WHITE PAPER ON MACHINE LEARNING IN 6G WIRELESS COMMUNICATION NETWORKS

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This paper is a compilation of ideas presented by various entities at the 6G Wireless Summit 2020. It does not reflect agreement on all the included technology aspects by all the involved entities.


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Abstract

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This white paper discusses various topics, advances, and projections regarding machine learning (ML) in wireless communications. Sixth generation (6G) wireless communications networks will be the backbone of the digital transformation of societies by providing ubiquitous, reliable, and near-instant wireless connectivity for humans and machines. Recent advances in ML research have enabled a wide range of novel technologies such as self-driving vehicles and voice assistants. Such innovation is made possible by the availability of advanced ML models, large datasets, and high computational power. In addition, the ever-increasing demand for connectivity will require even more extensive innovation in 6G wireless networks. Consequently, ML tools will play a major role in solving the new problems in the wireless domain. In this paper, we offer a vision of how ML will impact wireless communications systems. We first provide an overview of the ML methods that have the highest potential to be used in wireless networks. We then discuss the problems that can be solved by using ML in various layers of the network such as the physical, medium-access, and application layers. Zero-touch optimization of wireless networks using ML is another interesting aspect discussed in this paper. Finally, at the end of each section, a set of important future research questions is presented.

Introduction

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Today's technological aspirations represent tomorrow's reality with technologies such as holographic telepresence, eHealth and wellness applications, pervasive connectivity in smart environments, industry 4.0 and massive robotics, massive unmanned mobility in three dimensions, augmented reality (AR), and virtual reality (VR), to name only some. Each technology is expected to require more effective and efficient wireless communications than ever. Therefore, 6G wireless networks must provide broadband, near-instant, and reliable connectivity to enable massive data exchange at different frequencies by using a large variety of technologies. Moreover, the trend in the evolution of these technologies is toward more intelligent devices in the Internet of Things (IoT) that will require more reliable, efficient, resilient, and secure connectivity. As the connected objects become more intelligent, it becomes difficult to deal with their complexity by using the communications network statically, simply, and rigidly. The same needs will likely emerge for other "traditional" services such as phone calls or video streaming, where the wireless communications network will no longer merely provide a connection between two or more people but will bring the need to properly authenticate both parties, guarantee the security of data fluxes, and recognize possible abnormal behaviors and events. Data exchanges will need to support much more than just pure data exchanges. They will also exchange information, knowledge, and experience along with the data's past, present, and potential future properties. We can easily anticipate that greater and greater amounts of data will be transferred through the future wireless communications networks. More added value applications and services will heavily depend on such data exchanges. Machine learning (ML) will help implement a basic functionality to guarantee the efficiency of future wireless communications networks, while representing the enabling technology for several added-value applications and services. ML on the wireless communications nodes can enable several advanced services and quality of service functionalities for the proposed applications.

Current wireless networks heavily rely on mathematical models that define the structure of the communications system. Such mathematical models often do not reflect the systems accurately. Moreover, there are insufficient mathematical models for some of the building blocks of wireless networks and devices, and the modeling of such blocks therefore becomes challenging. The optimization of wireless networks also requires heavy mathematical solutions that are often inefficient in terms of computational time and complexity, while consuming considerable energy. The above-mentioned mathematical models and solutions will most likely fall short of improving the capacity and performance of wireless networks that are expected to meet the stringent requirements that will be set by 6G applications [1]. ML will therefore play a crucial role in 6G wireless networks, because it is capable of modeling systems that cannot be presented by a mathematical equation. Moreover, it is expected that it will be possible to use ML tools to replace heuristic or brute-force algorithms to optimize certain localized tasks. Meanwhile, it is envisioned that ML will enable real-time analysis and automated zero-touch operation and control in 6G networks. Such intelligence will rely on the availability of data streamed from wireless devices in a timely manner, especially in extreme applications such as real-time video monitoring and extended reality (XR). To fully leverage these capabilities, the network should support ML-native agents that can be freely placed and moved to the required network locations.

Furthermore, additional ML actions or predictions could be performed by mobile devices and reported to the network to assist in decision making in resource management, making mobile devices an integral part of the infrastructure resource. 6G networks are expected to employ ML agents for multiple functions, including optimization of the radio interface, adaptive beamforming strategies, network management, and orchestration. Such functionality will require data from different domains and sources in the network. This poses additional requirements for the efficiency of data transfer to avoid the transmission and storage of massive amounts of data that may never be utilized over network management interfaces.

ML algorithms should be deployed and trained at different levels of the network: management layer, core, radio base stations, and in mobile devices, possibly with the assistance of the network itself (e.g. via configuration and/or device programmability). These new paradigms may drive the need for a ML-native and data-driven network architecture implemented as network functions within the network and management domains, possibly requiring data from different sources. Meanwhile, physical-layer algorithms (e.g. link adaptation), as well as higher layer algorithms (e.g. mobility), can be optimized with the controlled and predictable deployment of ML agents. Currently, such algorithms tend to be deployed statically, whereas allowing them to change dynamically would open them up to enhanced performance and utilization. Moreover, allowing automated configuration of the network reduces the need for expensive hands-on human work.

The white paper provides a vision for the role of ML in wireless communications by discussing the various network problems that can utilize learning methods as shown in Fig. 1. A detailed examination of the problems at different layers of the communications protocol stack is provided. ML in the security of wireless networks and standardization activities are also discussed.

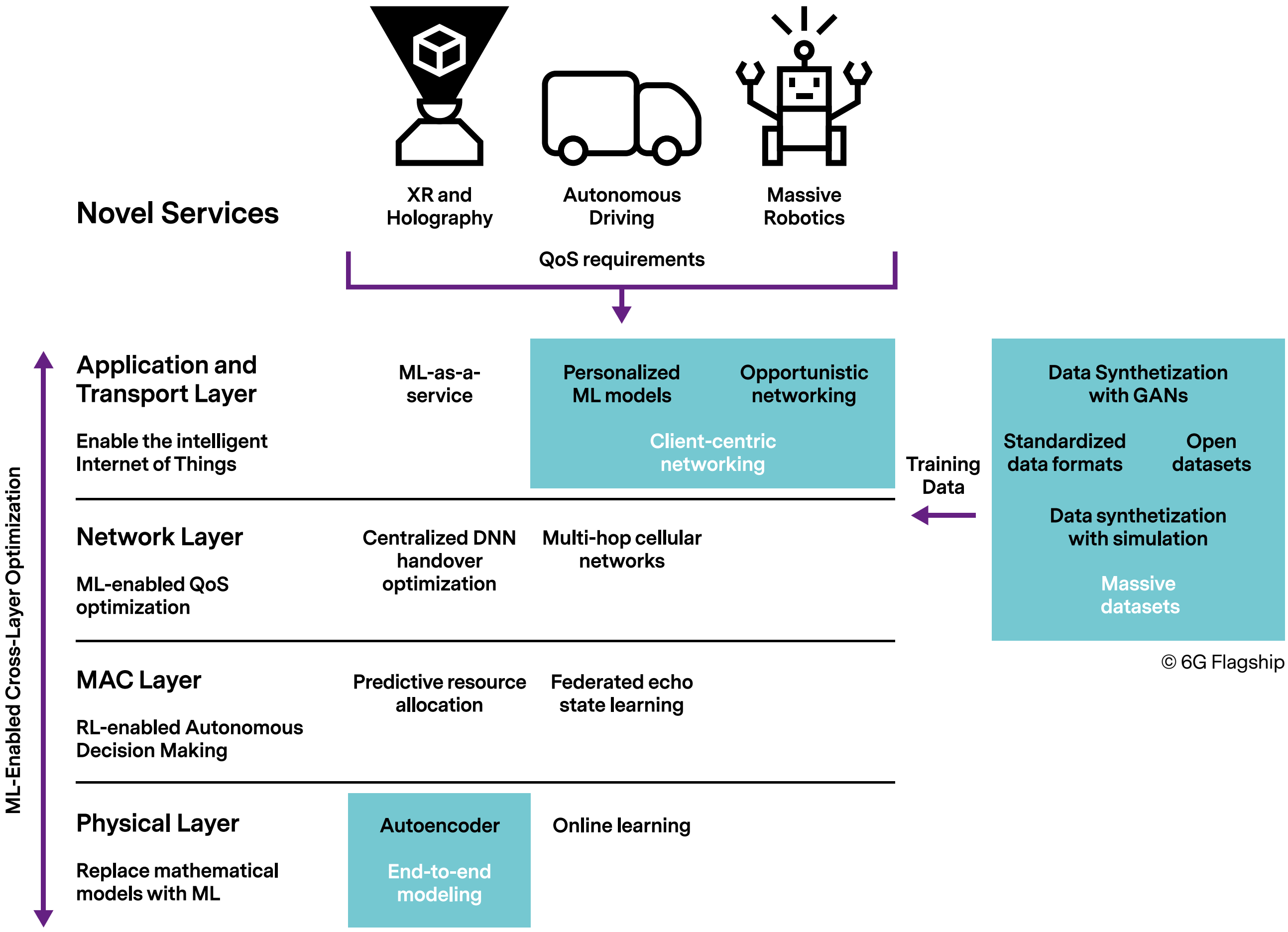

Figure 1: Characterization of remote areas and a classification of connectivity problems.

