

Artificial Neuronal Networks for Empowering Radio Transceivers: Opportunities and Challenges

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Abstract— With the advances in wireless communications towards beyond 5G (B5G) and 6G networks, new signal processing and resource management methods need to be explored to overcome the channel impairments and other radio and computing obstacles. In contrast to the conventional methods which are based on classic digital communications structures, B5G and 6G will leverage artificial intelligence (AI) to configure or adapt the radios and networks to the operational context. This requires the ability to reformulate legacy transceiver structures and drive research, development and standardization that can leverage the amount of data that is available and that can be processed with the available computing technology. This paper describes this vision and discusses successful research that justifies it as well as the remaining challenges. We numerically analyze some of the tradeoffs when replacing the physical layer receiver processing with an artificial neural network (ANN).

Index Terms—ANN, Equalizer, Hidden Layers.

I. INTRODUCTION

Wireless communications have gone through decades of innovation. Cellular communications networks have provided true mobile broadband services since the deployment of 4G long-term evolution (LTE). 5G networks will expand the wireless connectivity and networking for extended use cases beyond mobile broadband, where low latency, high reliability or massive connectivity is needed. Although 5G technology and systems are still being enhanced by academia and industry, 6G proposals are already underway and it is a valid question to ask what 6G will be. Before we can answer this question, we first need to look at the requirements.

Compared to 5G, 6G systems are needed to satisfy the increasingly heterogeneous communications requirements of applications and services, and to enable new applications and services. Some of the envisaged requirements are [1]:

- ultra-high data rates of up to 1 Tb/s;
- ultra-high energy efficiency;
- massive low-latency access and response
- operation in extended frequency bands, from microwave to visible light communications.

As predicted in [1], the future of 6G will shift from network software to network intelligence. For instance, two important features of 5G, software defined networking (SDN) and network functions virtualization, have enabled evolving modern communications networks to software-based virtual networks. However, by having more heterogeneous and more complex networks, softwarization alone is insufficient to support 6G.

Artificial intelligence (AI) is driving many applications and services of modern information technology (IT) systems. The advances in computing have motivated scientists to consider AI for designing and operating future wireless networks. Recent research has shown that it is feasible to apply machine learning (ML) to radio frequency (RF) signal processing, baseband signal processing and higher layer processing [2]. AI will impact 5G systems [3], but it is expected to be the foundation of next generation wireless networks.

Our vision of 6G is that of an intelligent network that builds on top of software-defined radios (SDRs) and SDN, and merges them into an end-to-end software configurable system with node, edge and central network intelligence. Fig. 1 illustrates this. 6G will use AI agents to control network functions; other functions may implement AI processing algorithms. Moreover, AI will be used to calibrate, configure and maintain the network functions as well as ensure the integrity of the subsystem, system and network.

This paper surveys trends and recent results of AI empowered radio communications. We identify the opportunities as well as the research and technological challenges and analyze the performance and tradeoffs for a simple use case. Section II provides an overview of AI and artificial neural networks (ANN), in particular, and compares the opportunities and challenges for trending uses of AI in modern wireless communications contexts. Section III analyzes the performance of an ANN-based equalizer and demodulator that substitutes established baseband signal processing solutions of radio receivers. We describe the working principles, evaluate different ANN structures, and discuss the design tradeoffs. Section IV draws the conclusions.

II. B5G AND 6G NETWORKS AND THE ROLE OF AI

A. Cellular Network Evolution

The goal of 5G is to provide wireless communication services that can support various user applications, industrial verticals, and mission critical services, among others. Therefore, 5G aims at supporting three service types: ultra reliable low-latency communications, enhanced mobile broadband and massive machine-type communications. New performance criteria in terms of reliability, latency, capacity, density of connections, spectral efficiency, throughput, and so forth are suggested for the above application categories which need to be addressed by 5G systems. To satisfy these criteria, the key technologies include massive multiple-input multiple-output

