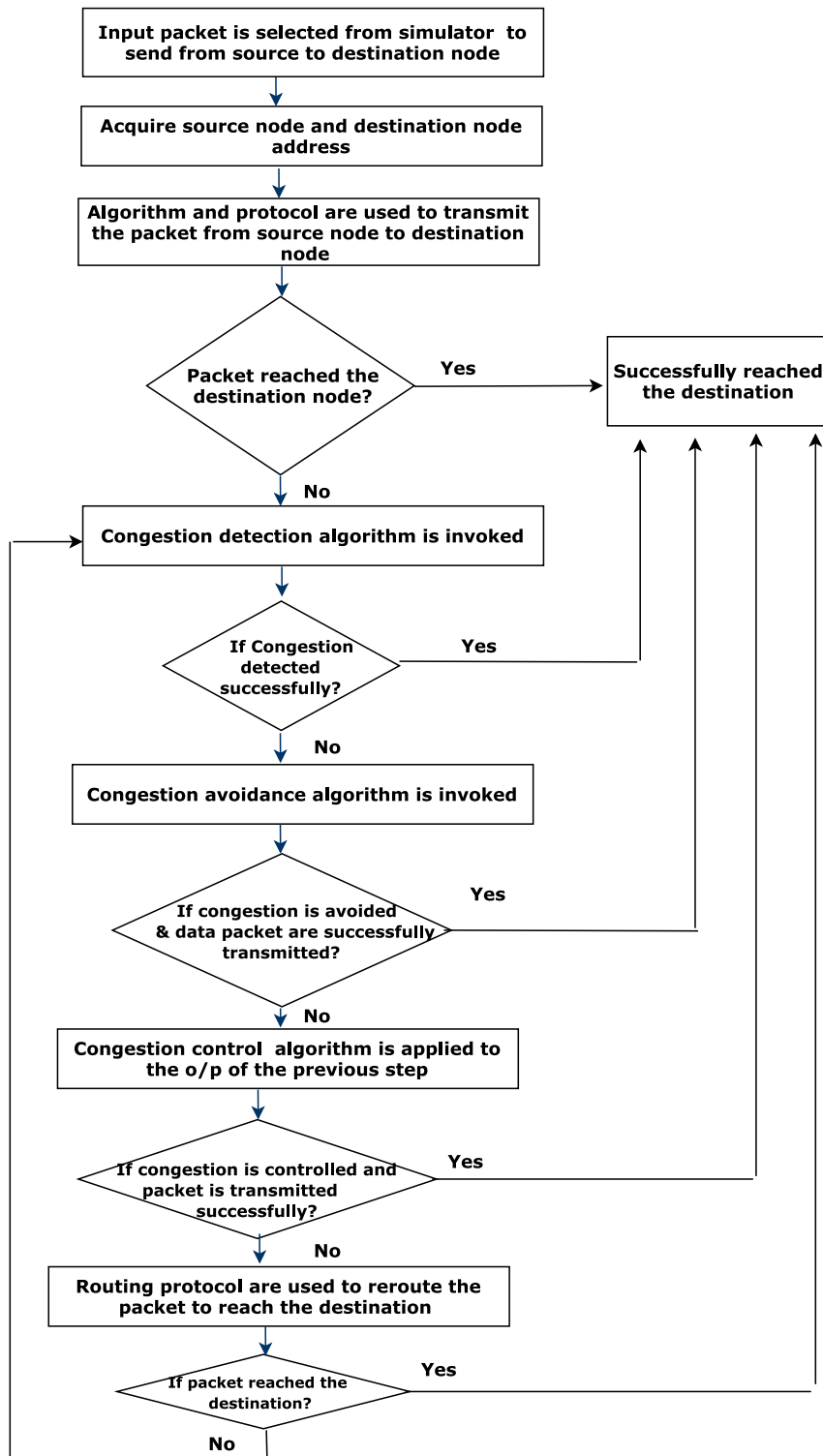


Fig. 6. General congestion control implementation flow chart.

are missing at the receiver node then it is considered that the packet has been lost due to congestion. The algorithm has enhanced the throughput, fairness, and friendliness of other methods (Chen et al., 2019).

The Adaptive Congestion Control-Carrier Sense Multiple Access (ACC-CSMA) protocol is proposed that senses the channel using the backoff index to analyze the congestion level. In this topology, the network is divided into a primary and secondary network that consists

of primary and secondary devices that may create congestion. If congestion is detected as very high in the channel the protocol advises the secondary device to join the secondary network and reach its destination without congestion (Zhuo et al., 2019). Instead of sending information through IoT devices by the cellular user during uplink communication, it schedules with drones and thus the congestion in the channel is reduced. This algorithm performs an online congestion mechanism (Hattab and Cabric, 2020).

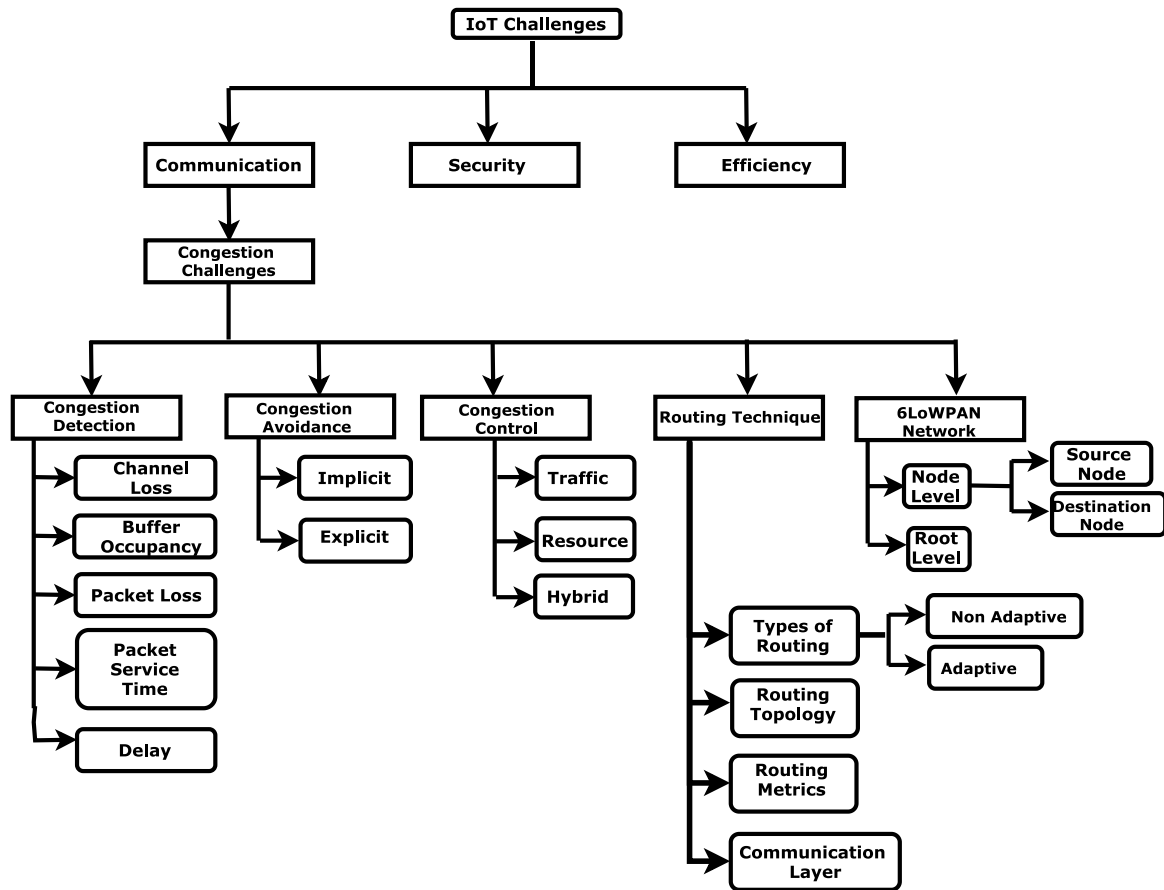


Fig. 7. Taxonomy of IoT network congestion challenges.

The congestion level is explained by considering a smart city case study in that many users try to retrieve the same information like parking spots, traffic monitoring, weather condition, etc. When the number of arrival packets increases to the gateway the cache hit rate increases and congestion occurs. Therefore, to overcome this a new multi-gateway architecture, resource caching policy, and Multi-Criteria Decision Making (MCDM) based load balancing technique is introduced to this environment to improve the connectivity without any packet loss. The algorithm provides benefits in terms of network capacity and reliability (Banaie et al., 2020).

5G communication, Cloud/Edge computing-based network is expected more in the future. To improve the QoS the novel scheduling approach called Scheduling Approach for Heterogeneous Content-centric IoT (SAHCI) has been proposed to have effective communication without packet loss between the heterogeneous node and different types of packets that are been prioritized. Based on the highest priority the packet will be forwarded (Al-Turjman et al., 2019; Mamo et al., 2020; Beitelspacher et al., 2020).

When devices are at different locations the throughput is unfair in the IEEE 802.11 network. The detection of congestion is done when there is a buffer overflow in the Access point or if MAC discards due to re-transmission failure. So, to avoid this an Adaptive VBS algorithm has been proposed that monitors the queue and estimates the Transmission Control Packet (TCP) packet loss probability and throughput fairness using a simple mathematical framework that avoids congestion (Pokhrel and Williamson, 2018).

To upgrade the performance of the QoS network in the MAC layer a new algorithm with a Clear Channel Assignment (CCA) mechanism is proposed to detect the congestion by adjusting the contention window of the affected node. It provides a good estimate for loss probability

and increases the throughput in IoT network (Chitrashekharaiah et al., 2022).

Summary: Congestion detection is a procedure or technique that identifies abnormality in ordinary traffic. Abnormality is pointed out as a packet that has not been transferred from the source node to the destination node (Ahmed and Paulus, 2017). Fig. 8 explains the process of detecting congestion. The congestion detection section provides vital information on the recent research in IoT. 70% of the algorithm uses buffer occupancy as a parameter. More than channel load, latency, packet service time parameter, etc., buffer occupancy demonstrates the presence of congestion. The techniques used to detect the congestion in IoT network is summarized in Table 5. Table 6 highlights the use of 3 parameters to identify congestion. Future research solutions in detecting the congestion in IoT networks can be summarized as

- Congestion may be identified and reduced more effectively by bringing computing capabilities closer to IoT devices and analyzing data at the edge of the network. By doing so, the central network infrastructure's load can be lessened and the latency can be decreased.
- Congestion detection algorithms can have a better understanding of the network and make better decisions at each layer (physical, MAC, and network) to increase the accuracy of congestion detection.

Challenges in detecting congestion in IoT networks can be summarized as

- Scalability
- Heterogeneity
- Dynamic network topology

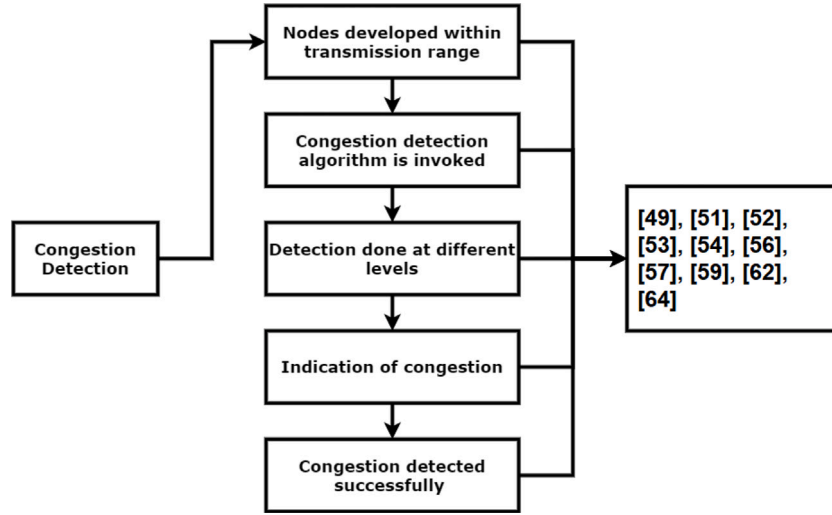


Fig. 8. General structure of congestion detection.

4.2. Congestion avoidance

The technique that is used to avoid congestion, monitors network traffic flow. This section provides an analysis of the recent existing research works related to congestion avoidance in IoT.

Wireless mesh networking is the latest internet framework. If it is connected to an IoT network, it experiences congestion and restriction in bandwidth. So, to avoid this Integrated Markov State transition, an Open-Loop Smart Caching (MST-OLSC) algorithm is proposed for constant data flow rate and overflow of packets. This algorithm uses the Markov state transition scheduling algorithm that uses to identify patterns and make predictions to learn the sequential data. The author also suggests an open-loop smart caching algorithm to increase the packet delivery ratio. In this technique for each data packet, the token is attached to it such that before transmitting the data packet, the token is added to the bucket or buffer. Depending upon the number of tokens present in the bucket, its relevant packets are transmitted to the network thus, the congestion is avoided in the network. The simulation results show that the suggested approach outperforms existing techniques regarding packet delivery rate, end-to-end latency, and energy usage. Yuvaraj and Saravanan (2021). The Eq. (1) expresses that the packet delivery rate is calculated as a percentage by dividing the number of received packets by the number of sent packets and multiplying the result by 100. From all the packets transmitted, this rate represents the percentage of packets that successfully arrived at their destination such that congestion is avoided.

$$\text{packetdeliveryrate} = \frac{\text{packetreceived}}{\text{packetsend}} * 100 \quad (1)$$

IoT invention has taken rapid growth in technology and raised new challenges concerned with data delivery without packet loss in the heterogeneous network, with nodes having different buffer sizes. To overcome this, the Imperialist Competitive Algorithm (ICA) with Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) algorithm is designed. The aim of this protocol is to maximize the fitness function that consists of 3 parameters they are choosing nodes with more energy, added memory, and neighborhood. To avoid congestion, the memory capacity of a node is calculated with the fraction between the Initial Buffer Size (IBS) and the remaining space of the buffer. The mathematical Interpretation of congestion avoidance is made just after the buffer overflows (Hamidouche et al., 2019), which is calculated using the fitness of the buffer as shown in Eq. (2). From the equation the “*numberofneighbour*” indicates the number of neighboring buffers that are linked to the present buffer, and the “*currentBatteryPower*” indicates the buffer’s current battery power. Battery power could be taken into

account in congestion avoidance tactics even though it is not directly related to congestion, particularly in wireless or mobile networks. The maximum number of packets or data units that the buffer can hold is indicated by the term “*capacity (i)*”. Larger capacity buffers may be better able to handle incoming traffic and prevent congestion. And “*Suitability*” denotes a further aspect unique to the problem domain that improves the buffer’s fitness.

$$\text{Fitness}(i) = \text{Coefficient}_1 * \text{numberofneighbour} + \text{Coefficient}_2 * \text{currentBatteryPower}(i) + \text{Coefficient}_3 * \text{Capacity}(i) + \text{Suitability} \quad (2)$$

The packet transmission process is done through Handshake Sense Multiple Access with Collision Avoidance (HSMA/CA) protocols that consist of one of the four events during the packet transmission. These events are

- Notify-To-Sense (NTS) collision.
- Blocking at SU transmitter.
- Blocking at SU Receiver.
- Successful transmission.

In case of an NTS collision, all nodes use the Backoff mechanism to avoid the collision. In this mechanism, the Backoff counter is assigned to each node, if the Backoff slot is idle, the Backoff counter is decreased by one and this process continues till it expires. The first expired node can transmit the NTS packet. In this way, the collision can be avoided (Shafiq et al., 2019). The probability of an event collision occurring with NTS packets is defined in Eq. (3). Prob refers to Probability, CCP refers to Clear Channel Probability, PTP refers to Packet transmission Trail Probability

$$\text{Prob}(1) = \text{CCP}(1 - \prod_{k=2}^{SU})[1 - \text{PTP} * \text{CCP}] \quad (3)$$

Allowing an end-to-end network without congestion and data loss is one of the most important technological issues facing the 6G mobile network. The devices in this network use a wide range of internet that causes low speed in surfing, which is nothing but traffic congestion. To cope with the internet speed a network congestion-avoiding mechanism is proposed. This algorithm sub-sliced the network into more networks, called slice admission control, and performs its function without collision (Sharma and Borole, 2020). This situation is expressed in Eq. (4). By taking into account only those hosts that receive packets within the allotted time, the formula effectively determines the likelihood of packet delivery. It is assumed that if a packet is received by a host

Table 5

Summary of articles related congestion detection in IoT networks.

Author/ Year of Publication	Proposed work objective	Algorithm used	Detection of congestion	Routing Topology	Indication of Congestion	Routing Metric	Gap Area
Khadak Singh Bhandari <i>et al.</i> , 2018 (Bhandari <i>et al.</i> , 2018).	To chooses the optimized path based on multiple routing metrics	CoAR	Parent Node	DODAG	1. Buffer Occupancy 2. Present and past traffic trends.	Queue utilization, Residual energy, Expected transmission count, Neighborhood index	Queue utilization, and expected transmission count are cost-effective.
Emilio Ancillotti <i>et al.</i> , 2018 (Ancillotti <i>et al.</i> , 2018).	To choose the optimized path based on the traffic load and routing	CoAP-R	Sensor Node	Tree	1. Buffer Occupancy 2. Present and past channel loading	Throughput, Bandwidth	The algorithm leads to more congestion at the parent node.
Farag <i>et al.</i> , 2020 (Farag <i>et al.</i> , 2020).	To identify and manage 6TiSCH network congestion.	TSCH	Parent node	DODAG	Buffer Occupancy	HL Criterion and LB Criterion	Slightly increase in end to end(E2E) delay.
Taj rahman1 <i>et al.</i> , 2018 (Rahman <i>et al.</i> , 2018).	1. To tackle traffic congestion 2. Detecting the object continuously 3. Maximizing throughput	CDCAPC	Receiving node	Dynamic tree	Buffer Occupancy	Hop by hop delay, Data Loss	Boundary nodes are not defined.
Lal Pratap Verma <i>et al.</i> , 2020 (Verma and Kumar, 2020).	To modify the transmission rate in accordance with the network's condition.	Delay-based	Sender node	Dumbbell	Network delay	Bandwidth, Throughput.	It is only suited for lightweight IoT applications.
Yating Chen <i>et al.</i> , 2019 (Chen <i>et al.</i> , 2019).	To find the packet loss in hybrid wireless and wired channel.	NB-TCP	Receiver node	Wired LAN	Channel level	Throughput, Fairness index,	If congestion is heavy then the NB-TCP method may not perform better.
Shuguo Zhuo <i>et al.</i> , 2019 (Zhuo <i>et al.</i> , 2019).	To allow many devices to communicate in the primary channel without congestion.	ACC-CSMA	Sink node	IEEE 802.15.4	Channel level	Latency, Throughput	The algorithm utilizes high power consumptions.
Banaie <i>et al.</i> , 2020 (Banaie <i>et al.</i> , 2020).	To improve the performance, and to increase the access speed in IoT edge network.	Multi-Gateway AHP	Gateway	Single hop with multiple overlapping gateway.	Buffer occupancy	Available resources, link quality, and resource load.	The algorithm does not support different traffic classes
Fadi Al-Turjman <i>et al.</i> , 2019 (Al-Turjman <i>et al.</i> , 2019).	To reduce packet dropping rate and increase QoS.	SAHCI	Server	Wired Lan	Buffer Occupancy	Time Latency, reliability and database.	As it does not provide strict priority the proposed outcome is not satisfied in QoS.
Shiva Raj Pokhrel <i>et al.</i> , 2018 (Pokhrel and Williamson, 2018).	To improve connectivity, throughput fairness, and bandwidth requirements.	Adaptive VBS	Access point.	WLAN	Buffer Occupancy	Interferences, signal strength, channel impairment.	Due to increasing in wireless channel errors the upload and download in fair throughput has a small gap.

before the given time limit, there was no packet collision or interference and the packet was effectively transmitted.

$$DeliveryProbability = Slice(endhost < Timealloted) \quad (4)$$

In a constrained network, TCP may consist of lots of retransmission and low throughput. The sender continuously sends the same packet until it gets a link acknowledgment from the receiver. Repeatedly

sending the same packet to the same destination leads to congestion. So to avoid this, there exists a scheme that adjusts the retransmission timer according to the estimated RTT and enhances TCP performance. This retransmission timer for each connection is decreased by 0.5s and expires soon once the timer reaches zero. Retransmission is performed during the bandwidth is free and thus the congestion is avoided (Lim, 2020). Eq. (5) shows that by enhancing the retransmission timer the

Table 6

Summary of various articles in congestion detection with 3 parameters.

Author/year of publication	Congestion Occurrence		Congestion Notification		Congestion control		
	Node Level	Channel Level	Implicit	Explicit	Traffic control	Resource control	Hybrid control
Khadak Singh Bhandari et al., 2018 (Bhandari et al., 2018).	Yes	–	Yes	–	–	Yes	–
Emilio Ancillotti et al., 2018 (Ancillotti et al., 2018).	Yes	–	–	Yes	–	Yes	–
Taj rahman1 et al., 2018 (Rahman et al., 2018).	Yes	–	Yes	–	Yes	–	–
Lal Pratap Verma et al., 2020 (Verma and Kumar, 2020).	Yes	–	Yes	–	Yes	–	–
Yating Chen et al., 2019 (Chen et al., 2019).	–	Yes	Yes	–	–	Yes	–
Shuguo Zhuo et al., 2019 (Zhuo et al., 2019).	–	Yes	–	Yes	–	Yes	–
Banaie et al., 2020 (Banaie et al., 2020).	Yes	–	–	Yes	–	Yes	–
Fadi Al-Turjman et al., 2019 (Al-Turjman et al., 2019).	Yes	–	–	Yes	–	Yes	–
Shiva Raj Pokhrel et al., 2018 (Pokhrel and Williamson, 2018).	–	Yes	–	Yes	–	Yes	–

collision can be avoided. RT refers to RetransmissionTimer, nbackoff is retransmission timer, and RT increases up to 48 s.

$$RT = \max(RTO \ll nbackoff, 48s) \quad (5)$$

IoT devices that use short TCP flows in-home WiFi network, serve as different, compared to transport layer protocol and it also shares dynamic wireless medium. Based on Markov regenerative processes, an Adaptive Admission Control (AAC) mechanism, queue management policy, and Restricted Access Window (RAW) algorithm are proposed at the WiFi access point to increase response time and fairness of IoT traffic. A group of devices with a common window can be allowed to access the shared channel at one time and the rest of the devices at another time, by this action the congestion is avoided (Pokhrel et al., 2020). The congestion avoidance equation is shown in Eq. (6). From the equation P is the probability to compute the loss packet, μ is the uplink/downlink traffic generated by IoT devices, i is the IoT devices, and qt is its expected buffer size.

$$P_b^i(t) = \left(\frac{\mu_i(t)}{\theta_i(t)} \right)^{\frac{qt}{N}} \quad (6)$$

The author Kalita and Khatua (2021) suggests that as the devices increase Markov chain-based model degrades the performance of the network. Therefore a Channel Condition-based Dynamic Beacon Interval (C2DBI) scheme is been proposed. If the measured signal strength is higher than the clear channel assessment, then a shared shot is treated as the free channel and it is occupied, then the proposed algorithm dynamically alters the beacon interval value based on the congestion status in the shared slot. To identify whether the channel is congested or not it makes use of the channel busyness ratio parameter and avoids congestion. The Eq. (7) divides the total number of busy shared slots by the total number of unoccupied shared slots. The CBR, which measures the percentage of time slots that are currently busy or occupied in the shared channel, is produced by this division. With a higher CBR, more of the shared channel is likely to be in use, which could suggest increased traffic or congestion. A lower CBR, on the other hand, means that a smaller fraction of the shared channel is filled, which denotes

lower traffic or less congestion.

$$ChannelBusyRatio = \frac{Busysharedslots}{(Busysharedslots + Emptysharedslots)} \quad (7)$$

An IoT network refers to the collection of IoT devices that communicate and share resources, although the network cannot able to share resources among different devices, or if all devices request the same resources at a time, then congestion occurs. So to overcome this problem TCP Westwood (TCPW) algorithm, adaptive sliding window algorithm, and poling TCPW are designed to develop status reports in the RLC protocol stack. In the TCPW algorithm, if it receives NACK or if polling timing overruns, or if the congestion window reaches a threshold value, then congestion avoidance will initiate and adjust buffer availability and reduce transmission delay, thus congestion is avoided in the IoT networks (Zhou et al., 2019). The Eq. (8) expresses that if the buffer usage of the sliding window on the receiver side is more than half then to avoid congestion the below equation is executed. The status prohibition timer in the sliding window is denoted as $t_{StatusProhibit}$, while the reordering timer is represented by $t_{Reordering}$.

$$t_{StatusProhibit} = 1.5 * t_{Reordering} \quad (8)$$

The formation of M2M communication on mobile networks contributes universal service to IoT systems. The number of devices connected to the network may access the resources simultaneously. This huge approach results in congestion and collision in random access channels (RACH). So to overcome this a Dynamic Backoff Collision Resolution scheme (DBCR) is introduced that reuses the Backoff Indicator (BI) value based on several devices connected to it. Meantime, if the request arises beyond the available resources, the devices randomly wait for a particular period that is dynamically generated. After the allotted time ends, the devices may retry the request, thus it identifies and avoids congestion (Althumali et al., 2020). The Eq. (11) explains the collision rate in the network. It calculates the CollisionRate by dividing the number of colliding preambles by the mean delay. As more preambles collide or experience delays, a higher collision rate signals a higher risk of congestion. A lower collision rate, on the other hand,

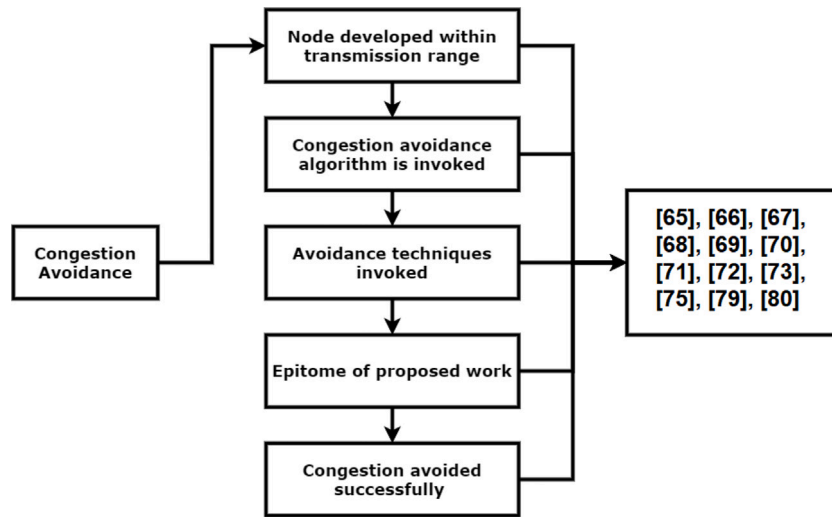


Fig. 9. General structure of congestion avoidance.

denotes a lower level of congestion, with fewer collisions and shorter delays.

$$CollisionRate = \left(\frac{NumberOfCollidedPreamble}{MeanDelay} \right) \quad (9)$$

Smart grid data networks (Shahinzadeh et al., 2019) consist of different subnets among them one subnet is SGNAN, its objective is to connect the home appliance and communicate without congestion. This subnet consists of a sender, receiver, and gateway. The gateway analyzes various data packet that enters and exit from the SGNAN network, which leads to an uncontrolled data transmission rate. So to avoid this, a congestion control mechanism that is based on the Learning technique is considered. It also incorporates Decision Tree-based Congestion Control (DTCC) and Neural Network Congestion Control (NNCC) mechanisms to avoid congestion. Two components make up this mechanism. First, train the chosen data, and second, determine if a packet will be transferred without congestion. This article represents two mechanisms to avoid congestion (Astudillo et al., 2020).

