Marie Skłodowska Curie Action

WINDMILL

Machine Learning for Wireless Communications

H2020-MSCA-ITN-ETN

Grant Agreement Number: 813999

WP6–System-wide Cognitive Optimisation Schemes

D6.1–State of the art on context acquisition & anticipatory optimisation techniques for network optimisation

Contractual Delivery Date:	Month 20 (August 2020)
Actual Delivery Date:	August 31, 2020
Responsible Beneficiary:	UNIPD
Contributing Beneficiaries:	AALTO, BOSCH
Dissemination Level:	Public
Version:	Draft

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 813999.

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Document Information

Document ID:	WP6/D6.1
Version Date:	August 31, 2020
Total Number of Pages:	61
Abstract:	Future wireless networks attempt to combine different types of communication for various applications thereby leading to a high number of devices needed to be integrated and handled efficiently. Hence, the need for network optimization in future wireless networks, such as 5G networks and beyond, has become very important as large number of devices requesting a certain data rate would need high amount of bandwidth and advanced resource management algorithms to maintain an appreciable quality of service and quality of experience. In order to handle largely variable requirements, prediction and estimation of wireless network state parameters, such as channel state, user data requirement, user mobility, are needed to calculate optimal network configurations for a certain application at certain time for a certain user. So, in this document, we describe the different methodologies and schemes proposed for anticipatory or predictive networking and optimization schemes proposed based on the different types of anticipatory information from the wireless networks.
Keywords:	Anticipatory Networking, Machine Learning, 5G Networks, Contextual Information, Optimization Schemes

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List of Acronyms and Abbreviations

AP Access Point

AoI Age of Information

ANN Artificial Neural Network

AGM Arithmetic-Geometric Mean

AOA Angle of Arrival

ALQ Average Link Quality

ARIMA Auto Regression Integrated Moving Average

AWGN Additive White Gaussian Noise

BS Base Station

BER Bit Error Rate

CF Collaborative Filtering

CR Cognitive Radio

CRN Cognitive Radio Network

CSI Channel State Information

CNN Convolutional Neural Network

CoMP Coordinated Multipoint

CSMA Carrier Sense Multiple Access

CL-IDA Cross-layer Interference and Delay Aware Metric

DDPG Deep Deterministic Policy Gradient

DNN Deep Neural Network

DP Dynamic Programming

DQN Deep Q-Network

DRL Deep Reinforcement Learning

DSP Digital Signal Processor

DTMC Discrete Time Markov Chain

D2D Device to Device

DBNG Deep Belief Network and Gaussian Model

ESN Echo State Network

ETX Expected Transmission Count

ETT Expected Transmission Time

FDD Frequency Division Duplexing

FEV Fully Electric Vehicle

FNN Feed Forward Neural Network

FDD Frequency Division Duplexing

GAN Generative Adversarial Network

GMM Gaussian Mixed Model

GPR Gaussian Process Regression

GPU Graphics Processing Unit

GBSM Geometry based Stochastic Model

GBDT Gradient Boosting Decision Tree

GECR Genetic algorithm-based energy-efficient clustering and routing algorithm

GPS Global Positioning System

HCRAN Heterogeneous Cloud Radio Access Network

HetNet Heterogeneous Networks

HGMM Hidden Gaussian Markov Model

HMM Hidden Markov Model

IRS Intelligent Reflecting Surface

IoV Internet of Vehicles

IoT Internet of Things

KNN K-Nearest Neighbors

LSTM Long Short-Term Memory

LP Linear Program

ILP Integer Linear Program

MILP Mixed-Integers Linear Program

MAC Medium Access Control

MC Markov Chain

MCS Modulation and Coding Scheme

MDP Markov Decision Process

ML Machine Learning

MISO Multiple-input Single-output

MPC Model Predictive Control

MF Matrix Factorization

MIMO Multiple-Input Multiple-Output

mmWave Millimeter Wave

MIP Mixed Integer Programming

MANET Mobile Ad-hoc Network

MLR Multinomial Logistic Regression

MIMO Multiple Input Multiple Output

NLoS None Line of Sight

NOMA Non-Orthogonal Multiple Access

NB Naive Bayes

OFDMA Orthogonal Frequency Division Multiple Access

OLSR Optimized Link State Routing

OS Operating System

QoS Quality of Service

QoE Quality of Experience

RAN Radio Access Network

RB Resource Block

RF Radio Frequency

RL Reinforcement Learning

RSSI Received Signal Strength Indicator

RRH Radio Remote Head

RNN Recurrent Neural Network

RRM Radio Resource Management

RBF-NN Radial Basis Function Neural Network

RLRP Radio Link Reliability Prediction

RSU Road Side Unit

SISO Single-Input Single-Output

SJE Stationary Joint Eigentensor

SVD Singular Value Decomposition

SBS Small Base Station

SVM Support Vector Machine

SVR Support Vector Regression

SP Service Provider

SCA Successive Convex Approximation

SDS-TWR Symmetric Double Sided Two Way Ranging

SMS Short Message Service

SDN Software Defined Network

SINR Signal-To-Interference-plus-Noise

TOA Time Of Arrival

TDOA Time Difference of Arrival

TPU Tensor Processing Unit

MP-TCP Multipath Transmission Control Protocol

UAV Unmanned Aerial Vehicle

UE User Equipments

URLLC Ultra Reliable Low Latency Communication

UWB Ultra Wide Band

V2I Vehicle to Infrastructure

V2V Vehicle to Vehicle

V2X Vehicle-to-X

VANET Vehicular Ad Hoc Network

VM Virtual Machine

WLAN Wireless Local Area Network

WSAN Wireless Sensor and Actuator Network

WSN Wireless Sensor Network

WMN Wireless Mesh Network

1. Introduction

Future wireless networks attempt to combine different types of communication for various applications thereby leading to a high number of devices needed to be integrated and handled efficiently. Hence, the need for network optimization in future wireless networks, such as 5G networks, has become very important as large number of devices requesting a certain data rate would need high amount of bandwidth and advanced resource management algorithms to maintain an appreciable quality of service and quality of experience. Satisfying these requirements with traditional optimization schemes would result in high computational costs to find optimal solutions for different types of applications. In order to handle largely variable requirements, prediction and estimation of wireless network state parameters, such as channel state, user data requirement, user mobility, are needed to calculate optimal network configurations for a certain application at certain time for a certain user. To predict the network behaviour, the system must continuously track the performance of the network.

Predictions of such network state parameters can be performed using multiple different techniques such as Time Series Predictive Modelling, Probabilistic Forecasting, Similarity Based Classification and Regression Analysis [1]. In Time Series Predictive Modelling, network parameters are estimated by modelling wireless networks as auto-regressive and moving average model [2]. Probabilistic Forecasting shows that parameters can be estimated by modelling networks as probability processes such as Markov Process [3]. Similarity Based Classification finds relations between parameters and gather similar parameters to predict future network parameters [4]. Lastly, Regression Analysis or Machine Learning learns about the parameters and determines dependencies so as to predict different network parameters [5–8].

Hence, in this document, we describe the different methodologies and schemes proposed for anticipatory networking and optimization schemes based on the different types of anticipatory information from the wireless networks. Chapter 2 mentions the motivation for anticipatory networking and optimization based on the anticipatory schemes. Chapter 3 describes the methodologies to gather different types of contextual information for anticipatory techniques. Chapter 4 describes the techniques to generate anticipatory information from the working context. Chapter 5 discusses the different types of techniques designed to optimize the system based on the anticipatory information. Chapter 6 discusses the various applications that are tackled by using the different proposed optimization schemes.

2. Motivation

Predictions of parameters in wireless networks is a huge challenge, due to the inherent randomness of these systems. To overcome such a challenge, knowledge regarding the wireless network parameters has to be gained. Also, such knowledge has to be interpreted by the system so as to create optimal configurations based on the requirements of the network. To do so, large amount of data is necessary to be analyzed and models have to be created based on such analysis. The state of the art systems such as Time Series Predictive Modelling and Probability Forecasting depend on accurate modelling of all network parameters but are unable to find relations between such parameters implicitly. Hence, they are tedious to pursue for a dynamic network such as the 5G system, which will incorporate multiple different applications. Also, similarity based classification is hindered as predictions of parameters is difficult for the model if there are no instances for such predictions in the data. Hence, it is limited to certain network optimization configurations and cannot account for unknown interaction between different parameters for various network configurations, which is needed in 5G networks when dealing with various devices for different applications. The most ideal approach for network optimization is the usage of Machine Learning especially Artificial Neural Networks or Deep Neural Networks, that have the capabilities to gather and learn about large amount of information of network parameters and create relations between such parameters to predict the optimal network configurations for the current state of the system. To learn and predict network parameters, artificial neural networks employ different methodologies such as supervised learning, unsupervised learning, reinforcement learning and transfer learning. These techniques are incorporated to generate models which are highly efficient for prediction of wireless network parameters as well as determining optimal network configurations for such parameters.

This approach is novel due to the fact that future networks need to integrate multiple different types of devices and need to analyze large amount of information from such devices which is not quite prominent in the current network setup. Also this approach is possible due to the advancement in processors, especially GPUs, which enables to process large amount of information using parallel computing. Hence, usage of deep neural networks to predict wireless network parameters for optimization is essential for future wireless networks such as 5G and beyond 5G systems.

