A Review of Machine learning Use-Cases in Telecommunication Industry in the 5G Era

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Abstract— **With the development of the 5G and Internet of things (IoT) applications, which lead to an enormous amount of data, the need for efficient data-driven algorithms has become crucial. Security concerns are therefore expected to be raised using state-of-the-art information technology (IT) as data may be vulnerable to remote attacks. As a result, this paper provides a high-level overview of machine-learning use-cases for data-driven, maintaining security, or easing telecommunications operating processes. It emphasizes the importance of analyzing the role of machine learning in the telecommunications sector in terms of network operation.**

Keywords—Machine-learning, Telecommunications industry, Artificial intelligence.

I. INTRODUCTION

With a growing number of subscribers and increasing their demand for higher quality services, Communication Service Providers (CSPs) need to invest a huge amount of effort and resources in automating and optimizing operational services. Also, with the development of 5 G and Internet of Things (IoT) applications leading to a vast amount of data, efficient data-driven algorithms have become crucial. Similarly, security concerns over the vast amount of traffic in the network have been significantly raised. Therefore, machine learning (ML) technologies are a promising approach to reducing network congestion, optimizing, improving network quality, and enhancing customer experience. IoT and 5 G infrastructure should lead to the use of ML technologies in various industries, sectors, and the telecommunications sector.

With around 63.5% of the current telecommunications infrastructure, many telecommunications operators have begun to invest and test the implementation of machine learning algorithms in the operational network and business decisions [1]. The forecast of global deployment of ML in the telecommunications industry by 2023 will reach $1 billion, with the Compounded Annual Growth Rate (CARG) accounting for 32% of future market research [2]. Investments in the telecommunication industry are projected to be $36.7 billion annually by 2025 (see Fig. 1) [3]. The monitoring and management of network operations represent 61% of the overall use cases. Other use cases will include virtual customer service and marketing assistants, intelligent customer relationship management (CRM) systems, and cybersecurity. ML has been greatly expanded in various industries, including electricity, water, healthcare, etc .... but the telecommunications sector should be the leading industry hosting the other sectors, particularly with the development of 5G. Explicitly, each machine should be able to learn the execution of a particular task, to keep the performance to a certain level based on the experience, where the system aims to keep reliably repeating the execution of the task to improve the performance. ML algorithms can be classified into two types of learning techniques; supervised and unsupervised, where "supervised/ unsupervised" indicates whether the data samples have labeled or not in the database.

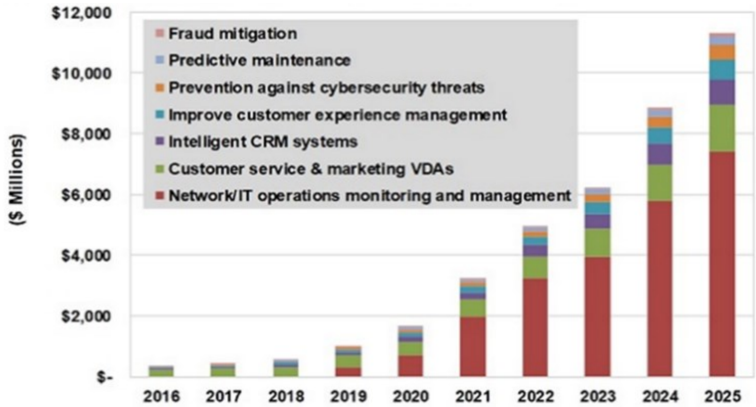

Fig. 1. Investments in ML by use-case [3].