Healthcare monitoring applications use IoT-based wearable computing devices that are connected to the sensor (Farahani et al., 2018). To remotely monitor high-risk patients, there should be a routing protocol such that it has a minimum delay and higher throughput for emergency packets that reach the destination without any congestion. In this article, the author proposes a Priority-based Congestion avoidance Routing Protocol (PCRP) to avoid congestion and transmit the packet to its destination. PCRP is a multi-hop routing protocol and uses a three-parameter to find the best path they are Signal Noise Ratio (SNR), Residual Energy (RE), and Node Congestion Level (NCL). The NCL parameter is used to see whether there is sufficient space to transmit a packet at a high data rate in the network. Thus the congestion is avoided (Awan et al., 2019). Congestion on a node can be calculated using the below Eq. (10)

$$CurrentQueueSize = Q_{Total} - Q_{free} \quad (10)$$

Congestion of data packets in IoT networks will increase due to the increase of IoT devices. To avoid this currently, the destination nodes will control the congestion by using congestion control schemes such as Tahoe, Reno, newReno, and cubic (Ahmad et al., 2020). The increase in data traffic connected by IoT devices would degrade the network throughput. So the flow congestion avoidance algorithm is proposed that is controlled by the network in software-defined networking (SDN). The algorithm uses the utilization of the switch by dividing the current bitrate by the maximum bitrate. If the utilization of the switch is more than the threshold value then the SDN controller set a new route to prevent the congestion (Song et al., 2016).

The heterogeneous network consists of different network topologies. During the transmission of a packet from device to device, the packet may be delayed or lost in the network. So to overcome this problem, the TCP-Siam congestion control protocol is introduced in this article that makes use of the Markov Decision Process (MDP) mechanism to store the packets. If congestion occurs then it increases the window size and stores the packet else it retains the target window size. Thus, the congestion is avoided (Toprasert and Lilakiataskun, 2017). The author uses Eq. (11) to avoid congestion by increasing its window size.

$$W_{n+1} = W_n + \alpha \quad (11)$$

Summary: If the congestion state exceeds the threshold value that is set by the user, then the algorithm enters a new state known as congestion avoidance. This section mainly deals with the main objective function of the algorithm. Each article has implemented congestion avoidance techniques. To avoid the occurrence of congestion each article has calculated the collision rate in different approaches. The flow of avoiding congestion is explained in Fig. 9. A summary of congestion avoidance algorithms with their advantages and disadvantages is explained in Table 7. Table 8 highlights the use of 3 parameters to avoid congestion. The study of the existing work leads to the observation that.

- The congestion avoidance techniques are very less implemented in the dynamic and heterogeneous network.
- Very less congestion avoidance mechanism is implemented through machine learning approaches.

Future research solutions in avoiding the congestion in IoT networks can be summarized as follows:

- Utilize predictive analytics approaches to foresee congestion occurrences in IoT networks and take proactive measures to avoid congestion. Congestion can be anticipated in advance by examining historical data, traffic patterns, and contextual information. Then, proactive measures like resource allocation, load balancing, and traffic rerouting can be put into place to prevent congestion before it happens.

Challenges in avoiding congestion in IoT networks can be summarized as

- Limited Bandwidth
- Resource Constraint

Table 7

Summary of congestion avoidance techniques in IoT network.

Author/ Year of publication	Objective of proposed system	Proposed Algorithm Used	Avoidance Technique Used	Quick fix of the Proposed work	Advantages	Gap Area
Yuvaraj <i>et al.</i> , 2020 (Yuvaraj and Saravanan, 2021).	To avoid congestion and increase data delivery ratio	Integrated Markov State transition and open loop smart caching (MST-OLSC).	Open loop smart caching	1.RTT sample. 2.Bufferoff Policy	Reduces End-to-end delay	Energy Consumption was not analyzed.
Ranida Hamidouche <i>et al.</i> , 2019 (Hamidouche <i>et al.</i> , 2019).	To avoid congestion an extensive analysis of the use of sensors in IoT is performed.	Grey Wolf Optimizer (GWO) and Whale Optimizer Algorithm (WOA) together with Imperialist Competitive Algorithm(ICA) Protocol.	Grey Wolf Optimizer (GWO) and Whale Optimizer Algorithm (WOA)	Store the overloaded packets in the alpha cache.	This protocol can be applied for e-health applications	It does not guarantee an optimal solution.
Muhammad Shafiq <i>et al.</i> , 2019 (Shafiq <i>et al.</i> , 2019).	To resolve spectrum shortage through dynamic spectrum allocation	Handshake sense multiple access collision avoidance (HSMA/CA)	BackOff mechanism	By Increasing time delay	Reporting the result to PU in has very short time	Algorithm is unable to distinguish the source of the signal.
Prajakta Borole <i>et al.</i> , 2020 (Sharma and Borole, 2020).	To avoid congestion and delay challenges for existing network	Edge assisted congestion control scheme	Network slicing mechanism	End-to-end network, slicing using delay	Security and efficiency of network increase	Detail implementation of code is not expressed.
Chansook Lim <i>et al.</i> , 2020 (Lim, 2020).	To reduce TCP retransmission without decreasing throughput.	Delay based congestion control	Retransmission timer, BackOff	Increase global buffer size.	Implementing the RDC mechanism, many retransmission packets can be avoided	If the random loss rate increases the frequency of connection fails in the network. Limited TCP window size.
Shiva Raj Pokhrel <i>et al.</i> , 2019 (Pokhrel <i>et al.</i> , 2020).	To implement TCP for IoT application and avoid congestion	Adaptive Admission Control (AAC)	RAW approaches	Maintain separate small queue in Access Point	Congestion is detected and avoided in channel-based and dynamic buffer occupancy	AAC admits the packets in AP queue that can affect the service rate and delay requirement.
Chenhong Zhou <i>et al.</i> , 2019 (Zhou <i>et al.</i> , 2019).	To assure the data transmission efficiency and minimize its delay.	TCP Westwood	Adaptive Sliding window algorithm	, RTT	Delay, Bandwidth and size of the congestion is updated dynamically	This algorithm cannot distinguish between channel quality & link congestion that reduce system performance.
Huda Dakhilallah Thumali <i>et al.</i> , 2020 (Althumali <i>et al.</i> , 2020).	To modify the Backoff indicator and to reduce the collision rate dynamically	Dynamic Backoff Collision resolution(DBCR) scheme	Backoff mechanism	Allocate time dynamically to each device	Improves energy efficiency for M2M devices	There is a Constraint in packet arrival distribution efficiency.
Juan Pablo <i>et al.</i> , 2020 (Astudillo <i>et al.</i> , 2020).	To avoid congestion and improve QoS	Congestion Control Based on Machine Learning	1.DTCC 2. NNCC	Proper Data Set is given to DTCC & NNCC	Two mechanisms are implemented & gains effective communication without congestion	Emergency awareness and fairness in network resources were not considered.
Khalid M Awan <i>et al.</i> , 2019 (Awan <i>et al.</i> , 2019).	To have a minimum delay, higher throughput, optimal energy consumption, efficient resource utilization in all sensor nodes in the network	Priority-based congestion-avoidance routing protocol (PCRP)	Node Congestion Level (NCL)	Uses Data aggregation and filtering process	Energy Consumption is reduced and network stability increases.	Movability of sensor nodes due to body movement is not considered.
Seungbeom Song <i>et al.</i> , 2016 (Song <i>et al.</i> , 2016).	To avoid congestion at the end devices.	Congestion avoidance algorithm using SDN-Controller	Open flow configuration protocol	Uses Switch to reroute the packet where there is no congestion	It can control and monitor the whole network	No high Bandwidth and cannot satisfy the requirement of throughput
Thongchai Toprasert <i>et al.</i> , 2017 (Toprasert and Lilakiataskun, 2017).	To optimize the congestion control in heterogeneous network	TCP-Siam	Markov Decision Process (MDP) mechanism	Increases Window Size	Based on transition state(CA-open, CA_recovery,CA_loss) congestion is avoided	1.Wireless mesh network is not considered at lower layer. 2.The wire link is not configured.

Table 8

Summary of various articles on congestion avoidance with 3 parameters.

Author/year of publication	Congestion Occurrence		Congestion Notification		Congestion Control		
	Node Level	Channel Level	Implicit	Explicit	Traffic control	Resource control	Hybrid control
Yuvaraj <i>et al.</i> , 2020 (Yuvaraj and Saravanan, 2021).	Yes	–	Yes	–	–	Yes	–
Ranida Hamidouche <i>et al.</i> , 2019 (Hamidouche <i>et al.</i> , 2019).	Yes	–	–	Yes	–	Yes	–
Muhammad Shafiq <i>et al.</i> , 2019 (Shafiq <i>et al.</i> , 2019).	–	Yes	Yes	–	Yes	–	–
Prajakta Borole <i>et al.</i> , 2020 (Sharma and Borole, 2020).	–	Yes	–	Yes	Yes	–	–
Chansook Lim <i>et al.</i> , 2020 (Lim, 2020).	Yes	–	–	Yes	Yes	–	–
Shiva Raj Pokhrel <i>et al.</i> , 2019 (Pokhrel <i>et al.</i> , 2020).	Yes	–	Yes	–	Yes	–	–
Chenhong Zhou <i>et al.</i> , 2019 (Zhou <i>et al.</i> , 2019).	–	Yes	–	Yes	–	Yes	–
Huda Dakhilallah Thumali <i>et al.</i> , 2020 (Althumali <i>et al.</i> , 2020).	–	Yes	–	Yes	Yes	–	–
Juan Pablo <i>et al.</i> , 2020 (Astudillo <i>et al.</i> , 2020).	Yes	–	Yes	–	Yes	–	–
Khalid M Awan <i>et al.</i> , 2019 (Awan <i>et al.</i> , 2019).	Yes	–	–	Yes	Yes	–	–
Seungbeom Song <i>et al.</i> , 2016 (Song <i>et al.</i> , 2016).	–	Yes	Yes	–	Yes	–	–
Thongchai Toprasert <i>et al.</i> , 2017 (Toprasert and Lilakiatsakun, 2017).	–	Yes	–	Yes	Yes	–	–

4.3. Congestion control

The mechanism that controls the data packet entering into the congested network is referred to as congestion control. This section provides an analysis of the recent existing research works related to congestion control in IoT.

Information-Centric Networking (ICN) focuses on identifying and sending the information to the host rather than creating a connection between the host to have communication (Pruthvi *et al.*, 2023). To increase the network performance and reduce the congestion rate, an adaptive congestion control mechanism is proposed in a hierarchical ICN-based model. This mechanism incorporates a chunk-by-chunk partitioning scheme as a network management policy. The author has evaluated and simulated this algorithm in ndnSIM and proved that the model can provide higher throughput with less cache hit range (Sukjaimuk *et al.*, 2018a).

In the ICN network, abundant request packets are generated for that which causes high traffic and congestion to occur (Sukjaimuk *et al.*, 2018b). A smart congestion control mechanism for green IoT sensors is proposed that is enabled in the ICN network to minimize congestion. The author also proposes an adaptive sensor scheduling algorithm. In this scheme, if the system identifies a sensor level less than the threshold value then the server does not transmit the packet, it transmits the packet performs caching, and forwards the data without congestion (Sukjaimuk *et al.*, 2018d).

In SDN-IoT, a high-speed transmission channel is a basic need for successful communication. To prevent traffic jams and assess the incoming traffic load, the author suggests a deep learning-based method for traffic load prediction. If congestion is discovered, a partly channel assignment algorithm called Deep Learning based Partially Channel

Algorithm (DLPOCA) based on deep learning is triggered to allocate channels to each SDN-IoT. Integrating the above two methods to prevent congestion and allocate the proper channel to SDN-IoT results in TP-DLPOCA. With the use of the C++/WILL API, the suggested algorithm is configured and tested. The algorithm selects deep-CNN as the training structure, and the simulation output shows nearly 100% accuracy (Tang *et al.*, 2018).

The performance of the network is being evaluated by one of the important criteria which is congestion control. For sensor IoT networks and ICN, this becomes a vital challenge. A dynamic congestion control mechanism is suggested and implemented in the hierarchical ICN model. The proposed network system carries the content and priority-based delay time. Adaptive content lifetime and cache management strategy are also transmitted together to control the congestion. The algorithm is simulated in the ndnSIM simulator. The evaluation result proves that the ICN model can reduce congestion and traffic load (Sukjaimuk *et al.*, 2018c).

The heavy network traffic from the huge volume of data reduces the IoT network's performance due to congestion. Unique congestion control solutions, such as the queue management strategy, must be developed in order to address the difficulties of congestion in IoT networks. A unique Priority Queue-based Token Bucket Algorithm (PQTBA) is proposed in this article as a method of reducing congestion in IoT networks. To classify network traffic into priority groups in accordance with real-time needs, the PQTBA employs a preemptive/non-preemptive approach with a discretionary rule. In terms of throughput, packet loss ratio, and energy usage, the suggested approach performs noticeably better than the most recent techniques (Anitha *et al.*, 2023).

IoT networks need to handle the vague growth of data traffic as the number of sensor devices increases. This leads to congestion and loss of

packets. A congestion control mechanism has been proposed that aims to make dynamic decisions to transmit the packet, network condition, Quality of Service, and buffering the traffic. The algorithm makes use of the function known as Congestion Control Engine (CCE) to decide alternatively buffering traffic. Thus, the proposed method controls the happening of congestion using the procedural method, the foremost step is inspecting the packet, and then detecting the congestion with the help of a Random Access Network (RAN) and CCE, if congestion is found the packet is redirected to other path and finally, the content will be delivered (Nasimi et al., 2018).

Edge computing is drastically increasing in the sensor network, and lots of problems related to it are great challenges for researchers to solve. Load balancing among edge servers is a major research topic. This scheme is classified into 4 phases: threshold value, Load edge selection, data replacement, and data search. Based on the heavy load on the router it selects the neighboring host and retransmits the packet. The simulation result proves that the proposed method is more effective than general edge computing. The main benefits of this scheme are that it can effectively distribute the load and share the resource among different servers, but the load sharing near the cloud is not performed (Mogi et al., 2018).

5G network, implements Mobile Edge Computing (MEC), Network Function Virtualization (NFV), and software-defined networking technologies to launch a flexible and robust network with various IoT devices. As there is a diverse development in the network the flow control of the data has to be maintained, and the MEC with container-based virtualization technology is proposed. IoT gateway effectively increases the Quality of Service. The proposed method MEC has two functions: The Traffic Offloading Function (TOF) and Radio Network Information Service (RNIS). These two functions are based on a flow control mechanism that provides more flexibility and deplorability in the virtualized platform. Thus the flow of data is controlled (Hsieh et al., 2018).

The issue of network congestion in the IoT is a major problem that is addressed using the CoCoA++ algorithm proposed by the author (Rathod et al., 2019). CoCoA algorithm (Gomez et al., 2016) reveals the inability in network congestion that uses RTT samples, so the author uses a delay gradient that gives an exact estimate of network congestion. The author also enhances the CAIA delay Gradient and probability Backoff Factor that is implemented in the Cooja simulator provided by Contiki OS.9. The CoCoA++ algorithm first updates the RTT Gradient of RTT (minimum) and RTT (maximum) and then estimates the RTO. For a new set of transactions based on the RTO and probability BackOff Factor the packet is sent. If congestion is found and the delay is applied then it retransmits the packet (Yi and Cai, 2019). Thus, congestion is avoided. This is deployed and evaluated in a real testbed using FIT/IoT-Lab.

5G network uses IoT applications to have effective communication with many sensor nodes. Concurrently transmitting the data to other nodes is one of the major characteristics of IoT applications. Because of this, 5G provides large bandwidth, high data transfer speed, and low delay. TCP and SCTP reduce 5G and IoT performance. Thus, a machine learning model based on the Decision Tree (DT) algorithm is proposed. The model is developed based on the training dataset to determine the optimal alternative that can enhance the performance. The source checks the congestion window (cwnd) and threshold value (sssthresh) before transmitting the data. If the acknowledgment is not received, the source initiates the recovery phase. Once it receives the acknowledgment, the source determines whether the congestion window value is less than or equal to the slow start threshold value. If so, the packet is transmitted; otherwise, the congestion avoidance phase is revoked. Thus the network shows good performance for not having congestion (Blanton et al., 2009; Najm et al., 2019a).

The author has proposed the spike ISDN-IoT architecture that is applicable in healthcare applications. In the SDN intelligent stack the

author has proposed two intelligent controllers that have the capacity to estimate the flow of packets in the sensing area. PRSNN consists of the proposed controller that works proactively to estimate the flow of packets. Selecting the cluster head and its members is done reactively on an ANN controller. The proposed method estimate the packet rate that coordinates the number of active sensor node with the available capacity of the buffer to avoid buffer overflow and congestion in the network (Al-Jamali and Al-Raweshidy, 2021).

Congestion control is the basic mechanism for designing and implementing Multipath Transmission Control Protocol (MPTCP) that provides devices to communicate concurrently. IoT networks consist of heterogeneous traffic with high dimensional states and various QoS features. The existing MPTCP algorithm is unable to perform effectively. So, to overcome this, a Free SDN-based adaptive actor-critic deep reinforcement learning framework based on a Fuzzy Normalized Neural Network (FNDRL-CC) is proposed. The proposed method computes an Actor-Critic function that provides end-to-end training to the critic and network. It also consists of an action to be performed if congestion occurs. Therefore, this mechanism avoids congestion and transmits the packet successfully. The proposed algorithm is simulated in Ubuntu Linux 16.04LTS and verified the effectiveness in terms of goodput. However, this method consumes lots of time and has an extra delay (Naeem et al., 2020).

IoT application uses a huge amount of data transmission in the network that leads to high traffic flow. So to avoid this congested network that leads to packet loss, a proportional Integrator Differentiator (PID) controller is proposed. To secure IoT data flow the main role is to implement a superior hybrid-hill climbing immune algorithm which is very reasonable, simple, and fast. The important feature of an immune algorithm is that it can organize a large number of packets, and can identify anomaly detection, distributed collaboration, memory protection, pattern recognition, learning capabilities, and adaptation. The Hill-Climbing algorithm finds the optimal path from the current node to the near neighbor node. The simulated result shows that the proposed PID controller by the immune hill climbing algorithm is higher in terms of buffer occupancy in switch and source rate. Thus it avoids the congestion in the network (Muhannad and Shatnawi, 2020).

WSN IoT networks have different kinds of applications that satisfy the user's needs. All the application stored in IoT devices requires an internet connection through which it communicates and performs the desired task. During this process, the resource of the WSN controls the memory utilization of the network, network bandwidth, and network power consumption, and there may exit the traffic in the network. In IoT, to control the congestion and its consistency, CoAP Protocol (Betzler et al., 2016) is used. This protocol reduces consumption in memory utilization and minimizes network power consumption. A new approach to predict congestion control with the best technique is considered. The author uses an enhanced network transmission rate policy to control congestion. During packet congestion, the total transmission time of the packet is summated with the interval time of transmission and total waiting time caused by packet loss. The experiment proves that IoT network optimization using CoAP leads to latency, power, and performance being sustainability achieved (Oyewobi et al., 2021). Hence the proposed IoT network architecture with CoAP is optimized in terms of all network parameters. It also enhances the transmission rate by discovering the appropriate RTO by Congestion (Swarna and Godhavar, 2020).

CoAP (Anon, 2014b) implements Retransmission Timeout (RTO) and Binary Exponential Backoff (BEB) to control the congestion. If there is any large number of retransmissions from BEB, the source needs to wait for a long period and if RTO (Anon, 2014a) is lower than round trip time, then this algorithm eventually fails. So to overcome this drawback CoCo-RED (Suwannapong and Khunboa, 2019) was developed for enhancing the efficiency of congestion in CoAP. This technique uses three protocols RTO Calculation, buffer management,

and retransmission. As network congestion is high, to improve the performance CoCo-RED implements a Revised Random Early Detection (RevRED) algorithm (Tariq et al., 2020) and Fibonacci Pre-increment Backoff (FPB) algorithm to adjust the RTO. To handle high congestion these two mechanisms have been improved in EnCoCo-RED (Suwanapong and Khunboa, 2020). The author Bansal and Kumar (2020) analyzes and proposes the Distance-Based congestion control CoAP (DCC-COA) to calculate the flow rate and to handle congestion in IoT networks. The author Lee et al. (2016) proposes a new congestion control scheme for CoAP based on RTT. An experiment was conducted with real IoT devices and accordingly improved the performance in terms of throughput and success rate transmission.

The article discusses the requirement for congestion control techniques that are specially designed for CoAP in IoT applications. It draws attention to the distinctive features of IoT networks, including their constrained bandwidth, energy consumption, and irregular connectivity. These features make it necessary to build congestion control strategies that take into account the unique needs and constraints of IoT devices. The suggested architecture aims to maximize network use while minimizing the effect on limited devices. It focuses on the effectiveness of congestion control techniques. It probably examines several strategies that can be used with the CoAP protocol, including adaptive rate control, congestion detection, and congestion window management (Makarem et al., 2022).

This research proposes a method for congestion-aware data transfer on mobile and restricted IoT networks. The study offers a mechanism for congestion-aware data transmission to solve this congestion issue. To maintain congestion awareness and efficiency, hop-to-hop communication is used, and the choice of the next hop is made after taking into account a number of factors. The suggested method chooses the best next hop by using multiparameter-based decisions made using the Analytic Hierarchy Process (AHP). The suggested approach is best suited to contexts with constrained resources, heavy traffic, and a need for rapid data packet delivery. The proposed method surpasses state-of-the-art techniques in terms of buffer overflow mitigation (by 2%), average delay reduction (by 4%), throughput (by 6%), and packet delivery rate (by 7.5%) according to a comparison with them (Maheshwari et al., 2023).

The challenge is to come up with the best way to inform the network manager of a node's congestion situation while maintaining optimal network performance. The author offers a novel congestion notification technique to address the aforementioned issue by effectively aggregating the congestion state of all nodes along a particular routing path into a block termed Congestion Information Block (CIB). In the suggested architecture, it is up to the network management entity to gather data on congestion notifications to decide how to reduce congestion (based on a rule-based model or a machine learning model, etc.). As a result, the suggested method takes advantage of the node's buffer occupancy to determine whether a certain routing path is congested. A CIB is used to collect nodes' status information (buffer occupancy) hop by hop. Leaf nodes or any intermediary node between the leaf and the network manager start the transmission of the CIB. The network manager is free to select the CIB initiators. Each node along the routing path will include its congestion state in every data packet that is forwarded to the network manager. Typically, the packet payload contains a binary value indicating each node along with the routing path's Congestion Information (CI). The manager will be able to identify all the nodes affected by the congestion control decision in this manner using the CIB indexes set to "1" (Aboubakar et al., 2021). Thus congestion is avoided in the network.

The paper suggests Delay-based Adaptive Congestion Control (DACC), a queuing delay variation-based adaptive congestion control TCP variant that considers the existence of background flows. Round-Trip-Time (RTT) and bottleneck queue size are the main factors used in delay-based congestion management rules of the TCP to identify

congestion. These regulations, however, are not accurate because they only take into account the contribution of their own data flow to congestion detection. These policies also experience multiple packet losses that force retransmissions and lower channel use.

