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Abstract—The year 2019 witnessed the rollout of 5G standard, which promises to offer significant data rate improvement over 4G. While 5G is still in its infancy, every there has been an increased shift in the research community for communication technologies beyond 5G. The recent emergence of machine learning (ML) approaches for enhancing wireless communications and empowering them with much-desired intelligence holds immense potential for redefining wireless communication for 6G. In this article, we present the challenges associated with traditional ML and signal processing approaches, and how combining them towards a model-driven approach can revolutionize the 6G physical layer. The goal of this article is to motivate hardware-efficient model-driven deep learning approaches to enable embedded edge learning capability for future communication networks.

I. INTRODUCTION

Fifth generation (5G) wireless communication are promising a significant leap forward with respect to 4G. 5G, as standardized by third-generation partnership project (3GPP) has undergone two releases, i.e., Rel-15 and Rel-16. The year 2021 marks 16 years of 5G conceptualization and research and the second year of 5G commercialization and deployment. 5G wireless technology aims at supporting three generic services according to International Telecommunication Union (ITU)-Radiocommunication sector; (i) enhanced mobile broadband, to enable stable connections with very high peak data rates, (ii) massive machine-type communication, to support a massive number of Internet of Things (IoT) devices, and (iii) ultra-reliable low-latency communication, to enable low latency links with very high reliability from a limited set of devices [1]. The connectivity patterns are sporadic and specified by outside events.

With 5G still in the deployment and evaluation phase, recent research has been focusing on beyond-5G communications. The ITU-Telecommunication standardization sector Focus Group (FG-NET-2030) intends to study the capabilities of network for the year 2030 and after to support revolutionary communication technologies. This study is collectively called Network 2030. Network 2030 envisions revolutionary communication experience with holographic-type services, digital teleportation, tactile communications with immersive experience. To achieve these goals, Network 2030 requires very high bandwidth communication with undetectable latencies. Although Network 2030 cannot be synonymous with 6G, the new technology paradigms and mechanisms developed in the context of Network 2030 can be potentially applied to future 6G networks. Embracing this spirit, the European Technology Platform organized the Future Communications Summit to define the R&D roadmap in Europe and USA for initiating discussions on enabling technologies and services towards 6G. Telecom companies and organizations are taking the lead in commencing advanced research and innovation in 6G wireless communication. For example, the Academy of Finland launched a flagship program, 6G-Enabled Wireless Smart Society and Ecosystem - 6Genesis - in 2018 with the goal of conducting research on 6G and its key enablers such as distributed computing and artificial intelligence (AI), materials and antennas for 6G circuits, etc.

6G research will span across diverse realms such as nanoscale materials for system on chip communication subsystems, advanced physical layer techniques, medium access and routing approaches, intelligent edge computing, among others. The race for being the key innovators in this space is attract-
ing more research groups to 6G research. While 4G offered data rates up to 100 Mbps, its successor 5G improved the data rate by 100× and is intended to support a maximum of 10 Gbps - 20 Gbps. The envisioned 6G is intended to offer 1 Tbps, i.e., a 100× improvement over 5G. The emerging communication requirements for 6G are [2]:

- Ultra high-speed data delivery offering peak data rates up to 1 Tbps;
- Ultra-low (undetectable ~ 0.1ms) latency with very high reliability (10⁻⁹ frame error rate);
- Support ultra-dense networks (massive IoT), i.e., at least 10× device density device/km²;
- Intelligent adaptive radio with Machine Learning (ML) on the edge;
- Very high energy efficiency (~ 1pJ/bit) to reduce the overall network energy consumption;
- Very high spectrum efficiency;
- Cost-efficient computational platforms such as FPGA, ASIC.

With these requirements in sight, 6G aims at unparalleled, intelligent, connected, high speed, and cost-efficient devices. An intelligent physical (PHY) layer is fundamental and inevitable to achieving the envisioned communication requirements.

ML will be a prominent catalyst in this direction. ML is a subset of AI. In 1959, Mr. Arthur Samuel, one of the pioneers of AI research, defined ML as a field of study that gives computers the ability to learn without being explicitly programmed. ML has been vastly applied to computer vision, biomedical engineering, speech processing, social networking study, pharmaceuticals, etc. ML in wireless communication is emerging as a promising field [3].

