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Literature Survey on Improvement of Performance in Wireless Networks using Machine Learning

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Abstract **– The paper presents a systematic survey that reviews the latest research efforts that focus on machine learning based on improving the performance of wireless networks, while processing all layers of the protocol stack: PHY, MAC and network. It provides the domain needed for data processing machine learning methods and techniques to help non-mechanical learning professionals understand everything that has been discussed strategies. The review is then presented in activities using ML-based methods upgrade wireless connection settings to achieve improved network service quality and quality-experience.**

Index Terms - Machine Learning, Wireless Networks

I. INTRODUCTION

Increased data production is present in all scientific disciplines [1], such as computer vision, speech recognition, finance, marketing and sales, pharmacy, personal health care, agricultural accuracy, politics, etc. Until recent years, this trend has been less pronounced in the realm of wireless networks, largely due to the lack of 'great knowledge' and insufficient communication capacity. However, in the era of Fifth Generation (5G) and Internet-of-Things (IoT) mobile applications, the flood of big data over a wireless network domain continues. For example, large amounts of data generated by ubiquitous sensors used in smart cities, intelligent infrastructure, environmental monitoring of precise farming, intelligent IoT grid networks, etc. It is expected that 28.5 billion machines will be connected to the internet 2022 [2], which will create a huge global network of "objects" and the demand for wireless services will grow at an unprecedented rate. On the other hand, a set of existing communication technologies are increasingly competitive with the same limited and limited resources of radio spectrum that suppress the need to improve their coexistence and make better use of rare spectrum resources. Similarly, in mobile systems, mobile data usage is increasing exponentially; according to Ericsson's latest travel report now has 5.9 billion mobile broadband subscriptions worldwide, generating more than 25 Exabyte's monthly wireless data traffic [3], growth close to 88% between Q4 2017 and Q4 2018.

Machine learning (ML) is increasingly being used to develop advanced methods that can automatically extract patterns and predict styles, based on environmental measurements and performance indicators as input. Such patterns can be used to enhance parameter settings for different protocol layers, e.g., PHY, MAC or network layer. For example, consider Figure 1, which shows a building with a variety of wireless access technologies, capable of collecting large amounts of attention Wireless devices, processing and feeding ML algorithms that produce patterns can help make better decisions to improve performance parameters and improve network service quality and information-quality.

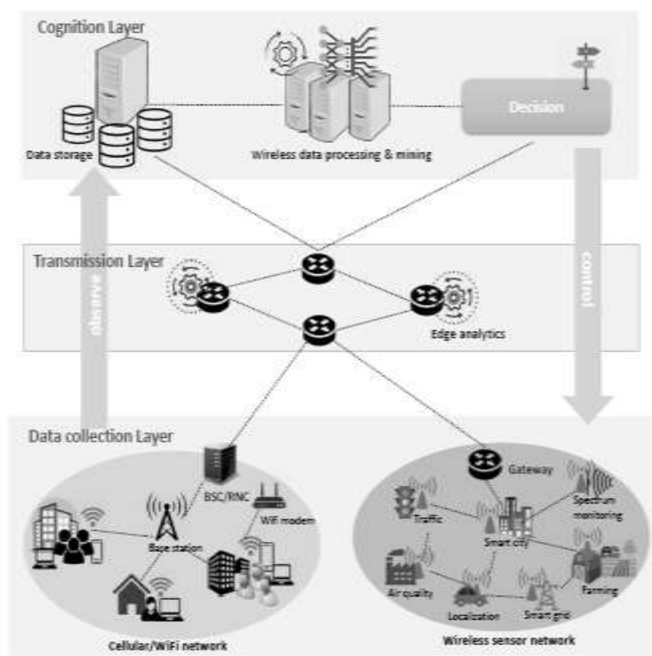

Figure 1. Architecture for wireless big data analysis.

II. LITERATURE REVIEW

The authors in [4] use ML to optimize network resource allocation in mobile networks. Namely, each base station observes the traffic of a particular network sin a mobile network. Then, a CNN model uses this information to predict the capacity required to provide accommodations for the future traffic demands for services associated to each network.

