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A Reinforcement Learning based Cognitive Approach for Quality of Experience Management in the Future Internet

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Executive Summary

Future Internet design is one of the current priorities established by the EU. The EU FP7 *FI-WARE* project is currently trying to address the issues raised by the design of the *Future Internet Core Platform*.

This thesis aims at providing an <u>innovative contribution</u> to the definition of the Future Internet Core Platform Architecture, in the frame of the “La Sapienza” University research group activities on the FI-WARE project.

The reference architecture proposed by the “La Sapienza”University research group, called *Cognitive Framework Architecture*, is based on two main elements, incorporating the main “cognitive” functions: the *Cognitive Enablers* and the *Interface to Applications*.

The <u>first goal</u> of this thesis is the design of the *Application Interface*architecture, focusing on the key “cognitive” role of the Interface, related to the Application Requirements Definition and Management. The Application Requirements are defined in terms of *Quality of Experience(QoE)* Requirements.

The proposed Interface, called *Cognitive Application Interface* (CAI), is based on three main elements: the *Application Handler*,the *Requirement Agent* and the*Supervisor Agent*.

The key element from the QoE perspective is the *Requirement Agent*: it has the role of dynamically selecting the most appropriate *Class of Service* to be associated to the relevant Application in order to “drive” the underlying network enablers to satisfy the target QoElevelthat is required for the Application itself.

The *QoEfunction*is defined taking into account all the relevant factors influencing the quality of experience level as it is “globally” perceived by the final users for each specific Application (including Quality of Service, Security, Mobility and other factors).The proposed solution allows to manage single Applications assigning to them quantitative *QoE target values* and “driving” the underlying network elements (enablers) to reach(or approach) them.

The proposed approach models the QoE problem in terms of a *Reinforcement Learning* problem, that is a *Markov Decision Process*, where the RL *Agent* role is played by the

Requirement Agent and the Environment is modelled as a Markov Process with a specific *state* space and *reward* function.

Considering that the Environment model (network dynamics) is *not known* a priori, the Author suggests to use "model-free" Reinforcement Learning methods, such as *Temporal Difference*(TD) RL methods and, in particular, the *Q-Learning algorithm*.

The Cognitive Application Interface can be implemented in real network scenarios such as *fixed*and*mobile access networks*, where resource limitations and bottlenecks are present, because over-provisioning cannot be used, and specific network mechanisms and solutions are necessary to guarantee the required Quality of Experience.

The second goal of this thesis is a concrete implementation of the proposed Cognitive Application Interface, in order to test behaviour and performance of the proposed Reinforcement Learning based QoE problem solution.

For implementation and simulation purposes, the *QoS case* has been considered: this is a specific case, where the Application QoE is defined in term of *Quality of Service* metrics.In the QoS case*, throughput*, *delay* and *loss rate*parametershave been considered.The proposed *QoE function* assigns different *weights* to the QoS *parameters*and allows to guarantee a satisfactory granularity in defining Application QoE requirements.

The considered network scenarios and the proposed Cognitive Application Interface are implemented using the *OPNET* tool, a license-based SW platform that is widely used for both academic and industrial applications in the ICT field.The network model is implemented using a *Dumbbellnetwork*.The Supervisor Agent and the Requirement Agent algorithms are implemented using the C^{++}language version supported by OPNET; in particular, the Requirement Agent is implemented using a standard version of the *Q-Learning* algorithm.

Several *simulations* have been run in order to test behaviour and performance of the proposed Cognitive Application Interface and algorithms, considering *single* and *multiple application scenarios*with different network congestion levels.

In order to test the performance of the proposed solution, in each simulation scenario "*static cases*", where Classes of Services are permanently associated to the Applications, are compared with "*dynamic cases*", where each Requirement Agent dynamically selects the most appropriate Class of Service to be associated to the relevant Application, in order to "drive" the network elements to satisfy the required QoS level.

As known,traditional Quality of Service (QoS) management solutions typically operate on a *per-flow* basis, permanently associating each application with a *static* Class of Service andsupporting it on an appropriate *flow,* then managing traffic relevant to different flows/classes with different priorities, without guaranteeing any specific Application target QoS level.

The *simulationresults* clearly show that the dynamical Class of Service selection and management, made possible by the co-ordinated action of the Supervisor and the Requirement Agents, assures a significant improvement of the QoS performance of the relevant Applications in relation to the traditional QoS approach, based on static Class of Service mapping and management.

As known, the classic Q-Learning algorithm has impressive convergence properties, but they are only guaranteed in *single-agent* scenarios: a promising *hybrid* solution for overcoming the limitations of this algorithm when used in *multi-agent* systems, combining it with a *game-theory* based approach, is the *Friend or Foe algorithm.*

Starting from this consideration, an alternative RL solutionhas been investigated in the final part of this work, based on a *two-Agent* scenario, where each Requirement Agent plays against a "Macro-Agent", incorporating all the other Requirement Agents, and "learns to act" using a *FriendorFoe algorithm.*

Some *preliminary tests*have been run on this solution, considering one of the scenariosalready implemented for the standard Q-Learning version (in particular: a multi-application scenario with medium congestion level): the obtained results show an improvement in the algorithm performance, with respect to the standard version.

Thanks

First of all, a particular thank is due to Prof. *Francesco Delli Priscoli*, who proposed me this opportunity to apply my never forgotten passion for mathematics, science and innovation to something that is "concrete" and "useful" for the Future Internet development.

The PHD study and research activities gave me the chance to integrate my educational background (master degree in *Mathematics* in 1990) and professional carrier (in *Telecom Italia's* group companies, since 1991) with a new experience, very important and enriching from the cultural, professional and human perspectives.

ICT Innovation, a key driver for the socio-economic development of European Countries, requires a stricter collaboration between Industries and Academies and between private and public organizations, as experienced in the most recent EU Programmes and Initiatives.

I would like to express my thanks to my Company Management and the Human Resources staff, for giving me the opportunity to collaborate with the University "La Sapienza" during this thesis work on innovative ICT topics, related to the *FutureInternet* design and development.

I would like also to thank the researchers and PHD students working in the "La Sapienza" University research group coordinated by Prof. Delli Priscoli for their collaboration on specific problems addressed in my thesis work, in particular *Antonio Pietrabissa*, *Vincenzo Suraci* and *Marco Castrucci*.

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Thesis Outline

*Chapter 1*introduces the *Future Internet* main concepts, illustrating the main limitations of the present Internet design, and presents the innovative "*cognitive approach*" proposed by the "La Sapienza" University research group working on the UE 7FP *FI-WARE project*. The FI-WAREprojectand the wider *Future Internet PPP Programme*aredescribed in Annex *(Annex A)*.

Chapter 2 expands on a possible *architecture* which could realize the above mentioned cognitive approach. In the proposed architecture, called "*Cognitive Future Internet Framework*", the key "cognitive" roles are played by the *Cognitive Enablers* (CE) and by the *Application Interface*.

*Chapter 3*proposes a possible *architecture* of the Application Interface,focusing on the key cognitive function of the Interface, that is defining proper Application requirements and solving the Quality of Experience (QoE) management problem. In the proposed architecture, called *Cognitive Application Interface* (CAI), the key role is played by the *Requirement Agents*. Each Requirement Agent has the role of dynamically selecting the most appropriate "Class of Service" to be associated to the relevant Application in order to "drive" the underlying Network Enablers to satisfy the Application Requirements and, in particular, the target *QoE* level.

Chapters 4 and *5* illustrate the theoretical framework considered in this thesis work, introducing the *Markov Decision Processes*and the *Reinforcement LearningProblem* and describing possible approaches and solutions.

Chapter 6 illustrates the proposed RL-approach for solving the QoE problem addressed in this thesis work. Itexplains why the Reinforcement Learning approach has beenfollowed, considering several alternative approaches and methods developed in *Control* and *Artificial Intelligence* fields. Then, it illustrates why the *Temporal Difference*class of RL algorithms and, in particular, why the Q-learning algorithm has beenchosen. Finally, it illustrates some hybrid solutions combining Reinforcement Learning and Games Theory (*Learning in Games*).One of these solutions (*Friend or Foe algorithm*) seems promising in terms of overcoming some limitations of the RL (Q-Learning) approach when adopted in *multi-agent systems*.

*Chapter 7*describes the *proposed solution* to implement the Cognitive Application Interface, approaching and solving the QoE problem: for the reasons illustrated in the previous chapter, itis modelled as a *Reinforcement Learning* problem where the RL Agent role is played by the Requirement Agent. The Requirement Agent is modelled as a RL Agent, with a proper*action space*and able to learn to make optimal decisions based on experience with the *Environment,* that is modelled withan appropriate *state space* and *reward function*.The RL Agent can be implemented using an appropriate *model-free* Reinforcement Learning algorithm: for the reasons explained in the previous chapter, the *Q-Learning* algorithm has been chosen.

Chapter 8 illustrates the *Quality of Service (QoS) case*, where the QoE is defined through basic QoS metrics and parameters. The general Application Interface proposed in chapter 8 is particularised in the QoS case, that is the object of the implementation and simulation phase of this thesis work.

*Chapter 9*introduces some *real network scenarios*, considering fixed and mobile access networks, and illustrates how the proposed Interface elements can be mapped on the network entities.

Chapter 10 illustrates the *implemented network scenario*, describing the simulation tool (OPNET) and illustrating the implemented Model Specification.

Chapter 11 describes the *simulated scenarios* and the main *simulation results*.Some details on the implementation (OPNET code) are provided in Annex (*Annex B*).

Chapter 12 illustrates an *alternative RL solution*, based on a two-agent system, where each Requirement Agent plays against a "Macro-Agent", incorporating all the other Requirement Agents, and "learns to act" through a *Friend or Foe* algorithm. A preliminary simulation result is also presented: it seems promising in terms of improving the RL algorithm performance.

Chapter 13 concludes the thesis, summarising the work and the results obtained, illustrating advantages and limitations of the proposed approach and solutions and giving recommendations for further improvements and*future work.*

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1. INTRODUCTION

1.1. Future Internet: a view

Future Internet design is one of the current priorities established by the UE. The EU FP7 FI-WARE project is currently trying to address the issues raised by the design of the Future Internet Core Platorm.

This chapter introduces the *Future Internet* main concepts, illustrating the main limitations of the present Internet design, and describes the innovative *cognitive approach* proposed by the "La Sapienza"University research group working on the FI-WARE project. The FI-WARE project and the wider *Future Internet PPP Programme* are described in Annex (*Annex A*).

First of all, a definition of the *entities* involved in the Future Internet, as well as of the Future Internet target, can be given as follows:

- Actors represent the entities whose requirement fulfillment is the goal of the Future Internet; for instance, Actors include users, developers, prosumers, network providers, service providers, content providers, etc.
- Resources represent the entities that can be exploited for fulfilling the Actors' requirements; example of Resources include services, contents, terminals, devices, middleware functionalities, storage, computational, connectivity and networking capabilities, etc.
- Applications are utilized by the Actors to fulfill their requirements and needs exploiting the available resource; for instance social networking, context-aware information, semantic discovery, virtual marketplace, etc.;

In the "La Sapienza" University research group vision, the Future Internet target is to allow Applications to transparently, efficiently and flexibly exploit the available Resources, aiming at achieving a satisfaction level meeting the personalized Actors' needs and expectations. Such expectations can be expressed in terms of a properly defined *Quality of Experience* (QoE), which could be regarded as a personalized function of Quality of Service (QoS), security, mobility,… parameters.

In order to achieve this target, the Future Internet should overcome the following main limitations:

(i) A *first limitation* is inherent to the traditional layering architecture which forces to keeping algorithms and procedures, lying at different layers, independent one another; in addition, even in the framework of a given layer, algorithms and procedures dealing with different tasks are often designed independently one another. These issues greatly simplify the overall design of the telecommunication networks and greatly reduce processing capabilities, since the overall problem of controlling the telecommunication network is decoupled in a certain number of much simpler sub-problems. Nevertheless, a major limitation of this approach derives from the fact that algorithms and procedures are *poorlycoordinated*, impairing the efficiency of the overall telecommunication network control. The issues above claim for a stronger coordination between algorithms and procedures dealing with different tasks.

(ii) A *second limitation* derives from the fact that, at present, most of the algorithms and procedures embedded in the telecommunication networks are *open-loop*, i.e. they are based on off-line "reasonable" estimation of network variables (e.g. offered traffic), rather than on real-time measurements of such variables. This limitation is becoming harder and harder, since the telecommunication network behaviours, due to the large variety of supported services and the rapid evolution of the service characteristics, are becoming more and more unpredictable. This claims for an evolution towards closed-loop algorithms and procedures which are able to properly exploit appropriate real-time network measurements. In this respect, the current technology developments which assure cheap and powerful sensing capabilities favour this kind of evolution.

(iii) A *third limitation* derives from the large variety of existing heterogeneous Resources which have been developed according to different heterogeneous technologies and hence embedding *technology-dependent* algorithms and procedures, as well as from the large variety of heterogeneous Actors who are playing in the telecommunication arena. In this respect, the requirement of integrating and virtualizing these Resources and Actors so that they can be dealt with in an homogeneous and virtual way by the Applications, claims for the design of a technology-independent, virtualized framework; this framework, on the one hand, is expected to embed algorithms and procedures which, leaving out of consideration the specificity of the various networks, can be based on abstract advanced methodologies and, on the other hand, is expected to be provided with proper virtualizing interfaces which allow all Applications to benefit from the functionalities offered by the framework itself.

Some initiatives towards Future Internet are trying to overcome some of the above described limitations, e.g., GENI [Ge], DARPA's Active Networks [Da], argue the need for programmability of the network components. Some other initiatives [Ch] extend this with argumentation for declarative networking, where the behavior of a network component is specified using some high-level declarative language, with a software-based engine implementing the behavior based on that specification. Further results have been achieved in [Te] where a Proactive Future Internet (PROFI) vision addresses interoperability of the network elements programmed by different organizations, and the need for flexible cooperation among network elements using semantic languages.

The most recent studies on Future Internet present only preliminary requirements [Ga] and rarely try to propose feasible layered architectures [Va].

The innovative architectural concept proposed by the "La Sapienza" University research group working on the FI-WARE project[see Ca]is illustrated in the nextparagraph, expanding ideas preliminarily introduced in [De-1] and [De-2].

The need to manage heterogeneous resources, over heterogeneous systems, requires a cognitive approach: a"*cognitive framework*",based on semantic virtualization of the main Internet entities, is proposed.

The next paragraph, outlines how the present Internet limitations can be overcome thanks to the proposed Future Internet Architecture concept, based on the so called*Cognitive Future Internet Framework,*which is a disruptive overlay, operated by semantic-aware and technology neutral *Enablers*, where the most relevant entities involved in the Internet experience converge in a homogeneous system by means of *virtualization* of the surrounding environment.

By means of dynamic *enablers* and proper *interfaces*, the Cognitive Framework can operate over heterogeneous environments, translating them into semantic-enriched homogeneous metadata.The virtualization allows the Cognitive Framework to manage the available resources using advanced, technology independent algorithms.

1.2. Future Internet Architecture concept

The concept behind the proposed Future Internet architecture, which aims at overcoming the three limitations mentioned in the previous paragraph, is sketched in Figure 1. As shown in the figure, the proposed architecture is based on a so-called "Cognitive Future Internet Framework" (in the following, for the sake of brevity, simply referred to as "Cognitive Framework") adopting a modular design based on middleware "enablers".

The enablers can be grouped into two main categories: the *Semantic Virtualization Enablers* and the *Cognitive Enablers*.

The Cognitive Enablers represent the core of the Cognitive Framework and are in charge of providing the Future Internet control functionalities. They interact with Actors, Resources and Applications through *Semantic Virtualization Enablers.*

The Semantic Virtualization Enablers are in charge of virtualizing the heterogeneous Actors, Resources and Applications describing them by means of properly selected, dynamic, homogeneous, context-aware and semantic aggregated metadata. Indeed in order to overcome the increasing heterogeneity of Future Internet, it is necessary to describe the different entities (i.e. Actors, Resources and Applications) by using a homogeneous language based on a common semantic. There already exist theoretical solutions to cope with semantic metadata handling (i.e. ontologies) and technological solutions (XML - eXtensible Markup Language, RDF - Resource Description Framework, OWL - Ontology Web Language, etc.). The use of semantic metadata allows to make an abstraction of the underlying complexity and heterogeneity. Heterogeneous network nodes, applications and user profiles can be virtualized on the basis of their homogeneous, semantic description. In order to let a new entity be an asset of the Future Internet architecture, a correspondent semantic virtualization enabler is needed in order to translate its technology dependent characteristics (e.g. information, requirements, data, services, contents…) into technology neutral, semantically virtualized ones, to be used homogeneously within the Cognitive Future Internet Framework. The other way around, the Semantic Virtualization Enablers are in charge to translate the technology independent decisions, taken within the Cognitive Future Internet Framework, into technology dependent actions which can be actuated involving the proper heterogeneous Actors, Resources and Applications.

The Cognitive Enablers consist of a set of modular, technology-independent, interoperating enablers which, on the basis of the aggregated metadata provided by the

Semantic Virtualization Enablers, take consistent control decisions concerning the best way to exploit the available Resources in order to efficiently and flexibly satisfy Application requirements and, consequently, the Actors' needs. For instance, the Cognitive Enablers can reserve network resources, compose atomic services to provide a specific application, maximize the energy efficiency, guarantee a reliable connection, satisfy the user perceived quality of service and so on.

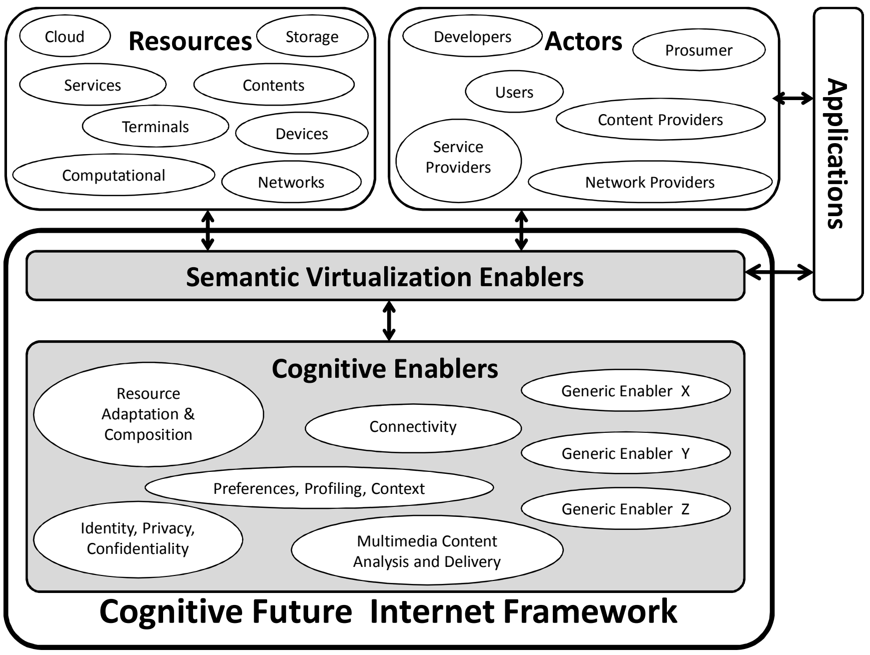


Figure 1- Proposed Cognitive Future Internet Framework conceptual architecture

Note that, thanks to the aggregated semantic metadata provided by the Semantic Virtualization Enablers, the control functionalities included in the Cognitive Enablers have a technology-neutral, multi-layer, multi-network vision of the surrounding Actors, Resources and Applications. Therefore, the information enriched (fully cognitive) nature of the aggregated metadata, which serve as Cognitive Enabler input, coupled with a proper design of Cognitive Enabler algorithms (e.g. multi-objective advanced control and optimization algorithms), lead to cross-layer and cross-network optimization.

The Cognitive Framework can exploit one or more of the Cognitive Enablers in a dynamic fashion: so, depending on the present context, the Cognitive Framework activates and properly configures the needed Enablers. In this respect,a fundamental Cognitive Enabler, namely the so-called *Orchestrator* has the key role of dynamically deciding for each application instance, consistently with its requirements and with the present context, the Cognitive Enablers which have to be activated to handle the application in question, as well as their proper configuring and activation/deactivation timing.

In each specific environment, the Cognitive Framework functionalities have to be properly distributed in the various physical network entities (e.g. Mobile Terminals, Base Stations, Backhaul network entities, Core network entities). The selection and the mapping of the Cognitive Framework functionalities in the network entities is a critical task which has to be performed case by case by adopting a transparent approach with respect to the already existing protocols, in order to favour a smooth migration.

It should be evident that the proposed approach allows to overcome the three above-mentioned limitations:

(i) Concentrating control functionalities in a single Cognitive Framework makes much easier to take consistent and coordinated decisions. In particular, the concentration of control functionalities in a single framework allows the adoption of algorithms and procedures *coordinated* one another and even jointly addressing in a one-shot way, problems traditionally dealt with in separate and uncoordinated fashion.

(ii) The fact that control decisions can be based on properly selected, aggregated metadata describing, in real time, Resources, Actors and Applications allows *closed-loop* control, i.e. networks become *cognitive*, as further detailed in the next chapter.

(iii) Control decisions, relevant to the best exploitation of the available Resources can be made in a *technology independent* and *virtual* fashion, i.e. the specific technologies and the physical location behind Resources, Actors and Applications can be left out of consideration.In particular, the decoupling of the Cognitive Framework from the underlying technology transport layers on the one hand, and from the specific service/content layers on the other hand, allows to take control decisions at an abstract layer, thus favouring the adoption of advanced control methodologies, which can be closed-loop thanks to the previous issue. In addition, interoperation procedures among heterogeneous Resources, Actors and Applications become easier and more natural.

2. *COGNITIVE FRAMEWORK ARCHITECTURE*

The Cognitive Framework introduced in the previous chapter is a *distributed framework* which can be realized through the implementation of appropriate *Cognitive Middleware-based Agents* (in the following referred to as ***Cognitive Managers***) which will be transparently embedded in properly selected physical network entities (e.g. Mobile Terminals, Base Stations, Backhaul Network entities, Core Network entities).

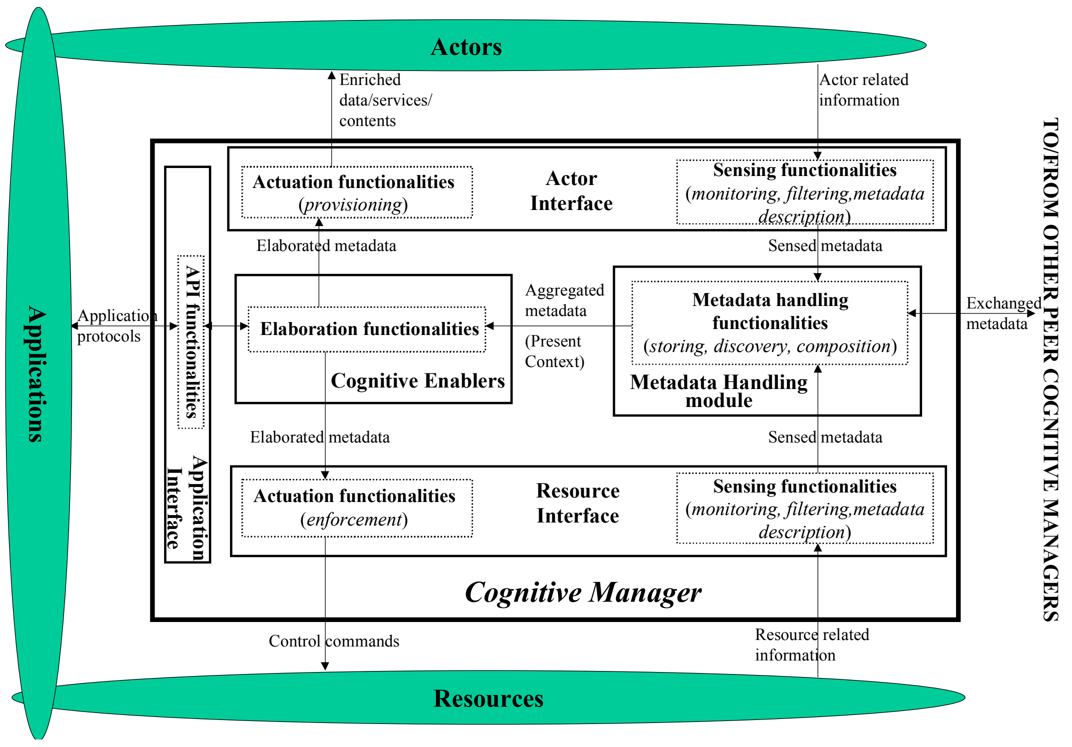
The proposed conceptual framework cannot be mapped over an existing telecommunication network in a unique way. Indeed, the software nature of the Cognitive Manager allows a transparent integration in the network nodes. It can be deployed installing a new firmware or a driver update in each network element. Once the Cognitive Manager is executed, that network node is enhanced with the future internet functionalities and becomes part of the Future Internet assets.

2.1. The Cognitive Manager

Figure 2 outlines the high-level architecture of a generic Cognitive Manager, showing its interfacing with Resources, Actors and Applications: these last show a certain degree of overlapping with Resources and Actors since, for instance, services, depending on their roles, can be included both in Applications and in Resources; likewise, providers, depending on their roles, can be included both in Applications and in Actors.

Figure 2 also highlights that a Cognitive Manager will encompass five high-level functionalities, namely the Sensing, Metadata Handling, Elaboration, Actuation and API (Application Protocol Interface) functionalities. The Sensing, Actuation and API functionalities are embedded in the equipment interfacing the Cognitive Manager with the Resources (*Resource Interface*), with the Actors (*Actor Interface*) and with the Applications (*Application Interface*); these interfaces must be tailored to the peculiarities of the interfaced Resources, Actors and Applications.

The Metadata Handling functionalities are embedded in the so-called *Metadata Handling module*, whilst the *Elaboration functionalities* are distributed among a set of *Cognitive Enablers*. The Metadata Handling and the Elaboration functionalities (and in particular, the Cognitive Enablers which are the core of the proposed architecture) are independent of the peculiarities of the surrounding Resources, Actors and Applications.



Actors
Applications
Resources
Enriched data/services/ contents
Actor related information
Actuation functionalities (provisioning)
Actor Interface
Sensing functionalities (monitoring, filtering,metadata description)
Elaborated metadata
Sensed metadata
Application protocols
API functionalities
Application Interface
Elaboration functionalities
Cognitive Enablers
Aggregated metadata
(Present Context)
Metadata handling functionalities (storing, discovery, composition)
Metadata Handling module
Exchanged metadata
TO/FROM OTHER PEER COGNITIVE MANAGERS
Elaborated metadata
Sensed metadata
Actuation functionalities (enforcement)
Resource Interface
Sensing functionalities (monitoring, filtering,metadata description)
Cognitive Manager
Control commands
Resource related information

Figure 2 - Cognitive Manager architecture

With reference to Figure 1, the Sensing, Metadata Handling, Actuation and API functionalities are embedded in the Semantic Virtualization Enablers, while the Elaboration functionalities are embedded in the Cognitive Enablers.