ML approaches will drive the 6G vision as well as be driven by 6G requirements. ML at PHY layer holds the potential to perform intelligent signal processing that can offer significant performance enhancements over traditional approaches. However, the majority of ML research for the PHY layer is computational as well as memory-intensive, thus requiring high performing computing platforms to implement them. High energy efficiency is a key requirement of the 6G vision and therefore ML at the PHY layer must be designed to support the cost, energy, and memory constraints of the platform. In this article, we will analyze the potential candidate ML-based PHY layer approaches to revolutionize the embedded, lightweight, edge intelligence for 6G architecture. The intelligent signal processing vision to support the 6G communication requirements is shown in Fig. 1. As promising as it sounds, the road to 6G will witness a whole new dimension of communication and computing challenges.

II. NEED FOR EDGE INTELLIGENCE

Intelligent connectivity will be paramount to realizing 6G whereby the connected IoT devices can learn the dynamic, instantaneous parameters to make rapid decisions rather than relying on a central entity or cloud [4]. Such cognitive and rapid decision making will significantly improve the quantitative and qualitative communication in a dense deployment, Vehicle-to-everything, intelligent drone networking, among others. The intelligence here refers to the capability to learn how to perform a task with ML. This involves allowing the device to learn by providing significant training data.

Deep learning (DL) is a subset of ML whereby the patterns in the presented data are learned by propagating them through the layers of a neural network (NN) to make accurate predictions. Such rapid decision-making is essential to realize the ultra-low latency requirement of the 6G networks. The instantaneous cognitive decision-making of the edge devices by virtue of lightweight ML approaches will be key to achieve energy-efficient, ultra-low latency, edge computational capability. Furthermore, the ability to support such intelligent approaches on low cost platforms such as FPGAs [4], [5] or ASICs
Future communication networks will involve dense deployments whereby each device must make autonomous decisions with undetectable latency. Furthermore, to prolong the network lifetime, energy-efficient device operation is essential. Traditional algorithmic signal processing models involve solving numerical optimization which typically entails longer iterations to converge. This might impact the system's energy consumption as well as latency. Additionally, scalability of the solution for dense deployments must be given consideration.

DL solutions are increasingly applied to solve complex signal processing tasks such as massive multiple-input multiple-output (MIMO) channel estimation and detection, beamforming, forward error correction (FEC) decoding, signal recognition, etc [3]. However, DL solutions usually require significant training and the dense architecture requires computationally intensive platforms such as Graphics Processing Units (GPUs). Further, the black-box nature of NNs introduces a new subset of challenges such as incomprehensibility and unpredictability. Hence, we are presented with three broad challenges: resource-crunch, computational complexity, black-box nature. Incorporating domain knowledge into the DL architectures could potentially expedite the training process and convergence while improving the model performance. In this direction, deep unfolding [6] approaches - algorithmic unrolling of signal processing models infused with trainability using DL strategies - is gaining traction. We envision such model-driven approaches might get significant traction in future 6G networks with immense performance gains and implementation ease.

III. LIMITATIONS OF BLACK-BOX NEURAL NETWORK APPROACHES

DL has proven its merit as a powerful ML tool in fields such as computer vision, speech recognition, robotics, and natural language processing. The past few years have witnessed the expansion of DL in the wireless communication and signal processing domains. DL has been applied to automatic modulation classification, signal intelligence [7], dynamic spectrum access, path loss prediction modeling, cross-layer optimization, scheduling, resource allocation, antenna array processing, symbol detection, forward error correction, among others. With these rapidly advancing DL solutions for wireless communication, the current radio architectures will witness a paradigm shift towards intelligent radio for future wireless networks.

Traditionally, a NN is largely a black-box that lacks the interpretability to infer how it learns a specific task. Although DL techniques have demonstrated high accuracy in certain tasks such as signal or image classification, we still have limited insight into how it makes certain decisions. Since signal processing algorithms or wireless network optimizations rely on principled approaches whereby the operator can infer the rationale behind a model response, the incomprehensible nature of DL hinders its widespread deployment. In [8], an end-to-end communication system is represented by a deep NN referred to as autoencoder. The different entities of an end-to-end communication system such as transmitter, channel, and receiver are each represented by a dense feed-forward neural network (FNN). The autoencoder is trained under ideal scenarios using stochastic gradient descent (SGD). The authors assume a simple additive white Gaussian noise channel in their study. However, in practical scenarios, the ideal conditions assumed to simplify training cannot be directly applied and the FNN architectures are infeasible for resource-constrained IoT platforms.

