Model Identification and Control of Priority Queueing in Software Defined Networks

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Abstract

The heterogeneity of modern network infrastructures involves different devices and protocols bringing out several issues in organizing and optimizing network resources, making their coexistence a very challenging engineering problem. In this scenario, Software Defined Network (SDN) architectures decouple control and forwarding functionalities by enabling the network devices to be remotely configurable/programmable in run-time by a controller, and the underlying infrastructure to be abstracted from the application layer and the network services, with the final aim of increasing flexibility and performance. As a direct consequence identifying an accurate model of a network and forwarding devices is crucial in order to apply advanced control techniques such as Model Predictive Control (MPC) to optimize the network performance. An enabling factor in this direction is given by recent results that appropriately combine System Identification and Machine Learning techniques to obtain predictive models using historical data retrieved from a network. This paper presents a novel methodology to learn, starting from historical data and appropriately combining autoregressive exogenous(ARX) identification with Regression Trees and Random Forests, an accurate model of the dynamical input-output behavior of a network device that can be directly and efficiently used to optimally and dynamically control the bandwidth of the queues of switch ports, within the SDN paradigm. Mininet network emulator environment has been used to validate the prediction accuracy of the calculated predictive models, as well as the benefits of the proposed dynamic queueing control methodology in terms of Packet Losses reduction and Bandwidth savings (i.e. improvement of the Quality of Service).

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Introduction

A communication network involves the interconnection of a large number of devices, protocols and applications, as well as application, service and user specific Quality of Service (QoS) and Quality of Experience (QoE) requirements: the problem of optimizing the performance of such a complex distributed system while guaranteeing the desired QoS and QoE specifications is a very challenging engineering problem since the heterogeneity and complexity of such network infrastructures pose a number of challenges in effectively modeling, managing and optimizing network resources (e.g. see [1, 2] and references therein). A Knowledge Plane (KP) approach [3] has been proposed to enable automation, recommendation and intelligence by applying machine learning and cognitive techniques. However the KP approach has not been prototyped nor deployed because each node of traditional network systems, such as routers or switches, can only view and act over a small portion of the system. This implies that each node can learn only from a (small) part of the complete system and therefore it is very complex to design control algorithms beyond the local domain [4].

The applications of machine learning in networks is become crucial for future developments. Patcha and Park [5] have given a detailed description of machine learning techniques in the domain of intrusion detection. Nguyen and Armitage [6] focus on IP traffic classification. Bkassiny et al. [7] have studied learning problems in Cognitive Radio Networks, and surveyed existing machine learning based methods to address them. How machine learning techniques can be applied in wireless sensor networks has been investigated in [8]. Wang et al. [9] have presented the state-of-theart Artificial Intelligence based techniques applied to evolve the heterogeneous networks, and discussed future research challenges. Buczak and Guven [10] have researched on data mining methods for cyber security intrusion detection. Klaine et al. [11] have surveyed the machine learning algorithms solutions in self organizing cellular networks. How to improve network traffic control by using machine learning techniques has been studied in [12]. Similar to [5], Hodo et al. [13] also focus on machine learning based Intrusion Detection System. Zhou et al. [14] focus on using cognitive radio technology with machine learning techniques to enhance spectrum

utilization and energy efficiency of wireless networks. Chen et al. [15] have studied the neural networks solutions applied in wireless networks such as communication, virtual reality and edge caching. Usama et al. [16] have applied unsupervised learning techniques in the domain of networking. Although machine learning techniques have been applied in various domains, no existing works focus on the applications of machine learning in the domain of Software Defined Network (SDN).

Thanks to the recently introduced SDN paradigm [17, 18, 19, 20, 21] the control plane and the data plane are decoupled: this enables the possibility of learning (i.e. identifying) dynamical network models to be used for management and optimization purposes. Indeed, in SDN, network resources are managed by a logically centralized controller that owns a global view of the network: this feature provides the capacity of monitoring and collecting, in real-time, data on the network state and configuration as well as packet and flow-granularity information [22]. Recent advances in computing technologies such as Graphics Processing Unit and Tensor Processing Unit provide a good opportunity to apply promising machine learning techniques (e.g., deep neural networks) in the network field [23, 16]. Data is the key to the data-driven machine learning algorithms. The centralized SDN controller has a global network view, and is able to collect various network data. Based on the real-time and historical network data, machine learning techniques can bring intelligence to the SDN controller by performing data analysis, network optimization, and automated provision of network services. The programmability of SDN enables that the optimal network solutions (e.g., configuration and resource allocation) made by machine learning algorithms can be executed on the network in real time.

More in detail, a SDN controller device can configure the forwarding state of each switch by using a standard protocol called OpenFlow (OF) [24]. Thanks to the OF *counter variables* (e.g. flow statistics, port statistics, queue statistics, etc.), the controller can retrive information (feedback) from the network devices and store/process them for optimization purposes [25]. A SDN controller can supervise many aspects of traffic flow, as segment routing and queue management on switch ports. In [26] a heuristic method is proposed to balance the packet load among queues in order to reduce packet losses, which does not aim at providing an optimal solution.

Indeed, the most difficult challenge to be addressed in order to apply optimization techniques is to derive a predictive model of the queues of the switch behaviour. On this line of research, Cello *et al.* provide in [27] a predictive model for estimating QoS in order to detect the need for a re-routing strategy due to link saturation. However, this framework cannot be used to apply traffic optimization techniques. In [28] an initial effort is conducted

to derive a general hybrid systems framework to model the flow of traffic in communication networks. In [29] the authors provide a first formulation and implementation, based on hybrid systems theory, of a mathematical and simulative environment to formally model the effect of router/link failures on the dynamics of TCP and UDP packet flows belonging to different end-user services (i.e. http, ftp, mailing and video streaming). However, even though hybrid systems are very effective in modelling a network of routers, using such framework for implementing traffic optimization is out of question for computational complexity issues. A further research question focuses on designing strategies for periodic updating of network models, in order to maintain good performance despite the evolution of the real system [30].

To the best of the author knowledge the state of the art in deriving accurate dynamical models of communication networks still lacks of methods that exploit historical network data to learn (identify) a dynamical network model that can be directly used for optimal control (e.g. of segment routing and/or queue management) and is practical from the computational complexity point of view [1, 2, 31, 32, 33, 34, 35]. In this scenario, computing technologies such as graphic processing and tensor processing units represent a good opportunity to implement advanced control theoretic (e.g. Model Predictive Control - MPC) and machine learning algorithms (e.g. decision trees, deep neural networks, etc.) in the communication networks [23, 16, 36, 37]. In summary, the real-time programmability of SDN controllers and the availability of massive historical data enable the exploitation of data analysis and optimization techniques for improving networks efficiency and performance.

The goal of this thesis is to address this challenge exploiting control theory combined with Machine Learning techniques. Queues bandwidth control must rely on an accurate model for predicting queues state: a novel methodology to learn an accurate model of the dynamical input-output behavior of a switch device starting from historical data, that combines ARX identification with regression trees and random forests algorithms [38, 39, 40], has been presented as the main contribution of this work. At first a comparison between the prediction accuracy of the proposed technique with respect to Neural Network (NN) models has been shown. Then in a network emulation environment the proposed novel identification technique (differently from NNs, that provide nonlinear predictive models that are impractical for optimization) has been directly and efficiently used to control the bandwidth of the queues of switch ports with the final aim of reducing packet losses, and thus improving QoS, taking into account the priority of different services.

The manuscript is organized as follows: a background knowledge about SDN and Machine learning has been introduced in Chapter 1 and in Chapter 2 respectively, in Chapter

3 the network emulation environment has been illustrated; in Chapter 4 the model identification technique and its embedding in a MPC problem formulation solvable via Quadratic Programming (QP) has been described; in Chapter 5 the prediction accuracy and control performance validation using the proposed emulation environment has been provided.

PART I: Background Knowledge

Chapter 1

Software Defined Networks

In this chapter a brief background knowledge of architecture and workflow of SDN has been presented.

1.1 Architecture

The Open Networking Foundation (ONF) [41] is a nonprofit consortium dedicated to the development and standardization of SDN. The SDN paradigm has been defined by ONF as follows: "In the SDN architecture, the control plane and data plane are decoupled, network intelligence and state are logically centralized, and the underlying network infrastructure is abstracted from the applications" [17]. A SDN architecture is presented is composed by three main planes, including data plane, control plane and application plane. The architectural components of each plane and their interactions are shown in Figure 1.1. In the following, we will give a brief description of these planes and their interactions.

Data Plane : The data plane, or infrastructure plane, is the lowest layer in SDN architecture. This plane is composed by physical switches and virtual switches and others forwarding devices. Virtual switches are software-based switches, which can run on common operating systems such. Open vSwitch [42], Indigo [43] and Pantou [44] are three implementations of virtual switches. Physical switches are hardware-based switches. They can be implemented on open network hardware (e.g., NetFPGA [45]) or implemented on networking hardware vendors' merchant switches.Many networking hardware vendors such as HP, NEC, Huawei, Juniper and Cisco, have supported SDN protocols. Virtual switches support complete features of SDN protocols, while physical switches lack the flexibility and feature completeness. However, physical switches have a higher flow forwarding rate than virtual switches. SwitchBlade [46] and ServerSwitch [47] are two NetFPGA-based physical switches. These switches

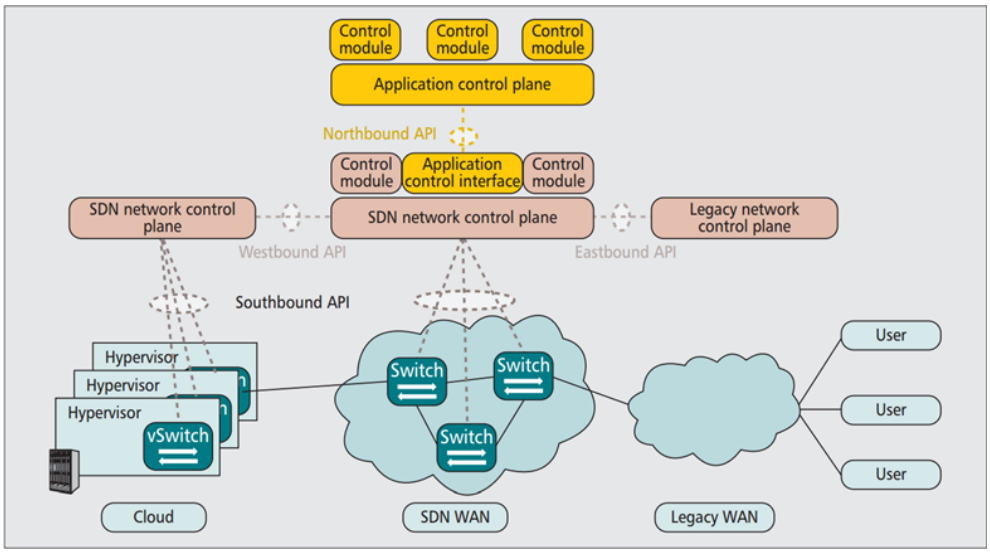


Figure 1.1: The high-level SDN architecture.

in data plane are responsible for forwarding, dropping and modifying packets based on instructions received from the Control Plane (CP) through Southbound Interfaces (SBIs).

Control Plane: The control plane is the "brain" of SDN systems, which can define network resources, dynamically choose forwarding rules and make network administration flexible and agile. The controller is responsable of many relevant tasks like:

- the communication between forwarding devices and applications;
- it exposes and abstracts network state information of the data plane to the application plane;
- it translates the requirements from applications into custom policies and distributes them to forwarding devices;
- provides essential functionalities that most of network applications need, such as shortest path routing, network topology storage, device configuration and state information notifications etc.

There are many controller architectures, such as Ryu [48], OpenDayLight, [49] NOX [50], POX [51], Floodlight [52] and Beacon [53]. Three communication interfaces allow the controllers to interact: southbound, northbound and eastbound/westbound interfaces. The SBIs are defined between the control plane and the data plane. They allow forwarding devices to exchange network state information and control policies with the CP and provide functions such as statistics reports, forwarding operations,

programmatic control of all device-capability advertisements and event notifications. OpenFlow [24] promoted by ONF is the first and the most popular open standard SBI. There exist other less popular proposals such as OVSDB [54], Protocol-Oblivious Forwarding (POF) [55] and OpenState [56]. With NBIs, automation, innovation and management of SDN networks has been facilitatethanks to the fact that applications can exploit the abstract network views provided by the CP. The ONF is trying to define the standard NBIs and a common information model. The eastbound/westbound interfaces are used in the multi-controller SDN networks. Due to the vast amount of data flows in such networks and the limited processing capacity of one controller the large-scale networks are always partitioned into several domains and each domain has its own controller. The eastbound/westbound interfaces are responsible for the communication among multiple controllers. This communication is necessary to exchange information in order to provide a global network view to the upper-layer applications. Onix [57] and HyperFlow [58] are two distributed control architectures. Because their eastbound/westbound interfaces are private, they cannot communicate with each other. To enable the communication between different types of SDN controllers, SDNi [59], East-West Bridge [60] and Communication Interface for Distributed Control plane (CIDC) [61] have been proposed as eastbound/westbound interfaces to exchange network information. However, the eastbound/westbound interfaces have not yet been standardized.