A few works consider summarizing the integration of ML in the telecommunications industry [4]-[8]. Qi et al. in [4] managed to find out the popularity of users per area and the prediction of market demand. Moreover, Mata et al. in [5] reviewed 148 machine learning use-cases in the literature to cover detailed processes in optical transmission. Furthermore, Xu, Mu, and Liu in [6] summarized a selective review of some of the mentioned machine learning in the literature. Furthermore, Chunxiao et al. in [7] briefly overviewed the ML use-cases in the operational systems and their compelling applications with 5G networks. Further, Roberto et al. in [8] summarized the machine learning use-cases in telecommunications and other sectors and interviewed some of the telecommunications operators to the mentioned use-cases. This work emphasizes the required telecommunications policies and regulations to facilitate this development. The challenges of the current telecommunication systems are investigated to include; lack of return on investment, changing customer needs, shortening technology cycles, poor rates innovation, etc... (see Fig. 2) [9]. The shortening technology cycles & poor rates innovation has 32% of the respondents, and lack of return on investment & changing customer needs have 69% of respondents. Therefore, the use-cases shall improve some of the mentioned challenges.

As a result, this paper extends the work of these findings. It provides a high-level summary of potential telecommun-ications use-cases and trends. It emphasizes the analysis of the role of machine learning in the telecommunications sector in terms of network operation. The paper is organized as follows: Section II discusses the proposed use-cases and highlights the importance of such use-cases and their incentives and regulations. Section III provides an overview of the future of the telecommunications industry through the use-cases mentioned above. It also assesses the advantages, dis-advantages, and challenges of the ideal system. Section IV concludes the work and discusses the future of work.

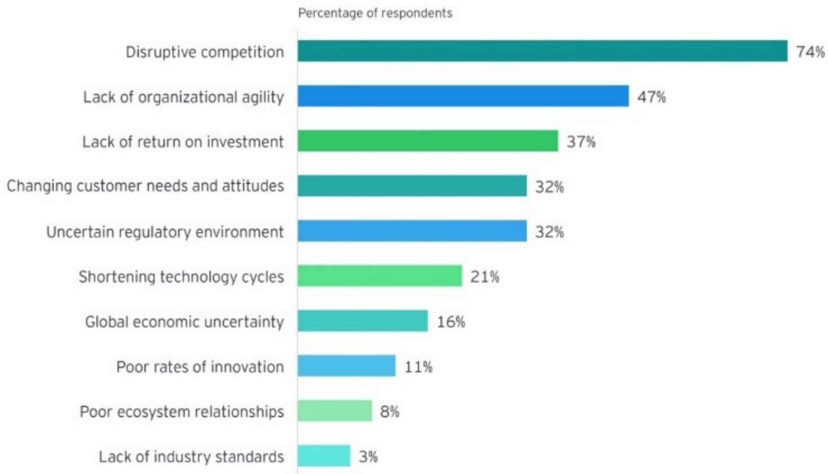

Fig. 2. Challenges of the current Telecommunication industry [9]

II. MACHINE-LEARNING USE-CASES IN TEECOMMUNICATION

A. *Proposed Use-cases*

1) *Network Automation and optimization/Network operation monitoring and management*

Automating the telecommunications network from the data extracted and interpreted from the network assets is the key to less network leakage and ease of handling. Once all network configurations and parameters are processed online, it is easy to optimize the existing infrastructure and not share the resource, but also in terms of the power consumption of the network. For example, some eNodeB could sleep if the traffic load would be like being served near eNodeB. As [10], about 63% of telecommunications operators have invested in machine learning to improve and optimize their infrastructure. To maintain network continuity better than third-party operators, this form of management should be able to make autonomous analysis and fast decision-making in real-time. A self-organizing network (SON) and a self-healing network (SHN) can be created, especially after the deployment of a software-defined network (SDN) in a variety of industries. Once a problem has arisen, corrective action is taken on a real-time basis on daily traffic. A few works are considered as follows in the literature:

a) Traffic monitoring: It is also mandatory as 5 G expects to host Industry 4.0, which combines Information Technology (IT) and Operational Technology (OT), i.e., the processing of traffic data. As a result, 5 G is expected to have traffic monitoring systems to mitigate cyber-physical systems and other network failures. This monitoring system operates at a higher level of the network and, without it, could lead the network to be attacked as a result of this IT adoption with IoT. Similar systems are deployed in several industries, such as water, energy, healthcare, etc.

