Artificial Intelligence in the Wireless Arena: Potential and Deployment Challenges

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This paper aims at describing the capabilities of artificial intelligence (AI) to tackle wireless communications challenges. From the physical to the application layer, we introduce certain AI frameworks that result in promising solutions to deal with current and forthcoming threats in the wireless operation. As described in this work, the adoption of AI techniques entails a substantial change in the wireless ecosystem where data as well as their owners become crucial. As a result, the roll out of AI techniques in wireless systems raises a plethora of questions. In this context, we describe the challenges observed by the wireless stakeholders when deploying AI.

Introduction

The success of artificial intelligence (AI) in tackling keystone problems of image processing started a new era where AI is being studied and used in many fields from natural language processing to military defense systems. In this context, the wireless communications stakeholders have shown a strong interest in including AI in their daily life engineering problems. Apart from being a simple yet powerful tool for trying to solve current and future problems that appear in the wireless communication field, AI introduces a crucial change in the ecosystem. Indeed, as the techniques need to rely on data, the owners of the data become a key player in the use of AI in the wireless infrastructure. Bearing in mind this paradigm change, it is of great importance to understand the potentials of AI in supporting different areas of the wireless communications systems in order to encourage the data owners to facilitate its different usages.

In this paper, we consider five key elements of the wireless communications; namely, spectrum management, air interface, access schemes, radio resource management and network automation. In all cases, we introduce how AI can support novel features to enhance each subsystem performance. After the mentioned description, we summarize the challenges in deploying AI. Furthermore, we indicate the impact of ethics in managing the available data for performing the described AI mechanisms.

AI for the Wireless World

Intelligent Spectrum Management

An efficient use of the spectrum has been addressed by many national regulatory agencies. Mainly two approaches have been considered for spectrum licensing: Collective Use of the Spectrum (CUS) and the Licensed Shared Access (LSA) or Authorized Shared Access (ASA). In the CUS regime the service providers rely on a general authorization where anyone can access a certain spectrum band, as long as compliance with pre-defined conditions is guaranteed. However, in this scenario no protection from interference can be claimed and users are not required to coordinate. On the other hand, in LSA/ASA the licenses are given on an individual fashion where a service provider can use a given frequency band in a certain geographic area, for a certain period of time. This later approach takes as an objective to ensure a quality-of-service (QoS) to the license holders so as to avoid the congestion of certain frequency bands.

In order to support intelligent and dynamic spectrum management and licensing (IDSML) procedure and simultaneously provide predictable QoS to the licensees, the spectrum management might use historical data of the different users and employ a learning procedure for accurately provide the most adequate spectrum assignment. This can be done via reinforcement learning as described in [1] and [2]. The functional block diagram of this approach can be found in Figure 1.

The spectrum controller will have regulatory interface for national spectrum regulators, and commercial spectrum database providers which will need to guarantee the IDSML procedure, while providing sufficient spectrum to licensees with a minimum of interference. The smart spectrum database concept [3] is a pre-cursor to the ML/AI based IDSML procedural spectrum management for future wireless networks.

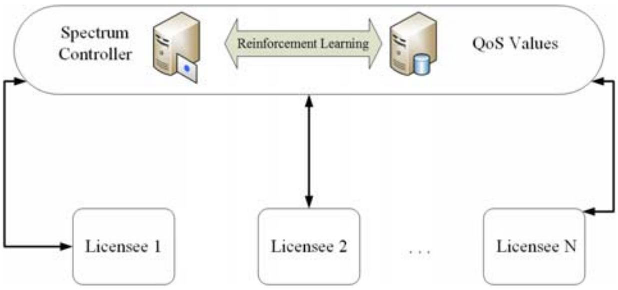

Figure 1 Machine learning approach to spectrum management.

Air Interface

Massive MIMO is going to be a key technology in new networks to deliver higher capacity. However, there are technical road blocks to efficiently tune massive MIMO. One of the challenges comes from a fast enough selection and optimization of the appropriate beam pattern. Key performance indicators (KPIs) such as the antenna tilt, the interference to noise ratio (INR), the Received Signal Strength (RSS) and the reference signal received power (RSRP) can be monitored and analyzed. To select the best beam pattern, AI enables massive MIMO to be effective. Indeed, AI allows a learning and iterative approach, to select the best beam pattern. Reinforcement learning (RL) algorithms can be adequate for tackling the mentioned challenge. Indeed, RL enables, during the exploration phase – exploration here means "let's discover my codebook, test the best response and select the best pattern", a very efficient discovery method. RL can been seen as a kind of unsupervised learning algorithm as the learning phase is done "in situ". RL includes two distinct phases: 1/ Exploration and when convergence is reached 2/ Exploitation. The algorithm uses a smart way, based on a technique called "Random Forest" to find out, as fast as possible, the best beam pattern.