The roles of the above-mentioned functionalities are the following:

1. *Sensing functionalities* are in charge of (i) the *monitoring* and preliminary *filtering* of both Actor related information coming from service/content layer (Sensing functionalities embedded in the Actor Interface) and of Resource related information (Sensing functionalities embedded in the Resource Interface); this monitoring has to take place according to transparent techniques, for example by means of the use of passive monitoring agents able to acquire information about the Resources (e.g., characteristic of the device, network performances, etc.) and about the Actors (e.g., user's profile, network provider policies, etc.), (ii) the formal description of the above-mentioned heterogeneous parameters/data/services/contents in homogeneous metadata according to proper ontology based languages (such as OWL);

2. *Metadata Handling functionalities* are in charge of the storing, discovery and composition of the metadata coming from the sensing functionalities and/or from metadata exchanged among peer Cognitive Managers, in order to dynamically derive the aggregated metadata which can serve as inputs for the Cognitive Enablers; these

aggregated metadata form the so-called *Present Context*;it is worth stressing that such Present Context has an highly dynamic nature;

3. *Elaboration functionalities* are embedded in a set of Cognitive Enablers which, following the specific application protocols and having as key inputs the aggregated metadata forming the Present Context, produce *elaborated metadata*to be provided to the Interfaces, aiming at (i)controlling Resource exploitation, (ii) providing enriched data/services/contents, (iii) providing to the Interfaces information allowing to properly drive and configure the API, Sensing and Actuation functionalities (these last control actions, for clarity reasons, are not represented in Figure 2);
4. *Actuation functionalities* are in charge of (i) proper translation in technology-dependent commands of the decisions concerning Resource exploitation and enforcement of these commands into the involved Resources (*Enforcement functionalities* embedded in the Resource Interface; see Figure 2); the enforcement has to take place according to transparent techniques, (ii) proper translation in technology-dependent terms of the data/services/contents elaborated by the Cognitive Enablers and provisioning of these enhanced data/services/contents to the right Actors (*Provisioning functionalities* embedded in the Actor Interface; see Figure 2).
5. *API functionalities* are in charge of interfacing the protocols of the Applications, managed by the Actors, with the Cognitive Enablers. In particular, these functionalities, also on the basis of proper elaborated metadata received from the elaboration functionalities, should derive "cognitive" *Application requirements* (as detailed in the following Chapter).

2.2. Potential advantages

The proposed approach and architecture have potential advantages which are hereinafter outlined in a qualitative way:

Advantages related to effectiveness and efficiency

(1) The Present Context, which is the key input to the Cognitive Enablers, includes multi-Actor, multi-Resource information, thus potentially allowing to perform the Elaboration functionalities availing of a very "rich" *feedback* information.

(2) The proposed architecture (in particular, the technology independence of the Elaboration functionalities, as well as the valuable input provided by the Present

Context) allows to take all decisions in a cognitive, abstract, coordinated and cooperative fashion within a set of strictly cooperative Cognitive Enablers. So, the proposed architecture allows to pass from the traditional layering approach (where each layer of each network takes uncoordinated decisions) to a scenario in which, potentially, all layers of all networks benefit from information coming from all layers of all networks, thus, potentially, allowing a full *cross-layer*, *cross-network optimization*, with a remarkable expected performance improvement.

(3) The rich feedback information mentioned in the issue (1), together with the technology independence mentioned in the issue (2), allow the adoption of innovative and abstract *closed-loop* methodologies (e.g. adaptive control, robust control, optimal control, reinforcement learning, constrained optimization, multi-object optimization, data mining, game theory, operation research, etc.) for the algorithms embedded in the Cognitive Enablers, as well as for those embedded in the Application Interface. These innovative algorithms are expected to remarkably improveboth performance and efficiency.

Advantages related to flexibility

(4) Thanks to the fact that the Cognitive Managers have the same architecture and work according to the same approach regardless of the interfaced heterogeneous Applications/Resources/Actors, *interoperation* procedures become easier and more natural.

(5) The transparency and the middleware (firmware based) nature of the proposed Cognitive Manger architecture makes relatively easy its embedding in any fixed/mobile network entity (e.g. Mobile Terminals, Base Station, Backhaul network entities, Core network entities): the most appropriate network entities for hosting the Cognitive Manager functionalities have to be selected environment by environment. Moreover, the Cognitive Manager functionalities (and, in particular, the Cognitive Enabler software) can be added/upgraded/deleted through *remote* (wired and/or wireless) *control*.

(6) The modularity of the Cognitive Manager functionalities allows their ranging from very simple SW/HW/computing implementations, even specialized on a single-layer/single-network specific monitoring/elaboration/actuation task, to complex multi-layer/multi-network/multi-task implementations

(7) Thanks to the flexibility degrees offered by issues (4)-(6), the Cognitive Managers could have the same architecture regardless of the interfaced Actors, Resources and Applications. So, provided that an appropriate tailoring to the considered environment is performed, the proposed architecture can actually *scale* from environments characterized by few network entities provided with high processing capabilities, to ones with plenty of network entities provided with low processing (e.g. *Internet of Things*).

The above-mentioned flexibility issues favours a *smooth migration* towards the proposed approach. As a matter of fact, it is expected that Cognitive Manager functionalities will be gradually inserted starting from the most critical network nodes, and that control functionalities will be gradually delegated to the Cognitive Modules.

Summarizing the above-mentioned advantages, we propose to achieve Future Internet revolution through a *smooth evolution*. In this evolution, Cognitive Managers provided with properly selected functionalities are gradually embedded in properly selected network entities, aiming at gradually replacing the existing open-loop control (mostly based on traditional uncoordinated single-layer/single-network approaches), with a cognitive closed-loop control trying to achieve cross-optimization among heterogeneous Actors, Applications and Resources. Of course, careful, environment-by-environment selection of the Cognitive Manager functionalities and of the network entities in which such functionalities have to be embedded, is essential in order to allow scalability and to achieve efficiency advantages which are worthwhile with respect to the increased SW/HW/computing complexity.

3. APPLICATION INTERFACE ARCHITECTURE

3.1. Introduction

The architecture outlined in the previous sections highlights the key importance of the *Interfaces* which, using as key input properly elaborated metadata, should be in charge of:

(i)properly selecting the heterogeneous information which is worthwhile to be monitored and translating it in homogeneous metadata (*sensing* functionalities),

(ii) properly translating in technology-dependent commands the decisions concerning Resource exploitation and enforcing these commands into the involved Resources (*actuation/enforcement* functionalities),

(iii) properly translating in technology-dependent terms the data/services/contents elaborated by the Cognitive Enablers and providing these enhanced data/services/contents to the appropriate Actors (*actuation/provisioning* functionalities)

(iv) deriving proper "cognitive" Application requirements (*API* functionality).

This Chapter elaborates on this last role (iv) which will be performed by the Application Interface and which, as explained in the following, introduces in the proposed architecture a further important “cognition” level (in addition to the one of the Cognitive Enablers); this is the reason why, in the following, we will talk about a "*Cognitive Application Interface*".

At present, at each *micro-flow* supporting a given Application instance *a* (in the following, for the sake of brevity, when referring to an "Application *a*", we mean an "Application instance *a*") is *statically* associated (statically, means for the whole application duration) a *Service Classk*(*a*), properly selected in the predefined set of Service Classes which the considered network supports. The various network procedures are in charge of guaranteeing to each Service Class a pre-defined performance level.

This approach has the inconvenient that, on the one hand, due to the very different personalized Application QoE Requirements, in general, no Service Class perfectly fits a given application, and, on the other hand, the static association between Applications and Service Classes prevents the possibility to adapt to network traffic variations. In addition, the fact that, at present, network control takes place on a *per-flow* basis, rather than on a *per-microflow* basis, entails further problems related to control granularity.

In order to overcome these inconveniences, a *dynamic* association between Applications and Service Classes is proposed: so, the Cognitive Application Interface, on the basis of proper feedback information accounting for the present network traffic situation, is in charge of selecting, at each time t_s, for each microflow supporting a given Application a the most appropriate Service Class, aiming at satisfying personalized Application QoE Requirements.

3.2. Key concepts underlying the Cognitive Application Interface

First of all, it is necessary to introduce appropriate *metrics* related to the micro-flows supporting the Applications. These metrics should refer to all the *factors* which can concur in the QoE definition (e.g. QoS, security, mobility,…).

Application QoE Requirementsshould be based on these metrics.

The parameters should (i) be useful for assessing the Application QoE, (ii) be technology independent, (iii) be so general as to encompass all kinds of possible Applications, (iv) be complex enough to reflect all possible Application requirements, but simple enough for not introducing useless complexity in the Cognitive Enablers which have to manage them, (v) be,as far as possible, easily monitored by the Sensing functionalities.

Each in-progress *microflow*[1] is associated to a **Service Class**. Traditionally, this association is *static* (i.e. it just depends on the nature of the established micro-flow and it does not vary during the microflow lifetime) and is made on a *per flow* basis. On the contrary, in the proposed Cognitive Application Interface, this association will be *dynamic* (i.e. it can be varied at each time instant t_s): this entails remarkable advantages as explained in the following.

As mentioned, according to the most recent trends, *network control* (as far as QoS, security, mobility,... are concerned) is typically performed on a *per-flow basis*.

Let k denote the generic Service Class and K denote the total number of Service Classes. As known, a *Flow* refers to the packets entering the network at a given ingoing

[1]By microflow we mean a flow of packets relevant to a given application and having the same requirements (for instance, a bidirectional teleconference application taking place between two terminals A and B, is supported by 4 microflows, i.e. an audio microflow from A to B, a video microflow from A to B, an audio microflow from B to A, a video microflow from B to A).

node $n \in N$, going out of the network at a given outgoing node $m \in N$, and relevant to in-progress connections associated to a given Service Class $k \in K$.

Each flow f is characterized by a set of *Flow Requirements*related to *QoS, Security, Mobility, etc.*.Note that the fact that each Flow (and not just each single micro-flow) is subject to a set of Flow Requirementslimits the complexity of the Elaboration functionalities, since these functionalities have to operate on a *per-flow* basis, rather than on a *permicro-flow* basis; in this respect, a given flow can aggregate many micro-flows. This issue is essential for guaranteeing *scalability*.

In the following, without loss of generality, we assume to refer to given ingoing and outgoing nodes, so that we can deal with a set of **Service Class Requirements**making reference to a set of **Service Class Parameters** identified by the selected metrics and to a set of **Service Class Reference Values**which characterize the Service Class in question.For instance, in the *QoS case*, we propose the Service Class Requirements, Parametersand Reference Values as defined in Chapter 8.

A key goal of the Elaboration functionalities included in the Cognitive Managers is to control the available Resources in such a way that, for each Service Class *k,* the associated Service Class Requirements are respected.

As mentioned above, in order to limit the complexity of the Elaboration functionalities, which is essential for guaranteeing scalability, a *limited* set of Service Classes should be foreseen.

For the sake of clearness, in the following, we will refer to the case in which an Application is supported by just *one micro-flow*: as detailed in the next paragraph, we can refer to this case without loss of generality.

At present, the *mapping* between Service Classes and Applications is *statically* performed: this means that a given Application is permanently associated a given Service Class, namely the one whose Service Class Requirements are expected, on average traffic conditions, to better ”approach” the Application QoE Requirements.

The traditional static approach could be very limiting due to the following reasons:

(A) considering the very large amount of possible different Application QoE Requirements, the QoE requirements of a given Application will not be, in general, satisfied by any Service Class. Even more, the Application QoE Requirements can even make reference to parameters not included in any set of Service Class Parameters;

(B) the fact that network control is performed on a per-flow basis rather than on a per-microflow basis can penalize some applications;

(C) the most appropriate mapping among Service Classes and Applications should vary depending on the performance actually offered by the Service Classes which could differ from the expected one due to various reasons (e.g. unexpected traffic peaks relevant to some Service Classes, low performances of the Elaboration functionalities, etc.).

The proposed solution intends to overcome the above-mentioned limitationsthanks to a *dynamic association* between Applications and Service Classes.As a matter of fact, the Cognitive Application Interface has the key role of *dynamically* selecting, on the basis of properly selected feedback variables, the most appropriate Service Classes which should be associated to the microflow supporting each Application instance (by "dynamical", we mean that the selection will vary while the Application is in progress).

The key criterion underlying the above-mentioned dynamical selection is to approach, as far as possible, a performance level meeting the personalized Application QoE Requirements.

Up to the author's knowledge, in the literature, different*QoE models* have been proposed, following a ***passive****network-centric* approach (with QoE “passively” measured from QoS or other network-based parameters), an ***active****user-centric* approach (with QoE “actively” derived gathering the user satisfaction) or a *combination* of them.The QoE definition is a very critical and challenging task, because the “real” user experience is highly *subjective* and dynamic.

In this respect, the approach followed in this thesis work is based on defining the **Application QoE Requirements** by providing:

1) **a QoE function h_a** allowing to compute for a given Application a, at each time instant t_s[2], on the basis of a set of values assumed, at time t_s (and/or at times prior

[2]We assume that network control takes place at time instants t_s periodically occurring with period T_s(i.e. $t_{s+1}= T_s+t_s$); the period T_s has to be carefully selected trading-off the contrasting requirement of more frequently changing the Service Classes supporting the Applications (which allows a better fitting among the

to $t_{s)}$, by properly selected *feedback variables*$\Theta(t_s,a)$, the *Measured QoE,* experienced by the Application *a,* hereinafter indicated as $QoE_{meas}(t_s,a)$:

$QoE_{meas}(t_s,a) = h_a(\Theta(t_s,a))$

2) **a target reference QoE** level, hereinafter indicated as $\boldsymbol{QoE_{target}(a)}$, whose achievement entails the satisfaction of the Actor using the Application *a.* This means that if $QoE_{meas}(t_s,a) \geq QoE_{target}(a)$the Actor in question is “satisfied”.

Note that the above-mentioned way of dealing with the Application QoE Requirements has the key advantage of being extremely *flexible* since it leaves completely open the QoE definition, allowing its *tailoring* to the specific environments and application types.

Note that even the feedback variables $\Theta(t_s,a)$ can be flexibly selected depending on the considered environment. They can be simply a proper subset of the Present Context; alternatively, they can be deduced by specific Elaboration functionalities by a proper processing of the Present Context.

For instance, the feedback variables $\Theta(t_s,a)$ can consist of proper metadata representing QoS/security/mobility performance measurements (e.g. delay or BER measurements); following an active user-centric approach, also *feedbacks* directly provided by the users can be considered.

We can now define the following ***error function***:

$e(t_s,a) = QoE_{meas}(t_s,a) - QoE_{target}(a)$

If the above-mentioned error is *negative*,at time t_s, the Actor using the Application *a* is experiencing a not satisfactory QoE (*underperforming application*). If the above-mentioned error is *positive*,at time t_s, the Actor using the Application *a* is experiencing a QoE even better than expected (*overperforming application*). Note that this last situation is desirable only if the network is idle; conversely, if the network is congested, the fact that a given Application *a* is overperforming is not, in general, desirable, hence it can happen that such

achieved Application performance and the expected ones), with the requirement of limiting the complexity of the Cognitive Application Interface (a more frequent updating means more demanding interface processing capabilities).

Application is subtracting valuable resources to another application a' which is underperforming.

In light of the above, the Cognitive Application Interface should *dynamically*determine, for each Application a,on the basis of (i) the monitoring of properly selected feedback variables $\Theta(t_s,a)$, and of (ii) the personalized Application QoE Requirements (expressed in terms of the function $h_a$and of the reference value $QoE_{target}(a)$), the most appropriate *Service Class*$k(t_s,a)$ to be associated to the microflow supporting the Application in question.

The *goal* of the above-mentioned dynamical selection is to avoid, as far as possible, the presence of underperforming applications from the achieved QoE point of view; in case this is not possible (e.g. due to a network congestion), the dynamical selection in question should aim at guaranteeing fairness among applicationsfrom the QoE point of view (e.g. the fact that a given application a should reach its $QoE_{target}(a)$ must not be got at the expenses of another application a' going away from its $QoE_{target}(a')$). More precisely, the dynamical selection in question should aim at minimizing the *errore*(t_s,a) for all the Applications simultaneously in progress at time t_s.

It is worth stressing that the above-mentioned Cognitive Application Interface task is performed on the basis of selected feedback variables, which means that the Application Interface becomes *cognitive*: this introduce in the proposed architecture a further level of cognition, in addition to the one guaranteed by the Cognitive Enablers embedded in the Elaboration functionalities.

It is fundamental also to stress that the proposed Cognitive Application Interface can be used in conjunction with any type of Enablers (regardless of the fact that such Enablers are cognitive or not) and these last can continue to operate according to their usual way of working. As a matter of fact, the proposed Cognitive Application Interfaceintroduces the "cognition" concept in a way which is completely decoupled from the Elaboration functionalities and from the possible presence of Cognitive Enablers within these last functionalities. In other words, thanks to the Cognitive Application Interface, the whole Future Internet Framework becomes closed-loop (i.e. cognitive) regardless of the actual way of working of the Enablers, which can be either *open* or *closed loop*.

Even more, the introduction of a Cognitive Application Interface is completely transparent with respect to the other Cognitive Manager modules, i.e. its insertion does not entail any modification of these last modules.

It is worth noting that the Cognitive Application Interface, by selecting a given Service Class for a given Application a, implicitly selects the associated *Service Class Requirements*; in this respect, remind that the (Cognitive) Enablers are in charge of driving Resource exploitation so that these Service Class Requirements are satisfied. If the (Cognitive) Enablers do not satisfactory perform their tasks, or, more in general, if the (Cognitive) Enabler way of accomplishing their task is not satisfactory from the QoE point of view, the Cognitive Application Interface should recognize such situation through the monitored feedback variables and accordingly react, re-arranging Service Class selection.In this sense, the Cognitive Application Interface can even remedy to possible (Cognitive) Enablers deficiencies.

It is worth stressing that the presented *dynamic* approach allows to overcome the above-mentioned limitations of the *static* one, due to the following reasons:

(A) the proposed approach allows to establish a plenty of different Application QoE Requirements (thanks to the fact that the function h_a is general); these requirements can even make reference to parameters not included in any set of Service Class Parameters(thanks to the fact that the feedback variables $\Theta(t_s,a)$ are general);

(B) the fact that each Application can have its own Application QoE Requirements (which is implicit in the Application QoE Requirement definition) entails a per-microflow control;

(C) a proper selection of the feedback variables entails the fact that the Cognitive Application Interface is able to perceive possible QoE performance impairments and should properly react.

Clearly, all the above-mentioned desirable features are achieved only if the dynamical selection of the most appropriate Service Class $k(t_s,a)$ is properly performed.

The proposed approach for performing this very complex task is based on the implementation, at the Cognitive Application Interface, of appropriate *closed-loopcontrol* and/or *reinforcementlearning* methodologies.

3.2.1. Applications supported by more than one microflow

In general, each Application a is supported by more than one microflow: let c_1, c_2,…, c_A denote the A microflows supporting the Application a.

Let $QoE_{target}(c_i)$ i=1,…,A denote the *Target Microflow Quality of Experience (QoE)* of the i-thmicroflow supporting the Application a. Such Target Microflow QoEs are defined so that achieving the target QoE for all the connections supporting a given Application a entails that the *Target Application QoE*, i.e. $QoE_{target}(a)$, is achieved.Let $QoE_{meas}(t_s,c_i)$ i=1,…,A denote the *Measured Microflow Quality of Experience(QoE)* of the i-thmicroflowsupporting the Application a, at time t_s (i.e. the QoE of the microflow c_i actually achieved at time t_s).

The target of the Cognitive Application Interface is to make an appropriate control so that $QoE_{meas}(t_s,c_i)$ approaches, as much as possible, $QoE_{target}(c_i)$ for any i=1,…,A, thus entailing that the *Measured Application QoE*, indicated as $QoE_{target}(a)$, approaches the Target Application QoE, i.e. $QoE_{target}(a)$.

Let h_{c_i} denote the personalized function allowing the computation of the Measured Microflow QoE relevant to the microflow c_i (namely, one the microflows supporting the Application a) on the basis of the feedback variables, i.e.:

$$QoE_{meas}(t_s,c_i) = h_{c_i}(\Theta(t_s,a))$$

Let g_a denote the personalized function allowing the computation of the Measured Application QoE on the basis of the Measured QoEs of the supporting microflows, i.e.:

$$QoE_{meas}(t_s,a) = g_a(QoE_{meas}(t_s,c_1), QoE_{meas}(t_s,c_2),\ldots, QoE_{meas}(t_s,c_A))$$

Note that, by construction:

$$QoE_{target}(t_s,a) = g_a(QoE_{target}(t_s,c_1), QoE_{target}(t_s,c_2),\ldots, QoE_{target}(t_s,c_A))$$

since, as previously stated, the target microflow QoEs are selected so that achieving the target QoE for all the microflows supporting a given Application *a* entails that the Target Application QoE, i.e. $QoE_{target}(a)$, is achieved.

In order to achieve the Target Application *a* QoE, it is sufficient to achieve the TargetQoE for all microflows c_i i=1,…,A supporting the Application *a.*This issue allows to decompose the problem of achieving the overall QoE for the Application *a* in *A* independent sub-problems each one referring to a supporting microflow c_i. This, in turn, allows to refer, in the following of this document, to an Application *a* with just a single microflow, without any loose of generality, thus also allowing a great simplification of the notations which can directly refer to the application *a* instead of to the supporting microflows. So, in the following, without loose of generality, we will simply refer to the problem of dynamically selecting the most appropriate Service Class associated to the Application *a* (more precisely, the most appropriate Service Class associated to the single microflow supporting the Application *a*).

3.3. Cognitive Application Interface architecture

The proposed Cognitive Application Interface architecture of a given Cognitive Manager is shown in Fig. 3, which is conceived as the explosion of the Application Interface block appearing in Fig. 2.

The architecture is organized according to a number of *Application Agents*which are embedded in the Cognitive Managers:each in progress Application *a* has its own Application Agent.

In other words, at a given time, the number of Application Agents is equal to the number of in progress Applications; this means that at each Application set-up a new Application Agent is created and at each Application termination the relevant Application Agent is deleted.

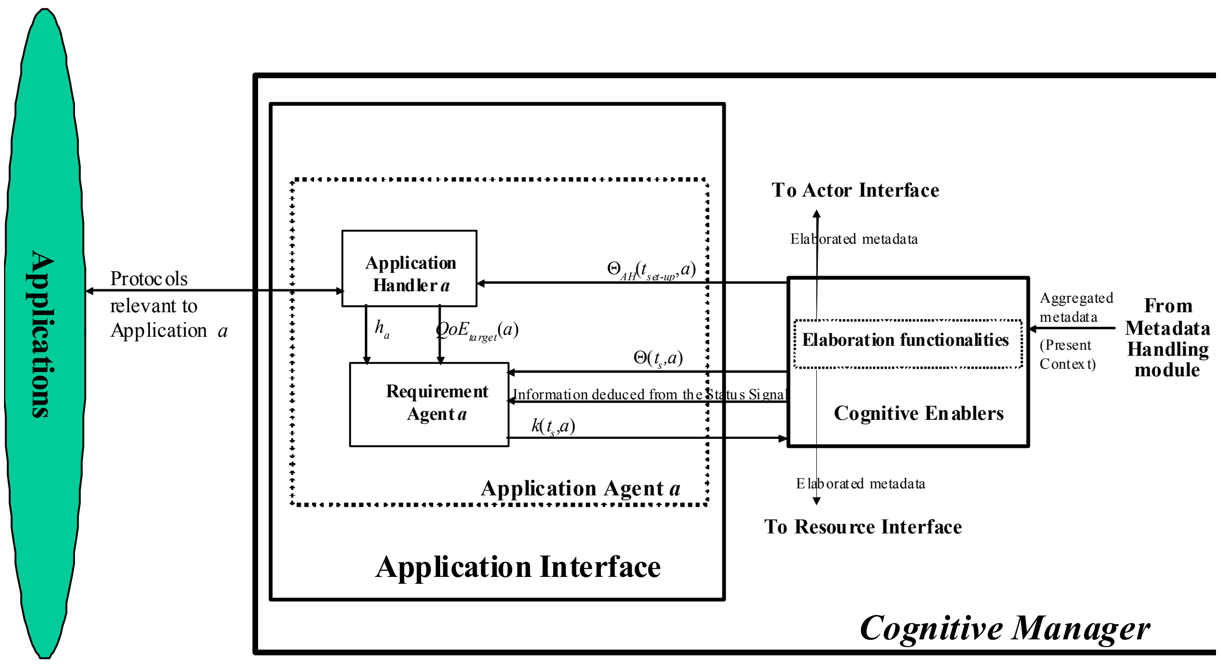


Figure 3 - Application Interface Architecture

Figure 3, for the sake of clarity, just shows a single Application Agent, namely the one relevant to the Application *a*, which, in the following, for the sake of brevity, will be simply referred as Application Agent *a*.

The Application Agent *a* consists of two *modules*: the so-called *Application Handlera* and the *Requirement Agenta* (see Fig.3).

The role of these entities (further detailed in the following) is as follows:

- the *Application Handlera* is in charge of interworking with the Application protocols in order to deduce, at the application set-up time,the function h_a and the target reference QoE level $QoE_{target}(a)$characterizing the Application *a* (see paragraph 3.3.1 for further details);
- the *Requirement Agenta* is in charge of dynamically selecting, at each time t_s, the most appropriate Service Class which should be associated to the microflow supporting the Application *a* (see paragraph 3.3.2 for further details).

It is important noting that, in general, the Application Handlers andthe Requirement Agentsrelevant to the various Applications can be included in Cognitive Managers embedded in network entities (e.g. Base Stations, Mobile Terminals, etc.) which can be placed at different physical, fixed or mobile, locations. The appropriate mapping of the above-mentioned Handlers/Agents in the network entities is a delicate task which have to be performed environment-by-environment; some instances of such mapping are provided in Chapter 9.

In this respect, it is fundamental stressing that a key requirement of the conceived architecture is *scalability* which can be assured, in consideration of the plenty of Applications simultaneously in progress in a considered network, only imposing that the signalling exchanges among Application Handlers,Requirement Agents and Supervisor Agent must be kept limited: otherwise, the network will be overwhelmed by the signalling overhead.

In particular, the Requirement Agents, which are in charge of dynamic tasks, should perform their decisions independently one another, without exchanging information one another. Clearly, this issue entails a very complex problem of *coordination* among the Requirement Agents of the considered network, since a Requirement Agent has to take decisions which impact on the utilization of Resources shared with other Requirement Agents without knowing the decisions taken by these last. In this respect, note that a Requirement Agent relevant to a given Application, by selecting, at a time t_s, a given Service Class for the micro-flow supporting the Application, also automatically selects the correspondent Service Class Requirements, whose satisfaction from the Elaboration functionalities entails the use of the network Resources shared with other Applications.

The proposed approach for coping with this very difficult task is to foresee a single Supervisor Agent in charge of making easier the coordination among Requirement Agentsby broadcasting, on a semi-real-time basis, a proper *Status Signal* accounting for the present overall network status (see paragraph 3.3.3 for further details).

The Supervisor Agent is not necessarilyembedded in a Cognitive Manager: it can just consists of a stand-alone equipment. In general, in a given network several Cognitive Managers and just one Supervisor Agent are present.

