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5G network congestion issue & their challenges in wireless Communication network

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Abstract

The 5G network is a next-generation wireless form of communication and the latest mobile technology. In practice, 5G utilizes the Internet of Things (IoT) to work in high-traffic networks with multiple nodes/sensors in an attempt to transmit their packets to a destination simultaneously, which is a characteristic of IoT applications. Due to this, 5G offers vast bandwidth, low delay, and extremely high data transfer speed. Thus, 5G presents opportunities and motivations for utilizing next-generation protocols, especially the stream control transmission protocol (SCTP). However, the congestion control mechanisms of the conventional SCTP negatively influence overall performance. Moreover, existing mechanisms contribute to reduce 5G and IoT performance. This paper provides an inclusive and comprehensive analysis of recent developmental endeavors toward 5G. It highlights salient features, i.e., flexibility, accessibility, and cloud-based service offerings, those are going to ensure the futuristic mobile communication technology as the dominant protocol for global communication.

Keywords: *5th Generation, Energy-efficient, Key Performance Indices, Radio Access Network.*

1. Introduction:

Wireless sensor networks have played a crucial role in communication in the past few decades due to their unique features (e.g., mobility and ease of connection), which make them a major carrier of data across networks [1–3]. Consequently, the communication revolution embraces various standard wireless networks. Numerous types of wireless networks exist, and mobile wireless communication is one of the most widespread because it offers high data bandwidth. Mobile wireless communication utilizes a transport layer to transfer data and launches a specific protocol for data transmission. The transport layer protocol uses a congestion control mechanism to ensure good network resource allocation, and the network operates optimally even when demands reach the maximum network resources and size. One of the most critical events of the transport layer protocol is congestion control over wireless

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networks. If this event is used in a mobile wireless communication platform such as 5G, and does not satisfy the requirements of the platform, then the performance of the wireless network will deteriorate

Congestion control shortage is one of the main causes of the decrease in the lifetime and energy of wireless sensor network (WSN) nodes [4,5]. This decrease leads to many other issues, such as delay, packet loss, and bandwidth degradation [6]. Network resources include buffer size, queue size, throughput, link bandwidth, and packet loss of intercommunication between nodes [7]. Congestion control influences diverse applications, such as event-based, continuous sensing, query-driven, and hybrid applications [8]. Congestion control is applied in different protocols in the transport layer, such as the transmission control protocol (TCP) and stream control transmission protocol (SCTP) [9]. Many conditions, such as packet collisions, interference, channel contention, and buffer overflow, require congestion control [4], whereas slow links, buffer size shortage, and slow processors do not need congestion control [7].

The 5G environment is applied in many fields and utilized for many purposes, such as smart cities [21], e-Health [22], and environmental surveillance [23]. Many approaches have been applied to the 5G environment in order to enhance the network performance [24]. The machine learning approach is effective and widely applicable. Thus, it can be implemented with the conventional congestion control mechanism to satisfy the demands of 5G Internet of Things (IoT) nodes/sensors networks. The aim of applying the machine learning method to congestion control is to predict the optimal parametric setting and path to send/receive data. Finding the optimal node reduces data traffic and packet loss and improves throughput[38].

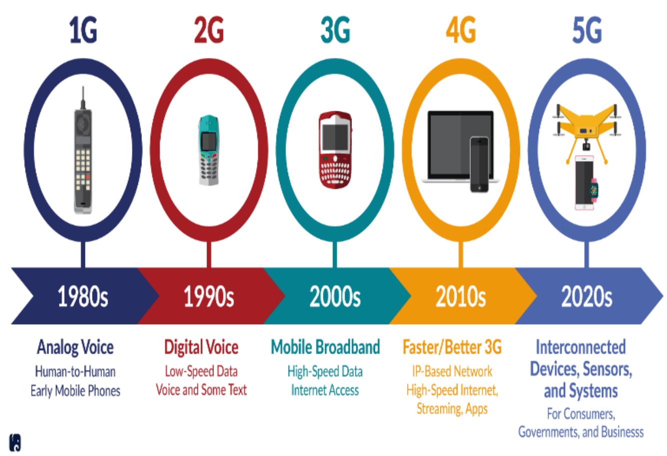

Figure 01: History Technology Generation

1.1 Difference between 5G & 4G

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Compared to third generation mobile networking, 4G enabled previously impossible quality video streaming and calling on the go, meaning live TV is now routinely watched on the daily commute. More video streaming, however, has increased congestion in the network.