Machine Learning Overview 3

ML models are computing systems that are used to learn the characteristics of a system that cannot be presented by an explicit mathematical model. These models are used in tasks such as classification, regression, and the interactions of an intelligent agent with an environment. Once a model learns the characteristics of a system (this is known as a trained model), it can efficiently perform the task using some basic arithmetical calculations. ML spans three paradigms, known as: a) supervised learning: where the model is learned by presenting input samples and their known associated outputs; b) unsupervised learning, in which there are no output labels, and the model learns to classify samples of the input; and c) reinforcement learning, where an agent interacts with an environment and learns to map any input to an action. The following provides a general overview of some ML methods.

3.1 Deep learning

Deep learning methods based on artificial neural networks (ANNs) have recently been able to solve many learning problems. The rise of the deep learning paradigm has mainly been fueled by the availability of sufficient computational power and access to large datasets. Many architectures exist in deep learning that are used for various tasks. In this section, we mention some of the most important deep learning architectures that are suitable for problems in wireless communications. Multilayer perceptrons (MLPs) are the basic models that are generally used in many learning tasks. Convolutional neural networks (CNN), which use convolution operation to reduce the input size, are often used in image recognition tasks. For learning tasks which require sequential models, recurrent neural networks (RNN) are most suitable. Autoencoder-based deep learning models are used for dimension reduction, and generative adversarial networks (GANs) are used to generate samples similar to the available dataset.

In the wireless communications domain, the amount of training data is still far from comparable with the huge datasets used by the big industry players for core applications of deep learning such as computer vision and speech recognition. The curse of dimensionality [2] means deep learning models require very large training datasets to achieve significant performance increases compared with simpler models. Another limiting factor is the network heterogeneity implied by the coexistence of different mobile network operators. Although standardized dataset formats could help to establish interoperability, implementations for network management functions may differ significantly between different operators. Moreover, business-oriented principles mean operators may prefer to keep their acquired data confidential. These factors lead to the conclusion that deep learning alone will not be the optimal solution for all data analysis tasks within 6G networks. Instead, a variety of application- and platform-dependent models will be required to enable cognitive decision making even on highly resource-constrained platforms like ultra-low power microcontrollers.

3.2 Probabilistic methods

There have been many recent advances in probabilistic ML and Bayesian inference [3] that could be used in 6G wireless networks. Compared with more classical frequentist methods, they provide a probability theory-based fundamental framework for handling prior knowledge and quantifying uncertainty, needed in noisy real-world learning and modeling scenarios such as data-rich 6G applications and services. Flexibility in handling small, limited, or incrementally growing datasets, non-parametric Bayesian methods such as Gaussian processes especially can provide promising interpretable techniques for modeling complex spatio-temporal and high-dimensional sensing and prediction problems in 6G networks. As non-parametric models grow on data, the computational complexity of these models is the biggest disadvantage compared with parametric models. However, there has been much work based on approximation methods such as variational Bayes, Expectation Propagation, and sampling approaches based on Markov chain Monte Carlo. Determining how to use these techniques to scale and distribute the data is one of the major challenges of wireless communications systems.

3.3 Reproducing Kernel Hilbert Space (RKHS)

Massive connectivity requirements in 6G will result in high interference, which will culminate in a significant performance bottleneck. Furthermore, massive connectivity will also involve serving a wide range of devices of various manufacturing qualities, resulting in the introduction of impairments due to diverse artifacts introduced by non-ideal hardware (nonlinear characteristics, I/Q imbalance and others) and high mobility, especially in the context of varied industry verticals where a fixed solution may not be applicable. To fulfill the promise of 10–100-fold data-rate improvement in these scenarios compared with 5G, Reproducing kernel Hilbert space (RKHS) -based solutions are particularly useful, because RKHS-based methods are computationally simple, scalable, and show significantly lower approximation error (even in the high-interference non-Gaussian environments that may be encountered in 6G) compared with contemporary polynomial filtering-based approaches. Recently, RKHS-based approaches have emerged as a panacea for the mitigation of a variety of impairments in the context of several applications in next-generation communications systems. As a consequence, several RKHS-based methods have been proposed for problems such as detection, tracking, and localization [4, 5]. In recent years, we have also witnessed tremendous research in deep learning being heavily used in wireless communications problems. However, there is a well-known concern regarding the sensitivity of deep learning-based approaches to hyperparameters. As an active area of research, recent advances further improve the performance of RKHS-based approaches by extracting features using RKHS Monte Carlo sampling and utilizing these features as input for deep learning-based approaches to enhance the performance of models used in 6G. In addition, RKHS-based deep-learning approaches are found to deliver improved performance compared with classical deep-learning algorithms, because these features are intrinsically regularized and supported by a strong analytical framework. Finally, RKHS-based solutions have fewer hyperparameters to tune in general, and several rules of thumb exist for learning them.

3.4 Federated learning

Traditional centralized ML algorithms [6] require mobile devices to transmit their collected data to the datacenter for training purpose. Due to privacy issues and communication overload, it is impractical for all wireless mobile devices to transmit their local data for training ML models. Federated learning (FL) is a distributed ML algorithm that enables mobile devices to collaboratively learn a shared ML model without data exchange among mobile devices. In FL, each mobile device and the datacenter has its own ML models. The ML model for each mobile device is called a local FL model; the ML model of the datacenter is called a global FL model. The ML model that is the training process of FL can be summarized as follows:

a. Each mobile device uses its collected data to train its local FL model and sends the trained local FL model to the datacenter.

b. The datacenter integrates the local FL models to generate the global FL model and broadcasts it back to all mobile devices.

c. Steps b. and c. are repeated until the optimal FL models to minimize FL loss functions are found.

From the FL training process, we can see that mobile devices must transmit the training parameters over wireless links. Hence, imperfect wireless transmission, dynamic wireless channels, and limited wireless resource (e.g. bandwidth) significantly affect the performance of FL. In consequence, a number of the existing works such as [7] and [8] have studied the optimization of wireless networks for the implementation of FL. Meanwhile, since FL enables mobile devices to collaboratively train a shared ML model without data transmission, it has been studied for solving wireless communications problems such as intrusion detection [9], orientation and mobility prediction, and extreme event prediction.

3.5 Reinforcement learning

In a reinforcement learning problem, an agent interacts with an environment and learns how to take actions. At every step of the learning process, the agent observes the state of the environment, takes action from the set of available actions, receives a numerical reward, and moves to the next stage. The agent aims to maximize the long-term cumulative reward. Many wireless problems such as resource allocation can be formulated as a reinforcement learning problem. Neural networks can be used in the reinforcement of learning problems as function approximators to learn the rewards that are generated by the environment or values of each state. Various deep reinforcement learning architectures can be used to solve many problems in wireless networks, such as power control, beamforming, and modulation and coding scheme selection. A major limitation of RL is its high reliance on training. However, there have been some recent advances toward reducing this reliance, particularly when dealing with extreme network situations. In particular, the concept of experienced deep reinforcement learning was proposed in [10], in which RL is trained using GANs that generate synthetic data to complement a limited existing real dataset. This work has shown that by gaining experience in response to extreme events, deep RL can adapt, recover, and converge more quickly.

The following research questions should be studied in the future:

- Which areas of 6G wireless networks will use deep learning?
- How to use deep reinforcement learning for the automation of 6G wireless networks?
- How can the goal of open data access be brought together with business-oriented mobile network operator interests?
- How can models be efficiently transferred to highly resource-constrained platforms?
- How can application- and platform-dependent models be dynamically selected and deployed?

4 ML at the Physical Layer

In recent years, ML has begun to penetrate all walks of life, including the field of wireless communication. The physical layer of traditional wireless communications is generally designed based on mathematical models, and several major modules are modeled and optimized separately. This design method can adapt to the fast time-varying characteristics of the physical layer, but often some nonlinear factors in the physical layer cannot be modeled. Research on and attempts to use ML in the physical layer of wireless communications have been conducted in recent years [11]. To continue making progress it will be necessary to integrate ML into the physical layer of 6G wireless systems. An overview of the enabling technologies for physical layer is provided in the 6G white paper on broadband connectivity in [53].