Another by-product of the black-box nature of DL architectures is its unpredictability. This is crucial in wireless communication where the stochastic nature of the channel, dynamic mobility, resource constraints of the radio platform, or device malfunctions, could result in novel scenarios (hence novel input data). For this reason, DL architectures for communication need to be extensively trained with as many stochastic scenarios as possible. We argue that although such extensive training is possible with high power computing platforms, it is impossible to capture all the inherent randomness of the deployed scenario to realize a comprehensive trained system. Consequently, a trained model will behave ideally in scenarios that it has seen during training while resulting in unpredictable (unstable) behavior in the novel scenarios. Even though recently proposed methods attempt to compensate for the effect of time-varying channels on DL-based inference tasks [5], such an unpredictable nature is undesired in critical communication systems that are used in telemedicine, disaster-response, tactical military ap-
Fig. 2: NN compression and acceleration

Density or compactness of NN is another factor that has a direct influence on the training time, inference time, and implementation platform. The density of NN refers to the number of hidden layers. The number of trainable parameters grows with the number of hidden layers in the network. The large amount of trainable parameters require a vast amount of training data to learn the task representation. A small training set will significantly deteriorate the NN performance due to poor generalization. Although there are regularization strategies to improve the generalization capability such as dropout, $L_p$ regularization, early stopping, batch normalization, among others, these strategies still rely on large scale training datasets. The inference time, referred to as the time taken for the NN to produce an output given an input, is key to maintain the system latency within the desired limits. Ultra-low latency in the scale of undetectable time of the order of $\mu s$ will require very fast inference speeds for use in future communication systems. The memory footprint of deep NN grows with the number of neurons and layers. This will become critical for memory-constrained platforms such as CPUs, FPGAs, ASICs, etc with only a few megabytes of memory. As an example, the ResNet-50 architecture with 50 convolutional layers requires 95 MB of memory for storage and over 3.8 billion floating-point multiplications when processing an image. Such computationally intensive and memory extensive architectures cannot be directly implemented on embedded computational platforms.

Recently, NN acceleration and compression techniques to address the implementation challenges entailed in the DL architectures have gained significant attention. Few of the NN acceleration and compression techniques are shown in Fig. 2. Although such deep compression techniques have been applied for computer vision tasks, their adoption in the wireless communication realm is in a nascent stage.

IV. Path Towards Intelligent 6G: Deep-Unfolded Approaches

Model-driven NN approaches can potentially benefit communication systems in terms of performance and inference speeds. In this section, we will discuss how the benefits of DL techniques can be fused with domain knowledge to mitigate the aforementioned disadvantages of black-box NN approaches.

A large number of signal processing tasks at the PHY layer can be represented by optimization problems which can be subsequently solved with iterative inference algorithms. Such iterative inference algorithms are usually computationally complex involving matrix inversion, eigen decomposition and incur large number of iterations to converge. For instance, Maximum-Likelihood detection can achieve optimal performance but has an exponentially growing complexity with the number of decision variables. Few suboptimal linear detectors such as Zero-Forcing and linear minimum mean squared error can offer reduced complexity detection but at the cost of detection performance. On the other hand, iterative detectors such as Approximate Message Passing (AMP) and Expectation Propagation are proposed for MIMO systems with moderate complexity and good detection performance.

Algorithmic solvers require careful parameter tuning, initialization, step-size selection, which affect the performance as well as convergence speed. In practice, these are set based on heuristics whereby they are arbitrarily initialized or computed based on exhaustive search in simulations. However, such heuristics-based approaches are prone to instability and yield suboptimal performance. Recently, an approach whereby the physics-based algorithmic models are infused with the powerful learning capability of NNs is gaining popularity in communication systems - model-driven NN. One such instance of model-driven NN is deep unfolding.

