ISSN: 0974-5823 Vol. 7 No. 5 May, 2022

International Journal of Mechanical Engineering

ANALYSIS OF VARIOUS AI BASED ALGORITHMS AND LEARNING PERSPECTIVE FOR 5G WIRELESS NETWORKS.

Snehasis Dey

Research Scholar,Sri Satya Sai University of Technology and Medical Sciences,M.P,India,

Dr.Prabodh Khampariya

Research Guide,Sri Satya Sai University of Technology and Medical Sciences,M.P,India,

Dr.Manish Jain

Research Coguide,Mandsaur University,Mandsaur,M.P.India

ABSTRACT – The deployment of 5G wireless communication system creates huge research opportunity in recent times. With new scenarios, new technologies, and new network architectures, the traffic management for 5G networks will present significant technical challenges as well as shows vast research gap between the previous and current technologies. In recent years, AI technologies, more specifically ML technologies, have demonstrated significant success in many application domains, suggesting their potential solution to help or solve the problem of 5G wireless communication traffic management. Here, we investigate the new characteristics of 5G wireless network traffic and discuss challenges present for 5G traffic management. Potential solutions and research directions for the management of recent wireless communication specifically 5G traffic, including distributed and lightweight ML algorithms and a novel AI driven content retrieval algorithm framework, are discussed and demonstrated.

KEYWORDS- Artificial Intelligence, ML,Neural Network, Traffic, Supervised Learning.

INTRODUCTION

Fifth generation (5G) wireless communication networks are reaching toward the final deployment and realization.5G is promised to offer ultra-fast and reliable wireless links. The deployment of 5G will drive the global mobile data traffic to 100 Exabytes per month by 2023 from 31.6 billion mobile devices, which is approximately nearly about double the current level [1]. In future 5G networks, the system complexity in terms of network architecture and wireless connection will increase substantially. On the other hand, the average accessible resource for each user/device will be rather limited. Consequently the explosive increase in data volume and user devices will bring significant challenges to the management and optimization of network traffic. Current research on 5G network traffic management has already driven conventional approaches purely based on communication theory to the limit. It will be extremely challenging to solve the traffic management problem for 5G networks and to achieve global optimal performance for the whole network. This suggests the need to adopt revolutionary solutions. A promising direction to tackle the challenges described above is to adapt artificial intelligence (AI) technologies to analyze and manage the traffic of 5G networks from network data [3]. AI technologies will not only reduce manual interventions in network traffic management, but also enable better network performance, better reliability, and more adaptive systems by drawing new insights from the networks and predicting the network traffic conditions and the users' behavior, enabling smarter decisions in an autonomous fashion. Machine learning (ML) and deep learning (DL) are two advanced AI methodologies that have attracted lots of interest to overcome the challenges of managing 5G network traffic [4–6]. However, existing research has highlighted the following limitations: Most existing reported research has only focused on the core network, and applied ML to solve the routing problem in the core network; there is little research on traffic control with respect to the 5G network. • For traffic control, to date most reported research has only focused on the network layer; there are only a few research reports on the application of AI technologies to the application layer and the semantic layer that shape the traffic by content recommendation with consideration of user interests. In this article, we investigate the new features and challenges in 5G wireless traffic caused by new scenarios, network architectures, and new service demands. Based on these analyses, we propose potential solutions and research directions based on the use of AI technologies in 5G networks. The remainder of this article is organized as follows. The next section introduces potential challenges in future 5G networks. Then we introduce deep-reinforcement learning and distributed and light-weight ML algorithms for 5G network traffic control. An AI assistant traffic shaping algorithm is then highlighted. Finally, conclusions are drawn in the final section.