Application Plane: The highest layer in the SDN architecture is the application plane. These applications can provide new services and perform business management, optimization and can obtain the required network state information through controllers' NBIs. Based on the received information and other requirements, the applications can apply some control logic to change network behaviors. The SDN-based applications have attracted a lot of attention from academia. Mendiola et al. [62] have discussed the impact of SDN on Traffic Engineering (TE) and surveyed the SDN-based TE solutions. Security in SDN has been surveyed in [63, 64, 65, 66, 67, 68]. Especially, Yan et al. [67] have researched on Distributed Denial of Service (DDoS) attacks in SDN-based cloud computing systems, and discussed future research challenges. Fault management in SDN has been surveyed in [69], which gives an identification and classification of the main fault management issues, and does valuable surveys and discussions about efforts that address those issues. Guck et al. [70] have studied the centralized QoS routing mechanisms in SDN, and introduced a novel Four-Dimensional (4D) evaluation framework. SDN has been deployed in many networks, such as transport networks [71], optical networks [72],

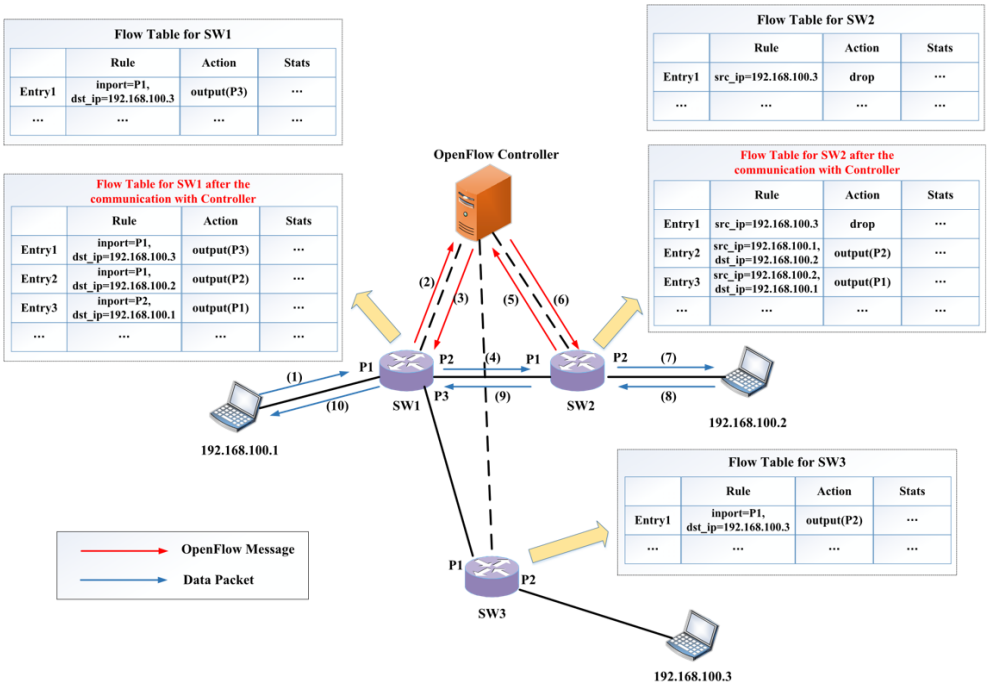


Figure 1.2: Example of OpenFlow-based SDN network.

wireless networks [73, 20], Internet of Things (IoT) [74], edge computing [75], Wide Area Networks (WAN) [76], cloud computing [77], Network Function Virtualization (NFV) [78, 79].

For more informations on SDN, please refer to [80, 81, 82, 83, 84, 85, 86, 87].

1.2 Workflow

To understand the SDN architecture, it is important to recall its basic operation. Figure 1.2 shows the working procedure of the OpenFlow-based SDN network [25]. Each OpenFlow switch has a flow table and uses the OpenFlow protocol to communicate with the SDN controller. The messages transmitted between the OpenFlow-based switches and the software-based controller are standardized by the OpenFlow protocol [53]. The OpenFlow controller can manage the traffic forwarding by modifying flow entries in switches flow tables. The flow table in the OpenFlow switch is comprised of flow entries to determine the processing actions of different packets on the data plane. When an OpenFlow switch receives a packet on the data plane, the packet header fields will be extracted and matched against flow entries. If a matching entry is found, the switch will process the packet locally according to the actions in matched flow entry. Otherwise, the switch will forward an OpenFlow PacketIn message to the controller (arrows 2 and 5). The packet header (or the

whole packet, optionally) is included in the OpenFlow PacketIn message. Then, the controller will send OpenFlow FlowMod messages to manage the switch's flow table by adding flow entries (arrows 3 and 6), which can be used to process subsequent packets of the flow. For example, by adding two flow entries (i.e., Entry2 and Entry3) at SW1 and SW2, the communications between 192.168.100.1 and 192.168.100.2 are allowed. However, packets from 192.168.100.3 to 192.168.100.2 are denied at SW2 due to security policies.

Chapter 2

Overview Of Machine Learning Algorithms

Machine learning is evolved from a collection of powerful techniques in AI areas. This new methods allows the system to learn useful structural patterns and models from training data. A machine learning approach consists of two main phases: training phase and decision making phase. At the training phase, after a data mining period of system input/output information, machine learning methods are applied to learn the system model using the training dataset. At the decision making phase, the system can obtain the estimated output for each new input by using the trained model. Machine learning algorithms can be distinguished into four main categories: supervised, unsupervised, semi-supervised and reinforcement learning. Each algorithm in Figure 2.1 is briefly explained with some examples. For a more insightful discussion on machine learning theory and its classical concepts, please refer to [88, 89, 90].

A. Supervised Learning

Supervised learning is a kind of labelling learning technique. Supervised learning algorithms are given a labeled training dataset (i.e., inputs and known outputs) to build the system model representing the learned relation between the input and output. After training, when a new input is fed into the system, the trained model can be used to get the expected output [91, 92]. In the following, we will give a detailed representation of supervised learning algorithms.

1) k-Nearest Neighbor (k-NN): In k-NN the classification of a data sample is determined based on the k nearest neighbors of that unclassified sample. The process of the k-NN algorithm is very simple: if the most of the k nearest neighbors belong to a certain class, the unclassified sample will be classified into that class. The higher the value of k is, the less effect the noise will have on the

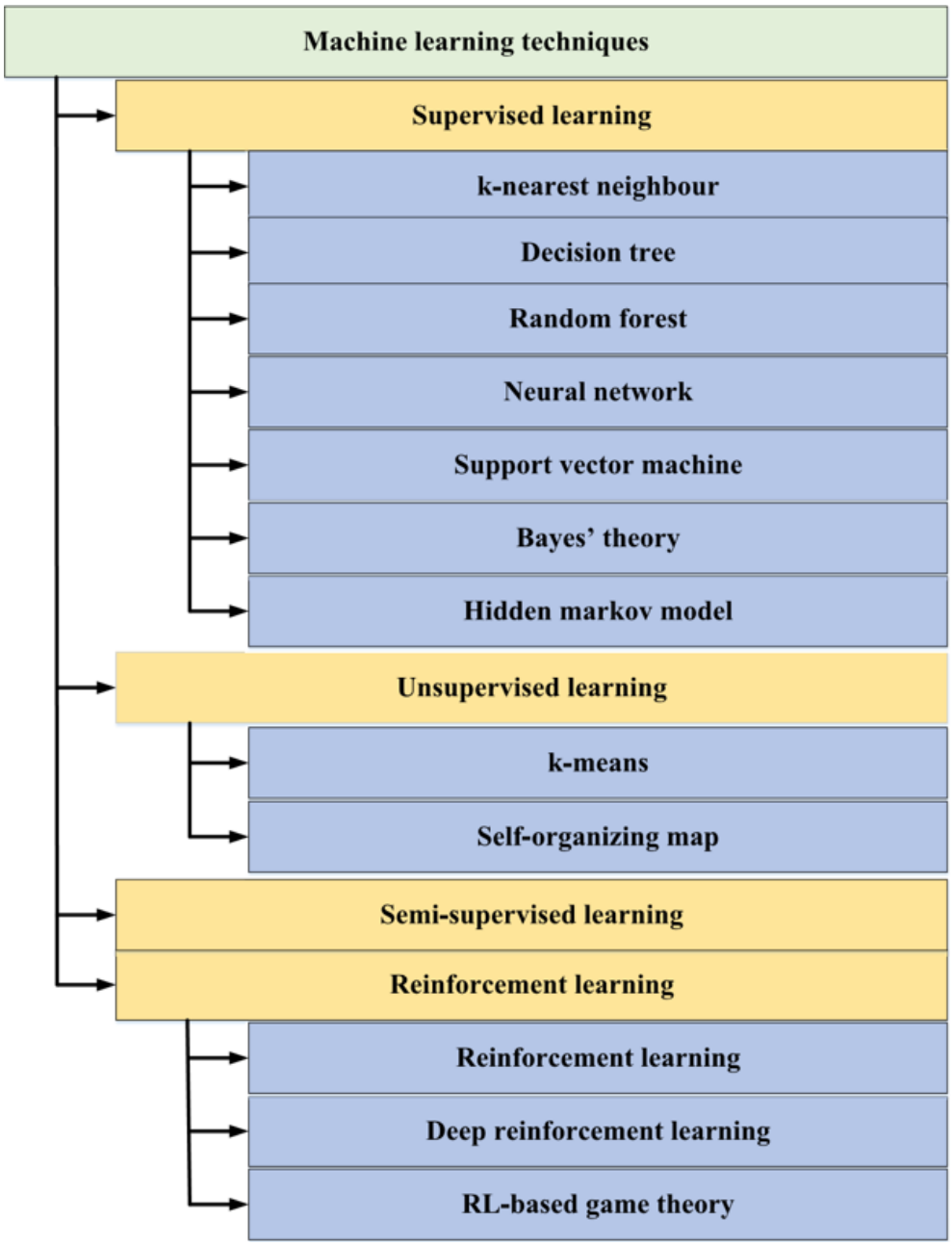


Figure 2.1: Common machine learning algorithms.

classification. Since the distance is the main metric of the k-NN algorithm, several functions can be applied to define the distance between the unlabeled sample and its neighbors, such as Chebyshev, City-block, Euclidean and Euclidean squared [93].

2) Decision Tree (DT): The DT performs classification through a learning tree. In the tree, each node represents a data feature, all branches represent the con-

junctions of features that lead to classifications, and each leaf node is a class label. The unlabeled sample can be classified by comparing its feature values with the nodes of the decision tree [94]. The DT has many advantages, such as intuitive knowledge expression, simple implementation and high classification accuracy. ID3 [95], C4.5 [96] and CART [97] are three widely-used decision tree algorithms. The biggest difference among them is the splitting criteria which are used to build decision trees.

3) Random Forest (RF): A RF [98] consists of many DT. To mitigate overfitting of DT method and improve accuracy, the random forest method randomly chooses only a subset of the feature space to construct each DT. The steps to classify a new data sample by using random forest method are:

a) put the data sample to each tree in the forest;

(b) Each tree gives a classification result, which is the tree's "vote";

(c) The data sample will be classified into the class which has the most votes.

4) Neural Network (NN): A neural network is a computing system composed by a large number of simple processing units, which operate in parallel to learn experiential knowledge from historical data [99]. Each neuron perform highly complex, nonlinear and parallel computations. In a NN, its nodes are the equivalent components of the neurons in the human brain. These nodes use activation functions to perform nonlinear computations. The most frequently used activation functions are the sigmoid and the hyperbolic tangent functions. Simulating the way neurons are connected in the human brain, the nodes in a NN are connected to each other by variable link weights. A NN has many layers. The first layer is the input layer and the last layer is the output layer and layers between them are the hidden layers. The output of each layer is the input of the next layer and the output of the last layer is the result. By changing the number of hidden layers and the number of nodes in each layer, complex models can be trained to improve the performance of NNs. NNs are widely used in many applications, such as pattern recognition. In figure 2.2 the most basic NN with three layers has been shown. An input has m features (i.e., $X_1, X_2, ..., X_m$) and the input can be assigned to n possible classes (i.e., $Y_1, Y_2, ..., Y_n$). Also, W_{ij}^1 denotes the variable link weight between the ith neuron of layer l and the jth neuron of layer $l+1$, and ak^l denotes the activation function of the kth neuron in layer l. There are many types of neural networks, which can be divided in