3. Contextual Information for Wireless Networks

Wireless Networks incorporate a ton of contextual information which can be very useful for their optimization. User information such as position and mobility as well as Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) provide essential information which can be used by the wireless systems to allocate resources and improve performance of the wireless network.
In this chapter, different types of contextual information that can be extracted from the wireless network are discussed. The chapter also discusses the works that are proposed to gather these contextual information and the use of the information in different applications. Section 3.1 discusses the techniques to gather and predict geographical contextual information. Section 3.2 discusses the techniques to gather and predict wireless link related information. Section 3.3 discusses the methodologies to predict user traffic in the network. Section 3.4 discusses the methodologies to gather social information about the users and applications related to this social information.

3.1. Geographical Context

Geographical context refers to the user information related to the physical environment. Prominently geographical context includes the position and mobility information regarding the users in the network, and also their trajectories. The difference between mobility and trajectory is that mobility refers to the prediction of the next position of the user, while trajectory refers to the prediction of the whole path of the mobile user. This information is essential while determining the configuration of the network and the requirements of the users so as to provide maximum Quality of Service (QoS) and Quality of Experience (QoE) to the users.

3.1.1. Position and Mobility Prediction

Position and mobility information is one of the most important contextual information to configure and manage a wireless system. Traditionally, the users periodically communicate their position information to the network infrastructure. But with the increase in the number of devices in the future wireless networks, these periodic updates may become difficult and may lead to loss in performance for the users. Also, the performance of the system depends on the accuracy of the position updates as well. To accommodate the increase in number of devices as well as the accuracy of the position updates, the research has focussed on predicting the future position of the users, and on developing mobility models so as to predict the movement of the users in the network.
To predict positions, multiple different methods have been proposed, from traditional algorithms such as Kalman filter based prediction schemes, to novel data driven models such as machine learning, deep learning and reinforcement learning based prediction schemes. In [9], a Deep Reinforcement Learning (DRL) algorithm for unsupervised location prediction is presented. The algorithm models the position of the Internet of Things (IoT) devices as a Markov Decision Process (MDP) and trains a DRL agent using RSSI gathered from the IoT devices to predict unknown position of the devices. In [10], the position of users is determined based on the phase, time of arrival, angle of arrival and signal strength of the

mmWave signals. It also presents an idea of using a machine learning algorithm to learn the signal strength, time of arrival and angle of arrival values and predict the location of the users. Following that, in [11], a map based position estimation mechanism is presented based on the attributes similar to those used in the previous work, i.e., angle of arrival and time of arrival, but also adds a multipath component which exploits the multipath nature of mmWave signals in the environment. Based on these information, a map of the environment is created by the system and the location of the user is determined based on the values obtained for the considered attributes. In [12], the authors use a temporal convolutional networks to determine the position estimates based on mmWave beam tracking. The temporal convolutional networks takes into account the mmWave beam signals from the user over a period of time and provides position estimates based on the previous position and trajectory. In [13], the position estimates are provided using Kalman filters to determine the position and trajectory of the vehicles in the network and find the optimal next hop for routing. In [14], each node calculates an area of coverage based on the probability of existence for the node to be in its coverage range. In [15], the authors created a dataset based on the RSSI and a random mobility model and trained a deep neural network to predict the future position of the users based on the RSSI. In [16], a dual Hidden Markov Model (HMM) is proposed. The first HMM predicts the position based on the WiFi RSSI and provides that as an input to the second HMM to determine the optimal Access Point (AP) based on the position estimate. Other approaches for the position and location prediction in different types of networks can be found in the surveys [17, 18].

3.1.2. Trajectory Prediction

Trajectory prediction is important as it enables the system to determine future positions of the user and optimize the system based on this information. To determine trajectory information about a user, the system has to take into account past positions over a period of time and predict the trajectory based on those positions. In [19], a Gaussian Mixed Model (GMM) is proposed which takes into account the position information over time from Global Positioning System (GPS) coordinates and determines the trajectory. It also incorporates the noise in the position information by modeling the position with a Gaussian Distribution. A maximum likelihood algorithm is used estimate the motion based on the position information and a Gaussian Process Regression (GPR) is used to predict the trajectory of the vehicle based on the trajectory data. In [20], two Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) and Echo State Network (ESN), are used to determine the trajectory for predicting resource allocation. In [21], user movement is predicted based on the GPS coordinates and timestamps collected from Twitter and training an ESN based on the position to determine the trajectory of the users. In [22], a LSTM is proposed to predict future position and using dead reckoning method to predict the tracjectory based on the predicted position.

3.1.3. Uncertainties in Predictions

The prediction algorithms discussed previously are not always accurate, i.e., uncertainties exist in the prediction algorithms. So it is important to take that into account, especially when accurate predictions can be very crucial for optimizing the network. In [13], the location prediction is determined by Kalman filter. But Kalman filter predictions have uncertainty. To tackle that, a mean squared error is calculated to determine the quality of the prediction.

In [23], the uncertainty is predicted using deep neural networks in wireless fingerprinting based on dead reckoning. In [24], the uncertainty in three dimensional localization, based on RSSI, Time Of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) and Symmetric Double Sided Two Way Ranging (SDS-TWR), is calculated based on sensitivity factor determined by partial differential equations. Based on the uncertainty calculated, the propagation of uncertainty in the position from each of the factors is determined.

3.2. Communication Link Context

Communication Link Context refers to the contextual information regarding the physical and abstract attributes of the wireless medium. Primarily, communication link refers to the channel over which the communication takes place, which is a physical attribute, as well as the quality of the channel or link, which is an abstract attribute based on the physical attribute. The link context information is crucial in wireless communication due to highly dynamic nature of wireless channels which leads to performance variations that are critical in a network containing large number of devices.

3.2.1. Channel State Prediction

To determine the channel state, the system needs to either gather continuous CSI updates from the user. But continuous updates increase the overhead especially for a network containing a large number of devices. In [25], the CSI is obtained for the uplink channel by the system and then used for uplink to downlink mapping to predict the channel state in the downlink channel. To predict the channel state, a deep neural network called SCNet is proposed which takes into account the uplink channel state for an Frequency Division Duplexing (FDD) Multiple Input Multiple Output (MIMO) system and predicts the downlink channel state. In [26], an LSTM is proposed to predict the next CSI based on the previous CSI. The LSTM structure is trained on the dataset created by gathering CSI obtained from a Rayleigh fading channel and then used to predict the next channel states based on previous channel states in a rolling prediction fashion (previous predictions are used to determine the next predictions). In [27], a combination of Convolutional Neural Network (CNN) and LSTM called OCEAN is used to predict CSI. A combination of frequency band, location, time, temperature, humidity, and weather conditions is used to train the network offline (historical data) and online (current data) and provides an online prediction for the channel state. In [28], a combination of Feed Forward Neural Network (FNN) and Radial Basis Function Neural Network (RBF-NN) is used to predict the channel parameters. The network is trained using an input of Transmitter (Tx) and Receiver (Rx) coordinates, Tx-Rx distance and carrier frequency, which are determined using real time measurements and a Geometry based Stochastic Model (GBSM). In [29], an LSTM is used to predict the channel state. The training dataset for the LSTM model is gathered by using the IEEE802.11p in-phase and quadrature-phase signals to gather the channel information using algorithms such as down sampling, frame detection, symbol alignment, frequency offset correction and training sequence extraction. The LSTM model is trained using the channel information obtained and then used to predict channel quality in vehicular networks.

3.2.2. Link State Prediction

Link State Prediction is crucial especially when determining the link quality to calculate metrics for data transmission so as to achieve an optimal network performance. In [30], a routing metric is proposed based on link quality estimation based on RSSI and Average Link Quality (ALQ), which is determined based on past measurements. Based on the link estimation, the next hop is chosen for routing in vehicular ad-hoc networks. In [31], the physical link is modelled based on the transmission energy consumption and a Mixed Integer Programming (MIP) optimization problem is presented which is solved by a deep neural network. In [32], a prediction algorithm is presented that anticipates link quality metric such as Expected Transmission Count (ETX) and Expected Transmission Time (ETT) to optimise the Optimized Link State Routing (OLSR) protocol. The link quality metric is predicted based on signal strength, which in turn is predicted based on linear regression. In [33], the Cross-layer Interference and Delay Aware Metric (CL-IDA) is estimated using multiple different machine learning techniques, such as multiple linear regression, support vector regression and Gaussian regression, and used as a metric for OLSR. In [34], a link quality state model is presented and based on the link quality model, a Kalman filter based link reliability prediction algorithm called Radio Link Reliability Prediction (RLRP) is presented which predicts the bounds of the reliability of existence of the link for the network.

3.3. Traffic Context

Traffic Context refers to the data traffic that is encountered in the wireless networks. Accurately predicting traffic demands in the network can be really crucial to satisfy the QoS and QoE requirements of the users, especially in a network containing a large number of devices.

3.3.1. Traffic Prediction

In [35], a traffic prediction algorithm called Coca-Predict based on traffic correlation and causality is presented. The algorithm uses correlation between traffic flows over time and over different cells in the area as well as traffic flows due to mobility and social events to predict the traffic at a particular place and time. The algorithm uses Auto Regression Integrated Moving Average (ARIMA), Deep Neural Network (DNN), Gradient Boosting Decision Tree (GBDT) and LightGBM [36]. In [37], an exponential smoothing is used to predict the traffic generated by the nodes in each duty cycle in Wireless Sensor Network (WSN). In [38], a Deep Belief Network and Gaussian Model (DBNG) is used to predict the traffic. The DBNG is used to predict the network traffic, which is modelled based on the previous traffic information and fluctuations in a Wireless Mesh Network (WMN). In [39], a Spatial-Temporal Cross-domain Neural Network (STC-Net) is presented which is trained via transfer learning, by using traffic information from clusters in the cellular network. In [40], a combination of a CNN and a parameter estimator is used to predict city-wide traffic. The parameter estimator is based on the distance between two cells in the cellular network of the city. In [41], a Gaussian Process based predictor is presented, which takes live data from the radio access networks and predicts traffic for a load-aware management tasks.