New Features and Challenges of Network Traffic in 5G Wireless Networks

Defined by the International Telecommunication Union (ITU), future 5G systems will have three major scenarios. The first is enhanced Mobile BroadBand (eMBB), which targets extremely high data rate to fulfill the high-speed data access requirement of emerging services such as 3D and Ultra-High-Definition (UHD) video transmission, and Virtual Reality (VR) applications. The second is massive Machine Type Communications (mMTC), which aims to provide high connection density (up to 200,000 devices/km2) and low data rate (1 to 100 kb/s per device) at low power consumption (up to 15 years battery life) to fulfill requirements of sensor networks used for smart city, the Internet of Things (IoT), and wearable device networks. Third, the Ultra-Reliable Low-Latency Communication (URLLC) scenario aims to provide extremely high reliability (99.999 percent) and low latency (< 1ms) wireless services used for control networks such as smart meters, high-speed train control, transport safety control, remote medical surgery services, and industrial robotic control. For these three scenarios, due to their different service foci, their data traffic characteristics are significantly different. For the eMBB scenario, in order to achieve an extremely high data rate for each user, the package size will be large, and most data will be transmitted in the downlink direction. For the mMTC scenario, most data will be transmitted in the uplink direction. Due to the high density of low-data-rate devices, the traffic of the mMTC scenario is largely discrete. For the URLLC scenario, in order to fulfill the requirements of low delay and high reliability, the data package size will be small, the Transmission Time Interval (TTI) will be short, and a short frame structure with Hybrid Automatic Repeat request (HARQ) will be used. Due to the more frequent feedback required to guarantee delivery success, lots of traffic will occur in the uplink direction, which makes the traffic of the URLLC scenario likely to appear balanced between the downlink and uplink directions. In Table 1, we summarize the system performance requirements and traffic features of the three major 5G scenarios. In the core network, all of the above types of data will be mixed. Due to the inherent traffic features of these three major 5G scenarios, which are significantly different, the traffic will be very dynamic and unpredictable. It is hard to predict traffic conditions and optimize using conventional traffic control methods, even with the assistance of some existing model-driven ML methods.

New Features and Challenges of 5G Traffic c Caused by New Network Structures

In future 5G networks, software-defined networking (SDN) is a key technology. By using SDN, the control and data planes can be naturally isolated, so the network management can be achieved through software-based application program interfaces rather than relying on hardware-dependent configurations. It can minimize hardware constraints, support speedy service provisioning, and promise network flexibility. A benefit arising from deployment of SDN is that network slicing will be deployed for 5G networks, enabling support of multiple virtual network functions running on a unified infrastructure. In the final deployed 5G network, eMBB, URLLC, and mMTC services will be independently operated on a unified physical infrastructure. However, due to the different performance requirements, there are significant differences in the network slicing requirements.

eMBB	Peak data rate: DL: 20 Gb/s, UL: 10 Gb/s User experienced data rate: DL: 100 Mb/s, UL: 50 Mb/s (dense urban) Area traffic capacity: DL: 10 Mb/s/m2 Latency: 4 ms	High data rate every user; downlink-dominated transmissions traffic; big data package transmission
URLLC	Latency: 1 ms Reliability:99.999 percent	Strict requirements on latency and reliability; frequently short path, small package transmission
mMTC	Connection density: 1 million devices/km2	Low data rate every user; high connection density; uplink-dominated transmissions

Table 1:System requirements in 5G

In order to provide high-speed large-volume data access to users, and to relieve the pressure on backbone networks, eMBB slicingtends to bring the data closer to users. It generates significant requirements for the resources to deploy caching in the mobile cloud engine of the local Data Centers (DCs). Thus, for the Embb scenario, the pressure of traffic will mainly occur in the downlink direction between the local DC and the User Equipment (UE). For URLLC slicing, as it has strict requirements on latency and reliability, its processing function units must be deployed as close as possible to the UE. A possible solution is that the data processing units in the mobile cloud engine in the central office DC are allocated to support highly frequent small packet transmission over a short distance. As a result, the traffic pressure of URLLC slicing will mainly occur between the central office DC and the UE. For mMTC slicing, there will be a smaller amount of network data interaction for each UE. However, due to the high connection density, its main traffic will occur in the uplink direction of the radio access network. All the data will be combined in the local DC and transmitted to the IoT server in the regional DC through the core network. If we consider the large volume of IoT data, the link between the local DC and regional may also bring some challenges. In Fig.1, the network structure of the 5G network is shown. Based on these statements, we can predict the following two challenges for network traffic management caused by new network structures of 5G networks:

• The 5G wireless network will be a heterogeneous network. The coexistence of different networks and the mixture of their traffic data with significantly different characteristics make the prediction, management, and optimization of network traffic a difficult task.