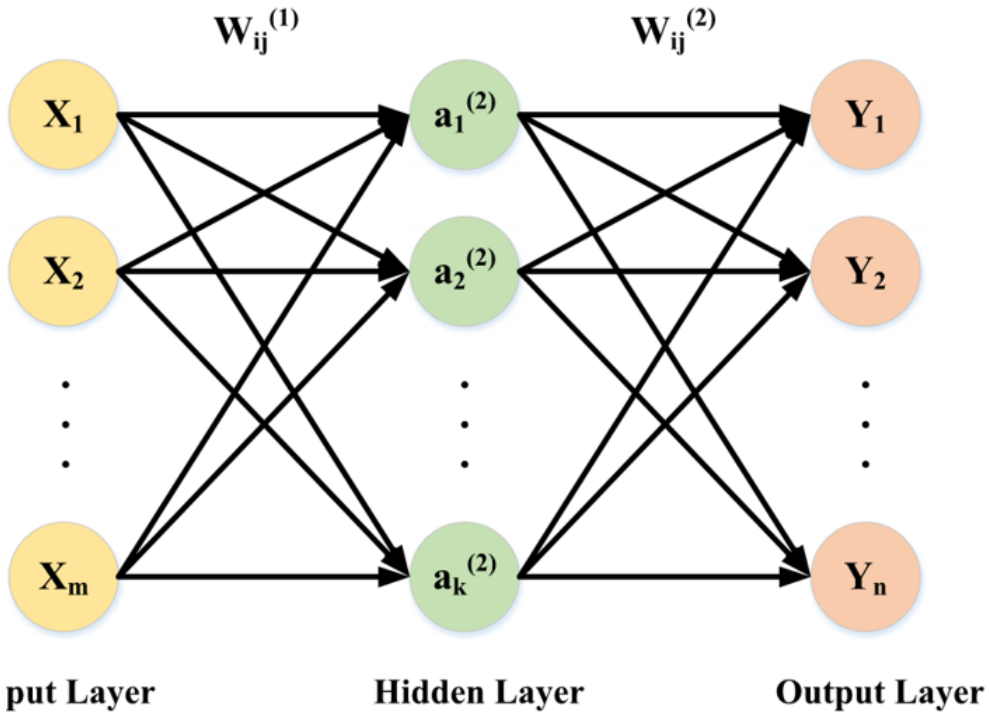


Figure 2.2: A basic neural network with three layers: an input layer, a hidden layer and an output layer.

supervised or unsupervised main group [100]. In the following, we will give a brief description of supervised neural networks.

a) Random NN: The random NN can be represented as an interconnected network of neurons which exchange spiking signals. The main difference between random NN and other neural networks is that neurons in random NN exchange spiking signals probabilistically. In random NN, the internal excitatory state of each neuron is represented by an integer called "potential". The potential value of each neuron rises when it receives an excitatory spiking signal and drops when it receives an inhibitory spiking signal. Neurons whose potential values are strictly positive are allowed to send out excitatory or inhibitory spiking signals to other neurons according to specific neurondependent spiking rates. When a neuron sends out a spiking signal, its potential value drops one. The random NN has been used in classification and pattern recognition [101].

b) Deep NN: Neural networks with a single hidden layer are generally referred to as shallow NNs. In contrast, neural networks with multiple hidden layers between the input layer and the output layer are called deep

NNs [102, 103]. To process high-dimensional data and to learn increasingly complex models, deep NNs with more hidden layers and neurons are needed. However, deep NNs increase the training difficulties and require more computing resources. In recent years, the development of hardware data processing capabilities and the evolved activation functions make it possible to train deep NNs [104]. In deep NNs, each layer's neurons train a feature representation based on the previous layer's output, which is known as feature hierarchy. The feature hierarchy makes deep NNs capable of handling large high-dimensional datasets. Due to the multiple-level feature representation learning, compared to other machine learning techniques, deep NNs generally provide much better performance [104].

c) Convolutional NN: Convolutional NN and recurrent NN are two major types of deep NNs. Convolutional NN [105, 106] is a feed-forward neural network. Local sparse connections among successive layers, weight sharing and pooling are three basic ideas of convolutional NN. Weight sharing means that weight parameters of all neurons in the same convolution kernel are same. Local sparse connections and weight sharing can reduce the number of training parameters. Pooling can be used to reduce the feature size while maintaining the invariance of features. The three basic ideas reduce the training difficulties of convolutional NNs greatly.

d) Recurrent NN: In feed-forward neural networks, the information is transmitted directionally from the input layer to the output layer. However, recurrent NN is a stateful network, which can use internal state (memory) to handle sequential data. Unlike a traditional deep NN, which uses different parameters at each layer, the recurrent NN shares the same parameters across all time steps. This means that at each time step, the recurrent NN performs the same task, just with different inputs. In this way, the total number of parameters needed to be trained is reduced greatly. Long Short-Term Memory (LSTM) [107] is the most commonly-used type of recurrent NNs, which has a good ability to capture long-term dependencies. LSTM uses three gates (i.e., an input gate, an output gate and a forget gate) to compute the hidden state.

5) Support Vector Machine (SVM): SVM is invented by Vapnik and others [108], which has been widely used in classification and pattern recognition. The basic idea of SVM is to map the input vectors into a high-dimensional feature space. This mapping is achieved by applying different kernel functions,

such as linear, polynomial and Radial Based Function (RBF). Kernel function selection is an important task in SVM, which has effect on the classification accuracy. The selection of kernel function depends on the training dataset. The linear kernel function works well if the dataset is linearly separable. If the dataset is not linearly separable, polynomial and RBF are two commonly-used kernel functions. In general, the RBF-based SVM classifier has a relatively better performance than the other two kernel functions. The objective of SVM is to find a separating hyperplane in the feature space to maximize the margin between different classes. The margin is the distance between the hyperplane and the closest data points of each class. The corresponding closest data points are defined as support vectors.

6) Bayes' Theory: Bayes' theory uses the conditional probability to calculate the probability of an event occurring given the prior knowledge of conditions that might be related to the event. The Bayes' theory is defined mathematically as the following equation:

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

where E is a new evidence, H is a hypothesis, $P(H|E)$ is the posterior probability that the hypothesis H holds given the new evidence E, $P(E|H)$ is the posterior probability that of evidence E conditioned on the hypothesis H, $P(H)$ is the prior probability of hypothesis H, independent of evidence E, and $P(E)$ is the probability of evidence E. In a classification problem, the Bayes' theory learns a probability model by using the training dataset. The evidence E is a data sample, and the hypothesis H is the class to assign for the data sample. The posterior probability $P(H|E)$ represents the probability of a data sample belonging to a class. In order to calculate the posterior probability $P(H|E)$, $P(H)$, $P(E)$ and $P(E|H)$ need to be calculated first based on the training dataset using the probability and statistics theories, which is the learning process of the probability model. When classifying a new input data sample, the probability model can be used to calculate multiple posterior probabilities for different classes. The data sample will be classified into the class with the highest posterior probability $P(H|E)$. The advantage of the Bayes' theory is that it requires a relatively small number of training dataset to learn the probability model [109]. However, there is an important independence assumption when using the Bayes' theory. To facilitate the calculation of $P(E|H)$, the features

of data samples in the training dataset are assumed to be independent of each other [110].

7) Hidden Markov Models (HMM): HMM is one kind of Markov models. Markov models are widely used in randomly dynamic environments which obey the memoryless property. The memoryless property of Markov models means that the conditional probability distribution of future states only relates to the value of the current state and is independent of all previous states [111, 112]. There are other Markov models, such as Markov Chains (MC). The main difference between HMM and other models is that HMM is often applied in environments where system states are partially visible or not visible at all.

B. Unsupervised Learning In contrast to supervised learning, an unsupervised learning algorithm is given a set of inputs without labels, thus there is no output. Basically, an unsupervised learning algorithm aims to find patterns, structures, or knowledge in unlabeled data by clustering sample data into different groups according to the similarity between them. The unsupervised learning techniques are widely used in clustering and data aggregation. In the following, we will give a representation of widely-used unsupervised learning algorithms.

1) k-Means: The k-means algorithm is used to recognize a set of unlabeled data into different clusters. To implement the kmeans algorithm, only two parameters are needed: the initial dataset and the desired number of clusters. If the desired number of clusters is k, the steps to resolve node clustering problem by using k-means algorithm are:

a) initialize k cluster centroids by randomly choosing k nodes;

b) use a distance function to label each node with the closest centroid;

c) assign new centroids according to the current node memberships;

d) stop the algorithm if the convergence condition is valid, otherwise go back to step *b)*.

2) Self-Organizing Map (SOM): SOM, also known as SelfOrganizing Feature Map (SOFM) [113], is one of the most popular unsupervised neural network models. SOM is often applied to perform dimensionality reduction and data clustering. In general, SOM has two layers, an input layer and a map layer. When SOM is used to perform data clustering, the number of neurons in the map layer is equal to the desired number of clusters. Each neuron has a weight

vector. The steps to resolve data clustering problem by using SOM algorithm are:

a) initialize the weight vector of each neuron in the map layer;

(b) choose a data sample from the training dataset;

(c) use a distance function to calculate the similarity between the input data sample and all weight vectors. The neuron whose weight vector has the highest similarity is called the Best Matching Unit (BMU). The SOM algorithm is based on competitive learning;

(d) The neighborhood of the BMU is calculated;

(e) The weight vectors of the neurons in the BMU's neighborhood are adjusted towards the input data sample;

(f) Stop the algorithm if the convergence condition is valid, otherwise go back to step (b).

C. Semi-Supervised Learning Semi-supervised learning is a type of learning which uses both labeled and unlabeled data. Semi-supervised learning is useful due the fact that in many real-world applications, the acquisition of labeled data is expensive and difficult while acquiring a large amount of unlabeled data is relatively easy and cheap. Moreover effective use of unlabeled data during the training process actually tends to improve the performance of the trained model. In order to make the best use of unlabeled data, assumptions have to be hold in semisupervised learning, such as smoothness assumption, cluster assumption, low-density separation assumption, and manifold assumption. Pseudo Labeling [114] is a simple and efficient semi-supervised learning technique. The main idea of Pseudo Labeling is simple. Firstly, use the labeled data to train a model. Then, use the trained model to predict pseudo labels of the unlabeled data. Finally, combine the labeled data and the newly pseudo-labeled data to train the model again. There are other semi-supervised learning methods, such as Expectation Maximization (EM), co-training, transductive SVM and graph-based methods. Different methods rely on different assumptions. For example, EM builds on cluster assumption, transductive SVM builds on low-density separation assumption, while graph-based methods build on the manifold assumption.

D. Reinforcement Learning

1) Reinforcement Learning (RL): RL [115, 116] involves an agent, a state space S and an action space A. The agent is a learning entity which interacts with

its environment to learn the best action to maximize its long-term reward. The long-term reward is a cumulative discounted reward and relates to both the immediate reward and future rewards. When applying RL to SDN, the controller generally works as an agent and the network is the environment. The controller monitors the network status and learns to make decisions to control data forwarding. Specifically, at each time step t, the agent monitors a state s_t and chooses an action a_t from the action space A, receives an immediate reward r_t which indicates how good or bad the action is, and transitions to the next state $st + 1$. The objective of the agent is to learn the optimal behavior policy π which is a direct map from the state space S to the action space $A(\pi : S \longrightarrow A)$ to maximize the expected long-term reward. From the behavior policy π, the agent can determine the best corresponding action given a particular state. In RL, value function is used to calculate the long-term reward of an action given a state. The most well-known value function is Q-function, which is used by Q-learning to learn a table storing all state-action pairs and their long-term rewards.

2) Deep Reinforcement Learning (DRL): The main advantage of RL is that it works well without prior knowledge of an exact mathematical model of the environment. However, the traditional RL approach has some shortcomings, such as low convergence rate to the optimal behavior policy π and its inability to solve problems with high-dimensional state space and action space. These shortcomings can be addressed by DRL. The key idea of DRL is to approximate the value function by leveraging the powerful function approximation property of deep NNs. After training the deep NNs, given a state-action pair as input, DRL is able to estimate the long-term reward. The estimation result can guide the agent to choose the best action.

3) RL-Based Game Theory: Game theory is a mathematical tool that focuses on strategic interactions among rational decision-makers. A game generally involves a set of players, a set of strategies and a set of utility functions. Players are decision-makers. Utility functions are used by players to select optimal strategies. In cooperative games, players cooperate and form multiple coalitions. Players choose strategies that maximize the utility of their coalitions. In non-cooperative games, players compete against each other and choose strategies individually to maximize their own utility. In the network field, it is often assumed that nodes are selfish. In non-cooperative games, players do not communicate with each other, and at the beginning of each play round, players do

not have any information about the strategies selected by the other players. At the end of each play round, all players broadcast their selected strategies, which are the only external information. However, each player's utility can be affected by the other players' strategies. In this case, adaptive learning methods should be used to predict the strategies of the other players, based on which each player chooses its optimal strategy. RL is a widely-used adaptive learning method, which can help players select their optimal strategies by learning from historical information such as network status, the other players' strategies and the corresponding utility. Thus, RL-based game theory is an effective decision-making technique.

In summary, supervised learning algorithms are generally applied to conduct classification and regression tasks, while unsupervised and reinforcement learning algorithms are applied to conduct clustering and decision-making tasks respectively.

PART II: Problem Formulations

Chapter 3

Network emulation environment

The Mininet environment [117] has been used to emulate a SDN network to validate the methodology that will be presented in terms of prediction accuracy and control performance. This software runs a collection of virtual network elements (i.e. end-hosts, switches, routers, and links) on a single Linux kernel using lightweight virtualization. To generate traffic the D-ITG generator [118, 119, 120] has been used.