3.3.2. Performance Analysis based on Traffic Analysis

Traffic prediction is not the only thing that can be considered to improve the system. Prediction of the performance for a certain type of traffic is also necessary. Performance prediction provides a good indication of the network configurations for a certain type of traffic. This helps in determining the network configurations that can be used in different scenarios. In [42], throughput is predicted based on the maximisation of the two local and global optimization problems. The local and global optimization problems address the traffic local to the user and as a whole in the network respectively. The throughput prediction is used to devise a scheduling based on Carrier Sense Multiple Access (CSMA) threshold. In [43], a channel throughput predictor is devised which takes into account the video streaming demand of the users in the cellular network and caches information at the nearest edge to obtain the required QoE. The predictor is devised as a optimization problem that takes into account channel utilization and buffer occupancy of the user to calculate the maximum throughput. In [44], a throughput predictor is designed based on device level data such as application and Operating System (OS) information and network level data such as channel quality and cell load in cellular network. The throughput predictor is designed using three different machine and deep learning techniques namely random forest, SVM and LSTM. In [45], a machine learning based prediction algorithm is presented to predict average throughput for video streaming applications. To predict the average throughput, the RSRP, RSRQ values for primary and neighbouring cell and SNR and CQI. In [46], the throughput prediction is designed for IEEE 802.11 networks. The predictor takes into account the relationship between two metrics which is devised from interference offered by multiple access points using directional antennas and omni-directional antennas.

3.4. Social Context

Social Context refers to the social information about the user in the wireless network. Social information contains the information regarding user interests and content preferences, mobility trends for the users and concentration of user-defined content in the network.

3.4.1. Social Context based caching

Caching refers to the temporary storage of content at the edge of the network so as to reduce load on the core networks for multiple redundant requests of the same content. Social context-based caching is necessary as it stores information locally, based on the user interests and other geographical and network specific aspects such as location and mobility of the users in the network. In [47], Proactive Caching-based Mobility Prediction (PCMP) is proposed, which predicts the nearest Road Side Unit (RSU) for caching information based on user content requests and mobility in Vehicular Ad Hoc Networks (VANETs). The predictor is designed using an LSTM that takes into account the mobility information and predicts the next RSU and proactively caches information requested by the user. In [48], a logical topology is defined by combining mobile users based on their behaviours so as to create a mobile ad-hoc cloud network and optimize the network delay for computing operations. In [49], a RL scheme is proposed to take into account the mobility in VANET. A deep Q algorithm is used to devise the optimal caching and computing allocation scheme based on the mobility of the users in the network. In [50], a social prediction algorithm using HMM based on user behaviour in social network is presented. Based on the user behaviour predictions, local cache is defined which stores the content based on the popularity predicted on the user behaviours.

3.4.2. Social Context based Mobility Prediction

Sometimes the system is not able to obtain mobility information from the users. To address such cases, a social context, such as previous interactions of the users with the system can be used to devise the mobility of the users. In [51], a Short Message Service (SMS) based mobility prediction scheme is defined by using SMS data to determine the location of the user and predict the mobility using two different algorithms, a MC model and Naive Bayes (NB) model. In [47], as discussed earlier, an LSTM based mobility prediction scheme is proposed. The proposed Proactive Caching-based Mobility Prediction (PCMP) predicts the nearest RSU for caching information based on user content requests and mobility in VANETs. Additionally, in [52], a survey of different mobility prediction models based on social interaction in urban areas is presented.

3.4.3. Social Context based Access Control

Social context can be considered to devise efficient access control and resource allocation schemes. Information such as social mobility in the network can be used to determine demand at different times of the day and year, so as to efficiently optimize the system. In [49], as discussed previously, an RL scheme is proposed to take into account the mobility in VANET. A deep Q algorithm is used to devise the optimal caching and computing allocation schemes based on the mobility of the users in the network. In [53], an ARIMA model is used to take into account user behaviour in Device to Device (D2D) networks and predict an optimal resource allocation strategy. It also takes into account the social correlations between users so as to optimize the overall network utility in a social community, i.e., a pool of users who have similar interests and behaviours. Additionally, in [54], an overall survey of socially aware resource allocation scheme in D2D networks is presented.

4. Anticipatory Techniques

This chapter will provide information and discuss the recent works on anticipatory networking, which apply different techniques to forecast further networking information based on contextual information obtained from network.
We have divided these techniques into three main categories and discussed them in details. These categories include: 1) *time series prediction*, that predict future values based on previously observed values; 2) *Probabilistic forecasting* methods, that make statements about the likelihood of the future events, based on available information; 3) *Data-driven* approaches, such as clustering, classification and regression that learn to make predictions by only relaying on data. In the following sections, we discussed these methods and their applications in networking and communications.

4.1. Time Series Prediction

The complex varying nature of wireless channel has been a subject of study of researchers for many years. Knowing how the channel behave can provide plentiful competitive advantages in terms of radio resource management, allowing for instance network operators to expand services for more users using the same amount of network resources while also maintaining strict QoS. Power control, resource blocks allocation, coding rate, transmit antennas, precoding codeword and constellation size are examples of transmission parameters that can be adjusted according to the prior knowledge of the channel condition, especially for applications that demand critical network requirements, such as Industry 4.0, tactile communication and Internet of Things.
To achieve this potential, we need to transmit signals in a closed-loop manner, receiving the CSI as a feedback from the receiver. This information can be understood as a time series that represents an estimation of the channel condition, describing the combined effect of, for instance, scattering, fading, and power decay. Nevertheless, this estimation might not be always precise. Either in frequency-division duplex (FDD) or time-division duplex (TDD) systems, problems of estimation accuracy are still raised, especially in high mobility or high frequency scenarios. This can be a serious shortcoming, notably when it comes 5G and beyond 5G network requirements, which are expected to increasingly explore the use of millimetre waves under high speed scenarios, such as autonomous vehicles and aerial navigation systems.
As precisely summarized in [55] and [56], many authors have been extensively demonstrating the impact of CSI inaccuracy over a wide variety of adaptive transmissions techniques, such as MIMO systems [57–59], beam-forming [60, 61], antenna selection [62], mobility management [63,64], precoding [65], interference coordination [66,67] and relaying [68,69]. In this regard, many authors have been proposing solutions to cope outdated CSI issues [56], which can be mostly categorized into three different classes:

1. sub-optimal methods [70], where imperfect CSI is assumed and only part of the full performance potential can be achieved;

2. passive methods [71], in which wireless resources (frequency, power, time, etc) are used to passively compensate the performance loss;

3. channel prediction methods [72], in which the main idea is trying to forecast the channel behavior in advance (future CSI values), without using any additional wireless resource.

In the past few years, prediction methods have been gaining increasingly more attention from researchers due to their impact on performance and efficient use of radio resources [55]. More in details we can distinguish the prediction methods according to two different models: autoregressive (AR) [73] and parametric (PR) [74]. Both represent classical approaches to establish a statistical modeling of the wireless channel. The PR models rely on estimating fading channel parameters (e.g., Doppler shift, delay spread, angles of arrival, etc), which is a process that can demand high computational complexity and be vulnerable to changes at the scenario. The AR models, in turn, are based on an autoregressive process to extrapolate future CSI values by linearly combining past and current CSI measures. Besides its simplicity compared to the PR approach, the AR models are very susceptible to additive noise [75] and not really deployed in practice.
More recently, an alternative methodology using Machine Learning (ML) has been raising as a promising candidate to enhance prediction methods [55]. Its biggest advantage is that the data-driven nature of ML can replace statistical modeling of the channel, thus avoiding all the drawbacks involving parameters estimation and additive noise handling. In this regard, many authors have been exploring ML techniques in different prediction tasks. In [76] and [77], the authors applied LSTM networks to tackle classical channel estimation problems, including high speed scenarios. In [78], the authors propose a CNN, a technique typically used in computer vision tasks, to extract complex CSI features from the channel and predicting CSI aging. A solution for MIMO channel prediction problem was proposed by the authors in [79] and [80] using RNNs. The authors in [81] propose a novel CSI prediction scheme for improving the performance of massive MIMO, Non-Orthogonal Multiple Access (NOMA), Coordinated Multipoint (CoMP), and physical layer security by applying multi-hidden layer neural network. The work proposed by the authors in [82] provides a very insightful application of LSTM and CNN models for predicting the CSI values in downlink channel by using information from uplink channel. Likewise, the authors in [83] extrapolates the downlink CSI values from observed uplink CSI information, but also considering both Single-Input Single-Output (SISO) and MIMO scenarios. This new proposed scheme actually outperforms the classic Wiener filter-based approach.

4.2. Probabilistic Forecasting

Probabilistic forecasting methods employ available information of system to make statements about the likelihood of the future events. In the following subsections we introduce two well-known statistical methods for probabilistic forecasting: *Markovian Models* and *Bayesian inference*.

4.2.1. Markovian Models

A Markov model is a stochastic model used to represent random changing systems in which future states only depend on the current state. This section will provide information about Markov Chain (MC), and its applications in anticipatory networking.

