International Journal of Computer Trends and Technology
ISSN: 2231 – 2803 / https://doi.org/10.14445/22312803/IJCTT-V68I12P101

Volume 68 Issue 12, 1-3, December 2020

Original Article

Computational Problems Addressed using Machine Learning (ML) In a 5G Network

Srinivasan Sridharan

Senior Engineer, IEEE.

16224 SE 10TH ST Bellevue,WA, USA – 98008

Received Date: 14 October 2020
Revised Date: 22 November 2020
Accepted Date: 24 November 2020

Abstract - *Machine learning (ML) is one of the key drivers for a Self-organizing 5G Network (SONs), and it greatly improves Operational and Maintenance (OAM) activities such as Software/Hardware upgrades, Key Performance Indicator Monitoring, etc. This Case study paper specifically reviews the Computational problems which can be addressed by leveraging Machine learning techniques in a MIMO capable 5G Standalone network.*

Keywords - *5G, machine learning (ML), Self-organizing Networks (SONs), 5G Standalone, Artificial Intelligence (AI), MIMO*

I. INTRODUCTION

5G stands for the Firth Generation of the wireless cellular standards defined by the third-generation partnership program (3GPP) organization, establishing the industry standards for wireless cellular communication. 5G can deliver ultra-high data rates in the volume of Gigabits per second (Gbps) when compared to 4G LTE. The network latency and efficiency are greatly improved, making 5G the next big technology that needs to be adopted. The research's main aim is to review the advantages of using machine learning (ML) in 5G standalone MIMO capable networks as the intentions of a 5G network revere demands of phrases of data-rate, reliability, latency, or efficiency with which mobile operators shall be in a position in imitation of revere whole of these requirements using shared network infrastructure's resources.

II. CASE STUDY ON ISSUES

5G cellular networks are known as key emerging services that would form a foundational basis for future network connections. However, the emergence of new services is not easy and obstructed by challenges such as flexibility, dynamism, cost-effectiveness, and intelligent solutions that restrict its implementation on a large scale basis.

Valente KP, Imran MA, Onireti O, Souza RD (2017) examined several challenges such as UDSC issues are faced while including advanced technologies such as ML in 5G applications. UDSC is associated with the collection of large volumes of management data that creates issues in managing network configuration and data complexity. Moreover, there is the creation of interference between prevailing pico, femto, and macrocells, creating challenges in 5G. Hetnets also create issues in the small and macro cells that disrupt the signals used by the users. As a result, there is a disruption in the signal-to-interference-plus-noise ratio (SINR) that adversely impacts network performance. Issues related to cost, insufficient control, and backhaul in UDSC application also create an issue in the adoption of ML in 5G.

Andrews JG, Buzzi S, Choi W, Hanly SV, Lozano A, Soong AC, Zhang JC (2014) analyzed that RAT selection challenges are also faced while incorporating 5G Hetnet into devices. Most of the electronic equipment and devices manufactured now a day support multiple RAT environments like 3G, 4G/LTE, Wi-Fi, Bluetooth, and potential 5G technologies. However, there is a requirement to adequately select intelligent RATs selection to provide an optimized experience to the users. Different RAT applications require maintaining different protocols, bandwidths, and frequencies, often creating complications in streamlining the single device. It impacts the performance of the device and degrades the capacity of the device to low levels.

Jiang C, Zhang H, Ren Y, Han Z, Chen K-C, Hanzo L (2017) analyzed that Massive MIMO challenges are faced while including ML with 5G. It includes pilot communication, architectural design, and full-dimension MIMO that hinder advanced technologies in the 5G. While considering pilot contamination, it includes issues related to pilot sequencing that is generally used to analyze the same cell's channel values. As a result, the same sequence can be reused by other users in a different cell. However, reusing leads to pilot contamination and disturbs the orthogonal uplink pilot sequences. It deteriorates the working of the channel, and it could not detect the cell estimates adequately. It results in the creation of a contaminated cell known as Channel State Information (CSI).