The presence of the above-mentioned broadcast Status Signal entails the presence of a certain signalling overhead. Nevertheless, the amount of such overhead can be kept rather limited thanks to the fact that:

- the signalling communication only occurs from the Supervisor Agent to the Application Agents, i.e. one-to-many, and no communication is foreseen from the Application Agents to the Supervisor Agent;
- the status signal only includes general network status information (i.e. not being tailored to the various Applications in progress); this means that a same Status Signal information is useful for many Application Agents;
- the Status Signal is sent only at times $t_l$periodically occurring with period T_l, with $T_l >> T_s$, i.e. according to a much slower time scale with respect to the real-time computations performed by the Application Agents. The period $T_l(T_l= t_{l+1}-t_l)$ has to be carefully selected trading-off the contrasting requirements of keeping the signalling overhead limited and of guaranteeing a timely update of the Status Signal.

3.3.1. Application Handler

The Application Handler a is in charge of *static* tasks, i.e. not real-time tasks which, in general, are performed just at the application set-up time, hereinafter denoted as $t_{set-up}(a)$.

The Application Handler is in charge of deducing the Application QoE Requirements, i.e.:

(i) the target reference QoE level, i.e. $QoE_{target}(a)$;

(ii) the personalized function h_a allowing to compute the Measured QoE$QoE_{meas}(t_s,a)$ on the basis of the feedback variables $\Theta(t_s,a)$.

The above-mentioned parameters serve as fundamental inputs for the Requirement Agent a (see Fig. 3).

The Application Handler a deduces the above-mentioned parameters on the basis of:

(i) its interaction with the peculiar protocols relevant to the Application a which allow the Application Handler to perceive the Application type;

(ii) the values assumed at connection set-up time $t_{set-up}(a)$ by a proper set of parameters $\Theta_{AH}(t_{set-up},a)$ consisting of a proper subset of the Present Context relevant to the Actor setting-up the Application a. As a matter of fact, the Application QoE Requirements depend both on the Application type and on the context surrounding the Actor setting-up the Application.

In practice, the Application Handler *a* can be realized through a simple look-up table mapping the possible Application types and some parameters describing the context relevant to the Actor setting-up the Application, with the parameter$QoE_{target}(a)$ and the function h_a.

3.3.2. Requirement Agent

The Requirement Agent is the actual *core* of the Cognitive Application Interface.

The Requirement Agent *a* is in charge of a *dynamic* task, i.e. a real-time task which is periodically performed at times t_s, periodically occurring with a period $T_s$which is expected to be much lower than the Application lifetime.

The Requirement Agent *a* is in charge of selecting, at each time t_s, the most appropriate Service Class, hereinafter indicated as $k(t_s,a)$ which should be associated to the micro-flow supporting the Application *a* (see Fig. 3).

The Requirement Agent *a* deduces $k(t_s,a)$ on the basis of (see Fig. 3):

(i) the Target Application QoE, i.e. $QoE_{target}(a)$ (input from the Application Handler *a*);

(ii) the personalized function h_a (input from the Application Handler *a*);

(iii) the values assumedby the feedback variables $\Theta(t_s,a)$ computed on the basis of *local* information monitored at the Cognitive Manager hosting the Requirement Agent *a;*

(iv) the Status Signal$ss(t_l)$ transmitted by the Supervisor Agent (see paragraph 4.4.3 for further details).

It is worth noting that the above-mentioned inputs to the Requirement Agent are of different nature: the inputs (i) and (ii) are *static* in the sense that are transmitted from the Application Handler to the Requirement Agent only at Application set-up and are not varied during the application lifetime. Conversely, the inputs (iii) and (iv) are *dynamic*, i.e. are continuously updated during the Application lifetime: nevertheless, the updating relevant to the input (iii) periodically occurs at times t_s with period T_s while the updating relevant to the input (iv) periodically occurs at times $t_l$with period T_l, i.e., since T_l>>T_s the former updates are much more frequent than the latter ones. As already explained, this is due to the fact that the input (iii) derives from parameter monitoring locally performed at the Requirement Agent, i.e. they do not need to use bandwidth for being transmitted; conversely, the input (iv) derives from parameter monitoring performed at the Supervisor Agent of the considered network, i.e. the broadcasting of such inputs waste bandwidth and hence the relevant update frequency has to be limited.

Moreover, note that, as shown in Fig. 3, conceptually, the inputs (iii) and (iv) arrive at the Requirement Agent from the Elaboration functionalities. Nevertheless, the task of these functionalities is expected to be just limited to the forwarding of properly selected measurements performed by the sensing functionalities (possibly, abstracted in metadata by the Metadata Handling functionalities) carried out at the Requirement Agent and at the Supervisor Agent.

Finally, note that the "cognition" characteristic of the Cognitive Application Interface, i.e. the closed-loop nature of the whole requirement identification system, just derives from the fact that the Requirement Agent can avail of the feedback dynamic inputs (iii) and (iv).

An appropriate way for exploiting this input is to embed in the Requirement Agent a proper *closed-loop control*and/or *reinforcementlearning* algorithm, having the fundamental role of dynamically selecting, at each time t_s, on the basis of the inputs (i),…,(iv), the most appropriate Service Classes; in other words, for each Application *a,* it has to select $k(t_s,a)$.

3.3.3. Supervisor Agent

The Supervisor Agent (in general, just one Supervisor Agent is present in the considered network) has the role of making easier coordination among the Requirement Agents. Such coordination is assured by periodically broadcasting, at time s t_l, a so-called *Status Signal*, indicated as $ss(t_l)$, including proper measurements related to the overall network situation. So, as shown in Fig. 3, the various Requirement Agents are fed with information deduced from the Status Signal. In this respect, note that the Status Signal can be pre-elaborated by the Elaboration functionalities, in order to extract the information which serve as input for the Requirement Agents.

It is important noting that the various Requirement Agents, being fed with information coming from a same Status Signal, can have a same vision of the present network situation.

This issue allows the algorithms embedded in the various Requirement Agents to avail of a common input: this makes much easier for them to take consistent decisions in spite of the fact that they do not exchange signalling information each another.

In the proposed approach the Supervisor Agent is a *passive* equipment in the sense that it does not take part in the decision process relevant to the Service Class selection, which is completely demanded to the algorithm embedded in the Requirement Agents. As a matter of fact, the Supervisor Agent has just to properly collect, format and broadcast appropriate measurement parameters.

The alternative solution in which the Supervisor Agent *actively* participates to the decision process has been carefully assessed, but has been discarded due to the difficulties deriving from the identification of separate decision roles between Requirement and Supervisor Agents as well as from the mutual coordination among the two decision processes.

4. MARKOV DECISION PROCESSES

4.1. Introduction

MDP (Markov Decision Process)is a *stochastic control framework* where decisions need to take into account uncertainty about many future events.

This chapter begins with the presentation of probability models for processes that evolve over time in a probabilistic manner (stochastic processes). After briefly introducing general stochastic processes, the reminder of the chapter focuses on a special kind of them, called Markov chains. Markov chains have the special property that probabilities involving how the process will evolve in the future only depend on the present state of the process, and so are independent of events in the past.

After that, Markov Decision Processes are presented as they allow to control the behavior of systems modeled as a Markov chains. In fact, rather than *passively* accepting the design of the Markov chain, MDP allows to *make a decision* on how the system should evolve by controlling the *transition* from a state to the following one. The objective of MDP is to choose the *optimal action* for each state that minimizes the cost (or maximizes the utility) associated for the system in being in each state, considering both immediate and subsequent costs (or utilities).

4.2. Stochastic processes

A *stochastic process* is defined to be an indexed collection of Random Variables $\{X_t\}$, where the index *t* runs through a given set *T*. Often *T* is taken to be the set of non-negative integers, and $X_t$represents a measurable characteristic of interest at time *t*. Stochastic processes are of interest for describing the behaviour of a system operating over some period of time. The current status of the system can fall into anyone of the $M + 1$ mutually exclusive categories called **states**. For notational convenience, in this chapter these states are labelled 0,1,…,*M*. The random variable X_t represents the state of the system at time *t*, so its only possible values are 0,1,…,*M*. The system is observed at particular points of time, labelled *t*=0,1,…. Thus, the stochastic process $\{X_t\} = \{X_0, X_1, X_2, ...\}$provides a mathematical representation of how the status of the physical system evolves over time.

This kind of processes is referred to as being a *discrete time* stochastic process with *finite state space*.

4.3. Markov chains

Assumptions regarding the joint distribution of $X_0, X_1, \ldots$ are necessary to obtain analytical results. One assumption that leads to analytical tractability is that the stochastic process is a Markov chain, which has the following key property: "a stochastic process X_t is said to have the Markovian property if:

$P\{X_{t+1} = j \mid X_0 = k_0, X_1 = k_1, \ldots, X_{t-1} = k_{t-1}, X_t = i\} = P\{X_{t+1} = j \mid X_t = i\}$, for t = 0,1,… and every sequence $i, j, k_0, k_1, \ldots, k_{t-1}$.

In words, this Markovian property says that the conditional probability of any future "event", given any past "event" and the present state $X_t = i$, is *independent* of any past event and depends only upon the present state.

A stochastic process $\{X_t\}$ (t = 0,1,2,…) is a Markov chain if it has the *Markovian property*.

The conditional probabilities $P\{X_{t+1} = j \mid X_t = i\}$ for a Markov chain are called (one-step) *transition probabilities*.

If, for each i and j, $P\{X_{t+1} = j \mid X_t = i\} = P\{X_1 = j \mid X_0 = i\}$, for all t = 0,1,2,… then the (one-step) transition probabilities are said to be *stationary*.

Thus, having stationary transition probabilities implies that the transition probabilities *do not change* over time. The existence of stationary (one-step) transition probabilities also implies that, for each i, j, and n (n =0,1,2,…), $P\{X_{t+n} = j \mid X_t = i\} = P\{X_n = j \mid X_0 = i\}$ for all t = 0,1,…. These conditional probabilities are called *n-step transitional probabilities*.

To simplify notation with stationary transition probabilities, let:

$$p_{ij} = P\{X_{t+1} = j \mid X_t = i\},$$

$$p_{ij}^{(n)} = P\{X_{t+n} = j \mid X_t = i\}.$$

Thus, the n-step transition probabilitiy $p_{ij}^{(n)}$ is just the conditional probability that the system will be in state j after exact n steps (unit of time), given it starts in state i at any time t.

Because the $p_{ij}^{(n)}$ are conditional probabilities, they must be non negative, and since the process must make a transition into some state, they must satisfy the properties:

$$p_{ij}^{(n)} \geq 0, \qquad \text{for all } i \text{ and } j;\ n = 0,1,2,\ldots,$$

$$\sum_{j=0}^{M} p_{ij}^{(n)} = 1, \qquad \text{for all } i;\ n = 0,1,2,\ldots$$

A convenient way to show all the n-step transition probabilities is the *n-step transition matrix*:

$$\mathrm{P}^{(n)} = \begin{matrix} p_{00}^{(n)} & p_{01}^{(n)} & \cdots & p_{0M}^{(n)} \\ p_{10}^{(n)} & p_{11}^{(n)} & \cdots & p_{1M}^{(n)} \\ \cdots & \cdots & \cdots & \cdots \\ p_{M0}^{(n)} & p_{M1}^{(n)} & \cdots & p_{MM}^{(n)} \end{matrix} \qquad \text{for } n = 0,1,2,\ldots$$

Note that the transition probability in a particular row and column is for the transition from the row state to the column state. When n =1, we drop the superscript n and simply refer to this as the *transition matrix*.

The Markov chains considered in this work have the following properties:

1. a *finite* number of states.
2. *stationary* transition probabilities.

The following *Chapman-Kolmogorov equations* provide a method for computing the n-step transition probabilities:

$$p_{ij}^{(n)} = \sum_{k=0}^{M} p_{ik}^{(m)} p_{kj}^{(n-m)}$$

for all $i = 0,1,\ldots,M$; $j = 0,1,\ldots,M$; and any $m = 1,2,\ldots, n-1$; $n = m+1, m+2,\ldots$

These equations point out that in going from state i to state j in n steps, the process will be in some state k after exactly m (less than n) states.

This expression enables the *n*-step transition probabilities to be obtained from the one-step transition probabilities recursively. Thus, the *n*-step transition probability matrix $\mathbf{P}^n$ can be obtained by computing the *n*th power of the one-step transition matrix **P**: $\mathbf{P}^{(n)} = \mathbf{P}^n$.

4.4. Properties of Markov chains

It is evident that the *transition probabilities* associated with the states play an important role in the study of Markov chains.

To further describe the properties of Markov chains, it is necessary to present some concepts and definitions concerning the states.

State j is said to be *accessible*from state i if $p_{ij}^{(n)} > 0$ for some $n \geq 0$. Thus, state j being accessible from state i means that it is possible for the system to enter state j eventually when it starts from state i. In general, a sufficient condition for *all* states to be accessible is that there exists a value of n for which $p_{ij}^{(n)} > 0$ for all i and j.

If state j is accessible from state i and state i is accessible from state j, then states i and j are said to communicate. In general:

1. any state communicates with itself (because $p_{ii}^{(0)} = 1$);
2. if state i communicates with state j, then state j communicates with state i;
3. if state i communicates with state j and state j communicates with state k, then state i communicates with state k.

As a result of these properties of communication, the states may be *partitioned* into one or more separate *classes* such that those states that communicate with each other are in the same class. If there is only one class, i.e., all the states communicate, the Markov chain is said to be *irreducible*.

It is often useful to talk about whether a process entering a state will ever return to this state. A state is said to be a *transient*state if, upon entering this state, the process may never returnto this state again. Therefore, state i is transient if and only if there exists a state j ($j \neq i$) that is accessible from state i but not vice versa, that is, state i is not accessible from state j. Thus, if state i is transient and the process visits this state, there is a positive probability (perhaps even a probability of 1) that the process will later move to state j and so will never return to state i. Consequently, a transient state will be visited only a finite number of times.

When starting in state *i,* another possibility is that the process *definitely* will return to this state. A state is said to be a *recurrent*state if, upon entering this state, the process definitely will returnto this state again. Therefore, a state is recurrent if and only if it is not transient. Since a recurrent state definitely will be revisited after each visit, it will be visited infinitely often if the process continues forever.

If the process enters a certain state and then stays in this state at the next step, this is considered a *return* to this state. Hence, the following kind of state is a special type of recurrent state: a state is said to be an *absorbing*state if, upon entering this state, the process *never will leave* this state again. Therefore, state *i* is an absorbing state if and only if $p_{ii}=1$.

Recurrence is a class property. That is, all states in a class are either recurrent or transient. Furthermore, in a finite-state Markov chain, not all states can be transient. Therefore, all states in an irreducible finite-state Markov chain are recurrent.

Another useful property of Markov chains is *periodicities*. The period of state *i* is defined to be the integer ($t > 1$) such that $p_{ii}^{(n)} = 0$ for all the values of *n* other than *t*, 2*t*, 3*t*,…and *t* is the largest integer with this property. Just as recurrence is a class property, it can be shown that periodicity is a class property. That is, if state *i* in a class has period *t,* the all states in that class have period *t.*

In a finite-state Markov chain, recurrent states that are aperiodic are called *ergodic*states. A Markov chain is said to be *ergodic*if all its states are ergodic states.

4.4.1. Long run properties of Markov chains

For any *irreducible ergodic* Markov chain, $\lim_{n\to\infty} p_{ij}^{(n)}$ exists and is independent of *i*.Furthermore,

$$\lim_{n\to\infty} p_{ij}^{(n)} = \pi_j > 0,$$

where the π_j uniquely satisfy the following *steady-state equations:*

$$\pi_J = \sum_{i=0}^{M} \pi_i p_{ij} \qquad \text{for } j = 0,1,\ldots, \text{M}$$

$$\sum_{i=0}^{M} \pi_i = 1$$

The π_j are called *steady-state probabilities* of the Markov chain. The term *steady-state* probability means that the probability of finding the process in a certain state, say *j,* after a large number of transitions tends to the value π_j independent of the probability distribution of the initial state.

It is important to note that the steady-state probability does notimply that the process settles down into one state. On the contrary, the process continues to make transitions from state to state, and at any step *n* the transition probability from state *i* to state *j* is still p_{ij}.

There are other important results concerning steady-state probabilities. In particular, if *i* and *j* are recurrent states belonging to different classes, then $p_{ij}^{(n)} = 0$ for all *n*. This result follows from the definition of a class.

Similarly, if *j* is a transient state, then $\lim_{n\to\infty} p_{ij}^{(n)} = 0$ for all *i*. Thus, the probability of finding the process in a transient state after a large number of transitions tends to zero.

If the requirement that all the states be *aperiodic* is relaxed, then the limit $\lim_{n\to\infty} p_{ij}^{(n)}$ may not exist. However, the following limit always exists for an *irreducible* (finite-state) Markov chain:

$$\lim_{n\to\infty}\left(\frac{1}{n}\sum_{k=1}^{n} p_{ij}^{(k)}\right) = \pi_j$$

where the π_j satisfy the steady-state equations.

This result is important in computing the *long-run average cost per unit time* associated with a Markov chain.

Suppose that a cost (or other penalty function) $C(X_t)$ is incurred when the process is in state $X_t$at time *t*, for $t = 0, 1, 2,\ldots$. Note that $C(X_t)$ is a random variable that takes on any one of the values $C(0)$, $C(1)$,…, $C(M)$ and that the function $C(\bullet)$ is independent of *t.* The expected average cost incurred over the first *n* periods is given by

$$E\left[\frac{1}{n}\sum_{t=1}^{n} C(X_t)\right].$$

By using the result that:

$$\lim_{n\to\infty}\left(\frac{1}{n}\sum_{k=1}^{n} p_{ij}^{(k)}\right) = \pi_j$$

it can be shown that the (long-run) *expected average cost per unit time* is given by:

$$\lim_{n\to\infty} E\left[\frac{1}{n}\sum_{t=1}^{n} C(X_t)\right] = \sum_{j=0}^{M} \pi_j C(j).$$

In addition, π_j can be interpreted as the (long-run) actual *fraction of time* the system is in state *j*.

4.5. Continuous time Markov chains

Until now it was assumed that the time parameter *t* was discrete (that is, *t* = 0,1,2,…). Such an assumption is suitable for many problems, but there are certain cases where a continuous time parameter (call it *t'*) is required, because the evolution of the process is being observed continuously over time. The definition of a Markov chain given before also extends to such continuous processes.

As before, the possible statesof the system are labeled as 0, 1, . . . , *M.* Starting at time 0 and letting the time parameter *t*' run continuously for $t \geq 0$, I let the random variable *X*(*t*') be the state of the system at time *t*'. Thus, *X*(*t*') will take on one of its possible (*M* + 1) values over some interval, $0 \leq t' < t_1$, then will jump to another value over the next interval, $t_1 \leq t' < t_2$, etc., where these transit points (t_1, t_2, . . .) are random points in time (*not* necessarily integer).

Now consider the three points in time (1) *t*' = *r* (where $r \geq 0$), (2) *t*' = *s* (where *s* >*r*), and (3) *t*' = *s* + *t* (where *t* >0), interpreted as follows:

t' = *r*	is a past time,
t' = *s*	is the current time,
t' = *s* + *t*	is *t* time units into the future.

Therefore, the state of the system now has been observed at times *t'* = *s* and *t'* = *r*. Label these states as *X*(*s*) = *i* and *X*(*r*) = *x*(*r*). Given this information, it now would be natural to seek the probability distribution of the state of the system at time *t'* = *s* + *t*:

$P\{X(s+t)=j \mid X(s)=i, X(r)=x(r)\}$ for *j* = 0,1,…, M.

Deriving this conditional probability often is very difficult. However, this task is considerably simplified if the stochastic process involved possesses the Markovian property.

A continuous time stochastic process $\{X(t');t'\geq 0\}$ has the Markovian property if $P\{X(s+t)=j \mid X(s)=i, X(r)=x(r)\}=P\{X(t+s)=j \mid X(s)=i\}$, for all *i*, *j* = 0,1,…, M and for all $r\geq 0$, *s*>*r*, and *t*> 0.

Note that $P\{X(t+s)=j \mid X(s)=i\}$ is a *transition probability*, just like the transition probabilities for discrete time Markov chains considered above, where the only difference is that *t* now need not be an integer. If the transition probabilities are independent of *s*, so that $P\{X(s+t)=j \mid X(s)=i\}=P\{X(t)=j \mid X(0)=i\}$ for all *s*> 0, they are called *stationary* transition probabilities.

To simplify notation, these stationary transition probabilities can be denoted by:

$$p_{ij}(t)=P\{X(t)=j \mid X(0)=i\},$$

where $p_{ij}(t)$ is referred to as the continuous time transition probability function. It is assumed that:

$$\lim_{t\to 0} p_{ij}(t)=\begin{cases}1 & if \quad i=j\\ 0 & if \quad i\neq j\end{cases}.$$

Now we are ready to define the continuous time Markov chains: a continuous time stochastic process $\{X(t');t'\geq 0\}$ is a continuous time Markov chain if it has the *Markovian property*.

In the analysis of continuous time Markov chains, one key set of random variables is the following: each time the process enters state *i*, the amount of time it spends in that state before moving to a different state is a random variable T_i, where *i* = 0, 1, . . . , *M*. Suppose that the process enters state *i* at time *t'* = *s*. Then, for any fixed amount of time *t* > 0, note that $T_i > t$ if and only if $X(t') = i$ for all t' over the interval $s \le t' \le s+t$. Therefore, the Markovian property (with stationary transition probabilities) implies that

$$P\{T_i > t+s \mid T_i > s\} = P\{T_i > t\}.$$

This is a rather unusual property for a probability distribution. It says that the probability distribution of the *remaining* time until the process transits out of a given state always is the same, regardless of how much time the process has already spent in that state. In effect, the random variable is *memoryless*; the process forgets its history. There is only one (continuous) probability distribution that possesses this property - the *exponential distribution.* The exponential distribution has a single parameter, call it *q,* where the mean is $1/q$ and the cumulative distribution function is:

$$P\{T_i \le t\} = 1 - e^{-qt}, \qquad \text{for } t \ge 0.$$

This result leads to an equivalent way of describing a continuous time Markov chain:

1. the random variable T_i has an exponential distribution with a mean of $1/q_i$
2. when leaving state *i*, the process moves to a state *j* with probability p_{ij}, where p_{ij} satisfy the conditions:

   $p_{ij} = 0$ for all *i*,

   $\sum_{j=o}^{M} p_{ij} = 1$ for all i
3. the next state visited after state *i* is independent of the time spent in state *i.*

Just as the transition probabilities for a discrete time Markov chain satisfy the Chapman-Kolmogorov equations, the continuous time transition probability function also satisfies these equations. Therefore, for any states *i* and *j* and nonnegative numbers *t* and *s* ($0 \le s \le t$):

$$p_{ij}(t) = \sum_{k=1}^{M} p_{ik}(s) p_{kj}(t-s).$$

A pair of states *i* and *j* are said to *communicate* if there are times t_1 and t_2 such that $p_{ij}(t_1) > 0$ and $p_{ji}(t_2) > 0$. All states that communicate are said to form a *class.* If all states form a single class, i.e., if the Markov chain is *irreducible*, then $p_{ij}(t) > 0$, for all $t > 0$ and all states i and j.

Furthermore, $\lim_{t\to\infty} p_{ij}(t) = \pi_j$ always exists and is independent of the initial state of the Markov chain, for j _ 0, 1, . . . , M. These limiting probabilities are commonly referred to as the *steady-state probabilities*(or *stationary probabilities*) of the Markov chain. The π_j satisfy the equations:

$$\pi_j = \sum_{i=0}^{M} \pi_i p_{ij}(t) \qquad \text{for } j = 0,1,\ldots, \text{M and every } t \geq 0 .$$

4.6. Markov Decision Processes (MDP)

Many important systems can be modeled as either a discrete time or a continuous time Markov chain. It is often useful to describe the behavior of such a system in order to evaluate its performance. However, it may be even more useful to *design* the operation of this system so as to optimize its performance. Therefore, rather than *passively* accepting the design of the Markov chain and the corresponding fixed transition matrix, it is possible to be *proactive*.

In fact, for each possible state of the Markov chain, it is possible to *make a decision* about which one of the several alternative actions should be taken in that state. The action chosen affects the transition probabilities as well as both the immediate and future costs from operating the system.

The *goal* is to choose the *optimal actions* for the respective states when considering both immediate and subsequent costs.

The decision process for doing this is referred to as *Markov Decision Process*.

A general model for a Markov Decision Process can be summarized as follows:

1. The *statei* of a discrete time Markov chain is observed after each transition ($i = 0,1,\ldots, M$).
2. After each observation, a *decision* (*action*) k is chosen from a set of K possible decisions ($k = 1,2,\ldots, K$). .
3. A *policy* is a *mapping* from each state i and action k to the probability of taking action k when in state i.

4. If decision (action) $d_i = k$ is made in state i, based on a policy π, an immediate *cost (*or *utility)* is incurred that has an expected value C_{ik}.
5. The decision (action) $d_i = k$ in state i determines what the *transition probabilities* will be for the next transition from state i. Denote these transition probabilities by $p_{ij}(k)$, for $j = 0,1,\ldots, M$.
6. The *objective* is to find an *optimal policy* according to some *cost criterion* which considers both immediate and future costs resulting from the future evolution of the process. Common criteria are to minimize the (long-run) *expected average cost (reward) per unit time* or the *expected total discounted cost*. The *discounted cost* criterionis preferable to the *average cost* criterionwhen the time periods for the Markov chain are sufficiently long that the *time value of money* should be taken into account in when adding costs in future periods to the cost in the current period. Another advantage is that the discounted cost can readily be adapted to dealing with a *finite-period* Markov Decision Process, where the Markov chain will terminate after a finite number of periods.

This model qualifies to be a Markov Decision Process because it possesses the Markovian property. In particular, given the current state and decision, any probabilistic statement about the future of the process is completely unaffected by providing any information about the history of the process.

This property holds here since (1) we are dealing with a Markov chain, (2) the new transition probabilities depend on only the current state and decision, and (3) the immediate expected cost also depends on only the current state and decision.

Several procedures can be used in order to find the optimal policy. One of them is to use the *exhaustive enumeration*, but this one is appropriate only for tiny stationary and deterministic problems, where there are only few relevant policies. In many applications where the number of policies to be evaluated is high, this approach is not feasible. For such cases, algorithms able to efficiently find an optimal policy can be used, such as *Linear Programming* and *Policy Improvement*algorithms. Several versions of these algorithms can be defined and implemented, with relatively small adjustments, considering different *cost* functions.

Reinforcement Learning methods can also be used to find the optimal policy: in the next section, the *Reinforcement Learning Problem* will be introduced and the main classes of methods and algorithms to solve it will be illustrated.

4.7. Multi-agent Markov Decision Processes

The goal of multi-agent systems' researchers is to find methods that allow to build complex systems composed of multiple autonomous agents who, while operating on *local* knowledge and possessing only limited abilities, are nonetheless capable of enacting the desired *global* behaviors.

The idea is breaking down what the system of agents should do into *individual agent behaviors* or "coordinating" agents' behavior in order to force them to achieve a global system's goal.

Multi-agent systems' research approaches the problem using the well proven tools from *game theory*, economics and biology and integrating them with ideas and algorithms from *artificial intelligence* research, such as *planning*, reasoning methods, search methods and *machine learning*. These disparate influences have led to the development of many different approaches, sometimes incompatible with each other or addressing different problems.