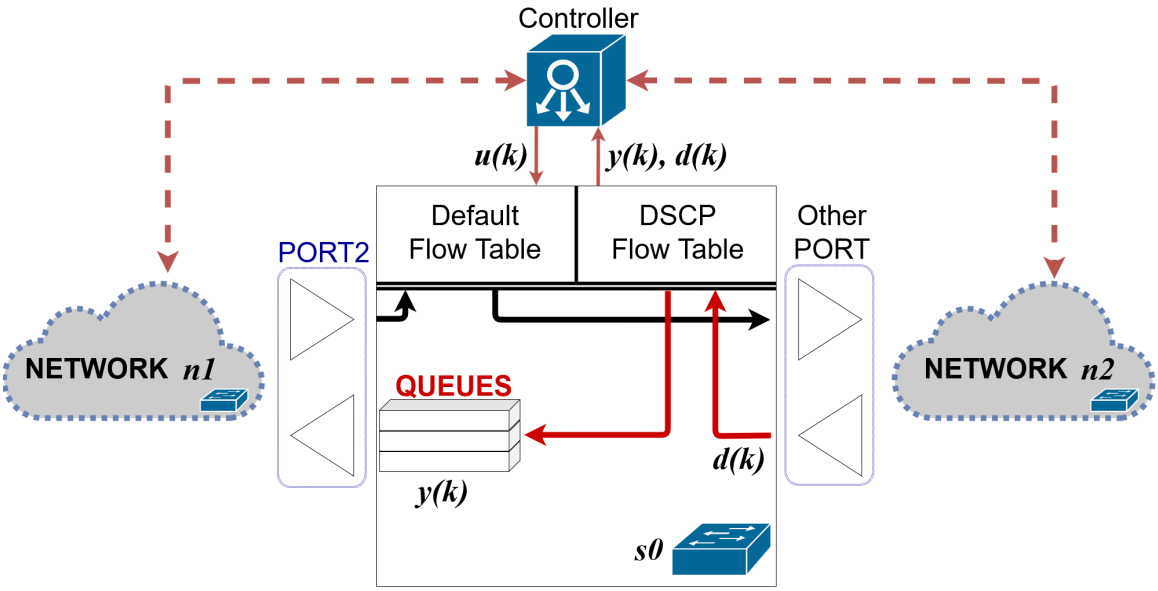


Figure 3.1: Mininet emulated network architecture.

A network architecture as in Figure 3.1 has been considered, which aims at representing a portion of a larger network where a bottleneck occurs. More precisely, a switch $s0$ with one input port and one output port, and a remote controller [42, 48] that dynamically manages the configuration of the queues of $s0$ has been emulated. The input of $s0$ is fed with more instance of D-ITG generating stochastic traffic, whose mean value follows the

pattern of a real data set (where packets are differentiated by their ToS - Type of Service - priority index) extracted from two days logs of a router of a large service provider network. Namely, the original real data set contains traffic of a real network incoming from a source geographic area and terminating in a destination geographic area, and is divided for each value of Differentiated Services Code Point (DSCP) with a sampling time of 5 minutes [121, 122]. DSCP is the modern definition of the Type of Service (ToS) field, in which the first 6 bits are the Differentiated Services field that are in common with ToS field, and the last 2 bits regard explicit congestion notification. The ToS field can specify the priority of a datagram and the request for a low delay addressing, a high throughput or a high reliability service. Following the implementation of many national service provider networks (see e.g. [123]), the 8 different values of the DSCP has been partitioned in three classes: the *Default* class (DSCPs $0, 1, 3$), the *Premium* (DSCPs $2, 4, 6, 7$), and the *Gold* class (DSCP 5): each queue has been assigned to a single queue, associated with a different priority.

Using D-ITG Sender and Receiver SW modules it has been possible to establish a connection between networks n1 and n2. In particular, 16 ITG modules have been initialized: 8 for each network, and within each network one for each DSCP index. These modules handle the sampling time interval (5 minutes), the inter-departure time stochastic distribution associated with the packet rate, the packet size stochastic distribution, the IP and port destinations, and the DSCP index. Regarding the controller SW module RYU has been used, which provides software components with well defined Application Programming Interfaces (API) that give the possibility to easily create new network management and control applications. Ryu supports various protocols for managing network devices, such as OpenFlow, Netconf, OF-config, etc. About OpenFlow, Ryu supports fully 1.0, 1.2, 1.3, 1.4, 1.5 and Nicira Extensions. For the used test-bed the 1.3 version has been chosen. In particular, APIs were used for queue control and counter recovery from the switches [124, 125]. The feedback information collected for the purposes of this work are the descriptions of switches, ports and queues, the number of packets received and transmitted on each port of a switch, the packets passing through the flow tables, the packet rate values of each queue and the packets transmitted by each single queue. In summary, the variables associated to the traffic and control signals in the closed-loop architecture are as follows:

- $d(k) \in \mathbb{R}^{10}$ is a measurable disturbance vector, i.e. representing variables that cannot be controlled. The first 8 components $d_1(k), \ldots, d_8(k)$ consist of the number of packets incoming in the switch $s0$ differentiated with respect to the 8 different values of the DSCPs. $d_9(k)$ and $d_{10}(k)$ are proxy variables, i.e. the hours and minutes of the day, which are very useful to the predictive model since traffic dynamics are tightly correlated with them, e.g. they are substantially different between night and day;

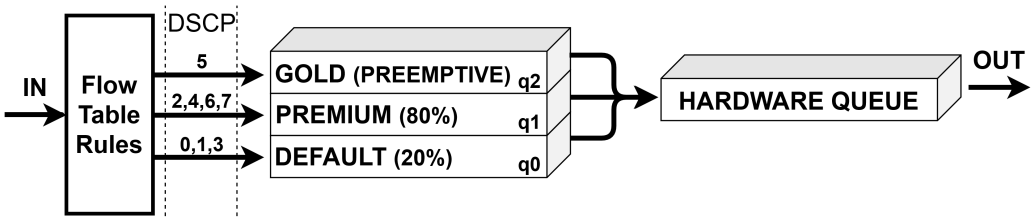


Figure 3.2: Static queues rate with routed packets relative to DSCP.

- $y(k) \in \mathbb{R}^3$ is the measured output vector, i.e. the variables to regulate. They consist of the number of packets outgoing from switch $s0$ differentiated with respect to the corresponding service class: $y_1(k)$ is the Default Queue output, $y_2(k)$ is the Premium Queue output and $y_3(k)$ is the Gold Queue output;

- $u(k) \in \mathbb{R}^3$ is the control input vector. Each component corresponds to the queue configuration of each service class: $u_1(k)$ is the Default Queue configuration, i.e. the maximum admitted bandwidth; $u_2(k)$ is the Premium Queue configuration, i.e. the maximum admitted bandwidth; $u_3(k)$ is the Gold Queue configuration, i.e. the minimum admitted bandwidth;

In this work the static control of queues used in the Italian service provider network of *Telecom Italia* [123] has been first applied in the chosen emulative scenario, which is depicted in Figure 3.2. To this aim 3 queues in $s0$ and has been defined and configured as follows: packets with the DSCP values 0, 1 and 3 (Default queue) are routed via queue 0, with maximum rate $u_1(k) = 20$*MB/s*$, \forall k$; the packets with values 2, 4, 6 and 7 (Premium queue) are routed on queue 1, with maximum rate $u_2(k) = 80$*MB/s*$, \forall k$; the packets with value 5 (Gold queue) are routed on queue 2, with minimum rate $u_3(k) = 100$*MB/s*$, \forall k$. To obtain this prioritization it has also been necessary to set the flow tables of $s0$ to discriminate incoming packets based on the DSCP value and the destination IP address, and re-route them to the desired queue. Also, to obtain a bottleneck situation in $s0$, the bandwidth of the output port of switch $s0$ has been setted at 100 *MB/s*. Using this configuration queue 2 uses the maximum capacity of the port to forward packets with preemptive priority, while the other two queues use the remaining bandwidth from 0 *MB/s* to the specified maximum bandwidth based on needs.
As will be shown in Section 5, using static priority control the queues will not be able to send all the packets incoming from network $n1$, and a dramatic amount of packets will be lost. This motivates the application of optimization techniques, which are enabled by the predictive models derived using the methodology described in the following section.

Chapter 4

Switched affine modeling via RT and RF

Problem formulation. In this section it is illustrated the methodology to apply the results proposed in [126, 127] to identify, starting from a set of collected historical data $\mathcal{D} = \{y(k), u(k), d(k)\}_{k=0}^{\ell}$ as illustrated in the previous section, a switching ARX model of input-output behavior of the traffic flow in a switch of a SDN network as follows:

$$x(k+j+1) = A'_{\sigma_j(x(k),d(k))}x(k) + \sum_{\alpha=0}^{j} B'_{\sigma_j(x(k),d(k)),\alpha}u(k+\alpha) + f'_{\sigma_j(x(k),d(k))}, \tag{4.1}$$

$j = 0, \ldots, N-1$, where $x(k) \doteq [y^\top(k) \cdots y^\top(k-\delta_y)\, u^\top(k-1) \cdots u^\top(k-\delta_u)]^\top \in \mathbb{R}^{n_x}$ is an extended state to characterize a switching ARX model, with $x_\iota(k) \doteq [y_\iota(k) \cdots y_\iota(k-\delta_y)\, u^\top(k-1) \cdots u^\top(k-\delta_u)]^\top \in \mathbb{R}^{\delta_y+1+3\delta_u}$, $\iota = 1, 2, 3$, N is the chosen future predictive horizon, and $\sigma_j : \mathbb{R}^{n_x+10} \to \mathcal{M} \subset \mathbb{N}$ is a switching signal that associates an operating mode in a finite set $\mathcal{M}$ to each pair $(x(k), d(k))$ and each prediction step j of the horizon. It is possible to directly use model (4.1) to setup the following problem, which can be solved using standard Quadratic Programming (QP) solvers:

Problem 1

$$\begin{aligned}
\underset{u_0,\ldots,u_{N-1}}{\textit{minimize}} \quad & \sum_{j=0}^{N-1} \Big((x_{j+1} - x_{\text{ref}})^\top Q\, (x_{j+1} - x_{\text{ref}}) + u_j^\top R u_j \Big) \\
\textit{subject to} \quad & x_{j+1} = A'_{\sigma_j(x_0,d_0)}x_0 + \sum_{\alpha=0}^{j} B'_{\sigma_j(x_0,d_0),\alpha}u_\alpha + f'_{\sigma_j(x_0,d_0)} \\
& u_j \in \mathcal{U} \\
& x_0 = x(k), d_0 = d(k) \\
& j = 0, \ldots, N-1.
\end{aligned}$$

As it is well known [128], Problem 1 is solved at each time step k using QP to compute the optimal sequence $u_0^*, \ldots, u_{N-1}^*$, but only the first input is applied to the system, i.e. $u(k) = u_0^*$. Note that, for any prediction step j, x_{j+1} only depends on the measurements $x_0 = x(k), d_0 = d(k)$ at time k, since they are the only available measurements at time-step k.

RT and RF background. Let us consider a dataset $\{y(k), x_1(k), \ldots, x_\eta(k)\}_{k=0}^{\ell}$, with $y, x_1, \ldots, x_\eta \in \mathbb{R}$. Let us suppose to estimate, using Regression Trees, the prediction of the (response) variable $y(k)$ using the values of predictor variables $x_1(k), \ldots, x_\eta(k)$. The CART algorithm [129] creates a RT structure via optimal partition of the dataset. It solves a Least Square problem by optimally choosing recursively a variable to split and a corresponding splitting point. After several steps the algorithm converges to the optimal solution, and the dataset is partitioned in hyper-rectangular regions (the leaves of the tree) $R_1, R_2, \cdots, R_\nu$. In each partition $y(k)$ is estimated with a different constant $\hat{y}_i$ $i = 1, \ldots, \nu$, given by the average of the samples of $y(k)$ falling in R_i, i.e.

$$\hat{y}_i = \frac{\sum\limits_{\{k|(x_1(k),\ldots,x_\eta(k))\in R_i\}} y(k)}{|R_i|} \tag{4.2}$$

Random Forests [130] are instead an averaging method that exploits a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The output prediction is given by averaging the predictions provided by all trees in the forest. It is possible to show that the error introduced by the forests quickly and almost surely converges to a limit as the number of trees in the forest becomes large. Such error also depends on the strength of the individual trees in the forest and the correlation between them. Thus, due to the Law of Large Numbers, Random Forests (differently from Regression Trees) do not suffer much variance and overfitting problems. For more details the reader is refered to [129, 130].