A (Discrete-time) MC is a sequence of random variables X_1, X_2, X_3, ..., where, probability of moving to the next state, is independent from the previous states and only depends on the current state (Markov property):

$$P(X_{n+1} = x|X_1 = x_1, X_2 = x_2, ..., X_n = x_n) = P(X_{n+1} = x|X_n = x_n). \tag{4.1}$$

MCs can be represented by a state-flow diagram, i.e., a directed graph in which the nodes indicate the states and the edges specify the probability of moving from one state to another. Fig. 4.1 shows a classical example of MC that models the "weather" process with three possible states: {*Sunny*, *Rainy*, *Snowy*}. As an example consider the observed state in the present time step is *Sunny*, then the probability that MC takes value *Sunny*, *Rainy*, *Snowy*, in the next time step, is 0.8, 0.19 and 0.01, respectively. The sum of all probability values of the outward edges from any state is equal to 1.

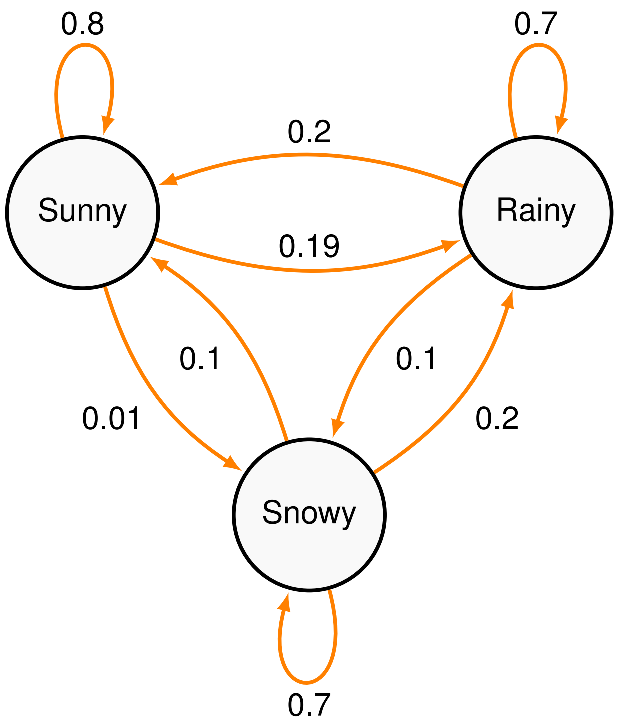


Figure 4.1: Example of state flow diagram of a MC.

Having the Markov transition probabilities, and the stationary distribution of the MC states could help to predict the behavior and the state of the system in future time steps. Markov modes have already been applied in wireless communication networks, mostly for user and vehicle positioning and mobility forecasting.
Several MC-based approaches have been proposed to predict the mobility and trajectory of locations of vehicles [84] and users [85,86] in VANETs [84], Heterogeneous Cloud Radio Access Networks (HCRANs) [87], and WSNs [88], employing different models such as Hidden Markov Model (HMM) [89], second-order Markov [90], and temporal Markov models [91]. The predicted mobility information can be used for different purposes like access point or service node selection [92,93], routing in VANETs [94] or WSNs [88,95] and traffic management [96]. To achieve more accurate results, some works have jointly applied Markov models with other techniques such as classification [97] and LSTM [98]. The Spatio-temporal

correlation that existed in users' mobility patterns has also been investigated in some literature [99–101]. The method in [99] takes into account the non-Gaussian characteristics and Spatio-temporal correlation of real human mobility data to present a Markov model for the human mobility prediction.
The authors of [100] proposed a hybrid MC model that can adaptively apply first or second-order MC to predict the future location of users, based on the quality of the mobility traces. They further presented the Zone of Interest discovery scheme in urban areas, utilizing the Spatio-temporal analysis. A HMM-based mechanism, namely CityTracker, is presented in [101]. It predicts the individual's trajectory and analyzes the representative citywide crowd mobility. The proposed algorithm can achieve a representative crowd mobility visualization in the target area by integrating individual trajectories. Markov models have also been applied in prediction of other networking parameters like as signal fading [102], energy [103], node status in WSNs [104] and indoor positioning [53]. A distributed probabilistic approach based on Hidden Gaussian Markov Model (HGMM) presented in [105], to predict sensor failure in WSNs.

4.2.2. Bayesian Inference

Bayesian inference is a statistical method that applies the Bayes theorem to update the probability of a hypothesis given new information. In fact, the Bayesian inference derives the *posterior probability*, given the *prior probability* of hypothesis and a *likelihood function* applying the Bayes' theorem:

$$p(\theta \mid y) = \frac{p(y \mid \theta) \cdot p(\theta)}{p(y)}, \tag{4.2}$$

where y and θ represent the data and the *hypothesis* whose probability may be affected by data. $p(\theta)$ indicates the prior probability (probability of θ before y data is observed). $p(\theta|y)$ is the posterior probability (probability of θ, given y). $p(y|\theta)$, called *likelihood*, represents the probability of y given θ.
Recently, Bayesian inferences have been applied to predict different networking parameters from mobility [106] to channel gain [107] and reliability [108]. The work in [106] employed Bayesian inference to devise a mobility prediction model for WSN. The authors of [109] presented a feature-based Bayesian method for content requests and popularity prediction in edge-caching networks. The authors of [108] proposed a service prediction model and applied the Bayesian network method to learn and predict the reliability of the mobile wireless network. A channel gain prediction method for mobile users that exploits the Spatio-temporal correlation in a Bayesian framework is presented in [107]. Traffic prediction is another application that has been considered in some recent works. A prediction algorithm is proposed in [110] based on the Bayesian Spatio-temporal model to predict the spatial distribution of traffic in the cellular network at different moments. In [111], a wireless traffic prediction is presented based on Bayesian seasonal adjustment.

4.3. Clustering, classification, and Regression for Context Acquisition

Clustering, classification, and regression are three of the most frequently used techniques for extracting useful information and predicting incidents in different applications. Context acquisition for wireless networks optimization is a field in which we can use the strategies mentioned above to extract information and optimize the resources based on that knowledge. In this section, we discuss a few selected methods in two main categories: similarity-based approaches and regression analysis.

4.3.1. Similarity-Based Approaches

The main goal in similarity-based approaches is to learn a similarity function between objects to reveal the similar latent structures in a dataset. They have a great variety of use cases in different applications, including ranking, recommendation systems, face verification, and speaker verification. These techniques have also been applied to anticipatory networking literature, which will be briefly discussed in the following, with reference to three main categories.

4.3.1.1. Collaborative Filtering (CF)

In collaborative filtering, which has been widely applied to recommendation systems, the underlying assumption is that if two people have the same opinion on an issue, they are more likely to have similar opinions on other issues. Based on this assumption, the CF techniques try to predict a user's opinion on an issue that is not rated by the user, given the preferences of other users.

Since there are a few comprehensive surveys on CF [112–114], we briefly introduce the concepts of CF, related to anticipatory networking in this section. In CF techniques, we usually have a matrix of size $n_u \times n_c$ in which n_u is the number of users, and n_c is the number of contents. The goal is to predict the missing values in this matrix.

There are two major categories of CF techniques: memory-based and model-based. In the memory-based methods, similar users are identified using similarity metrics like cosine similarity or Pearson correlation, and then the missing values are predicted using a weighted average over the ratings of the similar users on the contents.

Model-based approaches are another broad group of methods for CF in which machine learning algorithms including K-Nearest Neighbors (KNN), Singular Value Decomposition (SVD), Matrix Factorization (MF) and nArtificial Neural Network (ANN) are used to estimate the ratings of the unrated contents in the matrix.

Network caching is one of the critical concepts in ensuring QoE to the users. J. Yao et al. have recently published a thorough survey on caching strategies and techniques on mobile edge [115], in which several techniques have used different types of collaborative filtering. Huda S. Goian *et al.* have also published another comprehensive survey on caching-enabled networks from a popularity-based video caching perspective [116]. In this survey, there are a few works on neural-network-based CF. Another work proposes a collaborative multicast beamforming approach for content delivery in cache-enabled networks [117] in which the popularity of contents are estimated and, based on that, users are served using the cached content in Small Base Stations (SBSs).

Similar to popularity-based content caching, several works have proposed approaches to use users' locations to provide them with the proper content, including [118].

4.3.1.2. Clustering

Clustering is a broad group of unsupervised machine learning techniques that aims to identify different subsets of objects in a dataset in the way that the objects inside a group are similar to each other.