The *model* that has thus far gained more attention, probably due to its flexibility and its well established roots in game theory and artificial intelligence, is that of modeling agents as *utility maximizers* who inhabit some kind of *Markov Decision Process.*

Other popular models are the traditional artificial intelligence *planning model,* models inspired by *biology* (like evolutionary models) and models based on *logical inference* (that are very common in semantic or logical applications).

Agents can be *deductive* (able to deduce facts based on the rules of *logic*) or *inductive* (able to extrapolate conclusions from the given evidence or experience using *machine learning* techniques, such as *reinforcement learning* or *learning in games*).

The *Markov Decision Process* model as illustrated in the previous chapter represents the problem of a single agent, not a multi-agent system.

There are several ways to transform an MDP in a *multi-agent MDP.*

The easiest way is to simply place all the other agents effects into the *transition* function, that is assuming that other agents are not separate "entities" but merely part of the environment. This technique can work for simple cases where the agents are not changing their behavior because the *transition function* in a MDP must be *fixed*. In general, agents change their policies over time, either because of their learning process or because of inputs from the users.

A better method is then to extend the definition of MDP, to consider that each agent can take an action a_i at each time step. In this case, both the *transition function* and each agent's *reward function* will depend on a *vector* of actions: the actions (a_1, .., a_n) taken by all the agents.

The main problem is how to define the individual *reward function* of each agent in relation to a *globalutility function* of the multi-agent system, or, in other words, how to *coordinate* agents behaviors, enabling them to find "optimal policies" maximizing both *individual* and *global utility* functions.

Collective Intelligence theory aims to formalize those ideas and solve that problem. Several *reward functions* can be defined, such as *wonderful life* (a function assigning to each agent a reward that is proportional to its "contribution" to the global utility).

In general, simply setting each agent reward equal to the global utility function is not appropriate, because it can lead to agents receiving an uninformative reward (for example if only one agent behavior is bad but all other agents behave well, all agents will receive the same high reward and the first agent will be confused).

4.8. Partially Observable Markov Decision Processes (PO MDP)

In many situations the agent can only have an incomplete or incorrect knowledge of the state of the world. For example, it cannot fully sense the state or the observation process is subject to noise.

In this case the decision process can be modeled as a *PartiallyObservable MDP* (or POMDP). In order to define the POMDP we must introduce two new concepts: the *agent's beliefstate* (instead of the world's state) and an O*bservation model.*

The *agent's beliefstate b,* avector of size equal to the number of states, is a probability distribution over the set of possible states, indicating the probability that the agent is in that state.

The *Observation model* O(s,o) tells the agent the probability that will perceive observation o when in state s; the agent can use the observation it receives and the transition function to update its current belief.

It can be proven that solving a POMDP on a physical state is equivalent to solve a MDP on a belief state, with a new transition function and a new reward function.

In general the equivalent MDP has an infinite number of states, but the problem can be solved using specific algorithms grouping together beliefs into regions and associating actions with each region. Alternatively, POMDP problems can be modeled and solved using *Dynamic Decision Networks*.

5. REINFORCEMENT LEARNING

5.1. Introduction

Reinforcement learning is learning what to do in order to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of *machine learning*, but instead must *discover* which actions yield the most reward by *trying* them.

In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics (namely *trial-and-error* search and *delayed reward*) are the two most important distinguishing features of reinforcement learning.

Reinforcement learning is defined not by characterizing learning *methods*, but by characterizing a learning *problem*. Any method that is well suited to solving that problem can be considered a reinforcement learning method.

A full specification of the Reinforcement Learning problem in terms of optimal control of Markov Decision Processes is presented later, but the basic idea is simply to capture the most important aspects of the real problem facing a learning *agent* interacting with its *environment* to achieve a *goal*. Clearly, such an agent must be able to *sense thestate* of the environment to some extent and must be able *to takeactions* that affect the state. The agent also must have a *goal* or goals relating to the state of the environment. The formulation is intended to include just these three aspects (*sensation*, *action* and *goal*) in their simplest possible forms without trivializing any of them.

One of the challenges that arise in reinforcement learning and not in other kinds of learning is the trade-off between *exploration* and *exploitation*. To obtain a lot of reward, a reinforcement learning agent must prefer actions that it has already tried in the past and found to be effective in producing reward. But to discover such actions, it has to try actions that it has not selected before. The agent has to *exploit* what it already knows in order to obtain reward, but it also has to *explore* in order to make better action selections in the future.

The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at the task. The agent must *try* a variety of actions *and* progressively favour those that appear to be best. On a stochastic task, each action must be tried many times to gain a reliable estimate of its *expected reward*. The exploration-exploitation dilemma has been intensively studied by mathematicians for many decades.

Another key feature of reinforcement learning is that it explicitly considers the *whole* problem of a goal-directed agent interacting with an uncertain environment.

All reinforcement learning agents have explicit goals, can sense aspects of their environments, and can choose actions to influence their environments. Moreover, it is usually assumed from the beginning that the agent has to operate despite significant *uncertainty* about the environment it faces.

When reinforcement learning involves *planning*, it has to address the interplay between planning and real-time action selection, as well as the question of how environmental *models* are acquired and improved.

When reinforcement learning involves *supervised learning*, it does so for specific reasons that determine which capabilities are critical and which are not.

For learning research to make progress, important sub-problems have to be isolated and studied, but they should be sub-problems that play clear roles in complete, interactive, goal-seeking agents, even if all the details of the complete agent cannot yet be filled in.

5.2. Elements of a RL system

Beyond the *agent* and the *environment*, one can identify four main elements of a reinforcement learning system: a *policy*, a *reward function*, a *value function*, and, optionally, a *model* of the environment.

A *policy* defines the learning agent's way of behaving at a given time. Roughly speaking, a policy is a mapping from perceived *states* of the environment to *actions* to be taken when in those states. It corresponds to what in psychology would call a set of stimulus-response rules or associations. In some cases the policy may be a simple function or lookup table, whereas in others it may involve extensive computation such as a search process. The policy is the core of a reinforcement learning agent in the sense that it alone is sufficient to determine behaviour. In general, policies may be stochastic.

A *reward function* defines the *goal* in a reinforcement learning problem. Roughly speaking, it maps each perceived state (or state-action pair) of the environment to a single number, a *reward*, indicating the intrinsic desirability of that state. A reinforcement learning agent's sole objective is to maximize the total reward it receives in the long run. The reward function defines what are the good and bad events for the agent. In a biological system, it would not be inappropriate to identify rewards with pleasure and pain. They are the immediate and defining features of the problem faced by the agent. As such, the reward function must necessarily be unalterable by the agent. It may, however, serve as a basis for altering the policy. For example, if an action selected by the policy is followed by low reward, then the policy may be changed to select some other action in that situation in the future. In general, reward functions may be stochastic.

Whereas a reward function indicates what is good in an immediate sense, a *value function* specifies what is good in the long run. Roughly speaking, the *value* of a *state* is the total amount of reward an agent can expect to accumulate over the future, starting from that state. Whereas rewards determine the *immediate*, intrinsic desirability of environmental states, values indicate the *long-term* desirability of states after taking into account the states that are likely to follow, and the rewards available in those states. For example, a state might always yield a low immediate reward but still have a high value because it is regularly followed by other states that yield high rewards. Or the reverse could be true. To make a human analogy, rewards are like pleasure (if high) and pain (if low), whereas values correspond to a more refined and farsighted judgment of how pleased or displeased we are that our environment is in a particular state. Expressed this way, it is clear that value functions formalize a basic and familiar idea.

Rewards are in a sense primary, whereas values, as *predictionsof future rewards*, are secondary. Without rewards there could be no values, and the only purpose of estimating values is to achieve more reward. Nevertheless, it is values with which we are most concerned when making and evaluating decisions. Action choices are made based on value judgments. We seek actions that bring about states of *highest value*, not *highest reward*, because these actions obtain the greatest amount of reward for us over the long run. In decision-making and planning, the derived quantity called value is the one with which we are most concerned.

Unfortunately, it is much harder to determine values than it is to determine rewards. Rewards are basically given directly by the environment, but values must be estimated and re-estimated from the sequences of *observations* an agent makes over its entire lifetime. In fact, the most important component of almost all reinforcement learning algorithms is a method for efficiently estimating values. The central role of value estimation is arguably the most important thing we have learned about reinforcement learning over the last few decades.

The fourth and final element of some Reinforcement Learning systems is a *model* of the environment. This is something that mimics the behaviour of the environment. For example, given a state and action, the model might predict the resultant next state and next reward.

Models are used for *planning*, by which we mean any way of deciding on a course of action (a policy) by considering (predicting) possible future situations before they are actually experienced.

The incorporation of *models* and *planning* into Reinforcement Learning systems is a relatively new development. Early reinforcement learning systems were explicitly *trial-and-error learners*: what they did was viewed as almost the opposite of planning.

Nevertheless, it gradually became clear that reinforcement learning methods are closely related to Dynamic Programming methods, which do use models, and that they in turn are closely related to *state-space planning* methods (as illustrated in chapter 5.8 on learning and planning).

Modern Reinforcement Learning spans the spectrum from low-level, *trial-and-error learning* to high-level, *deliberativeplanning*.

The most important feature distinguishing Reinforcement Learning from other types of *learning* is that it uses *training information* that *evaluates* the actions taken rather than *instructs* by giving correct actions (training examples). This creates the need for *activeexploration*, for an explicit *trial-and-error* search for good behaviour.

5.3. The Reinforcement Learning Problem

The reinforcement learning problem is meant to be a straightforward framing of the problem of *learning from interaction to achieve a goal.*

The learner and decision-maker is called the *agent*. The thing it interacts with, comprising everything outside the agent, is called the *environment*. Agent and environment interact continually: the first selecting actions and the second responding to those actions and presenting new situations to the agent. The environment also gives rise to *rewards*, special numerical values that the agent tries to maximize over time. A complete specification of an environment defines a *task*, one instance of the reinforcement learning problem.

More specifically, the agent and environment interact at each of a sequence of discrete time steps, $t = 0,1,2,3,\ldots$. At each time step t, the agent receives some representation of the environment's *state*, $S_t \in S$, where S is the set of possible states, and on that basis selects an *action*, $a_t \in A(s_t)$, where $A(s_t)$ is the set of actions available in state s_t. One time step later, in part as a consequence of its action, the agent receives a numerical *reward*, $r_{t+1} \in R$, and finds itself in a new state, s_{t+1}. The next figure shows the agent-environment interaction:

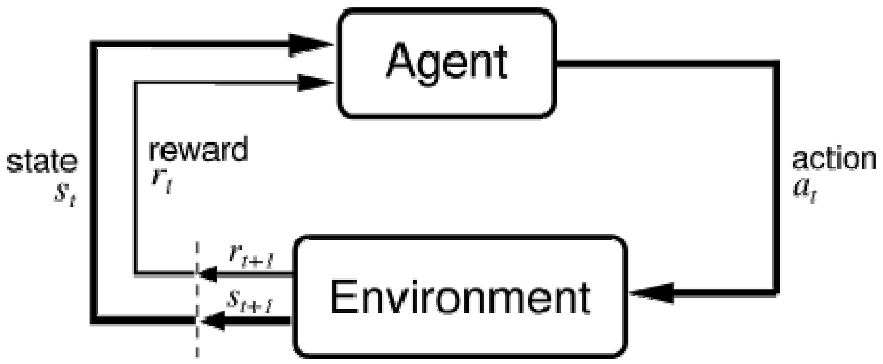


Figure 4- The agent-environment interaction in RL

At each time step, the agent implements a *mapping* from *states* to probabilities of selecting each possible *action*. This mapping is called the agent's *policy* and is denoted π_t, where $\pi_t(s,a)$ is the *probability* that $a_t = a$ if $s_t = s$. Reinforcement learning methods specify how the agent improves (changes, updates) its policy as a result of its experience.

In reinforcement learning, the purpose or *goal* of the agent is formalized in terms of a *reward signal* passing from the environment to the agent. Roughly speaking, the agent's goal is to maximize the *total amount of reward* it receives. This means maximizing not immediate reward, but *cumulative* reward in the long run.

The use of a reward signal to formalize the idea of a goal is one of the most distinctive features of reinforcement learning. Although this way of formulating goals might at first appear limiting, in practice it has proved to be flexible and widely applicable. The best way to see this is to consider examples of how it has been, or could be, used. For example, to make a robot learn to walk, researchers have provided reward on each time step proportional to the robot's forward motion. In making a robot learn how to escape from a maze, the reward is often zero until it escapes, when it becomes $+1$. Another common approach in maze learning is to give a reward of $-1$for every time step that passes prior to escape; this encourages the agent to escape as quickly as possible. You can see what is happening in all of these examples. The agent always learns to maximize its reward. If we want it to do something for us, we must provide rewards to it in such a way that in maximizing them the agent will also achieve our goals. It is thus critical that the rewards we set up truly indicate what we want accomplished. In particular, the reward signal is not the place to impart to the agent prior knowledge about *how* to achieve what we want it to do or about specific *sub-goals* to be reached (the agent could try tofind a way to achieve them without achieving the real goal).

The reward signal is your way of communicating to the robot *what* you want it to achieve, not *how* you want it achieved.

5.3.1. Returns

A more precise definition of what is meant with "maximize the total amount of reward received" is needed. If the sequence of rewards received after time step *t* is denoted $r_{t+1}, r_{t+2}, r_{t+3}, \ldots$, then what precise aspect of this sequence do we wish to maximize? In general, we seek to maximize the *expected return*, where the return, R_t, is defined as some specific function of the reward sequence.

In the simplest case the return is the sum of the rewards:

$$R_t = r_{t+1} + r_{t+2} + r_{t+3} + \ldots + r_T \qquad (5.1)$$

where T is a final time step. This approach makes sense in applications in which there is a natural notion of final time step, that is, when the agent-environment interaction breaks naturally into sub-sequences, called *episodes*, such as plays of a game, trips through a maze, or any sort of repeated interactions.

Each episode ends in a special state called the *terminal state*, followed by a reset to a standard starting state or to a sample from a standard distribution of starting states. Tasks with episodes of this kind are called *episodic tasks*. In episodic tasks we sometimes need to distinguish the set of all nonterminal states, denoted S, from the set of all states plus the terminal state, denoted S^+.

On the other hand, in many cases the agent-environment interaction does not break naturally into identifiable episodes, but goes on continually without limit. For example, this would be the natural way to formulate a continual process-control task, or an application to a robot with a long life span. Tasks of this kind are called *continuing tasks*. The return formulation (5.1) is problematic for continuing tasks because the final time step would be $T = \infty$, and the return, which is what we are trying to maximize, could itself easily be infinite. (For example, suppose the agent receives a reward of +1 at each time step.). Thus, a definition of return that is slightly more complex conceptually but much simpler mathematically is preferable.

The additional concept to be introduced is that of *discounting*. According to this approach, the agent tries to select actions so that the sum of the *discounted rewards* it receives over the future is maximized.

In particular, it chooses a_t to maximize the *expecteddiscounted return*:

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + ... = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \qquad (5.2)$$

where γ is a parameter, $0 \leq \gamma \leq 1$, called the *discount rate*.

The discount rate determines the *present value* of future rewards: a reward received k time steps in the future is worth only γ^{k-1} times what it would be worth if it were received immediately. If $\gamma < 1$, the infinite sum has a finite value as long as the reward sequence $\{r_k\}$ is bounded. If $\gamma = 0$, the agent is "myopic" or “opportunistic” in being concerned only with maximizing immediate rewards: its objective in this case is to learn how to choose a_t so as to maximize only r_{t+1}. If each of the agent's actions happened to influence only the immediate reward, not future rewards as well, then a myopic agent could maximize (5.2) by separately maximizing each immediate reward. But in general, acting to maximize immediate reward can reduce access to future rewards so that the return may actually be reduced. As γ approaches 1, the objective takes future rewards into account more strongly: the agent becomes more farsighted.

5.3.2. Unified notation for episodic and continuing tasks

As described previously, there are two kinds of reinforcement learning tasks, one in which the agent-environment interaction naturally breaks down into a sequence of separate episodes (*episodic tasks*), and one in which it does not (*continuing tasks*). The former case is mathematically easier because each action affects only the finite number of rewards subsequently received during the episode. It is therefore useful to establish one notation that enables us to talk precisely about both cases simultaneously.

To be precise about episodic tasks requires some additional notation. Rather than one long sequence of time steps, we need to consider a series of episodes, each of which consists of a finite sequence of time steps. We number the time steps of each episode starting anew from zero. Therefore, we have to refer not just to s_t, the state representation at time *t*, but to $s_{t,i}$, the state representation at time *t* of episode *i* (and similarly for $a_{t,i}$, $r_{t,i}$, $\pi_{t,i}$, T_i, etc.). However, it turns out that, when we discuss episodic tasks we will almost never have to distinguish between different episodes. We will almost always be considering a particular single episode, or stating something that is true for all episodes. Accordingly, in practice we will almost always abuse notation slightly by dropping the explicit reference to episode number. That is, I will write $s_t$to refer to $s_{t,i}$, and so on.

We need one other convention to obtain a single notation that covers both episodic and continuing tasks. We have defined the return as a sum over a finite number of terms in one case (4.5) and as a sum over an infinite number of terms in the other (4.6). These can be unified by considering episode termination to be the entering of a special *absorbing state* that transitions only to itself and that generates only rewards of zero.

5.4. Modelling the environment as a Markov chain

In the reinforcement learning framework, the agent makes its decisions as a function of a signal from the environment called the environment's *state*.

By "the state" we mean whatever information on the environment is available to the agent. We assume that the state is given by some pre-processing system that is nominally part of the environment.

The state signal should not be expected to inform the agent of everything about the environment, or even everything that would be useful to it in making decisions. What we would like, ideally, is a state signal that *summarizes past sensations compactly*, yet in such a way that all relevant information is retained. This normally requires more than the immediate sensations, but never more than the complete history of all past sensations. A state signal that succeeds in retaining all relevant information is said to be *Markov*, or to have *the Markov property*.

If an environment has the Markov property, then its *one-step dynamics* allow to predict the *next state* and expected *next reward* given the current state and action. One can show that, by iteration, one can *predict* all future states and expected rewards from knowledge only of the current state as well as would be possible given the complete history up to the current time.

It also follows that Markov states provide the best possible basis for choosing actions: that is, the best policy for choosing actions as a function of a Markov state is just as good as the best policy for choosing actions as a function of complete histories.

A reinforcement learning task that satisfies the Markov property is a *Markov Decision Process*, or *MDP*. If the state and action spaces are *finite*, then it is called a *finite Markov decision process (finite MDP)*. Finite MDPs are particularly important to the theory of reinforcement learning.

A particular finite MDP is defined by its *state* and *action* sets and by the *one-step dynamics* of the environment.

Given any state and action, *s* and *a*, the probability of each possible next state, *s'*, is:

$$P_{ss'}^{a} = \Pr\{s_{t+1} = s' \mid s_t = s, a_t = a\} \qquad (5.3)$$

These quantities are called *transition probabilities*.

Similarly, given any current state and action, *s* and *a*, together with any next state, *s'*, the *expected value of the next reward* is:

$$R_{ss'}^{a} = E\{r_{t+1} \mid s_t = s, a_t = a, s_{t+1} = s'\} \qquad (5.4)$$

These quantities, $P^a_{ss'}$ and $R^a_{ss'}$, completely specify the most important aspects of the *dynamics* of a finite MDP (only information about the distribution of rewards around the expected value is lost).

5.4.1. Value functions

Almost all reinforcement learning algorithms are based on estimating *value functions* - functions of states (or of state-action pairs) that estimate *how good* it is for the agent to be in a given *state* (or how good it is to perform a given *action* in a given *state*).

The notion of "how good" here is defined in terms of future rewards that can be expected, or, to be precise, in terms of *expected return*. Of course the rewards the agent can expect to receive in the future depend on what actions it will take. Accordingly, value functions are defined with respect to particular *policies*.

Recall that a *policy*, π, is a mapping from each state, $s \in S$, and action, $a \in A(s)$, to the probability $\pi(s,a)$ of taking action *a* when in state *s*.

Informally, the *value* of a state *s* under a policy π, denoted $V^{\pi}(s)$, is the *expected return* when starting in *s* and following π thereafter. For MDPs, we can define $V^{\pi}(s)$ formally as:

$$V^{\pi}(s) = E_{\pi}\{R_t \mid s_t = s\} = E_{\pi}\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_{t=s}\right\} \quad (5.5)$$

where $E_{\pi}\{\ \}$ denotes the expected value given that the agent follows policy π, and *t* is any time step. Note that the value of the terminal state, if any, is always zero. We call the function V^{π} the *state-value function for policy* π.

Similarly, we define the value of taking action *a* in state *s* under a policy π, denoted $Q^{\pi}(s,a)$, as the expected return starting from *s*, taking the action *a*, and thereafter following policy π:

$$Q^{\pi}(s,a) = E_{\pi}\{R_t \mid s_t = s, a_t = a\} = E_{\pi}\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, a_t = a\right\} \quad (5.6)$$

We call Q^{π} the *action-value function for policy* π.

The value functions V^{π} and Q^{π} can be *estimated* from *experience*.

A fundamental property of value functions used throughout reinforcement learning and dynamic programming is that they satisfy particular recursive relationships.

For any policy π and any state *s*, the following *consistency condition* holds between the value of *s* and the value of its possible successor states:

$$V^{\pi}(s) = \sum_{a} \pi(s,a) \sum_{s'} P^{a}_{ss'} \left[R^{a}_{ss'} + \gamma V^{\pi}(s') \right] \qquad (5.7)$$

where it is implicit that the actions, *a*, are taken from the set *A*(*s*), and the next states, *s*', are taken from the set *S*, or from S^{+} in the case of an episodic problem.

Equation (5.7) is the *Bellman equation for the state-value function* V^{π}. It expresses a relationship between the value of a state and the values of its successor states.Starting from state s, the agent could take any of some set of actions; from each of these, the environment could respond with one of several next states s', along with a reward. The Bellman equation averages over all the possibilities weighting each by its probability of occurring. It states that the value of the start state must equal the discounted value of the expected next state, plus the reward expected along the way.

The value function V^{π} is the *unique solution* to its Bellman equation.

5.4.2. Optimal value functions

Solving a reinforcement learning task means, roughly, finding a policy that achieves a lot of reward over the long run. For finite MDPs, we can precisely define an *optimal policy* in the following way. Value functions define a partial ordering over policies. A policy π is defined to be better than or equal to a policy π' if its *expected return* is greater than or equal to that of π' for all states. In other words, π > π' if and only if $V^{\pi}(s) \geq V^{\pi'}(s)$ for all $s \in S$.

There is always at least one policy that is better than or equal to all other policies: this is an *optimal policy*.

Although there may be more than one, we denote all the optimal policies by π*. They share the same state-value function, called the *optimal state-value function*, denoted V*, and defined as:

$$V^{*}(s) = \max_{\pi} V^{\pi}(s) \qquad (5.8)$$

for all $s \in S$.

Optimal policies also share the same *optimal action-value function*, denoted Q*, and defined as:

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) \qquad (5.9)$$

for all $s \in S$ and $a \in A(s)$. For the state-action pair (*s*,*a*), this function gives the expected return for taking action *a* in state *s* and thereafter following an optimal policy. Thus, we can write Q* in terms of V* as follows:

$$Q^*(s,a) = E\{r_{t+1} + \gamma V^*(s_{t+1}) \mid s_t = s, a_t = a\} (5.10)$$

Being V*the state value function for a policy, it must satisfy the self-consistency condition given by the Bellman equation for state value functions (5.7). Being V* the optimal value function, however, V* 's consistency condition can be written in a special form without reference to any specific policy. This is the Bellman equation for V*, or the *Bellman optimality equation*.

Intuitively, the Bellman optimality equation expresses the fact that the value of a state under an optimal policy must be equal to the expected return for the best action from that state:

$$V^*(s) = \max_{a} E\{r_{t+1} + \gamma V^*(s_{t+1}) \mid s_t = s, a_t = a\} \qquad (5.11)$$

and

$$V^*(s) = \max_{a \in A(s)} \sum_{s'} P^a_{ss'} \left[R^a_{ss'} + \gamma V^*(s')\right] (5.12)$$

The last two equations are two forms of the Bellman optimality equation for V*.

The Bellman optimality equation for Q* is, instead:

$$Q^*(s,a) = E\{r_{t+1} + \gamma \max_{a'} Q^*(s_{t+1},a) \mid s_t = s, a_t = a\} = \sum_{s'} P^a_{ss'} \left[R^a_{ss'} + \gamma \max_{a'} Q^*(s',a')\right] \ (5.13)$$

For finite MDPs, the Bellman optimality equation (5.12) has a *unique solution* independent of the policy. The Bellman optimality equation is actually a system of equations, one for each state, so if there are *N*states, then there are *N* equations in

*N*unknowns. If the *dynamics* of the environment ($R^a_{ss'}$ and $P^a_{ss'}$) are known, then in principle one can solve this system of equations for V*using any one of a variety of methods for solving systems of nonlinear equations. One can solve a related set of equations for Q*.

Once one has V*, it is relatively easy to determine an *optimal policy*. For each state *s*, there will be one or more actions at which the maximum is obtained in the Bellman optimality equation. Any policy that assigns nonzero probability only to these actions is an optimal policy. You can think of this as a one-step search. If you have the optimal value function, V*, then the actions that appear best after a one-step search will be optimal actions.

Another way of saying this is that any policy that is *greedy* with respect to the optimal evaluation function V* is an optimal policy. The term “greedy” is used in computer science to describe any search or decision procedure that selects alternatives based only on local or immediate considerations, without considering the possibility that such a selection may prevent future access to even better alternatives. Consequently, it describes policies that select actions based only on their short-term consequences.

The beauty of V* is that if one uses it to evaluate the short-term consequences of actions (specifically, the one-step consequences) then a greedy policy is actually optimal in the long-term sense in which we are interested because V* already takes into account the reward consequences of all possible future behaviour.

By means of V*, the optimal expected long-term return is turned into a quantity that is locally and immediately available for each state. Hence, a one-step-ahead search yields the long-term optimal actions.

Having Q* makes choosing optimal actions still easier. With Q*, the agent does not even have to do a one-step-ahead search: for any state *s*, it can simply find any action that *maximizes* $Q^*(s,a)$ (that is, following a *greedy* policy respect to Q*).

The action-value function effectively “caches” the results of all one-step-ahead searches. It provides the optimal expected long-term return as a value that is locally and immediately available for each state-action pair. Hence, at the cost of representing a function of state-action pairs, instead of just of states, the optimal action-value function Q* allows optimal actions to be selected without having to *know* anything about possible successor states and their values, that is, without having to *know* anything about the environment's *dynamics*.

Explicitly solving the *Bellman optimality equation* provides one route to finding an optimal policy, and thus to solving the reinforcement learning problem. However, this solution is rarely directly useful. It is akin to an *exhaustive search*, looking ahead at all possibilities, computing their probabilities of occurrence and their desirability in terms of expected rewards.

This solution relies on at least three assumptions that are rarely true in practice: (1) we accurately know the *dynamics* of the environment; (2) we have enough computational resources to complete the computation of the solution; and (3) the Markov property.

In most tasks, this solution cannot be exactly implemented, because various combinations of these assumptions are violated.