Switching ARX (SARX) model identification via RT. To derive a model as in (4.1), a new dataset $\mathcal{X} = \{x(k), u(k), d(k)\}_{k=0}^{\ell}$ has to be defined starting from $\mathcal{D}$. In order to apply MPC it is needed, for each component of $y(k)$, a model that can predict system's dynamics over a horizon of length N. The idea is to create $3N$ predictive trees $\{\mathcal{T}_{\iota,j}\}$, $\iota = 1, 2, 3$, $j = 0, \ldots, N-1$, each one to predict the 3 outputs components of the system over the N steps of the horizon. To create the tree structure, the RT algorithm (CART) partitions the dataset $\mathcal{X}$ into regions $\mathcal{X}_i$, such that $\biguplus \mathcal{X}_i = \mathcal{X}$, and assigns to each region a constant value given by the average of the output values of the samples that ended up in that leaf. In run-time, once the trees are created, and given a real-time measurement $(x(k), u(k), d(k))$ belonging to leaf i, the CART algorithm provides as a prediction the averaged value associated to the leaf as in (4.2). However, since the prediction provided by the RT is a constant value, it cannot be used to setup an MPC problem, thus the learning procedure needs to be modified to identify a modeling framework as in (4.7). To this end, $\mathcal{X}$ is partitioned in two disjoint sets $\mathcal{X}_c = \{u(k)\}_{k=0}^{\ell}$ of data associated to the control variables, and $\mathcal{X}_{nc} = \{(x(k), d(k))\}_{k=0}^{\ell}$ of data associated to remaining variables, and then apply the CART algorithm only on $\mathcal{X}_{nc}$ (this is to avoid that the MPC problem turns out into a Mixed Integer Quadratic Program, see [126, 127] for details); thus, $3N$ RTs $\{\mathcal{T}_{\iota,j}\}$ have been created, each constructed to predict the variable $y_\iota(k+j+1)$, and consequently $x_\iota(k+j+1)$. In particular, it is associated to each leaf ι, i_j, corresponding to the partition $\mathcal{X}_{nc,\iota,i_j}$, of each tree $\mathcal{T}_{\iota,j}$ the following affine model

$$x_\iota(k+j+1) = A'_{\iota,i_j} x(k) + \sum_{\alpha=0}^{j} B'_{\iota,i_j,\alpha} u(k+\alpha) + f'_{\iota,i_j}, \tag{4.3}$$

$$A'_{\iota,i_j} = \begin{bmatrix} a_1 & a_2 & \cdots & a_{\delta_y} & a_{\delta_y+1} & b_{\delta_y+2} & \cdots & b_{\delta_y+1+3(\delta_u-1)} & \cdots & b_{\delta_y+1+3\delta_u} \\ 1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 1 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 1 & \cdots & 0 \end{bmatrix},$$

$$B'_{\iota,i_j,\alpha} = \begin{bmatrix} b_{1,\alpha} & b_{2,\alpha} & b_{3,\alpha} \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix}, \ \alpha < j, \ B'_{\iota,i_j,j} = \begin{bmatrix} b_{1,\alpha} & b_{2,\alpha} & b_{3,\alpha} \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix}, \ f'_{\iota,i_j} = \begin{bmatrix} f \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{4.4}$$

where the coefficients of matrices A'_{ι,i_j}, $B'_{\iota,i_j,\alpha}$ and f'_{ι,i_j} are obtained in each leaf ι, i_j by fitting the corresponding set of samples solving the following Least Squares with inequality constraints problem:

Problem 2

$$\begin{aligned} \underset{\xi_{\iota,i_j}}{\textit{minimize}} \quad & \| \Lambda_{\iota,i_j}\xi_{\iota,i_j} - \lambda_{\iota,i_j} \|_2^2 \\ \textit{subject to} \ & f_{\min} \leq f \leq f_{\max} \\ & a_{\min} \leq a_j \leq a_{\max} \\ & b_{\min} \leq b_{\iota,\alpha} \leq b_{\max}, \end{aligned} \tag{4.5}$$

where ξ_{ι,i_j}, λ_{ι,i_j}, and Λ_{ι,i_j} contain respectively the parameters of matrices in (4.4), the predictions $x_\iota(k+j+1)$, and the current measurements of $x(k)$ and $u(k+\alpha)$. Linear inequalities (4.5) are used to constrain elements in ξ_{ι,i_j} to take into account physical system constraints and improve prediction accuracy. Model (4.3) can be easily compacted in the following form taking into account all the states $\iota = 1, 2, 3$:

$$x(k+j+1) = A'_{i_j}x(k) + \sum_{\alpha=0}^{j} B'_{i_j,\alpha}u(k+\alpha) + f'_{i_j}. \tag{4.6}$$

In particular, with the specific choice of $\delta_u = 0$ model (4.1) can be rewritten in the following state-space formulation

$$x(k+j+1) = A_{\sigma_j(x(k),\mathbf{u}^-(k),d(k))}x(k+j) + B_{\sigma_j(x(k),\mathbf{u}^-(k),d(k))}u(k+j) + f_{\sigma_j(x(k),\mathbf{u}^-(k),d(k))}, \tag{4.7}$$

where $\mathbf{u}^-(k) = [u^\top(k-1) \ \cdots \ u^\top(k-\delta)]^\top$ is the vector with the regressive terms of the input used to only grow the trees, and $\sigma_j : \mathbb{R}^{3(\delta_y+1)+3\delta+10} \to \mathcal{M} \subset \mathbb{N}$. Thanks to this new formulation the following proposition shows that model (4.6) is equivalent to model (4.7) for any initial condition, any switching signal and any control sequence.

Proposition 1 *[127] Let A'_{i_j}, $B'_{i_j,\alpha}$ and f'_{i_j}, $\alpha = 0, \dots, j$, $j = 0, \dots, N-1$, be given. If A'_{i_j} is invertible for $j = 0, \dots, N-1$, then there exists a model in the form*

$$\bar{x}(k+j+1) = A_{\sigma_j(\bar{x}(k),\mathbf{u}^-(k),d(k))}\bar{x}(k+j) + B_{\sigma_j(\bar{x}(k),\mathbf{u}^-(k),d(k))}u(k+j) + f_{\sigma_j(\bar{x}(k),\mathbf{u}^-(k),d(k))}$$

such that for any initial condition $\bar{x}(k) = x(k) = x_k$, any switching sequence $i_0, \dots, i_{N-1}$ and any control sequence $u(k), \dots, u(k+N-1)$, then $\bar{x}(k+j+1) = x(k+j+1)$, $\forall j = 0, \dots, N-1$.

As discussed in [127], from experimental findings it is possible to notice that the contribution in terms of model accuracy introduced by the choice of $\delta_u = 0$ is negligible, since previous control inputs are already considered in the tree structure choosing $\delta > 0$. Thus, in the rest of the paper it will be considered $\delta_u = 0$ and $\delta > 0$, i.e. only the regressive terms of the input in the tree structure learning will be used and not in the state definition.

SARX model identification via RF. RF-based models can be constructed exploiting the RT-based formulation: in particular, let us consider $3N$ RFs $\mathcal{F}_{\iota,j}$, $\iota = 1, 2, 3$, $j = 0, \dots, N-1$. For each tree $\mathcal{T}_\tau^{\mathcal{F}_{\iota,j}}$ of the forest $\mathcal{F}_{\iota,j}$, it is possible to estimate the coefficients a_*, b_* and f in (4.4) for each leaf ι, j, i_τ, i.e. $\tilde{\xi}_{\iota,j,i_\tau}$, solving Problem 2. With a small abuse of notation, let us indicate by $|\mathcal{F}_{\iota,j}|$ the number of trees in the forest ι, j. Then $\forall \iota, j$, the parameters to build matrices in (4.9) can be obtained by averaging parameters a_*, b_* and f, $\forall \tau = 1, \dots, |\mathcal{F}_{\iota,j}|$, i.e.

$$\tilde{\xi}_{\iota,j} = \frac{\sum_{\tau=1}^{|\mathcal{F}_{\iota,j}|} \tilde{\xi}_{\iota,j,i_\tau}}{|\mathcal{F}_{\iota,j}|}, \tag{4.8}$$

over all the trees of forest $\mathcal{F}_{\iota,j}$. At this point, starting from (4.3), it can be easily construct the following model, as in (4.6) to be used in the MPC formulation by combining for $\iota = 1, 2, 3$ the matrices in (4.4) coming either from the RTs or from the RFs:

$$x(k+j+1) = A'_{i_j}x(k) + \sum_{\alpha=0}^{j} B'_{i_j,\alpha}u(k+\alpha) + f'_{i_j}. \tag{4.9}$$

MPC problem formulation. It is used model (4.9) to formalize Problem 1 according to the SDN priority queueing problem:

Problem 3

$$
\begin{aligned}
\underset{\mathbf{u}}{\textit{minimize}} \quad & \sum_{j=0}^{N-1} \Big[(x_{j+1} - x_{\mathrm{ref},j})^\top Q (x_{j+1} - x_{\mathrm{ref},j}) + u_j^\top R u_j \Big] \\
\textit{subject to} \quad & x_{j+1} = A_{\sigma_j(k)} x_j + B_{\sigma_j(k)} u_j + f_{\sigma_j(k)} \\
& \Delta u_\iota^{\min} \leq u_{\iota,j} - u_{\iota,j-1} \leq \Delta u_\iota^{\max} \\
& u_\iota^{\min} \leq u_{\iota,j} \leq u_\iota^{\max} \\
& u_{1,j} + u_{2,j} \leq 100 \\
& x_0 = x(k),\ \mathbf{u}_0^- = [u^\top(-1)\ \cdots\ u^\top(-\delta)]^\top,\ d_0 = d(k), \\
& j = 0, \ldots, N-1,\ \iota = 1, 2, 3,
\end{aligned}
$$

where $\sigma_j(k) = \sigma_j(x(k), \mathbf{u}^-(k), d(k))$ (with a slight abuse of notation), $u_{\iota,j}$ is the ι^{th} component of the input u at time $k+j$; $\Delta u_\iota^{\min}$ and $\Delta u_\iota^{\max}$ are used to limit large variations on the inputs in 2 consecutive steps, in order to avoid that the queues drastically set to the minimum value and thus potentially increase packet losses during the next period; $u_\iota^{\min}$ and $u_\iota^{\max}$ define the bandwidth limits induced by the QoS requirements of the corresponding priority class. At each time step k the measurements of the variables in $\mathcal{X}_{nc}$ are collected, select the current matrices of (4.9) narrowing down the leaves of the trees, for $j = 0, \ldots, N-1$, solve Problem (3), and finally apply only the first input of the optimal sequence $\mathbf{u}^*$ found, i.e. $u(k) = u_0^*$.

Disturbance forecast. The knowledge at each time k of the future input traffic $(d(k+1), \ldots, d(k+N-1))$ can greatly improve the MPC performance. However, while the future values of the proxy variables (hours and minutes) are clearly well known, the knowledge of the future values of the first 8 component of the disturbance, i.e. number of packets incoming in the switches for each DSCP index are unknown at the current instant k. To address this problem $8(N-1)$ RFs $\mathcal{F}_{\iota,j}^d,\ \iota = 1, \ldots, 8,\ j = 0, \ldots, N-1$ have been built in order to provide a prediction $\hat{d}_\iota(k+j)$ of the 8 disturbance components $d_\iota(k+j)$ over the future time horizon: as widely illustrated in [126, 127] the technique previously described can be easily modified by appropriately redefining the dataset as $\mathcal{X} = \{(x(k), u(k), d(k), \ldots, d(k+N-1))\}_{k=1}^{\ell}$ for the training phase, and considering a switching signal in (4.7) given by $\sigma_j(k) = \sigma_j(x(k), \mathbf{u}^-(k), d(k), \hat{d}(k+1), \ldots, \hat{d}(k+j)), \forall j = 0, \ldots, N-1$, i.e. also depending at time k on the future input traffic.

PART III: Experimental Results

Chapter 5

Simulation results

In this section simulation results of the application of the proposed approach to SDN Priority Queueing identification and control will be provided. Standard RFs are used to derive predictive models of the disturbance components $d_1(k), \ldots, d_8(k)$, i.e. the switch input differentiated for each DSCP index, and validate the accuracy. Then the validation of accuracy of the predictive model of the output variable $y(k)$ derived as illustrated in Section 4 is shown: the predictive models (based on RTs and RFs) will be compared with Artificial Neural Networks, showing that RFs represent the ideal solution both in terms of prediction accuracy and computational complexity; then it will be illustrated the effect of iterative dataset updates in the prediction accuracy, both with and without prediction of the future disturbances. Finally it will be used the proposed predictive models to setup a MPC problem (see Problem 3), and validate the control performance in terms of packet losses reduction and bandwidth saving, both with and without prediction of the future disturbances. It will also be shown, as expected, that using accurate predictive models and applying MPC provides dramatic reduction of packet losses and increase of bandwidth saving with respect to the static bandwidth allocation policy used in Service Provider Networks as described in Section 3: even thought this result is not surprising, it is decided to quantify the gap to emphasize that much better performance can be obtained in real networks just collecting historical data and applying a controller that can be directly implemented using the accurate models of the proposed identification algorithm and Quadratic Programming solvers (which are well known to be very efficient).

In each of the aforementioned validations, 4 different predictive models have been exploited, using iteratively enriched data sets. More precisely, **OLD** is a predictive model identified with a data set of 5124 samples, collected with a sampling time of 5 minutes and obtained from network emulation with random values of the input $u(k)$; **1UP** is a predictive model identified with the **OLD** data set enriched with 3456 new samples obtained from network emulation when applying closed-loop MPC to define the input $u(k)$; **2UP** is a predictive model identified with the **1UP** data set enriched with 3168 new samples obtained from network emulation when applying closed-loop MPC to define the input $u(k)$; **3UP** is a predictive model identified with the **2UP** data set enriched with 6336 new samples obtained from network emulation when applying closed-loop MPC to define the input $u(k)$. An independent data-set composed by 1684 samples is used to validate the above models. All simulations have been ran on a UDOO x86 Advanced with an Intel Braswell N3160

processor up to 2.24 GHz and 4 GB of RAM [131].

