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A REVIEW OF APPLICATIONS OF SUPERVISED LEARNING TO FUTURE NETWORKS

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A review of applications of supervised learning to future networks

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ABSTRACT
We provide a broad overview of some of the promising applications of supervised learning to future networks. We include applications to both wireless and optical networks, restricting our focus to the physical, data link and network layers.

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GLOSSARY/ABBREVIATIONS

AMC	Automatic modulation classification
ASE	Amplified spontaneous emission
BER	Bit error rate
BLER	Block error rate
CD	Chromatic dispersion
CNN	Convolutional neural network
C-RAN	Centralised radio access network
CSI	Channel state information
DL	Deep learning
DNN	Deep neural network
EDFA	Erbium-doped fibre amplifier
EME	Electromagnetic environments
FBMC	Filter bank multicarrier
FWM	Four-wave mixing
GSNR	Generalised signal-to-noise ratio
IoT	Internet of things
IP	Internet protocol
ISM	Industrial, scientific, and medical
KNN	K-nearest neighbour
LSTM	Long short term memory network
LTE	Long-term evolution
MAC	Medium access control
MIMO	Multiple input multiple output
ML	Machine learning
MLE	Maximum likelihood estimation
mmWave	Millimetre wave spectrum
M-PSK	M-ary phase shift keying
NLPN	Nonlinear phase noise
NN	Neural network
NOMA	Non-orthogonal multiple access
N-SVM	Newton-based support vector machine
OFDMA	Orthogonal frequency division multiple access
OMA	Orthogonal multiple access
OPM	Optical performance monitoring
O-RAN	Open random access network
OSI	Open systems interconnection
OSNR	Optical signal to noise ratio
PMD	Polarisation mode dispersion
PRR	Packet reception rate
QAM	Quadrature amplitude modulation
QoE	Quality of experience
QoS	Quality of service
QoT	Quality of transmission
RACH	Random access channel
RF	Radio frequency
RNN	Recurrent neural network

RSA	Routing and spectrum assignment
RWA	Routing and wavelength assignment
SCMA	Sparse code multiple access
SE	Spectral efficiency
SER	Symbol error rate
SOM	Self-organised maps
SPM	Self-phase modulation
SVM	Support vector machine
TDMA	Time division multiple access
URLLC	Ultra-reliable low latency communication
WANET	Wireless ad hoc networks
WDM	Wavelength-division multiplexing
XPM	Cross-phase modulation

CONTENTS

1. INTRODUCTION

The vision for future communications is for networks with increasing connectivity which can transmit increasingly large volumes of data at increasingly high speeds. Due to their complexity, such networks can only be realised through data-driven automation which leverages available data. It is therefore widely accepted that artificial intelligence (AI) and its analytical engine machine learning (ML) are vital enablers of this vision (Toy, 2021).

The Electromagnetic Technologies group at NPL provides metrology support for some of the different technologies employed in communication networks, which includes both wireless radio and optical fibre communication. Meanwhile the Data Analytics and Modelling group have been developing frameworks for the trustworthy use of machine learning in metrology applications. In order to support the vision for future networks described above, it will be necessary for NPL to increasingly incorporate machine learning into metrology for communication networks.

The purpose of this report is to review some of the recently proposed ways in which machine learning might be used within future networks, with a particular focus on supervised learning and on those applications which are of most relevance to metrology. The aim is that this document is accessible to both the Data Analytics and Modelling and Electromagnetic Technologies groups, thereby helping to bridge their areas of expertise. With this aim in mind, we give background both on some of the main technologies relevant to future networks and on some of the relevant machine learning techniques.

In section 2, we review the terminology and basic understanding of the concepts used in communication networks and machine learning that will be used in the later sections. In section 3, we review ML techniques applied to wireless networks, with emphasis on 5G technologies. The examples presented in this section are taken from a comprehensive literature review (Kulin et al., 2021), along with (Ly and Yao, 2021; Santos et al., 2020; Tanveer et al., 2021) which focus on 5G technologies. In section 4, we review applications of ML to optical networks, with examples taken from the literature reviews (Gu et al., 2020; Mata et al., 2018). We give conclusions and pointers to future work in section 5.

2. BACKGROUND

2.1 FUTURE NETWORK TECHNOLOGIES

Recent trends in industry have been towards automation and data exchange, which have been coined the fourth industrial revolution, or Industry 4.0 (Gilchrist, 2016). As a result, communication networks have seen rapid development in the past few years. The number of devices connected to Internet Protocol (IP) networks is expected to be more than three times the global population by 2023. The Internet of Things (IoT) has become a prevalent system in which people, processes, data, and devices connect to the internet and each other. IoT devices are expected to account for half of the global connected devices by 2023. As well as the number of devices, users now require super-fast and reliable connections, hence the rollout of fifth generation (5G) mobile networks, with speeds expected to be 13 times higher than the average mobile connection by 2023. Additionally, fixed broadband speeds have doubled in the last four years, mainly due to the adoption of fibre optic broadband. With this drive for increased speed, capacity and connectivity of communication networks, there has been advancements in the technologies used ("Cisco Annual Internet Report (2018–2023) White Paper," 2020).

Before summarising the current and future technologies being used in building modern communication networks, we will first introduce the OSI model for communication systems. This will be used as a framework for explaining the various technologies used, and any ML applications.