"4G is reaching the technical limits of how much data it can quickly transfer across blocks of spectrum," explains Chris Mills head of industry analysis, at Tutela. "A major difference between 5G and 4G is this congestion will be eliminated." This mean no more five bars of networking signal at rush hour but an inability to access a web browser.

But arguably, 5G's biggest differentiator to 4G will be as a gateway for the Internet of Things-connected world at scale. Later iterations of 5G networking are expected to be revolutionary for data-driven industries, smart cities and infrastructure management because it will be possible to have many more devices working, reliably, securely and uninterrupted in the same area. Overall, due to the new technologies, spectrum and frequencies it uses, 5G has several benefits over 4G; higher speeds, less latency, capacity for a larger number of connected devices, less interference and better efficiency.

The rest of this paper is organized as follows. Section 2 presents related work on congestion control mechanisms, and studies regarding congestion control improvement. Section 3 Working of 5G network. Section 4 presents the conclusions and directions for future work.

2. Related Work:

Regarding the approaches to congestion control in WSN IoT highlighted by many studies, Sangeetha et al. [25] proposed a reduction of energy and data loss because of congestion across the network. Mainly, the topology of sensor nodes is attuned periodically at a regular time interval and node degree in order to improve the power consumption of sensor nodes, the interference, and provide an energy-efficient congestion-aware routing technique for WSNs—namely, survivable path routing (SPR). IoT applications use this protocol in networks with high traffic, since multiple sources are simultaneously trying to send their packets to a destination, as shown by Elappila et al. [26]. Singh et al. [27] developed a new congestion control algorithm for WSNs, where the conventional algorithms had high power usage and high complexity, and obtained the optimal rate by retransmission with congestion control, using a simple Poisson process. The routing protocol to select the optimized route proposed by Shelke et al. [28], based on opportunistic theory and by integrating suitable sleep scheduling mechanisms in order to decrease congestion in the network, increases individual node life, the entire network lifetime, and decreases division in the network. Godoy et al. [29] investigated and analyzed the environments that lead to congestion of the communication channel based on node configuration parameters: transmission time intervals, data packet generation rate, and transmitter output power level. The congestion control mechanism of the SCTP determines its performance in various environments. Many studies have

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mentioned that conventional SCTP congestion control algorithms over Long Term Evolution-Advanced (LTE-A) present poor performance in terms of various factors, such as congestion window size (cwnd), throughput (throu), and send/receive/lose packets. Thus, Najm et al. [30] proposed an improvement mechanism called IMP-SCTP for 4G networks based on multi-criteria decision making (MCDM). Meanwhile, Najm et al. [31] described the conventional SCTP congestion control mechanism over a high-bandwidth network such as 4G as having weak performance through a hands-on and systemic review related to SCTP congestion control. New techniques must be adopted to enhance the congestion control scheme. One of the most vital studies involved the improvement of the congestion control of TCP in wired/wireless networks by applying a supervised machine learning technique; the authors built an automatic loss classifier from a database obtained by simulations of random network topologies [32]. However, the simulation scenario was poor and simple. Furthermore, a fair and efficient distributed congestion control algorithm for tree-based communication in WSNs that seeks to adaptively assign a transmission rate to each node was developed as stated by Brahma et al. [33]. However, the validation process did not compare the proposed algorithm to a standard/traditional method or a related previous study. In research published by Jagannathan and Almeroth [34], the authors proposed a new model for multicast congestion control called TopoSense. However, a multicast sub-tree needed to be developed, and high congestion control at high rates was caused by dropping. Moreover, the link capacity calculation was poor, the interval size needed to be calculated, bursty traffic occurred, and control traffic needed to be minimized. Sunny et al. [5] proposed a generic controller that ensures the fair and efficient operation of Wireless Local Area Network (WLANs) with multiple co-channel access points, long-lived performance, TCP transfers in multi-AP WLAN, and improves performance issues of long-lived TCP transfers in multi-AP WLANs. Subsequently, many studies have adopted the DT concept in networks for various applications. For example, Katuwal et al. [35] proposed new multiple-classifier systems for multi-class classification problems. The proposed model is a combination of DTs (random forest and oblique random forest) with an efficient neural network (random vector functional link network). The result of model evaluation on 65 multi-class datasets was better than those on medium- and large-sized datasets. The model experiment on the multi-class datasets produced good results, and the model could perform similarly on large- and medium-sized datasets. The model considers the problem of multi-class classification and provides the same training datasets for two-class datasets. The result of the proposed ensemble of classifiers was better than those of other classifiers. Furthermore, Gómez et al. [36] compared the performance of various ensemble algorithms based on DT and presented a new classifier. The computational capacity of small network devices was not a crucial limitation. Hasan et al. [37] conducted a review of a machine-to-machine communication technology related to the system model architecture anticipated by diverse standards-developing organizations and prospective machine-to-