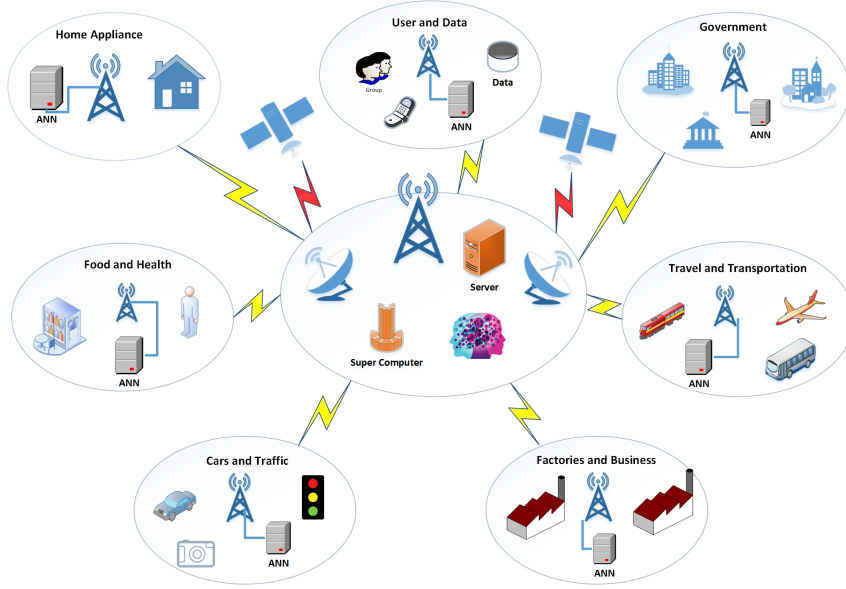


Fig. 1: An overview of 5G/6G-enabled network applications.

(MIMO), heterogeneous ultra-dense networks, new radio access technologies, mmWave access, advanced channel coding and decoding. Since 5G networks will be heterogeneous, serve numerous devices, and offer different operational modes 5G and beyond 5G (B5G) networks will be virtualized and implemented in part in Edge computing nodes and data centers using Cloud technology [11]. One of the key features of such networks is network segmentation, which will leverage new air interfaces that are designed to dynamically optimize spectrum resources allocated to subnetworks, services, or applications [12]. AI has been proposed as a promising solution to meet these increasingly heterogeneous networking demands.

B. AI Origins and Principles

Machines and systems which are able to learn and operate intelligently are defined as AI. With the advent of AI in the 1950s, being the result of the increasing improvement of modern computing and data storage technologies, AI research and development achieved important advancements, but also faced challenges. Academic research and industrial deployments, specifically in the software sector, has intensified in the recent years. There exist several real-world problems for AI, including data fitting, clustering and optimization, which are well suited for genetic algorithms or ANNs; However, features such as self-optimization makes AI a compelling target for cyber attacks [13]. In the broader IT industry, various problems are being solved employing AI-based learning techniques.

There are two broad categories for AI learning: supervised and unsupervised learning. A third learning approach is reinforcement learning, which can be considered in between supervised and unsupervised learning. It operates by interacting with the environment and learns by reinforcing the decision that lead to a good outcome. Supervised learning needs labeled data to train the network and configure it. Unsupervised learning does not need labeled data, but rather the network

extracts the important information on its own from the input data. Classification techniques such as k-means fall into the category of unsupervised learning. Neuronal networks can be unsupervised or supervised. Multi-layer perceptron neural networks, which we exemplify in Section III, use labeled data for training.

C. AI Adoption in Wireless Networks

Several review papers have been published about using ML and AI in wireless communications, especially in the context of 5G and 6G. In [12], the authors provide an overview of several communications problems where AI can be used and can outperform traditional communications techniques. They also discuss where the performance of AI algorithms may be not beneficial considering their complexity. In the 5G context, the authors propose applying AI at the physical (PHY) layer, where certain signal processing blocks in the transmitter and receiver are replaced by ANNs. In the context of 6G, [1] talks about how AI will be beneficial for the 6G architecture design and end-to-end optimization. It envisions the full PHY layer processing chain becoming an *intelligent PHY layer* where AI and, specifically, deep learning (DL) will enable self-learning and self-optimization. Additional recommendations on how to apply DL and AI at the PHY layer in a wireless communications system are presented in [9]. The paper discusses the application of AI in different channels and how to scale it to multiple transmitters and receivers. The results compare the block error rate (BLER) when using AI with the BLER of traditional transceivers to demonstrate the feasibility.

Table. I summarizes recent research efforts that explore AI for wireless communications with application to 5G/6G networks. These contributions show promising opportunities, but they also indicate the practical challenges which will lead to continuing research and future breakthroughs. The common theme of replacing the traditional model based signal

TABLE I: ANNs applied to advanced wireless communications and networking.