DACC, on the other hand, swiftly modifies the transmission rate in response to the current network circumstances. It intends to increase the precision of congestion control by taking into account background flows. About goodput, Packet Loss Ratio (PLR), inter-protocol fairness, intra-protocol fairness, and quick file transfers, simulation results highlight the importance of DACC (Verma et al., 2022b).

In the article Huang et al. (2014), the problem of congestion control in IoT for improving service performance has been investigated. A model of congestion control in IoT has been presented, and an improved RED control algorithm has been proposed. The performance of the proposed congestion control system has been analyzed using queueing analysis techniques. Extensive simulations have also been conducted to evaluate the performance of IRED and compare it with regular RED. The performance of the proposed congestion control has been indicated to achieve comparable delay performance and better throughput performance when compared to the standard RED. The easier implementation control mechanism of IRED makes it more suitable to be implemented in IoT.

In this article, a TCP Congestion Control Algorithm (CCA) that is suitable for installation on IoT devices is proposed. When determining new congestion windows, the algorithm seeks to detect the network status and take into consideration pertinent parameters. Similar to TCP Bottleneck Bandwidth and Round-trip propagation time (BBR), it uses two variables to set the congestion window. When dealing with changing Round Trip Times (RTT), TCP BBR is unjust, nonetheless. The proposed algorithm's throughput may suffer in situations with high RTT. This algorithm, in contrast to previous loss-based CCAs, looks at the growth in end-to-end delay to make sure that the congestion window (CWND) does not rise quickly and negatively impact other intra-protocols. The algorithm has completed testing, and the results show that it performs better than other traditional CCAs in terms of throughput while retaining a reasonable amount of fairness. It is important to keep in mind that the suggested algorithm has not been thoroughly evaluated on a wide range of devices with diverse capabilities, including different RTTs for various flows and traffic types (Hasan and Alisa, 2023).

Summary: Congestion control is a method that monitors the total amount of data entering the network to reach its destination. This process is monitored regularly to keep the traffic level at an acceptable value. Usually, congestion occurs at two levels one at the node level and another at the channel level. It can be controlled in three cases i.e. traffic, resource, and hybrid control. To control the congestion, notification is sent to the sender node in two forms: implicit (Thubert and Hui, 2011) and explicit notification. The general structure of controlling the congestion is explained in Fig. 10 and Table 9 gives a brief explanation of congestion occurrence, congestion notification, and congestion control. The study of the existing work leads to the observation that

- Very minimal implementation of hybrid congestion control of about 0.01% has been implemented in the articles.
- Implicit congestion notification for about 0.02% has been implemented in the articles.

Future research solutions in controlling the congestion in IoT networks can be summarized as

- The Design of the IoT protocol stack with consideration for congestion should be revisited and improved to incorporate congestion management methods at various layers. Congestion management-specific improvements to current protocols as well as the creation of brand-new protocols may be necessary.

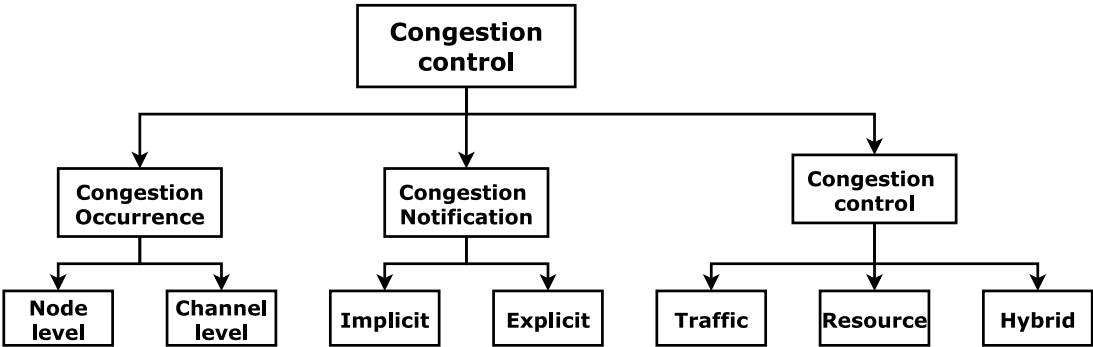


Fig. 10. General structure for congestion control.

Table 9
Summary of various articles on congestion control with 3 parameters.

Author/year of publication	Congestion Occurrence		Congestion Notification		Congestion control		
	Node Level	Channel Level	Implicit	Explicit	Traffic control	Resource control	Hybrid control
Sukjaimuk <i>et al.</i> , 2018 (Sukjaimuk <i>et al.</i> , 2018a).	Yes	–	–	Yes	Yes	–	–
Tang <i>et al.</i> , 2018 (Tang <i>et al.</i> , 2018).	–	Yes	–	Yes	–	Yes	Yes
Sukjaimuk <i>et al.</i> , 2018 (Sukjaimuk <i>et al.</i> , 2018c).	Yes	–	–	Yes	Yes	–	–
Nasimi <i>et al.</i> , 2018 (Nasimi <i>et al.</i> , 2018).	Yes	–	–	Yes	–	Yes	–
Mogi <i>et al.</i> , 2018 (Mogi <i>et al.</i> , 2018).	Yes	–	–	Yes	–	Yes	–
Hsieh <i>et al.</i> , 2018 (Hsieh <i>et al.</i> , 2018).	Yes	–	Yes		Yes	–	–
Pokhrel <i>et al.</i> , 2018 (Pokhrel and Williamson, 2018).	–	Yes	–	–	–	–	–
Vishal Rathod <i>et al.</i> , 2019 (Rathod <i>et al.</i> , 2019).	Yes	–	–	Yes	Yes	–	–
Najm <i>et al.</i> , 2019 (Najm <i>et al.</i> , 2019a).	Yes	–	Yes	–	Yes	–	–
Naeem <i>et al.</i> , 2020 (Naeem <i>et al.</i> , 2020).	Yes	–	–	Yes	Yes	–	–
Muhannad Quwaider <i>et al.</i> , 2020 (Muhannad and Shatnawi, 2020).	Yes	–	–	Yes	Yes	–	–
Al-Jamali <i>et al.</i> , 2020 (Al-Jamali and Al-Raweshidy, 2021).	Yes	–	Yes	–	Yes	–	–
Aboubakar <i>et al.</i> , 2021 (Aboubakar <i>et al.</i> , 2021).	Yes	–	Yes	–	–	Yes	–

- Create effective congestion feedback mechanisms that allow network elements and IoT devices to recognize and react to congestion signals. In order to implement proactive congestion control methods, may entail establishing congestion notification protocols or mechanisms for devices to share congestion information with the network.

Challenges in controlling congestion in IoT networks can be listed as

- Latency Consideration

- Security Consideration
- Standardization

5. Routing protocol in IoT

In order to exchange routing information among the nodes and choose the optimum path with the least amount of congestion, routing protocols are used. It is a collection of many algorithms, processes, and messages. This section offers an overview of recent research initiatives

that are currently being done on routing protocols for IoT congestion management.

IoT devices consist of low-battery sensors, and tiny and lightweight devices trying to communicate with others. The network layer in IoT is mainly designed to have efficient communication between routers and nodes. Routing the packet in the proper direction is a big challenge. Thus, the Routing Over Low-Power and Lossy network (ROLL) group reconciled the Routing Protocol for Low-Power and Lossy Networks (RPL) protocol to reach the expectation. As the number of devices increases in the network, RPL fails to service better results. To overcome this issue, the author [Ghafoor et al. \(2020\)](#) has introduced the CA-RPL clustered additive RPC protocol. This protocol uses DODAG topology with 50 to 600 nodes and exhibits an improvement in the network lifetime that avoids congestion.

A clustering-based routing algorithm is proposed that tries to overcome the problem of interference routing metrics and load balancing. If the packet is received from one end it checks its destination, if it is in its own network it will accept and reply to it. If the packet has to be forwarded then it refers routing table and forwards the packet to the next hop, if the routing table does not contain the routing details, then it implements RREQ/RREP procedure. Once the RREQ is generated the destination node details are updated in the routing table and hence all the packets can be delivered without any traffic load ([Li et al., 2018b](#)).

IoT enables internet connectivity devices to interact between them, these IoT applications are restricted to geographical limits. To overcome this restriction OppIoT network has been introduced. A GMMR routing protocol is proposed that uses Machine Language. This routing protocol in Machine learning utilizes soft clustering that uses a Gaussian mixture model. The GMM clustering model identifies the identical devices and floods the message to train them, which helps to identify the devices. It has 2 phases (a) GMM training — It uses the EM learning technique to create and train on the extracted dataset. It is a pre-processing phase, and (b) GMMR Routing phase — It can be used as the pre-trained model. This protocol uses a context-free routing protocol to avoid congestion ([Vidushi et al., 2019](#)).

There exists a rapid increase in IoT devices that communicate with M2M devices. A huge number of messages carried between two devices at a high speed may lead to data loss. So, to avoid this an Admission Control Message (ACM) algorithm is suggested for the M2M communicator. Based on the request and delay in transmitting the packet in the network the traffic congestion can be reduced ([Huang et al., 2018](#)).

Three well-known machine-learning methods have been used in this work to address the congestion issue. The outcomes of numerous performance parameters have been compared, and their approximation for the best value has been carried out. This investigation has produced some significant conclusions that are well-suited to theoretical justification. To reduce congestion in the IoT network, the Grey Wolf Optimization algorithm (GWO) has been used for the fitness function. Results from the Artificial Bee Colony (ABC) ([Shreyas et al., 2021a](#)) and Artificial Fish Schooling Algorithm (AFSA) have been compared to those from the proposed implementation of the Grey Wolf Optimization algorithm (GWO). In terms of performance metrics like network lifetime and throughput, the suggested technique beats the ABC and AFSA algorithm ([Manshahia, 2019](#); [Shreyas et al., 2020](#)).

In IoT, all the nodes receive information regarding neighbor nodes and dynamic topology that are useful for routing data in IoT networks. Based on these two parameters IoT devices are facing challenges in routing data opportunistically. To overcome this Hybrid Multi-Copy Routing Algorithm (HMCA) is proposed that uses fuzzy logic and a genetic algorithm for finding the optimal path in minimum hop count ([Srinidhi et al., 2019](#)).

IoT devices have increased drastically in a network, the congestion may occur during continuous communication between devices that lead to transmission delay and loss of packets. To overcome this Bandwidth Aware Routing Strategy (BARS) is considered that audits the

residual Bandwidth capacity and queue capacity. Before transmitting the packet to the network the algorithm calculates the available and consumed Bandwidth, and then delivers the packets thus it avoids congestion ([Akhtar et al., 2019](#)).

IoT accepts heterogeneous devices to convey information among themselves. If the node increases in the network, the communication also rises, then congestion occurs and packets get lost. To avoid this Adaptive Hybrid Congestion Control Problem (AHCCP) for RPL is proposed. Based on the congestion status the algorithm uses rate based method or alternative path selection. In the alternative path approach, it selects the optimal path with minimum hop count, low buffer occupancy, maximum link quality, low power dropping rate, and maximum throughput that control the congestion ([Chappala et al., 2020b](#)).

The LeapFrog Collaboration (LFC) mechanism is proposed in this paper to exploit spatial diversity and packet redundancy in compensating for the inherently lossy wireless medium in industrial networks. At its core, two parallel paths for a single data flow are computed by LFC, allowing nodes on one path to listen in on data transmissions along the other parallel path. Consequently, each data packet is provided with multiple opportunities to be received at the upper DODAG level. The performance evaluation results demonstrate that network reliability above 99% is achieved by LFC, while the delay performance is bounded, specifically providing an ultralow jitter performance of 15 ms. Ongoing work includes the further investigation of a more sophisticated scheduler to reduce unnecessarily active timeslots and, thereby, decrease energy consumption ([Koutsiamanis et al., 2018](#)).

The author [Praveen and Prathap \(2021\)](#) provides a hybrid optimization-based routing technique to handle resource allocation and routing challenges and provides a congestion-aware resource allocation and routing protocol (ECRR) for IoT networks. The suggested ECRR technique, which attempts to lessen total congestion between them, makes its first contribution by allocating large-scale IoT devices and gateways using a data clustering and metaheuristic algorithm. By adopting a queue-based swarm optimization technique to select a better route for incoming routes based on various restrictions, the second innovation enhances the route-finding mechanism. To show that the proposed system outperforms existing systems in terms of energy consumption, node lifetime, throughput, end-to-end delay, packet delivery ratio, and packet overheads, a simulation was run in NS-2.

The author [Safaei et al. \(2020\)](#) created a priority-based and energy-efficient routing using the RPL routing technique for IoT applications like health care, smart cities, etc. Congestion in the network results from the production of a significant amount of massive data for multimedia content. The suggested Prinerger routing strategy prioritizes video data, which is sent when the network is not overloaded. Audio and text data are less important, and transmission only starts when the network is busy. The TDMA time period that source-to-destination synchronization takes place. Experimental results show that the suggested one outperforms the QoS RPL (QPRL) in terms of lowest end-to-end delay, reduced routing overhead, and significantly reduced node utilization.

This study suggests the Reliable Path Routing (RPR) protocol for congestion control in critical IoT applications where timely packet delivery is essential. With its extensive network of networked devices, the IoT faces the difficulty of network congestion, which, if not effectively handled, can cause delays and packet failures.

The RPR protocol attempts to solve this issue by concentrating on choosing the best next-hop node for data transfer while taking into account variables like interference, buffer occupancy level, congestion level of the next-hop nodes, and path survivability. In order to reduce packet delays, the protocol generates a Node Selecting Factor (NSF) based on these factors and gives the buffer occupancy level a higher weight. For packet transport, the node with the greatest NSF value is chosen. Results from simulations show that the RPR protocol is

more effective than other protocols including SPR, CoAR, SGEAR, and CDTMLB. The RPR protocol improves packet delivery ratio by 7% while decreasing delay by 38% on average. In general, the RPR protocol delivers network congestion control capabilities for crucial IoT applications, enhancing packet delivery timeliness and reducing network congestion-related difficulties (Pushpa Mettilsha et al., 2021).

The Healthcare Internet of Things (HIoT) is a broad category of sensor-based computing devices used for applications related to healthcare monitoring. The goal of numerous research projects is to increase the efficiency of the healthcare industry while lowering expenses. Low power sensors, constrained computational power, and energy restrictions define these devices. The purpose of this work is to discuss and propose a congestion control routing protocol for HIoT, specifically for employing IoT sensor nodes to efficiently and rapidly relay emergency messages. The two main steps of the suggested algorithm are listed below. The packet forwarding window size is first predicted using a machine-learning technique. Second, data packets are divided into normal and prioritized categories and sent within the specified window sizes. The suggested congestion management routing protocol increases the system's effectiveness, as shown by theoretical comparisons (Upreti et al., 2021a).

Summary: Routing is the process that selects its path towards the destination, with the help of a routing table. In this section, a brief explanation of different routing protocols has been summated. The outline of this process is that each algorithm explains its routing protocol, metrics, topology used, and their outcomes in simulation. Thus, after review, the routing protocol plays a vital role in selecting the network path that does not leads to congestion. The summary of routing protocols to manage congestion in IoT is listed in Table 10. To provide QoS for the application LA-OF is the algorithm that dynamically reconstructs and updates the routing table in the parent node. The study of the existing work leads to the observation that,

- Organizing the network is mostly done in hierarchical-based routing rather than horizontal routing or location-based routing.
- Protocol operation was considered on a query-based routing

Future research solutions in controlling congestion through routing procedures in IoT networks can be summarized as follows:

- To manage congestion in IoT networks, look into hybrid routing strategies that combine various routing technologies. To effectively control congestion, this may entail combining multi-path routing with load balancing strategies or employing both proactive and reactive routing protocols.
- Congestion control routing systems for IoT networks should take security into account. Create routing algorithms that can identify and reduce congestion brought on by illegal activity, such as Distributed Denial of Service (DDoS) assaults, while making sure congestion control systems are resistant to security risks.

Challenges in controlling congestion through routing protocol in IoT networks can be listed as

- Delayed Feedback
- Dynamic network topology
- Limited congestion awareness

6. 6LoWPAN Network

An open standard called 6LoWPAN was developed by the Internet Engineering Task Force (IETF). Any low-power radio that adheres to this standard, such as Bluetooth Low Energy (BLE), Z-Wave, and 804.15.4, may interact with the internet (Higuera and Polo, 2010). This section highlights a few techniques that are used to detect, avoid, and mitigate the congestion only in the 6LoWPAN network.

Network congestion in IoT is an environment where packets are not transmitted to their destination due to higher throughput than the threshold value. So, to overcome this issue a Fuzzy Logic-based approach (FLCC) is adopted to detect and control congestion. The proposed FLCC uses different parameters like buffer occupancy, queue length, packet priority, packet size, and transmission rate in a 6LoWPAN network to detect and control congestion. To obtain the fuzzy output, the set of fuzzy rules, and set of possible inputs are defined in the system. Based on the output threshold value the mode of transmission is changed and thus it avoids the congestion in the system (Raiesh et al., 2017; Shreyas et al., 2019).

Congestion in the 6LoWPAN network reduces the network performance. Hence, the author proposed a Game Theory-based Congestion Control (GTCC). This algorithm uses the parent-change procedure to redirect the traffic flow to an alternative path. The protocol detects congestion by subtracting the packet service rate from the packet generation rate. The main drawback of this protocol is that it does not have a policy to reduce the source rate when non-congested nodes are not available (Sheu et al., 2015). Therefore, the author proposed a Game Theory-based Congestion Control Framework (GTCCF). In GTCCF, the network nodes are considered players. These nodes demand high data rates from another node which leads to congestion in the network and resource blocking. Therefore, to avoid this issue, the Lagrange multiplier is used to solve the existence and uniqueness of the Nash equilibrium concept. Before sending the packet, the GTCCF algorithm adjusts the node's sending rate. Network parameters such as throughput, end-to-end delay, network energy consumption, number of packets, and Weighted Fairness Index (WFI) are analyzed (Al-Kashoash et al., 2017b).

Based on the routing choice made at the network layer or adaption layer, respectively, it may categorize the 6LoWPAN routing scheme into two groups: the mesh-under and the route-over (Chowdhury et al., 2020b). The network layer determines the routing destination in a route-over routing scheme, whereas the adaptation layer determines it in a mesh-under routing scheme (Montenegro et al., 2007b).

Network performance and quality of service indicators in 6LoWPAN networks are strongly impacted by congestion brought on by high network traffic. In 6LoWPAN networks, there are two major tactics that are frequently used to manage and relieve congestion: resource control and traffic control. One of these tactics is frequently used in the current research on congestion control for 6LoWPAN networks.

The Optimization-Based Hybrid Congestion Alleviation (OHCA) algorithm is a unique congestion control method that integrates resource management and traffic management techniques into a hybrid approach. By utilizing the advantages of each technique, OHCA efficiently uses network resources. Grey relational analysis, a multi-attribute optimization technique, is used by the suggested approach to control resource usage. The packets are forwarded through uncongested parent nodes using a combination of three routing criteria (buffer occupancy, predicted transmission count, and queuing latency). In addition, OHCA makes use of optimization theory and the framework for maximizing network utility to achieve traffic control in situations where a non-congested parent node is not accessible. Using Lagrange multipliers and Karush–Kuhn–Tucker conditions, the algorithm determines the best transmission rates for nodes. In order to fulfill IoT application requirements, OHCA takes into account node priorities and application priorities. A limited optimization problem is used to describe the allocation of transmitting rates for applications. In comparison to the duty cycle-aware congestion control for 6LoWPAN networks and the queue utilization-based IPv6 routing protocol for low-power and lossy networks, OHCA shows an overall average improvement of 28.36% in throughput, 28.02% in weighted fairness index, 48.07% in end-to-end delay, 31.97% in energy consumption, and 90.35% reduction in buffer dropped packets (Al-Kashoash et al., 2017a).

Table 10

Existing articles related to routing technique in IoT.

Author/Year of publication	Study objective	Routing protocol/Algorithm	Routing Metric	Result Outcome	Routing Topology	Type of routing	Communication layer	Simulator Used	Advantages	Gap Area
Mishra et al., 2019 (Ghafoor et al., 2020).	To meet the challenges of the undefined scalable network to avoid congestion.	CA-RPL	ETX, HC, AE	PDR, End to End delay	DODAG	Non-adaptive	Network Layer	Cooja	Increases lifetime	Decrease in duty cycle of nodes
Jilong Li et al., 2018 (Li et al., 2018b).	To integrate the new routing metric to mitigate the congestion.	Cluster based routing algorithm	Interference and load balancing	End to end delay, lifetime of node	Mesh	Non-adaptive	MAC Layer	Simulator tool using C++ programming language	Has the ability 1.To self-heal, 2. efficient communication, 3. reduce the routing cost	While finding the destination node, it floods the packets to the entire network
Vidushi Vashishth et al., 2019 (Vidushi et al., 2019).	To find automated routing decisions to avoid congestion.	GMMR	Average Hop Count, Overhead Ratio, Delivery Probability, and Number of Dropped Messages	Delivery probability hop count, dropped message, overhead ratio.	Lack of network topology	Adaptive	Adaptive	ONE	It combines the benefits of context-aware and context-free routing protocol	Training phase in GMM is time intensive.
Huang et al., 2018 (Huang et al., 2018).	To minimize the requests given to the Access point to control the congestion.	Admission Control Algorithm	Delay sensitivity, QoS	Network Calculus, numerical experiment	Cluster	Non-adaptive	MAC Layer	Set up simulator using OMNet++ software	It is a priority based admission control model for M2M in smart cities	M2M is unable to take 4G communication channel
Mukhdeep Singh Manshahia 2019 (Manshahia, 2019).	To apply different congestion parameters to avoid it.	Grey Wolf Optimization (GWO) algorithm	Residual energy and throughput.	Network lifetime and throughput	Graph	Non-adaptive	Non-Adaptive	MATLAB	This algorithm works iteratively and optimize the result	The proposed algorithm can be proved on different technique like AI, neural network, neuro-fuzzy
N N, Srinidhi et al., 2019 (Srinidhi et al., 2019).	To find an excellent route such that congestion does not occur	HMCRA	Residual energy, speed, and distance	Delivery probability, Hop Count, Overhead ratio, Latency	Dynamic topology	Adaptive	Adaptive	ONE	To find the optimal path it uses fuzzy logic and Genetic Algorithm	Minimum lifetime of the network.
Akhtar et al., 2019 (Akhtar et al., 2019).	To avoid congestion based on bandwidth path and residual queue size	BARS	Bandwidth and queue	PDR, end-to-end device, packet loss, throughput	AODV	Adaptive	Cross Layer	NS2.35	Has a good sensing capability that reduces congestion in IoT & MANET	Congestion occurs in link layer has to be upgraded.
Chappala et al., 2020 (Chappala et al., 2020b).	To find the alternative optimal path if congestion occurs.	AHCCP	Sufficient Bandwidth, Maximum link quality, minimum buffer occupancy, Least hop count	PDR, throughput, packet loss, energy efficiency	Tree	Adaptive	Cross layer	NS3	Two technique has opted to choose the optimal path that avoids congestion	—
Ahsan Saleem et al., 2020 (Saleem et al., 2020).	To resolve the challenges of the dynamic and lossy environment on a routing protocol to avoid congestion.	LA-OF	Expected transmission count	energy consumption, packet reception ratio, and control overhead	DODAG	Adaptive	MAC layer	Cooja	Interaction within environment and update the EEC.	Learning automata can be applied to multiple networks.

The IoT concept brings out the real-world entity to the virtual world (The Internet). During transmission of the packet between the nodes, the inadequate resource may lead to congestion and packet loss. So, to avoid this issue the concept of Bird flocking to mentor the packet is adopted to avoid congestion. Hop-by-hop all the packets are transmitted to the destination in the network layer. To estimate the congested node, it uses eavesdropping. Thus, the simulation performance shows a good result in terms of less packet loss with the same input flow rate (Hellaoui and Koudil, 2015).

6LoWPAN networks have diverse IoT applications. ROLL working group has proposed many standard protocols one of them is the RPL routing protocol. The main problem they face in 6LoWPAN is congestion. To avoid this the author Al-Kashoash et al. (2016) proposes a new RPL objective function called (CA-OF). Whenever the node identifies that the buffer is full, it changes its parent node. QU-RPL Queue Utilization-based Routing Protocol for low power and lossy networks (Kim et al., 2015) performs a similar action to avoid congestion. This algorithm considers the neighboring node queue utilization and their hop distance to the border router.

In the 6LoWPAN network, all sensor nodes communicate through the root LoWPAN Border Router (LBR). This router found lots of

imbalances in energy consumption and traffic load. So to overcome this a multiple border router scheme is implemented that comprises of route selection algorithm and has transparent multiple LBR routing. To avoid traffic at the router level the alternative router is selected based on the rank that is evaluated by RPL. 6LoWPAN can choose the border routers spontaneously and connect with the internet effortlessly. Thus, it avoids congestion at the router level (Zheng et al., 2015).

Routing protocol for low power a lossy network requires continuous maintenance of the routing table which is a challenge in the network to have effective communication. So, to solve this problem the author Khelifi et al. (2015) proposes a PRO-RPL algorithm that rapidly identifies another parent node if it predicts that the parent node cost value fails. The algorithm calculates the “suffering index” value, based on this it decides to choose the alternative parent or to use a local repair mechanism to solve the packet loss due to congestion of the network or death of a node or it can be due to bad quality of the link. The changing of the parent node can also be done by calculating the rank value using MADM-Fuzzy (Shreyas et al., 2021b).