2.1.1 Open systems interconnection (OSI) model

The OSI model is a conceptual model that characterises and standardises the communication functions of a networking system (Day and Zimmermann, 1984). The communications between a computing system are split into seven hierarchical layers of abstraction: Physical, Data link, Network, Transport, Session, Presentation and Application. In this review, we will focus on the bottom three layers of the OSI model, also known as the media layers.

Physical layer

The first and bottom layer is the physical layer. It is responsible for the transmission and reception of unstructured raw data between a device and a physical transmission medium. It converts digital bits into electrical, radio, or optical signals. The physical layer addresses the challenges in transmission of RF and optical signals through physical media. It is characterised by physical quantities such as:

i. *Bit rate*, which is the total number of physically transferred bits per second over a communication link.
ii. *Modulation scheme*, which specifies the process of impressing information on a carrier signal through varying its properties such as amplitude, phase and frequency.
iii. *Transmission mode*, which defines the direction of signal flow between two connected devices.

Data link layer

The second layer in the data link layer and is responsible for the node-to-node link. It detects and corrects errors that may occur in the physical layer. It defines the protocol to establish and terminate a connection between two physically connected devices, and the flow control between them. The data link layer can be divided into two sublayers:

i. *Medium access control* (MAC) layer, which is responsible for controlling how devices in a network gain access to a medium and permission to transmit data.

ii. *Logical link layer*, which is responsible for identifying and encapsulating network layer protocols, and controls error checking and frame synchronisation.

Network layer

The third layer is the network layer. This provides the functional and procedural means of transferring packets of information across nodes in a communication network. Several layer-management protocols belong to the network layer. These include routing protocols, bandwidth management, and internet protocol (IP) address assignment.

In the following sections, we describe the communication technologies and machine learning applications in terms of the relevant layers of the OSI model.

2.1.2 5G Technologies

5G networks have certain characteristics that distinguish them from previous generations of mobile networks. All wireless devices communicate by radio waves with a cellular base station via fixed antennas, over frequency channels assigned by the base station. For 5G networks, the antennas transmit radio waves at shorter wavelengths (mmWaves), which have a larger frequency (30-300 GHz), and therefore greater peak data rates (~10 Gbit/s) compared with 4G (Tanveer et al., 2021). The disadvantage is that mmWaves have a shorter range, so higher gain antennas are needed, due to the increased loss. As well as speed, 5G networks have improved latency, which is the time delay between the source sending a packet to the destination and receiving it. Latency of 5G networks have reduced ten-fold (~10 ms) compared with 4G networks. Finally, 5G networks have improved connectivity (~10^6 devices km^{-2}), which is on average ten times larger than 4G networks.

To achieve such improvements in speed, latency and connectivity, 5G networks take advantage of specific technologies, which we describe below.

Massive MIMO

In multiple input, multiple output (MIMO) systems, both transmitter and receiver are equipped with an array of antennas. The previous iteration of mobile networks, 4G LTE (long-term evolution), uses MIMO, but 5G takes this technology further by adapting it to massive antenna configurations. Massive MIMO is based upon three key concepts:

i. *Spatial diversity*, where multiple antennas receive slightly different versions of the same signal, which are then combined to produce a higher quality signal.
ii. *Spatial multiplexing*, where multiple transition paths are used as additional channels for carrying data, thus increasing the capacity of the radio link.
iii. *Beamforming*, which is a type of radio frequency (RF) management in which a wireless signal is directed towards a specific receiving device. It provides a way to improve the gain of the transmitting or receiving antennas. Massive MIMO systems utilise 3D beamforming, by creating both horizontal and vertical beams, which is particularly useful in urban areas with high-rise buildings.

Multi-access edge computing (MEC)

MEC is a form of distributed computing architecture used in IoT. By running applications and processing tasks closer to user devices at the network edge, such as an IoT sensor, laptop or smartphone, network congestion is reduced, and applications perform better. MEC allows cellular operators to open their radio access network (O-RAN) to authorized third parties, such as application developers and content providers, compared with C-RAN, where access is centralised in the core network or cloud. O-RANs facilitate the use of ML algorithms on the network edge.

Non-orthogonal multiple access (NOMA)

In conventional orthogonal multiple access (OMA) techniques, capacity is typically optimised in communications by sending multiband signals in which several signals are sent simultaneously. Interference is minimised by ensuring that these signals are approximately orthogonal. Examples include time division multiple access (TDMA), orthogonal frequency division multiple access (OFDMA), and filter bank multicarrier (FBMC). However, they have high peak to average power ratio, and in the case of OFDMA, poor out of band performance. NOMA allows multiple users to operate in the same band at the same time, where they can be distinguished by power levels, and thus separated by the receivers through interference cancellation. This leads to improved energy and spectral efficiencies using NOMA compared with conventional techniques.

Network slicing

Network slicing is used in 5G networks where the physical network infrastructure is divided into virtual sub-networks, which operate independently. This is important for tailoring 5G mobile networks to different service level requirements in different parts of the network.

2.1.3 Optical Networks

Wireless technology, in the form of radio waves, are used in mobile networks such as 5G. However, to supply superfast broadband to all devices in the IoT also requires wired technology. This is because wired networks have more reliability and higher capacity, as well as greater security. The traditional medium for wired communication was copper wires, but this is now being replaced with fibre-optic cables.

Optical communication networks consist of fibre-optic cables, which transmit information by sending pulses of infrared light through an optical fibre. The light is a carrier wave that is modulated to carry information. Fibre-optic cable has advantages over traditional copper wire cabling due to high bandwidth, longer distance communication and immunity to electromagnetic interference. This is especially important with the development of massive MIMO and 5G technologies.