5.4.3. Optimality and approximations

We have defined *optimal value functions* and *optimal policies*.

Clearly, an agent that learns an optimal policy has worked very well, but, in practice, this rarely happens. For the kinds of tasks in which we are interested, optimal policies can be generated only with extreme computational cost.

Even if we have a complete and accurate *model* of the environment's dynamics, it is usually not possible to simply compute an optimal policy by solving the *Bellman optimality equation*.

A critical aspect of the problem facing the agent is always the computational *power* available to it, in particular, the amount of computation it can perform in a single time step.

The *memory* available is also an important constraint. A large amount of memory is often required to build up approximations of value functions, policies, and models.

In tasks with small, *finite* state and action sets, it is possible to form these approximations using arrays or tables with one entry for each state (or state-action pair). This is called the tabular case, and the corresponding methods are called *tabular methods*.

In many other cases of practical interest, however, there are far more states than could possibly be entries in a table: in these cases the functions must be approximated, using some sort of more compact parameterized function representation.

5.5. Methods for solving Reinforcement Learning problems

Three main classes of methods for solving the Reinforcement Learning problem can be distinguished:

- Dynamic Programming;
- Monte Carlo methods;
- Temporal-Difference methods.

Each class of methods has its strengths and weaknesses. In particular, Dynamic Programming methods are well developed mathematically, but require a complete and accurate *model* of the environment. Monte Carlo methods don't require a model and are conceptually simple, but are not suited for step-by-step incremental computation. Finally, temporal-difference methods require no model and are fully incremental, but are more complex to analyse. The methods also differ in several ways with respect to their efficiency and speed of convergence.

In the following chapters all these methods will be presented.In particular, DP and Monte Carlo methods will be illustrated at general level, without focusing on specific solutions and algorithms, while TD methods will be described in a more detailed way, focusing on three specific algorithms: *Sarsa*, *Q-Learning* and *R-Learning*.*Q-Learning* is the algorithm that has been chosen for solving the QoE problem addressed in this thesis work, for the reasons that shall be illustrated in the next chapter.

5.5.1. Dynamic Programming (DP)

The term Dynamic Programming (DP) refers to a collection of algorithms that can be used to compute *optimal policies* given a perfect *model* of the environment as a Markov Decision Process.

Classical DP algorithms are of limited utility in reinforcement learning both because of their strong assumption of a perfect model and because of their great computational expense, but they are very important theoretically.

DP provides an essential *foundation* for the understanding of the other two methods presented in this chapter. In fact, all of these methods can be viewed as attempts to achieve much the same results as DP, with less computation and without assuming a perfect model of the environment.

The key idea of DP (and of reinforcement learning in general) is the use of *value functions* to organize and structure the *search* for good policies.

The basic ideas and algorithms of Dynamic Programming as they relate to solving finite MDPs are Policy evaluation and Policy improvement.

Policy evaluation refers to the (typically) iterative computation of the *value functions* for a given policy. *Policy improvement* refers to the computation of an improved policy given the value function for that policy.

Putting these two computations together, we obtain *policy iteration* and *value iteration*, the two most popular DP methods. Either of these can be used to reliably compute *optimal policies* and *value functions* for finite MDPs given a very strong assumption: the complete knowledge of the MDP.

Classical DP methods operate performing a *full-back-up* operation on each state: each back-up updates the *value* of one state based on the value of all possible successor states and their probability of occurring. Full back-ups are closely related to the *Bellmann equations*. When the back-ups no longer result in any changes in values, convergence has occurred to values that satisfy the corresponding Bellmann equation. Just as there are four primary value functions (V^{π}, V*, Q^{π} and Q*), there are four corresponding Bellmann equations and four corresponding full-back ups.

Insight into DP methods and, in fact, into almost all reinforcement learning methods, can be gained by viewing them in terms of ***Generalised Policy Iteration*** (GPI).

GPI is the general idea of two interacting processes revolving around an approximate policy and an approximate value function. One process takes the policy as given and performs some form of *policy evaluation*, changing the value function to be more like the true value function for the policy. The other process takes the value function as given and performs some form of *policy improvement*, changing the policy to make it better, assuming that the value function is its value function.

Although each process changes the basis for the other, overall they work together to find a joint solution: a policy and value function that are unchanged by either process and, consequently, are *optimal*.In some cases (typically the classical DP methods) GPI can be proved to converge, in other cases convergence has not been proved, anyway the idea of GPI improves the understanding of DP methods (and of RL methods in general).

One special *property* of DP methods is that all of them update estimates of the values of states based on estimates of the values of successor states (they "*bootstrap*").

DP may not be practical for very large problems, but compared with other classic methods for solving MDPs, DP methods are actually quite *efficient*. If we ignore a few technical details, then the (worst case) time DP methods take to find an optimal policy is *polynomial* in the number of states and actions. In particular, *linear programming* methods can also be used to solve MDPs, and in some cases their worst-case convergence guarantees are better than those of DP methods. But linear programming methods become impractical at a much smaller number of states than do DP methods (by a factor of about 100). For the largest problems, only DP methods are feasible.

DP is sometimes thought to be of limited applicability because of the *curse of dimensionality*, the fact that the number of states often grows exponentially with the number of state variables. Large state sets do create difficulties, but these are inherent difficulties of the *problem*, not of DP as a solution method. In fact, DP is comparatively better suited to handling large state spaces than competing methods such as *direct search* and *linear programming*.

5.5.2. Monte Carlo methods

Monte Carlo methods can be considered the first *learning methods* for estimating value functions and discovering optimal policies based on experience (interacting with the environment).

Unlike the previous section, in this case we do not assume *completeknowledge* of the environment. Monte Carlo methods require only *experience* - sample sequences of states, actions, and rewards - from on-line or simulated interaction with an environment.

Learning from *on-line* experience is striking because it requires *no prior knowledge* of the environment's dynamics (model), yet can still attain optimal behaviour. Learning from *simulated* experience is also powerful. Although a *model* is required, the model is needed only to generate *sample transitions*, not the complete probability distributions of all possible transitions as is required by dynamic programming (DP) methods. In surprisingly many cases it is easy to generate experience sampled according to the desired probability distributions, but infeasible to obtain the distributions in explicit form.

Monte Carlo methods are ways of solving the reinforcement learning problem based on *averaging sample returns*. To ensure that well-defined returns are available, Monte Carlo methods can be defined only for episodic tasks. That is, we assume experience is divided into *episodes*, and that all episodes eventually terminate no matter what actions are selected. It is only upon the completion of an episode that value estimates and policies are changed.

Monte Carlo methods are thus *incremental* in an *episode-by-episode* sense, not in a *step-by-step* sense.

As for DP algorithms, Monte Carlo method is used to compute *policy evaluation*, *policy improvement* and *generalized policy iteration*. Each of these ideas taken from DP is extended to the Monte Carlo case in which only sample experience is available.

In particular, Monte Carlo methods can be defined following the global scheme of Generalised Policy Iteration.

GPI involves interacting processes of policy evaluation (a *prediction* problem) and policy improvement (a *control* problem).

Rather than use a model to compute the value of each state, they simply average many returns starting in the state. Being the state's value the expected return, this average can become a good approximation to the state's value.In control methods, *action-value functions* are approximated, because they can be used in improving the policy without requiring a model of the environment's transition dynamics.

Maintaining sufficient *exploration* on state-actions pairs is an issue in Monte Carlo methods: two approaches can be used to achieve this.

In *on-policy methods* the agent attempts to evaluate or improve the policy that is used to make decisions: it commits to always exploring and tries to find the best policy that explores.

In *off-policymethods* the agent also explores, but learns an optimal policy that may be unrelated to the policy followed, that is used to generate behaviour; this policy is said *behaviour policy*, while the policy that is learned (evaluated and improved) is said *estimation policy*.

An advantage of this separation is that the *estimation policy* may be deterministic (e.g., greedy), while the *behaviour policy* can continue to sample all possible actions, guaranteeing exploration.

Off policy Monte Carlo methods follow the behaviour policy while learning about and improving the estimation policy: the technique requires that the chosen behaviour policy have a nonzero probability of selecting all actions that might be selected by the estimation policy: to explore all the possibilities, the behaviour policy must be *soft*. To assure *convergence* of the estimation policy to the optimal policy, an off-policy Monte Carlo method can be implemented based on GPI (for computing Q*), maintaining an *ε-soft* *behaviour policy* while the *estimationpolicy* is the greedy policy with respect to Q, an estimate of Q*.

Let's recall that:

- *soft-policies* are policies such that $\pi_t(s,a)$ >0 for all states and actions,
- *ε-soft policies* are particular cases of soft-policies such that $\pi_t(s,a)$ ≥ ε/n for all states and actions for some epsilon, where n is the dimension of the action space.

ε is called "*exploration rate*".

A potential problem with Monte Carlo off-line methods is that, if non greedy actions are frequently selected, the learning could be very slow: there has been insufficient experience with off-policy Monte Carlo methods to assess how serious this problem is. This problem does not impact off line TD methods, that will be illustrated in the next chapter.

To conclude, we can say that Monte Carlo methods learn value functions and optimal policies from *experience* in the form of *sample episodes*.

This gives them at least three kinds of advantages over DP methods.

First, they can be used to learn optimal behaviour directly from interaction with the environment, with no *model* of the environment's dynamics.

Second, they can be used with simulation or *sample models*. For surprisingly many applications it is easy to simulate sample episodes even though it is difficult to construct the kind of explicit model of transition probabilities required by DP methods.

Third, it is easy and efficient to focus Monte Carlo methods on a small subset of the states. A region of *special interest* can be accurately evaluated without going to the expense of accurately evaluating the whole state set.

Finally, Monte Carlo methods may be less harmed by violations of the Markov property (because they do not bootstrap).

5.5.3. Temporal-Difference (TD) methods

TD learning is a more recent kind of learning method that can be used to solve the Reinforcement Learning problem.

As known, TD methods are more general than this: they are general methods for learning to make *long-term predictions* about dynamical systems. For example, TD methods may be relevant to predicting financial data, election outcomes, weather patterns, animal behaviour, demands on power stations or customer purchases.

It was only when TD methods were analysed as pure *prediction models* that their theoretical properties first came to be well understood.

In the following pages, TD methods will be illustrated within the context of Reinforcement Learning problems.

As usual, the overall RL problem can be divided into a *prediction* problem (the problem of evaluating a policy, that is estimating the value function for a given policy) and a *control* problem (the problem of finding an optimal policy).

TD methods are alternatives to Monte Carlo problems to solve the *prediction* problem. Similarly to DP and Monte Carlo methods, for the *control* problem TD methods use some form of the *Generalised Policy Iteration*, the idea that was introduced in dynamical programming.

The *prediction process* "drives" the value function to accurately*predict* returns for the current policy, while the *control process* "drives" the policy to improve locally (e.g. to be *greedy*) with respect to the current value function.

Both TD and Monte Carlo use *experience* (in following a policy) to solve the prediction problem. When the prediction process is based on *experience*, a complication arises concerning maintaining sufficient *exploration.* Similarly to Monte Carlo methods, TD methods can follow two approaches to deal with this complication: *on policy* and *off-policy* approaches.

Like Monte Carlo methods, TD methods can learn directly from raw experience without a *model* of the environment's dynamics, of its *reward* and *transition probability* distributions: this is a first advantages of TD methods over DP methods.

Like DP, TD methods update estimates based in part on other learned estimates, without waiting for a final outcome (they "*bootstrap"*).

The next most immediate advantage of TD methods over Monte Carlo methods is that they are naturally implemented in an on-line, fully incremental (*step-by-step*) fashion. With Monte Carlo methods the agent must wait until the end of an episode, because only then is the return known, whereas with TD methods the agent needs wait only one time step.

Surprisingly often the episode-by-episode operation turns out to be a critical point. Some applications have very long episodes, so that delaying all learning until an episode's end is too slow. Other applications are continuing tasks and have no episodes at all. Finally, some Monte Carlo methods must ignore or discount episodes on which experimental actions are taken, which can greatly slow learning.

TD methods are much less susceptible to these problems because they learn from each transition regardless of what subsequent actions are taken.

After a brief introduction on TD *prediction*, in the following paragraphs three TD *control* algorithms will be illustrated: one is on-policy (*Sarsa*) and the other two are off-policy (*Q-Learning* and *R-Learning*).

5.5.4. TD prediction

Both TD and Monte Carlo methods use *experience* to solve the prediction problem. Given some experience following a policy π, both methods update their estimate V of V^{π}. If a nonterminal state s_t is visited at time t, then both methods update their estimate $V(s_t)$ based on what happens after that visit.

Roughly speaking, Monte Carlo methods wait until the *return* following the visit is known, then use that return as a *target* for $V(s_t)$.

A simple Monte Carlo method suitable for non-stationary environments is:

$$V(s_t) \leftarrow V(s_t) + \alpha\left[R_t - V(s_t)\right] \qquad (5.14)$$

where R_t is the actual return following time t and α is a constant *step-size parameter*.

Let us call this method ***constant-α Monte Carlo***.

Whereas Monte Carlo methods must wait until the end of the episode to determine the increment to $V(s_t)$ (only then is R_t known), TD methods need wait only until the next time step. At time t+1 they immediately form a *target* and make a useful *update* using the observed reward r_{t+1} and the estimate $V(s_{t+1})$.

The simplest TD method, known as ***TD(0)***, is:

$$V(s_t) \leftarrow V(s_t) + \alpha\left[r_{t+1} + \gamma V(s_{t+1}) - V(s_t)\right] \qquad (4.19)$$

In effect, the target for the Monte Carlo update is R_t, whereas the target or the TD update is $\left[r_{t+1} + \gamma V(s_{t+1})\right]$.

Because the TD method bases its update in part on an existing estimate, we say that it is a *bootstrapping* method, like DP.

We know that:

$$V^{\pi}(s) = E_{\pi}\{R_t \mid s_t = s\} \qquad (5.15)$$

and

$$V^{\pi}(s) = E_{\pi}\{r_{t+1} + \gamma V^{\pi}(s_{t+1}) \mid s_t = s\} \qquad (5.16)$$

Roughly speaking, Monte Carlo methods use an *estimate* of (5.15) as a target, whereas DP methods use an *estimate* of (5.16) as a target.

The Monte Carlo*target* is an estimate because the expected value in (5.15) is not known; a *sample return* is used in place of the *real expected return*.

The DP *target* is an estimate not because of the expected values, which are assumed to be completely provided by a model of the environment, but because $V^{\pi}(s_{t+1})$ is not known and the current estimate, $V_t(s_{t+1})$, is used instead.

The TD *target* is an estimate for both reasons: it samples the expected values in (5.16)and it uses the current estimate V_t instead of the true V^{π}.

Thus, TD methods combine the *sampling* of Monte Carlo with the *bootstrapping* of DP, allowing to define algorithms combining the *advantages* of both methods.

The TD methods are today the *most widely used* reinforcement learning methods. This is probably due to their great simplicity: they can be applied on-line, with a minimal amount of computation, to experience generated from interaction with an environment; they can be expressed nearly completely by single equations that can be implemented with small computer programs.

But are TD methods sound? Certainly it is convenient to learn one guess from the next, without waiting for an actual outcome, but can we still guarantee *convergence* to the correct answer? Happily, the answer is yes.

For any fixed policy π, the TD(0) algorithm has been proved to converge to V^{π}:

- *in the mean* for a constant step-size parameter α if it is sufficiently small,

and

- *with probability 1* if the step-size parameter decreases according to the usual stochastic approximation conditions.

Let's remind that *stochastic approximation conditions* are:

$$\sum_{k=1}^{\infty} \alpha_k(a) = \infty \qquad \text{and} \qquad \sum_{k=1}^{\infty} \alpha_k^2(a) < \infty.$$

The first condition is required to guarantee that the steps are large enough to eventually overcome any initial conditions or random fluctuations. The second condition guarantees that eventually the steps become small enough to assure convergence.

Note that both convergence conditions are met for the *sample-average* case: $\alpha_k(a) = \frac{1}{k}$.

If both TD and Monte Carlo methods converge asymptotically to the correct predictions, then a natural next question is "Which gets there first?" At the current time this is an open question in the sense that no one has been able to prove mathematically that one method converges faster than the other. In practice, however, TD methods have usually been found to converge *faster* than *constant-α Monte Carlo* methods on stochastic tasks.

5.5.5. Sarsa: on-policy TD control

As usual, we follow the pattern of GPI, using TD methods for the evaluation or prediction part.

In order to trade-off between *exploitation* and *exploration*, an on-policy method will be followed. The first step is to learn an *action-value function* rather than a state-value function. In particular, for an on-policy method we must estimate $Q^{\pi}(s,a)$ for the current *behaviour policy* π and for *all states s and actions a.* This can be done using essentially the same TD method described above for learning V^{π} (TD(0)).

Recall that an episode consists of an alternating sequence of states and state-action pairs:

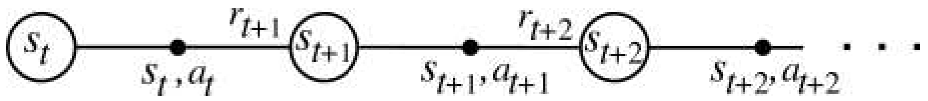


Figure 5- State and state-action pairs sequence

Now we consider transitions from state-action pair to state-action pair, and learn the value of state-action pairs. Formally these cases are identical: they are both Markov chains with a reward process.

The theorems assuring the convergence of *state values* under TD(0) also apply to the corresponding algorithm for *action values*:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)\right] \qquad (5.17)$$

This update is done after every transition from a nonterminal state s_t. If s_{t+1} is terminal, then $Q(s_{t+1}, a_{t+1})$ is defined as zero.

This rule uses every element of the quintuple of events, $(s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1})$, that make up a transition from one state-action pair to the next: this quintuple gives rise to the name *Sarsa* for the algorithm.

It is straightforward to design an on-policy control algorithm based on the Sarsa prediction method. As in all on-policy methods, we continually estimate Q^{π} for the *behaviour* policy π, and at the same time change π toward *greediness* with respect to Q^{π}.

The *convergence* properties of the Sarsa algorithm depend on how the behaviour policy π depends on Q. The use of an *ε–soft policy* converging in the limit to the *greedy policy* (for example: an *ε-greedy policy* with ε =1/t) is suggested.

Let's recall that ε-*greedy policies* are particular cases of *ε-soft policies* that, most of the time, select an action which has maximum estimated value but with probability ε select an action at random, that is non-greedy actions have the minimum probability of election, equal to ε/n, while greedy actions have probability of selection equal to 1- ε + ε/n, where n is the dimension of the action space.

5.5.6. Q-Learning: off-policy TD control

One of the most important breakthroughs in reinforcement learning was the development of an off-policy TD control algorithm known as *Q-learning*.

Its simplest form, *one-step Q-learning*, is defined by:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right] \quad (5.18)$$

where α is the *learning rate* (also called *step-size parameter*), γ is the *discount factor* and r_{t+1} is the reward associated to s_{t+1}.

In particular, the learning rate α determines to what extent the newly acquired information will override the old information. A factor of 0 will make the agent not learn anything, while a factor of 1 would make the agent consider only the most recent information. The discount factor γ determines the importance of future rewards. A factor of 0 will make the agent "opportunistic" by only considering current rewards, while a factor approaching 1 will make it strive for a long-term high reward. If the discount factor meets or exceeds 1, the Q values will diverge.

In this case, the learned *action-value function*, *Q*, directly approximates *Q**, the optimal action-value function, independent of the policy being followed (*behaviour* policy). This dramatically simplifies the analysis of the algorithm and enabled early convergence proofs. The *behaviour policy* still has an effect in that it determines which state-action pairs are visited and updated. However, all that is required for correct *convergence* is that *all pairs continue to be updated*. Under this assumption and a variant of the usual stochastic approximation conditions on the sequence of step-size parameters (ref. chapter 5.3.1), Q_t has been shown to *converge with probability 1* to *Q**.

The *behaviourpolicy,* that is used to generate experience, may be the *ε-greedy policy* with respect to the action-value function.

The Q-learning *algorithm* shown in procedural form is:

```
Initialize Q(s,a), s, α and ε.
Repeat (for each step):
Choose a from s using ε-greedy policy respect to Q, that is:
        If RAND < ε
        Then $a \leftarrow$ random action
        Else $a \leftarrow$ action that maximizes $Q(s,a)$
Take action a,
Observe state s', receive reward r
$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$
$s \leftarrow s'$
Decrease α and ε
Untils is terminal.
```

5.5.7. R-Learning: TD control for undiscounted continuing tasks

R-learning is an off-policy TD control method for the advanced version of the reinforcement learning problem in which one neither discounts nor divides experience into distinct episodes with finite returns. In this case one seeks to obtain the maximum reward per time step. The value functions for a policy, π, are defined relative to the *average expected reward per time step* under the policy, ρ^{π}:

$$\rho^{\pi} = \lim_{n\to\infty} \frac{1}{n} \sum_{t=1}^{n} E_{\pi}\{r_t\} \qquad (5.19)$$

assuming the process is *ergodic* (nonzero probability of reaching any state from any other under any policy) and thus that ρ^{π} does not depend on the starting state. From any state, in the long run the average reward is the same, but there is a transient. From some states better-than-average rewards are received for a while, and from others worse-than-average rewards are received. It is this transient that defines the value of a state:

$$\widetilde{V}^{\pi}(s) = \sum_{k=1}^{\infty} E_{\pi}\{r_{t+k} - \rho^{\pi} \mid s_t = s\} \qquad (5.20)$$

and the value of a state-action pair is similarly the transient difference in reward when starting in that state and taking that action:

$$\widetilde{Q}^{\pi}(s,a) = \sum_{k=1}^{\infty} E_{\pi}\{r_{t+k} - \rho^{\pi} \mid s_t = s, a_t = a\} \qquad (5.21)$$

We call these *relative values* because they are relative to the average reward under the current policy.

There are subtle distinctions that need to be drawn between different kinds of optimality in the undiscounted continuing case. Nevertheless, for most practical purposes it may be adequate simply to order policies according to their average reward per time step, in other words, according to their ρ^{π}. For now let us consider all policies that attain the maximal value of ρ^{π} to be *optimal*.

Other than its use of relative values, R-learning is a standard TD control method based on *off-policy GPI*, much like Q-learning.

It maintains two policies, a *behaviour policy* and an *estimation policy,* plus an action-value function and an estimated average reward. The *behaviourpolicy* is used to generate experience; it might be the *ε-greedy policy* with respect to the action-value function. The *estimation policy* is the one involved in GPI. It is typically the *greedy policy* with respect to the action-value function. If π is the estimation policy, then the action-value function, *Q*, is an approximation of Q^{π} and the average reward, ρ, is an approximation of ρ^{π}.

5.6. A unified view of RL methods: extended versions of TD methods

So far, three basic classes of methods for solving the RL problem have been illustrated: Dynamic Programming, Monte-Carlo methods and Temporal-Difference methods.

Although each class is different, these are not really alternatives in the sense that one must choose one or another: it is perfectly sensible and often preferable apply methods of different kinds simultaneously, that is to apply a *joint method* combining parts or aspects of more than one class.

As said, the TD algorithms presented in the previous chapter are the most widely used RL methods: this is mainly due to their great simplicity: they can be applied on-line, with a limited amount of computations, to experience generated from interaction with an environment; they can be expressed completely by single equations that can be implemented with small computer programs.

Anyway, these algorithms can be *extended* in several ways, making them slightly more complicated but significantly more powerful, and maintaining the essence of the original algorithms, that is the ability to process the experience on-line with relatively little computation, being driven by TD errors.

Considering that the TD algorithms illustrated in the previous chapter are *one-step*, *model-free* and *tabular,* they can be extended in three main ways, defining:

1) *multi-step* versions (a link to Monte Carlo methods),
2) versions that include a *model* of the environment (a link to DPand *planning)*
3) versions using *function approximation* rather than *tables* (a link to artificial neural networks).

In the next chapter, some extended versions of basic TD algorithms will be illustrated, considering, in particular, the *multi-step* versions: it is important to consider that, thanks to the introduction of *eligibility traces*, Monte Carlo methods and TD methods can be unified.

The last chapter includes some considerations about *learning* and *planning* and their possible integration.

5.7. Multi-step TD Prediction

In this chapter some multi-step versions of TD algorithms will be presented, starting from n-step TD methods and then illustrating *TD(λ)* and *Q(λ)*algorithms.

5.7.1. n-Step TD Prediction

Let's consider estimating V^π from sample episodes generated using π.

Monte Carlo methods perform a backup for each state based on the entire sequence of observed rewards from that state until the end of the episode. The backup of simple TD methods, on the other hand, is based on just the one next reward, using the value of the state one step later as a proxy for the remaining rewards. One kind of intermediate method, then, would perform a backup based on an intermediate number of rewards: more than one, but less than all of them until termination. For example, a two-step backup would be based on the first two rewards and the estimated value of the state two steps later.

The methods that use n-step backups are still TD methods because they still change an earlier estimate based on how it differs from a later estimate. Now the later estimate is not one step later, but n steps later. Methods in which the temporal difference extends over n steps are called n-step TD methods.

More formally, consider the backup applied to state s_t as a result of the state-reward sequence, $s_t, r_{t+1}, s_{t+1}, r_{t+2}, \ldots, r_T, s_T$ (omitting the actions for simplicity). It is known that in Monte Carlo backups the estimate $V_t(s_t)$ of $V^\pi(s_t)$ is updated in the direction of the complete return:

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^{T-t-1} r_T,$$

where T is the last time step of the episode. Let us call this quantity the *target* of the backup.

Whereas in Monte Carlo backups the target is the expected return, in one-step backups the target is the first reward plus the discounted estimated value of the next state:

$$R_t^{(1)} = r_{t+1} + \gamma V_t(s_{t+1}).$$

This makes sense because $\gamma V_t(s_{t+1})$ takes the place of the remaining terms $\gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^{T-t-1} r_T$. The point now is that this idea makes just as much sense after two steps as it does after one. The *two-step target* is

$$R_t^{(2)} = r_{t+1} + \gamma r_{t+2} + \gamma^2 V_t(s_{t+2}),$$

where now $\gamma^2 V_t(s_{t+2})$ takes the place of the terms $\gamma^2 r_{t+3} + \gamma^3 r_{t+4} + \cdots + \gamma^{T-t-1} r_T$. In general, the *$n$-step target* is

$$R_t^{(n)} = r_{t+1} + \gamma r_{t+2} + \gamma^2 + \cdots + \gamma^{n-1} r_{t+n} + \gamma^n V_t(s_{t+n}). \quad (1)$$

This quantity is sometimes called the "corrected n-step truncated return" because it is a return truncated after n steps and then approximately corrected for the truncation by adding the estimated value of the n-th next state. That terminology is descriptive but a bit long: usually it is also called as the *n-step return* at time t.

Of course, if the episode ends in less than n steps, then the truncation in an n-step return occurs at the episode's end, resulting in the conventional complete return. In other words, if $T - t < n$, then $R_t^{(n)} = R_t^{(T-t)} = R_t$.