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machine communication challenges and their intended state-of-the-art solutions. Leng et al. [38] proposed a new system for solving the flow table congestion problem in a software-defined network (SDN) based on a DT algorithm (C4.5) [38]. C4.5 was used to compress the flow entries in the data flow table in order to reduce the flow matching cost and time. This machine-learning-based online process in the SDN that is the first model to utilize a DT with a flow table. Then, a new trend of localization based on adaptive cluster splitting and AP reselection was proposed; Liang et al. [39] presented a new fingerprint-based indoor wireless LAN that adopts adaptive cluster splitting and access point reflection. However, only received signal strength (RSS) RSS was considered for fingerprinting, a large area of wireless technologies was not applied, and many other factors were not considered (e.g., packet loss, information of channel state, queue size, throughput). Following this trend, research published by Liu and Wu [40] used the machine learning approach (random forest algorithm) to predict traffic congestion. Variables such as weather conditions, road quality, time period, and type of day were used to build the model. However, many other factors, such as time and type of day (holiday), influence traffic congestion, make the prediction easy, and eliminate the need for prediction.

Furthermore, Soltani and Mutka [44] used the DT approach to translate cognitive video routing in a dynamic radio network. Background induction was used from the ending branches to find the optimal path to the root node in order to receive and construct the sent video. Following the trend of using machine learning DT techniques, Adi et al. [45] built a model to prevent denial of service over the hypertext transfer protocol (HTTP2). SVM, DT, naïve Bayes, and JRip DT were used for feature selection to determine important factors that influence false alarms. Using machine learning, the results demonstrated that the model is better than other models. Stimpfling et al. [46] proposed a method based on the DT algorithm in order to overcome the drawback of memory access as well as the size of the data structure. DT is considered as the optimizing point in the model because it reduces the searching time. Furthermore, Singh et al. [47] presented a new model to predict the noise of vehicular traffic. Four methods were used to build the model: DT, neural network, random forest, and the generalized linear model. The authors found that the random forest DT approach produced better prediction results than the other methods. To improve decryption efficiency over vehicular ad-hoc networks, Xia et al. [48] proposed a delegation scheme (CP-ABE) based on DT. DT was used to optimize the joined factors utilized for estimating the overhead of vehicle decryption. The results showed that DT had higher accuracy and precision than SVM and K-nearest neighbor and was thus the best choice for prediction. The authors of the botnet attacker detector in SDNs [49] deployed a machine learning method regardless of the packet payload reading, but the stats plan required extensive computation. Wu et al. [50] presented a scalable machine learning (ML) approach that detects and predicts video freezes online by using features extracted from network-based monitoring data; the proposed scheme determines discriminative

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features based on multi-scale windows by using the criterion of information gain (IG), but requests of audio segments are ignored, user interactivity is restricted, the cache between the delivery nodes and the video player is ignored, and the segment length is fixed. Chen et al. [51] presented an online data model for traffic condition prediction that is based on online open data by using DT and SVM; however, the model selected to predict a 30 min traffic condition and the former two services exceeded the set value. Abar et al. [52] predicted the quality of experience based on full-reference parameters Structural Similarity Index (SSIM) and Video Quality Model. (VQM), but they did not explain why k = 9 in a random forest was the best [39].