In an IoT network, nodes will communicate with each other, a router forwards packets towards their destination. A node within the network receives it and forwards it to another node. Usually, all nodes

will be in sleepy mode, if it wakes up it refreshes its routing table and then sends or accepts the packet. In such a situation the network faces lots of power consumption and loss of the packet. So, to avoid this HRPL is proposed that reduce traffic control using a time limit. HRPL improves the RPL protocol in minimizing the Energy Consumption (EC) and Routing Overhead (RO) and shows better performance (Yusoff et al., 2019, 2020).

The sensor nodes in the IoT network have a high data transmission that causes congestion at the intermediate node and also due to the retransmission of packets. So, to avoid this Non-cooperative Gaming for Energy-Efficient Congestion Control (NGECC) technique is introduced to formulate and find the optimal data-sending rate of the source node such that congestion does not occur at the parent node. The author uses a gaming problem that consists of the buffer loss and channel loss of each leaf node (Chowdhury et al., 2020a).

Routing in IoT and wireless sensor networks requires accurate monitoring of the area range due to many nodes. In shared transfer media, many nodes in networks lead to a collision in concurrent transmission. Because of these limitations, the Congestion Control Fuzzy Decision Making (CCFDM) method based on Fuzzy decision is proposed to detect, prevent, and reduce congestion in IoT networks. The sink node divides the network into the concentric sector to transmit the packet. Congestion is detected when the packet is overflowing from the queue to avoid the author merging the backpressure approach and avoiding congestion (Homaei et al., 2020).

The primary topic of this research is the loss-tolerant congestion control problem in 6LoWPAN networks, which has not been addressed in previous works. In order to connect Wireless Sensor Networks (WSNs) with the Internet and enable ubiquitous network interconnection of all things, the 6LoWPAN protocol stack is viewed as a promising approach. However, 6LoWPAN networks face a significant issue in terms of congestion control due to the spike in data traffic from wireless sensors. Packet loss is unavoidable when buffer overflows happen. The idea behind Loss-tolerant Congestion Control (DLCC) is to reduce congestion while preserving a manageable amount of packet loss via a buffer overflow. Deep Reinforcement Learning (DRL) is used in DLCC to address the state dimensionality curse. Additionally, by employing Lagrange multipliers to integrate the reward and loss requirements, packet loss limitations are controlled. In an online learning approach, the Lagrange multipliers are dynamically updated, enabling DLCC to choose the best congestion control strategy. According to the simulation results, DLCC successfully keeps the packet loss rate below the acceptable level even when there is congestion. The proposed DLCC algorithm displays higher energy efficiency, larger throughput, reduced average latency, and increased fairness when compared to existing hybrid congestion management methods (Hou et al., 2023).

The healthcare industry is one of the well-known fields that can profit from the IoT many ground-breaking capabilities. IoT integration in healthcare promises proactive, individualized, and linked healthcare. Recent developments in IPv6 over Low-Power Wireless Personal Area Networks and Wireless Sensor Networks offer hope for deploying the Internet of Healthcare Things. In order to implement such an application, resource-constrained medical sensing devices must provide real-time, time-critical, instantaneous, and zero information loss at a greater data rate. For researchers, these criteria provide brand-new obstacles. The serious problem of resolving congestion for the 6LoWPAN-based Internet of Healthcare Things (IoHT) network with constrained resources is openly discussed in this study. There is an analysis of the causes of congestion, the efforts needed to mitigate it, and the settings in which it occurs (Verma et al., 2023).

There are limits to the current fragmentation and forwarding methods used in lossy networks. The article introduces a brand-new approach or algorithm that deals with the difficulties of fragment forwarding in lossy networks. The suggested technique tries to improve packet forwarding performance by taking into account variables like packet

loss probability, network congestion, and available bandwidth. Based on current network conditions, it uses intelligent decision-making techniques to choose the best fragmentation and forwarding strategies. The results show that it is successful in lossy networks for lowering packet loss, increasing throughput, and lowering latency (Lenders et al., 2021).

A 6LoWPAN WBAN enables healthcare applications and monitoring by allowing a variety of body-worn sensors can collect and transmit data. However, for dependable and effective data transmission in such networks, establishing QoS and managing delay periods are essential.

The suggested approach creates an effective QoS-assured delay time control mechanism by combining the chaos-based Least Squares Approach (LSA) with game theory concepts. Chaos theory is used to boost convergence and the algorithm's capacity for exploration. By varying the weights attached to various metrics, LSA is used to optimize the QoS parameters, such as delay time. The program also presents a novel parent selection strategy that selects the parent node for every sensor node based on proximity, link quality, and node energy. This plan seeks to improve network performance and cut down on delays.

The proposed approach seeks to improve QoS and delay time control in 6LoWPAN WBANs by combining chaos-based LSA, game theory concepts, and the special parent selection strategy. The algorithm selects parent nodes based on a variety of characteristics and dynamically adjusts parameters to optimize network performance.

In order to demonstrate the usefulness of the suggested algorithm in terms of QoS assurance, delay time control, network efficiency, and energy consumption, the paper most likely includes simulation data or theoretical analysis (Illapu and Sivakumar, 2023).

Video streaming speed may be increased by the usage of MPD (Multiple Description Coding). However, there is a chance that sending data to low-cost data nodes would result in a high loss rate, which could lead to loss-based congestion control algorithms being wrong. This work suggests using an RTT-based reevaluation technique in the CUBIC congestion control algorithm to solve this problem. In high-loss networks, the congestion window size (cwnd) is frequently underestimated. The RTT pattern during MPD tasks is examined using simulations in a dumbbell network with various random loss rates. The outcomes show that the modified algorithm can efficiently correct the understated cwnd and increase download performance in high-loss networks. By combining this tactic with the delivery rate, it can be further improved. Chung (2023).

The article Al-Kashoash et al. (2018), uses queuing theory and Markov chain analysis to propose an analytical model for examining congestion in a 6LoWPAN network. The formulas for throughput at the sink and buffer loss probability are generated. Based on the Contiki 3.0 implementation, the real channel capacity of IEEE 802.15.4 is also computed, taking into account both un-slotted CSMA-CA with and without collisions. The results of the simulation show that our analytical congestion model is accurate and well-aligned with the simulation across a variety of scenarios and parameters. The simulation results also show the following conclusions:

1. Increasing the buffer size decreases buffer overflow at the leaf node but increases it at the intermediate node;
2. Increasing the number of leaf nodes causes an increase in network buffer overflow;
3. Increasing the offered load causes an increase in dropped packets at both the leaf and intermediate nodes.

For IoT sensor networks, a proposed adaptive hybrid congestion control mechanism is presented in this research. According to the type of traffic, the protocol divides packets sensed by end IoT devices into several priorities. The source node dynamically chooses a rate-based congestion control method or a different path for data transmission depending on the level of congestion. Results from simulations show that the proposed procedure, which is used in NS3, is effective. Metrics including packet delivery ratio, packet loss, throughput, and energy

efficiency are compared with those of existing methods (Chappala et al., 2020a).

The article Verma et al. (2022a) investigated various patient-centric IoHT applications to create a realistic resource-limited topological layout of IoHT for congestion estimation. A critical review was done of the current 6LoWPAN congestion methods. The number of packets lost at the node's buffer was proposed using an efficient buffer-loss estimation methodology based on queuing theory. The buffer was modeled as an M/M/1/K Markov Chain Queue, and the relationship between the probability of the buffer being empty or fully filled was established using the M/M/1/K Queue's equilibrium equation. Expressions for the estimated mean packet latency and total buffer-loss probability were generated for the resource-constrained IoHT network.

By comparing buffer-loss probabilities, the number of packets discarded at leaf and intermediate nodes, and the number of packets successfully received at the local sink node, an analytical model was employed to validate the buffer-loss estimation. When altering the number of leaf nodes, buffer size, offered packet load, and available channel capacity, the findings showed a strong correlation between the two models. Finally, in resource-constrained IoHT settings, the suggested model outperformed two comparable works. It effectively evaluated buffer loss and offered insightful information about congestion in IoHT networks, reducing the possibility of losing crucial medical data owing to buffer and channel losses.

An urgent problem that requires attention is congestion in the 6LoWPAN-based IoHT network, which is resource-constrained. This research investigates the occurrence of congestion, the required mitigation measures, and the congestion-contributing elements in IoHT networks. Buffer overflow is named a crucial factor in congestion that contributes to data loss. The likelihood of packet loss caused by various factors is estimated using an analytical model. The model figures out the likelihood of buffer loss, the number of lost packets, and the overall number of packets received at the local sink. The outcomes shed light on how network congestion affects performance as well as how well the suggested analytical model performs in calculating packet loss.

In conclusion, the article Verma et al. (2022a), clarifies the difficulties of congestion in resource-constrained IoHT networks and provides an analytical model to handle the possibility of packet loss owing to buffer overflow. The research makes a contribution to the comprehension and mitigation of congestion in IoT applications for healthcare, ensuring dependable and uninterrupted data transfer.

Managing articles under 6LoWPAN network congestion in highly dynamic or mobile deployments can be challenging because of the rapidly changing network conditions. Traffic load balancing, adaptive congestion control, real-time network monitoring, adaptive buffer management, prioritization, quality of service, congestion-aware MAC layer, traffic load, and dynamic routing are a few strategies that can be used in these situations to reduce congestion.

Summary: IoT has been considered a big challenge for researchers. IPv6 over 6LoWPAN is used for integrating the WSN through the sensor node. Implementing the TCP/IP in 6LoWPAN may cause problems that are related to the limitation of energy, bandwidth, buffer resource, and processing. TCP should set up the connection for data transmission and UDP requires some mechanism that has not proved congestion control. Therefore, one of the major drawbacks of 6LoWPAN is congestion which reduces packet loss, and energy consumption and degrades throughput. The study of the existing work leads to minimizing the power consumption in congested IoT networks (Besher et al., 2021). Existing works on routing techniques to avoid congestion control in 6LoWPAN are explained in Table 11. Congestion control in the 6LoWPAN network is summarized in Table 12. Future research solutions in controlling the congestion in 6LoWPAN networks can be summarized as

- To improve the ability of protocols to control congestion, consider modifying or improving them, such as the RPL protocol. In order to do this, protocol settings may need to be adjusted, congestion-aware metrics may need to be added, or already-existing protocols may need to incorporate congestion control techniques.
- Examine strategies for 6LoWPAN network traffic optimization and prioritization. Create algorithms that give priority to time-sensitive or critical traffic over non-essential traffic to ensure delivery on time and reduce congestion. Research traffic shaping techniques, rate control formulas, and QoS methods to enhance traffic patterns and resource distribution.

Challenges in controlling congestion in 6LoWPAN can be listed as

- Small Packet Size
- Resource Constraints
- Variable Link Quality

7. Simulators used to evaluate congestion

The main objective of IoT devices is to interact and cooperate between objects and things in the wireless network to communicate between them effectively. It is a common platform that provides a connective to different devices (Mehmood, 2017). To design and test the application or to observe the flow of the packet without using real IoT boards, we need the best IoT simulators. Therefore, this section explains different simulators, their pros and cons, and their features. In the virtual IoT lab, we should install large-scale IoT devices that collect and analyze the data. The last minute of this survey is to explain the main aspects of the simulators of IoT briefly and to explain the number of nodes in the scenario and their interaction among the nodes. There is a difference between simulators and emulators.

The software variable and configuration of an application can be created in the simulator whereas the emulator does not imitate all the software and hardware features of an application. To evaluate, and assess the performance of the actual system or to anticipate the performance of the system the simulator is used. On the other hand, if the testing is done for software that interacts with the hardware or integration of hardware or software, then an emulator is used. As a response to RQ3, some of the IoT Simulators are explained below.

- Iotify: It is the first cloud-based platform to build, validate, and test performance. It is a strong IoT simulator that permits the development of IoT applications in the virtual lab. It can form static or dynamic traffic. It is designed from the basic part to specific tests and simulations required for large-scale IoT systems. It is built with a realistic model that contains a battery, sensor, energy, and other parameters (Anon, 0000a).
- Omnet++: Omnet++ standing for Objective Modular Network is an open-source, discrete-event, modular, C++-based simulator. It is basically used for analyzing networks at the packet level. It uses a high-level language called NEtwork description (NED) for grouping simple modules into compound modules in a hierarchical fashion. These modules are used to communicate through message passing in the Omnet++ simulator (Varga, 2010; Cárdenas-Benítez et al., 2016).
- Cooja — Wireless sensor network uses cooja simulator, it executes in Contiki OS. It set a few norms in the simulator. The additional tools that are exhibited in cooja are Breakpoints, Radio message, Script editor, Bufferview, and Mote duty cycle (Mehmood, 2017).
- MaMMotH — It is an emulator that imitates the network traffic. In the real world, nodes are connected through the GPRS or IEEE 802.15.4, but in the emulator, it has to apply the same characteristic and check the traffic between the nodes or proxy or base station. In order to produce the communication against

Table 11

Summary of various articles on routing technique for congestion control in 6LoWPAN.

Author/Year of publication	Routing Protocol/ Concept	Routing metric	Routing Topology	Routing Mode	Routing Scheme	Simulator used
Raiesh <i>et al.</i> , 2017 (Raiesh <i>et al.</i> , 2017).	FLCCC algorithm	1.Buffer Occupancy 2.Queue Length 3.Packet Size 4.Packet Priority	DODAG	Non storing	Mesh under Routing	Cooja
Al-Kashoash <i>et al.</i> , 2017 (Al-Kashoash <i>et al.</i> , 2017b).	GTCCF	1. Throughput. 2.End-to-end delay. 3.Energy consumption. 4. Packet loss ratio. 5.Weighted fairness index	DODAG	Non storing	Route over routing	Cooja
Al-Kashoash <i>et al.</i> , 2017 (Al-Kashoash <i>et al.</i> , 2017a).	OHCA	1.Buffer Occupancy. 2.Queue Length. 3.Queueing delay	DODAG	Non storing	Mesh under and Route over routing	Cooja
Hellaoui <i>et al.</i> , 2015 (Hellaoui and Koudil, 2015).	Bird Flocking concept	1. Data Latency. 2.Packet loss ratio. 3.Packet delivery ratio	DODAG	Non Storing	Route over routing	Cooja
Al-Kashoash <i>et al.</i> , 2016 (Al-Kashoash <i>et al.</i> , 2016).	New RPL metric (CA-OF)	1.Buffer Occupancy. 2.Expected transmission count	DODAG	Non storing	Mesh under routing	Cooja
Khelifi <i>et al.</i> , 2015 (Khelifi <i>et al.</i> , 2015).	PRO-RPL maintenance scheme	1. Expected transmission count. 2.Energy Consumption. 3.Network lifetime	DODAG	Non storing	Route over routing	Cooja
Yusoff <i>et al.</i> , 2019 (Yusoff <i>et al.</i> , 2019).	HRPL	1.Control traffic overhead. 2.Latency. 3.Energy consumption	DADOG	Non storing	Mesh under and Route over routing	Cooja
Chowdhury <i>et al.</i> , 2020 (Chowdhury <i>et al.</i> , 2020a).	NGECC technique	1. Expected transmission count. 2.Bandwidth. 3.Link Quality	DODAG	Storing mode	Route over routing	Cooja

the proxy, the device can simulate each node and can be able to deploy a drop message (Looga *et al.*, 2012).

- SimIoT — It is a higher version of the CloudSim that is explicitly formed to test and simulate the IoT. It has the capacity to sense multiple data and process them simultaneously. It has a toolkit that will execute on dynamic and real-time multiuser. It is a simulator tool that models the communication between cloud and IoT devices (Anon, 2016).
- MobIoTsim — The main aim of this simulator is to execute and test the cloud application that is developed by the programmer. This simulates a greater number of IoT devices by generating real-time sensor data. If any critical sensor value is generated then it sends the notification message to the simulated device. IoT applications can be evaluated with handheld devices and the behavior of small IoT devices can be evaluated (Pflanzner *et al.*, 2016).

- IOTSim — To understand and analyze the impact and performance of IoT application IOTSim simulator support big data processing system such as MapReduce. It has the extended functionality of the Cloudsim simulator. It supports IoT-based applications by researchers and commercial organizations (Zeng *et al.*, 2017).
- ndnSim — ndnSim is a new release of the NS3-based Named Data Networking (NDN) simulator. Using this simulator, can create network topology and set parameters like node queue size, link delay, and link bandwidth (Mastorakis *et al.*, 2017).
- NS3 — NS Network Simulator is a name for a series of discrete-event, object-oriented, open-source network simulators. It is a powerful tool for network modeling and optimization. It supports an IP protocol like IPV6, IEEE 802.15.4, TCP/IP, IEEE 802.11, WiMAX, routing, 6LoWPAN, and Wi-Fi (Riley and Henderson, 2010).

Table 12
Congestion control in 6LoWPAN.

Au- thor/Year of publica- tion	Proposed work Objective	Reason for congestion	Detection of Congestion	Congestion control method	Advantages	Disadvantages
Rajesh <i>et al.</i> , 2017, Raiesh et al. (2017)	To detect and control Congestion	When the packet is transmitted more than the maximum threshold of network capacity	Node level	Transmission rate is adjusted to control congestion (Traffic method)	Prediction and mitigation of congestion is effective	To perform better, the system has to undergo more iteration.
Al-Kashoash <i>et al.</i> , 2017, Al-Kashoash et al. (2017b)	To control the congestion and resource as a non-cooperative game framework	When energy consumption and throughput increase	Root level	DIO message is sent to children node, and they change the parent node (Traffic method)	Improves QoS parameters	Occurrence of channel congestion has to be enhanced.
Al-Kashoash <i>et al.</i> , 2017, Al-Kashoash et al. (2017a)	To provide a hybrid solution to congestion	Without considering forwarding rate, Bandwidth, and other node sending rate	Root level/Node level	Traffic control strategy is applied (Traffic and resource method)	It makes use of traffic and resource control strategy.	Sometimes, the non-congested parent is not available and still congestion exists.
Hellaoui <i>et al.</i> , 2015, Hellaoui and Koudil (2015)	Network is built based on the concept of Bird Flocking to avoid congestion	When the packet is moved to the node that is unable to process it.	Node Level	Include two buffer filling parameters in the routing table that avoid the congestion (Resource method)	Uses eavesdropping to estimate congested node	Consume lots of power.
Al-Kashoash <i>et al.</i> , 2016, Al-Kashoash et al. (2016)	To revert and avoid the nodes and wireless channel that are congested	When there is high traffic load in network	Node level	Increase in Buffer size (Resource method)	Performance of CA-OF increases	Congestion control mechanism that uses both traffic and resource control has to be implemented.
Zheng <i>et al.</i> , 2015, Zheng et al. (2015)	6LoWPAN can implement multiple routers and transmit the packet without congestion	1. ICMP packets were increased. 2. PING was transmitted to provide transmission flow	Route level	Border router routes the packets to the right path. (Resource method)	This algorithm suits large-scale 6LoWPAN with different IP prefixes.	Mobility of LBR and invalidation of root LBR are not processed.
Khelifi <i>et al.</i> , 2015, Khelifi et al. (2015)	Predicts the node failure and chooses the nearest node as apparent.	1. Bad quality of the link. 2. Death of node.	Host level	Global repair mechanism (re-establish the entire network) (Resource method)	It does not require more memory	Consume more power and drain the energy of its low battery.
Yusoff <i>et al.</i> , 2019, Yusoff et al. (2019)	To enhance the RPL for 6LoWPAN network to overcome the QoS performance and congestion	Sending packet to sleepy devices	Host level	Use time limits and then flow the packets (Traffic method)	The network provides good Quality of Service	Waste in latency.
Chowdhury <i>et al.</i> , 2020, Chowdhury et al. (2020a)	To create energy efficient congestion avoidance function with basic performance metric	Sending packets with high data rate	Root level	Select alternative parent (Traffic method)	Maximum evaluation metrics are considered to check the performance of the network	Dynamic priority function to determine the parent node and minimize the energy consumption.

(continued on next page)

Table 12 (continued).

Au- thor/Year of publica- tion	Proposed work Objective	Reason for congestion	Detection of Congestion	Congestion control method	Advantages	Disadvantages
Homaei <i>et al.</i> , 2020, Homaei <i>et al.</i> (2020)	To implement hop by hop routing method without congestion	Funneling	Root level	Reduce transmission rate (Traffic method)	Dynamic evaluation is done when congestion occurs	Constraint of RPL is not consider.

- **Bevywise-IoT Simulator** — It is a free, GUI-based highly scalable IoT Device simulation suit that helps you simulate various scenarios needed for developing testing, and demonstrating real-time device and managing (Anon, 0000b).
- **EdgeCloudSim** — This simulator is used for Edge Computing query, redesigning the network and calculation and system administration capacities. It supports IoT performance in low bandwidth and overall network congestion. The most challenging in this simulator is security (Sonmez et al., 2017).
- **NetSim** — Simulation software for network devices, protocol modeling, and security application NetSim is used. This helps us to check the unmatched intensity, power, adaptability, and flexibility in the network. It covers a wide range of mobile networks, wired and wireless networks, IoT devices, and sensor networks (Jump and Lakshmanamurthy, 1993).
- **Ansys-IoT**— It applies to numerous IoT device issues. This simulator can verify and enhance the dependability, power usage, durability, and integrity of IoT devices (Anon, 0000c).

The Comparison of different Simulators with their advantages, type of network support, and protocol used are shown in Table 13.

8. Evaluation metrics

In an IoT network, a variety of metrics are employed to evaluate how well traffic performs in a crowded environment (Floyd, 2008). These parameters help us to assess the network performance when it is congested with the aid of the parameters.

With respect to RQ4, the primary evaluation metrics for congestion management in IoT are listed below. Table 14 represent the evaluation metrics used to control the congestion in the IoT networks for existing works. Fig. 11 plots a graph that shows several evaluation metrics in percentage

1. **Throughput:** Data successfully transmitted per unit of time are referred to as throughput. Usually, it is expressed in bits per second (bps) or bytes per second (Bps). Formally, it is represented as follows:

$$\text{Throughput} = (\text{Number of bits or bytes transmitted}) / (\text{Time taken to transmit}) \quad (12)$$

2. **Delay:** The amount of time it takes a packet to travel from its source to its destination. Usually, it is expressed in milliseconds (ms). Formally, it is represented as follows:

$$\text{Delay} = (\text{Time of Arrival}) - (\text{Time of Departure}) \quad (13)$$

3. **Jitters:** The varying delay that packets, encounter. The standard deviation of the delay or the difference between the greatest and smallest delay that packets experience is commonly used to measure it. Formally, it is represented as follows:

$$\text{Jitters} = \text{Standard deviation of } ((\text{Time of Arrival}) - (\text{Expected Time of Arrival})) \quad (14)$$

4. **Packet loss:** The proportion of packets that are unsuccessfully transmitted. It is commonly calculated as the ratio of lost packets to all packets sent. Formally, it is represented as follows:

$$\text{Packet Loss} = (\text{Number of Lost Packets}) / (\text{Total Number of Packets Sent}) \quad (15)$$

5. **Energy efficiency:** The proportion of energy used to transfer data to that energy (Poornima et al., 2023). Typically, it is expressed in bit/Joule or byte/Joule.

$$\text{Energy Efficiency} = (\text{Number of bits or bytes transmitted}) / (\text{Energy consumed}) \quad (16)$$

6. **Fairness:** The allocation of resources amongst different devices. It gauges the comparative effectiveness of each flow. Formally, it is represented as follows:

$$\text{Fairness index} = (\Sigma(\text{throughputs})^2) / (\text{Number of flows} * (\Sigma(\text{throughputs}^2))) \quad (17)$$

7. **Scalability:** The system's capacity to manage a growing number of devices or a growing volume of data. The number of linked devices the system can support can be used to measure it.
8. **Robustness:** The system's capacity to continue operating despite errors or other disturbances. The system's capacity to bounce back from malfunctions or interruptions can be used to evaluate it.

9. Learning-based congestion control

As a response to RQ5, this section explains the machine learning algorithms used to control congestion in the network.

The use of machine learning has significantly increased across a wide range of applications. The limitations of traditional CC algorithms in dynamic networks have given learning-based CC algorithms a fresh academic focus. As a result, we have taken into consideration studies that apply machine learning techniques for congestion control in various kinds of networks.

The high levels of flexibility, adaptability, and computational power offered by machine learning expand on conventional methods now employed in a variety of industries, including network operation and management. In the domain of networking, such as traffic engineering, performance optimization, and network security, many surveys have investigated machine learning techniques. Capabilities to learn from prior experience are greatly desired compared to conventional rule-based congestion control systems. This section discusses various network congestion prevention approaches that involve machine learning techniques. It is possible to categorize machine learning for network congestion control as follows

- Deep learning-based single-path congestion control
- Deep learning-based multi-path congestion control

Table 13

Summary of various IoT simulators.