The scaling-up of the networks in future generations will necessitate low-cost internet of things (IoT) devices that will involve low-specification hardware, such as analog-to-digital converters, power amplifiers to name a few. These are prone to hardware failures such as malfunctions in antennas or radiofrequency (RF) chains during the network operation, which may jeopardize the reliability of the machine type communication (MTC) links. Hardware impairments and losses in analog components are often mathematically intractable and commonly approximated with additive noise models. As a result, existing analytically-driven approaches to hardware impairments, are based on oversimplified models and are suboptimal in practice. This model mismatch is largely overlooked and can only be revealed through the application of *data-driven* approaches to the design of communications systems, as opposed to traditional *system-model driven* designs, and through experimental validation.

In this scope, learning-based approaches pose a prominent candidate for addressing such mathematically intractable paradigms, owing to a number of advantages [1], [5]: Firstly, a learning-based communication link allows an optimal data-driven architecture to be designed without the need for the system model to be analytically tractable, making it essential for the emerging communication scenarios above. Secondly, it can be optimized for the end-to-end performance, rather than independent block-by-block design that may be sub-optimal from a holistic point of view. Finally, through layered training the system is able to adapt to unpredictable changes, e.g. due to channel/hardware impairments/failures, to provide optimal performance without the need to re-design any system models. Accordingly, the application of learning-based approaches to dealing with hardware imperfections and failures, promises an exciting and fruitful research direction in the AI context.

Radio Access

With the rapid proliferation of innovative applications in the paradigm of massive IoT (mIoT), such as smart city, smart home, smart industrial, and vehicular communication, the demand of data traffic in wireless networks has grown explosively. Enabling massive wireless access for the mIoT network becomes extremely challenging due to the potential massive collisions from massive IoT devices with diverse data traffics, while performing random access (RA) procedure to request uplink channel resources for data transmissions. Results in [6][7] has already shown that the conventional RA schemes, such as access class barring (ACB), back-off, and power ramping schemes, become inefficient in terms of RA success probability as the number of IoT devices increases.

To effectively support the emerging mIoT ecosystem, the 3rd Generation Partnership Project (3GPP) partners have standardized a new radio access technology, namely narrowband-IoT (NB-IoT). To support various traffic with different coverage requirements, NB-IoT supports up to three coverage enhancement (CE) groups of IoT devices sharing the uplink resource in the same band. At the beginning of each uplink transmission time interval (TTI), the evolved node B (eNB) selects a system configuration that specifies the radio resource allocated to each group in order to accommodate the random access channel (RACH) procedure along with the remaining resource for data transmission. The key challenge is to optimally balance the allocation of channel resources between the RACH procedure and data transmission so as to provide maximum success accesses and transmissions in mIoT networks. Unfortunately, dynamic RACH and data transmission resource configuration optimization is an untreated problem in cellular networks.

Generally speaking, the eNB can observe the transmission receptions of both RACH (e.g., the number of successfully received preambles and collisions) and data transmission (e.g., the number of successful scheduling and unscheduling) for all groups at the end of each TTI. This historical information can be potentially used to predict traffic from all groups and to facilitate the optimization of future TTIs' configurations. Even if one knew all the relevant statistics, tackling this problem in an exact manner would result in a Partially Observable Markov Decision Process (POMDP) with large state and action spaces, which would be generally intractable. The complexity of the problem is compounded by the lack of a prior knowledge at the eNB regarding the stochastic traffic and unobservable channel statistics (i.e., random collision, and effects of physical radio including path-loss and fading).

In order to consider more complex and practical formulations of radio access techniques, RL emerges as a natural solution given the availability of feedback in the form of number of successful and unsuccessful transmissions per TTI. To solve the high-dimensional configurations problem in the multi-parameter multi-group scenario as defined in NB-IoT standard, deep RL can be the convergent capability of Q-learning by sacrificing the accuracy in resource configuration [8].

