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CONGESTION CONTROL FOR MMTC IN 5G CELLULAR IOT NETWORKS - A REVIEW OF REINFORCEMENT LEARNING AND NETWORK SLICING APPROACHES

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A B S T R A C T

Massive Machine Type Communications (mMTC) is one of 3 foundations of the Next Generation Networks (NGN). This inherent support that enables the Internet of Things (IoT) paradigm presents a significant challenge for cellular networks due to the sheer number of connected devices. MTC traffic is sporadic, and a simultaneous network access by these devices at time t0 can lead to a crippling congestion situation. The resultant service degradation cannot be tolerated in 5G network, which aims to provide ultra-reliable and low latency communications (URLLCs) and high Quality of Experience (QoE).

This paper reviews recent research efforts on addressing congestion management for mMTC in 5G Ultra- Dense Networks (UDN). Various approaches in literature are explored such as adaptive congestion control mechanisms, Reinforcement Learning, Resource Allocation Algorithms and data aggregation for mMTC traffic. The primary focus will be on Machine Learning Based solutions alongside network slicing.

This paper aims to provide a comprehensive overview of the diverse approaches to managing congestion in mMTC, synthesizing the literature and organizing them under key headings, identifying trends, open issues and future research directions.

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1. INTRODUCTION

Communication is essential for the transformation of the exabytes of generated data to be processed into valuable insights. It therefore becomes critical for the enablers of data communication meet the needs of the data-driven world.

1.1 Next Generation Networks

The Next Generation Networks mark a revolution in wire- less communication, starting with the 5th generation (5G) of cellular networks. 5G is built on 3 core pillars, these services namely: Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and Massive Machine Type Communications (mMTC). Consequently, 5G offers unmatched high-speed data trans- mission, low latency and massive device connectively as compared to its predecessors. It meets the needs of mod- ern applications such as Augmented Reality (AR), Virtual Reality (VR), 4K HD video streaming among others. The technologies that enable 5G are mmWave, massive MIMO, D2D communications and cognitive radio (Dogra et al., 2021).

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1.2 Machine Type Communication

Existing cellular networks have been primarily focused on Human Type Communication (HTC) and hence new techniques and design requirements are needed to adequately support Machine Type Communication. MMTC is concerned with networking for Machine to Machine Communication (M2M) - needing no human intervention (Sharma & Wang, 2020). The proliferation of the Internet of Things (IoT) Paradigm - where cities, vehicles, environment are all smart, and autonomously connected – mMTC finds its purpose in enabling this interconnection (Alsharif et al., 2024). MMTC is a core feature of NGNs, but there are supporting standards in existing cellular networks. These are Extended Coverage GSM (EC-GSM), the Narrow-Band IoT (NB-IoT), and the enhanced MTC (eMTC) (Narayanan et al., 2021).

1.3 Challenges

With connected IoT devices projected to grow to over 25 billion by 2030 (Gerodimos et al., 2023), the networks will be ultra-dense (UDNs) with over 1 million devices per km^2! (Dogra et al., 2021). With massive connectivity attendant technical challenges. The surge in data traffic puts a toll on massive IoTs which are resource-constrained; power, computation and storage. Much research is ongoing in edge and/or fog computing – offloading the computation from field devices to much powerful devices and servers situated at the edge (Dustdar & Murturi, 2020). There is scarcity of available bands on the radio spectrum for communication, but the MTCDs in need of connectivity keeps growing exponentially. In Ahmad et al. (2020), spectrum sharing via Cognitive Radio is explored as a promising solution. B5G networks propose using Optical Wireless Communication (OWC) as a remedy and also for all the high-speed benefits it comes with (Dogra et al., 2021). The most obvious challenge faced with regard to the volume of devices communication is congestion in the Radio Access Network (RAN). Managing this congestion therefore requires intelligent resource allocation strategies, efficient data aggregation techniques, and advanced access mechanisms. This paper will give an overview of the variety of approaches researchers are using to tackle the problem, with a particular focus on Reinforcement learning-based proposals and implementations that employ network slicing.

1.4 Related Works

The authors Sharma and Wang (2020) provide a comprehensive overview of mMTC in Ultra Dense Cellular IoT Networks. They explore quality of service (QoS) provisioning in UDNs and the associated challenges of the existing and emerging solutions that deal with the issues of congestion. They go on to provide a detailed overview of existing and emerging solutions to the RAN network, focusing on a low-complexity Q-learning approach for IoT. They also present a mathematical framework for performance analysis of Q-learning, citing a frame-based slotted ALOHA scheme.

In Salam et al. (2019), the authors provided a classification for various proposed solutions. In particular, data aggregation techniques for addressing the identified challenges, after having found insufficient content in literature regarding this technique.

The authors Abera et al. (2021) provided an extensive review of Reinforcement Learning approaches in Access Class Barring (ACB) scheme, one of several 3GPP schemes, classifying the solutions based on their characteristics.