Name of Simulator	Platform	Coding	API Interface	Testing Phase	Computational Area	IoT Architecture Layer	Type of network supports	Protocol used	Advantage
IoTify	Linux	Python, Java	REST	Integration	Commercial	Application layer & Network layer	WSN and Ethernet	MQTT, HTTP, CoAP, LWM2M, UDP and TCP	This simulator support IoT protocol testing, functional testing, IoT performance testing, and IoT security testing
OMNeT++	Linux, MacOS, Windows	C++, Java	OMNeT++ API references	Unit & Regression	Non-Commercial	MAC Layer	Ethernet, Wifi, GSM, UMTS, and LTE	TCP/IP	It saves the simulation result in textual and line-oriented format
Cooja	Linux	C, Java	REST	Integration	Commercial and Non Commercial	Perceptual layer & Network layer	Low-power wireless networks and WSN	RPL, 6LoWPAN and CoAP	1. COOJA is a synchronous reproduction. 2. It permits a client to join reproduced hubs from a few diverse deliberation levels.
MAMMoTH	Mac OS	Python , Java	REST	Integration	Commercial	Application & Network layer	WSNs network	MQTT and CoAP	Increasing advantages in cost, quality and speed
SimIoT	Windows	Java	REST	Integration	Non-Commercial	Application Layer	5G, LTE, Wireless, cognitive radio networks	MQTT, CoAP, HTTP, LoRaWAN and Zigbee	1. Support for modeling network. 2. Storage delay exists in the processing of IoT application
MobloTSim	Windows, Linux.	C++, C Sharp	REST	Integration, system testing	Commercial	Application layer & Network layer	IEEE 802.11 and 802.15.4, IoT	MQTT, CoAP, HTTP, Zigbee, Lo-RaWAN	1. More Efficient. 2. Open Source
IoTSim	Windows 7	Java	REST	Integration	Commercial	Application layer	WAN, SDN and IoT	MQTT, CoAP, HTTP, Zigbee, Lo-RaWAN	1.Support big data processing. 2. Support large scale multiple IOT application. 3. Support for modeling network and strong delay existing in processing
ndnSim	Ubuntu Linux 12.04	C++	NFD, ndn-cxx library	Unit	Non-Commercial	Network layer	NDN and IoT	IP network and NDN	1. It is an open-channel communication network. 2. All projects are in interactive process
NS-3	Linux, FreeBSD, macOS	C++, Python	REST	Integration	Commercial	Perceptual layer & Network layer	Wired, wireless, adhoc, cellular	TCP, UDP, IP, Ethernet, WiMAX	1. Allow enormous scope of the sensors 2. performance of convention
BevywisoIoT	Windows, Linux.	Python, Java	REST	Integration	Commercial	Network layer	IoT, Adhoc, Cellular	MQTT	1.It is designed to work on a sensor network. 2. It is low energy consumption
EdgeCloud	Linux	Matlab	SOAP	Integration	Commercial	Network layer	LAN, WAN, Hybrid and sensor		1. Support modeling virtualized resource, mobility,& Network. 2. Scalability. 3. Extensibility 4. Easy of conflict
NetSim	Windows, MacOS, Linux	C	SOAP	Integration	Non-Commercial	Perceptual layer & Network layer	Wireless, Sensor, Cellular, CRN	TCP/IP, AODV, DSR, LoRaWAN, MQTT	1. Availability of perception devices 2. Easy to include new conventions
Ansys	Windows, or Linux	Python, Java	REST	Integration	Commercial	Network layer	IoT and cloud	MQTT, CoAP, Zigbee, LoRaWAN	1. 3D electromagnetic simulation programming for planning and recreating 2.High-speed 3. RF and computerized gadgets 4.Unparalleled execution.

- Traditional shallow ML-based congestion control

Conventional approaches base their decisions on user feedback and predetermined guidelines, but congestion control that is learning-based will make intelligent decisions according to the most recent information available on network state and reward. As a result, using its acquired knowledge and experience, the congestion control agent can adjust to the changing network condition. The first attempt to use machine learning to control transmission congestion was made twenty years ago (Grieco and Mascolo, 2004). This work's core element is to modify the transmit window size adaptively based on a realistic assessment of packet loss. According to the many causes of packet loss, TCP has a different method for adjusting window sizes. The author Jay et al. (2019) presents Aurora, a deep RL-based congestion control technique. The results of the evaluations demonstrate that Aurora can compete

with state-of-the-art technology even with relatively little training. It is a particular use of RL for congested area management. To build a policy for mapping observable network data (such as latency and throughput) two options for rates and deep reinforcement learning are used.

The DRL-based solution aims to maintain high network utilization and reduce congestion by dynamically adjusting the sending rate of network flows. In DRL, the agent that interacts with the environment and learns from its experiences and observations is represented by a deep neural network. The environment's observations correspond to the status of the network, such as the number of packets in the buffer or the network usage, while the agent's actions correspond to changing the sending rate of network flows. In order to maximize a reward signal that measures the effectiveness of the network, the agent learns a policy that translates network states into actions. The agent is

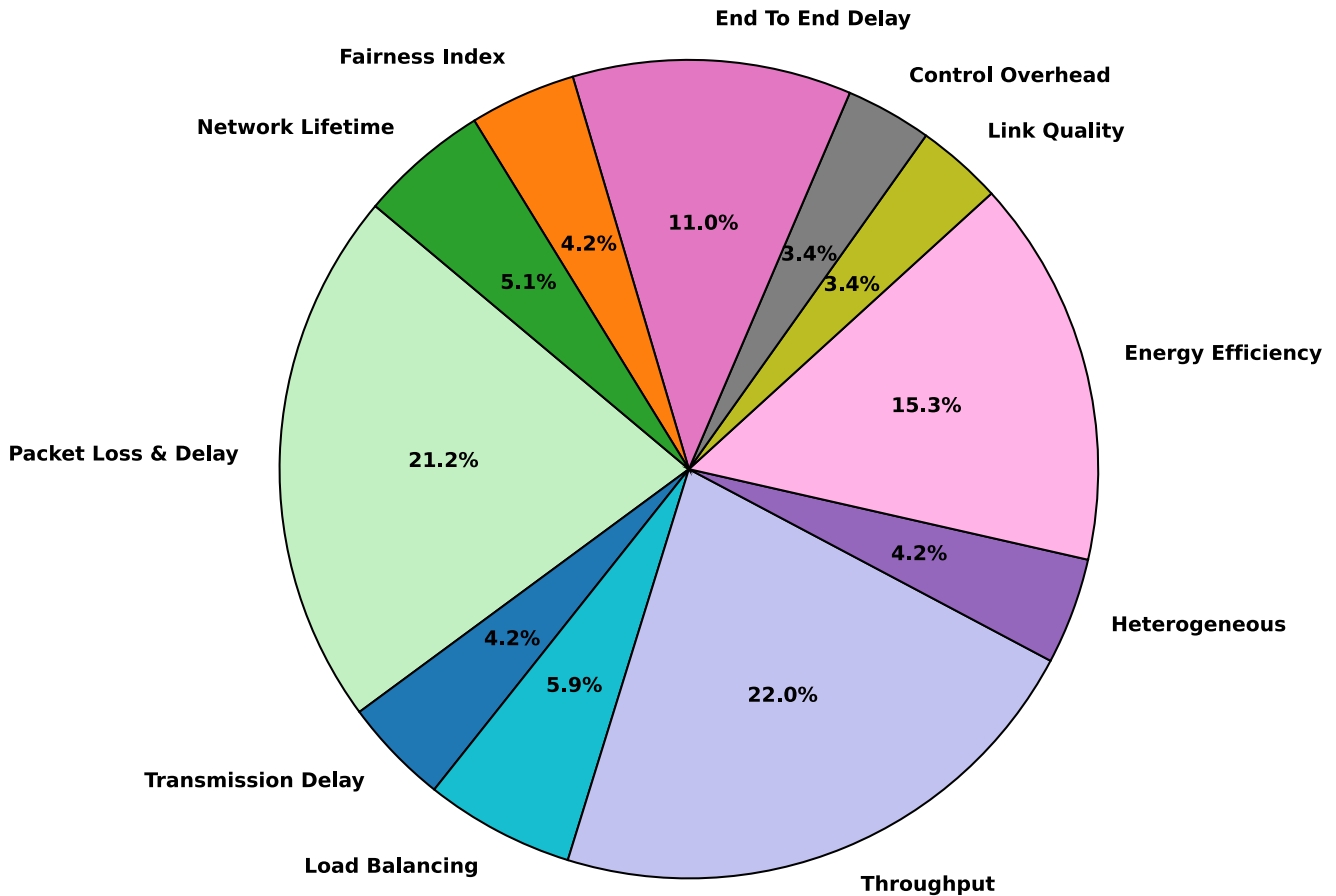


Fig. 11. Mapping of several evaluation metrics.

incentivized by the reward signal to maintain high network utilization and avoid congestion. As the agent interacts with the network and receives feedback in the form of incentives, the policy is taught through trial and error.

The authors hope to solve the drawbacks of conventional congestion management algorithms, which are frequently created using rule-based or heuristic approaches and might not be able to adapt to changing network conditions, by adopting DRL for congestion control. The DRL-based method may dynamically adapt to shifting network circumstances and improve network performance in real time.

The C4.5 DT technique outperformed other ML algorithms in terms of performance; it displays a tree-based graph that aids in determining the best option and path for congestion control. Due to its explicit presentation of all scenarios and highly scalable route selection, the resulting decision graph functions as an efficient way to reach a choice. The selection of the best nodes in a network can be influenced by a variety of variables, including low packet loss, high throughput, high queue size, and high congestion window. The amount of the training dataset may improve the degree of accuracy (Najm et al., 2019b).

For the SIoT scenario, which incorporates the use of multi-hop packet switching links into DTN opportunistic routing, the LGFCC algorithm is presented. In order to achieve the offloading of scheduling chores, the incomplete information game mechanism is specifically established, employing the game strategy approach based on reinforcement learning to migrate the scheduling tasks to the IoT nodes. Additionally, the LGFCC algorithm is suggested to control the game's tendency towards greed and speed up the process of reaching equilibrium in order to address the issue of sluggish convergence. The simulation and performance assessment of the suggested algorithm is then completed. As a consequence, in the SIoT scenario, the game

mechanism and the LGFCC algorithm perform better in terms of accelerating convergence and decreasing the bundle abort rate (Wang et al., 2019a).

The TCC-SVM model for an intelligent traffic congestion control system has been developed in this article. It could gather data from various sensor devices and analyze it to forecast traffic congestion. With a preprocessing layer to cope with missing values and improve the incoming data, a Support Vector Machine is utilized to anticipate congestion. The performance of the system may be impacted by a delay in the information being received from the previous junction, which is one of the limitations of this research (Ata et al., 2021).

Numerous diagnostic sensing devices are connected by the HIIoT to aid in patient diagnosis. Numerous emergency packets are sent through the IoT network in order to deliver these services. However, due to these devices' resource limits, it is sent to servers that are located far away for processing. Complicated healthcare analysis that is being processed in real-time must be transferred without error or delay to the server. Therefore, congestion-free transmission is required to prevent this delay. Therefore, a framework for a congestion control routing protocol for the IoT in healthcare is suggested in this research in order to facilitate the energy-efficient and congestion-free data forwarding of emergency packets (Upreti et al., 2021b).

The intelligent transportation system will be severely constrained by and affected by congestion in such a system. The performance of Wireless Sensor Network (WSN)-based IoT can be severely hampered by congestion issues, which leads to long delays, higher packet loss, and lower throughput. A unique Dynamic deep neural network based on a particle swarm optimization approach is suggested to address such restrictions. The PSO technique is used to optimize the weight parameters of the DDNN to improve performance. By evaluating

Table 14

Evaluation metrics for congestion control in IoT network.

Protocol/Algorithm used	Simulation used, Number of nodes used	Packet loss and Delay	Transmission delay	Load balancing	Network lifetime	Through put	Energy Efficiency	Link Quality	Control Overhead	Heterogeneous	End to End delay	Fairness Index
CoAR (Bhandari et al., 2018)	Cooja 16	YES				YES	YES				YES	
COAP-R (Ancillotti et al., 2018)	Cooja 112	YES										
TSCH (Farag et al., 2020)	MATLAB 50		YES	YES				YES				
CDCAPC (Rahman et al., 2018)	Program in java	YES									YES	
DELAY-BASED (Verma et al., 2019)	NS2 8	YES				YES						
NB-TCP (Chen et al., 2019)	NS2 1000					YES						YES
ACC-CSMA (Zhuo et al., 2019)	Test-bed 31	YES				YES						
Multi-Gateway AHP (Banaie et al., 2020)	MATLAB 200						YES				YES	
SAHCI (Al-Turjman et al., 2019)	Discrete event	YES										
Adaptive VBS (Pokhrel and Williamson, 2018)	NS2 45	YES	YES			YES						YES
MST-OLSC (Yuvaraj and Saravanan, 2021)	NS3 50-500						YES				YES	
GWO (Hamidouche et al., 2019)	MATLAB				YES		YES					
HMCRA (Srinidhi et al., 2019)	Simulation in C++			YES		YES				YES		
AAC (Pokhrel et al., 2020)	NS3 50					YES						
C2DBI (Kalita and Khatua, 2021)	Cooja Test-bed						YES					
TCP Westwood (Zhou et al., 2019)	MATLAB					YES						
DBCR (Althumali et al., 2020)	MATLAB 50	YES				YES						
TCP-Siam (Toprasert and Lilakiataskun, 2017)	NS-3	YES				YES				YES		
DLPOCA (Tang et al., 2018)	C++/WILL API 64	YES				YES				YES		
CA-RPL (Ghaffoor et al., 2020)	C++ 30			YES		YES	YES				YES	
GMMR (Vidushi et al., 2019)	ONE 180			YES			YES					
ACM (Huang et al., 2018)	OMNeT++	YES		YES							YES	
BARS (Akhtar et al., 2019)	NS2.3 50	YES				YES					YES	
AHCCP (Chappala et al., 2020b)	NS3 31	YES				YES	YES					
LA-OF (Saleem et al., 2020)	Cooja 20	YES					YES		YES			
FLCC (Raiesh et al., 2017)	Cooja MATLAB 35	YES					YES				YES	
GTCCF (Al-Kashoash et al., 2017b)	Cooja 20	YES				YES	YES				YES	YES
OHCA (Al-Kashoash et al., 2017a)	Cooja	YES				YES	YES				YES	YES
Bird Flocking (Hellaoui and Koudil, 2015)	Cooja 50	YES				YES					YES	
CA-OF (Al-Kashoash et al., 2016)	Cooja 35	YES				YES	YES					
Pro-RPL (Khelifi et al., 2015)	Cooja 30	YES			YES		YES					
Modified Slow start (Najm et al., 2019a)	NS2		YES					Yes				
GTCC (Sheu et al., 2015)	Cooja 26	YES				YES		YES			YES	
QU-RPL (Al-Kashoash et al., 2016)	Test bed 30	YES		YES							YES	
MEC (Hsieh et al., 2018)	Analytic Evaluation									YES		
PRSNN (Al-Jamali and Al-Raweshidy, 2021)	Mininet 120	YES			YES	YES	YES					
PCRP (Awan et al., 2019)	MATLAB 30				YES	YES	YES					
SDN-Controller (Song et al., 2016)	Mininet 40				YES	YES						
SGNAN (Astudillo et al., 2020)	NS 45		YES									
HRPL (Yusoff et al., 2019)	Testbed 40								YES			YES
NGECC (Chowdhury et al., 2020a)	Cooja 40		YES			YES	YES					YES
CIB (Aboubakar et al., 2021)	OMNeT++ 23					YES			YES			
LFC (Koutsiamanis et al., 2018)	COOJA 8	YES		YES		YES						
LBR (Zheng et al., 2015)	COOJA 12	YES						YES				
ECRR (Zheng et al., 2015)	NS2 200				YES	YES	YES		YES	YES		

the Energy consumption, Delivery ratio, Throughput, Overhead, and Packet delay using the current Genetic Algorithm based DNN (DNN-GA) and DNN approaches, the proposed DDNN-performance PSOs are examined (Kavitha et al., 2022).

The main objective of this research is to create congestion for 5G/6G networks in order to minimize congestion and maximize the use of the resources already existing in these networks. Although challenging, 5G/6G network connectivity is necessary for next-generation wireless networks and for commercial enterprises. The research community faces a significant problem in creating an intelligent decision-making framework for incoming network traffic that would confirm load balancing, restrict network communication catastrophe, and provide a backup in case of catastrophe or overcapacity scenarios. The 5G congestion control dilemma was addressed in this research paper by proposing a model based on a hybrid deep learning technique to predict the ideal congestion in 5G networks (Alnawayseh et al., 2022).

According to the author's citation, reinforcement learning-based TCP was originally proposed by Li et al. (2016). The effects of function optimization on CMAC and Fuzzy Kanerv-based TCP Q-learning are through throughput and latency. The amount of memory required for storing the procedure history can be drastically decreased in both methods. The proposed methodology, Fuzzy Kanerva-based TCP Qlearning, uses 1.2% less memory than pure Q-learning while still achieving performance that is comparable to pure Qlearning. Determine the ideal circumstances under which one of the two strategies may be preferred. Using simulation, the article demonstrates enhanced end-to-end network performance over the conventional new-Reno algorithm. Additionally, it shows how memory is essential for building the reinforcement learning exploration area

Reducing delay and packet loss and increasing the reliability of VANETs can be achieved by effective data congestion control. For detecting congestion, grouping messages, and managing data congestion,

the suggested technique consists of three units. To identify channel congestion in this technique, the level of channel usage is assessed. Algorithms for machine learning collect, filter, and cluster the messages. Depending on message size, message kind, and message validity the K-means algorithm groups the messages into groups. For each cluster, the arbitration interframe spacing, transmission range, and contention window size and rate are determined by the data traffic control unit (Taherkhani and Pierre, 2016).

Two learning-based TCP congestion control strategies for wired networks are suggested: LP-TCP, which is based on supervised learning, and RL-TCP, which is focused on reinforcement learning (RL-TCP). Both schemes' performance was evaluated in NS2 and contrasted with that of Q-TCP, Qa-TCP, and NewReno. In comparison to NewReno, LP-TCP offers a better trade-off between throughput and delay by setting a decision threshold. When compared to Qa-TCP, NewReno, and Q-TCP at different network settings, RL-TCP learns successfully in dynamic network situations and achieves greater throughput and/or delay. The simulation findings show that the traditional new-Reno technique is outperformed by both individual senders and multiple senders (Li et al., 2016; Kong et al., 2018).

The global strategy with a central controller is the main foundation of the reinforcement learning-based congestion control method. Nevertheless, this is impractical for different networks and has a considerable impact on the large-scale network's signaling overhead. A completely distributed online learning-based congestion control technique known as PCC-Vivace was proposed in the work in Dong et al. (2018). Based on the robust optimization capabilities of machine learning, the proposed congestion control method continually exploits action and determines the subsequent time slot. The utility function, which determines whether the activity being exploited is expert behavior or not, is mostly influenced by the feedback, including end-to-end loss rate and RTT. The utility, which is gathered sender side, represents the network state. As a result, the suggested algorithm is fully distributed and compatible with TCP as it exists today. Then, it is suggested to consider the several principal traffic flows using an enhanced optimization technique PCC Proteus (Meng et al., 2020). However, such imitations-based congestion control algorithms treated the network like a selfish, non-cooperative game in order to maximize their own utility, which was unfair to other nodes and resulted in a sudden drop in QoS for network users. Furthermore, handling large dimension data presents challenges for the deep learning structure. Consequently, the large-scale network cannot use the shallow learning structure.

Reinforcement learning can be utilized to dynamically reduce multi-path traffic for satellite networks in addition to the short-range terrestrial network, according to the work of Mai et al. (2019). This work is somewhat preliminary in terms of examining the specific characteristics of the satellite network. Compared to ground networks, the satellite network becomes more prone to packet loss. Also, when developing a congestion control algorithm, great consideration should be given to how adaptive satellite networks are. Later, researchers might think about improving congestion control based on deep learning.

Indigo (Yan et al., 2018) is a recently developed attractive imitation learning-based congestion control system. In contrast to earlier research, this work uses the LSTM deep learning structure to forecast the usefulness of the state-action relationship. Large amounts of data can be handled by the idea with a multidimensional space and capacity. The mapping is resolved just after offline training is finished, but this training procedure is offline. So, this concept might not be appropriate for a dynamic network, particularly one with changing topology.

Deepening the reinforcement learning value network is a different direction. Deep reinforcement learning is used by the authors in Jay et al. (2019) to identify complex patterns in the data throughput and network parameters and to train the policies for network congestion control measures. Comparing the PCC family protocols from the past (Dong et al., 2018). A good combination of packet loss and delay is

used to construct the reward function, and the proposal further expands the condition of the input to incorporate the three key properties of latency gradients, sending ratio, and latency ratio. When compared to the earlier shallow proposal, the deep structural one performs better in simulations in terms of delay and throughput.

The Q-learning-based TCP (QTCP) (Li et al., 2018c) is a powerful RL-based technique that successfully manages complicated social domains with a wide range of features and produces high-quality decision policies. Despite preconfigured rule-based TCP, QTCP learns the congestion management rules from experience and does not require any prior knowledge or network dynamics models. Because of this, the method can be used in many different network configurations. Additionally, the learning agent employs a novel generalized statement Kanerva coding method to cut down on training time and the required search state space. The author Nie et al. (2019) proposes TCP-RL, which employs reinforcement learning (RL) procedures to dynamically modify the Initial Window (IW) and Congestion Management (CM) in order to improve the effectiveness of TCP flow transmission. TCP-RL dynamically configures an appropriate IW for short flow through group-based RL and an appropriate CM scheme for long flow through deep RL depending on the most recent network conditions seen at the web service. The research proposes a centralized, (Xie et al., 2019). IW scheduling method for MEC environments. This initiative improves the flow throughput and focuses on reducing short-flow bottlenecks(FCT).

According to the research in Xu et al. (2019), an experience-driven, deep reinforcement learning-based MPTCP congestion control algorithm might be used to modify the MPTCP to operate with present-day and foreseeable complicated networks. In addition to updating the single congestion window of earlier reinforcement learning-based systems, the strategy simultaneously modifies all congestion windows of all flows for multi-paths. This study shows enhanced network performance in comparison to conventional methods and is flexible enough to accommodate extremely dynamic networks. Another research in Li et al. (2019) discusses applying reinforcement learning for MPTCP congestion control in heterogeneous networks. In addition to the states of flow, the proposal also takes router states into account. To improve Q-learning efficiency and hasten control convergence, the author of this paper also proposes a novel function estimating methodology. The primary area where the strategy outperforms conventional MPTCP is aggregate throughput. Yet, one drawback is that obtaining network information might cause unanticipated signaling overhead. A centralized reinforcement learning-based MPTCP congestion management technique is proposed in Naeem et al. (2020), which is based on the efficient SDN central controller.

Reinforcement learning can be utilized to dynamically reduce multi-path traffic for satellite networks in addition to the short-range terrestrial network, according to the work of Mai et al. (2019). This work is somewhat preliminary in terms of examining the specific characteristics of the satellite network. Compared to ground networks, the satellite network becomes more prone to packet loss. Also, when developing a congestion control algorithm, great consideration should be given to how adaptive satellite networks are. Later, researchers might think about improving congestion control based on deep learning.

In this research, it is argued that fair-sharing, which has been a long-sought objective in congestion control algorithms, may not always be a desirable property in Machine Learning (ML) training clusters. It has been proven that adding unfairness actually reduces the amount of time required for training for every job in a certain combination that is in competition. This particular set of occupations is called "compatible", and the compatibility criterion is established by means of a novel geometric abstraction. To find jobs that are completely compatible, the abstraction uses a circular representation of time and rotates the communication phases of jobs. In the average training iteration time of well-known ML models, this abstraction shows a considerable improvement of up to 1.3. The use of network links for job compatibility is

encouraged by resource management algorithms. Then, three strategies are suggested to lessen the effects of network congestion in ML training clusters: (i) adopting an adaptively unjust congestion control method; (ii) putting priority queues in place on switches; and (iii) using exact flow scheduling (Rajasekaran et al., 2022).

Previous distributed solutions have been unable to create globally optimal solutions in the setting of modern data centers hosting numerous types of workloads that demand both low latency and high throughput concurrently. The ability to immediately reduce congestion has also been a problem for earlier centralized methods. A proposal is presented for the Neighbor-aware Congestion Control method (NCC), which implements a “semi-distributed” strategy to build the congestion management system, to alleviate these shortcomings. NCC makes use of the quick communication among nodes inside a single switch. Each end host has an RL agent that can communicate real-time network information with all other end hosts connected to the same switch. With this strategy, all nodes inside the same switch can achieve a globally optimal status without experiencing the delays brought on by information sharing via centralized approaches. Numerous experimental findings show that NCC performs superior to other comparable approaches in a number of ways for a variety of network demands (Wang et al., 2023).

Effective congestion detection systems are crucial for congestion control. However, it has been discovered through careful observation and analysis that the current congestion detection systems in commonly used lossless networks like Converged Enhanced Ethernet and InfiniBand are insufficient. This deficiency results from their inability to comprehend how hop-by-hop flow controls and switch congestion-detecting behaviors interact. Ternary Congestion Detection (TCD) is a solution created especially for widely used lossless networks, to address this problem. TCD delivers precise congestion detection, identifying flows that cause congestion as well as flows that are only impacted by hop-by-hop flow controls. TCD defines ternary states for switch ports. To verify the efficacy of TCD, both a testbed implementation and in-depth simulations are carried out. Investigate the combination of rate control with TCD, too. Show through case studies that the use of TCD in combination with current congestion control techniques results in considerable gains with a 3.3x median and 2.0x 99th-percentile Flow Completion Time (FCT) slowing reduction (Zhang et al., 2021).