An *n-step backup* is defined to be a backup toward the n-step return. In the tabular, state-value case, the increment to $V_t(s_t)$ (the estimated value of $V^\pi(s_t)$ at time t), due to an n-step backup of s_t, is defined by

$$\Delta V_t(s_t) = \alpha \Big[R_t^{(n)} - V_t(s_t) \Big],$$

where α is a positive *step-size parameter*, as usual. Of course, the increments to the estimated values of the other states are $\Delta V_t(s) = 0$, for all $s \neq s_t$. Here the n-step backup is defined in terms of an increment, rather than as a direct update rule, in order to distinguish two different ways of making the updates. In *on-line updating*, the updates are done during the episode, as soon as the increment is computed. In this case we have $V_{t+1}(s) = V_t(s) + \Delta V_t(s)$ for all $s \in \mathcal{S}$. In *off-line updating*, on the other hand, the increments are accumulated "on the side" and are not used to change value estimates until the end of the episode. In this case, $V_t(s)$ is constant within an episode, for all s. If its value in this episode is $V(s)$, then its new value in the next episode will be $V(s) + \sum_{t=0}^{T-1} \Delta V_t(s)$

The expected value of all n-step returns is guaranteed to improve in a certain way over the current value function as an approximation to the true value function. For any V, the expected value of the n-step return using V is guaranteed to be a better estimate of V^π than V is, in a worst-state sense. That is, the worst error under the new estimate is guaranteed to be less than or equal to γ^n times the worst error under V:

$$\max_s \left| E_\pi\left\{ R_t^{(n)} \,\middle|\, s_t = s \right\} - V^\pi(s) \right| \leq \gamma^n \max_s |V(s) - V^\pi(s)| . \qquad (2)$$

This is called the *error reduction property* of n-step returns.

Because of the error reduction property, one can show formally that on-line and off-line TD prediction methods using n-step backups *converge* to the correct predictions under appropriate technical conditions. The *n-step TD methods* thus form a family of valid methods, with *one-step TD methods* and *Monte Carlo methods* as extreme members.

Nevertheless, n-step TD methods are rarely used because they are inconvenient to implement. Computing n-step returns requires waiting $n$steps to observe the resultant rewards and states. For large n, this can become problematic, particularly in control applications. For this reason, other multi-step TD algorithms are illustrated in the following paragraphs: *TD(λ)* and *Q(λ)algorithms*.

5.7.2. The Forward View of TD(λ): λ-returns

Backups can be done not just toward any *n-step return*, but toward any *average* of *n-step returns*.For example, a backup can be done toward a return that is half of a two-step return and half of a four-step return: $R_t^{ave} = \frac{1}{2}R_t^{(2)} + \frac{1}{2}R_t^{(4)}$. Any set of returns can be averaged in this way, even an infinite set, as long as the weights on the component returns are positive and sum to 1. The *overall return* possesses an error reduction property similar to that of individual n-step returns (15) and thus can be used to construct backups with *guaranteed convergence* properties.

Averaging produces a substantial new range of algorithms. A backup that averages simpler component backups in this way is called *a complex backup*.

The *TD(λ) algorithm* can be understood as one particular way of averaging n-step backups. This average contains all the n-step backups, each weighted proportional to λ^{n-1}, where $0 \leq \lambda \leq 1$ (Figure 7). A normalization factor of ($1 - \lambda$) ensures that the weights sum to 1. The resulting backup is toward a return, called the λ-*return*, defined by:

$$R_t^\lambda = (1-\lambda)\sum_{n=1}^{\infty} \lambda^{n-1} R_t^{(n)}.$$

Figure 8 illustrates this weighting sequence. The one-step return is given the largest weight, $(1-\lambda)$; the two-step return is given the next largest weight, $(1-\lambda)\lambda$; the three-step return is given the weight $(1-\lambda)\lambda^2$; and so on.

The weight fades by λ with each additional step, that is λ can be interpreted as the weighting sequence fading factor. After a terminal state has been reached, all subsequent n-step returns are equal to R_t. If we want, we can separate these terms from the main sum, yielding

$$R_t^\lambda \;=\; (1-\lambda)\sum_{n=1}^{T-t-1} \lambda^{n-1} R_t^{(n)} \;+\; \lambda^{T-t-1} R_t. \tag{3}$$

This equation makes it clearer what happens when $\lambda = 1$. In this case the main sum goes to zero, and the remaining term reduces to the conventional return, R_t. Thus, for $\lambda = 1$, backing up according to the λ-return is the same as the *Monte Carlo* algorithm. On the other hand, if $\lambda = 0$, then the λ-return reduces to $R_t^{(1)}$, the one-step return. Thus, for $\lambda = 0$, backing up according to the λ-return is the same as the *one-step TD method*, TD(0).

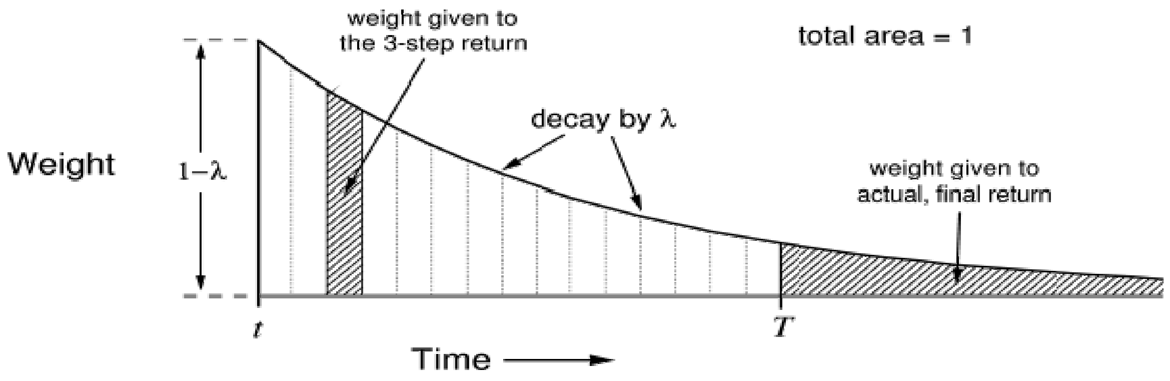


Figure 6- Weighting given in the λ-return to each of the n-step returns

The algorithm that performs backups using the λ-return is defined the λ-*returnalgorithm*. On each step, t, it computes an increment, $\Delta V_t(s_t)$, to the value of the state occurring on that step:

$$\Delta V_t(s_t) = \alpha\Big[R_t^\lambda - V_t(s_t)\Big]. \tag{4}$$

(The increments for other states are of course $\Delta V_t(s) = 0$, for all $s \neq s_t$.).

As with the n-step TD methods, the updating can be either on-line or off-line.

This approach is called the *theoretical*, or *forward*, view of a learning algorithm. For each state visited, the algorithm *looks forward* in time to all the future rewards and decide how best to combine them. It is possible to imagine a person riding the stream of states, looking forward from each state to determine its update, as depicted in Figure 9. After looking forward from and updating one state, the person moves on to the next and never have to work with the preceding state again. Future states, on the other hand, are viewed and processed repeatedly, once from each vantage point preceding them.

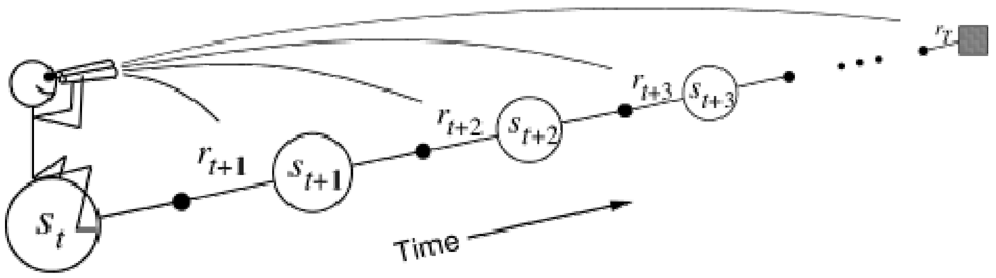


Figure 7 -Forward view of TD(λ) The algorithm decides how to update each state by looking forward to future rewards and states

The λ-return algorithm is the basis for the *forward view* of *eligibility traces* as used in the TD(λ) method (and formally defined in the following paragraph).

In fact, in the off-line case, the λ-return algorithm is the TD(λ) algorithm. The λ-return and TD(λ) methods use the λ parameter to shift from *one-step TD methods* to *Monte Carlo methods*. The specific way this shift is done is interesting, but not obviously better or worse than the way it is done with simple n-step methods by varying n.

Ultimately, the most compelling motivation for the λ way of mixing n-step backups is that there is a simple algorithm - TD(λ) - for achieving it. This is a practical issue rather than a theoretical one.

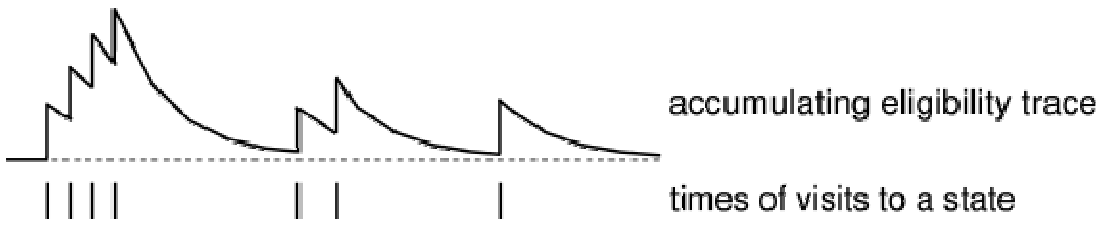
5.7.3. The Backward View of TD(λ): eligibility traces

The previous section presented the theoretical, or forward, view of the tabular TD(λ) algorithm as a way of mixing backups that parametrically shift from a one-step TD method to a Monte Carlo method. This section instead defines TD(λ) mechanistically, or according a backward view: it is possible to proof that this mechanism correctly implements the forward view. The mechanistic, or backward, view of TD(λ) is useful because it is simple both conceptually and computationally. In particular, the forward view itself is not directly implementable because it is non-causal, using at each step knowledge of what will happen many steps later. The backward view provides a causal, incremental mechanism for approximating the forward view and, in the off-line case, for achieving it exactly.

In the backward view of TD(λ), there is an *additional memory variable* associated with each state, its *eligibility trace*. The eligibility trace for state s at time t is denoted $e_t(s) \in \Re^+$. On each step, the eligibility traces for all states decay by $\gamma\lambda$, and the eligibility trace for the one state visited on the step is incremented by 1:

$$e_t(s) = \begin{cases} \gamma\lambda e_{t-1}(s) & \text{if } s \neq s_t; \\ \gamma\lambda e_{t-1}(s) + 1 & \text{if } s = s_t, \end{cases} \tag{5}$$

for all non-terminal states s, where γ is the discount rate and λ is the parameter introduced in the previous section. Henceforth we refer to λ as the *trace-decay parameter*. This kind of eligibility trace is called an accumulating trace because it accumulates each time the state is visited, then fades away gradually when the state is not visited, as illustrated below:



At any time, the traces record which states have recently been visited, where “recently” is defined in terms of $\gamma\lambda$. The traces are said to indicate the degree to which each state is eligible for undergoing learning changes should a reinforcing event occur. The reinforcing events we are concerned with are the moment-by-moment one-step TD errors. For example, the TD error for state-value prediction is

$$\delta_t = r_{t+1} + \gamma V_t(s_{t+1}) - V_t(s_t). \tag{6}$$

In the backward view of TD(λ), the global TD error signal triggers proportional updates to all recently visited states, as signalled by their nonzero traces:

$$\Delta V_t(s) = \alpha\delta_t e_t(s), \qquad \text{for all } s \in \mathcal{S}. \tag{7}$$

As always, these increments could be done on each step to form an on-line algorithm, or saved until the end of the episode to produce an off-line algorithm. In either case, equations ((18)-(20)) provide the mechanistic definition of the TD(λ) algorithm.

The backward view of TD(λ) is oriented backward in time. At each moment we look at the current TD error and assign it backward to each prior state according to the state's eligibility trace at that time. It is possible to imagine a person riding along the stream of states, computing TD errors, and shouting them back to the previously visited states, as suggested by Figure 11. Where the TD error and traces come together, we get the update given by (20).

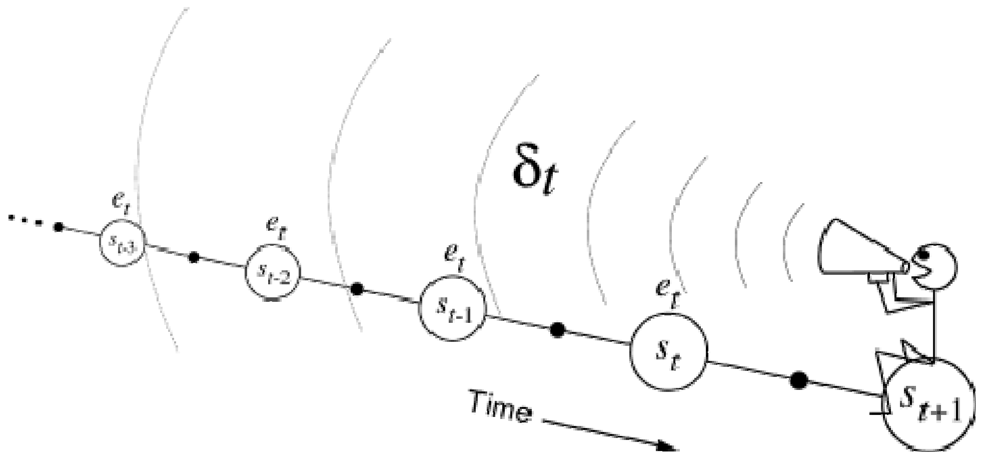


Figure 8- Backward view of TD(λ) - Each update depends on the current TD error combined with traces of past events

To better understand the backward view, consider what happens at various values of λ If $\lambda = 0$, then by (18) all traces are zero at t except for the trace corresponding to s_t. In terms of Figure 11, TD(0) is the case in which only the one state preceding the current one is changed by the TD error. For larger values of λ, but still $\lambda < 1$, more of the preceding states are changed, but each more temporally distant state is changed less because its eligibility trace is smaller, as suggested in the figure: it is possible to say that the earlier states are given less credit for the TD error.

If $\lambda = 1$, then the credit given to earlier states falls only by γ per step. This turns out to be just the right thing to do to achieve Monte Carlo behaviour. For example, remember that the TD error,δ_t, includes an undiscounted term of r_{t+1}. In passing this back k steps it needs to be discounted, like any reward in a return, by γ^k, which is just what the falling eligibility trace achieves. If $\lambda = 1$ and $\gamma = 1$, then the eligibility traces do not decay at all with time.

In this case the method behaves like a Monte Carlo method for an undiscounted, episodic task. If $\lambda = 1$, the algorithm is also known as TD(1). TD(1) is a way of implementing Monte Carlo algorithms.

Concluding, it is possible to proof that off-line TD(λ), as defined mechanistically above, achieves the same weight updates as the off-line λ-return algorithm: in this sense it is possible align the forward (theoretical) and backward (mechanistic) views of TD(λ).

Two different methods combining *eligibility traces* and *Q-learning* have been proposed that sometimes these are referred as *Watkins's* Q(λ) and *Peng's* Q(λ), after the researchers who first proposed them.

Let's recall that *Q-learning* is an off-policy method, meaning that the policy learned about need not be the same as the one used to select actions. In particular, Q-learning learns about the greedy policy while it typically follows a policy involving exploratory actions - occasional selections of actions that are suboptimal according to Q_t. Because of this, special care is required when introducing eligibility traces.

Suppose to back up the state-action pair s_t, a_t at time t. Suppose that on the next two time steps the agent selects the greedy action, but on the third, at time $t + 3$, the agent selects an exploratory, non-greedy action. In learning about the value of the greedy policy at s_t, a_t it is possible to use subsequent experience only as long as the greedy policy is being followed. Thus, it is possible to use the one-step and two-step returns, but not, in this case, the three-step return. The n-step returns for all $n \geq 3$ no longer have any necessary relationship to the greedy policy. Thus, unlike TD(λ), *Watkins's* Q(λ) does not look ahead all the way to the end of the episode in its backup. It only looks ahead as far as the next exploratory action.

Aside for this difference, however, Watkins's Q(λ) is much like TD(λ). Its look ahead stops at episode's end, whereas Q(λ)'s look ahead stops at the first exploratory action, or at episode's end if there are no exploratory actions before that.Actually, to be more precise, one-step Q-learning and Watkins's Q(λ) both look one action past the first exploration, using their knowledge of the action values.

The mechanistic or *backward view* of Watkins's Q(λ) is very simple. Eligibility traces are just set to zero whenever an exploratory (non-greedy) action is taken. The trace update is best thought of as occurring in two steps. First, the traces for all state-action pairs are either decayed by $\gamma\lambda$ or, if an exploratory action was taken, set to 0. Second, the trace corresponding to the current state and action is incremented by 1.

The overall result is:

$$e_t(s,a) = \mathcal{I}_{ss_t} \cdot \mathcal{I}_{aa_t} + \begin{cases} \gamma\lambda e_{t-1}(s,a) & \text{if } Q_{t-1}(s_t,a_t) = \max_a Q_{t-1}(s_t,a); \\ 0 & \text{otherwise,} \end{cases}$$

where, as before, $\mathcal{I}_{xy}$ is an identity indicator function, equal to 1 if $x = y$ and 0 otherwise.

The rest of the algorithm is defined by:

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\delta_t e_t(s,a),$$

where

$$\delta_t = r_{t+1} + \gamma \max_{a'} Q_t(s_{t+1}, a') - Q_t(s_t, a_t).$$

Unfortunately, cutting off traces every time an exploratory action is taken loses much of the advantage of using eligibility traces. If exploratory actions are frequent, as they often are early in learning, then only rarely will backups of more than one or two steps be done, and learning may be *little faster* than one-step Q-learning. *Peng's* Q(λ) is an alternate version of Q(λ) meant to remedy this. Under specific conditions this method may converge to Q^*, even if this has not yet been proved. Nevertheless, the method performs well empirically. Most studies have shown it performing significantly better than Watkins's Q(λ).

5.8. Learning and Planning methods

The term *planning* is used in several different ways in different fields. In particular, it can be used to refer to any computational process that takes a *model* as input and produces in output or improves a *policy* for interacting with the modelled environment.

A *model* of an environment can be defined as anything that an agent can use to predict how the environment will respond to its actions: given a state and an action, the model produces a prediction of the resultant next state and next reward. If the model is *stochastic*, then there are several possible states and rewards, each with some probability of occurring.

Some models (called *distribution models*) produce a description of all the possible next states and next rewards and their probability of occurring; other models (called *sample* *models*) generate samples according to the (unknown) probability distribution. An example of *distribution model* is that assumedin *Dynamic Programming* (based on the state transition probabilities and expected rewards).

Within Artificial Intelligence there are two distinct approaches to *planning* according to the above mentioned definition: *state-space* and *plan-space* planning..

In *state-space* approach*,* planning is viewed as a search through the state space for an *optimal policy* or a path to a goal. Actions cause transitions from state to state and value functions are computed over states.

In *plan-space* approach, planning is instead viewed as a search through the space of plans. Operators transform one plan into another and value functions, if any, are defined through the space of plans.

Referring to the state-space approach, it can be shown that there is a close relationshipsbetween *planning optimal behaviour* and *learning optimal behaviour,* because both processes involve estimating the same value functions. In fact, all state-space planning methods involve computing value functions as a key intermediate step toward improving the policy and compute their value functions by back-up operations applied to simulated experience.

The main difference with learning methods (such as Temporal Difference methods) is that whereas planning uses *simulated experience* generated by a model, learning methods use *real experience* generated by the Environment.

Learning and planning processes can be easily integrated, allowing both to update the same estimated value functions.

Moreover, all *learning* methods can be converted into *planning* methods, by applying them to *simulated* (or model-generated) *experience*, rather than to *real* experience: in this way, planning algorithms can be defined that are identical to learning algorithms but operating on different sources of experience.

Finally, *planning* methods can be integrated with *acting* and *model-learning.* By *model learning* we mean that when planning is done “on-line”, while interacting with the environment, new information gained from the interaction with the environment may be used to change (improve) the model and thereby interact with planning.

Examples of agents integrating planning and learning functionalities and able to “learn a model” using real experience and to “learn optimal policies” using both real experience (so-called “direct learning”) and simulated experience “(so-called “indirect learning”), are known in literature as “*Dyna agents*”. In Dyna architecture, both direct and indirect learning functions are achieved by applying Reinforcement Learning (typically Q-Learning) algorithms.

6. THE PROPOSED RL APPROACH

This chapter illustrates the proposed RL approach for modelling and solving the QoE problem addressed in this thesis work.

The first paragraph illustrates why the *Reinforcement Learning* approach was proposed, considering several alternative approaches and methods developed in *Control* and *Artificial Intelligence* fields.

The second paragraph illustrates why the Temporal Difference (TD) class of RL algorithms and, in particular, why the Q-learning algorithm was selected.

The third paragraph illustrates some hybrid solutions combining Reinforcement Learning and Games Theory (*Learning in Games*) and introducesan alternative RL approach, based on the *Friend or Foe algorithm*. This approach seemspromising in term of overcoming some limitations of the Q-Learning based solution when adopted in multi-agent systems.

6.1. Why Reinforcement learning

Several alternative approaches and methods were investigated, in order to select the most appropriate solution for solving the problem addressed in this thesis, considering, in particular, theories and methods developed in the Control, Statistics and Artificial Intelligence fields.

In particular, Optimal and Adaptive Control, Games Theory, Artificial Neural Networks, Evolutionary/Genetic Algorithms and Planning methods were analyzed.

The choice of a Reinforcement Learning approach derived, first of all, from the consideration that it seems natural and appropriate defining the QoE problem addressed in this thesis like a "*Reinforcement Learning Problem*", as illustrated in chapter 2.3: the problem of implementing a Requirement Agent able to make, dynamically, an optimal Class of Service choice, learning to make optimal decisions through direct experience in its ICT Environment and with the goal of satisfying the Target Quality of Service of the relevant Application without negatively impacting on the Global Quality of Service.

A second consideration drove the author to prefer a *model-free approach*, in order to satisfy some of the main Future Internet Architecture requirements: flexibility and independence from a specific technology and/or ICT domain or framework (to be known or learned "a priori" and "off-line").Consequently, *robust*, *optimal* and *adaptivecontrol* methods were not selected because they are typically model-based.

Artificial Neural Networks typically follow a *supervised*approach, based on Training examples (an external entity, the Supervisor, instructs the neural network on how to behave in specific training situations) while, as said, the addressed problem requests a unsupervised approach: the Requirement Agents must be able to learn from experience interacting with the Environment. Supervised learning is associative but not selective, meaning that is missing of the search (trial and selection of alternatives) component of trial and error learning methods. The Reinforcement Learning methods are characterized by an unsupervised approach because the RL agents learn through direct experience in interacting with the environment, following a trial and error approach.

Natural selection in evolution is a prime example of a selective process, but is not associative. *Evolutionary/genetic algorithms* were not selected because they are selective but not associative: they do not use policies or associations between environment's states and agent's actions and are not able to learn by interacting with the Environment.

Classic Artificial Intelligence *Planning* methods were not selected mainly because they are based on prediction models that must be "learned" in some way: the Reinforcement Learning approach seems more appropriate because it incorporates the learning function. It should be observed that Reinforcement Learning Agents incorporate learning/prediction and control functionalities and, when required, can be also efficiently integrated with Planning functionalities (as illustrated in the previous chapter on Learning and Planning).

Multi-Agent System approaches based on consensus, cooperation ornegotiation strategies were not adopted mainly because the need of *cooperation* and *coordination* between Agents typically determinates strong real time communication requirements, either between the Agents (in distributed models) or between the Agents and a centralized entity (in centralized models): these requirements seem to be not sustainable in Future Internet scenarios, particularly considering*Internet of Thing* scenarios, where an increasing number of “things” (objects or devices), with limited ICT and energy resources, shall be connected to the Internet platform.

As a final consideration, it is important to underline that the choice of a Reinforcement Learning approach for the reasons explained above doesn’t at all exclude the possibility of combining Reinforcement Learning with other approaches, methods and algorithms in order to better address, adopting *hybrid solutions*, specific problems that can arise when adopting “pure” RL solutions in multi-agent systems.

In the last chapter, some hybrid solutions developed in *Learning in Games* theory and combining Reinforcement Learning and Games Theory will be illustrated.One of those solutions (*Friend or Foe algorithm*) seems promising in order to overcome some limitations of the Q-Learning approach when adopted in multi-agent systems.

6.2. Why Q-Learning

As a first consideration, the choice of the specific RL algorithm for solving the problem addressed in this thesis work and to be implemented in the considered scenarios was strongly conditioned by the agents constraints: the agents have limited power and memory capabilities and, consequently, the implementation of simple and efficient algorithms, with a fast and simple learning processand a high speed of convergence to the optimal solution is considered mandatory.

After an accurate comparison between features, advantages and disadvantages of the three basic classes of RL methods as presented in the Chapter 5 (Dynamic Programming, Monte Carlo methods and Temporal-Difference methods), an algorithm belonging to the Temporal-Difference class was selected, for the reasons illustrated below.

As already said, Dynamic Programming methods are well developed mathematically, but require strong assumptions: in particular, they require a complete and accurate *model* of the environment as a Markov Process. Moreover, they requires a lot of computation time and memory. For all these reasons, they were discarded.

Temporal-Difference methods in several aspects are similar to the Monte-Carlo methods (in particular: they both do not require a model and operate performing sample-backups on the states and samplings, meaning that the value function updates involve estimations or expected value calculations) but, as said, they are fully *step-by-step* incremental, while Monte Carlo methods are not suited for step-by-step incremental computation. In Time Difference Methods the Agent learns at each *step*, while in Monte Carlo methods it only learns at the end of each *episode*: the learning process in TD methods is faster.

In addition, TD are “bootstrapping” methods, like DP ones. It should be noted that bootstrapping methods are of persistent interest in Reinforcement Learning because, despite some limited theoretical guarantees, in practice they usually work better than non-bootstrapping methods.

On the other side, a disadvantage of bootstrapping methods is that they perform well only in strict*Markov-tasks*.When the tasks are at least partially non-Markov, than the use of a pure Monte-Carlo method or of the *eligibility traces* (lambda-versions of TD algorithms) is indicated, because eligibility traces can be considered the first “line of defense” against non-Markov tasks (they do not bootstrap) and long-delayed rewards. It should be considered that eligibility traces require more computation than one-step methods but, in return, they offer faster learning, particularly when rewards are delayed by many steps.

In conclusion, assuming that our task is *Markov* and that rewards are not too long-delayed, a simple, efficient, *one-step TD algorithm*, able to guarantee a high speed of convergence to the optimal policy, was chosen: the off-policy *Q-Learning* algorithm.

6.3. An alternative proposal: the Friend or Foe algorithm

An interesting hybrid approach, combining Learning and Games Theory in *multi-agent system* frameworks, is that proposed by the *Learning in Games* theory and, in particular, by the so-called *multi-player Stochastic Games*.

The theory of Learning in Games studies the equilibrium concepts dictated by learning mechanisms. That is, while the “classic” Nash equilibrium is based on the assumption of “perfectly rational” players, in learning in games the assumption is that the agents use some kind of learning algorithm. The theory determines the equilibrium strategy that will be arrived at the various learning mechanisms and maps these equilibria to standard solution concepts, if possible.