b) Channel estimation and optimal handover: Hundreds of antennas and channel estimation in massive MIMO systems can lead to high-dimensional search-problems that can be realized using ML algorithms to ensure accurate, tailored channel detection [7]. This algorithm was used by Zhou et al. in [11] using SVM to estimate the noise level of the Gaussian channel in the MIMO-aided wireless network. In the same way, an optimal transfer can be made using ML algorithms in the core network. Moreover, these algorithms can be used to learn the pattern of mobile terminals in a variety of Spatio-temporal and device contexts, as investigated by Donohoo et al. in [12].

c) Sleeping off some cells: ML algorithms can use the learned user context to dynamically configure the network to save power while maintaining user satisfaction and not affecting the service provided. Five real user profiles (including location and usage) were processed on a similar system by Donohoo et al. in [12]. The result of this experiment showed that a successful forecast of energy demand was achieved by up to 90% using the nearest k neighbor (KNN) algorithm. As a result, with the prediction of users' demand for sleep, some NodeBs are highly applicable, along with the ability to provide a certain amount of processing. This also facilitates the identification of the optimal function split autonomously rather than the actual optimization problems of use, as discussed in our previous works [13][14].

d) Clustering: The association of heterogeneous cells with different cell sizes and connections with different technologies (i.e., Wi-Fi networks, D2D, etc.) is a common problem in 5 G networks. Interference with coordinated multi-point transmission (COMP) is avoided when small cell clustering occurs. According to an optimum offloading policy, users should be clustered, where clustered users should maintain high energy efficiency over D2D networks, and Wi-Fi should support optimum access points [7]. The Mixed-integer programming (MIP) problem was introduced to find the optimal partitioning of the gateway and the virtual channel allocation using the k-means clustering of Xia et al. in [15]. This model was proposed to classify the mesh access points (MAPs) into several groups.

e) Signal dimension reduction and Spectrum sensing: ML algorithms can be used to reduce the signal dimension of massive MIMO systems or to identify primary users' behavior in cognitive radio networks. A similar approach in the smart grid system is used to recover the simultaneous wireless transmission of intelligent meters to individual homes using PCA and ICA. The received signal had to be separated from the transmitted data by Qic et al. in[16]. This process improved transmission efficiency by avoiding the estimation of a channel in frames and a wide band. It also enhanced data security by eliminating interference and jamming signals. A similar example in cognitive radio networks where the ICA algorithm is used to distinguish and characterize the activities of PUs in the context of collaborative spectrum sensing by Nguyen et al. in [17].

f) Self-configuration of femtocells: ML algorithms can be used to maintain spectrum allocation by detecting unused spectral slots and selecting sub-channels from the available spectrum pool. The configuration of terminals supported by such femtocells is considered to reduce interference and meet the quality of service (QoS). Densification of small cell networks is another example of how Onireti et al. has managed and compensated cell outages in [18]. The network considers the allocation of users to small cell resource blocks and the maintenance of channel quality.

2) Data Driven Business Decisions

With the adoption of machine learning in such a vast amount of data, meaningful business insights can be extracted and interpreted. These insights can make the network faster, easier to resolve issues, efficient management of daily data, improved customer service, and better business decisions. User segmentation, churn prevention prediction of the lifetime value of users, product development, improving margins, price optimization, network fraud, asset well-being, and many more can be achieved by processing the network traffic using machine learning and big data technologies [19]. Tailored set up actions and steps for every customer can be realized for improving customer satisfaction. Moreover, Network services could be flourished and enhanced by knowing what users need at the moment.