The rapid growth of new Internet services like live video, 5G, VR, and the IoT has increased the demands for network throughput, latency, jitter, and loss. These needs are not met by the existing TCP protocol's poor bandwidth usage. This study introduces the RL-explore technique, which combines reinforcement learning (RL) and a bandwidth detection approach to address this problem. This technique allows for efficient network capacity utilization during model training. Additionally, RL-explore exhibits simpler training-phase convergence than other RL algorithms (Li et al., 2021).

To enable various IoT applications, the Satellite Internet of Things (SIoT) is widely used, especially in places where building a dependable terrestrial backhaul is difficult. Latency/Interrupt Tolerant Network (DTN) solutions are becoming increasingly popular due to SIoT's challenges with high transmission latency and interruption likelihood. Although satellite networks have a limited amount of storage capacity, DTN demands enough storage for the store-and-forward procedure. Network traffic is backed up as a result of this restriction, which lowers the QoS. In order to solve this problem, this study suggests the Limited Greedy Fast Congestion Control (LGFCC) algorithm. Multi-hop packet switching links are integrated into DTN opportunistic routing using a mechanism that makes use of incomplete information games and reinforcement learning. With this method, scheduling tasks are delegated to the IoT nodes that are accessing them, enabling quick congestion control and improving QoS in the SIoT scenario. Numerous findings show that the method decreases bundle abort rates by about 30% and speeds up convergence rates by about 60% (Wang et al., 2019b).

The options and potentials of congestion detection and prediction approaches in network monitoring systems are improved in this article with an emphasis on IoT networks, where such capabilities are widely desired. The deep learning-based Temporal Convolutional Network (TCN) model is used in this paper instead of state-of-the-art techniques. The Taguchi approach is additionally included to strengthen TCN's structure, which enhances traffic flow predictions. This chapter carefully investigates the additional options that deep learning models provide for identifying and forecasting congestion in IoT networks. TCN is compared against LSTM, GRU, SAE, and CNN LSTM through evaluation using real network traffic, and it is found that TCN produces better forecasting results. These results show how TCN may be used to efficiently forecast and detect congestion in IoT networks (Jain et al., 2022b).

9.1. Benefits of using learning-based congestion control approaches

Using learning-based congestion control methods in a network can have the following advantages:

- **Better Performance:** Learning-based congestion control methods optimize network performance by intelligently modifying congestion control parameters. These algorithms can determine the most effective congestion control tactics to increase throughput, decrease latency, and decrease packet loss by learning from past data and network feedback. This results in a better user experience and enhanced network performance.
- **Scalability:** Learning-based congestion control strategies can be created to grow smoothly with the complexity and size of the network. They are flexible enough to accommodate various network topologies, fluctuating traffic volumes, and various network configurations. These strategies can successfully handle congestion control in large-scale networks without requiring manual altering or configuration for each network part since they learn from the behavior of the network.
- **Robustness:** Compared to conventional, static methods, learning-based congestion control strategies may be more resistant to network dynamics and uncertainty. By regularly adjusting and enhancing congestion control tactics, they are able to deal with unforeseen events, changes in traffic patterns, and temporary congestion problems.
- **Efficient Resource Utilization:** Learning-based congestion control methods are designed to make the best use possible of network resources like bandwidth and buffer space. These strategies can provide effective resource allocation by dynamically modifying congestion control parameters based on acquired knowledge, preventing under- or over-utilization of network resources.
- **Adaptation to New Network Scenarios:** Congestion control methods that use learning-based methods are easily adaptable to new and developing network circumstances. These strategies can be used with many network settings, technologies, and protocols since they rely more on learning and adaptability than on pre-determined rules or assumptions. This adaptability enables efficient congestion control in a variety of dynamic network conditions (Jiang et al., 2021).

9.2. Loophole of implementing learning-based congestion control techniques

While learning-based congestion control methods provide a number of advantages, there are also some possible drawbacks to be aware of:

- **Computational Complexity:** Complex models may be used in some learning-based congestion control strategies, which call for a lot of computer power. This can provide difficulties, particularly on networks with few resources or on machines with finite processing power. To achieve practical deployment in real-world

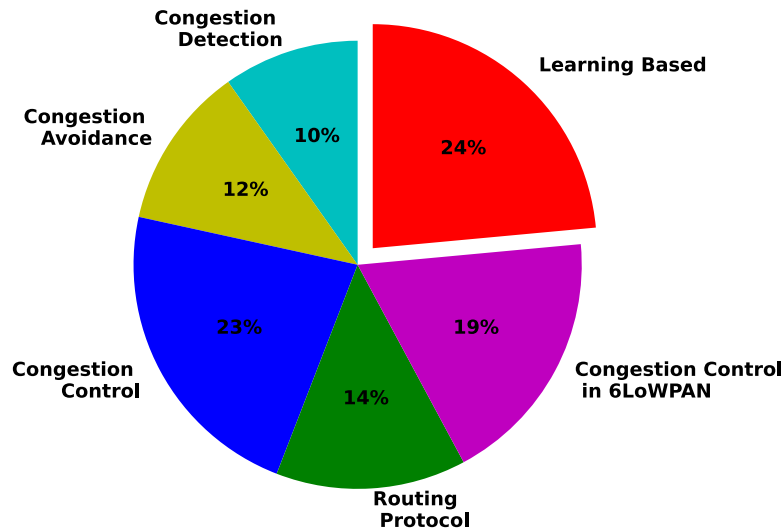


Fig. 12. Percentage distribution of congestion control in IoT networks.

networks, the overhead of developing and implementing complex learning models needs to be carefully assessed and optimized.

- **Overfitting:** When a learning-based model becomes overly specialized in the training data and unable to generalize successfully to new scenarios, overfitting has taken place. When the network faces conditions or traffic patterns that are significantly different from the training data, overfitting can have a negative impact on performance in the context of congestion control. To reduce overfitting, appropriate regularization methods and validation on a variety of datasets are crucial.
- **Training Data Bias:** Learning-based systems mainly rely on training data to make decisions, which might lead to bias. Incomplete or biased training data may result in biased or suboptimal congestion control behaviors. Biased data can be the result of constrained network constraints, particular traffic patterns, or inadequate scenario modeling. To prevent biases and promote successful learning, training data must be carefully chosen and diversified (Abbasloo et al., 2020).

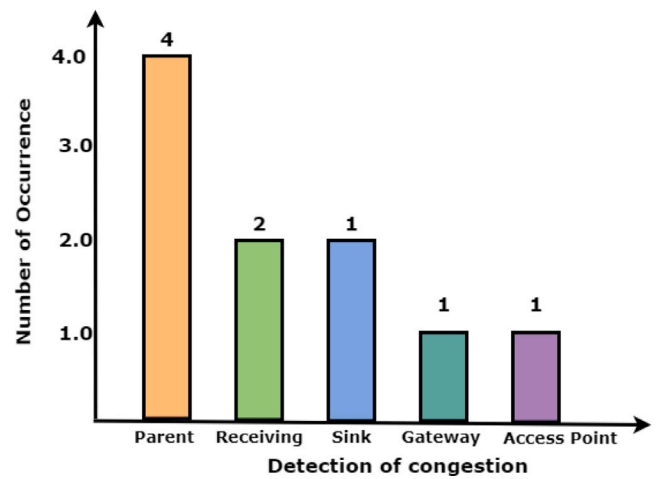


Fig. 13. Congestion detection of congestion at different nodes.

10. Survey outcome

The proposed works are validated in this section.

Concerning **RQ6**, results illustrated in Fig. 12 show the percentage distribution of literature in terms of congestion control, detection, avoidance, routing protocol, and congestion control in 6LoWPAN. For illustration, Out of all literature, 23% are based on congestion control, 12% are based on congestion avoidance, 19% are on congestion control in 6LoWPAN, 14% is on the routing protocol, 24% is on learning-based methods, and the remaining 10% are on congestion detection.

Answering **RQ7**, Fig. 13 depicts the distribution of congestion detection articles based on congestion detection at the different node levels. Four articles detected the congestion at the parent node level, two at the receiver node level, and each at the sink, gateway, and access point levels.

Concerning **RQ8**, Fig. 14 represents the number of articles distributed over the occurrence of the congestion notification methods and congestion level at congestion control. Eight papers are on explicit, and four papers are on implicit congestion notification methods. Ten authors control congestion at the node level and two authors control congestion at the channel level.

For **RQ9**, Fig. 15 represents the percentage distribution of the different simulators used to evaluate the existing works. The most used simulator is Cooja used by 30% of authors, 24% used NS simulator, 14%

used MATLAB, 27% of authors used other simulation environments, and 5% authors evaluated in the testbed.

Concerning **RQ10**, Fig. 16 shows the number of articles classified into congestion approaches and strategies in terms of evaluation type and simulators used.

The survey on congestion control techniques in IoT and 6LoWPAN networks would be beneficial in various practical applications, including:

- **IoT System Optimization:** The survey can help with IoT system optimization by helping to understand the various congestion control approaches and their evaluation metrics. It supports academics and practitioners in locating bottlenecks, adjusting congestion management parameters, and enhancing overall network performance, which improves resource utilization and quality of service in IoT contexts.
- **Protocol and Algorithm Development:** Using this study, researchers and programmers working on IoT and 6LoWPAN protocols can gain an understanding of the most recent congestion control methods and spot areas in need of additional innovation and development.
- **QoS Assurance:** For IoT applications that depend on real-time or dependable communication, it helps in the selection of suitable

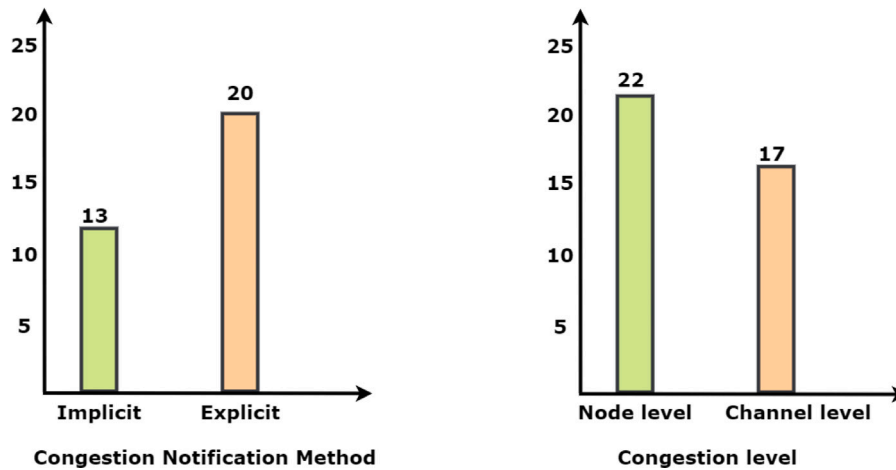


Fig. 14. Occurrence of congestion level and notification method.

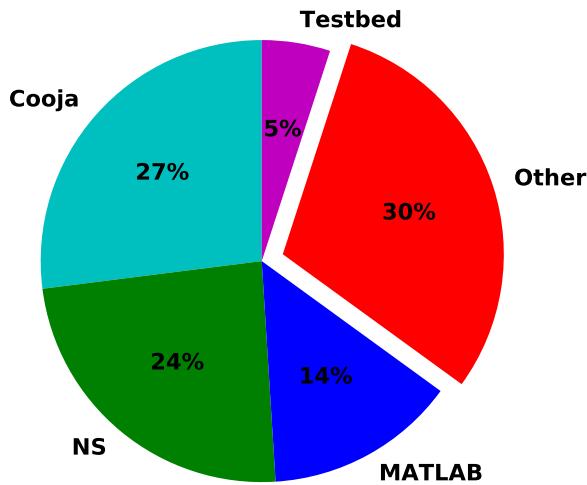


Fig. 15. Simulator used in performance evaluation.

congestion control algorithms that optimize factors like throughput, latency, packet loss, and fairness. This guarantees a positive user experience.

- **Network Management and Deployment:** Network administrators can configure and manage their networks to ensure effective traffic flow, reduce congestion, and maintain dependable connectivity by understanding various congestion management approaches, routing protocols, and evaluation metrics.
- **Network Security and Resilience:** The survey can aid in understanding how congestion control approaches can lessen the effects of attacks caused by congestion, guarantee network availability, and improve the robustness of IoT and 6LoWPAN networks against various threats and vulnerabilities.
- **IoT Application Development:** Application developers can benefit from the survey by learning more about congestion control tactics and selecting the optimal strategies for their IoT apps.
- **IoT Network Design:** The survey offers information on various routing protocols, congestion control approaches, and evaluation measures. With this knowledge, IoT network designers can choose routing protocols and congestion control strategies that will provide dependable and effective communication for their IoT installations.

11. Conclusion and open issues

The IoT is a growing field in the present research world. All objects are combined with Internet connectivity, and data is transferred among themselves. This data generation leads to congestion in the network. Hence this review paper describes a comprehensive survey on various aspects through techniques related to detecting, avoiding, and controlling congestion in IoT networks. Nearly 102 articles are selected as retained papers and most of the articles are journals and transactions based on congestion-aware techniques. We categorize them into congestion detection, congestion avoidance, congestion control, routing protocol, congestion in 6LoWPAN, and learning-based techniques.

This study gives a comprehensive summary of existing congestion awareness techniques, simulators used, and evaluation metrics. After a detailed survey, for (RQ1), Fig. 4 shows the distribution of papers year-wise. As a response to (RQ2), Table 4 shows the list of forums and most of the articles published by IEEE. Simulators used in literature are listed in Section 7 for (RQ3), and main performance metrics used to evaluate the existing works are listed in Section 8 for (RQ4). With respect to (RQ5), Section 9 shows how machine learning algorithms are used for congestion control. Most of the articles proposed are based on congestion avoidance shown in 12 for (RQ6). With respect to (RQ7), Fig. 13 shows four articles detected at the parent node. For (RQ8), Fig. 14 depicts eight articles using the explicit method, and ten articles avoid congestion at the node level. Cooja simulators are the most used simulator, as shown in Fig. 15 for (RQ9). Responding (RQ10), congestion-aware articles distribution in terms of evaluation type and simulator is shown in Fig. 16. The results of this survey could be advantageous for researchers in academia and industry to reduce congestion occurrence in IoT applications. For academic researchers to design congestion-less networks to increase network performance and for industrial research purposes to build congestion-less networks to improve efficiency in IoT applications. And at last, we conclude this study with future directions with open issues and challenges in terms of congestion-less IoT network as stated in (RQ11). There are several areas that provide strong guidance for future research in the field of IoT congestion control.

1. **Machine Learning and AI Techniques:** IoT networks should look into how Reinforcement learning, Deep learning, and data analytic methods might be used to create self-adaptive, intelligent congestion control systems that can improve performance by learning from network dynamics.
2. **Heterogeneity:** IoT networks are composed of a diverse range of objects, each of which has special capabilities and constraints. It may be difficult to provide a single congestion control system

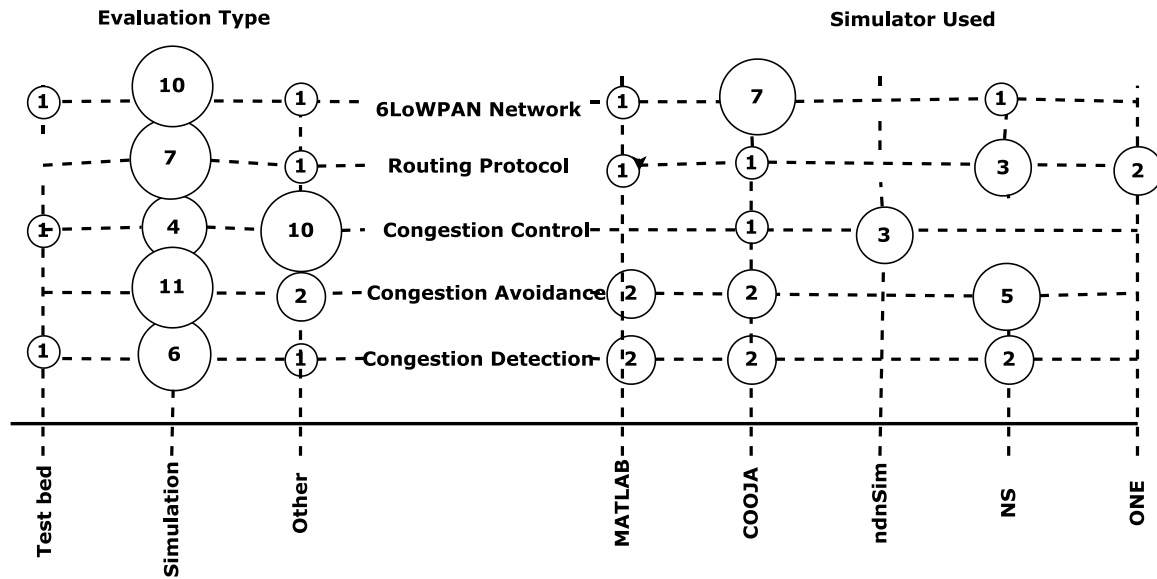


Fig. 16. Mapping of congestion approaches and strategies in IoT networks in terms of evaluation type and simulators used.

that is efficient across all devices as a result (Tahir and Ali, 2022).

3. **Limited bandwidth:** IoT devices frequently have limited processing power and bandwidth, which can make it challenging to control network congestion (Said, 2023).
4. **Security:** Congestion control strategies need to be built to protect against potential security hazards such as denial-of-service assaults (Arora et al., 2023).
5. **Scalability:** It can be challenging to scale congestion control solutions to handle the rising network traffic as the number of IoT devices keeps increasing (Campolo et al., 2023).
6. **Real-time constraint:** A lot of IoT applications have stringent real-time requirements and call for low-latency communication, which can be challenging on congested networks.
7. **Self-organizing network:** Because IoT devices might be dispersed over a wide area and in remote locations, it is challenging to use a centralized method to manage network congestion.
8. **QoS:** Varied traffic kinds and device types in the IoT have different QoS needs. Different degrees of QoS must be available from congestion management technologies based on the device and kind of traffic (Srinivasulu et al., 2023).
9. **Beyond 5G:** Developing congestion control strategies that are tailored to the unique characteristics of 5G and future network technologies, such as greater data throughput, lower latency, and a diverse range of connected devices.
10. **Computing on the Edge and in the Fog:** Creating congestion control solutions specifically for edge and fog computing environments, where processing and data storage take place closer to the data source.
11. **Quality of Experience (QoE):** Shifting attention from strictly technical measures to user-centric metrics such as QoE. Future congestion control systems may evaluate the effects of congestion on customer service, such as video quality while streaming or online gaming response.
12. **Cross-Layer Optimization:** Collaborating across multiple layers of the networking stack to enhance congestion control holistically.

Declaration of competing interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or

non-financial interest in the subject matter or materials discussed in this manuscript.

Data availability

No data was used for the research described in the article.

References

- Abbasloo, S., Yen, C.-Y., Chao, H.J., 2020. Classic meets modern: A pragmatic learning-based congestion control for the internet. In: Proceedings of the Annual Conference of the ACM Special Interest Group on Data Communication on the Applications, Technologies, Architectures, and Protocols for Computer Communication. SIGCOMM '20, Association for Computing Machinery, New York, NY, USA, pp. 632–647. <http://dx.doi.org/10.1145/3387514.3405892>.
- Abdelmaboud, A., Jawawi, D.N., Ghani, I., Elsafi, A., Kitchenham, B., 2015. Quality of service approaches in cloud computing: A systematic mapping study. *J. Syst. Softw.* 101, 159–179.
- Aboubakar, M., Roux, P., Kellil, M., Bouabdallah, A., 2021. A novel scheme for congestion notification in IoT low power networks. In: 2021 IFIP/IEEE International Symposium on Integrated Network Management. IM, pp. 932–937.
- Ahmad, M., Jabbar, S., Ahmad, A., Piccialli, F., Jeon, G., 2020. A sustainable solution to support data security in high bandwidth healthcare remote locations by using TCP CUBIC mechanism. *IEEE Trans. Sustain. Comput.* 5 (2), 249–259. <http://dx.doi.org/10.1109/TSUSC.2018.2841998>.
- Ahmed, A.M., Paulus, R., 2017. Congestion detection technique for multipath routing and load balancing in WSN. *Wirel. Netw.* 23 (3), 881–888. <http://dx.doi.org/10.1007/s11276-015-1151-5>.
- Akhtar, N., Khan, M.A., Ullah, A., Javed, M.Y., 2019. Congestion avoidance for smart devices by caching information in MANETS and IoT. *IEEE Access* 7, 71459–71471. <http://dx.doi.org/10.1109/ACCESS.2019.2918990>.
- Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., Ayyash, M., 2015. Internet of Things: A survey on enabling technologies, protocols, and applications. *IEEE Commun. Surv. Tutor.* 17 (4), 2347–2376.
- Al-Jamali, N.A.S., Al-Rawashidy, H.S., 2021. Intelligent traffic management and load balance based on spike ISDN-IoT. *IEEE Syst. J.* 15 (2), 1640–1651. <http://dx.doi.org/10.1109/JSYST.2020.2996185>.
- Al-Kaseem, B.R., Al-Dunainawi, Y., Al-Rawashidy, H.S., 2019. End-to-end delay enhancement in 6LoWPAN testbed using programmable network concepts. *IEEE Internet Things J.* 6 (2), 3070–3086. <http://dx.doi.org/10.1109/JIOT.2018.2879111>.
- Al-Kashoash, H.A.A., Al-Nidawi, Y., Kemp, A.H., 2016. Congestion-aware RPL for 6LoWPAN networks. In: 2016 Wireless Telecommunications Symposium. WTS, pp. 1–6. <http://dx.doi.org/10.1109/WTS.2016.7482026>.
- Al-Kashoash, H.A.A., Amer, H.M., Mihaylova, L., Kemp, A.H., 2017a. Optimization-based hybrid congestion alleviation for 6LoWPAN networks. *IEEE Internet Things J.* 4 (6), 2070–2081. <http://dx.doi.org/10.1109/JIOT.2017.2754918>.
- Al-Kashoash, H.A.A., Hafeez, M., Kemp, A.H., 2017b. Congestion control for 6LoWPAN networks: A game theoretic framework. *IEEE Internet Things J.* 4 (3), 760–771. <http://dx.doi.org/10.1109/JIOT.2017.2666269>.