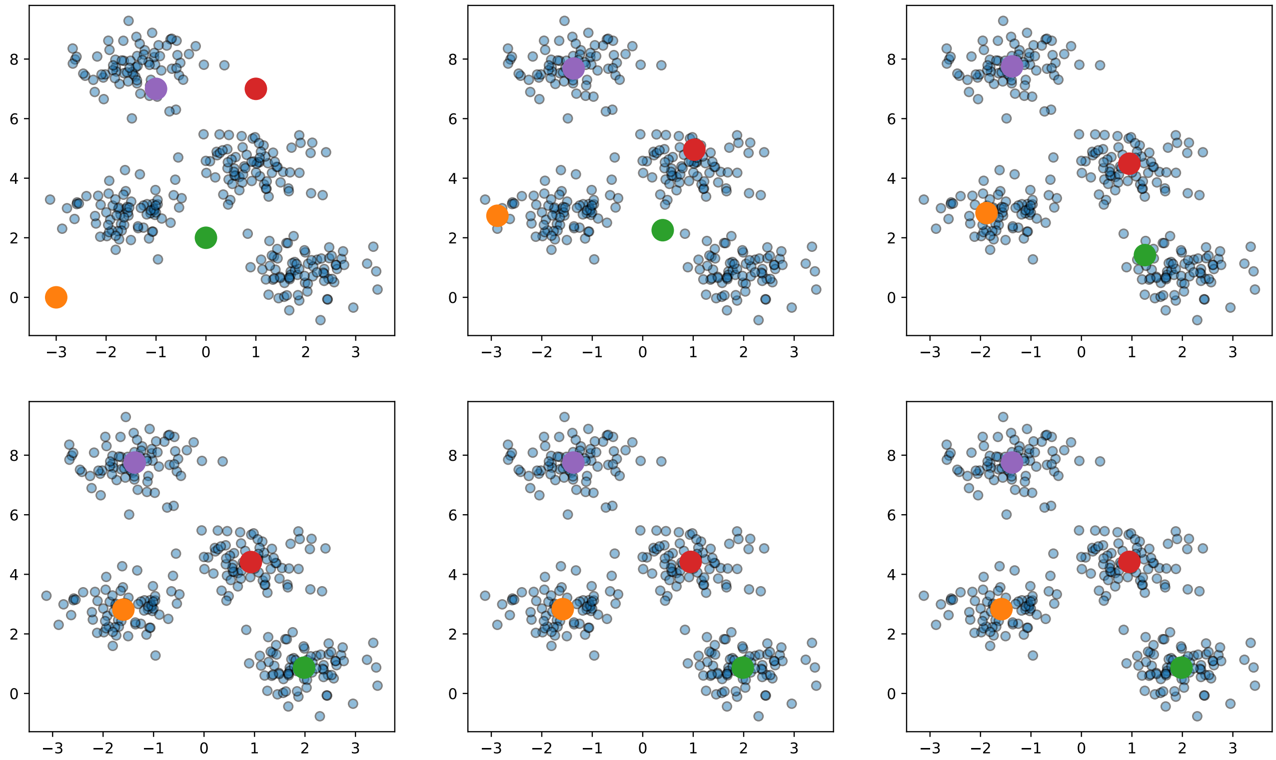


Figure 4.2: Example of k-means algorithm on a synthetic dataset after six steps with k equals to 4.

In this section, we briefly introduce the k-means clustering algorithm as one of the most frequently used clustering algorithms in anticipatory networking. We are given a dataset $x^{(1)}, ..., x^{(m)}$ with m points. Each of these points has a feature vector $x^{(i)} \in \mathbb{R}^n$ of dimension n. The goal is to assign group labels $c^i =, 1, 2, ..., K$, to each point in the dataset in such a way that the points in the same group are close with respect to a distance metric defined over the feature space.
The k-means algorithm is described in Algo. 1, and a step by step visualization of the algorithm on a synthetic dataset with $k = 4$ is shown in Fig. 4.2.

Algorithm 1: K-means Clustering Algorithm

initialize **cluster centroids** $\mu_1, \mu_2, ..., \mu_k \in \mathbb{R}^n$ randomly ;
while *the **centroids** are not stabilized* **do**
  for every i, set $c^i := \arg\max_j ||x^{(i)} - \mu_j||^2$;
  for each j, set $\mu_j := (1/||c^j||) \sum_{i=1}^{||c^j||} x^i$, where $||c^j||$ represents the number of data points in the j^{th} cluster
end

Different clustering algorithms, including k-means, have been applied to a broad range of cases in anticipatory networking. Optimizing the energy consumption in WSNs is one of the challenging problems for which a few clustering-based approaches have been proposed [119, 120].
Vehicular scenarios is another field in which clustering techniques play a significant role. To guarantee the stability of the self-organized communication structure in multimedia communication on the Internet of Vehicles (IoV), Kai Lin *et al.* propose a content-aware model [121]. In another work in the vehicular domain, [122], Ashit K. Dutta *et al.* introduce a hierarchical clustering protocol to optimize the resource utilization in the network and increase the overall lifetime. Aligned with the previous work, MCA-V2I [123] is a multi-hub clustering mechanism aiming to decrease the number of control messages and increase the stability by using a master/slave paradigm in IoV.

4.3.1.3. Decision Tree-Based Classification

Decision tree learning approaches are simple yet powerful models in ML either for classification or for regression tasks. They have a tree-like structure consisting of decision nodes and leaves. Decision nodes direct the data toward a proper leave, and the leaves are the labels of the classification task.
This simple ML method has been applied to a vast number of problems, and anticipatory networking is not an exception. Decision tree-based methods play an essential role in localization and positioning systems using Radio Frequency(RF) signals. Chanama *et al.* have studied different decision tree-based methods in indoor positioning systems [124]. Another group of researchers has proposed a None Line of Sight (NLoS) location tracking system based on decision trees that use Ultra Wide Band (UWB) technology [125].
Decision trees have also been considered for device type classification in WSNs [126], multi-object detection and classification in outdoor scenarios [127], and relay selection for dual-hop wireless communications [128].

4.3.2. Regression Analysis

Regression analysis is a powerful statistical tool for examining the relationship between a few independent variables with a dependent variable of interest. In anticipatory networking, a great variety of papers have used regression analysis for different tasks. In this section, we introduce three of the most useful regression techniques and their use cases in anticipatory networking.

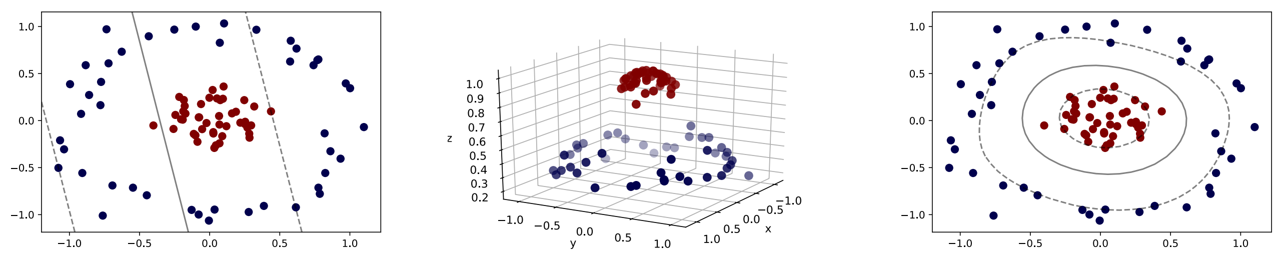
4.3.2.1. Support Vector Machine

SVM [129] is a discriminative classifier defined by a decision hyperplane separating instances of different classes with the maximum margin. There is a regression version of SVM named Support Vector Regression (SVR) sharing the same principles with SVM but for regression tasks. In this section, we briefly introduce SVMs and overview recently published works in anticipatory networking using SVM and SVR.
We explain SVM in a binary classification scenario which can be extended to multiple classes classification tasks too. Imagine we have a training dataset $\{(x_i, y_i) | x_i \in \mathbb{R}^n, y_i \in \{-1, 1\}, i =$

$1, 2, ..., M\}$, where x_i is the i^{th} training sample in an n dimensional space, y_i is the corresponding label for that sample, and M is the total number of training samples.
We assume that the samples are linearly separable, thus there is a hyperplane $w \cdot x - b = 0$ (where $W \cdot x$ is the inner product of W and x), which separates those two classes of samples. The optimization problem that yields decision hyperplane with the largest distance from the support vectors (the closest vectors to the decision hyperplane) is:

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2}||w||^2 \\ \text{s.t.} \quad & y_i(w^T x_i + b) \geq 1, i = 1, 2, ..., M. \end{aligned} \tag{4.3}$$

This optimization problem is not able to find an optimal hyperplane for non-linear decision boundaries. To solve this problem, kernel methods have been proposed. In kernel-based SVM instead of using the original input attributes x, we can transform the original input using a feature mapping function Φ and then apply the SVM. Since the equation (4.3) can be entirely written in terms of the inner product $x_i \cdot x_j$, we can simply replace $x_i \cdot x_j$ with $\Phi(x_i) \cdot \Phi(x_j)$. The linear model in the new space corresponds to a non-linear model in the original space.



(a) Linear kernel on a linearly non-separable synthetic dataset.

(b) The data after applying a Gaussian kernel to add a new dimension z.

(c) Classification with SVM with Gaussian kernel on a linearly non-separable synthetic dataset.

Figure 4.3: Examples of applying the SVM classifier with a linear and Gaussian kernels on a linearly non-separable synthetic dataset.

One of the most frequently used kernels in the literature is the Gaussian kernel: $\exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right)$. An example of applying a linear and Gaussian kernel-based SVM classifier on a non-linear synthetic data is shown in Fig. 4.3. When we apply the Gaussian kernel, the data become linearly separable in a space with more dimensions which is equal to a non-linear decision boundary in the original space. A recent and comprehensive survey on SVMs and their applications is [130]. Additionally, SVM attempts to find a decision boundary for the given supervised set while SVR attempts to find a curve that fits the supervised set.
B. Silva *et al.* proposed a machine learning-based context prediction system to boost vehicle-to-cloud communication [131]. In this work they have used SVR to predict the data rate by feeding three sets of features: mobility context, channel context, and application

context to the model. Another group of researchers has applied a non-linear SVR to cancel the self-interfering signal in full-duplex communication systems [132]. They have used two separate SVR models for predicting the real and the imaginary parts of the interfering signal. Coverage area detection [133] and network quality prediction [134–136] have also benefited from SVRs for building a coverage map and predicting the data rate in vehicular scenarios to improve the resource efficiency and the network reliability, respectively.