There are several levels of ML integration in a 6G wireless communications system. The first level uses ML only for some specialized functions. We should first consider using ML to replace some functions that are not currently well solved. For example, interference detection and mitigation, uplink and downlink reciprocity in FDD, and channel prediction should be considered. Problems still exist in these functions in current communications systems due to the lack of accurate models or nonlinearity.

The second level of integration is to update the existing discrete modules. The traditional design of each module is generally based on a linear model, so once the system encounters strong nonlinear factors, the performance of the system will decline sharply.

The third level of ML integration is the joint optimization of the modules in the physical layer. As mentioned above, the traditional design of the physical layer is divided into modules and optimized separately. For example, decoding, modulation and waveform are designed separately in the traditional design. Once the three are considered together, the complexity of the receiver is often too high to be optimized as a whole. However, it is unnecessary to design every kind of coding scheme carefully for ML. Nor is it necessary to consider every kind of constellation pattern. A near optimal end-to-end mapping mode can be obtained automatically by learning. The modules that should use ML in the physical layer for joint optimization merit future study.

The fourth level is the integration of ML and the existing model-based methods. Although the traditional model-based method is sometimes over-idealized, it can nevertheless describe the main characteristics of a process. If some existing model features are used for reference in the design process of ML and input into ML as additional information, it is likely to overcome some inherent defects of ML such as the need for huge training data, underfitting or overfitting, slow convergence, etc.

The above discussion provides an overview of how ML will be used in the physical layer of the communications systems. In the following, we provide a detailed view of some of the problems in the physical layer that can benefit from ML methods.

4.1 Research Areas

Some of the major research areas of the ML-driven PHY layer are channel coding, synchronization, positioning, and channel estimations. In dealing with these items, this section defines their definitions, providing their technical trends and prospects.

4.1.1 Channel coding

Channel coding is needed to overcome wireless channel imperfections and correct errors that may occur during transmission. The discovery of turbo coding, which is close to the Shannon limit, along with channel codes such as low-density parity check (LDPC) and polar codes, has been actively studied recently. The research direction of recent channel codes has been moving toward enabling a rapid coding and decoding process to support low latency services, while having a high-fidelity error correction capability. To solve complex problems of channel coding, studies are underway to apply deep learning to channel coding [12], [13]. To replace the channel coding portion of the communications system with deep learning, training is required for codeword lengths equal to at least hundreds of bits (control channel assumption), and the resulting output thus far remains tens of bits (16 or 32 by Polar Code). In other words, it is difficult to compare/predict whether the code length can actually be learned, and what the benefit will be in terms of computational complexity and time compared with the currently commercialized state-of-the-art. The difficulty of an increasing code length is that the number of codes to learn increases exponentially as the length of the code increases (e.g. to learn a codeword of length-n, 2n cases must be learned). Several attempts have been made to overcome this problem (e.g. learning all zero codewords), but there are as yet no clear findings. However, to be implemented in physical systems, the coding algorithm needs to consider not only performance but the computational complexity affecting the time spent decoding. For example, it is useful to graph optimal and suboptimal schemes in terms of both performance and time to help with the algorithm decision process. The graphs of these algorithms may not only be a function of time; they may also be differentiated by the parameters a system considers important (such as computational complexity or services provided).

4.1.2 Synchronization

In general, all wireless devices must go through time/frequency and cell synchronization procedures. Consequently, synchronization that meets system requirements is the starting point for nearly all standards, including 4G long-term evolution (LTE) and 5G new radio (NR). Accordingly, it is pivotal to have synchronization technology that meets system requirements for synchronization accuracy, even in the worst radio channel environment, the fastest mobile environment, and the highest carrier frequency offset (CFO) environment. An end-to-end auto-encoder (AE) -based communications system is likely to achieve global optimal performance with the possibility of implementing the communications system as an end-to-end deep neural network, including transmitter, channel model, and synchronization using a synchronization signal (SS) as a reference and receiver [11]. However, in the presence of sampling timing offset (STO) and sampling frequency offset (SFO) between transmitter and receiver, it is still too early to perform both synchronization and signal detection/decoding with only one auto-encoder (AE) -based deep learning neural network. Recent research has shown that deep learning technologies have used SS separately from signal detection/decoding [14], [15] to assist with forward error correction (FEC) -based synchronization [16] and classification-based synchronization [17].

4.1.3 Positioning

Current mobile positioning technology has identified the location of users in indoor or outdoor environments, based on various signals received from mobile devices or wireless channels using mathematical algorithms. However, a significant problem with the mathematical approach is that non-line-of-sight (NLOS) multipaths can cause significant positional errors. To solve this problem, ML methods have been employed using deep neural networks. To date, the deep learning technology applied to the location technology is primarily based on indoor scenarios, and existing fingerprint methods are characterized by the application of deep learning models. Received signal strength (RSS), channel state information (CSI), or hybrid information are used as input data for fingerprint-based deep learning.

The simulated and experimental results of most deep learning-based positioning technologies were used to generate learning data and measure performance in ideal environments such as static experimental environments. There is no guarantee that deep learning models, which represent the best performance in space A, will also perform well in space B. It is therefore necessary to develop a learning model that achieves acceptable performance due to its being less sensitive to changes in the environment or to generate a learning model for each environment. In real-world environments, input data may not be as easy to characterize as it was in static learning (e.g. RSS information missing, if the bulb is turned off when using a light sensor, the temperature changes, environmental changes by people/things not considered, etc.). It is therefore necessary to develop and analyze a learning network model that can operate as time-varying input data changes. Most positioning systems have been implemented by taking only one target environment into account. However, it is expected that the actual system will have interference effects in an environment with multiple people and multiple devices. The performance difference of the response of a deep learning-based location-level technology between the experimental and actual environment must therefore be analyzed during the research. Through this analysis, a deep learning technology with a robust ability to treat a variety of scenarios should be feasible through adaptive technology (e.g. combined with signal-processing technology) to adapt to the actual environment. A final deep learning solution would couple online learning with offline learning. A detailed view on positioning technologies is provided in 6G white paper on localization and sensing in [55].

4.1.4 Channel estimation

In many communications standards, including LTE and 5G NR, channel estimation is a vital module, which provides information about how the channel distorts the transmitted signal. Linear minimum mean square error (LMMSE) estimation can achieve optimal performance if the channel is linear and stationary. However, real channels may be nonlinear and nonstationary. Under such complicated channel conditions, the analytical form of the optimal estimator is difficult to derive. On the other hand, deep learning-based channel estimation can be optimized through the training of the neural network despite complicated channel environments. Moreover, channel estimation and other modules, e.g. equalization [18], can be realized in a single neural network. Hence, the separate modules in conventional communications systems can be jointly optimized to achieve better performance. Nevertheless, the existing deep learning-based channel estimation techniques have one common shortcoming. Since DNN must be trained offline because of requirements for long training periods and large training data, mismatches between real channels and channels in the training phase may cause a performance degradation. In future research, online training and constructing training data that matches real-world channel conditions might be a promising approach to overcome this problem.

4.1.5 Beamforming

At the physical level, intelligent beamforming and smart antenna solutions can greatly contribute to guaranteeing performance, stabilize the throughput, reduce sensitivity to interference, extend coverage, enable highly mobile applications, and reduce energy consumption. We have already witnessed the evolution of antenna technologies from relatively dumb and basic antennae to more advanced active antennae that progressively include increasing intelligence to utilize the knowledge of the environment and guarantee the optimization of radio links. This evolution is already an integral part of 5G communications and will be boosted further by 6G communication, in which all elements in the communications chain will be characterized by some level of intelligence, or at least a capacity to operate optimally following some degree of training. Again at this level, ML (and more specifically deep learning) can represent the optimal solution for supporting adaptive and real-time massive MIMO beamforming, follow mobility patterns to capture the structural information of the radio channels, coordinate beams with neighbor base stations, properly allocate power, adapt emission patterns for mobile devices, and exploit beamforming for added value services. Dedicated hardware other than dedicated algorithms can help implement efficient machine-learning solutions to support a new generation of intelligent beamforming and smart antennae.

4.1.6 Physical layer optimization with ML

At the physical layer, many optimization problems are non-convex, e.g. maximizing throughput by means of power control, multi-user spectrum optimization in multi-carrier systems, optimization of spectrum sensing for cognitive radios, and optimal beamforming formulated as a sum-rate maximization problem under a total power constraint, to name only a few. Such problems may be solved using dual decomposition techniques that require iterative algorithms, which in turn often cannot be computed in real time due to a high computational load. To alleviate the high computational complexity and resulting latency associated with existing iterative algorithms, heuristic solutions have been proposed for some physical layer problems such as beamforming design. Although heuristic solutions can be obtained with low computational delay, this benefit comes at the expense of performance loss. Yet deep learning techniques have great potential to find solutions to these problems in real time, while maintaining good performance and reducing computational delay. As such, deep learning is a powerful technique for designing, enhancing, and optimizing one or multiple functions in the physical layer for 6G. This includes CNNs for signal classification, and DNNs for channel estimation and signal detection.