• As SDN technology will be used in 5G networks, and its features of Network Functions Virtualization (NFV) and network slicing will be deployed, all services will be independently operated on a unified physical infrastructure. However, as all traffic will finally be mixed together, and the traffic features of different scenarios are significantly different, the mixture of all these networks' traffic will make the network unpredictable.

Machine Learning for 5G Network Traffic Control

The new scenarios and features of 5G network traffic detailed above raise a series of challenges for conventional traffic control strategies. To overcome these challenges, a large number of sophisticated decision making and inference processes are required to adaptively allocate/manage network resources, smartly schedule/choose routing

strategies, and promptly predict traffic condition for 5G networks. ML, and particularly recent advances in DL, offer promise in tackling these problems. In this section, we discuss 5G network traffic control from the perspective of three types of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning (RL). Since there are some surveys on supervised and unsupervised learning in existence [3], we focus on RL.

A Supervised Learning Perspective

Supervised learning [8] relies on a set of training samples labeled by a knowledgeable external supervisor (human or automatic) to train a model (Fig. 2a). The training data defines a mapping between the inputs and the desired labels for classification or regression problems. The model is then expected to infer in a reasonable fashion for new input examples. Applications of supervised learning applied to network management have been reported for selecting the network routing path, predicting traffic volume, and so on. Recently, DL (e.g., in convolutional neural networks) has also been shown to be more effective in network traffic management than traditional routing methods. However, supervised learning is usually expensive and labor- and data-intensive in the connotation of

large-scale training data for vast, heterogeneous 5G networks. For some traffic control problems, it is challenging to employ supervised learning since it is not always possible to find global optima for data annotation. Therefore, it would be more appealing to learn without the need for explicit labeling.

An Unsupervised Learning Perspective

Unsupervised learning aims to find and understand data structure automatically without external supervision. Figure 2b illustrates its use for a clustering problem. It has been widely used to reduce data complexity, model data distribution, detect network anomalies, and so on. Unsupervised learning for 5G network traffic control can facilitate probability modeling of the traffic pattern, congestion, and traffic conditions in the eMBB, mMTC, and URLLC scenarios. Therefore, enabling better forecasting of the status of network traffic, and also the network scheduling and configuration can be pre-set and adapted to network traffic and topology changes.

A Reinforcement Learning Perspective

RL [9] enables an agent to automatically learn an optimal decision by continuously interacting with its environment and maximizing its cumulative reward. Combined with DL, it can be a general- purpose framework tackling problems that were previously intractable, especially in complex settings with high-dimensional state and action

spaces. This new paradigm, termed deep reinforcement learning (DRL), has been demonstrated to build Alpha Go, which defeated a world champion at the game of Go. It offers significant potential to deliver intelligent traffic control systems for heterogeneous, ultra-dense 5G networks with highly dynamic topologies[10].