The common public radio interface (CPRI) protocol defines and standardises and transport and control specifications between the physical layer of the baseband unit (BBU) and the remote radio head (RRH), also known as the fronthaul. Flexible fronthaul configurations have become an essential ingredient for balancing latency, throughput, and reliability in advanced 5G applications (VIAVI, n.d.).

We will consider some of the most recent developments in fibre-optic communication.

Transmitters

The most common optical transmitters are light-emitting diodes and laser diodes. Laser diodes are more powerful, and so are required for applications that must transmit over long distances, with high data rates. For very high bandwidth efficiency, coherent modulation can be used to vary the phase of light in addition to the amplitude, enabling the use of more sophisticated modulation schemes such as quadrature amplitude modulation (QAM).

Amplification

Optical amplifiers are needed due to fibre attenuation and fibre distortion. They amplify the signal directly, without having to convert the signal to the electrical domain. The most common type are Erbium-doped fibre amplifiers (EDFAs). These amplifiers allow a very wide bandwidth, and operate independently of modulation format, enabling multiple data rates and modulation formats to coexist.

Wavelength-division multiplexing (WDM)

WDM allows the transmission of multiple channels of information through a single optical fibre by sending multiple light beams of different wavelengths through the fibre, each modulated with a separate information channel. This allows the capacity of optical fibres to be multiplied. EDFAs are important components of WDM networks.

2.2 MACHINE LEARNING TECHNIQUES

Traditional modelling of communication networks involves expert knowledge of the physical mechanisms involved and applying them to various scenarios of network configurations. This was reasonable when the networks were homogeneous, with small complexity. However, the explosion in number of devices and an industry push towards automation, with high data speeds and low latency, has resulted in networks becoming more complex. This has meant that traditional modelling can suffer from high computational cost due to the large amounts of data involved and be unable to capture the heterogeneous nature of future networks. Fortunately, this is where data-driven modelling, such as ML, can provide a useful alternative.

ML falls under the area of AI, which deals with all forms of automation. ML is a data-driven approach to understanding, and modelling systems. ML can be subdivided into three main areas as shown in Figure 1.

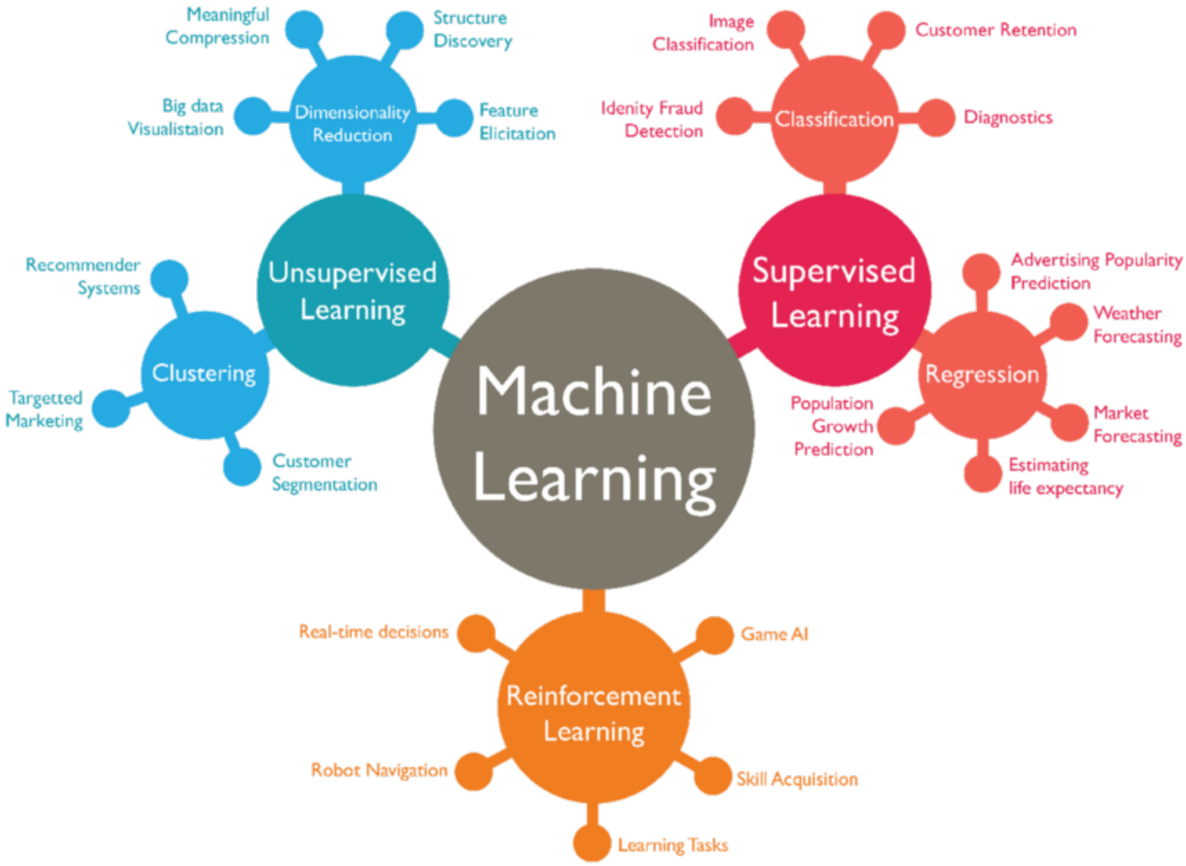

Figure 1 The different types of machine learning with examples (Khadka, 2017)

2.2.1 Unsupervised Learning

Unsupervised learning focuses on the structure of the dataset. The idea is to identify patterns in the data that can help give a better understanding of relationships between variables and observations. The two main areas in this field are clustering, which identifies similar points within the dataset, and dimensionality reduction, which looks to lower the complexity of the dataset by reducing the number of features. An example of where a dimensionality reduction technique is used in white space detection is given in (Ma et al., 2019).