Most of the previous studies frequently used decision tree machine learning to improve the network status without considering congestion control mechanisms over the recent environments (specifically the 5G IoT environment), even though DT presents a tree-based graph for prediction and classification. Therefore, DT should be developed for the prediction of the optimal congestion control mechanism among current congestion control transport protocol mechanisms in the 5G IoT environment. Despite these proposed methods, most studies only implemented machine learning capabilities in classifiers to improve network status without considering the current mechanisms required to adapt to new environments, such as advanced 4G and 5G, which could improve throughput and reduce end-to-end delay. Thus, 5G and the Internet of Things (IoT) represent a new era of applications and infrastructures that require the use of current mechanisms and protocols. Adapting to new environments is challenging in 5G, IoT, and current transport protocol mechanisms because transported protocols comprise the core of networks, which have unique characteristics compared with other protocols in mobile communication. The SCTP was introduced as the next-generation transport protocol to facilitate traffic in a way superior to conventional TCP and User Datagram Protocol (UDP). However, standard SCTP, TCP, and other transport protocols must be modified to suit the 5G environment. For these reasons, rapid response and reduced latency should be considered when improving a congestion control mechanism within 5G IoT networks. A demonstration of new approaches to overcome the limitation of current mechanisms should be considered to score the evaluation metrics of prediction and select the optimal techniques for congestion control as a means of achieving improved WSN performance in adjusting transport protocols for the improved support of 5G IoT environments [39].

3. Working of 5G network:

The introduction of 5G at scale will also see an increase in the number of devices on the network, which, by nature, will raise the level of congestion. However, it’s important to note that that the 5G released in 2020 will be significantly different than the broadband connection we will witness in 10 year’s time. As a result, although the number of devices will increase, so will the broadband service to

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accommodate said rise. In doing so, 5G will not only help in providing consistent broadband services across the day, but it will provide a 'blanket of capacity' wherein the daily issue of congestion will be elevated due to the high bandwidth and high-frequency spectrum bands. Additionally, it can help ease congestion in populated areas such as a stadium or even in rush hour in the city. As such, the mm Wave utilised on the 5G-only spectrum will be ideal for cities due to their short distance and high capacity. Moreover, later reiterations of 5G will allow for data-driven, data-consumed industries to nurture across the globe and all such devices to be working simultaneously, efficiently and uninterruptedly across the network.

Mass market adoption for 5G is expected to take place by 2022 with the APAC region pushing hard to implement the benefits. As such, being in the know is imperative not only as individual users but as organizations, as well. As a business, scaling in years to come means taking the lead with 5G. In order to take the lead in 5G deployment, partner with VIAVI, the driving force behind 5G since 2013. Our 5G test and verification solutions deliver essential visibility for 5G end-to-end programmable and dynamic networks. Test, enable and assure your business on 5G and optimize how you move forward with the experts in the industry [39].

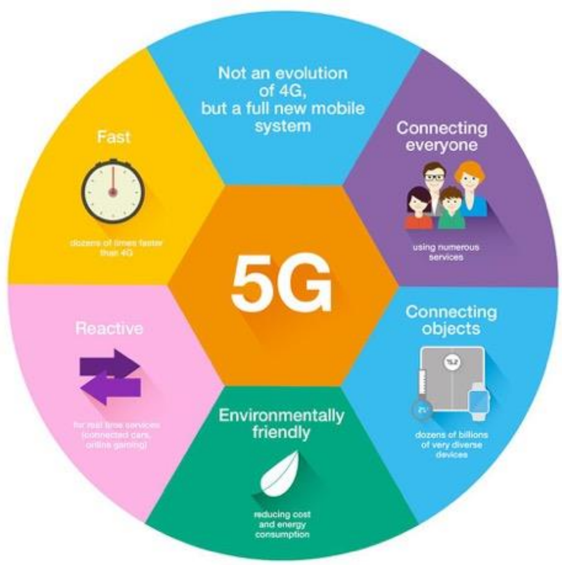

Figure 02: Working of 5G network

5G is a new digital system for transforming bytes - data units - over air. It uses a 5G New Radio interface, along with other new technologies, that utilises much higher radio frequencies (28 ghz compared to 700 mhz - 2500 mhz for 4G) to transfer exponentially more data over the air for faster speeds, reduced congestion and lower latency, which is the delay before a transfer of data begins following an instruction.