5.1 Disturbance predictive model validation

Having an accurate predictive model of the variable $d(k)$ (i.e. the switch input differentiated for each DSCP index) can be helpful to improve the model identification performance as well as the reference input $x_{\text{ref},j}$ $j = 1, 2, \ldots, N$ to follow in Problem 3. In this section standard RF algorithms are applied, with a regressive index of 15 steps and 30 trees for each forest, to obtain a predictive model of the disturbance over a predictive horizon of $N = 5$ (25 minutes): this choice of N has been taken considering the tradeoff between time complexity of the identification algorithm and the obtained identification accuracy.

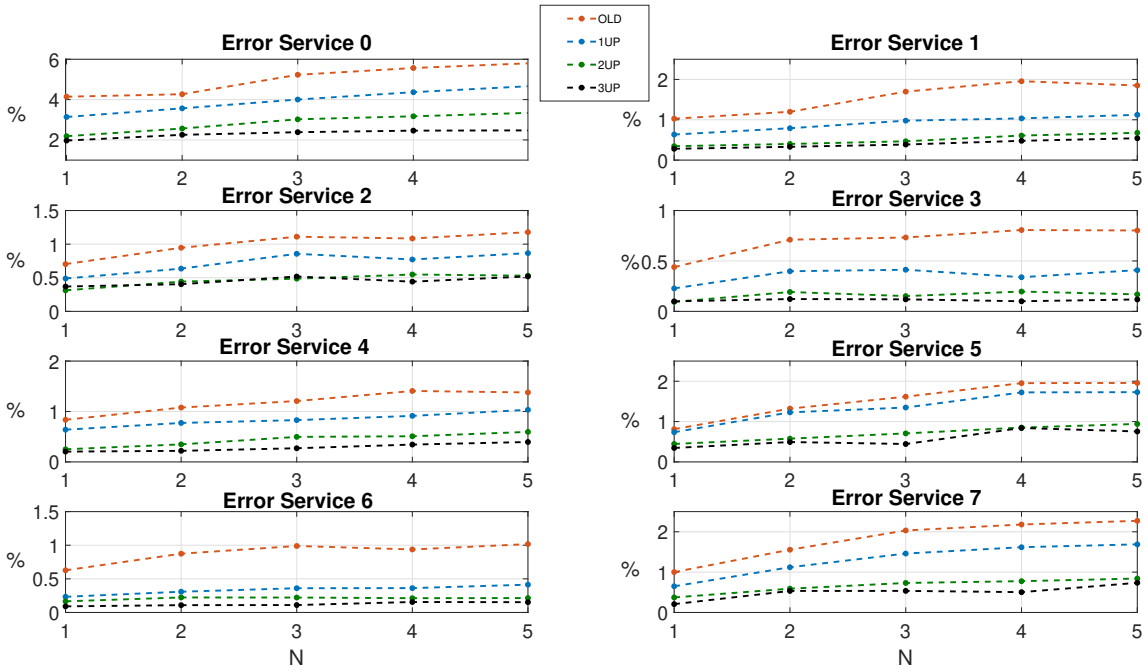


Figure 5.1: NRMSE of the disturbance predictive model over a time horizon of $N = 5$.

Figure 5.1 shows the Normalised Root Mean Square Error (NRMSE) of the predictive model of the disturbance signals (one for each of the 8 DSCP indices) over a time horizon of $N = 5$: the prediction error is worse for Service 0 ($4-6\%$) since it includes the majority of the packets that transit through the switch. For other services the NRMSE is at most 2.2% (Service 7) over all the predictive horizons. The improvement of the model accuracy when using larger (updated) data sets is evident, until a *saturation* is reached and further data do not help to improve the model accuracy: the NRMSE significantly reduces and for Service 0 it is even halved. Figure 5.2 plots, for Service 0 and in a time window of 500 samples (almost two days), the predictions of OLD, 1UP, 2UP and 3UP as well as the original data, and clearly highlights the better prediction of 2UP and 3UP with respect to OLD and 1UP.

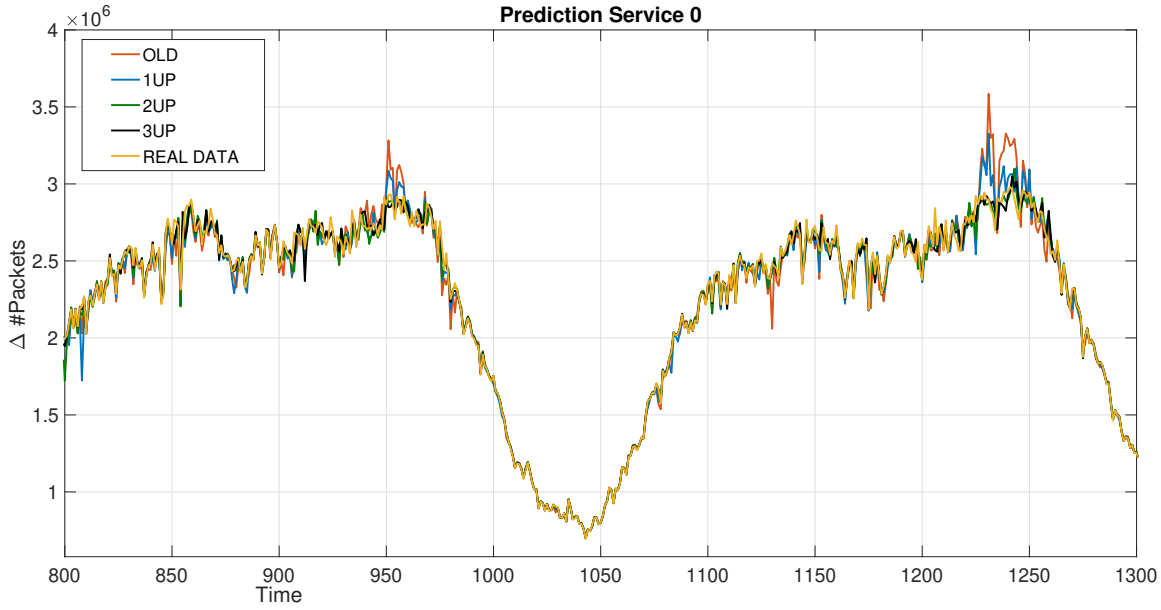


Figure 5.2: Comparison between the real traffic (YELLOW LINE) and the traffic prediction for the different models for Service 0.

5.2 Traffic predictive model validation on real network data

In addition to the validation of our predictive models of the incoming traffic over the Mininet environment, the accuracy has been also tested on data measured from a real network device (Ubiquiti EP-16) of an Italian internet internet provider (Sonicatel S.r.l.). Data collection has been performed using the software Cacti [**?**].
Since this device is part of a running commercial network, some constraints in data collection have forced to only measure the sum of all packets entering and leaving the device, and it has been possible to extract from such traffic only incoming VOIP packets: i.e., it has not been possible to extract packets differentiated for each DSCP. Moreover, it is not currently possible to apply any type of closed-loop control on the network device. For the above 2 reasons the control performance validation in the following sections is not based on this real traffic dataset.
About data analysis, 53 days of data measurements have been used for RF training and about 3 days for model validation. Figure 5.3 shows the prediction on three classes of packets: all packets received, all packets transmitted, VOIP packets received. The plots show that our methodology provides a very accurate prediction even on a real internet service provider network.

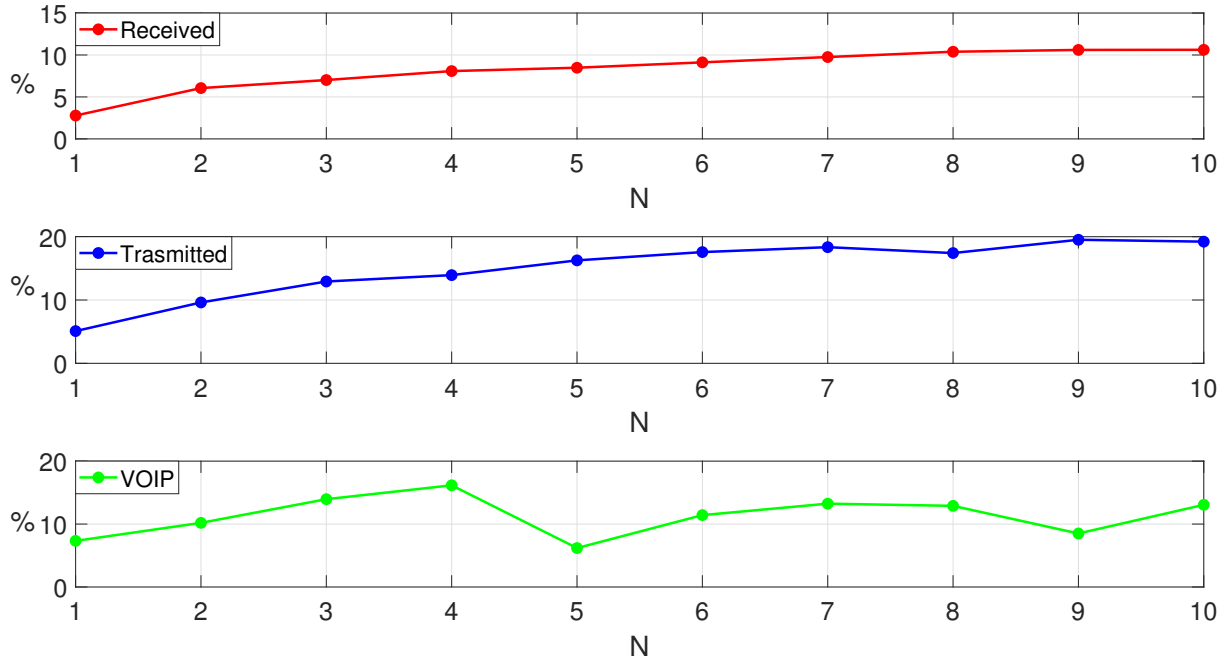


Figure 5.3: NRMSE of the packets predictive model over a time horizon of $N = 10$.

5.3 Queues predictive model validation

In this section a comparison of the accuracy of RT and RF predictive models with Artificial Neural Networks will be showed. A neural network is a collection of algorithms that identify underlying relations in a dataset: it consists of groups of connected neurons organized in layers, where the connections between neurons are modeled using weights. The signal produced with this linear composition is then fed into an activation function that is in general nonlinear. The reader is referred to [132] and references therein for more details. A wide number of tools to build Neural Networks have been developed during recent years, e.g. [133, 134, 135] just to mention a few: in this work it is exploited the Deep Learning Toolbox of Matlab to compare predictive models based on NNs with the methodology proposed in this paper, based on ARX combined RTs and RFs. It is considered here just OLD as the learning dataset and a predictive horizon $N = 5$.

To identify a RT (resp. RF) based predictive model of the queues it is trained a Regression Tree (resp. Random Forest) for each output and for each time horizon, with a total of 15 trees (resp. 15 forests each consisting of 30 trees). The main parameters used for the identification algorithm (see Section 4 and Problem 2) are summarized in Table 5.1. In particular, as done with δ in Equation (4.7), parameters δ_x and δ_d are considered as regressive terms of the state and disturbance that will be only used to grow the trees and the forests, i.e. $\sigma_j(k) = \sigma_j(x(k), \ldots, x(k-\delta_x), \mathbf{u}^-(k), d(k), \ldots, d(k-\delta_d))$. The regressive terms ($\delta_d$, δ_y, δ_x, δ_u, δ) and the minimum number of samples for each tree of each forest (MinLeaf) have been chosen, with a trial and error approach, considering that very small regressive

Table 5.1: Identification parameters

Parameters	Value	Parameters	Values
N	5	f_{min}	-100
δ_y	1	f_{max}	100
δ_x	5	a_{min}	-100
δ_u	0	a_{max}	100
δ_d	5	b_{min}	0
δ	5	b_{max}	10000
$\lvert\mathcal{F}_{ij}\rvert$	30	Minleaf	13

horizons and very large values for MinLeaf may lead to inaccurate prediction (as they do not provide sufficient information on the past) but very large regressive horizons and very small values for MinLeaf also lead to inaccurate prediction (as they interpolate very old data that might negatively affect the results and produce overfitting).

Regarding specific parameters used for running NN, and for the sake of a fair comparison, they have been tuned to obtain the best performance: in particular shallow networks of 2 layers are considered since deeper networks did not improve the accuracy and, instead, have the negative effect of increasing the sensitivity of the accuracy with respect to the initial conditions of the weights. Among the many algorithms for optimizing the weights of the neurons, the following will be considered: *Scaled conjugate gradient back-propagation* described in [136], which provided the best accuracy with respect to the dataset considered. Regarding the activation functions, both the classical sigmoid function (*LogSig*) and the Hyperbolic tangent sigmoid transfer function (*TanSig*) are used.