2.2.2 Supervised Learning

Supervised learning focuses on making predictive models. The essential idea is to build a model that given some input or predictor variables X, is able to predict an output or response variable Y, by estimating a function f such that $Y = f(X)$. If the response variable Y is continuous, this is a regression problem, whereas if the response variable is discrete, this is a classification problem. Traditional ML regression techniques include linear and generalised linear regression, and Gaussian process regression. Traditional ML classification techniques include logistic regression, k-nearest neighbour (KNN) models, support vector machines (SVMs), discriminant analysis models, naïve Bayes classifiers and binary decision trees. See (Kulin et al., 2021) for more detailed descriptions of the ML techniques mentioned here.

2.2.3 Reinforcement Learning

Reinforcement learning is concerned with how intelligent agents take actions in an environment to maximise some reward function. Reinforcement learning differs from supervised learning in that there does not need to be labelled data, and the space of data needs to be explored during the learning process. See (Masur and Reed, 2021) for examples of using reinforcement learning techniques to implement control loops within O-RAN.

2.2.4 Deep Learning

With advances in computational power, more powerful ML techniques can be implemented, such as ensembles of classifiers including random forests, and shallow or feed forward neural networks (NNs), which take an ever-increasing number of parameters. The power here is that NNs have more flexibility to approximate most functions f.

Whilst these techniques are useful for unstructured input data, they do not perform as well on structured data such as images or time-series, which are common in communication networks. This has led to the advancement of deep learning (DL) techniques, which is commonly considered to be a subset of ML techniques (see Figure 2). DL takes advantage of GPUs to estimate models using neural networks with typically ~10^6 parameters. These techniques can be applied to both classification and regression problems. The main examples of DL are convolutional neural networks (CNNs), which take convolutions of input images to include information about their structure, and recurrent neural networks (RNNs), which include information on past inputs. A more recent example of RNNs applied to time-series data are long-short term memory networks (LSTMs), which use information of both long- and short-time correlations between time inputs.

In this report, we mainly focus on applications of supervised learning. Examples of applying the techniques mentioned above to future networks will be shown in the following sections.

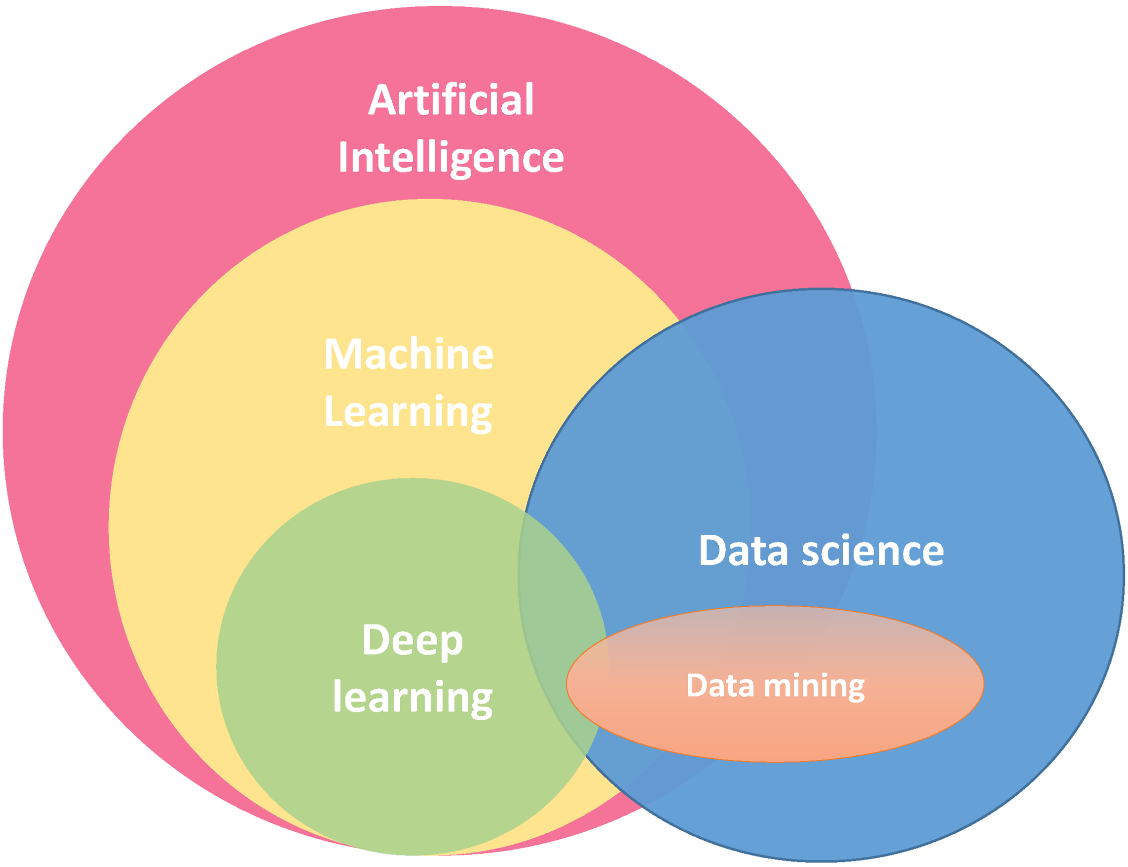

Figure 2 A Venn diagram of terminology in the field of AI (Kulin et al., 2021)