- Al-Kashoash, H.A., Hassen, F., Kharrufa, H., Kemp, A.H., 2018. Analytical modelling of congestion for 6LoWPAN networks. *ICT Express* 4 (4), 209–215. <http://dx.doi.org/10.1016/j.icte.2017.11.001>, URL <https://www.sciencedirect.com/science/article/pii/S2405959516302107>.
- Al-Kashoash, H.A., Kharrufa, H., Al-Nidawi, Y., Kemp, A.H., 2019. Congestion control in wireless sensor and 6LoWPAN networks: toward the Internet of Things. *Wirel. Netw.* 25, 4493–4522.
- Al-Turjman, F., Ever, E., Zikria, Y.B., Kim, S.W., Elmahgoubi, A., 2019. SAHCl: Scheduling approach for heterogeneous content-centric IoT applications. *IEEE Access* 7, 80342–80349. <http://dx.doi.org/10.1109/ACCESS.2019.2923203>.
- Aliyu, A., Abdullah, A.H., Kaiwartya, O., Cao, Y., Lloret, J., Aslam, N., Joda, U.M., 2018. Towards video streaming in IoT environments: Vehicular communication perspective. *Comput. Commun.* 118, 93–119. <http://dx.doi.org/10.1016/j.comcom.2017.10.003>, URL <https://www.sciencedirect.com/science/article/pii/S0140366417305121>.
- Alnawayseh, S.E., Al-Sit, W.T., Ghazal, T.M., et al., 2022. Smart congestion control in 5G/6G networks using hybrid deep learning techniques. *Complexity* 2022.
- Althumali, H.D., Othman, M., Noordin, N.K., Hanapi, Z.M., 2020. Dynamic backoff collision resolution for massive M2M random access in cellular IoT networks. *IEEE Access* 8, 201345–201359. <http://dx.doi.org/10.1109/ACCESS.2020.3036398>.
- Alvi, M., Abualnaja, K.M., Tariq Toor, W., Saadi, M., 2021. Performance analysis of access class barring for next generation IoT devices. *Alex. Eng. J.* 60 (1), 615–627. <http://dx.doi.org/10.1016/j.aej.2020.09.055>, URL <https://www.sciencedirect.com/science/article/pii/S1110016820305123>.
- Ancillotti, E., Bruno, R., Vallati, C., Mingozzi, E., 2018. Design and evaluation of a rate-based congestion control mechanism in CoAP for IoT applications. In: 2018 IEEE 19th International Symposium on "a World of Wireless, Mobile and Multimedia Networks". WoWMoM, pp. 14–15. <http://dx.doi.org/10.1109/WoWMoM.2018.8449736>.
- Andersen, A., Karlsen, R., Yu, W., 2018. Green transportation choices with IoT and smart nudging. In: *Handbook of Smart Cities, Software Services and Cyber Infrastructure*.
- Anitha, P., Vimala, H., Shreyas, J., 2023. PQTBA: Priority queue based token bucket algorithm for congestion control in IoT network. In: 2023 IEEE 8th International Conference for Convergence in Technology. I2CT, IEEE, pp. 1–7.
- Anon, 0000a. IoTIFY is industry's first cloud-based performance testing platform designed to help you build, validate and continuously monitor today's modern enterprise IoT applications. URL <https://iotify.io/>.
- Anon, 0000b. An Exhaustive IoT Simulator for IoT/MQTT Application Testing. URL <https://www.bevywise.com/iot-simulator/>.
- Anon, 0000c. Ansys 2021 R2 Accelerates Engineering Exploration, Collaboration and Automation. URL <https://www.ansys.com/en-in/technology-trends/iiot>.
- Anon, 2014a. Group communication for the constrained application protocol (CoAP). Internet Eng. Task Force (IETF) URL <https://datatracker.ietf.org/doc/html/rfc7390#page-19>.
- Anon, 2014b. Internet engineering task force (IETF), RFC 7252 – The constrained application. Internet Eng. Task Force (IETF) URL <https://datatracker.ietf.org/doc/html/rfc7252#page-25>.
- Anon, 2016. In: Bala, K. (Ed.), *ACM Trans. Graph.* 35 (2).
- Anon, 2022. MS Windows NT Kernel Description. . <https://explodingtopics.com/blog/iot-stats>. Accessed 28 November 2022.
- Arora, S., Batra, I., Malik, A., Luhach, A.K., Alnumay, W.S., Chatterjee, P., 2023. Seed: secure and energy efficient data-collection method for IoT network. *Multimedia Tools Appl.* 82 (2), 3139–3153.
- Astudillo, J., Rico-Novella, F., de la Cruz Llopis, L., 2020. Predictive traffic control and differentiation on smart grid neighborhood area networks. *IEEE Access* 8, 216805–216821. <http://dx.doi.org/10.1109/ACCESS.2020.3041690>.
- Ata, A., Khan, M.A., Abbas, S., Khan, M.S., Ahmad, G., 2021. Adaptive IoT empowered smart road traffic congestion control system using supervised machine learning algorithm. *Comput. J.* 64 (11), 1672–1679.
- Awan, K.M., Ashraf, N., Saleem, M.Q., Sheta, O.E., Qureshi, K.N., Zeb, A., Haseeb, K., Sadiq, A.S., 2019. A priority-based congestion-avoidance routing protocol using IoT-based heterogeneous medical sensors for energy efficiency in healthcare wireless body area networks. *Int. J. Distrib. Sens. Netw.* 15 (6), 1550147719853980. <http://dx.doi.org/10.1177/1550147719853980>.
- Banaie, F., Hossein Yaghmaee, M., Hosseini, S.A., Tashtarian, F., 2020. Load-balancing algorithm for multiple gateways in fog-based internet of things. *IEEE Internet Things J.* 7 (8), 7043–7053. <http://dx.doi.org/10.1109/JIOT.2020.2982305>.
- Bansal, S., Kumar, D., 2020. Distance-based congestion control mechanism for CoAP in IoT. *IET Commun.* 14, 3512–3520. <http://dx.doi.org/10.1049/iet-com.2020.0486>.
- Beitelspacher, S., Beshier, K.M., Zamshed Ali, M., 2020. Sensor driven priority routing of health care data packet in IoT network. In: 2020 IEEE 6th World Forum on Internet of Things. WF-IoT, pp. 1–7. <http://dx.doi.org/10.1109/WF-IoT48130.2020.9221478>.
- Beshier, K.M., Nieto-Hipolito, J.I., Buenrostro-Mariscal, R., Ali, M.Z., 2021. Spectrum based power management for congested IoT networks. *Sensors* 21 (8), URL <https://www.mdpi.com/1424-8220/21/8/2681>.
- Betzler, A., Gomez, C., Demirkol, I., Paradells, J., 2016. CoAP congestion control for the Internet of Things. *IEEE Commun. Mag.* 54 (7), 154–160. <http://dx.doi.org/10.1109/MCOM.2016.7509394>.
- Bhandari, K.S., Hosen, A.S.M.S., Cho, G.H., 2018. CoAR: Congestion-aware routing protocol for low power and lossy networks for IoT applications. *Sensors* 18 (11), URL <https://www.mdpi.com/1424-8220/18/11/3838>.
- binti Wan Abdullah, W.A.N., Yaakob, N., Badlishah, R., Amir, A., binti Yah, S.A., 2016. On the effectiveness of congestion control mechanisms for remote healthcare monitoring system in IoT environment — A review. In: 2016 3rd International Conference on Electronic Design. ICED, pp. 348–353. <http://dx.doi.org/10.1109/ICED.2016.7804665>.
- Blanton, E., Paxson, D.V., Allman, M., 2009. TCP Congestion Control. (5681), <http://dx.doi.org/10.17487/RFC5681>, RFC 5681, Request for Comments, RFC Editor. URL <https://rfc-editor.org/rfc/rfc5681.txt>.
- Campolo, C., Genovese, G., Singh, G., Molinaro, A., 2023. Scalable and interoperable edge-based federated learning in IoT contexts. *Comput. Netw.* 223, 109576. <http://dx.doi.org/10.1016/j.comnet.2023.109576>, URL <https://www.sciencedirect.com/science/article/pii/S138912862300021X>.
- Cárdenas-Benítez, N., Aquino-Santos, R., Magaña-Espinoza, P., Aguilar-Velazco, J., Edwards-Block, A., Medina Cass, A., 2016. Traffic congestion detection system through connected vehicles and big data. *Sensors* 16 (5), URL <https://www.mdpi.com/1424-8220/16/5/599>.
- Catarinucci, L., de Donno, D., Mainetti, L., Palano, L., Patrono, L., Stefanizzi, M.L., Tarricone, L., 2015. An IoT-aware architecture for smart healthcare systems. *IEEE Internet Things J.* 2 (6), 515–526. <http://dx.doi.org/10.1109/JIOT.2015.2417684>.
- Chappala, R., Anuradha, C., Murthy, P., 2020a. Adaptive alternative path and rate based congestion control for 6LoWPAN, WSN towards Internet of Things. *Indian J. Comput. Sci. Eng.* 11 (5), 446–453.
- Chappala, R., Ch, A., Sri, P., 2020b. Adaptive alternative path and rate based congestion control for 6LoWPAN, WSN towards internet of things. *Indian J. Comput. Sci. Eng.* 11, 446–453. <http://dx.doi.org/10.21817/indjcsce/2020/v11i5/201105085>.
- Chen, Y., Lu, L., Yu, X., Li, X., 2019. Adaptive method for packet loss types in IoT: An naive Bayes distinguisher. *Electronics* 8, 134.
- Chitrashekharaiah, Y., Srinidhi, N.N., Chouhan, D., Shreyas, J., Dilip Kumar, S.M., 2022. Energy-efficient lifetime and network performance improvement for mobility of nodes in IoT. In: Khanna, A., Gupta, D., Bhattacharyya, S., Hassanien, A.E., Anand, S., Jaiswal, A. (Eds.), *International Conference on Innovative Computing and Communications*. Springer Singapore, Singapore, pp. 421–430.
- Chowdhury, S., Benslimane, A., Giri, C., 2020a. Noncooperative gaming for energy-efficient congestion control in 6LoWPAN. *IEEE Internet Things J.* 7 (6), 4777–4788. <http://dx.doi.org/10.1109/JIOT.2020.2969272>.
- Chowdhury, A., Ikram, M., Cha, H.-S., Redwan, H., Shams, S., Kim, K.-H., Yoo, S.-W., 2020b. Route-over vs mesh-under routing in 6LoWPAN.
- Chung, Y.-Y., 2023. Modified CUBIC congestion avoidance for multi-side parallel downloading over lossy networks. In: *Proceedings of the 14th Conference on ACM Multimedia Systems*. Association for Computing Machinery, New York, NY, USA, pp. 474–477.
- da Cruz, M.A.A., Rodrigues, J.J.P.C., Al-Muhtadi, J., Korotaev, V.V., de Albuquerque, V.H.C., 2018. A reference model for Internet of Things middleware. *IEEE Internet Things J.* 5 (2), 871–883. <http://dx.doi.org/10.1109/JIOT.2018.2796561>.
- Deguchi, A., Hirai, C., Matsuoka, H., Nakano, T., Oshima, K., Tai, M., Tani, S., 2020. What is society 5.0? In: *Society 5.0*. Springer Singapore, pp. 1–23. <http://dx.doi.org/10.1007/978-981-15-2989-4.1>.
- Dong, M., Meng, T., Zarchy, D., Arslan, E., Gilad, Y., Godfrey, B., Schapira, M., 2018. {PCC} vivace: Online-learning congestion control. In: 15th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 18). pp. 343–356.
- Farag, H., Österberg, P., Gidlund, M., 2020. Congestion detection and control for 6tisch networks in IoT applications. In: *ICC 2020 - 2020 IEEE International Conference on Communications*. ICC, pp. 1–6. <http://dx.doi.org/10.1109/ICC40277.2020.9149365>.
- Farahani, B., Firouzi, F., Chang, V.I.C., Badaroglu, M., Constant, N., Mankodiya, K., 2018. Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare. *Future Gener. Comput. Syst.* 78, 659–676.
- Floyd, S., 2008. Metrics for the evaluation of congestion control mechanisms. (5166), <http://dx.doi.org/10.17487/RFC5166>, RFC 5166, Request for Comments, RFC Editor. URL <https://rfc-editor.org/rfc/rfc5166.txt>.
- Ghafoor, S., Khattak, D., Tahir, M., Mustafa, M., 2020. Home automation security system based on face detection and recognition using IoT. ISBN: 978-981-15-5231-1, pp. 67–78. <http://dx.doi.org/10.1007/978-981-15-5232-8.7>.
- Gillis, A.S., 2021. 75 Years ago, the doolittle raid changed history. [Online] URL <https://internetofthingsagenda.techtarget.com/definition/Internet-of-Things-IoT>.
- Gomez, C., Demirkol, I., Bormann, C., Betzler, A., 2016. CoAP simple congestion control/advanced.
- Grieco, L.A., Mascolo, S., 2004. Performance evaluation and comparison of Westwood+, new reno, and vegas TCP congestion control. *SIGCOMM Comput. Commun. Rev.* 34 (2), 25–38. <http://dx.doi.org/10.1145/997150.997155>.
- Guo, F., Yu, F.R., Zhang, H., Li, X., Ji, H., Leung, V.C., 2021. Enabling massive IoT toward 6G: A comprehensive survey. *IEEE Internet Things J.*
- Gupta, A.T., Gupta, H., Sharma, M., Khanna, P., 2021. A secure home automation prototype built on raspberry-pi. *arXiv:2109.14579*.
- Haka, A., Aleksieva, V., Valchanov, H., 2020. Comparative analysis of traffic prioritisation algorithms in 6LoWPAN networks. In: 2020 21st International Symposium on Electrical Apparatus & Technologies. SIELA, pp. 1–4. <http://dx.doi.org/10.1109/SIELA49118.2020.9167116>.
- Hamdan, O., Shanableh, H., Zaki, I., Al-Ali, A.R., Shanableh, T., 2019. IoT-based interactive dual mode smart home automation. In: 2019 IEEE International Conference on Consumer Electronics. ICCE, pp. 1–2. <http://dx.doi.org/10.1109/ICCE.2019.8661935>.

- Hamidouche, R., Aliouat, Z., Abba Ari, A.A., Gueroui, M., 2019. An efficient clustering strategy avoiding buffer overflow in IoT sensors: A bio-inspired based approach. *IEEE Access* 7, 156733–156751. <http://dx.doi.org/10.1109/ACCESS.2019.2943546>.
- Hasan, H.H., Alisa, Z.T., 2023. Effective IoT congestion control algorithm. *Future Internet* 15 (4), <http://dx.doi.org/10.3390/fi15040136>, URL <https://www.mdpi.com/1999-5903/15/4/136>.
- Hattab, G., Cabric, D., 2020. Energy-efficient massive IoT shared spectrum access over UAV-enabled cellular networks. *IEEE Trans. Commun.* 68 (9), 5633–5648. <http://dx.doi.org/10.1109/TCOMM.2020.2998547>.
- Hellaoui, H., Koudil, M., 2015. Bird flocking congestion control for CoAP/RPL/6LoWPAN networks. In: *Proceedings of the 2015 Workshop on IoT Challenges in Mobile and Industrial Systems*. In: *IoT-Sys '15*, Association for Computing Machinery, New York, NY, USA, pp. 25–30. <http://dx.doi.org/10.1145/2753476.2753480>.
- Higuera, J., Polo, J., 2010. Understanding the IEEE 1451 standard in 6LoWPAN sensor networks. In: *2010 IEEE Sensors Applications Symposium*. SAS, pp. 189–193. <http://dx.doi.org/10.1109/SAS.2010.5439427>.
- Homaei, M.H., Soleimani, F., Shamsirband, S., Mosavi, A., Nabipour, N., Várkonyi-Kóczy, A.R., 2020. An enhanced distributed congestion control method for classical 6LoWPAN protocols using fuzzy decision system. *IEEE Access* 8, 20628–20645. <http://dx.doi.org/10.1109/ACCESS.2020.2968524>.
- Hoque, M.A., Davidson, C., 2019. Design and implementation of an IoT-based smart home security system. *Int. J. Netw. Distrib. Comput.* 7, 85–92. <http://dx.doi.org/10.2991/ijndc.k.190326.004>.
- Hosseini Motlagh, N., Mohammadrezaei, M., Hunt, J., Zakeri, B., 2020a. Internet of Things (IoT) and the energy sector. *Energies* 13 (2), <http://dx.doi.org/10.3390/en13020494>, URL <https://www.mdpi.com/1996-1073/13/2/494>.
- Hosseini Motlagh, N., Mohammadrezaei, M., Hunt, J., Zakeri, B., 2020b. Internet of Things (IoT) and the energy sector. *Energies* 13 (2), 494. <http://dx.doi.org/10.3390/en13020494>.
- Hou, Y., He, H., Jiang, X., Chen, S., Yang, J., 2023. Deep reinforcement learning aided loss-tolerant congestion control for 6LoWPAN networks. *IEEE Internet Things J.* 1. <http://dx.doi.org/10.1109/IJOT.2023.3281482>.
- Hsieh, H.-C., Lee, C.-S., Chen, J., 2018. Mobile edge computing platform with container-based virtualization technology for IoT applications. *Wirel. Pers. Commun.* 102, <http://dx.doi.org/10.1007/s11277-018-5856-5>.
- Huang, J., Du, D., Duan, Q., Sun, Y., Yin, Y., Zhou, T., Zhang, Y., 2014. Modeling and analysis on congestion control in the Internet of Things. In: *2014 IEEE International Conference on Communications*. ICC, pp. 434–439. <http://dx.doi.org/10.1109/ICC.2014.6883357>.
- Huang, J., Xing, C.-C., Shin, S.Y., Hou, F., Hsu, C.-H., 2018. Optimizing M2M communications and quality of services in the IoT for sustainable smart cities. *IEEE Trans. Sustain. Comput.* 3 (1), 4–15. <http://dx.doi.org/10.1109/TSUSC.2017.2702589>.
- Huq, R., Moreno, K., Zhu, H., Zhang, J., Ohlsson, O., Hossain, M.I., 2015. On the benefits of clustered capillary networks for congestion control in machine type communications over LTE. <http://dx.doi.org/10.1109/ICCNC.2015.7288439>.
- Illapu, S.S.R., Sivakumar, V., 2023. An efficient chaos-LSA integrated game theory algorithm for a qos-assured delay time control mechanism with a unique parent selection strategy for a 6LoWPAN wireless body area network. *Appl. Nanosci.* 13 (4), 3053–3071.
- Imran, M.A., Zoha, A., Zhang, L., Abbasi, Q.H., 2020. Grand challenges in IoT and sensor networks. *Front. Commun. Netw.* 1, 7. <http://dx.doi.org/10.3389/frcmn.2020.619452>, URL <https://www.frontiersin.org/article/10.3389/frcmn.2020.619452>.
- Jain, V.K., Mazumdar, A.P., Faruki, P., Govil, M.C., 2022a. Congestion control in Internet of Things: Classification, challenges, and future directions. *Sustain. Comput. Inform. Syst.* 35, 100678. <http://dx.doi.org/10.1016/j.suscom.2022.100678>, URL <https://www.sciencedirect.com/science/article/pii/S221053792200021X>.
- Jain, V.K., Mazumdar, A.P., Govil, M.C., 2022b. Congestion prediction in Internet of Things network using temporal convolutional network: A centralized approach. *Def. Sci. J.* 72 (6).
- Jay, N., Rotman, N., Godfrey, B., Schapira, M., Tamar, A., 2019. A deep reinforcement learning perspective on internet congestion control. In: *International Conference on Machine Learning*. PMLR, pp. 3050–3059.
- Jiang, H., Li, Q., Jiang, Y., Shen, G., Sinnott, R., Tian, C., Xu, M., 2021. When machine learning meets congestion control: A survey and comparison. *Comput. Netw.* 192, 108033.
- Jump, J.R., Lakshmanamurthy, S., 1993. NETSIM: A general-purpose interconnection network simulator. In: *MASCOTS*.
- Kalita, A., Khatua, M., 2021. Channel condition based dynamic beacon interval for faster formation of 6tisch network. *IEEE Trans. Mob. Comput.* 20 (7), 2326–2337. <http://dx.doi.org/10.1109/TMC.2020.2980828>.
- Kanellopoulos, D., Sharma, V.K., 2022. Dynamic load balancing techniques in the IoT: A review. *Symmetry* 14 (12), 2554.
- Kavitha, T., Pandeeswari, N., Shobana, R., Vinothini, V., Sakthisudhan, K., Jeyam, A., Malar, A.J.G., 2022. Data congestion control framework in Wireless Sensor Network in IoT enabled intelligent transportation system. *Measurement: Sensors* 24, 100563.
- Khanna, A., Anand, R., 2016. IoT based smart parking system. In: *2016 International Conference on Internet of Things and Applications*. IOTA, pp. 266–270. <http://dx.doi.org/10.1109/IOTA.2016.7562735>.
- Kharrufa, H., Al-Kashoash, H.A., Kemp, A.H., 2019. RPL-based routing protocols in IoT applications: A review. *IEEE Sens. J.* 19 (15), 5952–5967.
- Khelifi, N., Oteafy, S., Hassanein, H., Youssef, H., 2015. Proactive maintenance in RPL for 6LoWPAN. In: *2015 International Wireless Communications and Mobile Computing Conference*. IWCMC, pp. 993–999. <http://dx.doi.org/10.1109/IWCMC.2015.7289218>.
- Kim, H.-S., Paek, J., Bahk, S., 2015. QU-RPL: Queue utilization based RPL for load balancing in large scale industrial applications. In: *2015 12th Annual IEEE International Conference on Sensing, Communication, and Networking*. SECON, IEEE, pp. 265–273.
- Kong, Y., Zang, H., Ma, X., 2018. Improving TCP congestion control with machine intelligence. In: *Proceedings of the 2018 Workshop on Network Meets AI & ML*. pp. 60–66.
- Koutsiamanis, R.-A., Papadopoulos, G.Z., Fafoutis, X., Fiore, J.M.D., Thubert, P., Montavont, N., 2018. From best effort to deterministic packet delivery for wireless industrial IoT networks. *IEEE Trans. Ind. Inform.* 14 (10), 4468–4480. <http://dx.doi.org/10.1109/TII.2018.2856884>.
- Kumar, N., Raubal, M., 2021. Applications of deep learning in congestion detection, prediction and alleviation: A survey. *Transp. Res. C* 133, 103432.
- Lee, J.J., Chung, S., Lee, B., Kim, K.T., Youn, H., 2016. Round trip time based adaptive congestion control with CoAP for sensor network. In: *2016 International Conference on Distributed Computing in Sensor Systems*. DCOSS, pp. 113–115.
- Lenders, M.S., Schmidt, T.C., Wählisch, M., 2021. Fragment forwarding in Lossy networks. *IEEE Access* 9, 143969–143987. <http://dx.doi.org/10.1109/ACCESS.2021.3121557>.
- Li, M., Huang, X., Jin, C., Pei, Y., 2021. A TCP congestion control algorithm based on deep reinforcement learning combined with probe bandwidth mechanism. In: *Proceedings of the 5th International Conference on Computer Science and Application Engineering*. CSAE '21, Association for Computing Machinery, New York, NY, USA, <http://dx.doi.org/10.1145/3487075.3487119>.
- Li, M., Si, P., Zhang, Y., 2018a. Delay-tolerant data traffic to software-defined vehicular networks with mobile edge computing in smart city. *IEEE Trans. Veh. Technol.* 67 (10), 9073–9086. <http://dx.doi.org/10.1109/TVT.2018.2865211>.
- Li, J., Silva, B.N., Diyan, M., Cao, Z., Han, K., 2018b. A clustering based routing algorithm in IoT aware wireless mesh networks. *Sustainable Cities Soc.* 40, 657–666. <http://dx.doi.org/10.1016/j.scs.2018.02.017>, URL <https://www.sciencedirect.com/science/article/pii/S2210670717312775>.
- Li, W., Zhang, H., Gao, S., Xue, C., Wang, X., Lu, S., 2019. SmartCC: A reinforcement learning approach for multipath TCP congestion control in heterogeneous networks. *IEEE J. Sel. Areas Commun.* 37 (11), 2621–2633.
- Li, W., Zhou, F., Chowdhury, K.R., Meleis, W., 2018c. QTCP: Adaptive congestion control with reinforcement learning. *IEEE Trans. Netw. Sci. Eng.* 6 (3), 445–458.
- Li, W., Zhou, F., Meleis, W., Chowdhury, K., 2016. Learning-based and data-driven tcp design for memory-constrained iot. In: *2016 International Conference on Distributed Computing in Sensor Systems*. DCOSS, IEEE, pp. 199–205.
- Lim, C., 2019. A survey on congestion control for RPL-based wireless sensor networks. *Sensors* 19 (11), <http://dx.doi.org/10.3390/s19112567>, URL <https://www.mdpi.com/1424-8220/19/11/2567>.
- Lim, C., 2020. Improving congestion control of TCP for constrained IoT networks. *Sensors* 20 (17), URL <https://www.mdpi.com/1424-8220/20/17/4774>.
- Looga, V., Ou, Z., Deng, Y., Ylä-Jääski, A., 2012. MAMMOTH: A massive-scale emulation platform for Internet of Things. 3, pp. 1235–1239. <http://dx.doi.org/10.1109/CISIS.2012.6664581>.
- Madakam, S., Ramaswamy, R., Tripathi, S., 2015. Internet of Things (IoT): A literature review. *J. Comput. Commun.* 3, 164–173. <http://dx.doi.org/10.4236/jcc.2015.35021>.
- Maheshwari, A., Yadav, R.K., 2020. Analysis of congestion control mechanism for IOT. In: *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. pp. 288–293. <http://dx.doi.org/10.1109/Confluence47617.2020.9058058>.
- Maheshwari, A., Yadav, R.K., Nath, P., 2023. Congestion aware data transmission in mobile and constrained IoT network. *Wirel. Pers. Commun.* 130 (3), 2121–2136.
- Mai, T., Yao, H., Jing, Y., Xu, X., Wang, X., Ji, Z., 2019. Self-learning congestion control of MPTCP in satellites communications. In: *2019 15th International Wireless Communications & Mobile Computing Conference*. IWCMC, IEEE, pp. 775–780.
- Makarem, N., Bou Diab, W., Mougharbel, I., Malouch, N., 2022. On the design of efficient congestion control for the constrained application protocol in IoT. *Comput. Netw.* 207, 108824. <http://dx.doi.org/10.1016/j.comnet.2022.108824>, URL <https://www.sciencedirect.com/science/article/pii/S1389128622000457>.
- Mamo, K., Beitelspacher, S., Nieto, J., Ali, M., 2020. Sensor initiated healthcare packet routing in congested IoT networks. *IEEE Sens. J.* PP, 1. <http://dx.doi.org/10.1109/JSEN.2020.3012519>.
- Manshahia, M.S., 2019. Grey wolf algorithm based energy-efficient data transmission in Internet of Things. *Procedia Comput. Sci.* 160, 604–609. <http://dx.doi.org/10.1016/j.procs.2019.11.040>, URL <https://www.sciencedirect.com/science/article/pii/S1877050919317405>.
- The 10th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN-2019) / The 9th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2019) / Affiliated Workshops.
- Mastorakis, S., Afanasyev, A., Zhang, L., 2017. On the evolution of ndnsm: An open-source simulator for NDN experimentation. *SIGCOMM Comput. Commun. Rev.* 47 (3), 19–33. <http://dx.doi.org/10.1145/3138808.3138812>.
- Mehmood, T., 2017. COOJA network simulator: Exploring the infinite possible ways to compute the performance metrics of IOT based smart devices to understand the working of IOT based compression routing protocols.