As far concerns the *Stochastic Games*, in many multi-agent applications the agents do not know the future rewards they will receive for their actions. Instead, they must take random actions in order to first *explore* the environment so that they may then determine which actions lead them to the best future rewards starting from certain states. That is, the agents live in a Markov chain and inhabit a *multi-agentMarkov Decision Process* (MDP).

As illustrated previously, the Reinforcement Learning is a very popular machine learning approach to formally define (and solve) this kind of problem.The Reinforcement Learning problem can be solved using several classes of methods and algorithms; as said, one of the most widely used RL algorithms is the Q-Learning algorithm, that requires a proper tuning of the *learning rate* α and of the *exploration rate* ε.

For the reasons illustrated in the previous chapter, a Q-Learning based approach has been followed to solve the QoE problem addressed in this thesis work. Unfortunately, the convergence properties of Q-Learning are impressive but they assume that only *one agent* is learning and that the Environment is *stationary*.

When multiple agents are learning, the reward's functions of each agent is no longer a function of the state and the agent's actions, but is a function of the state and all the agents' actions. That is, each agent's reward depends on the actions that other agents take, as captured by the multi-agent MDP framework illustrated previously (Chapter 4).

In multi-agent MDPs, it might be impossible for a Q-learning agent to *converge* to an optimal policy.

One possible solution to this problem is that of defining an *hybrid solution* combining the advantages of the Reinforcement Learning approach with the equilibrium concept of Games Theory.

In single agent problems, the target is defined in terms of finding an "optimal policy", that is maximizing the agent's discounted future rewards.In multiple agent systems the target could be defined in terms of maximising some global function of the agents' discounted future rewards (for example their sum, as in the "*social welfare*" case) or, alternatively, in terms of finding a particular *equilibrium*, more "interesting" from a convergence point of view, such as the *Nash Equilibrium Point* (NEP).

A NEP is defined as a set of policies such that no one agent will gain anything by changing its policy from its NEP strategies to something else.

As with the standard Nash equilibrium, it has been shown that a NPE always exists: every n-player discounted stochastic game possesses at least one NEP in stationary strategies.

In particular, a NEP can be found in a system where all the agents use a *Nash Q-Learning algorithm*, that is a combination of a Q-learning algorithm and a Nash equilibrium strategy. In this algorithm, each agent must keep n Q-tables, one for each agent in the population. These tables are updated using a formula similar to the standard Q-Learning one, but instead of using the Q-values to determine future rewards, it uses Nash Q-tables. That is, at each step, the algorithm assumes that the multi-agent MDP game is defined (induced) by the n Q-tables it has and then calculates a NEP for this problem. This can be an extremely expensive computation, harder than finding the Nash equilibrium for a game matrix.

The Nash Q-Learning algorithm is guaranteed to converge as long as enough time is given so that all state-action pairs are explored sufficiently and if two assumptions hold: the existence of an *adversarial equilibrium* and the existence of a *coordination equilibrium* for the entire game and for each game defined by the Q functions encountered during learning.

An adversarial equilibrium is one where no agent has anything to lose if the other agents change their policies from equilibrium, while a coordination equilibrium is one where all the agents receive the highest possible value (that is the "social welfare solution").

These assumptions can be relaxed by assuming that each agent *knows* whether the opponent is a "*friend*" (in this case a coordination equilibrium will be looked for) or a "*foe*" (in this case an adversarial equilibrium will be looked for).

With this additional information, each agent no longer needs to maintain n Q tables (one for each opponent) and can achieve convergence with only one, expanded, Q table. The relevant algorithm is called the ***Friend or Foe Q-Learning*** algorithm.

This algorithm implements the idea that, for each agent i, i's *friends* are assumed to work together to maximize i's value while i's *foes* work together to minimize i's value.

This algorithm always converges to a stable policy and converges to a NEP under the assumption that the game has an *adversarial equilibrium* or a *coordination equilibrium*.

Friend or Foe algorithm has several advantages over Nash Q-Learning. It does not require the learning of n *Q functions* (one for each one of the other agents) and it is easy to implement because it does not require the calculation of a NEP at each step. On the other hand, it does require to know if the opponents are friends or foes, that is whether exists a coordination or an adversarial equilibrium.

Neither algorithm deals with the problem of finding equilibria in cases without either coordination or adversarial equilibria: such cases are very common and require some degree of *cooperation* among otherwise selfish agents.

The theory of *learning in games* provides the designers of multi-agent systems with many useful tools for determining the possible *equilibrium points* of a system.

However, it is important to underline that, in general, the designers of multi-agent systems are not able to predict which equilibria, if any, the system will converge to (which "equilibrium solution" will emerge): this fact is due to two main reasons: the existence of unpredictable environmental *changes* that can affect the agents rewards and the fact that in many systems each agent has not access to other agents' *rewards*.

Learning agents are often used by system designers, but, in general, changes in the design of the system and learning algorithms affect *time of convergence.*

One problem with learning agents is that, as the agents change their behaviour, in a continuous effort to maximize their utility, the *rewards* for their actions will change, changing their expected utility. The system will likely have *non stationary dynamics*, because it will be always changing to match the new goal. While games theory indicates where the equilibrium points are (given that rewards stay fixed), multi-agent systems often never "get" to those (moving) points.

7. *COGNITIVE APPLICATION INTERFACE: THE PROPOSED RL FRAMEWORK*

The proposed Cognitive Application Interface is based on a *Reinforcement Learningframework.*

For the reasons illustrated in the previous chapter, the QoE problem addressed by the Application Interface can be modelled as a *Reinforcement Learning* problem, where the *RL Agent* role is played by the Requirement Agent.

The Requirement Agent must be able to learn to make optimal decisions based on experience with an*Environment,*to bemodelled with an appropriate *state space* and *reward function*, as illustrated in this chapter.

7.1. Supervisor Agent

At each time $t_l$the Supervisor Agent computes, for each Service Class k (from 1 to K), a set of parameters $\Theta_{SA}(t_l,k)$. The parameters $\Theta_{SA}(t_l,k)$ are computed by the Supervisor Agents by exploiting measurements taken in the time interval $[t_l–T_{\text{monit-l}}, t_l]$, where $T_{\text{monit-l}}$is a proper monitoring period.

In order to take these measurements, the Supervisor Agent can either directly monitor the traffic relevant to the in-progress applications, or set-up a few *probe applications* (i.e. not corresponding to applications set-up by the Actors) statically associated to the Service Classes k (from 1 to K). The most appropriate implementation has to be tailored to the reference scenario.

At each time t_l the Supervisor Agent broadcasts the monitored parameters $\Theta_{SA}(t_l,k)$ (for k=1,…,K) to all the Requirement Agents. These parameters are included in proper signaling messages, hereinafter referred to as *Status Signals* and indicated as $ss(t_l)$, where:

$$ss(t_l) = [\ \Theta_{SA}(t_l,1), \Theta_{SA}(t_l,2),\dots, \Theta_{SA}(t_l,K)]$$

The signalling overhead introduced by the Status Signal consists in broadcasting LK bits, where L is the number of bits necessary to code $\Theta_{SA}(t_l,k)$ and K is the total number of Service Classes, every $T_l$seconds, where T_l is the duration of the period between the broadcast of a given status signal and the next one, i.e. $T_l=t_{l+1}-t_l$. Indeed, this seems to be a very reasonable signalling overhead, even considering that we are referring to a broadcast signal (sent from the single Supervisor Agent to the many Requirement Agents) and no signalling is foreseen in the opposite direction (i.e. from the Requirement Agents to the Supervisor Agent).

According to this proposal, the information deduced from the Status Signal which fed the Requirement Agent in Fig. 3, are just the parameters $\Theta_{SA}(t_l,k)$, k=1,…,K.

7.2. Requirement Agent

The issues of this section applies to any Requirement Agent. Then, without loss of generality, let us consider a given Requirement Agent *a*, namely the one relevant to the Application *a*.

At each time $t_s$the Requirement Agent *a* receives from the Elaboration functionalities a set of *feedback parameters*$\Theta(t_s,a)$ referring to the application *a.*The parameters $\Theta(t_s,a)$ are computed by the Elaboration and Sensing functionalities by exploiting measurements taken in the time interval $[t_s–T_{\text{monit-s}}, t_s]$, where $T_{\text{monit-s}}$is a proper monitoring period.

The Requirement Agent *a* receives from the Application Handler *a* a function h_a which, at each time t_s, allows to compute the *Measured QoE*($QoE_{meas}(t_s,a)$) on the basis of the feedback parameters $\Theta(t_s,a)$, i.e.

$$QoE_{meas}(t_s,a) = h_a(\Theta(t_s,a)). \qquad (7.1)$$

Moreover, at each time t_l, the Requirement Agent *a* receives the Status Signal $ss(t_l)$ and hence the parameters $\Theta_{SA}(t_l,k)$ (k=1,…,K). The parameters $\Theta(t_s,k)$ should have the same nature as the parameters $\Theta_{SA}(t_l,a)$, so that the Requirement Agent *a*, by using the function h_a, can compute the so-called *QoE relevant to the Service Class k* (from 1 to K), hereinafter indicated as $QoE(t_l,a,k)$, in the following way:

$$QoE(t_l,a,k) = h_a(\Theta_{SA}(t_l,k))\text{with} \quad k=1,...,K \qquad (7.2)$$

The *global* information contained in the parameters $QoE(t_l,a,k)$ (k=1,…,K) provides an estimate of the general network state, by Service Class, analysed from the perspective of the Requirement Agent *a* (since the personalized function h_a is used for the computation of these parameters).

The parameter $QoE(t_l,a,k)$ represents an *estimate* of the QoE that the application a will experience at times $t_s$next to $t_l$if the Requirement Agent a selects the Service Class k. Such parameter is an estimate both because $t_s$is next to t_l and because the Supervisor Agent has a different perspective (as concerns parameters to be monitored) than the Requirement Agent a. Nevertheless, even though the parameters $QoE(t_l,a,k)$ are estimates, they seem appropriate in order to provide the Requirement Agent a with a rough preview of what is going to happen if the Requirement Agent will select, in the near future, the Service Class k. In this respect, note that the parameters $QoE(t_l,a,k)$ take into account the personalized way of the application a, to assess its own QoE, since such way is embedded in the function h_a.

On the basis of the above-mentioned information ($QoE_{meas}(t_s,a)$and $QoE(t_l,a,k)$, k=1,.., K), the Requirement Agent a has the key role of selecting, at each time t_s, the most appropriate Class of Service $k(t_s,a)$ to be associated to the micro-flow supporting the Application a, aiming at the target Application QoE mentioned in chapter3.2.

In order to perform the above-mentioned very critical selection, the Requirement Agent is provided with a *Reinforcement Learning* algorithm, as detailed in the next paragraph.

7.3. The Reinforcement Learning problem

The main elements of the considered Reinforcement Learning problem (state space, action space and reward function) are defined as follows.

The action that the Requirement Agent a has to perform is to select,at each time t_s, the proper Service Class $k(t_s,a)$. The action space dimension is equal to K (number of Service Classes).

As far concerns thestate variables, a suitable selection, at time t_s,includes$QoE_{meas}(t_s,a)$,$QoE(t_l,a,1)$,$QoE(t_l,a,2)$,…,$QoE(t_l,a,K)$, possibly normalized with respect to $QoE_{target}$and quantized.

The state space dimension is $N^{\wedge K+1}$, where K is the number of Classes of Service and N is the number of possible QoE levels: in order to keep the state space dimension limited, N should be carefully defined. Consequently, the *state-action value matrix Q* has dimension equal to $N^{\wedge K+1}$x K.

In this way, the Reinforcement Learning algorithm of the Requirement Agent *a* is provided with a suitable information set including:

(i) *local* information contained in the parameter $QoE_{meas}(t_s,a)$ reflecting the local situation taking place at the Requirement Agent *a*,

(ii)*global* information contained in the parameters $QoE(t_l,a,k)$ (k=1,…,K) providing an estimate of the general network state analysed from the perspective of the Requirement Agent *a* (since the personalized function h_a is used for the computation of these parameters).

Finally, as far concerns the<u>reward function</u>$r(t_s)$, a promising choice is the following:

$$r(t_s) = -[QoE_{meas}(t_s,a) - QoE_{target}(a)]^2 = -e(t_s,a)^2$$

By adopting this function, whenever the measured QoE is different from the target QoE the reward is negative (that is, the agent is punished), and is equal to zero only when $QoE_{meas}(t_s,a) = QoE_{target}(a)$. In this way, we push the Requirement Agent to drive the Service Class selection so that the Measured QoE approaches the Target QoE.

A possible <u>alternative reward function</u> is the following:

$$r(t_s) = -[QoE_{meas}(t_s,a) - QoE_{target}(a)]^2 \quad \text{if } QoE_{meas}(t_s,a) \leq QoE_{target}(a);$$
$$r(t_s) = 0 \quad \text{if } QoE_{meas}(t_s,a) \geq QoE_{target}(a).$$

This reward function differs from the previous one if $QoE_{meas}(t_s,a) \geq QoE_{target}(a)$; in this case the reward is zero, i.e. we do not penalize nor award the Requirement Agent for achieving a Measured QoE higher than the Target QoE.

The rationale behind this difference lies in the fact that if the application relevant to a given Requirement Agent *overperforms*, consuming resources at the expenses of the applications relevant to other Requirement Agents (that underperform), the reward function of these last Requirement Agents should drive the overall system to move resources from the Requirement Agent a to the other Requirement Agents; otherwise, the RA can continue to use the available resources.

8. COGNITIVE APPLICATION INTERFACE: THE QOS CASE

In this and in the following chapters the concepts introduced so far will be particularized to the *Quality of Service* of in progress Applications.

Nevertheless, it is worth stressing again that all the concepts introduced so far can also be applied to all other issues which impact on the QoE (e.g. security, mobility, contents, etc.); as a matter of fact, in order to include even these other issues, it is sufficient to properly define the relevant metrics and requirements and the personalized QoE function h_a allowing to measure the QoE of the Application a as a function of the parameters considered in the metrics in question.

8.1. QoS Metrics and Requirements

The proposed QoS **Metric** is based on the following QoS **Service Class Parameters:**

- *D(f,t): Transfer delay (sec)* for the traffic relevant to the flow f at time t is the average delay experienced by its packets from the time they entered the network to the time *t* when they arrive to the outgoing node.
- $R_{adm}(f,t)$: *Admitted bit rate* (bps) for the traffic relevant to the flow *f* at time *t* is the bit rate of traffic to be carried by the network.
- L(*f,t*): *Loss Rate*(bps) for the traffic relevant to the flow *f* at time *t* is the traffic lost in the network (due to possible drops, caused by congestion/overflow, or errors, caused by the physical link techniques).

Each QoS Service Class*k* makes reference to the following QoS **Service ClassReference Values:**

- $D_{max}(k)$: *Maximum transfer delay* (sec)
- $R_{adm-min}(k)$: *Minimum guaranteed (committed)bit rate* (bps);
- $L_{max}(k)$: *Maximum Loss Rate (bps)*;

Taking into account the introduced Service Class Parameters, for a Service Class *k,* the associatedQoS **Service Class Requirements**, for each monitoring period, are the following:

$D(f,t) \leq D_{max}(k)$ (8.1)

$R_{adm}(f,t) \geq R_{adm-min}(f)$ (8.2)

$L(f,t) \leq L_{max}(f)$ (8.3)

The task of the Elaboration functionalities in the Cognitive Managers is to control the Resource exploitation of the network so that for every Service Class, the previous inequalities are, as far as possible, simultaneously satisfied.

8.2. Cognitive Application Interface: an example with QoS

As it has already been stressed in Chapter 3, the number of QoE/QoS Service Classes is a limited and hence, in general, the QoE/QoS Requirements of a given Application do not match with any predefined Service Class Requirements.

So, referring to the QoS Metric introduced in the previous paragraph, in general, the *personalized* QoE/QoS Requirements of a given Application *a* make reference to the following QoE/QoS**Application Reference Values**:

- $D_{max}(a)$: *Maximum transfer delay* (sec)
- $R_{adm\text{-}min}(a)$: *Minimum guaranteed bit rate* (bps)*;*
- $L_{max}(a)$: *Maximum Loss Rate (bps)*;
- $QoE_{target}(a)$: *Target reference QoE level.*

As for the *personalized* function h_a allowing the computation of the QoE experienced by the Application *a*(rif. Chapter 7.2),two options are suggested.

- A<u>first</u> considered <u>option</u> is to identify $QoE_{meas}(t_s,a)$ with the **Link Availability**$L_A(a,t_s)$ of the Application *a,* defined as the percentage of time, computed over the time interval $[t_0, t_s]$, in which the following inequalities are simultaneously met:

  $D(a,t) \leq D_{max}(a)$

  $R_{adm}(a,t) \geq R_{adm\text{-}min}(a)$

  $L(a,t) \leq L_{max}(a)$

  where the parameters $D(a,t)$, $R_{adm}(a,t)$ and $L(a,t)$ refer to the micro-flow supporting the Application *a.* In this case the *personalized* function h_a can be identified with a very simple algorithm which, on the basis of (i) the values assumed by the parameters $D(a,t)$, $R_{adm}(a,t)$ and $L(a,t)$ in the time interval $[t_0, t_s]$ and (ii) the QoSApplication Reference

Values $D_{max}(a)$, $R_{adm\text{-}min}(a)$ and $L_{max}(a)$, computes the corresponding Link Availability $L_A(a,t_s)$.

- Asecond considered option is the following **weighted QoE function**:

$$QoE_{meas}(t_s,a) = \alpha_1 \min[1, 1 - (R_{adm\text{-}min}(a) - R_{adm}(a,t_s))/ R_{adm\text{-}min}(a)] + \alpha_2 \min[1, 1 - (D(a,t_s) - D_{max}(a))/ D_{max}(a)] + \alpha_3 \min[1, 1 - (L(a,t_s) - L_{max}(a))/ L_{max}(a)]$$

where $\alpha_1, \alpha_2, \alpha_3$ are three constants in the range [0,1],subject to the constraint$\alpha_1 + \alpha_2 + \alpha_3 = 1$,to be selected according to the relative importance granted to admitted bit rate, delays and los rate.

The second function allows to define in a smoother and more granular way the global quality actually perceived by the Actors, considering the *QoS degradationlevel*associated to each QoS parameter and weighting each QoS parameter according to its relative importance.

8.2.1. Supervisor Agent in the QoS case.

In this section we will particularize to the QoS case what has been presented, in the general case, in chapter 7.1.

At each time $t_l$the Supervisor Agent computes, for each Service Class k (from 1 to K), the following set of parameters $\Theta_{SA}(t_l,k)$:

$$\Theta_{SA}(t_l,k) = [D_{meas\text{-}SA}(t_l,k), L_{meas\text{-}SA}(t_l,k), R_{adm\text{-}meas\text{-}SA}(t_l,k)]$$

where $D_{meas\text{-}SA}(t_l,k)$, $L_{meas\text{-}SA}(t_l,k)$, $R_{adm\text{-}meas\text{-}SA}(t_l,k)$are measurements referring to the parameters introduced in Section 6.1, taken by the Supervisor Agent in the time interval $[t_l - T_{\text{monit-l}}, t_l]$, where $T_{\text{monit-l}}$is a proper monitoring period, and referring to the various Service Classes k(from 1 to K).

At each time t_l, the Supervisor Agent broadcasts to all the Requirement Agents the following Status Signal$ss(t_l)$:

$$ss(t_l) = [\Theta_{SA}(t_l,1), \Theta_{SA}(t_l,2),\ldots, \Theta_{SA}(t_l,K)]$$

8.2.2. *Requirement Agent in the QoS case*

In this section we will particularize to the QoS case what has been presented, in the general case, in chapter 7.2.

Without loss of generality, let's consider a given Requirement Agent *a*, namely the one relevant to the Application *a*.

At each time t_s,the Requirement Agent *a* receives from the Elaboration functionalitiesthe following set of parameters $\Theta(t_s,a)$ referring to the Application *a:*

$$\Theta(t_s,a) = [D_{meas}(t_s,a), L_{meas}(t_s,a), R_{adm\text{-}meas}(t_s,a)]$$

where $D_{meas}(t_s,a)$, $L_{meas}(t_s,a)$, $R_{adm\text{-}meas}(t_s,a)$are measurements referring to the parameters introduced in the section 6.1, taken by the Requirement Agent in the time interval $[t_s{-}T_{\text{monit-s}}, t_s]$, where $T_{\text{monit-s}}$is a proper monitoring period.

Then, at each time t_s, on the basis of these parameters and of the function h_a, the Requirement Agent *a* can compute the *Measured QoEQoE*$_{meas}(t_s,a)$, as defined in chapter 7.2 (formula 7.1).

Moreover, at each time t_l, the Requirement Agent receives the Status Signal and, on the basis of the relevant parameters and of the function h_a, can compute the *QoE relevant to the Service Class kQoE*(t_l,a,k) (from 1 to K), as defined in chapter 7.1 (formula 7.2).

On the basis of the above-mentioned information, the Requirement Agent *a* has the key role of selecting, at each time t_s, the most appropriate Service Class $k(t_s,a)$ to be associated to the micro-flow supporting the Application *a*. In order to perform the above-mentioned critical selection, the Requirement Agent is provided with a Reinforcement Learning algorithm.

The *state* variables, the *action* and the *reward function* characterizing the Reinforcement Learning problem are those defined in chapter 7.3.

9. REAL NETWORK SCENARIOS

In this chapter we focus on possible real network scenarios in which the approach presented in this thesis can be adopted.

Referring to the QoS case, we are going to examine the case of access networks (both in the wired and wireless scenario), since these type of networks are in general characterized by limited bandwidth capability, an issue that is particularly critical from the QoS point of view. The access networks can be considered as the actual bottleneck of the end-to-end connectivity from the QoS point of view, whilst the core network can be assumed as overprovisioned from the bandwidth point of view, that means that it does not introduce meaningful delays, losses, or throughput limitations, and hence not actually impacting on the QoS.

So, in the following, we deal with the fixed, cellular and ad-hoc access network cases, focusing on the physical positioning of the Application Handler, Supervisor Agent and Requirement Agent within the Cognitive Managers embedded in the various network entities.

9.1. Fixed Networks

A fixed access network is composed by several fixed terminals, connected to the core network by means of a Gateway.

Downlink side (from the Gateway to the fixed terminals)

This is the case occurring whenever a fixed user triggers an application entailing a download (e.g. of a video file) from the network up to the fixed terminal.

In this case, the *Application Handler* has to be placed in the Cognitive Manager embedded in the fixed terminal running the application in question. By so-doing the Application Handler can easily interact with the Application protocols and with the user, in order to deduce the parameter QoE_{target}, as well as the function h for QoE computation. According to the concept sketched in Fig. 3, QoE_{target} and h have to be sent to the Requirement Agent (see Fig. 9). This figure refers to the case in which three Applications (with the corresponding three Requirement Agents (RAs)) involving three different Fixed Terminals are present.

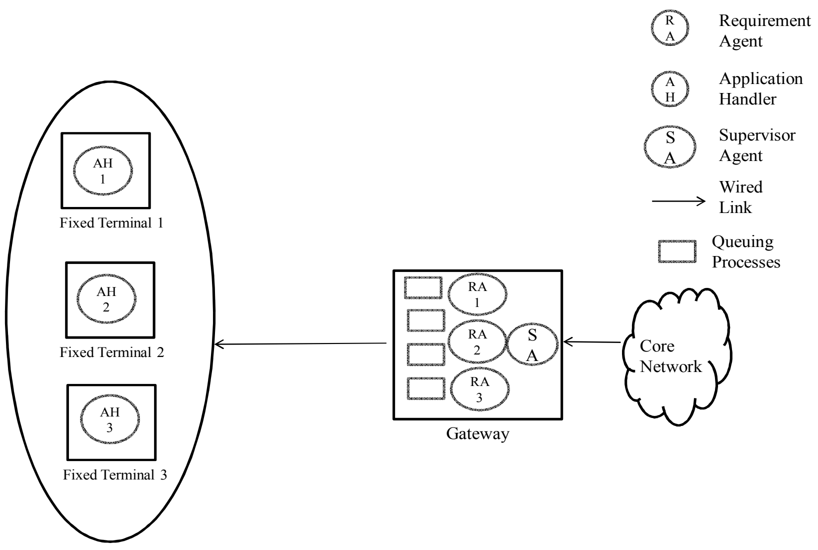


Figure 9 - Application Interface Architecture:-Fixed network - Downlink Side

The *Requirement Agent* has to be placed in the Cognitive Manager of the Gateway since this last is in a position suitable for assessing the performance parameters *D, R_{adm}, BER* of the considered application, which can be easily deduced by monitoring the queues in which the packets relevant to the application in question are temporary stored waiting for being transmitted over the wired link. In Figure 9 the queues monitored by Requirement Agents are depicted: each of these queues is associated to a specific Service Class and stores the packets relevant to the associated Service Class (in the previous example we assume there are four possible Classes of Service).

Note that, in this particular case, the Requirement Agents relevant to applications running in fixed terminals served by a same Gateway are all placed in the Gateway itself. So a *cooperative approach* would be possible, likely yielding to better performance than the adopted non cooperative Q-learning algorithm.

As far as the *Supervisor Agent* is concerned, it is in charge of obtaining global information on the network, and for this reason we identify its natural position inside the Cognitive Manager of the Gateway. In order to compute the parameters $\Theta_{SA}(t_l,k)$ (necessary for generating the Status Signal to be transmitted to the Requirement Agents) for each Class of Service the Supervisor Agent can monitor the downlink traffic that flows across the gateway directed to the fixed terminals.

Note that, in this particular case, the transmission of the Status Signal from the Supervisor Agent to the Requirement Agents does not entail any bandwidth consumption since the Supervisor and the Requirement Agents are all co-located at the Gateway. Thus, just in this case, the period T_s can even coincide with the period T_l.

Uplink side (from the fixed terminals to the Gateway)

This is the case occurring whenever a fixed terminal triggers an application entailing an upload (e.g. from the fixed terminal to the core network).

In this case, as in the previous case, the Application Handler has to be placed in the Cognitive Manager embedded in the fixed terminal running the application in question, to deduce the parameter QoE_{target}, as well as the function h for QoS/QoE computation. According to the concept sketched in Fig. 3, QoE_{target} and h have to be sent to the Requirement Agent (see Fig. 10). This figure refers to the case in which three Applications (with the corresponding three Requirement Agents (RAs)) involving three different Fixed Terminals are present.