Reference	Main Contributions	Challenges
[4]	- Compares the traditional model-based approaches and the emerging AI-based solutions for wireless networks and discusses the role of ANN for the future of wireless communications - Provides a thorough explanation of ML and DL, the different architectures and algorithms	- Computational complexity, especially during the learning process - A lot of data needed for an ANN to result in satisfactory performance - Difficulty to gather sufficient amount of data within the coherence time of the channel - Distributed ANN might lead to instabilities - Difficulty to achieve robustness against corrupted data
[5]	- Covers the difficulties of applying conventional ML and signal processing approaches to wireless communications and how combining these methods can revolutionize the PHY layer of 6G - Proposes hardware-efficient model-driven DL approaches	- Performance limited to the accuracy of the optimization problem - Difficulty of online learning, which is needed for the dynamic nature of the proposed scenario - Choosing the best appropriate hyper parameters and loss functions for the convergence of the system - Security
[6]	Analyze the wireless channel statistics and estimates the angle of arrival for massive MIMO using a DL	- Computational complexity - Convergence time for optimizing the network
[7]	Explains the opportunities and issues using AI for classification and management of nonlinearity in 6G and future wireless systems considering deep learning based optimization	Input noise, which can lead to disastrous system configurations
[8]	Compares neuroscience and wireless communication theory in two ways, namely, what neuroscience offers to 6G and how 6G systems provide new visions to study the brain	Accurate new models for the brain that can be used in a wireless network framework and vice versa
[9]	- Proposes an end-to-end wireless communication system using an autoencoder - Designs signals using AI (ANN) - Shows how the proposed ANN structure optimizes itself for different wireless channels	- Limited data sets - Determining the optimal data representation, loss-function and training strategies - The need for complex-valued neural networks to properly represent the baseband representation of wireless signals
[10]	- Traffic flow and vehicle trajectory prediction based on gaussian mixture models (GMM) - Network congestion and handoff control by fuzzy Q-learning approach	- High complexity of the method to train and point millimeter wave beams in vehicular networks - Security during training

processing structures with data-driven learning solutions is that data needs to be available for training. Moreover, the dynamics of wireless networks require dynamic adjustments and, hence, retraining, which can be costly in terms of computational complexity and time. While ANNs are flexible and can model nonlinearity that is inherently present in RF, when the characteristics change, the trained ANN may fail to provide acceptable performance. ANNs lack accuracy if the training data is corrupted or not representative and they lack robustness if environmental or operational parameters change. Specifically, the dynamics of wireless channels, systems, and communications context can lead to unexpected behavior of such data-driven solutions. The data dependency can also be exploited to harm the network [14]. Hence, the robustness of AI-controlled network functions needs to be investigated prior to relying on those in production networks.

III. ANN MODEL AND NUMERICAL ANALYSIS

A. ANN Model

In order to illustrate the feasibility of an AI-empowered wireless receiver and discuss the design tradeoffs, we study the performance of an ANN-based equalizer and demodulator

compare the system performance in terms of the bit error rate (BER) with the optimal Maximum Ratio Combining (MRC) receiver.

The AI system employed in this paper falls in the category of supervised learning. Labeled data is needed for supervised learning. Therefore, a portion of a data block that is sent over the wireless channel is dedicated to pilot symbols, which are known to the receiver. The received pilots are used to configure the ANN whose role is to equalize or mitigate the channel impairments and facilitate coherent data demodulation at the receiver. This process typically consists in determining the weights associated with the neurons given a network architecture. This process is known as training where the training data are the pilot symbols that form part of the control signals and are well-specified in modern communications protocols to enable highly efficient communications.

If we assume L hidden layers, the k -th output neuron of the proposed ANN is

$$y_k(\mathbf{x}, \mathbf{w}) = \alpha \left(\sum_{j=0}^M w_{kj}^{(L)} \beta \left(\sum_{q=0}^Q w_{jq}^{(L-1)} \gamma \dots \sigma \left(\sum_{i=0}^D w_{iq}^{(1)} x_i \right) \right) \right). \quad (1)$$

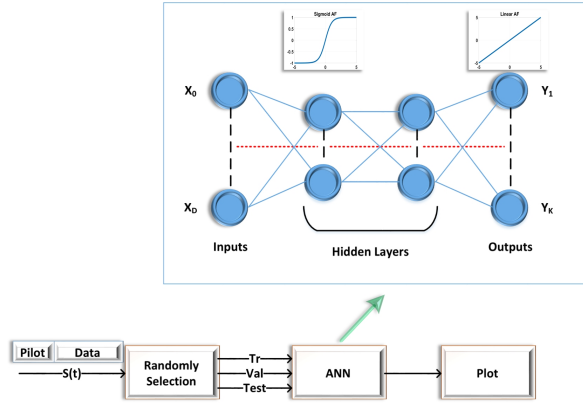


Fig. 2: Multi Layer Perceptron (MLP) structure employed for learning with sigmoid and linear activation functions.