1.5 Contribution

This paper seeks to explore Reinforcement learning approaches employed across the varying classes of solutions. This review will explore recent RL based additions to literature and seek to place them in their respective classes.

2. RAN CONGESTION SOLUTIONS

In this section, we explore classification of Random Access Techniques for addressing congestion in cellular networks.

2.1 Categorization

Third Generation Partnership Project (3GPP) has specified multiple candidate solutions for RACH congestion in cellular networks. These schemes are (i) Access Class Barring, (ii) MTC-Specific backoff, (iii) dynamic resource allocation, (iv) Slotted random access, (v) separate RA resources and (vi) pull-based/Paging-based (Sharma & Wang, 2020).

Additional schemes are presented in [2], these are (i) Group-based RA Scheme, (ii) Code-Expanded RA Scheme and (iii) Tree-based RA scheme. The authors in Ahmad et al. (2020) identified 3 emerging solutions as (i) Machine Learning-Based Techniques, (ii) Distributed Queueing, and (iii) SDN and Virtualization.

Authors in (Salam et al., 2019) had a different classification of solutions based on the access mechanisms. These include the (i) 3GPP set of schemes, (ii) MTC Clustering, (iii) Cloud-based MTC and (iv) Data aggregation.

3. REINFORCEMENT LEARNING SOLUTIONS

Machine Learning (ML) is transforming every industry, cellular communications inclusive. With an Intelligent Agent able to make optimal decisions based on model, or detection of patterns in its environment, ML enables accomplishments that will be otherwise impossible to attempt manually. ML techniques can, and is being used to address the growing complexities in each successive generation of cellular net- works. In fact, B5G networks will have Artificial Intelligence has a core aspect of the technology (Dogra et al., 2021).

3.1 Reinforcement Learning

Reinforcement Learning is of three categories under Machine Learning, the other two being Supervised and Unsupervised learning. RL is especially suited for the dynamic wireless IoT/mMTC environments for reasons: (i) the agent interacts with its environments and learns from experience based on an action-reward feedback loop, consequently (ii) does not require labelled training data set to function and (iii) can be operated in a distributed manner (Sharma & Wang, 2020). The reinforcement learning system is shown in Figure 1.

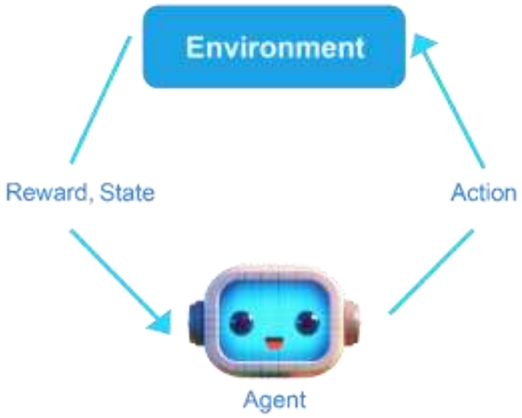

Figure 1. Reinforcement Learning diagram

Recent works employing Reinforcement Learning techniques are analyzed in this section.

It will be observed that majority of the papers explored in here employ Queue-Learning (Q-learning), which is one of the RL techniques. The reason for this trend is that Q-learning is not so demanding on computational resources and its easily implemented in a distributed fashion, making it suitable for resource-constrained IoT devices (Sharma & Wang, 2020). Variants of Q-Learning have been used in the literature reviewed, these are (i) Collaborative Q-Learning, (ii) Situation-Aware Adaptive Q-Learning, (iii) Fuzzy-Logic Based Adaptive Q-Learning and (iii) Model-Based Q-Learning.

To cater for MTCDs with varying QoS requesting access, the authors in Gao et al. (2023), propose a back-off based scheme based on Deep Reinforcement Learning (DRL). The authors had identified that this consideration of QoS requirements were insufficient in the literature reviewed. Here, the MTCDs are grouped into virtual small cells and their services into four categories based on QoS requirements. This is done by the system model upon which the QoS objection is generated for each group. The Actor-Critic algorithm then designs a back-off access strategy for each group, maximizing each QoS utility. For this algorithm, the state transfer was modelled as a Markov Decision Process (MDP).

In the establishing of connection between the User Equipment (UE) and Base Station (BS), termed the random access procedure, the predefined backoff indicator is responsible for determining the random wait time for retransmission. In a massive access scenario, collisions and congestion are inevitable due the fixed backoff indicator.

The authors in Kim et al. (2023), proposed using and Intelligent agent to automatically adjusts this value based on the state of the network. Two RL algorithms were employed, Q-learning and Deep Deterministic Policy Gradient (DDPG) – a variant of the model-free actor-critic algorithm as seen in Gao et al. (2023). The performance analysis of these algorithms had DDPG ahead of Q-learning, in success rate and rewards metric.