A simple paradigm model is considered in Chunxiao et al. work in [7] (see Fig. 3). Observations or features are extracted from the transmitted signals to be processed. Afterward, an evaluation of utility services and cost are processed for selection of action. This simple paradigm could work on many data in business decisions, where different evaluations are considered: an example, an experiment of data mining of users, networks, and traffic in telecommunications utility. Daily human interaction with the networks and the services are processed to understand user behaviours and interact. The proposed system by Martin & Joakim in [20] was put good use to observe the usage of users patterns which facilitate for operators to add personalized user content and ad, a mobile billboard community for matching member ads, mobile phone-based marketing, consumer profiling together with grocery retailers, and automated tagging of media files.

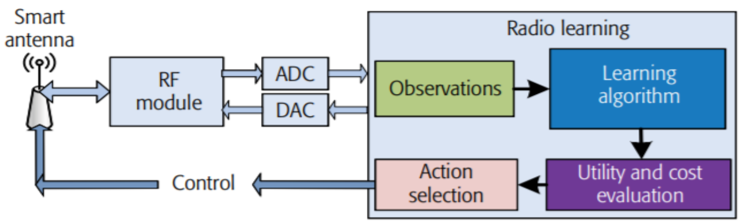

Fig. 3. A simple ML paradigm

3) Preventive Maintenance and fault /Fraud detection

The capability of fixing the runtime issues in the telecommunication hardware such as cell towers, power lines, etc. is the key objective in this use-case. With the processing of traffic coming from the network, it is possible to predict network failure assets based on the previous patterns. This facilitates proactively fixing issues without interruption of the service, such as data center services, cell towers, power lines, etc.… Also, anomaly detection can be realized on the network traffic to detect any anomaly (abnormal behaviours) in the network. The abnormality could result from a network fault (malfunction) or Cyber-physical (CP) attack. Several functions process the traffic for network-wellbeing, CP attacks, users' consumption, operation-process, etc.… In the case of detection of any anomaly, an alarm is raised to the operators for immediate action.

Further, some works propose autonomous decision-making based on the insights that come from the traffic detection system. Other industries, such as water, energy, and healthcare, developed data validation data streams using blockchain and smart contracts [21] [22]. The data is assumed to be transparent, secure, and accessible by network users.

4) Robotic Process Automation, Customer service bots and virtual Assistants

Gartner states that 68% of customer service leaders think that bots and virtual assistants will make a large impact in the next two years [23]. This is because the assigned tasks for the chatbots are increasing every day using speech bots and natural language voice response systems (IVRs). These bots listen from requests/inquiries of the users directly on websites, applications, messages, etc. Then they gather details, look up information, perform operations, and report results. These capabilities are enabled using machine-learning algorithms in language processing, intent prediction, conversation management, and response generation. These bots could deal with some operational or financial issues. If these systems are updated to have modern application program interfaces (APIs), then the bots could get the information quickly. If these systems are not modernized (as the common situation in many industries), fortunately, robotic process automation (RPA) is a solution for that, it is a system that can navigate the difficult-to-access systems [24]. The RPA has been installed in the back office for a while. It helps the assets automate the repetitive tasks in finance, accounting, operations, HR, and IT [24].

B. Statistics of Use-cases

The importance of the discussed use-cases can be observed from the investments (see Fig. 4). Network Automation and optimization/Network operation monitoring and management have invested almost 69% in 2020 and similar percentages until 2025 [3]. It has more than two-thirds of the investments as it will improve the operational process and makes overall the network more intelligent to adopt industry 4.0, big data, and IoT movements. Then Data-Driven business decision and Customers bots and virtual assistants have equal investments ratio of 12% due to the need for improving users' satisfaction for increasing industry profits [3] Finally, Protective maintenance and Fraud detection has the 6% of investments in 2020 which slightly increases in the next five year because of the increase of the awareness of happening of data fraud.