Recent research on physical layer optimization that exploits ML includes a deep learning framework for the optimization of multi-input/multi-output downlink beamforming [19]. The CNN-based solution takes expert knowledge into account, such as uplink-downlink duality and the known structure of the optimal solutions. The proposed beamforming neural network (BNN) is shown to achieve a good trade-off between performance and computational complexity. Open questions in this context include providing solutions for imperfect CSI and multi-cell scenarios.

If joint optimization of functional blocks in the physical layer is considered, and the channels are too complex for modeling, deep learning models are the best solutions for achieving performance improvement. Conventionally, the channel estimation based on the pilot estimation and the signal detection based on channel estimation are executed separately one after the other. In [20], which considers the channel as a black box, a fully connected DNN with five layers is implemented for joint channel estimation and detection. The received signals corresponding to both the transmit signals and the pilots are taken as inputs of the DNN to recover the transmit signals as outputs. This DNN has been shown to be more robust to the number of pilots than conventional methods and can address complicated channel distortions.

Future directions in physical layer optimization with an ML focus on the paradigm of an autoencoder that has been introduced in [21], aiming for a deep learning-based end-to-end physical layer architecture. In this approach, transmitter and receiver components are jointly optimized in the presence of a given channel. Autoencoders of the deep learning network for building the end-to-end physical layer modules consider designing a communications system as an end-to-end reconstruction optimization task. The autoencoder would jointly learn transmitter and receiver realizations without the need for expert knowledge and modules. Given the complexity associated with building end-to-end physical layers, it is currently more feasible to exploit deep learning techniques to design, enhance, and optimize one or multiple functions in the physical layer for 6G.

4.2 Implementation of ML at the physical layer

While power, cost, and size are always considerations in implementing neural networks, they are of extreme importance in implementing ML algorithms in user equipment (UE) or at the cell edge. Additional considerations during simulation and prototyping of ML in UE devices need to be taken into account to optimize the physical realization of designs. Implementations may be software-centric early in the design-phase. However, the only way to achieve acceptable battery life while processing real-time data is to migrate to a HW-centric solution. The following sections outline the three main phases of development and the expected requirements of an artificial neural network (ANN) during them. It is expected that training will occur during the simulation and prototype phases. For a final product, the feed-forward network will be ported to the physical device where weights are still software-defined, but other features may be fixed in the hardware design.

Simulation

The first stage in the development of a wireless modem is typically a software simulation of the physical layer transmitter and receiver. The air interface is simulated with a channel model that attempts to recreate real-world conditions such as noise, fading, multipath, Doppler spread, and path loss. Various aspects of the receiver can be implemented in an ANN. These are discussed in this paper. At this point, ML will take place in ANNs where the number of nodes, layers, connections, activation functions, and back propagation loss functions must all be flexible while the network trains. During this initial stage, the many parameters and characteristics of the ANN will need to be identified with trade-offs between performance and physical resources. Although the training of an ANN is not performed in real time, performance considerations remain important, because there are practical limitations to how long simulations can run. Offloading ML algorithms from a Central Processing Unit (CPU) to a Graphics Processing Unit (GPU) can increase performance 10- or 100-fold [22]. In addition, specific ANN accelerators may improve performance even more, but they are not always suitable for supporting the back-propagation required for training [23].

In order to train an ANN, many different channel models need to be employed and run in a Monte Carlo style simulation with multiple trials. Each trial run with a different random seed can be fairly complex to generate and take hours to run, because the model simulates impairments at the symbol rate. How well the ANN will model real-world conditions depends on the quality and diversity of the channel models. For illustrative purposes, if we have 30 channel models, each is run 20 times with randomized data, and the simulation takes eight hours to run, resulting in 200 days of run time. This shows that these simulations need to run in parallel on a high-end grid or cloud-based engine. It is also obvious that we want to reduce simulation time by offloading the ANN to specialized hardware. A major task during simulation is to identify the structure and features of the neural network. If we wish to compare the performance of several activation functions or vary the numbers of connected nodes in each layer, we can see that the computing resources required in the simulation stage are vast.

A major part of the design with any ML algorithm in the physical layer is to determine the inputs to the ANN. Filtered outputs such as channel estimator data, FFT output, pilot symbols, and possibly uniquely filtered data are all candidates as inputs to the ANN. Raw I/Q samples would likely overwhelm any reasonably sized ANN and result in convergence taking far too long – if it proves possible at all. Hooks into the processing stack are required to bring out any raw data that is required as an input to the ANN. Outputs such as bit error rate (BER), signal to interference plus noise ratio (SINR), and cyclic redundancy check (CRC) validation will also need to be fed back into the loss function.

Prototyping

After simulation, a prototype platform will typically be developed, utilizing a field-programmable gate array (FPGA) as the main processing engine [24]. It is desirable to run the platform in real time, or at least at a scaled down rate such as 1/2 or 1/4 of the real-time sampling rate. We wish to transmit and receive over the air in the band of interest so that we are not limited to training with predefined channel models, as in the simulation stage. In this case, ANNs can be trained over a wide set of conditions that include varying distance, rural or urban environments, speed, and weather. It is important to be careful to ensure when training in one scenario that the ANN does not "forget" previous scenarios. For example, the system may adapt well to a rural environment, but after training in an urban environment, the performance in a rural environment may suffer [25].

IP cores can be synthesized into an FPGA to implement a DNN [26]. These cores, such as Xilinx's Deep Learning Processor Unit (DPU), are highly configurable, allowing the user to allocate resources such as DSP slices, block RAM, UltraRAM, and convolutional architecture. However, these settings only allow choosing from a fixed set of possible architectures, so an extremely efficient design to fit exactly what is required is impossible. There are also now chips, such as the Xilinx Versal [27], in which up to 400 inference engines are built into the FPGA. This will allow for much flexibility and speed in the design.

There is also an open-source framework for accelerating deep neural networks on FPGAs called DnnWeaver (dnnweaver.org). The framework allows a developer to specify the ANN architecture from a high level. The tool then automatically generates Verilog code. It is also platform-independent, so it is not specific to one manufacturer over another.

With the end goal of an efficient ASIC, after acceptable performance is found, the ANN must be analyzed for optimization. It has been shown [23] that reducing the number of bits in fixed point multipliers, even from 32 bits to 16, can result in only a very small performance loss but use almost one-eighth of the power and area of the die. Even quantization to 8 bits can result in little inference loss [28]. Weights that are close to zero can be pruned so that memory is saved in addition to computational resources, as shown in [28], with minimum accuracy loss. The assumption is that the number of nodes and layers in an ANN would not change significantly when porting the design to an application-specific integrated circuit (ASIC).

Product phase

Any final product with an ANN to facilitate physical layer processing must place strict limits on the number of nodes, layers, and bits in fixed point MAC operations. Once the design is ported to an ASIC, it will be assumed that a fully trained ANN will be imported to the design. However, there must still be some flexibility in updating the network too to ensure that weights and some connection information can be updated through software downloads.

Design considerations must be made regarding which inputs and outputs will be available to/from the ANN. Allowing the ANN to reside on a separate co-processor requiring moving data off chip can take up more than the available timeline. Any ANN would have to be treated the same as any physical layer processing block, in which the data is readily available, and the neural net is part of the processing chain.

4.3 Future directions

It is expected that deep learning technology will be employed for the wireless transmission of the 6G mobile communications infrastructure in the next ten years by conducting practical learning online as part of the model trimming approach to overcome differences in performance based on the learned wireless channel model and actual wireless channel environment.