Additionally, pilot communication increases the volume of antennas, which causes designing problems in massive-MIMO. Sultan K, Ali H, Zhang Z (2018) examined the architectural design associated with MIMO design and its application across antennas. Massive-MIMOs are supported with powerful antennas that have several power amplifiers. In this design, the several low amplifiers must be connected in an integrated way to map the servers between the antennas. However, the entire setting of the network causes huge installation costs and limits advanced technology in 5G.

Alnoman A, Anpalagan A (2017) analyzed that full-dimension MIMO is associated with cellular networking based on 2D directional antennas. It is mainly attached in the form of the horizontal plane that is controlled by beam pattern radiation. This arrangement restricts the antennas' volume and uses only the azimuth angle dimension for networking and establishing connections. Thus, MIMO's use gets restricted and could be improved by adding a vertical plane to the dimension of an elevated angle. This concept is known as 3D MIMO, which helps increase the efficacy of the 5G network. Nadeem Q-U-A, Kammoun A, Alouini M-S (2018) examined that FD-MIMO is related to the issue faced while implementing and estimating the channel performance. As a result, there is the creation of issues related to azimuth and elevation beamforming due to many channels.

Wei L, Hu RQ, Qian Y, Wu G (2014) examined that OFDM challenges impact the implementation of ML in the 5G network system. There are several access applications such as FBMC and GFDM that create configuration and implementation issues. On the other hand, D2D challenges are faced while detecting proximity and integrating networks. As a result, it creates issues in the secure transfer of data and deteriorates the network coding scheme. Therefore, self-interference depreciation is to be included to enhance throughput and multi-mode selection procedure. Ma Z, Zhang Z, Ding Z, Fan P, Li H (2015) examined that CRN challenges create interferences between primary and secondary users that increase the risks of attacks and impacts the frequency sharing capacity of the networks. Additionally, SDN and NFV challenges are also faced when incorporating NFV with 5G network service providers. The 5G network service providers mainly use NFV to perform decoupling functions.

It is mainly associated with building flexible networks in certain hardware components. However, such implementation of NFV with 5G creates issues related to performance management and evaluation and significantly limits its application.

MacCartney GR, Zhang J, Nie S, Rappaport TS (2013) examined that high path loss challenges create issues related to augmenting in mm-waves' transmission frequencies that lead to loss of omni-directional path as it was higher than the microwave bands. An antenna array is a technique that is used to attain mm-wave communication. However, the antenna array technique is under research concerning the application in a 5G mm-wave network. Antenna arrays are based on beam forming that helps to establish mm-wave communication and overcome the losses. On the other hand, in a narrow beam, the rays are generally integrated that produce low spectrum overlap conditions and bring improvements in QoS. However, the major issue with the narrow beam application is that it increases sensitivity with movement that creates high processing complexity.

Hossain E, Hasan M (2015) analyzed that Full-duplex (FD) communication challenges are faced while integrating advanced technologies with 5G networking. FD communication is based on self-interference (SI) mitigation that facilitates FD transmission by using SI mechanisms. However, in this application, the interference between various BSs is high, which causes loss of path and shadowing issues. As a result, there is improper power allocation management and a lack of synchronization between FD communication modes. Valente KP, Imran MA, Onireti O, Souza RD (2017) examined E2E connectivity challenges in ML adoption with 5G. It is based on dense and heterogeneous user applications that create decision-making issues related to cell connection. The major issue arises in analyzing the mobile connections as several complicated networks and applications are taken into account. Thus, it can be said that several computational issues such as FD communication challenges, RAT selection challenges, Network slicing (NS) issues, and UDSC challenges are faced while implementing ML techniques for 5G networks.

III. CONCLUSION

As per the above-discussed facts, it can be concluded that Machine Learning (ML) adds excellent value to the 5G network in several ways. Machine Learning can predict variations in several Key Performance Indicators used and address computation issues in a MIMO 5G Network. Network anomalies can be detected and avoided for improving network performance.

REFERENCES

[1] Alawe, I., Ksentini, A., Hadjadj-Aoul, Y., Bertin, P., & Kerbellec, A. (2017, September). On evaluating different trends for the virtualized and sdn-ready mobile network. In 2017 IEEE 6th International Conference on Cloud Networking (CloudNet) 1-6. IEEE.