Deep unfolding refers to the process of unfolding the iterations of a physics-based inference algorithm to form a layered structure analogous to NN. Deep unfolded signal processing combines the benefits of both DL and domain knowledge of the signal processing models to improve the model performance with computationally simpler architectures as in Fig. 3. For instance, if an iterative inference algorithm has $N$ iterations, deep unfolding will result in an $N$-layered NN with trainable parameters based on
Fig. 3: Deep unfolded signal processing

the model. The parameters can be learned with tools from DL such as backpropagation, SGD, etc. Here, we will review a few signal processing tasks that have been significantly improved with deep unfolding.

A. Trainable Iterative Soft Thresholding Algorithm

Iterative Soft Thresholding Algorithm (ISTA) is a powerful signal processing tool for sparse signal recovery. ISTA is known for solving the Lasso problem, a $l_1$ penalized regression problem for estimating more number of variables ($v$) than observations ($n$), i.e., $v > n$. ISTA is a two-step process involving a linear estimation and a soft-thresholding based shrinkage process.

TISTA [9] adopts a similar structure to ISTA by unfolding the iterations of ISTA. Here, the step-size for each iteration of the recursive ISTA is considered as a trainable parameter. Further, the thresholding of the original ISTA is replaced with a minimum mean squared error (MMSE) estimator and an MMSE-based shrinkage. Two scalar variables within the MMSE estimator are also learned. Hence, the $N$-iteration ISTA is unfolded into an $N$-layered architecture with $N+2$ trainable parameters. TISTA adopts an incremental training strategy to mitigate the vanishing gradient problem. TISTA demonstrated significantly faster convergence than AMP and learned iterative shrinkage thresholding algorithm [10]. The incremental training strategy is a mini-batch SGD approach rather than training the whole network at once. In the mini-batch SGD, training is performed by splitting the training data into mini-batches and performing a gradient descent update after processing each mini-batch. The computational efficiency was demonstrated by implementing and evaluating TISTA on an Intel Xeon(R) 6-core CPU rather than GPU.

B. Self Interference Cancellation of Full-Duplex Radios

Transceiver systems with the ability to transmit and receive simultaneously on the same frequency band - Full-Duplex (FD) radios - have the potential to double the spectral efficiency of a point-to-point radio link. Incorporating such radios in future networks can have a major impact by doubling the achievable data rates. However, the self-interference (SI) caused by such FD radios is a serious limiting factor that is slowing down its widespread adoption. Hence, the SI mitigation of FD radios is a hot topic in wireless communication.

SI mitigation involves estimating the SI signal and subtracting it from the received signal. The work in [11] studies the performance gains of unfolding a state-of-the-art polynomial SI cancellation approach with deep unfolding. In the unfolded method, the weighted polynomial sum expression is unfolded into an FNN with one hidden layer. Notably, the unfolded structure is very simple with just 13 neurons (nodes). The weights can be learned by supervised learning with backpropagation. In supervised learning, the NN approximates the relation between presented input and output data based on labeled training samples (desired input-output relation explicitly stated). The loss function is defined by the euclidean distance between the actual and desired outputs. The unfolded NN is trained with mini-batch SGD.

The computational efficiency and hardware implementation is demonstrated on Xilinx Virtex-7 FPGA and Fully Depleted Silicon On Insulator ASIC. The unfolded SI canceller achieved lower computational complexity and 22% lower datapath quantization bit-width while offering the same performance as the polynomial canceller. Further, the polynomial canceller required twice as much DSP slices on FPGA compared to the unfolded approach. Similar superior hardware efficiency (81%) was achieved with the unfolded approach on ASIC.

C. Alternating Direction Method of Multipliers Unfolded MIMO Detection

MIMO wireless communication is a means to significantly improve spectral efficiency as well as the link data rate. MIMO detection is a fundamental problem which have been under study for decades. Several existing MIMO detection algorithms involve
sphere decoding, conditional ML decoding, lattice decoding, AMP, etc. But as large scale massive MIMO systems evolve, the detection must be scalable for a rising number of antennas in terms of hardware efficiency as well as bit error performance. For example, the sphere decoder performs a search algorithm to perform the ML detection but with exponential complexity in the number of transmit antennas. Hence, for a massive MIMO system, such an exponential complexity will be detrimental to the latency as well as energy efficiency of the device.