- Meng, T., Schiff, N.R., Godfrey, P.B., Schapira, M., 2020. PCC proteus: Scavenger transport and beyond. In: Proceedings of the Annual Conference of the ACM Special Interest Group on Data Communication on the Applications, Technologies, Architectures, and Protocols for Computer Communication. pp. 615–631.
- Mirela Catalina, T., Capusneanu, S., Topor, D., Staras, A., Hint, M., Stoenică, L., 2020. Motivations for the use of IoT solutions by company managers in the digital age: A Romanian case. *Appl. Sci.* 10, 6905. <http://dx.doi.org/10.3390/app10196905>.
- Mishra, N., Verma, L.P., Srivastava, P.K., Gupta, A., 2018a. An analysis of IoT congestion control policies. *Procedia Comput. Sci.* 132, 444–450. <http://dx.doi.org/10.1016/j.procs.2018.05.158>, URL <https://www.sciencedirect.com/science/article/pii/S1877050918308925>, International Conference on Computational Intelligence and Data Science.
- Mishra, N., Verma, L.P., Srivastava, P.K., Gupta, A., 2018b. An analysis of IoT congestion control policies. *Procedia Comput. Sci.* 132, 444–450.
- Mogi, R., Nakayama, T., Asaka, T., 2018. Load balancing method for IoT sensor system using multi-access edge computing. In: 2018 Sixth International Symposium on Computing and Networking Workshops. CANDARW, pp. 75–78. <http://dx.doi.org/10.1109/CANDARW.2018.00023>.
- Montenegro, G., Hui, J., Culler, D., Kushalnagar, N., 2007a. Transmission of IPv6 packets over IEEE 802.15.4 networks. (4944), <http://dx.doi.org/10.17487/RFC4944>, RFC 4944, RFC Editor, Request for Comments. URL <https://www.rfc-editor.org/info/rfc4944>.
- Montenegro, G., Kushalnagar, N., Hui, J., Culler, D., 2007b. Transmission of IPv6 packets over IEEE 802.15.4 networks. (4944), RFC 4944, Request for Comments, Internet Engineering Task Force. URL <http://www.ietf.org/rfc/rfc4944.txt>.
- MR, P., HS, V., 2023. Mobility-based optimal relay node selection for IoT-oriented SDWSN. In: Proceedings of the 2023 ACM Southeast Conference. pp. 201–205.
- Muhammad, Q., Shatnawi, Y., 2020. Congestion control model for securing Internet of Things data flow. *Ad Hoc Netw.* 106, 102160. <http://dx.doi.org/10.1016/j.adhoc.2020.102160>, URL <https://www.sciencedirect.com/science/article/pii/S1570870519306651>.
- Naem, F., Srivastava, G., Tariq, M., 2020. A software defined network based fuzzy normalized neural adaptive multipath congestion control for the Internet of Things. *IEEE Trans. Netw. Sci. Eng.* 7 (4), 2155–2164. <http://dx.doi.org/10.1109/TNSE.2020.2991106>.
- Najm, I.A., Hamoud, A.K., Lloret, J., Bosch, I., 2019a. Machine learning prediction approach to enhance congestion control in 5G IoT environment. *Electronics* 8, 607.
- Najm, I.A., Hamoud, A.K., Lloret, J., Bosch, I., 2019b. Machine learning prediction approach to enhance congestion control in 5G IoT environment. *Electronics* 8 (6), 607.
- Nasimi, M., Habibi, M.A., Han, B., Schotten, H.D., 2018. Edge-assisted congestion control mechanism for 5G network using software-defined networking. In: 2018 15th International Symposium on Wireless Communication Systems. ISWCS, pp. 1–5. <http://dx.doi.org/10.1109/ISWCS.2018.8491233>.
- Nie, X., Zhao, Y., Li, Z., Chen, G., Sui, K., Zhang, J., Ye, Z., Pei, D., 2019. Dynamic TCP initial windows and congestion control schemes through reinforcement learning. *IEEE J. Sel. Areas Commun.* 37 (6), 1231–1247.
- Ojje, E., Pereira, E., 2017. Simulation tools in Internet of Things: A review. In: Proceedings of the 1st International Conference on Internet of Things and Machine Learning. IML '17, Association for Computing Machinery, New York, NY, USA, <http://dx.doi.org/10.1145/3109761.3158400>.
- Oyewobi, S., Djouani, K., Kurien, A., 2021. Using priority queuing for congestion control in IoT-based technologies for IoT applications. *Int. J. Commun. Syst.* 34, <http://dx.doi.org/10.1002/dac.4709>.
- Pflanzner, T., Kertesz, A., Spinnewyn, B., Latré, S., 2016. MobIoTsim: Towards a mobile IoT device simulator. In: 2016 IEEE 4th International Conference on Future Internet of Things and Cloud Workshops. FiCloudW, pp. 21–27. <http://dx.doi.org/10.1109/W-FiCloud.2016.21>.
- Pokhrel, S.R., L. Vu, H., Cricenti, A.L., 2020. Adaptive admission control for IoT applications in home WiFi networks. *IEEE Trans. Mob. Comput.* 19 (12), 2731–2742. <http://dx.doi.org/10.1109/TMC.2019.2935719>.
- Pokhrel, S.R., Williamson, C., 2018. Modeling compound TCP over WiFi for IoT. *IEEE/ACM Trans. Netw.* 26 (2), 864–878. <http://dx.doi.org/10.1109/TNET.2018.2806352>.
- Poornima, M., Vimala, H., Shreyas, J., 2023. Holistic survey on energy aware routing techniques for IoT applications. *J. Netw. Comput. Appl.* 213, 103584.
- Praveen, K., Prathap, P.J., 2021. Energy efficient congestion aware resource allocation and routing protocol for IoT network using hybrid optimization techniques. *Wirel. Pers. Commun.* 117 (2), 1187–1207.
- Pruthvi, C., Vimala, H., Shreyas, J., 2023. A systematic survey on content caching in ICN and ICN-IoT: Challenges, approaches and strategies. *Comput. Netw.* 109896.
- Pushpa Metilsha, J., Sandhya, M., Murugan, K., 2021. RPR: Reliable path routing protocol to mitigate congestion in critical IoT applications. *Wirel. Netw.* 27, 5229–5243.
- Rahman, T., Yao, X., Tao, G., 2018. Consistent data collection and assortment in the progression of continuous objects in IoT. *IEEE Access* 6, 51875–51885. <http://dx.doi.org/10.1109/ACCESS.2018.2869075>.
- Raiesh, G., Swetha, C., Privanka, R., Vaishnavi, R., 2017. Congestion control in 6Lo WPAN networks using fuzzy logic (FLCC). In: 2017 Ninth International Conference on Advanced Computing. ICAC, pp. 369–374. <http://dx.doi.org/10.1109/ICAC.2017.8441179>.
- Rajasekaran, S., Ghobadi, M., Kumar, G., Akella, A., 2022. Congestion control in machine learning clusters. In: Proceedings of the 21st ACM Workshop on Hot Topics in Networks. HotNets '22, Association for Computing Machinery, New York, NY, USA, pp. 235–242. <http://dx.doi.org/10.1145/3563766.3564115>.
- Rathod, V., Jeppu, N., Sastry, S., Singala, S., Tahiliani, M.P., 2019. CoCoA++: Delay gradient based congestion control for internet of things. *Future Gener. Comput. Syst.* 100, 1053–1072. <http://dx.doi.org/10.1016/j.future.2019.04.054>, URL <https://www.sciencedirect.com/science/article/pii/S0167739X18308677>.
- Riley, G.F., Henderson, T.R., 2010. The ns-3 network simulator. In: Wehrle, K., Güneş, M., Gross, J. (Eds.), Modeling and Tools for Network Simulation. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 15–34. http://dx.doi.org/10.1007/978-3-642-12331-3_2.
- Risteska Stojkoska, B.L., Trivodaliev, K.V., 2017. A review of Internet of Things for smart home: Challenges and solutions. *J. Clean. Prod.* 140, 1454–1464. <http://dx.doi.org/10.1016/j.jclepro.2016.10.006>, URL <https://www.sciencedirect.com/science/article/pii/S095965261631589X>.
- Safaei, B., Monazzah, A.M.H., Ejlali, A., 2020. ELITE: An elaborated cross-layer RPL objective function to achieve energy efficiency in Internet-of-Things devices. *IEEE Internet Things J.* 8 (2), 1169–1182.
- Said, O., 2023. A bandwidth control scheme for reducing the negative impact of bottlenecks in IoT environments: Simulation and performance evaluation. *Internet Things* 21, 100682. <http://dx.doi.org/10.1016/j.iot.2023.100682>, URL <https://www.sciencedirect.com/science/article/pii/S2542660523000057>.
- Saleem, A., Afzal, M.K., Ateeq, M., Kim, S.W., Zikria, Y.B., 2020. Intelligent learning automata-based objective function in RPL for IoT. *Sustainable Cities Soc.* 59, 102234. <http://dx.doi.org/10.1016/j.scs.2020.102234>, URL <https://www.sciencedirect.com/science/article/pii/S2210670720302213>.
- Sethi, P., Sarangi, S., 2017. Internet of Things: Architectures, protocols, and applications. *J. Electr. Comput. Eng.* 2017, 1–25. <http://dx.doi.org/10.1155/2017/9324035>.
- Shafiq, M., Ahmad, M., Khalil Afzal, M., Ali, A., Irshad, A., Choi, J.-G., 2019. Handshake sense multiple access control for cognitive radio-based IoT networks. *Sensors* 19 (2), URL <https://www.mdpi.com/1424-8220/19/2/241>.
- Shah, S.K., Tariq, Z., Lee, Y., 2018. Audio IoT analytics for home automation safety. In: 2018 IEEE International Conference on Big Data. Big Data, IEEE, pp. 5181–5186.
- Shahinzadeh, H., Moradi, J., Gharehpetian, G.B., Nafisi, H., Abedi, M., 2019. IoT architecture for smart grids. In: 2019 International Conference on Protection and Automation of Power System. IPAPS, pp. 22–30. <http://dx.doi.org/10.1109/IPAPS.2019.8641944>.
- Sharma, D.Y., Borole, P., 2020. 6G network access and edge-assisted congestion rule mechanism using software-defined networking. 13, pp. 107–112.
- Sharma, C., Gondhi, N.K., 2018. Communication protocol stack for constrained IoT systems. In: 2018 3rd International Conference on Internet of Things: Smart Innovation and Usages. IoT-SIU, pp. 1–6. <http://dx.doi.org/10.1109/IoT-SIU.2018.8519904>.
- Sheu, J.-P., Hsu, C.-X., Ma, C., 2015. A game theory based congestion control protocol for Wireless Personal Area networks. In: 2015 IEEE 39th Annual Computer Software and Applications Conference, Vol. 2. pp. 659–664. <http://dx.doi.org/10.1109/COMPSAC.2015.21>.
- Shreyas, J., Chouhan, D., Akshatha, A., Udayaprasad, P., SM, D.K., 2020. Selection of optimal path for the communication of multimedia data in Internet of Things. In: 2020 6th International Conference on Advanced Computing and Communication Systems. ICACCS, IEEE, pp. 477–481.
- Shreyas, J., Kumar, S., 2020. A survey on computational intelligence techniques for internet of things. In: International Conference on Communication and Intelligent Systems. Springer, pp. 271–282.
- Shreyas, J., Singh, H., Bhutani, J., Pandit, S., N, N.S., Dilip, K.S.M., 2019. Congestion aware algorithm using fuzzy logic to find an optimal routing path for IoT networks. In: 2019 International Conference on Computational Intelligence and Knowledge Economy. ICCIKE, pp. 141–145. <http://dx.doi.org/10.1109/ICCIKE47802.2019.9004351>.
- Shreyas, J., Singh, H., Tiwari, S., Srinidhi, N., Dilip Kumar, S., 2021a. CAFOR: congestion avoidance using fuzzy logic to find an optimal routing path in 6LoWPAN networks. *J. Reliab. Intell. Environ.* 1–16.
- Shreyas, J., Singh, H., Tiwari, S., Srinidhi, N.N., Kumar, S., 2021b. CAFOR: congestion avoidance using fuzzy logic to find an optimal routing path in 6LoWPAN networks. *J. Reliab. Intell. Environ.* <http://dx.doi.org/10.1007/s40860-021-00134-5>.
- Song, S., Lee, J., Son, K., Jung, H., Lee, J., 2016. A congestion avoidance algorithm in SDN environment. pp. 420–423. <http://dx.doi.org/10.1109/ICOIN.2016.7427148>.
- Sonmez, C., Ozgovde, A., Ersoy, C., 2017. EdgeCloudSim: An environment for performance evaluation of edge computing systems. In: 2017 Second International Conference on Fog and Mobile Edge Computing. FMEC, pp. 39–44. <http://dx.doi.org/10.1109/FMEC.2017.7946405>.
- Srinidhi, N.N., Nagarjun, E., Kumar, S.M.D., 2019. HMCRA: Hybrid multi-copy routing algorithm for opportunistic IoT network. In: 2019 International Conference on Smart Systems and Inventive Technology. ICSSIT, pp. 370–375. <http://dx.doi.org/10.1109/ICSSIT46314.2019.8987796>.
- Srinivasulu, M., Shivamurthy, G., Venkataramana, B., 2023. Quality of service aware energy efficient multipath routing protocol for internet of things using hybrid optimization algorithm. *Multimedia Tools Appl.* 1–30.
- Sukjaimuk, R., Nguyen, Q., Sato, T., 2018a. Adaptive congestion control in information-centric networking for the IoT sensor network. *J. Adv. Simul. Science. Eng.* 5, 17–28. <http://dx.doi.org/10.15748/jasse.5.17>.

- Sukjaimuk, R., Nguyen, Q.N., Sato, T., 2018b. Dynamic congestion control in information-centric networking utilizing sensors for the IoT. In: 2018 IEEE Region Ten Symposium. Tensymp, pp. 63–68. <http://dx.doi.org/10.1109/TENCONSpring.2018.8691983>.
- Sukjaimuk, R., Nguyen, Q., Sato, T., 2018c. Dynamic congestion control in information-centric networking utilizing sensors for the IoT. pp. 63–68. <http://dx.doi.org/10.1109/TENCONSpring.2018.8691983>.
- Sukjaimuk, R., Nguyen, Q.N., Sato, T., 2018d. A smart congestion control mechanism for the green IoT sensor-enabled information-centric networking. *Sensors* 18 (9), URL <https://www.mdpi.com/1424-8220/18/9/2889>.
- Suwannapong, C., Khunboa, C., 2019. Congestion control in CoAP observe group communication. *Sensors* 19 (15), URL <https://www.mdpi.com/1424-8220/19/15/3433>.
- Suwannapong, C., Khunboa, C., 2020. EnCoCo-RED: Enhanced congestion control mechanism for CoAP observe group communication. *Ad Hoc Netw.* 112, 102377. <http://dx.doi.org/10.1016/j.adhoc.2020.102377>.
- Swarna, M., Godhvari, T., 2020. Enhancement of CoAP based congestion control in IoT network - a novel approach. *Mater. Today Proc.* 37, <http://dx.doi.org/10.1016/j.matpr.2020.05.817>.
- Tafa, Z., Milutinovic, V., 2021. Machine learning in congestion control: A survey on selected algorithms and a new roadmap to their implementation. *arXiv preprint arXiv:2112.15522*.
- Taherkhani, N., Pierre, S., 2016. Centralized and localized data congestion control strategy for vehicular ad hoc networks using a machine learning clustering algorithm. *IEEE Trans. Intell. Transp. Syst.* 17 (11), 3275–3285.
- Tahir, M., Ali, M.I., 2022. On the performance of federated learning algorithms for IoT. *IoT* 3 (2), 273–284.
- Tang, F., Fadlullah, Z.M., Mao, B., Kato, N., 2018. An intelligent traffic load prediction-based adaptive channel assignment algorithm in SDN-IoT: A deep learning approach. *IEEE Internet Things J.* 5 (6), 5141–5154. <http://dx.doi.org/10.1109/JIOT.2018.2838574>.
- Tariq, M.A., Khan, M., Raza Khan, M.T., Kim, D., 2020. Enhancements and challenges in CoAP—A survey. *Sensors* 20 (21), <http://dx.doi.org/10.3390/s20216391>, URL <https://www.mdpi.com/1424-8220/20/21/6391>.
- Thubert, P., Hui, J., 2011. Compression format for IPv6 datagrams over IEEE 802.15.4-based networks. (6282), <http://dx.doi.org/10.17487/RFC6282>, RFC 6282, Request for Comments, RFC Editor. URL <https://rfc-editor.org/rfc/rfc6282.txt>.
- Toprasert, T., Lilakiatasun, W., 2017. TCP congestion control with MDP algorithm for IoT over heterogeneous network. In: 2017 17th International Symposium on Communications and Information Technologies. ISCIT, pp. 1–5. <http://dx.doi.org/10.1109/ISCIT.2017.8261189>.
- Tseng, C.H., 2016. Multipath load balancing routing for Internet of Things. *J. Sensors* 2016, 4250746:1–4250746:8.
- Upreti, K., Kumar, N., Alam, M.S., Verma, A., Nandan, M., Gupta, A.K., 2021a. Machine learning-based congestion control routing strategy for healthcare IoT enabled wireless sensor networks. In: 2021 Fourth International Conference on Electrical, Computer and Communication Technologies. ICECCT, pp. 1–6. <http://dx.doi.org/10.1109/ICECCT52121.2021.9616864>.
- Upreti, K., Kumar, N., Alam, M.S., Verma, A., Nandan, M., Gupta, A.K., 2021b. Machine learning-based congestion control routing strategy for healthcare IoT enabled wireless sensor networks. In: 2021 Fourth International Conference on Electrical, Computer and Communication Technologies. ICECCT, IEEE, pp. 1–6.
- Varga, A., 2010. OMNeT++. In: *Modeling and Tools for Network Simulation*. Springer, pp. 35–59.
- Verma, H., Chauhan, N., Awasthi, L.K., 2023. Modelling buffer-overflow in 6LoWPAN-based resource-constrained IoT-healthcare network. *Wirel. Pers. Commun.* 129 (2), 1113–1128.
- Verma, H., Chauhan, N., Chand, N., Awasthi, L.K., 2022a. Buffer-loss estimation to address congestion in 6LoWPAN based resource-restricted 'Internet of Healthcare Things' network. *Comput. Commun.* 181, 236–256.
- Verma, L.P., Kumar, M., 2020. An IoT based congestion control algorithm. *Internet Things* 9, 100157. <http://dx.doi.org/10.1016/j.iot.2019.100157>, URL <https://www.sciencedirect.com/science/article/pii/S2542660519302598>.
- Verma, L.P., Sharma, V.K., Kumar, M., Kanellopoulos, D., 2022b. A novel delay-based adaptive congestion control TCP variant. *Comput. Electr. Eng.* 101, 108076. <http://dx.doi.org/10.1016/j.compeleceng.2022.108076>, URL <https://www.sciencedirect.com/science/article/pii/S0045790622003317>.
- Verma, L.P., Verma, I., Kumar, M., 2019. An adaptive congestion control algorithm. *Modelling Meas. Control A* 92, <http://dx.doi.org/10.18280/mmc.a.920105>.
- Vidushi, V., Chhabra, A., Sharma, D., 2019. GMMR: A Gaussian mixture model based unsupervised machine learning approach for optimal routing in opportunistic IoT networks. *Comput. Commun.* 134, 138–148.
- Waheed, A., Khan, N.H., Zareei, M., Islam, S.U., Jan6, L., Umar, A.I., Mohamed, E.M., 2021. Traffic queuing management in the Internet of Things: An optimized RED algorithm based approach. *Comput. Mater. Continua* 66 (1), 359–372. <http://dx.doi.org/10.32604/cmc.2020.012196>, URL <http://www.techscience.com/cmc/v66n1/40452>.
- Wang, P., Valerdi, R., Zhou, S., Li, L., 2015. Introduction: Advances in IoT research and applications. *Inf. Syst. Front.* 17 (2), 239–241. <http://dx.doi.org/10.1007/s10796-015-9549-2>.
- Wang, Z., Zhang, J., Zhang, X., Wang, W., 2019a. Reinforcement learning based congestion control in satellite internet of things. In: 2019 11th International Conference on Wireless Communications and Signal Processing. WCSP, IEEE, pp. 1–6.
- Wang, Z., Zhang, J., Zhang, X., Wang, W., 2019b. Reinforcement learning based congestion control in satellite internet of things. In: 2019 11th International Conference on Wireless Communications and Signal Processing. WCSP, pp. 1–6. <http://dx.doi.org/10.1109/WCSP.2019.8928132>.
- Wang, H., Zheng, K., Reiss, C., Shen, H., 2023. NCC: Neighbor-aware congestion control based on reinforcement learning for datacenter networks. In: Proceedings of the 51st International Conference on Parallel Processing. ICPP '22, Association for Computing Machinery, New York, NY, USA, <http://dx.doi.org/10.1145/3545008.3545074>.
- Xie, R., Jia, X., Wu, K., 2019. Adaptive online decision method for initial congestion window in 5G mobile edge computing using deep reinforcement learning. *IEEE J. Sel. Areas Commun.* 38 (2), 389–403.
- Xu, Z., Tang, J., Yin, C., Wang, Y., Xue, G., 2019. Experience-driven congestion control: When multi-path TCP meets deep reinforcement learning. *IEEE J. Sel. Areas Commun.* 37 (6), 1325–1336.
- Yan, F.Y., Ma, J., Hill, G.D., Raghavan, D., Wahby, R.S., Levis, P., Winstein, K., 2018. Pantheon: the training ground for internet congestion-control research. In: 2018 {USENIX} Annual Technical Conference ({USENIX} {ATC} 18). pp. 731–743.
- Yi, C., Cai, J., 2019. A truthful mechanism for scheduling delay-constrained wireless transmissions in IoT-based healthcare networks. *IEEE Trans. Wireless Commun.* 18 (2), 912–925. <http://dx.doi.org/10.1109/TWC.2018.2886255>.
- Yusoff, N., Zakaria, N., Sikora, A., Jubin, S.E., 2019. 6LoWPAN protocol in fixed environment: A performance assessment analysis. pp. 1142–1147. <http://dx.doi.org/10.1109/IDAACS.2019.8924283>.
- Yusoff, N.H.M., Zakaria, N.A., Sikora, A., Jubin Sebastian, E., 2020. HRPL protocol for 6LoWPAN smart home system: A performance assessment analysis. In: 2020 IEEE 5th International Symposium on Smart and Wireless Systems Within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems. IDAACS-SWS, pp. 1–5. <http://dx.doi.org/10.1109/IDAACS-SWS50031.2020.9297079>.
- Yuvaraj, N., Saravanan, G., 2021. Markov transition and smart cache congestion control for IoT enabled wireless mesh networks. *Peer Peer Netw. Appl.* 14, 58–68.
- Zeng, X., Garg, S., Strazdins, P., Jayaraman, P., Georgakopoulos, D., Ranjan, R., 2017. IOTSim: A simulator for analysing IoT applications. *J. Syst. Archit.* 72, 93–107.
- Zhang, Y., Liu, Y., Meng, Q., Ren, F., 2021. Congestion detection in lossless networks. In: Proceedings of the 2021 ACM SIGCOMM 2021 Conference. SIGCOMM '21, Association for Computing Machinery, New York, NY, USA, pp. 370–383. <http://dx.doi.org/10.1145/3452296.3472899>.
- Zheng, L., Ge, W., Liu, Z., Luo, P., 2015. Implementation of multiple border routers for 6LoWPAN with ContikiOS. p. 31 (6). <http://dx.doi.org/10.1049/cp.2015.0221>.
- Zhou, C., Zhao, J., Liu, H., 2019. Adaptive status report with congestion control in NB-IoT. In: 2019 Sixth International Conference on Internet of Things: Systems, Management and Security. IOTSMS, pp. 1–5. <http://dx.doi.org/10.1109/IOTSMS48152.2019.8939217>.
- Zhuo, S., Shokri-Ghadikolaei, H., Fischione, C., Wang, Z., 2019. Online congestion measurement and control in cognitive wireless sensor networks. *IEEE Access* 7, 137704–137719. <http://dx.doi.org/10.1109/ACCESS.2019.2943011>.



Anitha P. received the B.E degree in 2005 and the M.Tech degree in 2010 from Visvesvaraya Technological University. She has 16 years of teaching experience presently working in Department of Technical & Collegiate Education, Government of Karnataka. She is currently pursuing the Ph.D. degree in Computer Science with University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bangalore, India. Her current research interests include the Internet of Things, with a focus on Controlling the congestion in IoT networks, Sensor Networks, Data Science and Artificial Intelligence.



Dr. H.S. Vimala Professor and Chairperson, Department of Computer Science & Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, K.R.Circle, Bangalore. She has received Ph.D. in the area of Image Processing in Computer Science and Engineering. She has published 9 papers in International/National Journals, and Conferences. She is involved in research and teaching B.E, M.Tech and Ph.D. students of Computer Science and Engineering and she guided more than 150 research projects for UG/PG students. She has 35 years of teaching experience in Department of computer science and Engineering UVCE, K.R.Circle, Bangalore. Currently she is guiding 7 research scholars in UVCE. She is a co-author of 5 books and published one book. Her research areas are Image processing, Sensor Networks, Internet of Things.



Dr. Shreyas J. received the B.E degree in 2013 M.Tech degree from Visvesvaraya Technological University. He has received full time Ph.D. degree from Bangalore University in 2021. All the three degrees are in Computer Science and Engineering discipline. He has completed Ph.D. in the area of Internet of Things and Artificial Intelligence in the Department of Computer Science and Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bangalore. He is currently working as Assistant Professor, Dept. of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India. He is involved in research, and teaching B.E and M.Tech student of Computer Science and Engineering and has more than 5

years of teaching experience. He has published more than 50 papers in International Journals including Elsevier, Springer, Inderscience and International Conferences. He has received two best paper awards in Hong kong and Dubai each during International Conferences. He has more than 8 years of research, academia and industrial experience. He has worked as a reviewer for various reputed journals including IEEE, Elsevier, Springer, Johny Wiley, etc publishers and international conferences. He also served as Guest editor, editorial member, session chair, etc. for various journals and conferences. He has filed and published two patents. His current research lies in the area of Sensor Networks, Artificial Intelligence of Things, Swarm Intelligence and Machine Learning.