In general, DRL contains three major elements:

- A policy function, which defines the agent's behavior
- A value function, which evaluates how good each state and/or action is
- A model of the environment, which represents an agent's learned knowledge of the environment

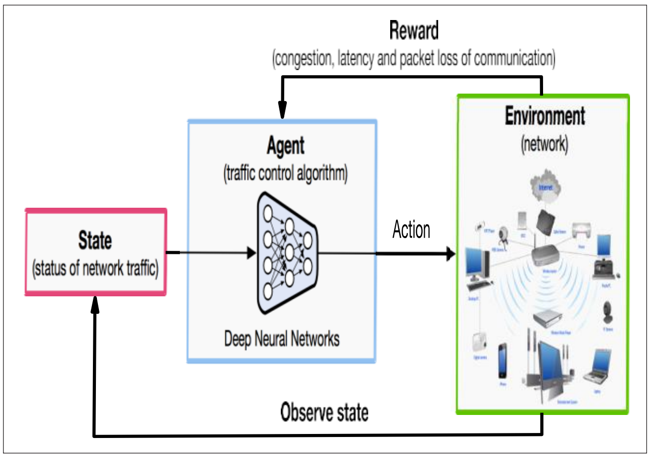

Fig.1 :Traffic control algorithm

As shown in Fig.1 above, in the context of network traffic control, an agent as the traffic control algorithm learns from direct interactions with its environment representing the 5G network. The agent senses the state of the environment to some degree and takes actions (e.g., selecting the routing protocols) that affect the state. By interacting with the environment and discovering which actions yield the greatest reward, the agent gradually learns the optimal policies. The reward can be determined through management of communication congestion, latency, packet loss, and so on. One typical DRL algorithm is Deep Q-Networks (DQN), which represents the value function with a deep neural network. Note that RL is different from supervised learning, which is not concerned with interaction and reward. It is also different from unsupervised learning, which usually focuses on how to discover hidden structure of unlabeled data. Based on this DRL architecture, adaptive and intelligent network traffic control algorithms can be developed. The agent learns how to deliver a package to its destination as quickly and robustly as possible by reducing the latency and network congestion. Since no labeled data is needed, this algorithm can learn adaptive strategies automatically. More importantly, it enables lifelong learning capability for the traffic control system. Specifically, when excessive traffic delay and heavy congestion degrade the network performance, conventional traffic control systems cannot learn from the experience or understand the situation for the future. In contrast, DRL-based methods can learn routing information and traffic patterns from this experience and successfully manage the massive network traffic when this situation occurs next time. This means DRL-based traffic control systems can evolve their performance continually over time and eventually be adequate in various scenarios. Existing work has shown the effectiveness of RL based traffic control and routing of wireless sensor networks. However, to the best of our knowledge, there is no work on 5G network traffic control based on DRL.

Dataset and Training for Machine Learning Models in 5G Networks

Data is essential to train ML models. However, in contrast to fields (e.g., computer vision) where ML techniques have been widely adopted, the wireless communication community has limited access to large-scale datasets for the design of ML models. This has hindered the development and application of ML models in wireless communication.

Dataset: There are several possible means to generate datasets for 5G networks. For supervised learning, simulation is a low-cost option with ground truth being directly available for many traffic control applications. However, the generalization ability needs to be carefully evaluated when deploying the trained models in reality since the 5G networks and their scenarios are too complex to accurately simulate. Alternatively, the training labels can be generated from traditional methods, and a self-supervised learning mechanism can be utilized. However, the quality of the training data is highly dependent on the performance of the traditional methods used to generate labels. Besides, for traffic control and management in 5G wireless networks, there are still many open challenges with no effective solution in existence. In contrast, RL is more appealing as it does not need labels for training. It can be simply trained with rewards that are determined by the requirements on traffic control. More importantly, the data collection and model training can take place online with lifelong learning through continuously interacting with the environments. This is one of the big advantages of RL for 5G networks.

Training: The training of ML models for 5G networks can vary greatly, according to where the trained model is to be deployed and which type of ML algorithm is used. The training can be carried out on high-performance computing (HPC) clusters, network embedded systems (e.g., end-user devices), and cloud computing servers. For supervised learning, models are usually trained offline with a prepared dataset on HPC and deployed later in the 5G networks. Depending on where they are going to be hosted, some parts of the 5G networks may have to be temporarily out of service for model testing and deployment. RL training does not have this problem since it runs and interacts, simultaneously with the services of the 5G networks. Therefore, the training procedure needs to be inherent in the 5G networks. More importantly, the performance of RL improves over time while consistently exploring its optimal policies.