In [5] a self-adapting MAC layer is proposed. It is composed of two parts a reconfigurable MAC architecture that can switch between different MAC protocols at run time, and a trained MAC engine that chooses the most appropriate MAC protocol for the existing network condition and application necessities. The MAC engine is solved as a classification problem using a decision tree classifier.

In [6], deep convolution neural networks (CNNs) are applied directly on complex time domain signal data to classify modulation formats. The authors demonstrated that CNNs outperform expert engineered features in combination with traditional ML classifiers, such as SVMs, k-Nearest Neighbors (k-NN), Decision Trees (DT), Neural Networks (NN) and Naive Bayes (NB). An alternative method, is to learn the modulation format of the received signal from different representations of the raw signal.

In [7], CNNs are employed to study the modulation of various signals using the in-phase and quadrature (IQ) data demonstration of the raw received signal and two additional data representations without disturbing the simplicity of the input. It is presented that the amplitude/phase representation outpaced the other two, signifying the importance of the choice of the wireless data representation used as input to the deep learning technique so as to decide the most ideal mapping from the raw signal to the modulation scheme.

In [8] the authors were able to detect non-Wi-Fi interference on Wi-Fi product. They collected energy samples through the spectrum from the Wi-Fi card to excerpt a diverse set of features that seizure the spectral and temporal properties of wireless signals (e.g., central frequency, bandwidth, spectral signature, duty cycle, pulse signature, inter-pulse timing signature, etc.). They used these features and examined performance of two classifiers, SVM and DT. The idea is to embed these functionalities in Wi-Fi APs and clients, which can then implement a suitable extenuation mechanism that can rapidly react to the presence of significant non Wi-Fi interference.

The authors of [9] suggest an energy efficient rendezvous mechanism irrepressible to interference for WSNs based on ML. Specifically, due to the energy restrictions on sensor nodes, it is of great significance to save energy and extend the network lifetime in WSNs. Old-fashioned mechanisms such as Low Power Listening (LPL) and Low Power Probe (LPP) rely on low duty cycling (scheduling the radio of a sensor node between ON and OFF compared to always-ON methods) depending on the incidence of a signal (e.g., signal strength). However, both suffer performance deprivation in noisy environments with signal interference incorrectly regarding a non-ZigBee interfering signal as a concerned signal and improperly keeping the radio ON, which increases the probability of false positives.

In [10] LSTMs are used to model the progressive relationships of the mobile traffic distribution and perform estimating together with stacked Auto Encoders for spatial feature extraction. Experiments with a real-world dataset demonstrate greater performance over SVM and the Autoregressive Integrated Moving Average model.

In [11] a MAC selection engine for WSNs based on a DT model chooses which is the preeminent MAC protocol for the given application QoS requirements, existing traffic pattern and ambient interference levels as input. The candidate protocols are TDMA, BoX-MAC and RI-MAC.

The authors of [12] employ Neural networks to predict the user's quality-experience in cellular networks, based on average user throughput, number of active users in a cell, average data volume per user and channel quality indicators, demonstrating high prediction accuracy. Given the dynamic nature of wireless communications, a traditional one-MAC-fit-all approach cannot meet the challenges under significant dynamics in operating conditions, network traffic and application requirements. The MAC protocol may deteriorate significantly in performance as the network load becomes heavier, while the protocol may waste network resources when the network load turns lighter.

III. Conclusion

A number of surveys emerged on ML applied in wireless networks. It is observed that some of the existing works focus on addressing specific wireless networking tasks as wireless signal recognition), some on the usage of specific ML techniques like deep learning techniques), while others on the aspects of a specific wireless environments are IoT, WSN, CRN, looking at broad application scenarios for localization, security, environmental monitoring, Therefore, it is realized that none of the works elaborate ML for optimizing the performance of wireless networks, which is critically affected by the propagation of wireless devices, networks, technologies and increased user traffic demands.

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