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This new interface, which uses millimetre wave spectrum, enables more devices to be used within the same geographic area; 4G can support about 4,000 devices per square kilometre, whereas 5G will support around one million. This means more Netflix streaming, voice calls and You Tube carried, without interruption, over the limited air space.

5G also uses a new digital technology called Massive MIMO, which stands for multiple input multiple output, that uses multiple targeted beams to spotlight and follow users around a cell site, improving coverage, speed and capacity. Current network technologies operate like floodlights, illuminating an area but with lots of wastage of the light/signal. Part of the roll-out of 5G involves installing Massive MIMO and 5G New Radio to all mobile network base stations on top of the existing 4G infrastructure.

3.1 How does 5G work in terms of bandwidth, latency and spectrum?

Each operator owns blocks of spectrum which is a range of electromagnetic radio frequencies used to transmit sound, data, and video across a country. This spectrum is added together to create their total network capacity which determines how fast they can transfer data.

“Today an operator might have 100 mhz of entire spectrum to use for all of its UK customers, but eventually with 5G this will increase to around 1,000 mhz - that is the real change with 5G,” explains Mr Mills.

This will also create much less latency in the system meaning data will be transferred in real time. Latency for 4G is around 20-30 milliseconds, but for 5G it will reach well below 10 milliseconds, and in best cases around 1 millisecond delays, according to Mats Norin, program manager at 5G For Industries, Ericsson Research.

	3G	4G	5G
Deployment	2004-05	2006-10	2020
Bandwidth	2mbps	200mbps	>1gbps
Latency	100-500 milliseconds	20-30 milliseconds	<10 milliseconds
Average Speed	144 kbps	25 mbps	200-400 mbps

Figure03: Comparison 3G vs 4G vs 5G in terms of Bandwidth, Speed & Latency

3.2 Security in 5G

Many of these use cases could benefit from network slicing - splitting of the network to tailor speed, capacity, coverage, encryption and security - which can be achieved much more easily with 5G.

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"Slicing offers manufacturers and others a dedicated network with which they can fully control and support their IoT solutions for reliable communications, with guaranteed quality of service and Cloud or Edge-based computation," says Dritan Kaleshi, head of Technology, 5G at Digital Catapult.

This can provide an additional element of security not afforded by WIFI, which is shared with others on the spectrum and is therefore more easily interfered with, and less easily achieved with 4G.

3.3 Futuristic scenarios and 5G compliance:

The society of 2020 will be a connected society. The IoT together with intelligent and integrated sensor systems and inhome sensor networks will change the way people lead their lives. "Smart living" people will require constant and ubiquitous mobile connectivity to the network to upload their activity data and IoT control commands, thus generating a "massive reporting" uplink data flow [2]. Massive machine to machine communication and critical machine to machine communication will play pivotal roles in service delivery and industry operations. Vehicular ad-hoc networks (VANETs) are constantly advancing. By 2020, VANETs integrated with cellular networks will be in operation as VANET cloud, leading to a smarter and safer transportation system [3]. When the number of devices connected to the Internet passes tens or hundreds of billions in the coming decade, the offloading of networked data on unlicensed bands will play a critical role in network load balancing, providing guaranteed bit rate services and a reduction in control signaling. Hence, it is important that 5G will provide seamless compatibility with dense heterogeneous networks to satisfy the high demand of real-time traffic, so that end users will experience smooth connectivity to the network [4].

4. Conclusion:

The current expectation and future evolution of the 5G is promising to enable new services and quality of experience (QOE) across the user community. As very challenging at the same time because of the resource constrained-nature of the network which has compelled research community to ensure that the requirements for massive deployment of MTC applications are achieved for globally connected things. So, this article provides a comprehensive review of some recent initiatives toward a green, flexible, and mostly dominant 5G mobile communication standard.

However, there still exists open research challenges for effective control and management of the IoT networks. For future evolution of the 5G, it is therefore recommended to develop a context-aware congestion control (CACC) scheme for controlling network issue.

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