Distributed and Lightweight ML Algorithms for Optimizing Traffic in 5G mMTC and ULLRC Scenarios

Existing ML algorithms mainly focus on computer vision, natural language processing, and robotics with powerful Graphics Processing Unit (GPU) or Central Processing Unit (CPU) enabled computing to operate in real time. However, communication systems are full of resource-constrained devices (e.g., embedded and IoT systems), especially in the mMTC scenario. Therefore, the AI algorithms for communication networks should not only learn complex statistical models that underlie networks, consumers, and devices, but also effectively work with embedded devices having limited storage capabilities, computational power, and energy resources. It is challenging but highly rewarding to develop lightweight ML algorithms, especially DL models, for embedded systems.

In current applications, AI algorithms are typically executed centrally in one single node (in a centralized location) with full access to the global dataset and a massive amount of storage and computing. In the 5G mMTC scenario, as millions of devices will be connected in high density, it is impossible to transfer all data from every single terminal to a center. Also for the URLLC scenario, due to its requirement for high reliability and low latency, data should be processed as close to the user as possible. However, due to the limited computing capability of IoT devices, it is impossible to run conventional centralized ML algorithms in one single device. Currently, the following existing technologies have been studied to enable the development of distributed and lightweight ML algorithms for wireless communications:

• Advanced parallel computing for mobile devices, such as the Tegra GPU device from Nvidia

• Novel distributed computing schemes, such as fog computing and edge computing

• High-level deep learning development library and toolbox for embedded devices, such as Tensor Flow Lite

• Emerging distributed ML frameworks such as the geo-distributed ML system (Gaia) [11]

In Fig.2 below, a potential deployment scheme of distributed and lightweight ML algorithms for 5G wireless networks is shown. In this framework. cloud computing, fog computing, and edge computing have all been considered. In the cloud server, as it has more computation capability, complex centralized large-scale ML algorithms will be run. In the fog computing node, as its computing capability is limited, lightweight ML algorithms will be run. As for the edge computing node, due to its extremely limited computing capability and power constraint, it is impossible for a single node to run the entire ML algorithm; thus, distributed lightweight algorithms will be run here.

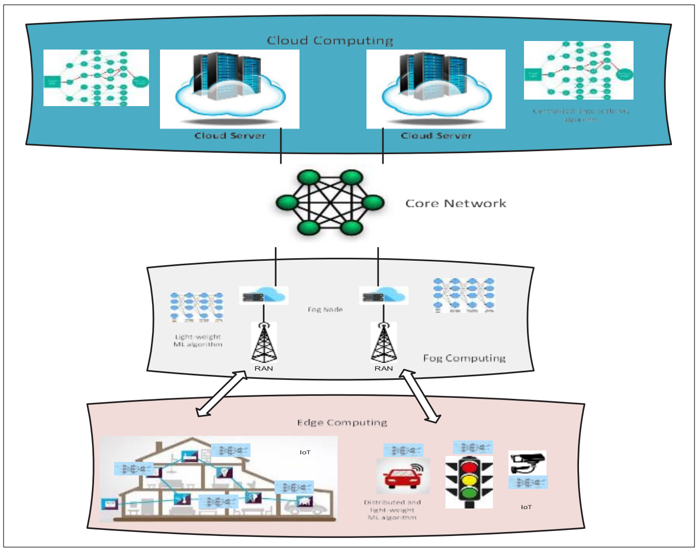

Fig.2 : Distributed and lightweight ML algorithms in 5G

AI Assistant Content Caching, Recommendation, and Delivery Algorithms for Traffic Shaping in 5G Networks

In general, a personalized content retrieval service has two basic tasks: content recommendation and

content delivery. The first task is to predict the interest of the user based on contextual information such as the user’s historical preference, social relationships, and location,, and recommend content in which the user might be interested. The second task is to deliver the contents to users with Quality of Service (QoS) guarantee. Based on this statement, we can find the user’s Quality of Experience (QoE) of a personalized content retrieval service, which is determined by two parts:

• Whether the content recommendation is accurate and able to catch the interest of the user

• Whether the process of accessing recommended contents is convenient and smooth Recently, some researchers have used AI technologies to improve the performance of content retrieval service systems. Most work is focused on using AI technology in the semantic layer to improve the accuracy of content recommendation [12]. For the content delivery task, most existing papers have considered it as a communication issue and separated it from the recommendation task. However, it has been proved that joint optimization over recommendation and transmission will bring greater improvement to the QoE [13]. In this condition, aside from the accuracy, the data access experience will be considered as an issue for content recommendation.

In good traffic conditions, content in the format of large-volume transmit data such as UHD video will be recommended to the user, while in the congested traffic situation, content in the most appropriate format would be recommended. Previous research has mostly focused on a single user’s QoE in existing wireless networks. In 5G networks, in addition to the user’s QoE, the efficiency of data access also needs to be considered as it has significant influence on the traffic feature of the whole network. Here, we propose a content ML assistant recommendation algorithm framework in 5G networks to optimize the data transmission efficiency and shape the data traffic from the application layer.

AI assistant content retrieval algorithm framework:

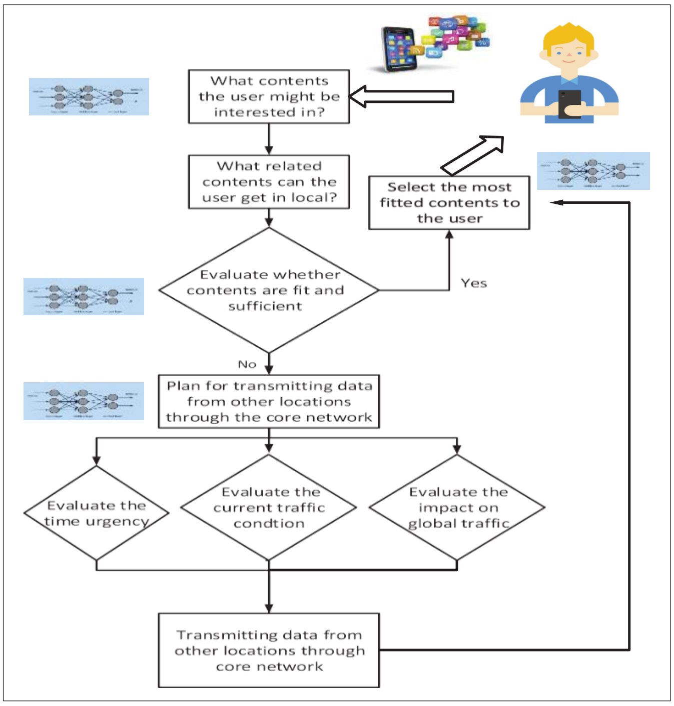

Figure 3. AI assistant content retrieval algorithm framework.

In the 5G network, especially for the eMBB scenario, data will be brought closer to the user.

Hence, in content retrieval, most recommended content will be stored in the cache of a mobile cloud engine at a local DC. The basic principle of this algorithm is to try to use as much local data as possible. If more data need to be transmitted from another location through the core network, its requirement in time and the current traffic will first be reviewed. The procedure of the algorithm is shown in Fig 5. First, the requirement for content potentially interesting to a user is obtained from the semantic layer. Then the local controller will check what local content is valid, and evaluate whether this content is sufficient. If it is, the controller will select the most relevant content with high quality and recommend it to the user. It is necessary to note that the controller can use all local non-confidential data to serve its different users. If more data should be transmitted from another DC, the controller will first check the current traffic status of the network and the urgency of transmission, and then decide the time slot and the format of contents to be transmitted. In this scheme, ML algorithms will be used for user requirement analysis, content recommendation, making a data transmit decision, and traffic prediction. By using this algorithm scheme, on the basis of guaranteed user's QoE, we can provide novel traffic optimization through the traffic shaping feature of AI assistant content retrieval service.