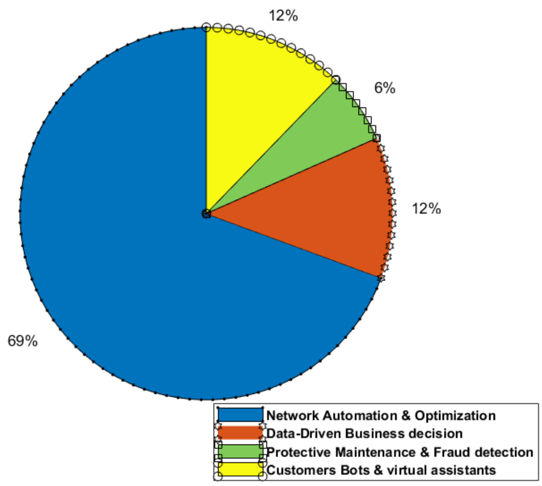

Fig. 4. Statistics of the investments of the proposed use-cases [3]

C. Incentives and regulations of the Use-cases

This transformation of the processes is expected to reduce cost, improve service quality, and increase user satisfaction. Moreover, some new services may happen to improve users' satisfaction. Both of these improvements have implications for regulations. Regulators will need to understand the specific process of ML algorithms to set the correct incentives to maximize the outcomes [8]. A lack of effective competition is often a prerequisite for the regulation of network industries. Regarding AI, the first important question is, therefore, whether AI will lead to more or less competition in network industries in the coming years, leading to less or more regulation. Sunk costs, the economics of scale and scope, and network effects are the recognized regulatory practices [25].

III. FUTURE TELECOMMUNICATIONS SYSTEM: ADVANTAGES, DISDVANTAGES AND LIMITATIONS

There is no doubt that ML will make the network and the edge more intelligent and pave the way for a next-generation telecommunication system. The future telecommunication system is expected to have the mentioned four ML use-cases and autonomous decision-making (see Fig. 5). Moreover, the advances of the cloud, hardware, and many open-source frameworks (e.g., network function virtualization) will promote in making this system happen. Human intervention will be optional in making sure that the network is going in sequence.

Such a system will automate the data flow, process the traffic on a real-time basis, save the detected attack cases, calculate the risk of spreading attacks, provide insights to the operators about the network second by second, etc. the contrast. This increases the risk that the network will be attacked as the network assets (will be connected to the internet). The telecommunication assets may be vulnerable for attacks such as ransomware, Denial-of-service (DoS), and others, and the fact that the assets could be unauthorized controlled by an illegal individual is terrifying. However, ML processing should address these risks along with state-of-the-art security measures such as white & black employee lists, data encryption, secure channel transmission, etc. The opportunities for the development do not only stop at mentioned ML use-cases, but also covers augmented reality, speech analytics, and much more (see Fig.6) [23]. Some works also consider blockchain as a secure platform for many industries, including telecommunication yet, it is still under development and maturing the use-cases.