3. WIRELESS NETWORKS

3.1 PHYSICAL LAYER

3.1.1 Automatic modulation classification (AMC)

Modulation is the process of impressing information on carrier signals. It is important to detect the modulation scheme from the emitter to perform the correct demodulation at the receiver. AMC can provide insight about the type of communication systems and emitters present in the wireless network, and allow localisation, identification, and jamming of hostile signals.

Traditional approaches to this problem were focused on maximum likelihood estimation (MLE) (Ozdemir et al., 2015, 2013; Wimalajeewa et al., 2015), or feature engineering (Nandi and Azzouz, 1998). However, MLE techniques can suffer from high computational complexity, whereas feature engineering approaches require expert knowledge, and may only perform well on specialised problems. To alleviate these issues, ML algorithms such as support vector machines (SVM), were used (Hassanpour et al., 2016). Although these methods generalise well, and have improved speed and performance, expert knowledge is still required for the feature engineering step. Due to the increasing complexity of current networks, with combinations of homogeneous and heterogeneous signals, the process of feature engineering is becoming more challenging. This motivates the use of deep neural networks to self-learn features. For example, in (O'Shea et al., 2016), it was shown that CNNs outperform expert feature based methods. Since then, the architecture of the CNN has been improved to reduce computational time, with applications for wireless networks that require low-latency (Hermawan et al., 2020). However, deep learning-based AMC models are susceptible to adversarial attacks, which can significantly degrade performance. The authors of (Sahay et al., 2021) showed that interference can be drastically reduced in CNNs and RNNs with a detection and mitigation strategy.

3.1.2 Spectrum sensing

Spectrum sensing is used to characterise spectrum occupancy, and thus identify the devices and signals present in a local network. This can help in effective interference avoidance and improve coexistence mechanisms. For example, it is crucial that technologies operating in the industrial, scientific & medical (ISM) frequency bands can identify which other emitters are present. Examples include:

i. Classification using a CNN of radar signals in the presence of Wi-Fi and Long-Term Evolution (LTE) transmissions (Selim et al., 2017).
ii. Recognition of LTE and Wi-Fi transmissions to select the appropriate LTE configuration using CNN classifiers (Maglogiannis et al., 2019).
iii. Detection of licensed users, for the purpose of accessing unused licensed bands, using four ML methods including k-nearest neighbours, SVMs, logistic regression and decision trees to predict spectral occupancy (Soto et al., 2018).
iv. Detection of 4G LTE/5G/Bluetooth & IoT signals in congested electromagnetic environments (EME) using a CNN open set classifier which adds an unknown class detection algorithm to detect signals from unknown classes (Shebert et al., 2021).

3.1.2 White space detection

The rapid increase in wireless devices and services has resulted in the need for additional radio spectrum. At present, most of the spectrum has been allocated to different legacy services, such as TV, radio, cellular, and satellite systems. However, most licensed spectrums are not fully utilised under the existing static spectrum allocation strategy. Various spectrum regulatory organisations across the world have opened the spectrum in the UHF television band for secondary access, commonly referred to as TV white space. If accurately detected and utilised through dynamic spectrum sharing, white spaces offer a valuable new opportunity for high speed wireless communications.

The authors of (Ma et al., 2019) used an unsupervised learning technique called self-organised maps (SOM) to understand the usage variations among different locations and time periods in London. In (Saeed et al., 2017), a model was developed using SVM and naïve Bayes classifiers, combining locally measured signal features and location to more efficiently detect white space availability.

3.1.3 Channel state information estimation (CSI)

CSI refers to the known channel properties of a communication link. This information describes how a signal propagates from transmitter to the receiver and represents the combined effect of, for example, scattering, fading, and power decay with distance. Estimating CSI can help to adapt transmission to the current channel conditions, to improve the whole communication.

Traditional CSI estimation usually has high computation complexity and is not scalable to 5G technologies such as massive MIMO. Deep learning can be useful in CSI estimation for massive MIMO systems. Examples include:

i. CSI prediction using features such as frequency band, user location, time, temperature, and humidity in two indoor and outdoor scenarios (Luo et al., 2020);
ii. Using vehicular channels, where the Doppler rate varies from one packet to another, making CSI estimation difficult (Mehrabi et al., 2019).

3.1.4 Signal coder/decoder schemes

Signal coding is the process of representing information in a way that realises a desired communications objective such as analogue-to-digital conversion, low bit rate transmission, or message encryption. Due to the unstable nature of channels, some disturbances and noise can cause data corruption. The goal is to decode signal data with minimal error and latency.

One method using ML techniques is to represent transmitter, channel, and receiver as one deep neural network that can be trained as an autoencoder. An autoencoder can encode the radio signals by reducing the complexity within the hidden layers of the DNN. Applications include minimising the block error rate (BLER), and jointly optimising multiple transmitter-receiver pairs competing for capacity (O'Shea and Hoydis, 2017).