In contrast to (Salam et al., 2019), the authors in Orim et al. (2023) argued standalone Data Aggregation solutions increase latency. Identifying the insufficiency of 3GPP's ACB techniques, the authors proposed combining RL with Data aggregation to resolve congestion. A similar approach to Gao et al. (2023) is used, in that MTCDs of different services (representative of their QoS; critical MTCDs and delay-tolerant MTCDs) are clustered and access requests aggregated. The network model consists of critical (cMTCDs) and delay-tolerant (dMTCDs), a single eNodeB and cluster heads (CHd). cMTCDs access the eNB directly while dMTCDs access requests are aggregated by the cluster heads. The Q-learning data aggregation scheme (QDAS) algorithm defined as an MDP, is implemented on the cluster heads requesting eNB access. It is observed that the QoS requirements of the cMTCDs are met, with high throughput for dMTCDs. This proposed scheme outperformed 3GPP ACB scheme while meeting energy constraints in addition.

The authors in Chowdhury and De (2021) proposed delay-aware priority access classification (DPAC), to dynamically prioritize cMTCDs based on the packet delay due to ACB. DPAC is a modification of the ACB, which is one of the most effective 3GPP techniques. Starting off with Q-Learning and upgrading to a fine-tuned Deep Q Network (DQN), the proposed framework outperformed the conventional ACB and other schemes in both homogenous and heterogenous traffic scenarios.

In (Jadoon et al., 2022), the authors propose a multi-agent DRL for a slotted ALOHA RA system. In particular, they define a novel performance metric to measure fairness termed Age of Packet (AoP). This was deemed necessary as the non-symmetric Exponential Backoff transmission strategies expressed in literature suffered from a condition known as the capture effect – this is where one node hogs the channel and worsen the delay status of the remaining nodes. Simulation results proved this solution to be effective than the baseline Exponential Backoff schemes, however the authors acknowledged the need to scale for a larger number of users.

3.2 Network Slicing

Network slicing is an architecture enabling multiple virtual and logical networks on the same single physical network infrastructure (Xing et al., 2023). Network slicing is technology is enabled by Software Defined Networking (SDN) and Network Function Virtualization (NFV) (Yang et al., 2022). Technology. Each slice is independent, scalable and providing customized services.

This dynamic approach, paired with RL can deliver effective management of massive access.

The authors in Orim and Mwangama (2024) proposed a network-slicing random access scheme (NSRAS) that combines network slicing with Q-learning during the Random Access procedure. In this approach, cMTCDs and dMTCDs are put in slices. The Q-learning orchestrator algorithm, implemented on the BS, dynamically varies the number of slices and assigning MTCDs to them based on the state of the network. By using power ramping in the physical layer, the BS is able to prioritize cMTCDs while keeping the collision proportion of the dMTCDs minimum.

By enhancing the isolation of network slices, the access success rate increases. The authors in Xing et al. (2023) presented, a hierarchical RL mechanism to do this. Q-learning algorithm is distributed on the MTCDs to subsequently obtain a unique preamble for each upon convergence. Deep Q-Learning is implemented on the BS to optimally apportion the preamble resource pool. By working cooperatively, the Distributed algorithm and centralized algorithm were seen to improve access success rate as the preamble collisions reduced due to learning.

Taking full advantage of the flexibility and features of SDN/NFV, the authors in Yang et al. (2022) proposed a QoS-aware dynamic resource allocation strategy for each mMTC network slice. Modelling the resource allocation process as an MDP, the authors employ the Actor-Critic algorithm to solve. The performance analysis showed the Actor-Critic algorithm having better convergence, surpassing the greedy algorithm and the random access scheme. This is presented as a viable solution for NGNs.

In Chen et al. (2020), the authors propose an SDN-Based Adaptive Transmission Protocol for Time-Critical Services (SDATP) to realize superior End-to-End performance for mMTC network slices. It features in-path packet caching and retransmission, which reduce retransmission delays in case of a loss, the cache saving the sender node this work. These functions are activated on both the sending and receiving edge switches. A heuristic algorithm is applied to determine optimal caching; node placement, probabilities and number of such nodes. It also features link congestion detection and control. Caching-to-Caching congestion control is used between two edge switches, these use the SDATP proposed data formats while TCP congestion control is used between end host and an edge switch. Massive Industrial IoT (IIoT) was used as a case study and simulation results proved SDATP to be very effective.

4. CONCLUSION

This paper has given an overview of 5G Cellular Network and the core mMTC service, an enabler of the Internet of Everything. It has highlighted the associated challenges, particularly congestion in simultaneous massive Radio Network access. Several approaches to handling congestion have been explored such as varying backoff parameters, prioritizing time-critical devices and caching.

Recent research outputs in addressing these challenges in mMTC are increasingly employing Reinforcement Learning as the benefits are tremendous. The critical issue then becomes selecting the right algorithm and fine-tuning it for optimum performance to match the dynamic real-world network environment, outside of simulation software. It has been observed that ACB based solutions abound in literature, as it is one of the best techniques in managing congestion. Future research works must explore the potential of the other candidate schemes proposed by 3GPP. More research must also tend towards congestion management in 5G employing advanced access techniques such as SCMA, NOMA. The use of network slices to provide high throughput is quite promising and needs more research.

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