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Review

Neural networks in wireless networks: Techniques, applications and guidelines

Nauman Ahad [a,*], Junaid Qadir [a,b], Nasir Ahsan [c]

[a] School of EE and CS (SEECS), National University of Sciences and Technology (NUST), Pakistan
[b] Information Technology University (ITU)-Punjab, Lahore, Pakistan
[c] University of Sydney, Australia

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ABSTRACT

The design of modern wireless networks, which involves decision making and parameter optimization, is quite challenging due to the highly dynamic, and often unknown, environmental conditions that characterize wireless networks. There is a common trend in modern networks to incorporate artificial intelligence (AI) techniques to cope with this design complexity. While a number of AI techniques have been profitably employed in the wireless networks community, the well-established AI framework of neural networks (NNs), well known for their remarkable generality and versatility, has been applied in a wide variety of settings in wireless networks. In particular, NNs are especially popular for tasks involving classification, learning, or optimization. In this paper, we provide both an exposition of common NN models and a comprehensive survey of the applications of NNs in wireless networks. We also identify pitfalls and challenges of implementing NNs especially when we consider alternative AI models and techniques. While various surveys on NNs exist in the literature, our paper is the first paper, to the best of our knowledge, which focuses on the applications of NNs in wireless networks.

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* Corresponding author at: Information Technology University (ITU)-Punjab, Lahore, Pakistan.

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1. Introduction

While computers are typically utilized in a problem solving capacity, traditionally this capacity has been restricted to the cases where the solution can be explicitly programmed. There are many problems in wireless networks where general programming techniques do not provide optimal or generalizable solutions. For example, it is very difficult to write programs that could allow cognitive radios to learn and adapt, or predict user mobility to optimize wireless network resources. Advances in artificial intelligence (AI) and machine learning (ML) allow computers to overcome this restrictive constraint by enabling inference and complex decision making (attributes that are typically associated with human intelligence). In particular, computer systems can use machine learning algorithms and techniques to learn from data allowing these systems to classify and predict (Mitchell, 1997, 2006). Broadly speaking, ML involves detecting patterns and learning correlations between input and output from past data. This knowledge is then used to extrapolate outputs, or infer, on future input data. ML is a vast field encompassing many different kinds of systems which themselves use many different models.

Artificial Neural Networks (ANNs), or simply Neural Networks (NNs) (Haykin and Network, 2004)—the focus of this survey paper —constitute one of the most popular ML models in the literature. ANNs are composed of artificial 'neurons' interconnected together in a structure that aims to mimic the neural processing (organization and learning) of biological neurons and its behavior. NNs seek to emulate the learning system of the human brain that itself consists of a large number of biological neurons interconnected in networks that govern all aspects of human behavior. ANNs are modeled on human brain and use a network of nodes called artificial neurons to form complex systems. The ways in which these nodes are placed and are connected lead to different kinds of NN models.

Broadly speaking, ML systems can be categorized into three kinds of learning systems: (i) supervised learning; (ii) unsupervised learning; and (iii) reinforcement learning. Using these learning systems, NNs can predict outputs for a set of given inputs.

Historically speaking, starting from the work on perceptrons, NNs were devised in a model that involved supervised learning. This means that the NNs learned using a labeled data set, for which correct outputs are given for inputs. NNs continued to evolve and mostly found applications in supervised learning settings. Techniques were introduced over time that allowed NNs to learn in unsupervised settings in which no labeled data was available. Most of the modern day advancements in NNs such as deep NNs make the use of unsupervised learning. This is better suited for real-world problems where labeled data set is not available. The applications of such deep NNs in wireless networks are yet to be seen. Such applications, however, may be dominant in the future. NNs have found applications in vast variety of engineering fields including image processing (Egmont-Petersen et al., 2002), control theory (Hunt et al., 1992), data analytics, digital communications (Ibnkahla, 2000) among various applications.

The strength of NNs lies in their ability to provide generalized solutions through an architecture that is able to learn to improve its performance. NNs comprise of a number of elements called nodes that are configured in layers and connected to other nodes by links with a certain weight. The behavior of NNs is determined through (i) the way nodes are connected together into a network, and (ii) the adaptive link weights between these nodes that are tuned by a learning algorithm. Simply speaking, NNs are essentially a network of weighted, additive values with “nonlinear transfer functions”.

In this paper, the applications of NNs in wireless networks are discussed. NNs have been used in various types of wireless networks ranging from wireless sensor networks (WSNs) to cognitive