For 5G networks, deep learning models can be used to learn the coding/decoding process of a MIMO-NOMA system in order to minimise the error in users signals (Kang et al., 2020). DNNs can also be used to minimise the bit error rate (BER) in a code-based NOMA technique called sparse code multiple access (SCMA) systems (Kim et al., 2018). Finally, designing channel codes under low latency constraints was achieved in (Jiang et al., 2019) using a recurrent neural network (RNN) based encoder and decoder.

3.1.5 Fault detection

Fault detection systems are very important to achieving ultra-reliable low latency communication (URLLC). For example, mission-critical industrial automation applications demand stringent timing and reliability guarantees for data collection, transmission, and processing. Deep learning can be used to detect and locate antenna faults in mmWave systems (Chen et al., 2019), to reduce operational cost.

3.1.6 Beamforming

Determining the optimal phase shift and amplitude of each antenna to maximise the gain is a complex problem. The authors of (Maksymyuk et al., 2018) implemented a reinforcement learning algorithm that can adapt the signal concentration based on the number of users located in a given area. If there are many users in a small area, the solution may produce a more targeted signal. Meanwhile, if users are spread out over a wide area, a signal with wide coverage will be sent.

Predicting device location is a complex task in mmWave systems due to the radiation reflected from most visible objects. The authors of (Gante et al., 2018) used a deep learning model to predict user position based on beamformed fingerprints.

3.2 DATA LINK LAYER

The MAC sublayer in wireless networks is used to allocate limited resources in a flexible way. Instead of a centralised architecture using base stations to control and distribute resources, nodes in wireless ad hoc networks (WANETs) coordinate resources. Given the changing network and environmental conditions, designing a MAC protocol that fits all conditions is a major challenge. Thus, ML techniques for efficiently sharing resources have been explored.

3.2.1 MAC identification

These techniques are typically applied in cognitive radios, which can automatically detect available channels within the wireless spectrum. They can also infer spectrum holes, which are frequency bands that have been allocated to network users but are not being used at the time. Spectrum sensing can help with determining the frequency range, but not the timing information. MAC protocol identification can be used to determine these timings, and thus improve network performance as a result. As a recent example, the authors of (Zhang et al., 2020) used spectrograms of various MAC protocols as inputs to a CNN classifier.

3.2.2 Spectrum sensing at the packet level

As with spectrum sensing in the physical layer, the goal is to identify interference which degrades network performance. However, at the MAC sublayer the focus is on using features of interfered channels and packets. For example, in (Hithnawi et al., 2015) the authors used energy variations during packet reception and the quality of corrupted packets as inputs to a decision tree classifier, to determine if communication is viable, and characterize the best coexistence mitigation strategy.

3.2.3 Spectrum prediction

Instead of determining the current spectrum and state of the network, an alternative approach is to make predictions of wireless medium availability, and thus make decisions in advance. Examples include:

i. Using neural networks to determine whether the medium is busy or idle based on the network history (Mennes et al., 2018).
ii. Sharing time slots among multiple time-slotted networks using deep reinforcement learning (Yu et al., 2019).

3.3 NETWORK LAYER

3.3.1 Performance prediction

The goal here is to forecast network performance or optimise network parameters in order to adapt the network to environmental conditions and improve quality-of-service (QoS) and quality-of-experience (QoE). Examples include:

i. Selecting optimal MAC parameters using neural networks to reduce collisions, packet loss, and latency (Al-Kaseem et al., 2017);
ii. Predicting users' QoE in cellular networks with neural networks, using features such as the number of active users in a cell and average data volume (Pierucci and Micheli, 2016).

Having a fixed MAC protocol is a problem for dynamic networks where there might be significant performance drop when the network load is heavier, and a waste of resources when lighter. Decision trees were used to train adaptive MAC sublayers which select the appropriate protocol for the given QoS requirements, traffic patterns and environmental interference level (Sha et al., 2013).

One final application is accurate link estimation, where ML can be used to predict the link quality based on physical layer information and packet reception rate (PRR) (Liu and Cerpa, 2011). In this example, naïve Bayes, logistic regression and neural network classifiers were compared.

3.3.2 Traffic prediction

Predicting future network use can help with network resource management and planning. In order to reduce energy consumption of cellular networks, sleeping mechanisms in base stations have been introduced. However, previous algorithms based on deterministic traffic variation have become unsuitable for highly fluctuating networks. Thus, the authors of (Hu et al., 2015) used a modified wavelet neural network to predict future traffic of base stations.

In network slicing, suitable allocation of resources to each slide requires knowledge of the user traffic. The authors of (Bega et al., 2019) created DNNs to forecast capacity in individual network slices.

3.3.3 Anomaly detection

Anomaly detection systems are important to identify malicious network flows that may impact users and the network performance. Developing these systems remains a challenge due to the large data volume generated in 5G systems. Cyber security defence systems can be learnt using deep learning models that are capable of extracting features from network flows and the quick identification of cyber threats (Fernández Maimó et al., 2019).

Deep learning can also be applied to detect anomalies in the network traffic. Cell outages can result from sleeping cells, which can cause interruption and reduce QoS and QoE. Sleeping cells can emerge due to failures in the antenna hardware, or random access channel (RACH) failures due to RACH misconfiguration. A deep learning approach was applied to detect such anomalies (Hussain et al., 2019).

4. OPTICAL NETWORKS

4.1 PHYSICAL LAYER

ML techniques in the physical layer of optical networks are used to optimise optical transmission between transmitter and receiver nodes within the network. Below we mention some main applications.