4.3.2.2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are universal function approximators consisting of neurons grouped in multiple layers (input, hidden, and output layers). ANNs can be used for different tasks including clustering, classification and regression. Each neuron receives the input vector X from the previous layer, multiplies them by a vector of weights W, applies a summation over them, adds a bias term b, and finally uses an activation function (Sigmoid, Tanh, ReLU, ELU, etc.) g to introduce non-linearity:

$$\hat{y} = g(W^T \cdot X + b). \tag{4.4}$$

To train an ANN, the forward and a backward pass is used. In the forward pass, a chain rule is applied to determine the gradient and in the backward pass, a back propagation mechanism is used to adjust the weights and biases of the layers by using an optimizer such as Adam, RMSProb, Gradient Descent, Momentum, etc. Using this technique, we try to minimize the loss function to update learning parameters of the network. A loss function is dependent on the optimization problem to be solved and the dataset used for training the ANN. With the advance of computational resources like Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) and abundance of data, especially in networking, ANNs have increasingly gained attention in the literature.

CSI estimation is one of the key challenges in wireless communications. OCEAN [27] is an online neural network model that uses CNN and LSTM to predict CSI in 5G wireless communication systems. SCNet [25] is another ANN model that aims to predict the downlink CSI in Base Station (BS) of a FDD MIMO communication system using an autoencoder-like design which not only reduces the redundancy of data but also makes it more robust to noise.

Additionally, Millimeter Wave (mmWave) communication is a relevant component of 5G and beyond. Beam selection and blockage prediction are two of the most important challenges in these systems. M. Alrabeiah et al. [137] have proposed a deep learning-based approach to tackle these challenges using ResNet18 [138] architecture.

Context-aware wireless communication optimization is another direction to which a few ANN-based approaches have been applied. J. Ren et al. have proposed a deep learning model using CNN to extract fine-grained features and the applied SVM classifier to classify the applications in a wireless network to improve QoE [139]. Another group of researchers have used ANNs as well as other classifiers like SVMs for classifying the Wireless Local Area Network (WLAN) traffic to reduce the power consumption [140].

5. Wireless Network Optimization Techniques using Anticipatory and Context Aware Techniques

This chapter will focus on optimization techniques based on anticipatory networking solutions. From a high-level prospective, we have divided these techniques in two main categories. First, we discussed traditional approaches to solve convex optimization problems, and latter, we introduced different methods for solving non-convex optimization problems. These methods include: Model Predictive Control (MPC), Reinforcement Learning (RL), Deep Neural Network (DNN) and Game theory, that is introduced in the rest of this chapter.

5.1. Optimization Approaches for Convex Optimization Problem

In general, a mathematical optimization problem has the form of

$$\begin{aligned} \text{minimize} \quad & f_0(x) \\ \text{s.t.} \quad & f_i(x) \leq b_i, i = 1, ..., m \end{aligned} \tag{5.1}$$

where $x = (x_1, ..., x_n)$ is a vector called *optimization variable* of the problem, $f_0 : \mathbb{R}^n \rightarrow \mathbb{R}$ is the *objective function*, $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$, $i = 1, ..., m$ are the *constraint functions*, and $b_1, ..., b_m$ are the *bounds* for the constraints. A vector x^* is called optimal, if for any z that satisfies all the constraints, we have $f_0(z) \geq f_0(x^*)$.
We generally define different *classes* or *families* of optimization problems based on the form of the objective and constraint functions. For example, an optimization problem is called *Linear Program (LP)* if the objective and the constraint functions are linear, i.e.,

$$f_i(\alpha x + \beta y) = \alpha f_i(x) + \beta f_i(y) \tag{5.2}$$

for all $x, y \in \mathbb{R}^n$ and for all $\alpha, \beta \in \mathbb{R}$. LP has more specific types: Integer Linear Program (ILP) in which the optimization variable vector is integer and Mixed-Integers Linear Program (MILP) in which the optimization variable vector is a mixture of integer and real values.
A specific and very important type of optimization classes is called *convex optimization*, which is a generalization of the LP. A optimization problem, is said to be convex when the objective and constraint functions are all convex, i.e.,

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \tag{5.3}$$

for all $x, y \in \mathbb{R}^n$, and for all $\alpha, \beta \in \mathbb{R}$, with $\alpha + \beta = 1, \alpha \geq 0, \beta \geq 0$.
Resource allocation in anticipatory networking is usually modeled as a LP, ILP, MILP or a convex optimization problem, in which the resources are considered as the optimization variables and the prediction is modeled through the constraints of the problem [1]. N. H. Bidoki *et al.* have proposed a two-objective LP approach to optimize the Value of Information (VoI) of the data being sent by sensors over a wireless communication network and energy consumption [141]. In the first objective function they try determine the paths and sleep schedule of each node while maximizing the VoI of the sensed data. In the second problem, they focus on minimizing the overall energy consumption of the network.

Another power allocation scheme is investigated in an integrated radar-communication system [142]. The authors have formulated the target detection problem as an LP optimization. They have shown that the low probability of intercept-based optimal power allocation performance can be improved by using their approach.
Another group of researchers have proposed a secrecy rate optimization scheme to increase the physical layer's security and increase the spectrum efficiency through full-duplex wireless communication [143]. First, they design a mixed integer and non-linear programming paradigm, they then relax this problem into a LP through reformulation-linearization technique.
A. Alsharoa *et al.* proposed a MILP optimization-based approach in an Unmanned Aerial Vehicle (UAV) scenario to optimize the transmit power levels and trajectories of the relaying UAVs with the aim of maximizing the data rate transmission of the ground users with an undirect link [144]. In particular, they have proposed a two-step approach. In the first step, they have utilized MILP to optimally determine the users-UAVs associations and UAVs' transmit power levels. In the the second step, a recursive method based on shrink-and-realign process is presented to optimize the UAVs trajectories.

5.2. Optimization Approaches for Non-Convex Optimization Problem

5.2.1. Model Predictive Control

Model Predictive Control (MPC) [145, 146] is an advanced process control method that optimizes a sequence of actions in dynamic systems by solving a finite horizon open-loop optimal control problem. The MPC technique has been widely applied in multi-variable constrained control problems. However, because of its mathematical complexity and large computational cost, it is only practical for processes with slow dynamics.
MPC has been recently applied to solve some problems in wireless communications. The work in [147] takes advantage of MPC to present a holistic approach for Virtual Machine (VM) placement in cloud data centers by considering conflicting performance metrics, such as counteracting hardware outages or software aging issues, security policies, perceived service level, and power requirements. An explicit MPC method is presented in [148] to reduce the energy consumption of a Fully Electric Vehicle (FEV) by predicting the preceding vehicle movements. A congestion control framework for infrastructure-based Cognitive Radio Networks (CRNs) is presented in [149] where an active queue management algorithm based on multiple MPC is proposed. In [150], the authors define a decentralized MPC mechanism for traffic control in freeways by considering a lossy communication channels. An autonomous IoT model predictive controller for linear multi-agent systems in the presence of imperfect network is presented in [151] to solve the data losses in communication channels. The authors of [152] applied MPC to co-design control and routing of Wireless Sensor and Actuator Networks (WSANs).
The authors of [153] used MPC to present an energy-efficient communication model for relay-assisted UAV networks. Some works applied the MPC to provide collision avoidance in UAV systems. A collision avoidance system for UAVs in civil arispace is presented in [154] that applies a distributed reactive MPC for trajectory tracking. A hierarchical collision avoidance system based on online path planning, distributed MPC, and geometric reactive

control approaches for multiple fixed-wind UAVs is presented in [155]. The effects of the collision avoidance mechanism on the mobility of UAV swarms is investigated in [156].

5.2.2. Reinforcement Learning

Reinforcement Learning (RL) is a machine learning approach for sequential decision making problems in which an agent learns to interact with the environment in an action-reward loop. The environment is modeled as a Markov Decision Process (MDP), which is represented by $(\mathcal{S}, \mathcal{A}, \mathcal{P}, r, \gamma)$ where $\mathcal{S}$ defines different states of the environment, $\mathcal{A}$ is a finite set of possible actions (action space) and $\mathcal{P}$ is transition probability matrix where the element $p_{ss'}$ determines the probability of transition from state s to s' in a step. The term r indicates the reward function $r : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ which represents the reward that the agent obtains by moving from state s to s' by taking action a. The term γ is a discount factor used to the trade-off between immediate and long-term rewards and for mathematical tractability of non-episodic environments. As shown in Fig. 5.1, in each time step t the agent observes a state s_t and takes the action a_t. The environment reacts to the action, moves to the new state s_{t+1}, and returns the reward r_{t+1} to the agent. The ultimate goal for a RL algorithm is to maximize the cumulative future reward.