Radio Resource Management

Both academia and industry agree that early adoptions of the 5G infrastructure shall accommodate a flexible network configuration able to provide services to an extremely large variety of services and clients. This network architecture design is coined as network slicing and, in contrast to current pre-5G networks, it aims to provide granular and heterogeneous services. That is, the whole network is separated into different slices each of them tackling a specific service requirement (IoT, mobile edge computing…).

Efficiently guaranteeing certain service level agreements (SLAs) among the different slices is a cumbersome and computationally demanding task. First, dynamic demands impose different and heterogonous slices over time, promoting a very short time-to-react to the network orchestrator. In this context, the network slicing optimization has to rely on heuristic approaches that have a very low computational complexity. Second, although SLAs are currently being established with clear metrics, tenants might impose other requirements such as the quality-of-experience (QoE) perceived by the end user whose modelling hinders the overall network optimization.

In light of the above discussion, network orchestrators shall consist of tools with low processing time that are able to manage the different network slices while maintaining an efficient radio resource usage.

Current network slicing optimizers' proposals (e.g. [9]) consist of computationally demanding operations, leading to slow reactive network responses to slices time varying user requests. In order to conceive quicker reactive network slicing controllers yet providing efficient network usages, the use of AI tools might be one of the key elements [10].

In one hand, supervised deep learning regression methods can tackle the power control optimization and the user scheduling process [11]. This machine learning model assumes that the network controller is able to perfectly model the communication system and a synthetic data set could be available for designing the deep neural network. The main rationale of this approach entails that a deep neural network shall properly infer the results of other computationally demanding algorithms with a substantial decrease of the computational time.

On the other hand, when modelling the system involves challenging technical issues, the system designer can resort to model-free reinforce learning mechanisms [12] that are able to provide efficient slices configurations via an iterative process. In contrast to the supervised learning methods, reinforce learning techniques only requires access to the performance results of the network given a configuration. That is, a fully mathematical model of the slices performances is not required. This characteristic makes this machine learning model adequate when dealing with difficult QoE metrics or complicated network deployment where simple metrics such as delay or rate might be influenced by different external agents.

Network Automation

Communication Service Providers (CSP) own critical and valuable data which can be seen as the new oil for the industry. Unfortunately, and this for a long time, CSPs were unable to extract and leverage this data. Time has changed and CSPs have clearly understood the importance of these data jewels. On top of delivering value-added services, CSPs expect to differentiate themselves thanks to the QoE and QoS delivered to the subscribers. The old way of operating networks, where network administrators were applying configuration changes, were monitoring the outcome of the changes and were tuning up again the network, is still in function in operational centres. However, this optimization loop and process will not be enough to face the upcoming network revolution where video consumption will be at its highest and where very large number of objects of different nature will be connected to the network.

CSPs handle many daily customer interactions due to network quality issues. Alarm events can be notifications of network faults and provide indication of network quality degradation. Handling of alarms has great impact on both the operational costs and the quality of services offered to customers. The alarms are highly heterogeneous and this trend is steadily increasing as the network infrastructure is upgraded and expanded. Due to these factors, managing the alarms constitutes a challenging task that cannot be performed manually at an optimal manner. Therefore, through the appropriate management of such alarms it will be possible to proceed to improved customer management and assistance for optimal content delivery. Specifically, it should be noted that the provisioning of a superior QoE to users is a very challenging task, as it depends not only on the content itself, but also on the network quality, at the specific location during the specific time. Moreover, the device status may also play a role. If users experience significant delays or other transmission issues, they will complain and may abandon the service permanently, leading to a loss of revenue for operators and content providers.

In fact, a differentiation in terms of QoE delivered by the operators to subscribers or partners will be achieved if network problems do not simply occur. The best approach is not healing or even self-healing, but predicting and thus preventing. One way to avoid network faults is to anticipate potential network degradation or outages. Predictive analysis of the performance of systems and networks, dynamic and proactive allocation of resources are critical components of next generation network manager systems (NMS). The ability to collect, store, move, model data in a structured or unstructured data storage and a reliable data flow while monitoring, displaying and reporting, in real time, the performance of the network and its resources is really important to succeed in the 5G era. In order to achieve this goal, CSPs will have to leverage powerful reporting and, or closed-loop optimization systems maximizing the usage data collected from the network.

The following table summarizes the challenges described in this Section and how AI can handle them.