More specifically, we first predict the impact and uncertainty regarding deep learning-driven PHY layer technologies, as shown in Figure 2. The classification criteria in this figure are as follows. Performance degradation due to offline learning and actual mismatch in the wireless

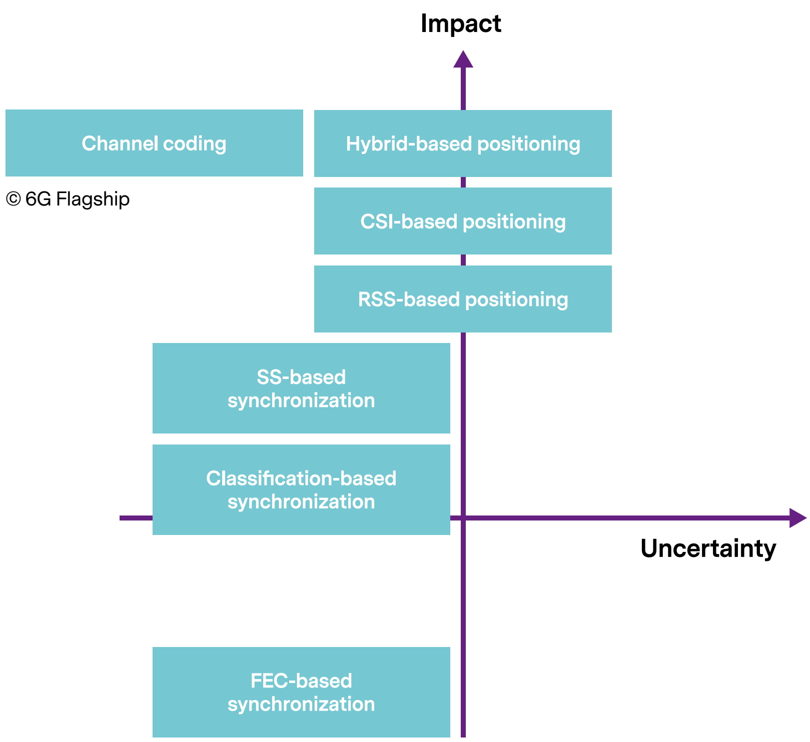

Figure 2: Impact and uncertainty regarding deep learning-driven PHY layer technologies.

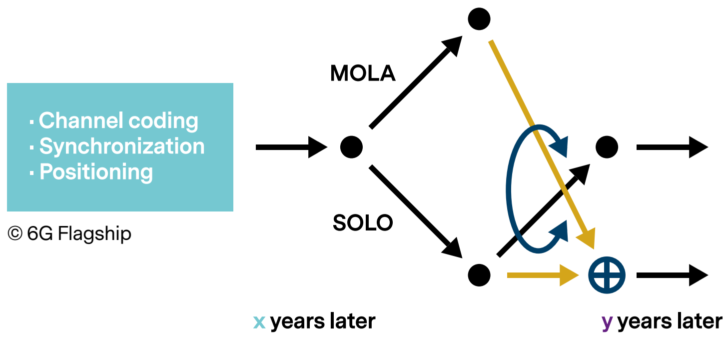

Figure 3: Research direction regarding deep learning-driven PHY layer technologies.

channel environment is expected to be relatively higher for positioning items. Because channel coding assumes radio channel compensation, the effect of radio channels is reduced in the form of colored noise. Furthermore, synchronization is undertaken not to perform any channel estimation but a correlation greater than the synchronization signal length for a given radio channel, which may be less affected by environmental inconsistencies. However, positioning is based on the fact that it is directly related to the nature of radio channels and is therefore more likely to be affected by environmental inconsistencies.

Secondly, as shown in Figure 3, we outline the research direction regarding deep learning-driven PHY layer technologies. From now until x years[21], it is expected to have two directions as follows. The first is multi-offline learning and adaptation (MOLA), which will perform offline learning on a number of channel models in advance, file-up to the system, and monitor the actual radio channel characteristics to apply the appropriate offline learning to the system. The second is single offline learning and online learning (SOLO), which identifies the performance sensitivity of each radio channel characteristic factor, applying offline learning based on the least sensitive factors to the actual system, and online learning to adapt to the actual online radio channel characteristics. Next, it is expected that after y years, either MOLA or SOLO will be used, depending on the radio channel situation. The classification criteria in this figure are as follows. MOLA is expected to take a long time, because it will require vast numbers of data bases and memory amounts, but is expected to be used effectively in some wireless channel environments. In addition, in radio channel environments that are not covered by MOLA, SOLO is expected to be applied semi-optimally, but this is a prediction; it should not be ruled out that if SOLO can cover MOLA in both performance and implementation terms, the former will eventually be used.

The following research questions should be studied in the future:

- Which problems in the physical layer could be solved by ML, and which methods are most suitable?
- Is end-to-end communications system design possible using deep learning?
- How can deep learning be used to optimize the physical layer?
- What are the implementation issues of using ML methods in the physical layer?
- How does deep learning-based physical layer optimization perform on real data obtained from the testbeds that operate in actual physical environments?
- How does deep learning-based physical layer optimization perform under imperfect CSI, channel correlation, and other imperfections?
- How can deep learning-based physical layer optimization be combined with the intelligence in upper layers?
- How can the training workload of deep learning models for physical layer optimization be reduced by using recent advances in deep learning such as domain adaptation and transfer learning?
- How can training data be reduced by applying the advances of generative adversarial networks to generate artificial data in the physical layer?

[21] Depending on the degree of performance deterioration caused by offline learning and actual wireless channel environment mismatch, x may differ for each item. If it is based on Figure 3, channel coding, synchronization, positioning is listed by item, with the smallest x value.

ML at the Medium Access Control Layer

5

The medium access control (MAC) layer of cellular networks performs tasks such as user selection, user pairing for MIMO systems, resource allocation, modulation and coding scheme selection, power control of uplink transmissions, and random access and handover control. Given their complexity, several heuristic algorithms are currently in place to address these problems. There are no optimal solutions for these problems in real environments. ML tools must be leveraged to significantly enhance the MAC scheduler to provide significant gains in real environments. Although optimal solutions are unavailable, significant thought must go into how to train ML models for these problems. Hence, reinforcement learning frameworks are most suitable for problems in which the network can adapt to varying user conditions such as channel conditions and learn the optimal strategies. For example, a scheduler must learn to predict the buffer traffic characteristics, speed, and channel variations over time and use these predictions to make intelligent scheduling decisions. Care must be taken, because the state-action space can grow very quickly in such a situation. Intelligent deep reinforcement learning algorithms that can deal with combinatorial action spaces and multi-agent environments must be explored for these problems. In the following, we provide some use cases for which ML can be used in MAC-layer communications.

5.1 FL for orientation and mobility prediction in wireless virtual reality networks

An elegant and interesting use of federated learning (FL) to solve wireless communications problems is presented in [29]. It minimizes breaks in presence (BIP) that can detach virtual reality (VR) users from their virtual world. The model in [29] considers a set of base stations (BSs) that services a set of wireless VR users over both uplink and downlink. The uplink is used to track information transmission; the downlink is used for VR image transmission. VR users can operate at both mmWave and sub-6 GHz frequencies. The sub-6 GHz band is used to track information transmission; the mmWave band is used to track VR image transmission. In contrast to the existing VR works such as in [30–32], which assume the VR users are static, the VR users' locations and orientations in [29] affect the BIPs of each VR user. Since mmWave band is used for VR image transmission, the blockage effect caused by the human body is considered. The purpose of [29] is therefore to minimize the BIP of each VR user by adjusting user association. To determine user association, the orientation and mobility of each VR user must be proactively determined.

A federated echo state network (ESN) prediction algorithm is used to proactively determine users' orientations and mobility. The input of the federated ESN is the historical orientations and mobility of each user. The output of the federated ESN is the future orientations and locations of each user. At each training iteration, each BS only need to transmit the ESN parameters to other BSs without transmitting users' orientation and mobility data. When the training process is completed, the federated ESN algorithm can predict the locations and orientations of each user. Given the predictions of each VR users' locations and orientations, the BSs can optimize user association to minimize the BIP of each user and enhance VR quality of experience.

5.2 Predictive resource allocation in machine-type communications

Most Internet-of-Things (IoT) applications have devices that are stationary or of low mobility, and the traffic originating from such IoT devices has specific patterns. ML-based predictive resource allocation is therefore possible using the "fast uplink grant" [33]. Such a predictive resource allocation will decrease the latency of the network and alleviate problems associated with the random access process for machine-type communications (MTC) [34]. Some initial results and directions on the predictive resource allocation for MTC are presented in [35]. However, many open problems remain to be solved. The first is to study various types of data traffic originating from MTC and find the right tools to solve the source traffic prediction problem. For example, event-driven traffic prediction requires sophisticated ML tools for event detection and traffic prediction. The second is optimal predictive resource allocation using online decision-making tools in various systems such as non-orthogonal multiple access (NOMA), massive MIMO, and cell-free massive MIMO. It is therefore clear that ML will play a major role in enabling predictive resource allocation mechanisms in future MTC networks. An overview of MTC networks and the related technologies is provided in 6G white paper on MTC in [54].