As a metric of the prediction accuracy in Figure 5.4 is shown a comparison between the Normalized Root Mean Square Errors (NRMSE) of the different identification approaches for each priority class and over a horizon up to $N = 5$. Regarding queue 0 (Default) NNs perform better than RT and RF, but in queues 1 (Premium) and 2 (Gold), characterised by higher priority, RF provides the best performance. Queue 0 is characterised by a larger NRMSE with all identification techniques: this is due to the fact that, having the lowest priority, it suffers more packet losses and this can negatively affect the prediction accuracy. The validation emphasizes that RTs, even thought very simple and fast to compute, are often affected by overfitting and variance issues, i.e. small variations of the training data result in large variations of the tree structure and, consequently, of the predictions. Regarding NNs, they provide a less accurate model in 2 cases over 3. Indeed, by analyzing the dataset distribution, it is possible to notice a peculiar regular grid pattern that can be very well approximated by hyper-rectangles: since RTs and RFs base their prediction on hyper-rectangular dataset partitions, the better performance with respect to NNs is reasonable. For queue 0, even thought NNs perform better, it is important to remark that their predictive model is based on nonlinear functions: this makes the derived model impractical for real-time control as the corresponding MPC formulation turns into a nonlinear optimization problem, for which there is no approach that can guarantee neither a global optimal solution nor a reasonable computation time. In addition to this, even obtaining a closed mathematical form of the predictive function of a Neural Network starting from neurons and weights

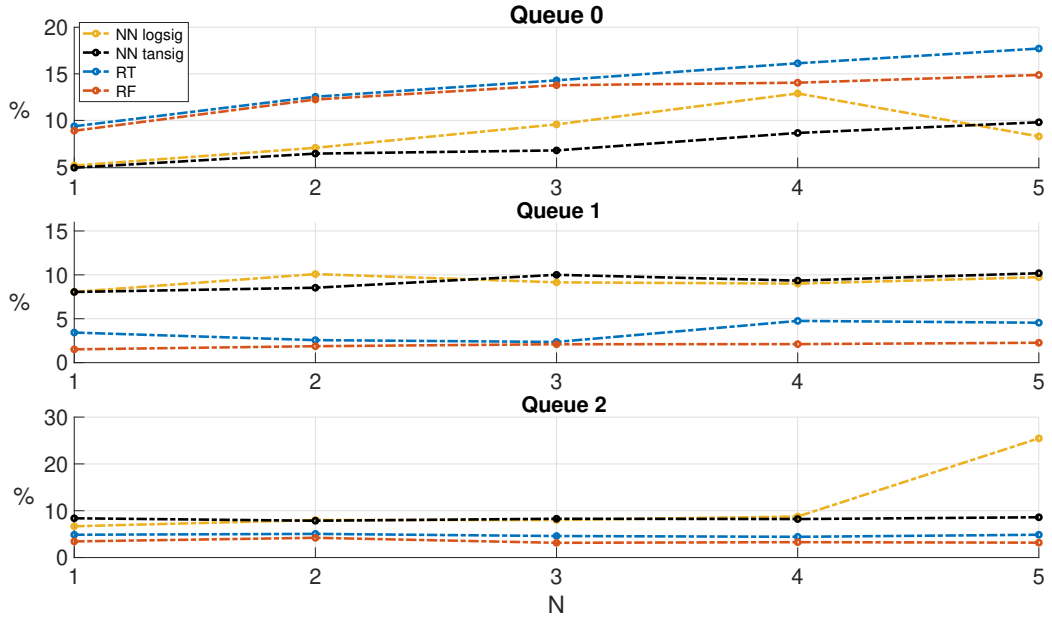


Figure 5.4: NRMSE, up to $N = 5$ and for each priority class, for RT (blue), RF (red), NN with sigmoids as activation function (yellow) and NN with hyperbolic tangent as activation function (black).

is not always an easy task, because of the highly nonlinear interconnections between the different layers. For all these reasons it will be only used, from now on, RF-based models which provide the best choice both from the accuracy and the computational complexity points of view. In the following it is illustrated the effect of iterative dataset updates in the prediction accuracy, both with and without prediction of the future disturbances.

Figure 5.5 and Figure 5.6 plot the NRMSEs respectively without and with prediction of the future disturbances. The assumption of future disturbance forecast, as expected, provides much better prediction accuracy. The positive effect of updated data sets is also clear, providing accuracy improvements up to 50%: as will be also discussed in the next section, the most relevant prediction accuracy improvement takes place moving from OLD to 1UP or from 1UP to 2UP, while the 3UP model does not improve much.

Remark 1 *In the simulations shown in this work, data are generated without major modifications of the traffic daily pattern: for this reason enriching the data set converges to a saturation of the model accuracy, as discussed above. Nevertheless, the capability of the proposed methodology to iteratively learn from new data is fundamental as, in real life, changes in the traffic patterns do occur, and model updates are necessary to maintain the model accuracy and the control performance.*

5.4 Control performance

In this section a control loop is setup, where the (Mininet) network emulator and the (Ryu) controller run in two different computers, and synchronize/exchange data using a shared

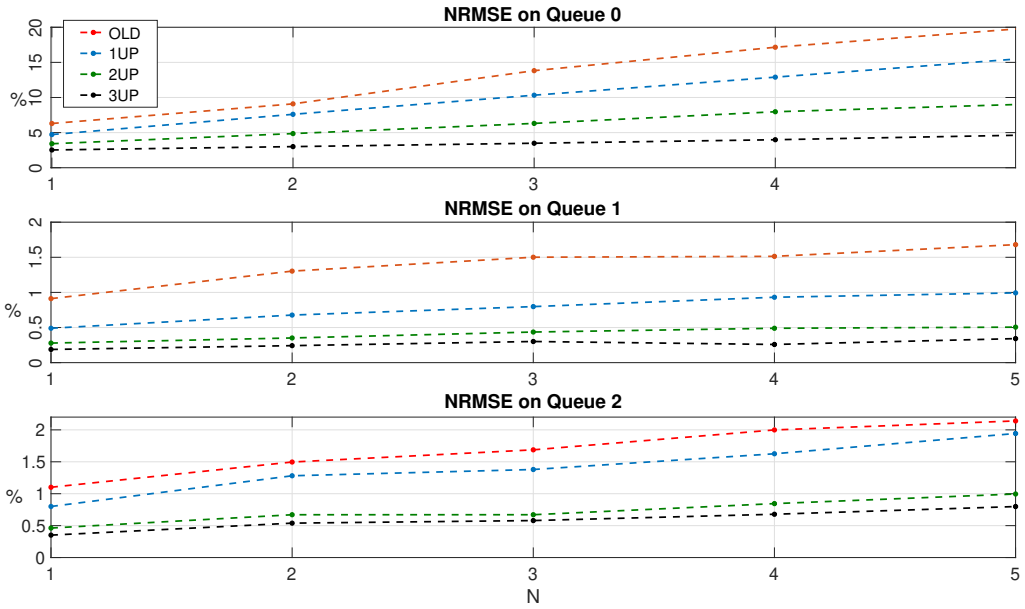


Figure 5.5: NRMSE of the queues output predictive model over a time horizon of $N = 5$, without prediction of the future disturbances

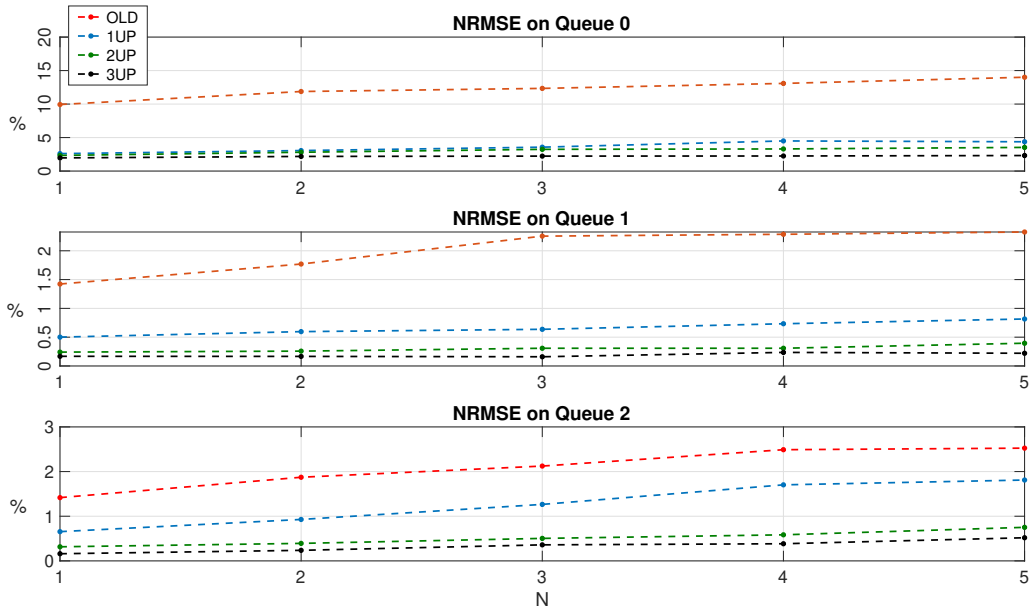


Figure 5.6: NRMSE of the queues output predictive model over a time horizon of $N = 5$, with prediction of the 4-steps future disturbances

file. Namely, the SW controller module is ready to be directly used on a real SDN-based network, with just some minor modifications in the data exchange with the switch devices. The controller implements MPC using the predictive models validated in the previous sec-

tions: at each time step, it solves Problem 3 and optimally updates the bandwidth of the different queues. The cost matrices Q and R of Problem 3 respectively weight the output $y(k)$ of the system (i.e. the packet transmission rate for each queue) and the control input $u(k)$ (i.e. the bandwidth assigned to each queue). Since R is required to be positive definite but it makes no sense assigning a penalty to the choice of $u(k)$, the choice has been $R = 10^{-5} \cdot \mathbb{I}$, where the identity matrix $\mathbb{I}$ multiplies a very small value. Matrix $Q = diag(1, 10^4, 10)$ has been assigned as a diagonal matrix, where the choice of the different diagonal components is related to the priority level of each queue. The remaining constraints of Problem 3 are reported in Table 5.2. In what follows it is validated the control performance both with-

Table 5.2: Constraints in Problem 3

Parameters	Value	Parameters	Values
$\Delta u_1^{\min}$	1	$\Delta u_1^{\max}$	30
$\Delta u_2^{\min}$	20	$\Delta u_2^{\max}$	30
$\Delta u_3^{\min}$	20	$\Delta u_3^{\max}$	20
$u_1^{\min}$	10	$u_1^{\max}$	45
$u_2^{\min}$	55	$u_2^{\max}$	80
$u_3^{\min}$	80	$u_3^{\max}$	100

out and with prediction of the future disturbances. The values of $x_{\text{ref},j}$ in the optimization problem represent the reference values chosen for tracking system output: indeed, as the objective is to minimize packet losses, it is minimized the difference between the packets received by the hosts $d(k)$ and those transmitted by the queues $y(k)$ over the horizon N. In case there are no prediction of future disturbances, $x_{\text{ref},j} = x_{\text{ref}} = d(k)$ will be equal to the current disturbance measurement and constant over all the predictive horizon; if instead there is a prediction of future disturbances, $x_{\text{ref},j}$ will be equal to such forecast. In this section are compared only models OLD, 1UP and 2UP, since model 3UP does not provide any substantial improvement.

Figures 5.7 and 5.8 plot the cumulative packet losses respectively without and with prediction of the future disturbances. The packet loss rate when the control is performed exploiting the OLD model and without disturbance forecast is around 123% larger than all other cases (and, of course, incomparably smaller than the static control case [123]). It is also clear from the plots that 1UP and 2UP without disturbance forecast and OLD, 1UP and 2UP with disturbance forecast provide very similar performance. Authors' interpretation is that OLD models without disturbance forecast have not enough information to provide good accuracy, but they can be easily improved either with a data set update (which however requires 10 days for 1UP and 20 days for 2UP of additional data) or using a predictive disturbance model.

Figure 5.9 illustrates the bandwidth savings showing the recurrence of the different bandwidth usage during the simulations, respectively without and with prediction of the future disturbances. Without disturbance forecast it is exploited up to $25MB/s$ using the OLD model, while it is exploited at most $22MB/s$ and $21MB/s$ respectively for models 1UP and 2UP. Using disturbance forecast, as expected, even less bandwidth is exploited.

In conclusion to this section, it will be shown the gap between priority queueing control performance of MPC, obtained solving Problem 3 and based on the proposed RF predictive

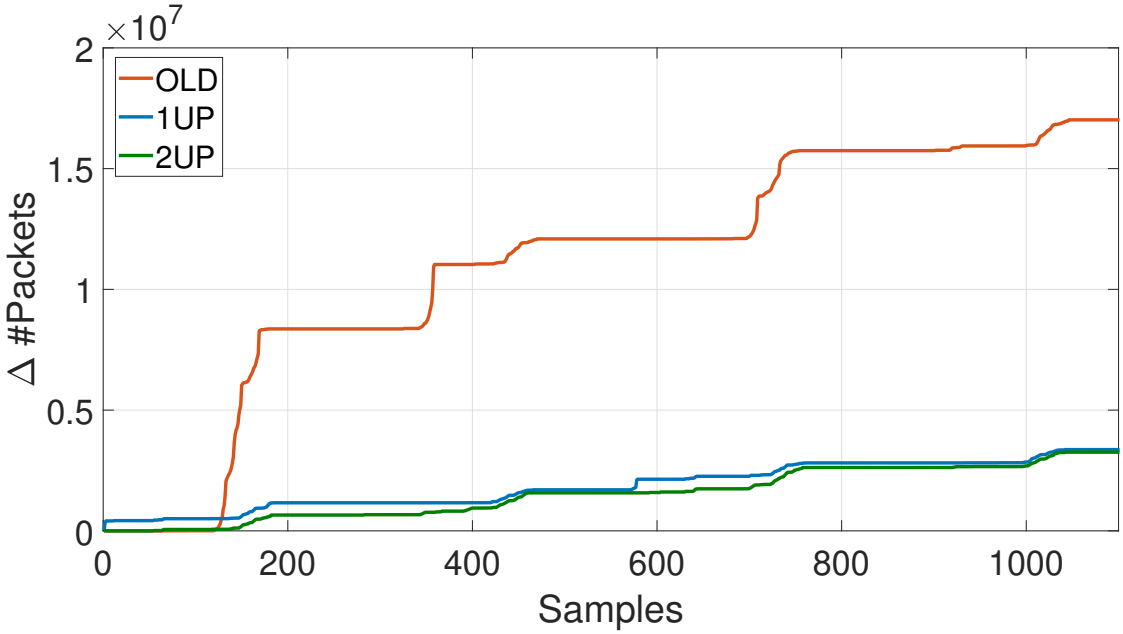


Figure 5.7: Cumulative Packet Losses without prediction of the future disturbance.