Wireless Topic	**Threats**	**AI support**
Spectrum management	✓ Guaranteeing a SLA to the spectrum incumbents in a dynamic environment.	✓ Spectrum assignment based on predictive QoS to incumbents.
Air interface	✓ Ultra-fast beam assignment in massive MIMO. ✓ Robustness to hardware impairments.	✓ Beam management via reinforcement learning. ✓ Data-based air interface design.
Radio access	✓ RACH decision and user scheduling in mIoT scenarios.	✓ Deep reinforcement learning based on the number of successful and unsuccessful transmissions.
Radio resource management	✓ Network slicing optimization in heterogeneous networks.	✓ Mimicking computationally demanding optimization techniques via deep learning regression.
Network management	✓ Unpredictable network failures and outages.	✓ Data based QoE predictions in order to pre-emptively manage the network malfunctionings.

Table 1 *Summary of potentials in deploying AI for wireless communications*

Rolling out AI in the Wireless Infrastructure

Deploying AI tools

Future wireless networks will be characterized by an unprecedented level of complexity, which is beyond the capabilities of traditional design techniques in terms of both performance and complexity. A promising way to face this challenge, and thus an enabler of future wireless networks, is AI, and in particular the use of deep learning based on artificial neural networks (ANN), which has the potential to provide a novel design framework able to achieve near-optimal system performance with a complexity in line with the real-time constraints of online implementations [13]. The main barrier towards this goal is represented by the large amount of data required by ANNs approaches, which might be difficult to acquire in the wireless context, due to both privacy and cost problems. However, at the same time, the wireless application of ANNs also offers the possibility to significantly reduce the amount of measurements and live data that is needed. Indeed, as opposed to other fields of science where mathematical models are scarce and deep learning relies only on data, mathematical models for communication networks optimization are very often available, even though they may be simplified and inaccurate. It was shown in [14],[15] that (possibly inaccurate) analytical models can be used in synergy with AI-based, data-driven methods, leading to a significant reduction of the amount of data required to carry out performing system designs, as well as striking a much better complexity-performance trade-off compared to traditional resource management techniques.
A big question in this context is whether it is better to take a cloud/centralized approach, in which all data is stored in a central "artificial brain" where a large ANN carries out all computations and operates the whole network, or whether it is more convenient to take a distributed approach, spreading the intelligence across all network segments and devices. It is our opinion that, although a cloud-based AI would be conceptually simpler, its unique use is not viable for three major reasons:

- Already present networks are required to ensure strict end-to-end communication latencies, which will become stricter in the future. This makes cloud-based AI not feasible due to the additional delays to wait for cloud processing and feedback.
- Future wireless networks will have privacy and security as key requirements. This makes it problematic for end-users devices to share information/data with the cloud.
- In order to ensure ubiquitous service delivery, connectivity should be ensured even in areas and/or times in which only a poor connection to the cloud exists. Therefore, solely relying on cloud intelligence is not recommended.

For these reasons, a mobile AI approach is needed, where each network device will be endowed with intelligence, and will thus be able to self-organize based on local information and data. To this end, we envision two possible approaches.

In distributed AI, each network component (e.g. base stations, access points, user equipment) is an independent decision-maker, which is equipped with its own ANN, that is trained by a local dataset that is built by local measurements. This approach does not require any interaction among the network infrastructure and edge-terminals, as far as data sharing and processing are concerned, thus significantly reducing feedback overheads. On the other hand, it makes it difficult to control the evolution of the whole wireless network and might lead to network failures. Letting each edge component operate based on local information and experience could potentially lead to inconsistencies in the behavior of the different network components, leading to malfunctioning and even network crashes. Research in this context should be aimed at developing new mechanisms to study the evolution of AI-based wireless networks, understanding whether suitable equilibria points naturally exist, or whether the system can be forced to evolve towards desirable operating points.

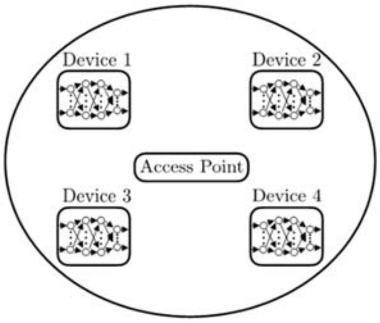

***Figure 2** Distributed wireless infrastructure for AI.*

Figure 2 depicts a possible architecture of a cell wherein all devices associated to the access points are fully self-organizing through the use of their own ANN. No connection exists between the devices and the access points as far as ANN operation is concerned.