5.3 Predictive power management

Energy consumption is a crucial factor in the design of wireless networks. Besides the environmental factor, the requirement for IoT devices to have a long battery life is one of the key drivers of the continuous exploration of techniques to conserve energy for future 6G networks as well. Energy conservation can be performed at different layers of the system. However, it may be most effective at the MAC layer because of the direct control of the radio consuming the maximum power. Therefore, using ML techniques to predict traffic and segregate the packet based on priority can improve the performance of adaptive power saving mechanisms.

Moreover, current wireless networks employ transmit power control or retransmissions to improve system performance in high interference scenarios. Such an approach has a detrimental impact on system performance in energy efficiency. Predicting the transmit power based on actual network conditions could result in the improved energy and spectrum efficiency of the overall system. Naturally, reinforcement learning techniques are most suitable for power control problems.

By deploying ML based algorithms to study the cell-level traces collected in a real network, it is possible to devise models based on predicted traffic patterns, and contextual data for different cells and the corresponding load metrics. These models can learn the behavior of neighboring interfering users and adjust the sleeping scheduling and transmit power accordingly. Moreover, such models can be used to dynamically switch BSs on and off to conserve energy at higher levels as well.

5.4 Asymmetric traffic accommodation

Wireless data traffic is asymmetric in nature. The two main duplexing schemes that current wireless networks employ are time division duplexing (TDD) and frequency division duplexing (FDD). In TDD systems, addressing the issue of asymmetric traffic is simple and can be managed based on the downlink and uplink traffic load. However, in FDD systems, the downlink and uplink frequency bands are separated by the frequency gap to provide isolation from self-interference. Although much progress has been made in providing efficient cancellation of such interference and enabling a true full-duplex system, it is still not sufficiently mature. In FDD systems, the symmetric allocation of resources between the uplink and downlink results in their underutilization. ML techniques can help to provide intelligent solutions to such problems through the seamless integration of data traces collected from cells to enable proactive MAC functions rather than traditional reactive ones.

Recently, the flexible duplex complex has been introduced. This allows the dynamic allocation of resources in both the time and frequency domain simultaneously, instead of static TDD and FDD addressing asymmetric traffic. Flexible duplexing allows matching the resource based on traffic pattern, even in a single paired FDD. Yet the use of TDD allows granularity in the allocation of resources to the symbol level instead of the carrier level in FDD. Deploying flexible duplexing for broadband communications may be possible where downlink traffic is greater, and uplink resources are reallocated for downlink transmission. In this case, downlink traffic will show interference from neighboring cell uplink users with low transmit power, and the corresponding downlink power can therefore be adjusted. ML-based algorithms can drive such techniques proactively, because the entire concept is based on traffic patterns and network activity, resulting in increased system performance.

The following research questions should be studied in the future:

- What is the role of predictive models in the MAC layer?
- How will ML help in resource allocation in wireless networks?
- How could asymmetric traffic prediction benefit from ML?
- What ML methods could be used for MTC networks and what kind of problems it can solve?
- How will FL be used to address mobility for virtual reality?

ML for Security of Wireless Networks

6

This section briefly discusses the role ML will play in the security of future wireless systems. First, a general roadmap to 6G security is provided, followed by a discussion of security aspects in the wireless medium. A comprehensive study of the security aspects of future wireless networks is given in [52].

6.1 The road to 6G Security

The integration of massive IoT and the provision of new services such as smart homes, hospitals, transportation, and electric grid systems in 5G will pose a challenge for security features. Among the prominent solutions governing network security, ML-based solutions have received the most attention because of the exacerbating amount of traffic expected in 5G. In 6G, speeds will grow by many times, latency will be non-observable, connectivity will be poised to be ubiquitous, and critical infrastructures will be automated using the underlying network infrastructure. The network security paradigm will therefore further shift toward extremely agile, dynamic, and autonomous systems. ML-based security solutions will thus be inevitable.

With the conglomeration of diverse IoT devices and services, unmanned aerial vehicles (UAVs), vehicle to infrastructure (V2I), and smart home appliances within 6G networks, differentiating between a security attack and legitimate traffic will be practically impossible or unmanageable without using ML tools. The analysis of enormous amounts of data to monitor network traffic-in-transit for security will require designing proactive, self-aware, and self-adaptive ML techniques. Since critical infrastructure such as electrical smart grids, transportation, and healthcare systems will be connected, proactive security measures will require continuous intelligence gathering and the use of intelligence to mitigate the possibility of security risks and lapses. This will necessitate vast storage and computing resources in an almost zero-latency vicinity. Such systems will thus require the use of ML to proactively transport ML-based security systems to different network perimeters, as well as scaling the required resources dynamically with no delay. Hence, ML will be a stepping stone to predict and provide the required security systems in those perimeters on one hand and extending the necessary resources through scaling up the resources from the pool of available virtual resources on the other.

ML-based security approaches need to be considered from end-to-end network perspectives in 6G. Currently, ML has been used in different services, parts of networks, and networked nodes. In 6G, the use of ML must be synchronized across the network. Consider the case of intelligent ML-based spectrum sharing. Intelligent spectrum sharing requires the spectrum information to be securely shared among peers competing for the same frequency slot. The first case would be to secure the sharing of information among the contending and provider peers. ML can be used to recognize the legitimacy of the contending peers, allowing for the secure sharing of information. However, having adjusted the upper layers after hopping to the available spectrum as agreed by the providing and contending peers, security will still need to be in place. An example might be the adjustment of secure routing procedures in the network layer due to a decision taken in the physical layer. Such systems employing ML in each layer, e.g. in the physical layer regarding secure spectrum sharing and in the network layer regarding secure route establishment and security of the payload afterwards, will require synchronized ML procedures.

6.2 Wireless security

The inherent openness of the wireless medium makes it susceptible to interference. Interference can be either intentional or unintentional. Unintentional interference can be caused by devices close to us that may transmit at higher power levels as instructed by their controllers. Intentional interference, on the other hand, corresponds to adversarial attacks on a system. Adversarial attacks are detrimental for a system, because they may hamper communication among various nodes and potentially halt important communication. Two aspects of wireless security must be studied – defense and attack. Defensive mechanisms include cryptography and the like, while attack refers to mechanisms in which an attack such as jamming or eavesdropping is proactively performed to secure the future transmissions. Such security-related studies not only allow for the analysis of system vulnerabilities but enable an enemy system's capabilities to be undermined.

The fast pace of research in the field of ML may enable every device to possess some sort of intelligence that can be used either positively or negatively. If such capabilities exist with malicious devices, i.e. those that intend to cause interference, this threatens the security of the various devices coexisting in the same environment. It is thus extremely important that devices be intelligent if everything about the adversary is to be known to limit the effectiveness of attacks.

Typically, such problems have been addressed via game theory or optimization frameworks. While they afford good insights, they often assume static environments or static action space for an adversary, etc., which may not be the case when an adversary themselves possesses ML capabilities. We must therefore study these systems from both attack [37] and defense [38] perspectives. From an attack perspective, we need to design ML models that can learn the environment in real time and prevent the adversary communicating or interfering with the required network. From a defense perspective, we need to design a communications system that is robust against any attack. Adversarial ML mechanisms can also be used to design robust techniques.

The following research questions should be studied in the future:

- What role does machine learning play in 6G Security (beyond ML-based security in 5G)?
- What aspects of physical-layer, MAC-layer, and network-layer security can be addressed via machine learning?
- How and where does machine learning in security find use cases? What examples are there in defense applications?

ML at the Application Layer

7

ML solutions directly embedded within the wireless communications nodes at the lower layers, with advanced features such as context awareness, performance optimization, and multi-agent reinforcement learning, will enable a more reliable and stable per-user and per-application data rate, peak data rate, air-interface latency, spectrum efficiency, and energy efficiency. At the same time, embedded ML solutions on the wireless communications nodes at the transport layer or the application layer, with sensor fusion techniques and the capacity to run ML as a service, will improve experience sharing, remote control capacity, seamless connectivity, and services.

In particular, context-aware systems will provide the capacity to implement services that maximize the application's safety while minimizing its explicit interaction with the environment. In general, a set of rules must be specified for the possible contextual configurations, and each rule is assigned to a specific service in the context-aware system. This is a common problem in determining and limiting the set of possible context configurations. Instead of a rule-based approach, ML can be used to predict all possible and meaningful context configurations. This ML approach can use the previous choice of service and adapt to a new choice of service from the user/application feedback information. A variety of ML techniques can help to develop general-purpose context-aware applications without needing to define the context's a priori rules and elements. This context-aware application may provide service proactively by using different types of learning algorithm in an operational environment that can be smart and continuously changing. User preferences (the choice of services) may also change over time, meaning an adaptive learning algorithm would certainly be preferable. The middleware layer plays a vital role in the context-aware system. Middleware is responsible for context modeling, context reasoning, and controlling sensors and data sources, appliances, and devices based on the decision from the context-aware application layer.