4.1.1 Transmitters

Higher order modulation formats ranging from 16 to 64 QAM aim to increase spectral efficiency (SE) of transmission, at the expense of lower SNR. This requires precise characterization of amplitude and phase noise within lasers. Traditional approaches apply coherent detection in combination with digital signal processing (DSP). These approaches can suffer from computational cost and lack of scalability. The authors of (Zibar et al., 2015) used Bayesian expectation maximisation techniques to accurately characterise laser amplitude and phase noise that outperforms these conventional approaches, even in the presence of large measurement noise.

4.1.2 Optical amplification control

EDFAs extend the reach of transmitted optical signals by performing amplification of WDM channels in the optical domain. ML techniques can be applied to improve the operation of EDFAs within optical fibre transmission. The authors of (Huang et al., 2016) characterised the channel dependencies of power excursions in multi-span EDFA links using kernelized linear regression with a radial basis function. This was extended in (Huang et al., 2017) to handle power excursions in dynamically changing spectral configurations. The authors used ridge regression to determine the magnitude of impact due to a given sub-channel, and logistic regression to specify whether the contribution will result in an increase or decrease in the discrepancy among post-EDFA powers.

4.1.3 Performance monitoring

In network control and management, one must monitor and adapt to physical parameters of transmitted optical signals such as optical signal to noise ratio (OSNR), polarisation mode dispersion (PMD) and chromatic dispersion (CD). This allows network diagnosis in order to act against malfunctions. The work of (Xiaoxia Wu et al., 2009) studies the applications of NNs to optical performance monitoring (OPM). However, these techniques require knowledge of bit-rate and modulation format. An alternative approach using a DNN trained on raw asynchronously sampled data was used for OSNR monitoring (Tanimura et al., 2016). For systems using higher order QAM schemes, (Thrane et al., 2017) used a NN for OSNR estimation, and an SVM for modulation format classification.

4.1.4 Optical fibre nonlinearities

Nonlinear effects can occur within optical fibres in a variety of ways. Examples include self-phase modulation (SPM), where an optical signal alters its own phase; cross-phase modulation (XPM), where one signal affects the phases of all others; and four-wave mixing (FWM), whereby signals with different frequencies interact to produce mixing sidebands. These effects can limit the information capacity of optical fibre systems. These effects interact with amplified spontaneous emission (ASE) noise resulting in nonlinear phase noise (NLPN) and can lead to degradation in performance of modulation schemes that encode the phase of the optical signal (Demir, 2007).

Traditional approaches to mitigating NLPN have focused on using information of the fixed fibre link, such as in (Lau and Kahn, 2007), where analytical expressions for symbol MLE decision boundaries and symbol error rate (SER) were derived for specific phase modulation schemes. Such approaches can suffer from computational complexity for practical implementation. ML techniques can be incorporated into DSP to allow more accurate symbol detection in a more efficient way. A nonlinear SVM classifier was used in (Wang et al., 2015) to mitigate NLPN in optical transmission systems modulated with M-ary phase-shift keying (M-PSK), and demonstrated increases in maximum transmission distance. Generalising higher order modulation formats, such as 16 QAM coherent transmission systems, the authors of (D. Wang et al., 2016) used a k-nearest neighbour multi-class classifier. This approach was extended to more advanced systems, with improved SE, such as 16 QAM coherent optical orthogonal frequency division multiplexing (CO-OFDM) systems (Giacoumidis et al., 2017). In this case a fast Newton-based support vector machine (N-SVM) was used to extend the optimum launched optical power.

4.1.5 Quality of transmission (QoT) estimation

Optical networks performing WDM are made up of optical fibres, which can transport different data channels simultaneously by using different wavelengths combined with optical nodes, which perform routing based on the wavelength. The problem of selecting an appropriate route and wavelength so that two routes sharing a link are not assigned the same wavelength is called the routing and wavelength assignment (RWA) problem. RWA must establish lightpaths such that the quality of data transmission is ensured. As such, efficient and effective lightpath QoT estimation prior to deployment must be made. The authors of (Mata et al., 2017) developed a binary SVM that classifies lightpaths into high and low quality based on a user-defined Q-factor, which is inversely related to the bit error rate (BER). An alternative metric for estimating QoT is the generalised signal-to-noise ratio (GSNR), which takes account of ASE. This was considered by (Usmani et al., 2021), who compared multiple ML classifiers.

4.1.6 Failure identification

Given the volume of data, identifying faults may be more critical in optical networks than in wireless networks. Fibres can be broken, giving major routing issues in a network. Once they have been identified and localised at the physical level, they can be managed at the network level. One such approach (Shariati et al., 2019) focuses on the detection of common filter-related failures such as filter shift and tight filtering, which deform the shape of the optical spectrum. Decision trees and SVMs were used as single and multiple classifiers to determine the failure type. The authors (Ruiz et al., 2016) study the effects on QoT monitoring parameters (such as received power and BER) of tight filtering and inter-channel interference failures. Specifically, they use Bayesian networks to give a probability of whether there is a failure in the link, and what type it is. Then, the system can reconfigure the lightpath to solve the BER degradation.

4.2 NETWORK LAYER

4.2.1 Traffic and resource prediction

Traffic prediction can be used for network configuration and resource allocation to increase the flexibility of optical networks. Historical traffic data is plentiful as network operators need to monitor security and operational issues. This allows data-driven ML techniques to provide useful predictive models.