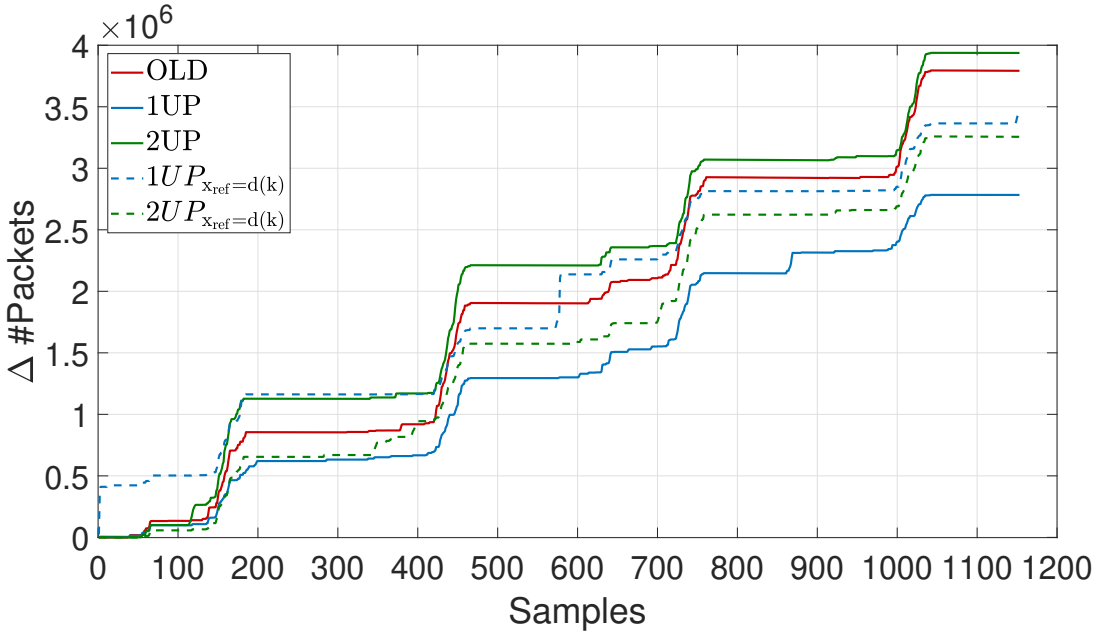
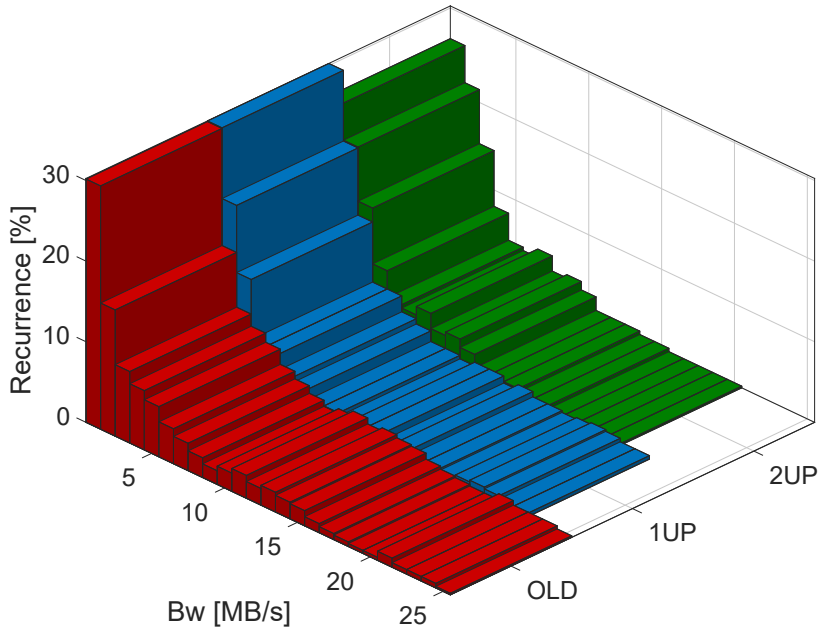
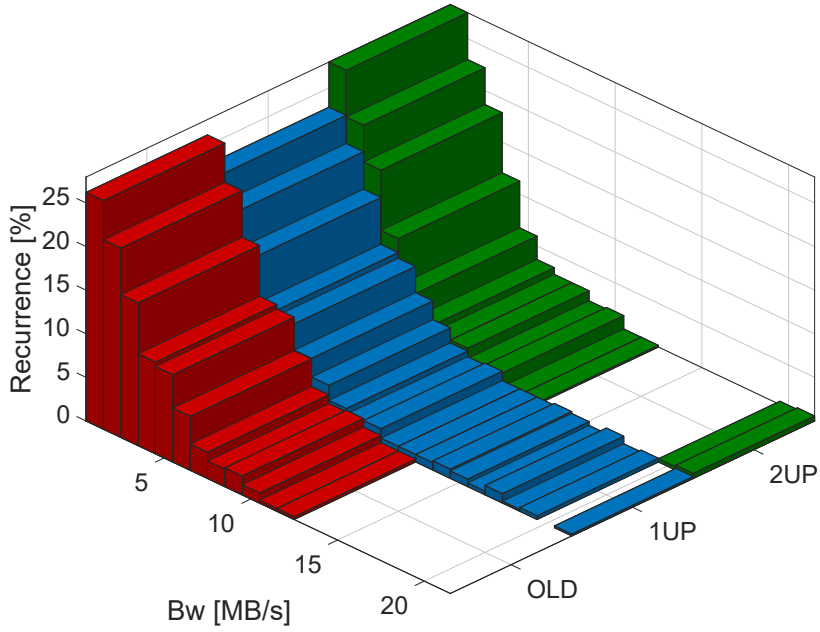


Figure 5.8: Comparison between Cumulative Packet Losses with (solid lines) and without (dashed lines) prediction of the future disturbance.

model, with the static control policy adopted by service provider networks in [123]. Figure 5.10 highlights the dramatic improvement of MPC with respect to static control: the red line shows the incoming traffic, the blue line shows the sum of the packets sent from the queues, and their difference represents packet losses. Until the $400th$ sample static control has been implemented as in [123], generating many packet losses due to queues saturation.



(a)



(b)

Figure 5.9: Bandwidth saving comparison without (a) and with (b) prediction of the future disturbances.

From that sample to the end of the experimentation MPC is implemented using RF-based model, and the packet loss is drastically reduced: quantitatively, after 700 sampling periods the cumulative number of dropped packets with the static policy is about $5.5 \cdot 10^8$ versus $6.6 \cdot 10^6$ with MPC, with a decrease of $5.434 \cdot 10^8$ lost packets (-88%). Even thought the improvement of MPC with respect to static control is not surprising, much better performance

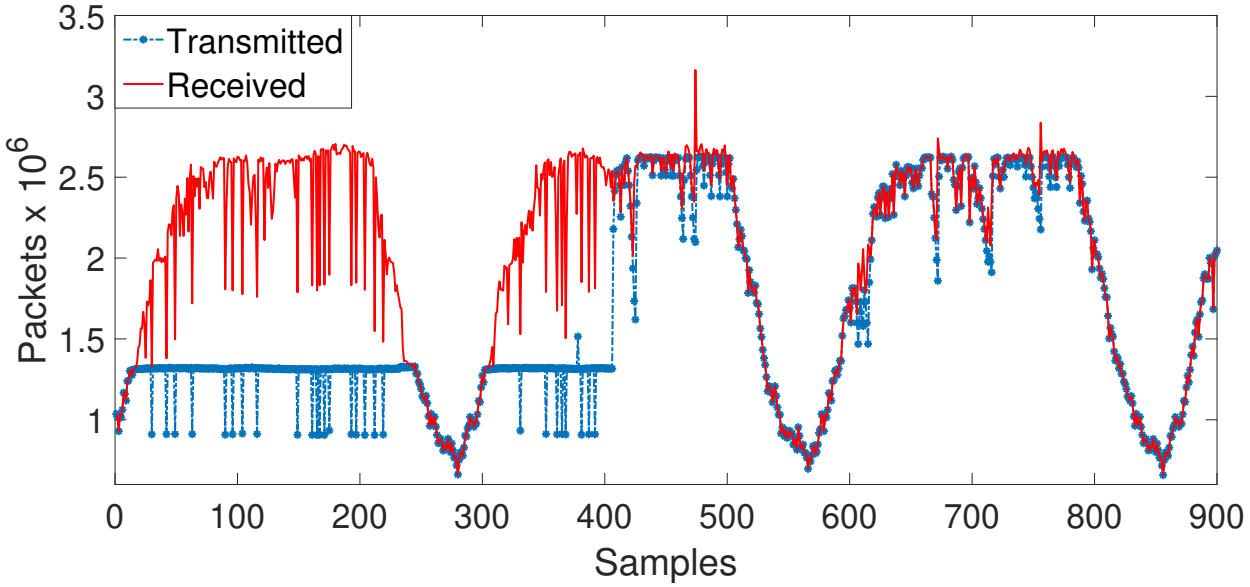


Figure 5.10: Static controller up to the $400th$ sample, then MPC controller.

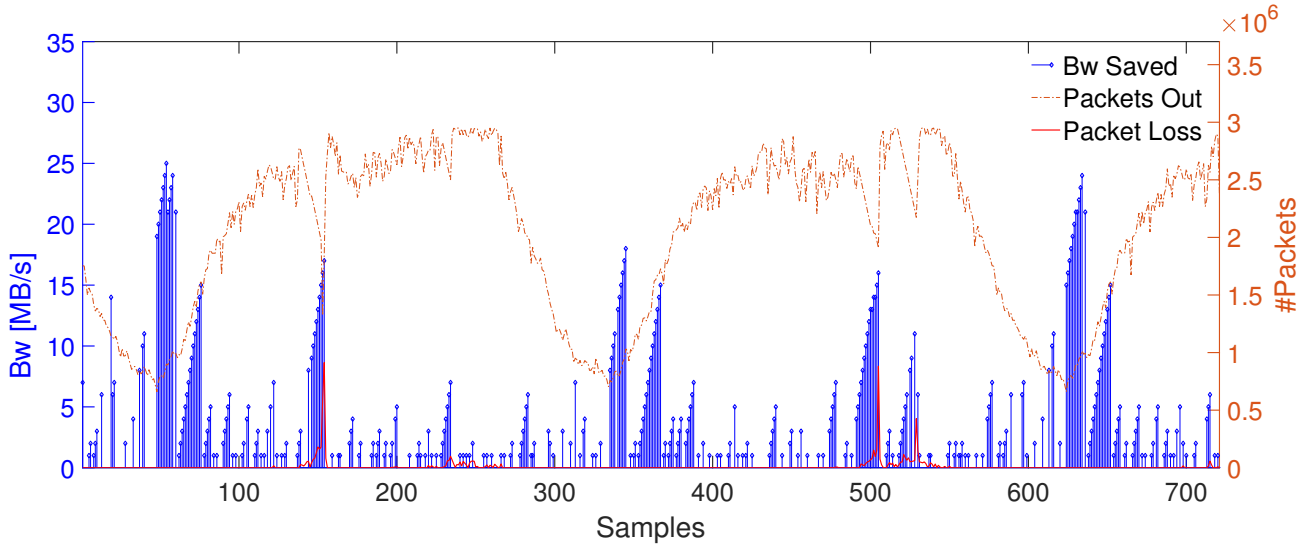


Figure 5.11: MPC controller: packets sent from the queues (orange), packets lost (red), bandwidth saving (blue).

can be obtained in real networks just collecting historical data and applying a controller that can be directly implemented using the accurate models of the proposed identification algorithms and Quadratic Programming standard solvers.

Chapter 6

Conclusion

In this paper a new methodology to derive accurate models for priority queueing in Software Defined Networks, in order to enable the application of advanced optimization techniques such as MPC, has been developed and validated over the Mininet network emulator framework. The obtained simulative results validate the prediction accuracy both of the incoming traffic and of the input/output behavior of a switch device in a SDN-based network. They also provide promising insights on the potential impact of predictive models combined with MPC in terms of packet losses reduction and bandwidth savings in real networks. In future work it has been planned to validate these results over real network devices, instead of using Mininet.

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