On the contrary, in federated AI [15] the aim is to balance between the purely distributed AI approach and the unfeasible and sole cloud-based AI approach. Federated learning distributes the data and computation tasks among a federation of local network devices that are coordinated by a central node. Like in the distributed AI approach, each member of the federation has its own ANN, which is locally trained based on local information/data. After this first phase, each member of the federation transmits to the coordinator the settings of its own ANN, which are then merged to come up with a refined model that is shared among all members of the federation. The amount of feedback between the local nodes and the coordinator should be tuned trading-off between the level of overhead that can be accepted and the performance that must be achieved.

Figure 3 depicts a possible architecture of a cell in a wireless network where the federated learning approach is employed. Each device of the federation, as well as the coordinator, has its own ANN. Each local device trains its own ANN based on local information, and then feeds back to the coordinator information about the resulting ANN configuration. By leveraging these local configurations, the coordinator ANN is trained.

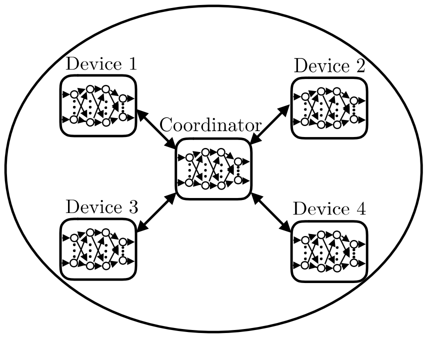

Figure 3 *Federated wireless infrastructure for AI.*

AI Challenges

Telecom operators see AI as almost the unavoidable technology enabling to maintain or even reduce the operational expenditures (OPEX) significantly while delivering higher QoS to the end-users. CSPs will be looking at AI for various reasons. On top of enhancing their business ability, the adoption of AI will be driven by the increased complexity of the network. Indeed, with the advent of 5G, networks will be handling more spectrum, more and varied bandwidths, additional radio technologies, dealing with lower latencies enabling to reach new business territories like on-line tactile applications while benefiting from always more computing power. AI has the power to change the networks from reactive networks, to predictive and finally proactive networks. All of these reasons will benefit for the wide spread of AI in telecoms

However, AI is not seen as the grail technology by everyone. A few factors, not necessarily negligible, may slow down the adoption of AI by the industry. The first reason may rely on the difficulty to fully assess the real benefits AI can bring in daily work despite the fact the market feels it is the way to go. Another reason is also a human, emotional reason: people in the industry may perceive AI as a potential threat to jobs. Right or wrong, this is a reality, AI proponents will have to deal with. But even if the AI advocates pass these barriers, the need to adapt existing operations processes will be a heavy, cumbersome and tedious task and will need support from the top management in organizations adopting AI. An additional obstacle will be the expected transparency of AI. Indeed, delivering AI as a black box may be enough in some cases for basic actions (e.g. like how to optimize parameter settings during a roll-out phase) but would not be acceptable during certain or healing phases. Operators who could not be in the position to explain what happened and why it happened could be reliable to liabilities. Here in lies the next obstacle, which is the training data set accuracy and inclusiveness, and might result in a biased decision making which can be detrimental to the company and its customer base. This is why explainable AI will be sooner or later necessary. All these factors will need, undoubtedly, to be addressed from a successful adoption of AI by the market and the telecommunications industry.

Importantly, in the dynamic wireless transmission scenarios of the future, the training overheads for learning based AI solutions may pose a particular challenge. As an example, typical learning tools available have been developed for applications such as computer vision, speech recognition, or natural language processing, where training time and overheads are not a key factor. In a dynamic wireless environment where the transceivers will need to adopt to changing channels, hardware responses, or event dynamic link connectivity, the overheads of re-training the system are paramount. Solutions inspired by layered training such as incremental or reinforcement learning will inevitably become key in addressing such environments.

The widespread adoption of AI pose severe challenges to the speed and power consumption of existing computing systems. A recent Nature editorial put it succinctly by asking the question "Does AI have a hardware problem?", the author's answer being a definitive "yes" [16]. Present day von Neumann computing architectures require constant shuffling of data between storage and CPU, providing a critical performance bottleneck. Most clock cycles are wasted in moving data rather than computing, while physical separation of memory and processing builds in latency. AI systems, which strive to mimic some functions of the brain, have a significant power cost. While the human brain expends ~20W, large AI systems can consume tens of kW. Scaling up becomes prohibitive; for example, a simulation of a neural network approaching the complexity of the human brain (10^{10} neurons and 10^{14} synapses), running on the Lawrence Livermore Sequoia supercomputer, consumed 7.9MW [17]. This six order of magnitude mismatch in power efficiency is largely because of the "von Neumann bottleneck". Optimized graphic processing units (GPUs) and tensor processing units (TPUs) offer significant benefit, but still consume orders of magnitude more power than biology when performing similar tasks, and do not offer the fault and noise tolerance of biological systems.