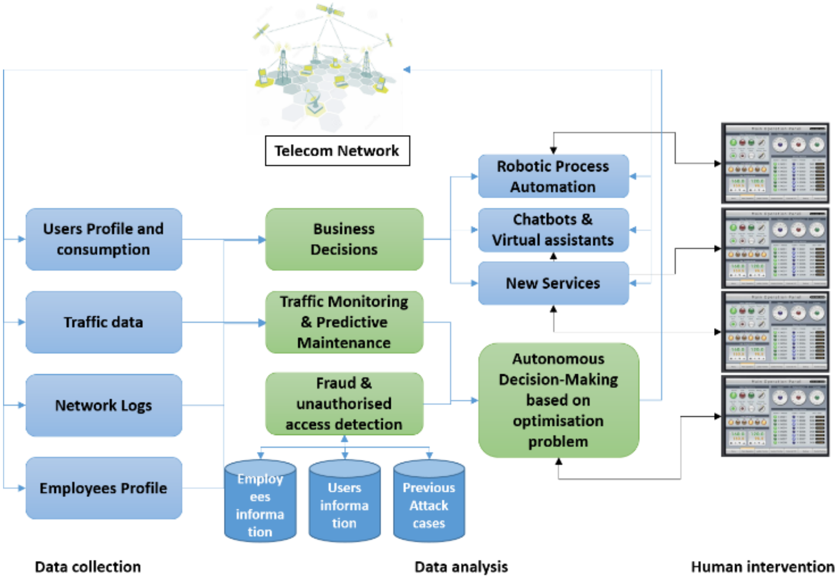

Fig. 5. Intelligent Data flow of future telecommunication system

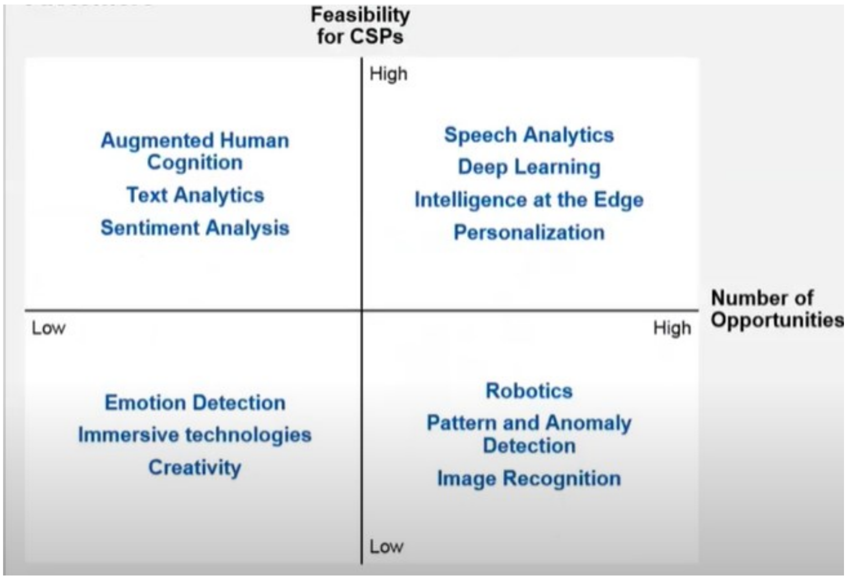

Fig. 6. Development opportunity Map [23]

IV. Conclusions and Futurework

This paper provides a high-level overview of machine-learning use-cases either for data-driven, maintaining security, or easing the operational processes in telecommunications. It emphasizes analyzing the role of machine learning in the telecommunications sector in terms of network operation. Four use-cases are realized in this study, which are; Network Automation and optimization/Network operation monitoring and management, data-driven business decision, bots of the customers, and virtual assistants, and Protective maintenance & Fraud detection. These use-cases cover operational technology improvement as long as the satisfaction of the users and adding new services.

In addition, the Telecommunication industry has been the leading industry that many other industries rely on to adopt new electronics or communication standards. Therefore, an automated intelligent system that can process data traffic is mandatory not only for the automation of the industry but also for security. Making all the new assets and physical components connected with a specific database puts all networks at a large risk with the common security measures. Accordingly, having Machine-learning capabilities to process the data is mandatory. Moreover, other intelligent systems such as bots, virtual assistants, and Robotic Process Automation (RPA), along with the data-driven business decisions, will enhance the users' satisfaction and Customer relationship management. Finally, based on this survey, almost 70% of the investments go for the automation and telecommunication traffic analysis and some operational processes in the core network. Then 24% of the investments improve the experience of the users and their relationship with the industry through artificial bots, automatic robots, and decision-analysis. The rest of the 6% go for the predictive maintenance and fraud detection system, and investments in this system are expected to increase in the next couple of years with the increasing number of frauds happening across most industries.

This work can be extended to propose an automation system architecture that can analyse the data traffic and user profile & usage behaviour for detecting abnormal user consumption, which can be further investigated in the manipulation of the network. Additionally, the network's autonomous decision-making can be considered in case of alerts raised during the machine-learning detection process. The decision will be the result of an optimization problem of many factors: spread factor, infection time, recovery time, etc.

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