Making ML available as a service on wireless communications nodes will add flexibility and power to communications networks. Four key trends are making ML more accessible to users and companies: (1) improved processing power; (2) reduced data storage and processing costs; (3) expanded data availability; and (4) improved techniques such as the emergence of cloud-based deep learning solutions. Hybrid cloud and fog computing are likely to further extend such accessibility by making ML available as a service for users and applications in the application layer of wireless communications nodes. Edge intelligence is another important element that will play a vital role in 6G systems. A detailed view of the edge intelligence and wireless systems provided in the related white paper [56].

7.1 ML for 6G network performance management automation

5G advanced/6G mobile networks have become more complex, demanding smarter network features and approaches to handle any key performance indicator (KPI) degradation, anomaly detection, and trend prediction to keep the KPI within the required thresholds [39]. This can be achieved by applying ML- and software-defined networking (SDN) solutions. ML will enhance the decision-making process to keep excellent KPI network service levels.

For 6G, a new approach is required for the management and implementation of radio access networks (RAN). Some examples of improvements include adding ML to baseband processes, using a virtualized container-based RAN compute architecture, and running the containers close to mobile edge computing (MEC) servers to achieve latency as low as 1ms. 6G virtualization for

RAN and CORE alike is moving to container-based applications from open stack VM-based applications due to efficiency and security. ML enables anomaly detection in KPI trend spikes, success and failure rates, handover KPIs, accessibility KPIs, and availability KPIs, as well as integrity, privacy, and security KPIs.

Enabling ML modeling for accessibility, availability, mobility, and traffic performance using the 6G network real-time data extracted from UE measurement reports will enhance and automate network performance management to keep KPIs within predefined thresholds. ML will enable the automation of the management of 6G dynamic mobile networks with smart adaptive cells. This could enhance the performance of coverage, throughput, QoS prediction, automatic network configuration, power control, operation, maintenance, fault management, power saving, and beam management. Figure 4 shows the management aspects of ML-enhanced 6G network performance.

7.2 ML-aided UAV control

One of the major ultra-reliable low-latency communications (URLLC) applications is to control UAVs over wireless links in new mission-critical scenarios, such as providing emergency wireless networks for disaster zones and delivering first aid kits in rescue missions [40]. The control of UAVs requires a guarantee of stability which is only possible if the wireless communications can assure case-specific targets of ultra-reliability and low latency. In 5G URLLC, transmission techniques such as short packet transmission and spatial/frequency/temporal diversity are considered to achieve the 99.999% reliability and 1ms. latency targets. However, considering control techniques to guarantee (physical) stability allows the relaxing of the latency and reliability requirements for transmission in mission-critical applications [41, 42]. Additionally, due to various (communication and/or control) constraints, the communication and control co-design (CoCoCo) in real-time UAV use cases and many other automation applications can become a very complex problem. To overcome the complex nature of CoCoCo problems, the regression/adaptation/learning capabilities in ML methods can be utilized. In the following, two use cases of CoCoCo are briefly described.

In the first use case, a single UAV is controlled by a ground controller to reach a target destination. At each control cycle, the UAV state (the velocity and distance to the destination at each time instant) is downloaded to the controller, and the optimal action (acceleration) computed by an ANN in the controller is uploaded (UL) to the UAV within a deadline. The UL transmission power can be tuned based on the download latency to meet the deadline. When the environment dynamics have been learned, and the transmission cost becomes high, the UAV switches to autonomous mode by receiving the ANN model from the ground controller [43]. The UAV is thus always controlled by a well-trained ANN, even in completing the desired mission.

Another use case considers a swarm of autonomous UAVs dispatched from a source to a target destination.

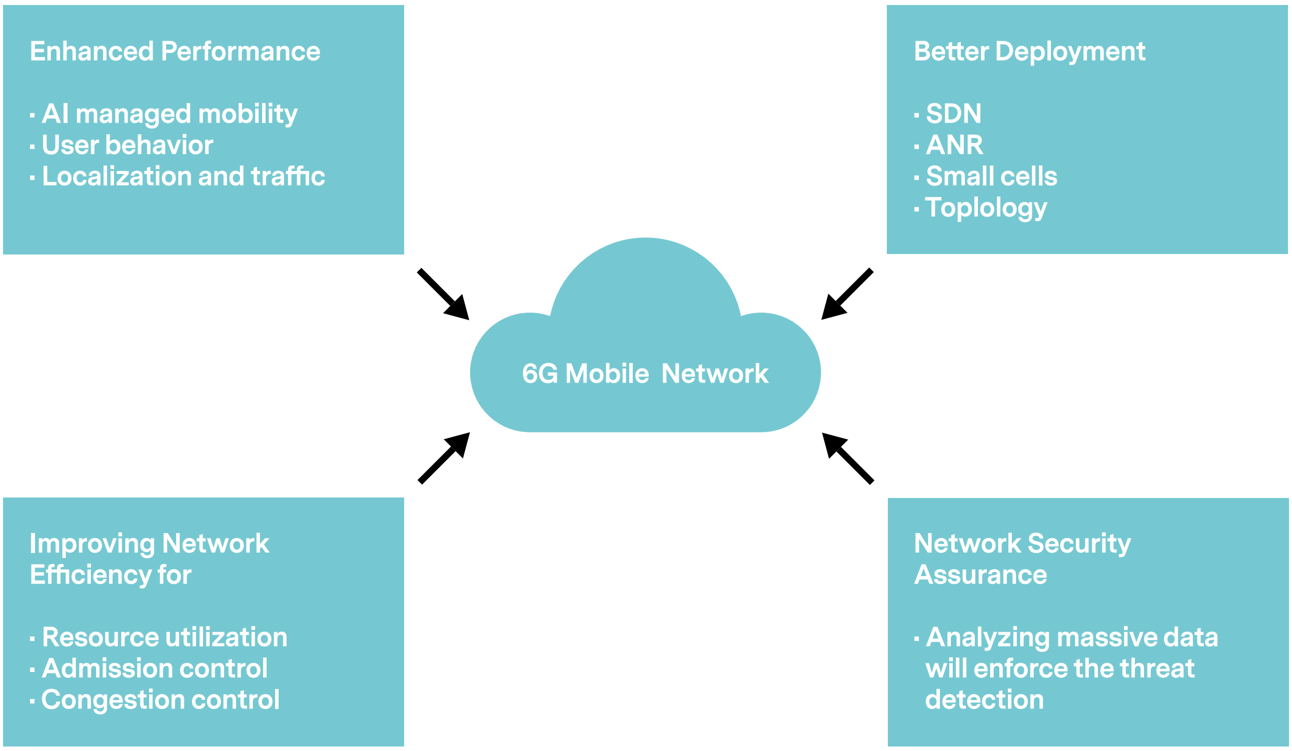

Figure 4: ML enhanced 6G network performance management.

Each autonomous UAV is controlled by running a pair of ANNs to obtain a mean-field (MF) approximation of other UAVs states (MF neural network) and then to compute its optimal action (action ANN). To reduce the risk of collision, the action ANN is affected when the relative distance of UAVs becomes small, or their relative speed becomes large. The stability of this control method is guaranteed when the initial states of the UAVs are exchanged. Moreover, this ANN-based control method can reduce transmission power [41, 44].

In both examples, ML and communication are considered together and the reliability, safety, and energy consumption of the UAV control are improved. This method of control, in which both ML training and communications benefit from each other is extensively studied in [45]. Other possible ML and communications co-design use cases such as [46] intelligently utilize communications resources with the help of predictions provided by the ML, and [47] solves a distributed ML problem in a communications-efficient way. Based on these research examples, considering communications and ML/control can provide many advantages. However, control and communications co-design remains a challenging issue that needs to be addressed further in 6G.

7.3 Opportunistic data transfer in vehicular networks

Parallel to the technological advances driving the development of 6G networks, road vehicles are subject to a stepwise evolution process that aims to improve traffic safety and efficiency by introducing means of connectivity and automation. As a side-effect of this development, the manifold sensing capabilities of modern cars will allow us to exploit vehicles as moving sensor nodes that can cover large areas and provide highly accurate measurements. Crowdsensing-enabled services such as the distributed generation of high-definition environment maps will then allow vehicles to improve the situational awareness of the vehicles themselves.

Data transfer in vehicular networks is a challenging task, because the channel dynamics depend on a large amount of external and environment-specific impact factors. Vehicular communications systems must be compliant with very high velocities on highways and be able to cope with sporadic line-of-sight situations in inner cities. As a result, moving vehicles frequently encounter low-connectivity regions where link loss and packet errors are highly probable, resulting in the need for retransmissions.