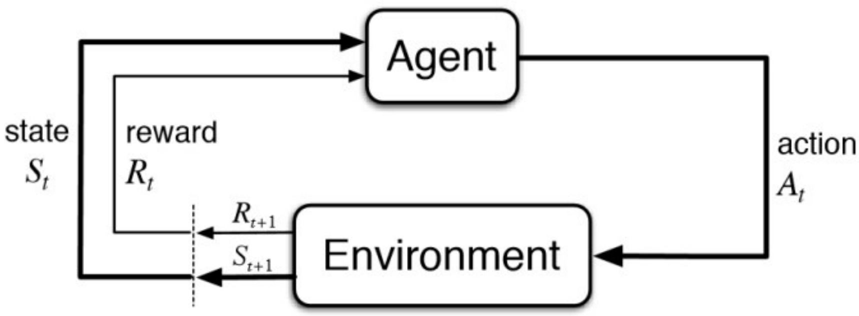


Figure 5.1: Action-reward loop in RL

The behavior of an RL agent in state s is described by a policy $\pi(s)$, which is defined as a probability distribution over the action space. The agent learns to optimize the policy to increase the reward obtained over time.
The objective of training an agent is to find the optimal policy π^*, which tells the agent which action to take in a certain state. So, by starting from s_t the goal of the agent is to maximize the expected reward (return) until the end of episode. This goal is summarised as follows:

$$G_t = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r(s_{t+k}, a_{t+k}).|s_0 = s_t\right] \tag{5.4}$$

5.2.2.1. Q-Learning

For most real-world applications, the transition probability $\mathcal{P}$ is unknown, and thus, it is difficult to estimate the policy π^*. Hence, to provide reliable policy estimations, Q-learning can be used. Q-learning is a famous off-policy (against the on-policy and actor-critic) algorithm that utilizes a lookup table, known as Q-table, to store Q-values for all action-state pairs. A

Q-value for (s, a) pair under a policy π tells us how much is good being in state s and taking action a and thereafter following policy π. The optimal Q-table can be obtained by randomly initializing and iteratively updating it by using the Bellman Equation:

$$Q^{*}(s, a) = r(s, a) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}). \tag{5.5}$$

To avoid local optima and create a balance between exploration and exploitation, Q-learning adopts the ϵ-greedy algorithm, where the agent can exploit its previous knowledge by selecting action $a = \arg\max_{a' \in A} Q(s, a')$ with probability $1 - \epsilon$ or explore the environment by selecting a random action with probability ϵ.
RL has recently attracted a lot of attention in the communication community, and many researchers have modeled wireless systems as a MDP and applied RL techniques to tackle them. Q-learning has recently been considered in several papers, but here we will discuss only on a few of the most recent and significant ones. In [157], the authors presented a Q-learning based method to maximize the spectral efficiency in multi-service wireless systems. Channel selection problem for cognitive radio networks is considered in [158]. A Multi-objective optimization routing protocol for flying Ad Hoc networks, exploiting Q-learning is presented in [159]. In [160], a Q-learning based algorithm proposed to control the sleep mode in 5G networks adaptively.
The main issue with the tabular setting of the Q-learning algorithm is that it assumes the states are discrete, which is very uncommon in real-world applications. Most real-world systems have a huge and continuous state space that is impossible to represent in a tabular manner. One solution, known as Deep Q-Network (DQN) or more generally deep RL consists in approximating Q using DNNs as discussed in the next section.

5.2.2.2. Deep Reinforcement Learning

In DQN, the Q function is approximated by minimizing the squared error between Bellman equation and the DNN estimation: $(Q(s_t, a_t, ; \theta) - Q^{\text{target}})^2$, where θ is the DNN parameters, and Q^{target} is the target Q function given by:

$$Q^{\text{target}} = r(s_t, a_t) + \gamma \max_{a_t+a} Q(s_{t+1}, a_{t+1}.\theta) \tag{5.6}$$

The use of experience replay memory and target-network makes the learning process more stable [161].
Introducing the DQNs, made it possible to apply RL in many real world problems, including in wireless communication. A comprehensive survey on applications of DRL in communication networks is provided by [162–164]. Some other surveys exist in the literature that investigate the DRL papers in a certain topic. The authors in [165] discussed the application of DRL for resource management in 5G Heterogeneous Networkss (HetNets). The DRL protocols for VANETs, is considered in [166], while dynamic spectrum allocation based on RL in cognitive radio networks is presented in [167].
Some optimization frameworks based on RL are considered in recent works. In [168] the authors introduced unified model-based and model-free reinforced-unsupervised frameworks, to solve the variable and functional optimization problems. They employed unsupervised learning for the known model of the environment while incomplete, they used reinforcement learning algorithms to learn the model.

DRL-based resource management methods for wireless networks has been widely considered in recent researches [169], for solivng different problems like traffic scheduling in roadside communications [170], cellular network traffic [171], and 5G Medium Access Control (MAC) layer [172], or power control for spectrum sharing in Cognitive Radios (CRs) [173]. DRL. The Age of Information (AoI)-aware Radio Resource Management (RRM) in Vehicle to Vehicle (V2V) communication network is investigated in [174], by modeling the stochastic decision-making procedure as a discrete-time single-agent MDP. They proposed a proactive algorithm based on LSTM and DRL techniques to address the partial observability and overcome the curse of dimensionality. A DRL-based framework is presented in [175, 176] to provide model-free Ultra Reliable Low Latency Communication (URLLC) in downlink of Orthogonal Frequency Division Multiple Access (OFDMA) systems. In particular [175] proposed a framework to allocate power and Resource Blocks (RBs) to users, considering their end-to-end reliability and latency without any modeling assumption of traffic or packet sizes. In [176], the authors propose a new Generative Adversarial Networks (GANs)-based approach to pre-train the DRL agent on mixed real and synthetic dataset to expose the agent to a broad range of network conditions.

Resource allocation is a classical control problem in wireless communication that modeled as MDP and solve by RL in some works. Some papers presented model-driven DRL assisted resource allocation for ultra-dense cellular networks [177, 178]. The authors of [179] presented a traffic and Channel-aware OFDMA resource allocation, while incremental RL for dynamic resource allocation is investigated in [180]. A circumstance-independent resource allocation method is presented in [181] to address the different network circumstances with a single policy. An actor-critic-based RL framework for dynamic channel access presented in [182]. Some other recent works considered resource allocation in vehicular networks [183–186]. As an example, a resource allocation method is presented in [186], where the base station applies graph-based techniques to allocate channels in a centralized manner, and the vehicles employ DRL to realize distributed power control. One can find a survey Multi-agent RL methods for vehicular networks in [187].

The QoS, as an important networking parameters is considered in some RL frameworks. A QoS-constrained resource allocation for multiservice networks is presented in [188]. DRL is employed in [189] to present a power control scheme for quality-driven video transmission. A power-efficient resource allocation framework for cloud Radio Access Networks (RANs) is presented in [190]. The authors of [191] modeled the predictive power allocation for mobile video streaming as a DRL problem and resorted to Deep Deterministic Policy Gradient (DDPG) to learn the proper policy. A predictive power allocation mechanism for video streaming over mobile networks with deep RL is presented in [191, 192].

DRL is also a hot topic in HetNets and most of the papers applied DRL techniques to jointly control and optimize different networking parameters. As a matter of fact, a joint dynamic channel access and power control using DRL is considered in [193] while [194] considered the joint power control and user association in mmWave HetNets. A joint user association and resource allocation optimization is considered by the authors in [195, 196], while [197] is investigated the user association optimization jointly with power control. An self-optimization framework based on contextual bandit is presented in [198] that jointly applies energy control and interference coordination.

The RL is also considered in adaptive Modulation and Coding Scheme (MCS) selection in cognitive HetNets [199, 200] and high throughput wireless networks [201]. Some newer papers investigated the possibility of employing hierarchical and multi-agent RL framework in wireless systems. The paper in [202] proposed a multi-agent RL for dynamic power allocation. A hierarchical distributed optimization algorithm for multi-agent reinforcement learning is presented in [203]. RL has recently been applied in some modern communication problems like resource management in network slicing [204–206] or Intelligent Reflecting Surface (IRS) optimization in Multiple-input Single-output (MISO) communication systems [207,208].

5.2.3. Optimization Approaches based on Data Driven Model Prediction

Data driven approaches have shown a significant success in a wide range of applications and wireless communication optimization is not an exception. The abundance of data in wireless networking make it a suitable field to apply data driven models to optimize different characteristics of the network from energy efficiency to spectrum sharing.
Haibo He *et al.* propose a deep reinforcement learning based framework to optimize the energy efficiency for distributed cooperative spectrum sharing [209]. They formulate the energy efficiency problem as a combinatorial optimization problem and integrate the graph neural networks and deep reinforcement learning techniques to optimize it. The role of the graph neural network in their architecture is to embed the sensor network's graph-structured data into a feature vector of a fixed length. Due to the unavailability of the optimal solution, they have used a deep reinforcement learning approach to optimize the problem.
A. Zappone *et al.* proposed an interesting approach for wireless optimizations [210]. By embedding the prior expert knowledge into a neural network architecture, they decreased the amount of data needed for the training of the model. They applied the proposed approach to the energy-efficiency optimization problem in wireless communication. In the power allocation optimization domain, another deep-learning enabled online energy-efficient mechanism has been proposed [211]. They have designed an ANN architecture to receives the network communication channels and estimate the power allocation to each user.
Another group of researchers have utilized a data driven optimization method to optimize detection in terms of Bit Error Rate (BER), which in turn, enables reliable communication over Additive White Gaussian Noise (AWGN) and multi-path Rayleigh fading channels with bandwidth constraints [212]. They have used auto-encoders to estimate the received signal and a fully-connected layer to detect the symbol.
System capacity and service coverage trade-off in cellular wireless communication networks is another optimization problem for which a deep-learning enabled approach called DECCO is proposed [213]. In this work, a data driven optimization mechanism is used to derive group alignment of user signal strength and minimum Signal-To-Interference-plus-Noise (SINR) during coverage and capacity optimization.