5G based applications using Neural network:

5G wireless communication will prove to be an important solution for smart cities that require large MIMO antennas, device densities, extreme node density, great bandwidth and high carrier frequency. Some of the widest areas in which 5G finds its applications are massive machine type communications, ultra reliable low latency communications and enhanced wireless mobile broadband. Moreover, 5G will prove to be very beneficial by connecting the spectrum and air interface of 5G with Wi-Fi and LTE, enabling cost-efficient, easily-available, scalable, reliable and global connectivity solutions providing seamless user experience and high coverage. These vital characteristics of 5G have driven the internet towards expanding into smart cities. However, when using in smart cities, there are some extra features that need to be involved in it such as an improvement in the Quality of Service, low latency and high data rate.5G wireless communication will find its place in a number of applications such as cloud service providers and tenants, infrastructure, mobile network operators and various other stakeholders. The interconnection of standalone IoT systems using the 5G networks or internet will lead to a number of cyber security challenges, resulting in exposure of sensitive information [10]. As the use of 5G increases, mobile-edge computing and fog computing will play a crucial role in self network management, data analytics and decentralized applications [11]. Hence deep learning techniques are introduced as a solution for cyber security issues in 5G to trace network anomalies. In Intrusion Detection system and Web security domain, a mobile cloud computing based wireless network that uses 5G to mitigate threats are commonly implemented [12].

A Random Neural network [13][14] is made up of n-neurons and each network of the neuron at a particular time 't' can be denoted as the equation below:

$$(t) = [k_1(t), k_2(t), \ldots \ldots \ldots, k_i(t)]$$

where $k_i(t)$ denotes the neuron potential in a given time t. Using the spikes in terms of amplitude, the neurons communicate with each other. The following are the representation of the different spikes transmitted:

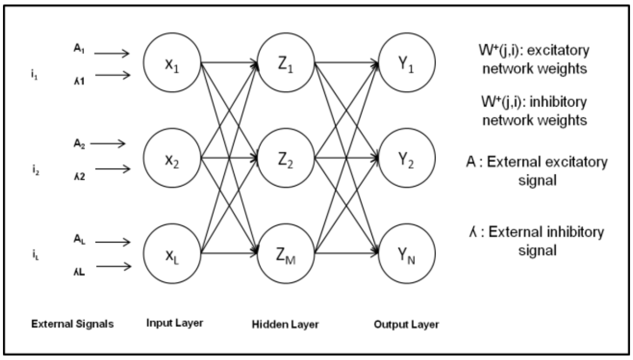

Fig4: A Random Neural Network for 5G communication

- When a negative spike occurs, it is detected as an inhibition signal which causes a fall of the neuron potential by one unit, $k_n(t^+) = k_m(t) - 1$
- When a positive spike occurs, it is detected as an excitation signal and will cause the neuron potential to increase by a unit, $k(t^+) = k_m(t) + 1$ where the receiving neural is m and $k_m(0)$ will have no effect.
- If the potential is positive, the neurons will accumulate signals and use it to fire. This process will occur in a random fashion and the spikes that are fired at this instancewill have a rate r(i) and are independent in inter-spike intervals, distributed in an exponential fashion.
- A random neural network will comprise of the following parts namely Decentralized information, Neural Chain Network, Validation and Data and Private key.