Client-based context-aware network optimization techniques such as opportunistic data transfer and multi-connectivity offer the potential to improve performance without requiring an extension of the actual network infrastructure. Consequently, ML-based data rate prediction allows the selection of network interfaces and scheduling of data transmissions based on the anticipated resource efficiency. A window of delay tolerance relates to application-specific requirements for the age of the information about the sensor measurements. This approach allows us to proactively detect and avoid highly resource-consuming transmissions.

Although first feasibility studies [48] that make use of passive downlink indicators have practically demonstrated the achievable benefits of this approach, purely client-based techniques are almost unaware of the network load and the potentially available resources within the connected cell, which ultimately limits the achievable data rate prediction accuracy.

Within 6G networks, these limitations could be overcome through a cooperative approach in which the network infrastructure actively shares its load information with the clients via control channels as shown in Fig. 5.

7.4 Software development aspects

For real-world usage, choosing an ML model to solve a specific problem cannot be solely decided based on prediction performance metrics. Limitations on computation, energy resources, and response time requirements will affect software technologies used to extract data, store it, train ML models, and make predictions. However, relying on ML for networking and wireless communications will also have a profound impact on the software development practices needed for providing results while ensuring quality.

Research into the engineering of ML solutions in wireless communications must also address implementation challenges. If the trend in software development of wireless systems shifts increasingly toward ML-based methods, the main challenge will be related to the engineering paradigm shift from deterministic, classic requirements-driven projects and processes toward data-driven monitoring, data extracting, learning, and cycle prediction in the development of systems and services. Consequently, one of the first steps is that existing engineering tools, methods, and processes should be evaluated based on their adaptability to the described ML-driven development loop. This provides an overarching understanding of the magnitude of change and investment required in industry domains.

In parallel, with data science and ML gaining in popularity, software problems specific to the field will also became apparent. Systems that rely heavily on ML not only share the same issues that other software systems encounter, but have additional long-term shortcomings that can incur high maintenance costs in real-world usage. In recent years, DataOps, a movement inspired by DevOps, has emerged to better deal with the problems specific to data science and ML [49]. This movement aims to pro-

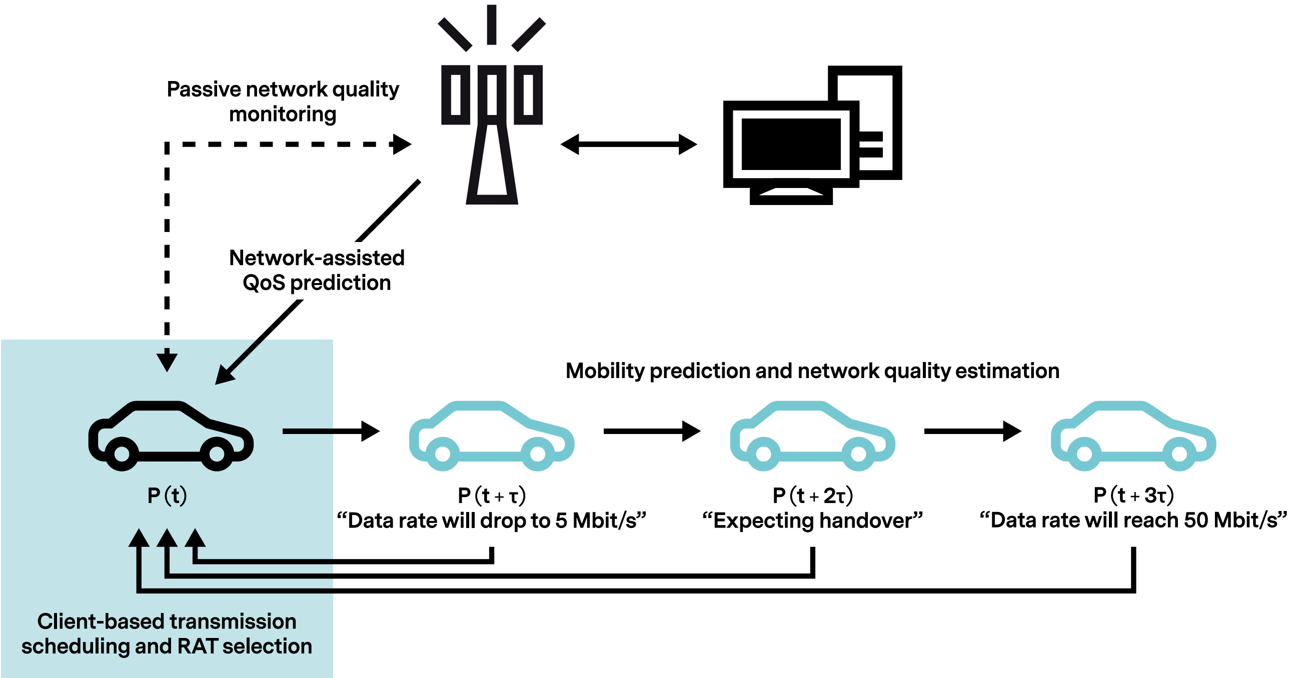

Figure 5: Opportunistic data transfer in vehicular networks.

vide development processes and software technologies to improve quality, while delivering data-based solutions in a rapidly changing world. To provide ML solutions on a large scale for wireless systems, 6G will have to embrace development practices from agile software development, DevOps, and DataOps. Moreover, movements like DevOps and DataOps are relatively new and in an ever-evolving state. Because networking and wireless communications have specific requirements of their own, developers will need extensive knowledge of 6G requirements and systems, as well as ML.

The following research questions should be studied in the future:

- How will ML enable, enhance, and automate network performance management for 6G Mobile networks?
- How will ML enable, enhance, and automate 6G mobile network optimization?
- What existing software development practices, processes, and technologies will be needed in incorporate ML in large-scale real-world networking and wireless communications technologies?
- What are the specific requirements of 6G that will require the adaptation of existing or creation of new agile, DevOps, or DataOps practices, processes, and technologies?

Level	Task categories					
	Execution	Awareness	Analysis	Execution	Execution	Execution
L0	Manual operating network	Human	Human	Human	Human	Human
L1	Assisted operating network	Human & network system	Human & network system	Human	Human	Human
L2	Preliminary autonomous network	Network system	Human & network system	Human & network system	Human	Human
L3	Intermediate autonomous network	Network system	Network system	Human & network system	Human & network system	Human
L4	Advanced autonomous network	Network system	Network system	Network system	Network system	Human & network system
L5	Fully autonomous network	Network system	Network system	Network system	Network system	Network system

Table 1: Network Automation Level

Standardization Activities 8

Various standardization bodies such as 3GPP and the International Telecommunication Union (ITU), along with trade organizations such as the 5GAA (5G Automotive Association), have started evaluating ML in 5G and future networks. From a standardization perspective, ML models and algorithms will not be standardized [50]. Other bodies such as the ORAN alliance have started defining open interfaces to exchange relevant information between various parts of the protocol stack. Specifically, they have introduced the names of entities such as "real-time intelligent controller" and "non-real-time intelligent controller". A non-real-time RIC is one where the training for the ML models happens using the data captured by lower layers. This learning happens very slowly – hence, "non-real-time".

This learned model is fed into the real-time RIC, which uses this model on real-time data and makes real-time decisions in an online fashion. Such systems can be deployed in core networks or in RAN, based on the type of data that can be collected.

The discussion about introducing ML capabilities to the 3GPP RAN standards is still in the preliminary stage. The autonomous network is an important topic for RAN, considering the complexity of future networks. Six levels of automation are proposed for RAN. Level zero (L0) starts with a manual operating network; L5 entails fully autonomous networks with no human involvement at any stage. The levels and tasks are summarized in Table 1 [51]. Additionally, it is also required to define

- signaling support for ML training and execution,
- data required by the ML algorithms either reported by the user equipment (UE) or collected from an Next-Generation Radio Access Network (NG-RAN) node, and
- outputs generated by the algorithms to be delivered to the network, including the network functions and core network.

If a UE has the capability of supporting at least part of the ML inference engine on board locally, it becomes relevant to study how the ML-enabled UE obtains an updated ML model and intermediate output, based on dynamic environment changes and application. It is unfeasible to pre-load all possible models on board because of limited storage space on the UE. ML model downloading or transfer learning is therefore required. ITU-T Rec. Y.3172 defines a technology-agnostic logical architecture model for high-level machine-learning requirements in future networks such as interfaces, support for heterogeneous data sources, machine learning mechanisms. The actual underlying network technology (e.g., 4G, 5G, 6G, IEEE 802.11) is virtually mirrored by a digital twin – referred to as a closed-loop subsystem – which is utilized to safely explore the outcomes of different machine-learning-enabled acting options.

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