Deep MIMO detection presented in [12] unfolds the iterative Alternating Direction Method of Multipliers (ADMM) algorithm into a simpler DNN architecture. Notably, the authors present a 40-layer architecture for performing detection in a $160 \times 160$ massive MIMO system. The ADMM algorithm is unfolded by untying the non-negative penalizing parameter such that it is expressed in terms of two parameters; one that accounts for the channel gain and the other is a trainable parameter. Additionally, the projection function at each layer is untied to include another trainable parameter. The approach does involve a matrix inversion but it is performed only once and not performed at each layer to maintain lower computational complexity. The mean squared error between the model predictions and the desired output is the loss function to train the model. The unfolded architecture was implemented on Intel core i7-CPU to demonstrate implementation on a lighter platform. The 40-layered architecture demonstrated promising runtime of $\sim 2.8$ ms.

D. Unfolded Biconvex 1-bit Precoding for Massive MU-MIMO

Massive multiuser MIMO (MU-MIMO) will be widely used in the downlink of future 6G networks to improve the spectral efficiency by 10 fold or more. Massive MU-MIMO will involve base stations equipped with hundreds of antennas to communicate with multiple users in the same time-frequency footprint. Efficient precoding techniques in the downlink are essential to suppress the multi-user interference. However, the scalability issues of conventional precoding and detection algorithms is a serious limiting factor. Deep unfolding techniques integrate the benefits of domain knowledge and the strong learning ability of NN to offer superior performance without complexity increase or same model performance at reduced complexity.

The non-linear biConvex 1-bit PrecOding (C2PO) algorithm [13] for 1-bit massive MU-MIMO was optimized with NN in [14] referred to as NNO-C2PO. This was accomplished by unfolding the iterations of the C2PO algorithm to represent layers of NN and learn per-iteration parameters with back-propagation. Learning per-iteration parameters alleviates the need for manual parameter tuning which can be a tedious task under dynamic channel conditions. In this way, NNO-C2PO offers automated tunability of the parameters ensuring robust operation under varying channel effects. The NNO-C2PO was demonstrated to achieve similar performance to C2PO at 50% fewer iterations. Further, under line-of-sight and non-line-of-sight channels NNO-C2PO achieved the target error performance at 4 dB lower transmit power than C2PO demonstrating energy-efficient operation.

Deep unfolding can be applied to advanced FEC encoding-decoding, signal recognition to facilitate adaptive modulation-coding, joint channel estimation and symbol detection, adaptive transmission power control, and wide range of PHY layer techniques to develop embedded edge learning platforms for 6G communications. The top-down approach to implementing deep unfolding for fundamental signal processing applications is shown in Fig. 4. The advantages of such an approach, as opposed to traditional optimization and NN techniques, are summarized as follows:

(i) Predictability offering performance guarantees.
(ii) Unfolded models are principled and interpretable.
(iii) Substantially few training parameters and consequently easy to train.
(iv) Hardware-efficient in terms of power, computation, and storage requirements.
(v) Support low-cost computational platforms.
(vi) Lightweight models with faster inference potentially result in low latency communication.

![Fig. 4: Deep unfolding methodology](image)
V. FUTURE RESEARCH DIRECTIONS

In this article, we presented the diverse ways in which deep unfolded signal processing can enable 6G communication systems with embedded edge learning platforms. The improved reliability, simplified architecture, accelerated convergence, significantly less memory, and computational requirements are paramount in realizing the primary 6G communication objectives. We briefly discussed a few unfolded architectures aligned in this direction to support hardware-efficient operations. Below is a list of open issues that we believe will motivate further research:

Accuracy. Accuracy of the optimization problem can severely impact model performance. Misrepresented models and assumptions will be detrimental to the performance. Hence, it is essential to verify model accuracy prior to unfolding.

Online learning. The stability of the model can be dependent on the training data. Therefore, meta-learning schemes whereby novel scenarios are learned online without forgetting the acquired knowledge must be investigated. Such online learning, adaptive system can address the dynamic nature of the deployed scenario.

Convergence. Per-layer trainable parameters and loss functions will have a direct influence on the convergence. Carefully chosen learning strategies can accelerate the rate of convergence.

Physical layer security. Incorporating unfolded physical layer security schemes at the chip level will prove extremely beneficial for future secure communication.

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