[2] Aliu, O. G., Imran, A., Imran, M. A., & Evans, B. (2012). A survey of self-organization in future cellular networks. IEEE Communications Surveys & Tutorials, 15(1), 336-361.

[3] Alnoman A, Anpalagan A Towards the fulfillment of 5G network requirements: technologies and challenges. Telecommun Syst 65(1): International Conference on Communications Workshops (2008) 37-41. IEEE.

[5] Andrews JG, Buzzi S, Choi W, Hanly SV, Lozano A, Soong AC, Zhang JC What will 5G be? IEEE J Sel Areas Commun 32(6): (2014) 1065–1082.

[6] Andrews, J. G., Buzzi, S., Choi, W., Hanly, S. V., Lozano, A., Soong, A. C., & Zhang, J. C.. What will 5G be?. IEEE Journal on selected areas in communications, 32(6), (2014) 1065-1082.

[7] Bashir, A. K., Arul, R., Basheer, S., Raja, G., Jayaraman, R., & Qureshi, N. M. F. (2019). An optimal multitier resource allocation of cloud RAN in 5G using machine learning—transactions on Emerging Telecommunications Technologies, 30(8), e3627.

[8] Bithas, P. S., Michailidis, E. T., Nomikos, N., Vouyioukas, D., & Kanatas, A. G. (2019). A survey on machine-learning techniques for UAV-based communications. Sensors, 19(23), 5170.

[9] Chabbouh, O., Rejeb, S. B., Choukair, Z., & Agoulmine, N. (2016, May). A novel cloud RAN architecture for 5G HetNets and QoS evaluation. In International Symposium on Networks, Computers, and Communications (ISNCC) 1-6. 2016. IEEE.

[10] Foerster, J., Assael, I. A., De Freitas, N., & Whiteson, S. Learning to communicate with deep multi-agent reinforcement learning. In Advances in neural information processing systems. 2016. 2137-2145.

[11] Sridharan, S. Systems and methods for authorization and billing of users for wireless charging. US Patent No.9,972,037. Washington, DC: US Patent and Trademark Office. (2018).

[12] Sridharan, S.(2016). Ue initiated an evolved packet core (epc) and ip multimedia subsystem (ims) network usage optimization algorithm for lte capable smartphones connected to wireless lan (Wi-Fi) network. US Patent No.20160088677A1. Washington, DC: US Patent and Trademark Office.

[13] Sridharan, S. Network initiated an evolved packet core (epc) and ip multimedia subsystem (ims) network usage optimization algorithm for lte capable smartphones connected to wireless lan (Wi-Fi) network. US Patent No.20160088678A1. Washington, DC: US Patent and Trademark Office. (2016).

[14] Hochreiter, S. JA1 4 rgen Schmidhuber."Long Short-Term Memory". Neural Computation, 9(8). (1997).

[15] Hossain E, Hasan M (2015) 5G cellular: key enabling technologies and research challenges. IEEE Instrum Meas Mag 18(3) 11–21.

[16] Imran, A., Zoha, A., & Abu-Dayya, A. Challenges in 5G: how to empower SON with big data for enabling 5G. IEEE Network, 28(6) (2014) 27-33.

[17] Jiang C, Zhang H, Ren Y, Han Z, Chen K-C, Hanzo L Machine learning paradigms for next-generation wireless networks. IEEE Wirel Commun 24(2) (2017) 98–105.

[18] Khorsandroo, S., Noor, R. M., & Khorsandroo, S. (2013). A generic quantitative relationship to assess the interdependency of QoE and QoS. KSII Transactions on Internet and Information Systems (TIIS), 7(2), 327-346.

[19] Lateef, H. Y., Imran, A., & Abu-Dayya, A. A framework for the classification of self-organizing network conflicts and coordination algorithms. In 2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) 2898-2903. IEEE.

[20] Ma Z, Zhang Z, Ding Z, Fan P, Li H Key techniques for 5G wireless communications: network architecture, physical layer, and mac layer perspectives. Sci China Inf Sci 58(4) (2015) 1–20.