5.2.4. Optimization Approaches based on Game theory

Game theory was originally developed for analyzing the interactive decision processes, predicting the outcomes of interactions, and identifying optimal strategies in economics. The selfish nature of wireless communication systems in which each User Equipments (UE) competes with other UEs to obtain resources to maximize its spectral efficiency and QoE makes it a suitable domain for applying game theory techniques [214].

Game theory based wireless communication optimization techniques fall into three main categories: one-to-one (each UE is assigned to a single resource and vice versa), one-to-many (each UE is assigned to a single or multiple resources and vice versa), many-to-many (multiple UEs are assigned to multiple resources and vice versa).

T. Liu *et al.* [215] propose a game theory based approach in caching-enabled heterogeneous cellular networks to minimize UEs' transmission latency and maximize QoE. They decouple the problem into a two-stage matching problem. In the first stage they define a many-to-many matching problem of matching Small Base Stations (SBSs) who have cached certain files to UEs (SBSs-UEs), and in the second stage they formulate the problem as a many-to-one matching game of associating each Service Provider (SP) with SBSs (SP-SBSs). Another group of researchers have studied the problem of user clustering and power assignment in a D2D communication with NOMA scheme in wireless cellular networks using a two-stage approach [216]. In the first stage, they define two one-to-many matching games to associate each cellular and D2D user with a cluster (sub-channel) and in the second stage they propose a Successive Convex Approximation (SCA)-based with Arithmetic-Geometric Mean (AGM) approximation approach for power allocation.

6. Applications of Optimization Techniques in Wireless Networks

Optimization techniques in wireless networks have been used to address a variety of applications across the stack. In this chapter, we discuss the applications of such optimization techniques based on anticipatory information from the wireless network.

6.1. Physical Layer

In the current literature, we can find numerous optimization techniques applied to the network PHY layer. In [217], the authors investigate the problem of how to maximize the sum rate of a 2-user uplink mm-wave-NOMA system, proposing a sub-optimal solution where the original problem is divided into two sub-problems: one is a power control and beam gain allocation problem, and the other is a beamforming problem under the constant-modulus (CM) constraint. The authors in [218] propose a centralized as well as a distributed power control algorithm, aiming to maximize the capacity of a D2D network. They consider a scenario of licensed and unlicensed spectrum, showing by simulations that the proposed approach could increase the throughput of the D2D networks compared with current state-of-the-art methodologies. In [219], the authors address the energy efficiency optimisation problem of a NOMA 5G wireless network. The proposed idea is based on improving energy efficiency of 5G terminals while satisfying the constraints on maximum transmit power budget, minimum data rate, and minimum harvested energy per terminal. The proposed scheme is compared with an exhaustive search method, showing convergence to a stable optimal value.

The authors in [220] propose a new approach for multiple access in the fifth generation (5G) of cellular networks called power domain sparse code multiple access (PSMA). They compare the PSMA with other proposed NOMA strategies from the perspective of receiver complexity and system performance, showing that PSMA significantly outperforms other NOMA techniques while imposing a reasonable increase in complexity to the system, considering both aspects of transmitter and receiver.

We can check in [221] a flexible mechanism for Discontinuous Reception (DRX) proposed for 5G networks, where the goal is to minimize the energy usage of user devices for applications of video streaming while preventing buffer underflows. The authors show that the proposed approach can provide an energy reduction usage by up to 60% compared to static DRX setups.

The work in [222] proposes a novel channel state feedback scheme, where the minimum number of feedback bits is calculated with respect to the channel reconstruction error. The authors compare the proposed approach with other traditional feedback schemes, showing analytically and numerically the advantages of the proposed solution, especially in conditions of low SNR.

A pilot placement optimization problem is proposed by the authors in [223] for the radio access in 5G vehicle-to-everything communications to support Internet of Vehicles applications. The authors formulate the problem as a MDP, aiming to find enhanced pilot patterns for assisting OFDM technology. Simulation results show that the proposed scheme was able to effectively track fast time-varying vehicular channels.

In [224], the authors provide an optimization algorithm for calculating the joint maximum-likelihood estimation of channel and clipping level at the receiver side of IoT-based OFDM networks. These network scenarios are typically characterized for having lots of low-cost low-power transmitters and more complex receiver nodes, such as a base station. Numerical evaluations show that the proposed estimator was capable to achieve almost the same performance of a perfect estimator, where both channel and clipping level are perfectly known.

6.2. MAC Layer

At MAC layer, a main focus has been on applying optimization techniques for radio resource allocation and error correction. In [225], the authors propose a novel scheduling framework that is able to select different scheduling policies according to the states of the scheduler by using RL principles. The main goal is minimizing packet delay and packet loss rates for attending the strict 5G network requirements. Simulation results show that the proposed scheme outperforms traditional packet schedulers.
Likewise, the authors in [226] also propose a scheduling framework based on a RL strategy. Their idea is to optimize QoS provision management for heterogeneous traffic. The proposed scheme is capable of maximizing the average scheduling time when heterogeneous QoS requirements are met for diverse traffic classes, achieving a performance up to 50% higher than state-of-the-art solutions.
The work proposed in [227] provides a solution for the ultra-reliable low-latency communications (URLLC) and enhanced mobile broadband (eMBB) coexistence on the same radio spectrum. The authors introduce a novel scheduler framework that aims at optimizing a cross-objective function, where the critical URLLC QoS is guaranteed while extracting the maximum possible eMBB ergodic capacity. Simulation results show that the proposed scheme guarantees instant scheduling for sporadic URLLC traffic, and with minimal impact on the overall ergodic capacity, overcoming state-of-the-art scheduling proposals from both industry and academia.
In [228], the authors optimize the hybrid automatic repeat request (HARQ) operation of 5G URLLC networks. The problem is formulated according to a non-convex and mixed integer programming, which is analytically intractable. The authors came up with a solution based on optimizing a repetition coding scheme, and showing, by simulation results, minimization o the required bandwidth to achieve URLLC traffic requirements.
Likewise, the authors in [229] also propose a solution for optimizing HARQ operation in order to achieve URLLC requirements. The proposed scheme applies the queuing delay model based on the Pollaczek-Khinchine (P-K) formula, aiming to optimize bandwidth considering HARQ of 5G URLLC communication. Analytical and simulation results show that the proposed mechanism was able to reduce bandwidth requirements by up to 64.8% compared to traditional approaches.
The work established in [230] utilizes Tennessee Eastman (TE) process model to create a novel concept for communication-edge-computing (CEC) loop, introducing an optimization problem for achieving the defined CEC efficiency with focus on industrial IoT applications. The authors derive a new uplink (UL)-based communication protocol, that was able to outperform typical HARQ performance in terms of latency, reliability, and bandwidth efficiency.

6.3. Network Layer

In Network Layer, the optimization techniques are mainly applied to routing problems. In [13], a location error resilient routing scheme is proposed for VANETs. It predicts the location of the vehicles in the network using Kalman filter and creates a routing directory to decide the next forwarding node in the network. The protocol is designed to optimize the selection of the next forwarding node to maximise the throughput and minimise the routing load in the network.

In [231], a Genetic algorithm-based energy-efficient clustering and routing algorithm (GECR) is presented which takes into account the location of the nodes and devise routing and clustering strategies in WSN. The cluster head selection and next hop forwarding node is devised by modelling the optimization problem and solving it using a genetic algorithm. The algorithm aims to maximise the network time and minimise the energy consumption in the network. Similarly in [232], a multi objective pareto optimization approach is proposed to solve the problem of clustering and routing while taking into account energy efficiency, reliability and scalability.

In [233], an optimization problem called minimum broadcast power is discussed and is solved using a hybrid particle swarm optimization algorithm (H-PSO). The H-PSO aims at minimising the transmission power so as to conserve energy in broadcast mode of transmission in wireless ad-hoc network.

In [234], a non supervised deep learning based routing algorithm is proposed to optimize traffic load in wireless Software Defined Networks (SDNs). The SDN controller trains CNN to take into account traffic information and network performance such as path delay and make routing decisions based on these experiences.

In [235], a multihop routing scheme based on classification using machine learning techniques for Mobile Ad-hoc Networks (MANETs) is presented. In this scheme, the algorithm takes into account the battery power utilization and internal storage of a node to determine the next hop and eventually the whole route. To do so, each neighbouring node is classified using three classification techniques namely Multinomial Logistic Regression (MLR), SVM and KNN are used.

6.4. Application Layer

In Application Layer, the optimization techniques are generally applied to performance predictions over wireless network for applications. In [43], an adaptive HTTP video streaming approach is discussed which takes into account the performance variations due to the dynamic nature of wireless networks. The system predicts the channel throughput and maximises the average download segment level or video quality while taking into account the channel utilization and end user buffer. Similarly, in [45], a throughput prediction scheme is proposed which also takes into account channel information to optimize and improve the video streaming quality.

In [236], a multi-stage ML is presented by combining an unsupervised feature extraction with a supervised classifier to extract the *quality-rate* characteristic of unknown videos that can be used in QoE-aware video admission controls and resource management.

In [237],

In [238], a flow rate allocation algorithm over Multipath Transmission Control Protocol (MP-TCP) is defined called Energy Distortion Aware MP-TCP. The protocol aims to minimising the energy consumption while maximising video quality. The optimization problem takes into account the channel quality, delay, and video streaming requirement to provide an optimized flow allocation and energy consumption.
In [239], a cross layer UDP based protocol which takes into account the wireless links to provide a guaranteed performance. It basically optimizes functions such as in order delivery, forward error correction and flow control so as to minimise delay and overhead in the wireless network.

7. References

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