The output of each hidden layer is the input to the next layer and $x_0 = 1$ for simplicity to account for biases in the learning process. Parameters $\alpha, \beta, \dots$ represent the activation functions (AF) in each hidden layer and emphasize that each layer can have its particular AF. In the proposed ANN structure, the AF in the hidden layers is the sigmoid function:

$$y(x) = \frac{2}{1 + e^{-2x}} - 1. \quad (2)$$

The reason of using the sigmoid AF is that it bounds the signal scale of neurons to between -1 and 1. This makes the learning process faster and the ANN reaches the local or global optimum quicker. In other words, when the input signal scale at the neurons in the inner hidden layers are far from each other, it results in excessive oscillation of the weight update by the gradient descent approach. The linear AF is applied for the output layer with the aim of comparing the ANN output with the target to estimate the error. Fig. 2 clarifies the employed structure.

The question that arises is about the best structure of the ANN, specifically what the number of layers and neurons per layer should be. As stated in [15], our goal is to minimize the error function with respect to the target values which are the pilot symbols here $\mathbf{T} = \{t_1, t_2, \dots, t_n\}$ as follows:

$$E(w) = \frac{1}{2} \sum_{n=1}^N \{y(x_n, w) - t_n\}^2. \quad (3)$$

Because of the nonconvex structure of $y(x_n, w)$, it is difficult to devise an approach to determine the optimum ANN structure and weights for the above error function. Therefore, we numerically analyze different ANN architectures.

B. Simulations

We propose different ANN architectures for the ANN-based equalizer and demodulator and use the mean square error (MSE) metric for their evaluation. It is worth noting that the proposed ANN starts learning symbol-by-symbol, instead of using a batch learning method. To put it simple, symbol-by-symbol detection results in lower complexity and lower input dimension which allows reaching the near global optimum

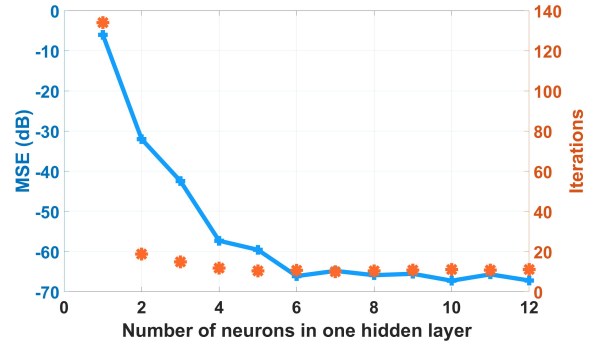


Fig. 3: Increasing the number of neurons in a network with a single hidden layer.

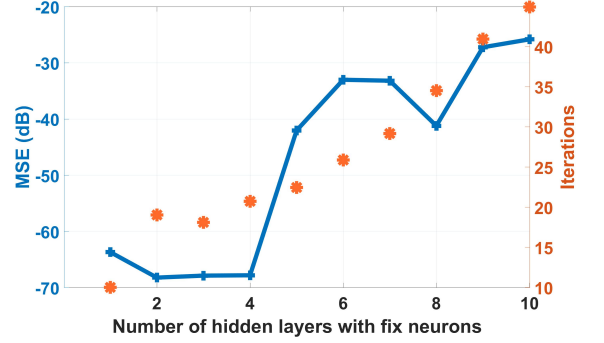


Fig. 4: Increasing the depth of the ANN for a fixed number of six neurons in each hidden layer.

through the learning process. For the sake of simplicity, we use quadrature phase shift keying modulation. Higher order modulation, multi-channel communications, and other channel models can be equivalently analyzed.

As Fig. 3 shows, the performance of the ANN improves significantly when increasing the number of neurons in a single hidden layer and reaches a steady state with six neurons. This means there is no gain in further increasing the number of neurons. Moreover, the number of iterations needed to obtain the best weights is also shown. With 6 neurons in the hidden layer a MSE of -66 dB is achieved after only 10 iterations.