Current datacentres, which house switches, storage systems, servers, and routers, are based on electronic packet switches. However, optical switching-based interconnecting architectures have proved effective in reducing or eliminating the electronic components due to their high-energy efficiency. The characteristics of inter-datacentre traffic are dynamic due to its applications. This brings challenges to the underlying inter- (and intra-) datacentre optical networks (Yoo et al., 2012).

Predictions of the traffic and resource requirement is essential for adaptive network control and management. The authors of (Guo and Zhu, 2018) proposed a DNN-based method for bandwidth resource requirement prediction *inter*-datacentre optical networks. DNN-based methods were also employed in modelling *intra*-datacentre optical networks to predict traffic properties such as traffic arrival time and resource consumption (Yu et al., 2018). This information can be used to adjust the traffic queue to reduce path blocking probability. As well as feed-forward DNNs, LSTMs can be used for traffic remaining time prediction, which provide information for traffic aggregation in optical datacentre networks (Singh and Jukan, 2018).

4.2.2 Resource assignment

In optical networks, there are multiple types of resources to be assigned, such as wavelength, spectrum, and modulation format. Here we focus on applications of ML to RWA problems, which consider optimal routes and an optical wavelength for each IP service, and routing and spectrum assignment (RSA) problems, which attempts to allocate suitable spectrum slots to a requested lightpath. These problems have usually been formulated as a constrained optimisation problem and solved with integer linear programming. However, more recently, ML techniques have been applied to RWA and RSA problems.

The RWA problem can be formulated as a multi-class classification problem where the inputs are the network states such as topology, capacity and available wavelengths, and the outputs are the RWA configurations for such states. ML models including logistic regression and DNN were trained on a WDM network (Martín et al., 2019), achieving near-optimal RWA with reduced computational time in comparison with integer linear programming.

4.2.3 Failure management

When an optical network suffers a failure, an immense loss of data will occur. Protection algorithms to combat failures fall into two camps: passive methods, which are only implemented after a failure occurs, and preferred proactive methods, which provide an early-warning system by detecting some potential failures. ML can be applied to proactive methods by learning the relationship between current network status and future network failures. Data from a WDM network was used in (Wang et al., 2017) by applying double exponential smoothing with an SVM to predict failure given indicators of the network state.

Due to the complexity of network topology and the connectivity of network components, it is also a challenge to localise a failure. The work of (Zhao et al., 2019) used deep neural evolution networks (DNEN) to locate failures in WDM networks. DNENs generate a series DNNs and use crossover and mutation to optimise the training.

5. CONCLUSIONS AND FURTHER WORK

Due to its powerful ability to leverage data to capture the behaviour of complex systems, ML is rising to increasing prominence in the deployment of communications networks. We have seen in this report that ML techniques are applicable across the range of technologies being developed for future networks, including massive MIMO, fibre-optics and massive machine-type communication. ML also has the potential to be used within every layer of abstraction: from adaptive signal processing in the physical layer, to spectrum intelligence at the data link layer, through to adaptive system-level optimisation at the network level.

There is still a great deal of work to be done to bring about the integration of these new technologies into commercial products and services. This process is being driven in part through the development of standards, most notably those released by the ITU-T Focus Group on Machine Learning for Future Networks (ITU-T, 2022).

In this report, we focus mostly on supervised learning techniques applied to specific application areas in future networks. Supervised learning can be applied where large volumes of labelled data are readily available. This is the case in the physical layer where it is easy in an experimental setting to vary multiple parameters of wireless or optical signals. Areas such as beamforming power selection, error-correction coding, transmitter classification, channel modelling, white space detection and signal sensing can all take advantage of supervised learning techniques. See (Luo, 2020) for more detailed analysis of ML techniques applied to these areas, which typically take advantage of modern deep learning algorithms.

However, when moving to the network level and beyond, the complexity and heterogeneity of network and system level states mean that only partial information is available, and therefore supervised learning may not be applicable. In this case, typically one wishes to apply real-time ML techniques that can adapt to new information about the network and adjust parameters accordingly to enhance metrics such as QoE and QoS. This is where reinforcement learning techniques can become more powerful. Areas such as dynamic spectrum access (Zhao and Sadler, 2007), cognitive radio management and allocation (W. Wang et al., 2016), coverage and capacity optimization (Phan et al., 2017), and wireless edge caching (Zhong et al., 2018) can all take advantage reinforcement learning techniques. An exploration of applications of reinforcement learning to communications networks is left for future work.

It is crucial for the adoption of ML approaches that they can be incorporated into communications networks in a trustworthy manner, and in this context the issues of most concern are robustness and generalisability, uncertainty quantification, and cybersecurity and privacy. These are all topics of current research interest in a generic sense, and NPL's ML work is focused on the challenge of trustworthy ML; see for example (Thompson et al., 2021). An important challenge for the metrology community is to understand the specific requirements for trustworthy ML in the context of future networks.

Recent ITU standards address the use of ML in future networks (ITU-T, 2022). Recommendations are provided on an architectural framework for the integration of machine learning into 5G and future networks (ITU Y.3172), a framework to evaluate intelligence levels across different parts of the network (ITU Y.3173), and a framework for data handling in support of machine learning (ITU Y.3174). These standards have been used to guide contributions to the ITU Global Challenge on AI and Machine Learning in 5G (ITU, 2020). It will be important for NPL to become familiar with these and other standards in order to guide case studies in which ML is implemented within communications networks, and also to engage with these standards as our perspective on trustworthy ML for communications develops.

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