[21] MacCartney GR, Zhang J, Nie S, Rappaport TS (2013) Path loss (2017) 101–116.

[4] Amirijoo, M., Frenger, P., Gunnarsson, F., Kallin, H., Moe, J., & Zetterberg, K. (2008, May). Neighbor cell relation list and physical cell identity self-organization in LTE. In ICC Workshops- IEEE

models for 5G millimeter-wave propagation channels in urban microcells. In: 2013 IEEE global communications conference (GLOBECOM), 3948–3953.

[22] Mars, A., Abadleh, A., & Adi, W. Operator and Manufacturer Independent D2D Private Link for Future 5G Networks. arXiv preprintarXiv:1911.00303.https://arxiv.org/ftp/arxiv/papers/1911/1911.00303.pdf. 2019.

[23] Moysen, J., & Giupponi, L. From 4G to 5G: Self-organized network management meets machine learning. Computer Communications, 129, 2018.248-268.https://arxiv.org/pdf/1707.09300.pdf

[24] Mumtaz, S., Huq, K. M. S., & Rodriguez, J. (2014). Direct mobile-to-mobile communication: Paradigm for 5G. IEEE Wireless Communications, 21(5), 14-23.

[25] Nadeem Q-U-A, Kammoun A, Alouini M-S (2018) Elevation beamforming with full dimension mimo architectures in 5G systems: a tutorial. arXiv preprint arXiv:1805.00225

[26] Nishiyama, H., Kawamoto, Y., & Takaishi, D. On OFDM-based resource allocation in LTE radio management system for unmanned aerial vehicles (UAVs). In 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall) (pp. 1-5). IEEE.

[27] Zhang, Y., Yao, J., & Guan, H. Intelligent cloud resource management with deep reinforcement learning. IEEE Cloud Computing, 4(6) (2017). 60-69.

[28] Srinivasan Sridharan. A Literature Review of Network Function Virtualization (NFV) in 5G Networks. International Journal of Computer Trends and Technology, 68.10, (2020). 49-55.

[29] Srinivasan Sridharan. Machine Learning (ML) In a 5G Standalone (SA) Self Organizing Network (SON) International Journal of Computer Trends and Technology 68.11, (2020) 43-48.

[30] Srinivasan Sridharan. (, 2020). 5G Cloud Network Resource Slicing – A Literature Review. International Research Journal of Engineering and Technology (IRJET) 7(11), November 2020 https://irjet.net/volume7-issue11 S.No: 01

[31] O'Shea, T., & Hoydis, J. An introduction to deep learning for the physical layer. IEEE Transactions on Cognitive Communications and Networking, 3(4), (2017) 563-575.

[32] Srinivasan Sridharan. Network Function Virtualization (NFV) Design Considerations for a 5G Network Using Network Slicing Methodology. International Research Journal of Engineering and Technology (IRJET) 7(12) (2020).

[33] Perez, J. S., Jayaweera, S. K., & Lane, S. Machine learning aided cognitive RAT selection for 5G heterogeneous networks. In IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom) 1-5. 2017. IEEE.

[34] Sultan K, Ali H, Zhang Z Big data perspective and challenges in next-generation networks. Future Internet 10(7) (2018) 56.

[35] Valente KP, Imran MA, Onireti O, Souza RD A survey of machine learning techniques applied to self-organizing cellular networks. IEEE Commun Surv Tutor 19 (2017) 2392–2431.

[36] Valente KP, Imran MA, Onireti O, Souza RD A survey of machine learning techniques applied to self-organizing cellular networks. IEEE Commun Surv Tutor 19 (2017) 2392–2431.

[37] Wei L, Hu RQ, Qian Y, Wu G Enable device-to-device communications underlaying cellular networks: challenges and research aspects. IEEE Commun Mag 52(6) (2014) 90–96.

[38] Xu, Y., Yin, F., Xu, W., Lin, J., & Cui, S. Wireless traffic prediction with scalable Gaussian process: Framework, algorithms, and verification. IEEE Journal on Selected Areas in Communications, 37(6), (2019) 1291-1306.