Fig. 4 plots the ANN performance as a function of the depth of the network for a fixed number of six neurons per layer. This can provide insights on how the equalizer performs using a deep neural network. As the results show, there is no significant difference in the performance between

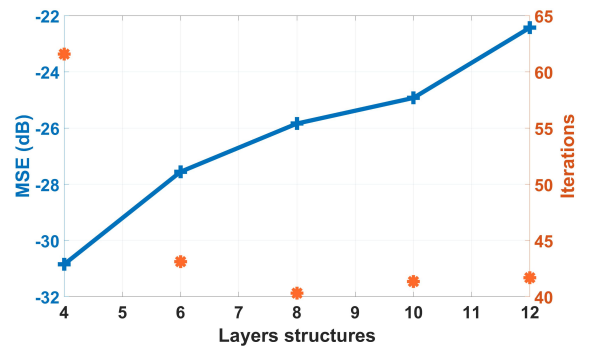


Fig. 5: Varying the number of neurons and hidden layers.

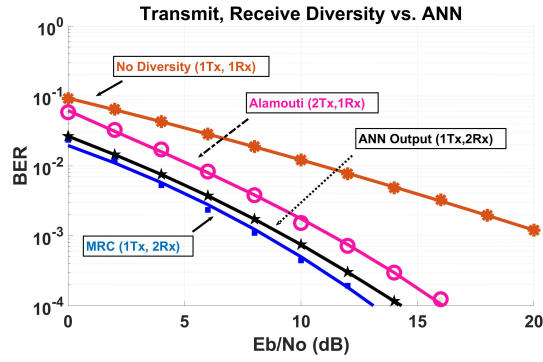


Fig. 6: Comparison between transmit and receive diversity techniques and the ANN equalizer and demodulator.

1 and 4 hidden layers. With more than four hidden layers, the performance deteriorates sharply. Adding additional layers adds more complexity and over fitting could be one reason for this degradation in performance. We conclude that only one hidden layer with six neurons suffices here. Slightly better performance is achieved with two hidden layers at a cost of slower convergence in determining the weights.

Next we vary both the number of neurons and hidden layers simultaneously. This ANN architecture resembles that of an autoencoder. For instance, the index six refers to the $[6, 4, 2, 4, 6]$ ANN layer structure, i.e. three hidden layer with symmetry in the number of neurons per layer. Fig. 5 plots the results that show a higher MSE and more iterations when compared to the previous results. This indicates that this kind of neural network structure is not suitable for this application.

Fig. 6 finally evaluates the proposed ANN (one hidden layer with 6 neurons) with transmit/receive diversity techniques in a frequency selective Rayleigh fading channel with parameter $\sigma^2 = 1$. Although the ANN does not have any information about the channel and uses only 5 percent of the data for training, it is within 1 dB of the BER performance of the MRC with perfect channel state information (CSI). Moreover, since we have two antennas in the receiver and the transmitted symbols are complex, we need to apply the real and imaginary part of symbols separately to the ANN; therefore, we have 4 neurons in the input layer. The stochastic gradient descent momentum algorithm is employed for updating weights with the aim of reaching the global optimum. The BER curves for both transmit diversity using Orthogonal Space Time Block Codes (OSTBC) [16] and no diversity are included here for reference.

IV. CONCLUSIONS

This paper discusses the opportunities and challenges of AI-empowered radios with focus on the PHY layer. In order to illustrate the working principles of an ANN for implementing part of a radio receiver, and to examine the knobs and tradeoffs, we compare different architectures. Specifically, we vary the number of neurons in each layer and the number of hidden layers to evaluate the system performance and the iterations needed to find the optimum weights. The results show two things: The ANN receiver performs comparably to

the conventional receiver in terms of BER. With only one hidden layer and six neurons it achieves -66 dB MSE after only 10 iterations, which is very fast. Moreover, by considering two additional channels—multiple-input, single-output for diversity at the transmitter and single-input, multiple-output for diversity at the receiver—the results show the effectiveness of a simple ANN equalizer and demodulator without CSI.

Ongoing research has shown the promising applications of different AI methods to manage or implement different parts of modern wireless networks. AI will play a dominant role for 6G network operations. The main challenges are the availability of quality data for training, the training complexity, and the robustness and security of data-driven network architectures. Research and development needs to address those systematically to understand the remaining risks and limitations of AI applied to wireless communications. We envisage AI working in conjunction with traditional model based methods, complement them, and gradually replace them where feasible.

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