The international technology roadmap for semiconductors (ITRS) and the United States department of energy office of science recognize this as a key challenge, stating in 2015: "*Well-supported predictions … indicate that conventional approaches to computation will hit a wall in the next 10 years … Novel approaches & new concepts are needed…*" [18].

As we begin to deploy AI systems both at the heart of communication systems and as edge computing elements for the IoT, such power consumption issues will severely limit the possibility of integrating AI and communication unless significant effort is directed to more efficient hardware solutions. While these will undoubtedly include further optimization of coprocessors (GPUs, TPUs), more ambitious solutions, such as non-von Neumann approaches, are required in the long term.

Challenges
✓ Need to adapt the network operations processes. ✓ AI perceived as a threat for the employment rate in telecom operators. ✓ AI may act as a black box may generate liability issues between parties if no explainable mechanisms in place to explain what happened and why it happened. ✓ Power consumption of existing AI hardware is too high to support either large-scale rollout or distributed edge computing for IoT.

Table 2 *Summary of challenges in deploying AI for wireless communications*

Ethics

In recent months and weeks, some important studies have been issued on the topic of ethics for handling data. One of the first was issued by the French commission nationale de l'informatique et des libertés (CNIL) in 2017. Amongst the six policy recommendations elaborated by the CNIL, the recommendation #2 is directly related to the usage of AI in wireless networks: "*Making algorithmic systems comprehensible by strengthening existing rights and by rethinking mediation with users*".

At the time of writing, the latest report on ethics has been issued by the European Union in April 2019. The EU has released a report including recommendations and requirements to achieve trustworthy AI: "*AI Ethics Guidelines for Trustworthy AI – April 2019*". In this comprehensive report, one requirement on "privacy and data governance" relates to the point raised above. A few key additional needs apply directly to wireless networks as well. In light of the mentioned report, to realize trustworthy AI-based wireless networks the following requirements will have to be fulfilled:

- Technical robustness and safety.
- Privacy and data governance.
- Transparency.
- Accountability.

Both reports, the one from the French CNIL and the one from the European Union, highlight the need of explicability, transparency and accountability. These requirements are paramount with the advent of 5G. 5G will enable new businesses and address vertical ones such as the automotive, transport and logistics or health industries for instance. Accountability and liability will be of the utmost importance. In case problems arise, the 5G network provider will have to explain what happened, why it happened and when the decision was taken. As a consequence, network providers will need to have access to logs, traces and understand the type of algorithms used while having access to the details to the logics that conducted to certain actions. However, it has to be noted that not all actions empowered by AI taken by the network will be needed to be fully explainable. For example, fault monitoring and analysis enhanced by AI to reveal concealed anomalies may not need to deliver a full detailed explanation of the intelligence used. On the other hand, an algorithm guaranteeing a very low latency delivered by a 5G network instantiation (5G slice) for health care and remote surgery for instance, will need to deliver details in case of any issue arise due to legal liabilities and the fact that AI does not work in a lawless world. It is the same for connected cars or intelligence transportation. As soon as legal responsibilities are at stake, the network powered by AI must be a trustworthy AI based network and be able to explain its actions. Next generation wireless networks will be continuing to play a major transformative role and deliver technical and social benefits to the society. AI will not doubt enhance the way wireless networks behaves and make them the central nerve system of the future economy. But the success of it will be relying on secure, trustworthy applied AI in networks guaranteeing the privacy of everyone.

Conclusions

AI is a hot topic nowadays and has achieved huge breakthroughs in the recent years and months. AI is transformative and will be embedded in each link of the overall chain of the telecom system. We envision to see AI almost everywhere: in connected devices, machines, objects, automobiles and many connected things but also in all pieces composing the network like base stations, controllers or core network equipment. However, we need to be aware that this AI proliferation and pervasiveness will generate potential entanglement to need to be solved. Indeed, we can expect AI in each device to process data close to the source to complement the cloud, especially for latency-sensitive and mission-critical applications. AI in the device will also be useful when the device is disconnected from the network and the cloud. Furthermore, the role of ethics in ruling the interchange of information between data owners and AI procedures will be of key importance.

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