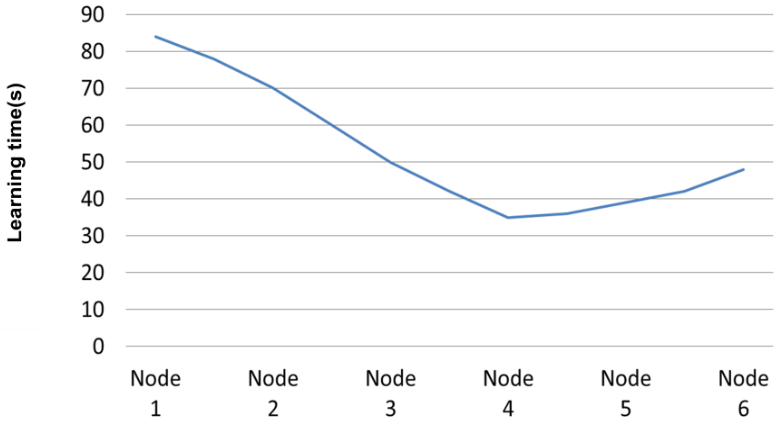

Fig 5: Learning in 5G network simulation

CONCLUSION

In this article, we have discussed the traffic characteristics of 5G networks as well as the challenges they will present for traffic management of 5G networks arising from new usage scenarios, new network architectures, and new network services. ML for 5G traffic control includes supervised learning, unsupervised learning, and DRL for managing 5G traffic, which have been introduced. Distributed and lightweight ML algorithms for optimizing the uplink traffic in 5G mMTC and ULLRC scenarios have been discussed. A novel AI assistant content retrieval algorithm framework for optimizing the data traffic in the content retrieval services of future 5G networks has also been proposed. There are many further opportunities that will arise for the use of AI and ML techniques in future 5G networks.

REFERENCES

[1] M. Shafi *et al.*,"5G: A Tutorial Overview of Standards, Trials, Challenges, Deployment, and Practice," *IEEE JSAC*, vol. 35, no. 6, June 2017, pp. 1201–21.

[2] N. Kato *et al.*, "The Deep Learning Vision for Heterogeneous Network Traffic Control: Proposal, Challenges, and Future Perspective," *IEEE Wireless Commun*., vol. 24, no. 3, June 2017, pp. 146–53.

[3] S. Chinchali *et al*., "Cellular Network Traffic Scheduling with Deep Reinforcement Learning," *Proc. AAAI 2018*, New Orleans, LA, Feb. 2018.

[4] Z. Zhao *et al.*, "User Preference Learning for Online Social Recommendation," *IEEE Trans. Knowl. Data Eng*., vol. 28, no. 9, Sept. 2016, pp. 252–34.

[5] T. M. Mitchell, *Machine Learning*, McGraw-Hill, Inc., 1997.

[6] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, vol. 116, Cambridge Univ. Press, 1998.

[7] Z. Xu *et al*., "Experience-Driven Networking: A Deep Reinforcement Learning Based Approach," *Proc. IEEE INFOCOM 2018*, HI, Apr. 2018.

[8] K. Hsieh *et al.*, "Gaia: Geo-Distributed Machine Learning Approaching LAN Speeds," *Proc. USENIX NSDI 2017*, MA, Mar. 2017, pp. 629–47.

[9] Y. Li *et al.*, "Joint Content Recommendation and Delivery in Mobile Wireless Networks with Outage Management," *Entropy*, vol. 20, no. 1, Jan. 2018, pp. 64–88.

[10] I. Portugal, P. Alencar, and D. Cowan, "The Use of Machine Learning Algorithms in Recommender Systems: A Systematic Review," *Expert Systems with Applications*, vol. 97, May 2018, pp. 205–27.

[11]Kong, Y., & Yu, T. (2018). A deep neural network model using random forest to extract feature representation for gene expression data classification. *Scientific reports*, *8*(1), 1-9.

[12]Vijayakumar, T. (2019). Comparative study of capsule neural network in various applications. *Journal of Artificial Intelligence*, *1*(01), 19-27.

[13]Muneera, B. H., Janeera, D. A., Shankar, B. M., & Anita, S. D. R. (2020, September). Edge Preserving Filter Selection for Noise Removal and Histogram Equalization. In 2020 International Conference on Smart Electronics and Communication (ICOSEC) (pp. 567-571). IEEE.