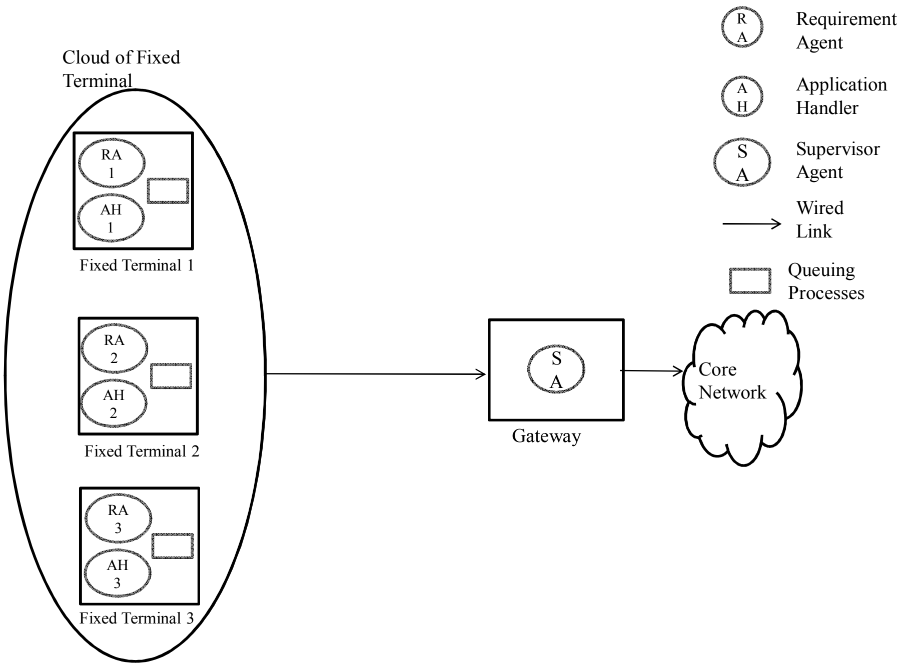


Figure 10Application Interface Architecture: Fixed network - Uplink side

The *Requirement Agent* has to be placed in the Cognitive Manager of the Fixed Terminal since this last is in a position suitable for assessing the performance parameters *D*, R_{adm}, *BER* of the considered application, which can be easily deduced by monitoring the queues in which the packets relevant to the application on question are temporary stored waiting for being transmitted over the wired link. Note that, in this case, the Requirement Agents relevant to applications running in different fixed terminals are all placed in different physical position. So, such Requirements Agents could not exchange information one another, thus justifying the adopted non cooperative Q-learning algorithm.

As far as the *Supervisor Agent* is concerned, similar considerations apply as the ones described in the previous section. Just note that, in this particular case, the transmission of the Status Signal from the Supervisor Agent to the Requirement Agents entails bandwidth consumption since the Supervisor and the Requirement Agents are all located at the Gateway and at the Fixed Terminals respectively. A possible way, in order to limit such a consumption, is to select the period T_l much longer than the period T_s.

9.2. Mobile Networks

9.2.1. Cellular Network

<u>*Downlink side (from the Base Station to the mobiles)*</u>

This is the case occurring whenever a mobile user triggers an application entailing a download (e.g. of a video file) from the network up to the mobile terminal.

In this case, the *Application Handler* has to be placed in the Cognitive Manager embedded in the mobile terminal running the application in question to deduce the parameter QoE_{target}, as well as the function *h* for QoE computation. Hence, these values have to be sent to the Requirement Agent (see Figure 11). This figure refers to the case in which three Applications (with the corresponding three Requirement Agents (RAs)) involving three different Mobile Terminals are present.

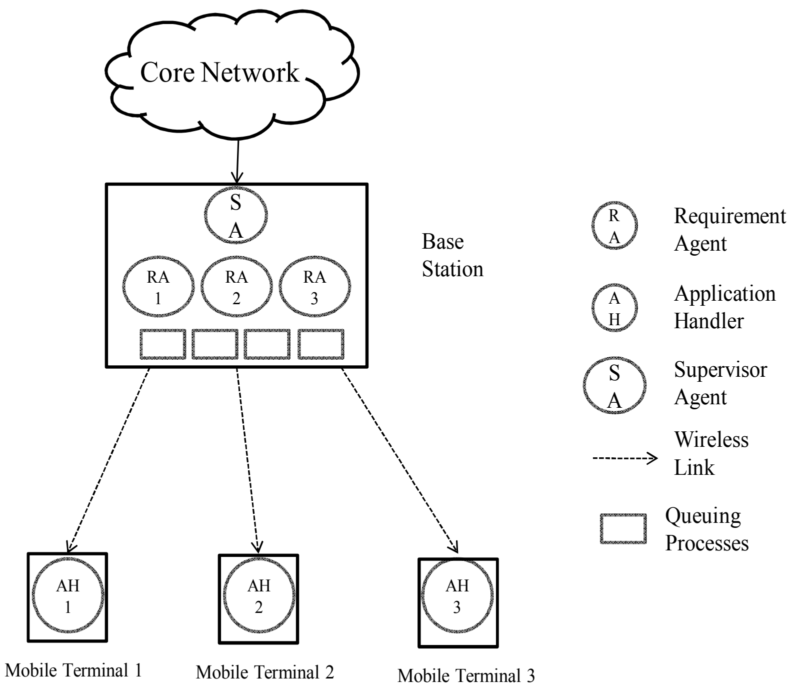


Figure 11- Application Interface Architecture: Cellular Network - Downlink Side

The *Requirement Agent* has to be placed in the Cognitive Manager of the Base Station since this last is in a position suitable for assessing the performance parameters *D*, R_{adm}, *BER* of the considered application, which can be easily deduced by monitoring the queues in which the packets relevant to the application on question are temporary stored waiting for being transmitted over the air interface. In Figure 11 the queues monitored by Requirement Agents are depicted: each of these queues is associated to a specific Service Class and stores the packets relevant to the associated Service Class (in the previous example we assume there are four possible Class of Service).

Note that, in this particular case, the Requirement Agents relevant to applications running in mobile served by a same Base Station are all placed in the Base Station itself. So, such Requirements Agents could exchange information one another without introducing signalling overhead: this means that, just in this particular case, a cooperative approach would be possible, likely yielding to better performance than the adopted non cooperative Q-learning algorithm. Nevertheless, the approach proposed in this thesis has the major advantage of being applicable even in all scenarios (e.g. see in the following) in which an heavy signalling exchange (as it would be required in a cooperative case) among Requirement Agents is not feasible or efficient. .

As far as the *Supervisor Agent* is concerned, it is in charge of obtaining global information on the network, and for this reason we identify its natural position inside the Cognitive Manager of the Base Station. In order to compute the parameters $\Theta_{SA}(t_l,k)$ (necessary for generating the Status Signal to be transmitted to the Requirement Agents) for each Class of Service the supervisor Agent can: (i) monitor the downlink traffic that flows across the base station directed to the mobile terminals relevant to in progress applications triggered by the mobile terminals, and/or (ii) monitor the downlink traffic relevant to so-called *probe applications*, i.e. fake applications, set by the Supervisor Agent with *dummy mobiles* (i.e. with mobile terminals placed at a convenient distance of the Base Station and handled by the network operator) just with the aim to measure the parameters $\Theta_{SA}(t_l,k)$.

Note that, in this particular case, the transmission of the Status Signal from the Supervisor Agent to the Requirement Agents do not entail any bandwidth consumption since the Supervisor and the Requirement Agents are all co-located at the Base Station. Thus, just in this case, the period T_s can even coincide with the period T_l.

Uplink side (from the mobiles to the Base Station)

This is the case occurring whenever a mobile user triggers an application entailing an upload (e.g. from the mobile terminal to the fixed network).

In this case, as in the previous case, the *Application Handler* has to be placed in the Cognitive Manager embedded in the mobile terminal running the application in question. By so-doing the Application handler can easily interact with the Application Protocols and with the user, in order to deduce the parameter QoE_{target}, as well as the function h for QoS/QoE computation. According to the concept sketched in Fig. 3, QoE_{target} and h have to be sent to the Requirement Agent (see Fig. 12). This figure refers to the case in which three Applications (with the corresponding three Requirement Agents (RAs)) involving three different Fixed Terminals are present.

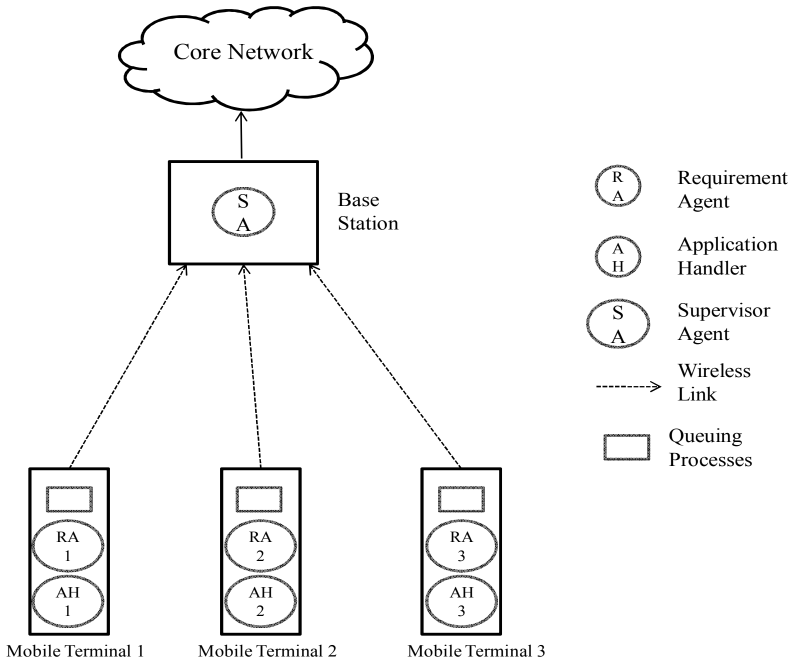


Figure 12 - Application Interface Architecture: Cellular network -Uplink Side

The *Requirement Agent* has to be placed in the Cognitive Manager of the Mobile Terminal since this last is in a position suitable for assessing the performance parameters *D*, R_{adm}, *BER* of the considered application, which can be easily deduced by monitoring the queues in which the packets relevant to the application on question are temporary stored waiting for being transmitted over the air interface. Note that, in this case, the Requirement Agents relevant to applications running in different mobiles are all placed in different physical position. So, such Requirements Agents could not exchange information one another, thus justifying the adopted non cooperative Q-learning algorithm.

As far as the *Supervisor* Agent is concerned, similar considerations apply as the ones described in the previous section. Jus note that, in this particular case, the transmission of the Status Signal from the Supervisor Agent to the Requirement Agents entail bandwidth consumption since the Supervisor and the Requirement Agents are all located at the Base Station and at the Mobile Stations respectively. So, in order to limit such a consumption, motivates the period T_l has to be selected much longer than the period T_l.

9.2.2. Ad-hoc Network

In ad-hoc networks, differently from cellular networks, direct mobile-to-mobile communication can be admitted. So, mobiles can communicate one another either directly (i.e. in a single-hop fashion) if they are in mutual visibility, or exploiting other mobiles as communication bridges (i.e. in a multi-hop fashion); in addition, at least one mobile in the network is provided with the so-called *gateway* functionalities, i.e. it can be connected with the outside world. Usually, the ad-hoc mobiles self-organize themselves in *clusters* where each cluster dynamically elects a *cluster coordinator mobile* which is usually *dynamically* selected as the mobile located in the position closest to the cluster baricenter (from the radio-electrical point of view) (see Fig. 13). Note that all mobiles are provided with the cluster coordination functionalities since they are all potentially eligible as cluster coordinators.

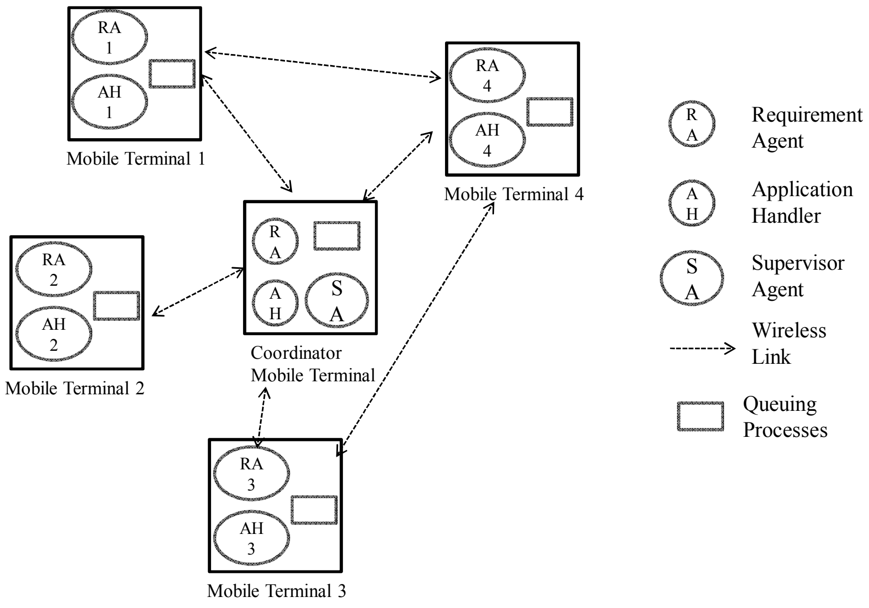


Figure 13 - Application Interface Architecture: Ad-hoc network

In this scenario the *Application Handler* has to be placed in the Cognitive Manager embedded in the mobile terminal triggering the application in question, for the same reasons as the ones exposed for the cellular network scenario. In addition, a *Requirement Agent* has to be placed in the Cognitive Manager of each mobile terminal in charge of transmitting the traffic coming from or directed to the mobile triggering the application, again for the same reasons as the ones exposed for the cellular network scenario (see Fig. 8). Note that, in the multi-hop case, the Application Handler has to carefully select the QoE_{target} to be assigned to the various Requirement Agents embedded in the mobiles involved in the multi-hop transmission, since the composition of the QoE_{target} imposed to the single hops have to generate the QoE_{target} associated to the multi-hop. Note that, once these assignments have been performed each hop can evolve independently of one another.

As far as the *Supervisor Agent* is concerned, it can be conveniently placed in the Cognitive Manager of the cluster coordinator mobile since this last, by definition, due to its baricentral position within the cluster, has the best vision of the present performance occurring within the cluster.

10.IMPLEMENTED NETWORK SCENARIO

This chapter illustrates the adopted simulation tool (OPNET) and the implemented *Model Specification*, describing the Network Model, the QoS policy and the Requirement and Supervisor Agent algorithms.

10.1. Simulation tool: OPNET

Originally developed at MIT, OPNET (Optimized Network Engineering Tools) Modeller has been introduced in 1987 as the first commercial network simulation tool and actually provides a comprehensive development environment supporting the modelling of communication networks and distributed systems.

Both behaviour and performance of modelled systems can be analysed by performing discrete event simulations; it's worth highlighting that the OPNET environment incorporates editors and tools for all phases of a study, including model design, simulation, data collection and data analysis. This paragraph, which aims at providing an overview of OPNET capabilities and structure, is divided into the following four sub-sections:

- *Key System Features*: enumerates salient and distinctive characteristics of the OPNET software;
- *Typical Applications*: presents some applications typically addressed with OPNET and some of the features that provide direct support for those applications;
- *Modelling Methodology*: describes the OPNET approach to each phase of the modelling and simulation project and presents fundamental modelling constructs;
- *Editors and Tools*: introduces the editors and tools that constitute the OPNET environment; each editor, as far as each generic tool, supports a particular phase or sub-phase of the simulation and modelling project.

10.1.1. Key System Features

OPNET is a vast software package with an extensive set of features designed to support general network modelling and to provide specific support for particular types of network simulation projects. This section aims at providing a brief enumeration of some of the most important OPNET capabilities:

- *Object orientation*: systems specified in OPNET consist of objects, each with configurable sets of attributes. Objects belong to “classes” which provide them with their characteristics in terms of behaviour and capability. Definitions of new classes are supported in order to address as wide a scope of systems as possible. Classes can also be derived from other classes, or “specialized” in order to provide more specific support for particular applications;
- *Specialized in communication networks and information systems*: OPNET provides many constructs relating to communications and information processing, ensuring high leverage for modelling of networks and distributed systems;
- *Hierarchical models*: OPNET models are hierarchical, naturally paralleling the structure of actual communication networks;
- *Graphical specification*: wherever possible, models are entered via graphical editors. These editors provide an intuitive mapping from the modelled system to the OPNET model specification;
- *Flexibility to develop detailed custom models*: OPNET provides a flexible, high-level programming language with extensive support for communications and distributed systems. This environment allows realistic modelling of all algorithms, communications protocols and transmission technologies;
- *Automatic generation of simulations*: model specifications are automatically compiled into executable, efficient, discrete-event simulations implemented in the C programming language. Advanced simulation construction and configuration techniques minimize compilation requirements;
- *Application-specific statistics*: OPNET provides numerous built-in performance statistics that can be automatically collected during simulations. In addition, modellers can augment this set with new application-specific statistics that are computed by user-defined processes;
- *Integrated post-simulation analysis tools*: performance evaluation and trade-off analysis require large volumes of simulation results to be interpreted. OPNET includes a sophisticated tool for graphical presentation and processing of simulation output;

- *Interactive analysis*: all OPNET simulations automatically incorporate support for analysis via a sophisticated interactive "debugger";
- *Animation*: simulation runs can be configured in order to automatically generate animations of the modelled system at various levels of detail and can include animation of statistics as they change over time. Extensive support for developing customized animations is also provided;
- *Application program interface (API)*: as an alternative to graphical specification, OPNET models and data files may be specified via a programmatic interface. This is useful for automatic generation of models or to allow OPNET to be tightly integrated with other tools.

10.1.2. Typical Applications

As a result of the capabilities that were described in the previous sections, OPNET can be used as a platform to develop models of a wide range of systems. Some examples of possible applications are listed below:

- *Standards-based LAN and WAN performance modelling*: detailed library models provide major local-area and wide-area network protocols. The library also provides configurable application models, or new ones can be created;
- *Inter-network planning*: hierarchical topology definitions allow arbitrarily deep nesting of sub-networks and nodes and large networks are efficiently modelled; scalable, stochastic and/or deterministic models can also be used in order to generate network traffic;
- *Research and development in communications architectures and protocols*: OPNET allows specification of fully general logic and provides extensive support for communications-related applications. Finite state machines provide a natural representation for protocols;
- *Distributed sensor and control networks, "on-board" systems*: OPNET allows development of sophisticated, adaptive, application-level models, as well as underlying communications protocols and links. Customized performance metrics can be computed and recorded, scripted and/or stochastic inputs can be used to drive

the simulation model, and processes can dynamically monitor the state of objects in the system via formal interfaces provided by statistic wires;

- *Resource sizing*: accurate, detailed modelling of a resource's request-processing policies is required to provide precise estimates of its performance when subjected to peak demand (for example, a packet switch's processing delay can depend on the specific contents and type of each packet as well as its order of arrival). Queuing capabilities of Proto-C provide easy-to-use commands for modelling sophisticated queuing and service policies; library models are provided for many standard resource types;

- *Mobile packet radio networks*: specific support for mobile nodes, including predefined or adaptive trajectories; predefined and fully customisable radio link models; geographical context provided by OPNET network specification environment.(Radio version only);

- *Satellite networks*: specific support for satellite nodes, including automatic placement on specified orbits, a utility program for orbit generation and visualization and, finally, an orbital configuration animation program. (Radio version only);

- *C3I and tactical networks*: support for diverse link technologies; modelling of adaptive protocols and algorithms in Proto-C; notification of network component outages and recoveries; scripted and/or stochastic modelling of threats; radio link models support determination of friendly interference and jamming.

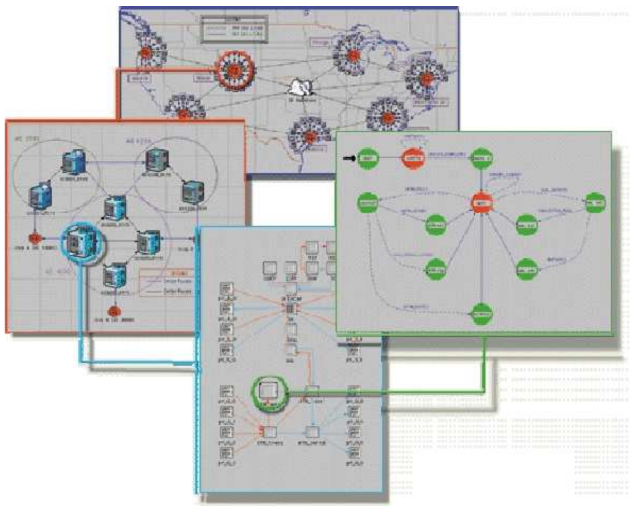
10.1.3. Modelling Methodology

As previously stated, OPNET is provided with a number of editors and tools, each one focusing on particular aspects of the modelling task. These tools fall into three major categories that correspond to the three phases of modelling and simulation projects: specification, data collection and simulation and results analysis. These three phases are necessarily performed in sequence and generally form a cycle, due to a return to the specification phase at the end of the analysis phase. Moreover, the specification phase is actually divided into two parts: initial specification phase and re-specification phase, with only the latter belonging to the cycle.

Specification phase:

The workflow for OPNET (i.e. the steps required to build a specific network model) is based on three fundamental levels, the Project Editor, the Node Editor and the Process Editor. OPNET network models define the position and interconnection of communicating entities, or nodes. Each node is described by a block structured data flow diagram, or OPNET node model, which typically depicts the interrelation of processes, protocols and subsystems. Moreover, each programmable block in a node model has its functionality defined by an OPNET process model, which combines the graphical power of a state-transition diagram(FSM) with the flexibility of a standard programming language (C^{++}) and a broad library of pre-defined modelling functions. OPNET makes use of graphical specification of models wherever appropriate. Thus, the model-specification editors all present a graphical interface in which the user manipulates objects representing the model components and structure. Each editor has its specific set of objects and operations that are appropriate for the modelling task on which it is focused. For instance, the Project Editor makes use of node and link objects; the Node Editor provides processors, queues, transmitters, and receivers; and the Process Editor is based on states and transitions.

As a result, since no single paradigm of visual representation is ideally suited for all three of the above mentioned model types, the diagrams developed in each editor have a distinct appearance and OPNET models fit together in a hierarchical fashion, as shown in the following screen samples:



Data collection and simulation:

The objective of most modelling efforts is to obtain measures of a system's performance or to make observations concerning a system's behaviour. OPNET supports these activities by creating an executable model of the system. Provided that the model is sufficiently representative of the actual system, OPNET allows realistic estimates of performance and behaviour to be obtained by executing simulations through the exploitation of both the Simulation tool and the Interactive Debugging Tool. Several mechanisms are provided to collect the desired data from one or more simulations of a system; for example, OPNET supports both local (related to an object) and global (related to the overall system) statistics and modellers can take advantage of the programmability of OPNET models to create proprietary forms of simulation output. Moreover, OPNET simulations can generate animations that are viewed during the run, or "played back" afterwards. Several forms of predefined or "automatic" animations are provided (packet flows, node movement, state transitions, and statistics). In addition, detailed, customized animations can be programmed if desired.

Results and analysis

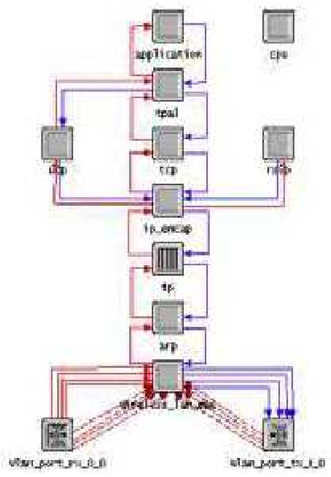
The third phase of the simulation project involves examining the results collected during the simulation phase. OPNET provides basic access to this data in the Project Editor and more advanced capabilities in the Analysis Tool, which provides a graphical environment that allows users to view and manipulate data collected during simulation runs. In particular, standard and user-specified probes can be inserted at any point in a model to collect statistics. Simulation output collected by probes can be displayed graphically, viewed numerically, or exported to other software packages. First and second order statistics on each trace as well as confidence intervals can be automatically calculated. OPNET supports the display of data traces as time-series plots, histograms, probability density and cumulative distribution functions. Graphs (as with models at any level in the OPNET modelling hierarchy) may be output to a printer or saved as bitmap files to be included in reports or proposals.

10.1.4. Editors and Tool

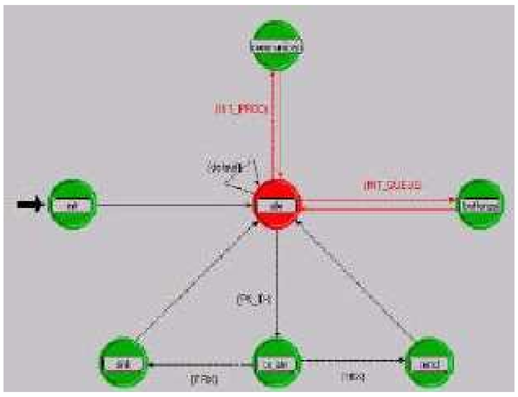
OPNET supports model specification with a number of tools or editors that capture the characteristics of a modelled system's behaviour. Because it is based on a suite of editors that address different aspects of a model, OPNET is able to offer specific capabilities to address the diverse issues encountered in networks and distributed systems. To present the model developer with an intuitive interface, these editors break down the required modelling information in a manner that parallels the structure of actual network systems. Thus, the model-specification editors are organized in an essentially hierarchical fashion. Model specifications performed in the Project Editor rely on elements specified in the Node Editor; n turn, when working in the Node Editor, the developer makes use of models defined in the Process Editor. The remaining editors are used to define various data models, typically tables of values, that are later referenced by process or node level models. This organization is depicted in the following list:

- *Project Editor*: the Project Editor is used to construct and edit the topology of a communication network model. A network model contains only three fundamental types of objects: sub-networks, nodes, and links. There are several varieties of nodes and links, each offering different basic capabilities. In addition, each node or link is further specialized by its "model", which determines its behaviour and functionality. The Project editor also provides basic simulation and analysis capabilities. Finally, it's worth highlighting that the entire system to be simulated is specified by the corresponding network model;

- *Node Editor*: the Node Editor is used to specify the structure of device models. These device models can be instantiated as node objects in the Network Domain (such as computers, packet switches, and bridges). In addition to the structure, the node model developer defines the interface of a node model, which determines what aspects of the node model are visible to its user. This includes the attributes and statistics of the node model. Nodes are composed of several different types of objects called modules. At the node level, modules are "black boxes" with attributes that can be configured to control their behaviour. Each one represents particular functions of the node's operation and they can be active concurrently. Several types of connections (packet streams, statistical wires and logical associations) support flow of data and control information between the modules within a node. The following picture represents a generic Node Model:



- *Process Editor*: The Process Editor is used to specify the behaviour of process models. Process models are instantiated as processes in the Node Domain and exist within processor and queue modules. Processes can be independently executing threads of control that perform general communications and data processing functions. They can represent functionalities that would be implemented both in hardware and in software. In addition to the behaviour of a process, the process model developer defines the model's interfaces, which determines what aspects of the process model are visible to its user. This includes the attributes and statistics of the process model. Process models use a finite state machine (FSM) paradigm to express behaviour that depends on current state and new stimuli. FSMs are represented using a state transition diagram (STD) notation. The states of the process and the transitions between them are depicted as graphical objects, as shown by the following figure:



OPNET also offers other editors among which: the Link Model Editor (to create, edit and view link models), Packet Format Editor (to develop user define packet format models) and Antenna Pattern Editor(to create, edit, and view antenna patterns for transmitters and receivers).

10.2. Model Specification

In this chapter the simulated Model, including the Network model, the QoS policy and the implemented Supervisor and Requirement Agent algorithms are described.

10.2.1. Network model: the Dumbbell network

All the networks described in Chapter 9 (Cellular, Ad-hoc and Fixed Access Network), even though different among them, have in common a same basic layout: a bottleneck link, characterized by a limited capacity, on which many applications can transmit. For this reason, without loss of generality, we decided to test our framework with the so called "Dumbbell network", shown in the following Figure:

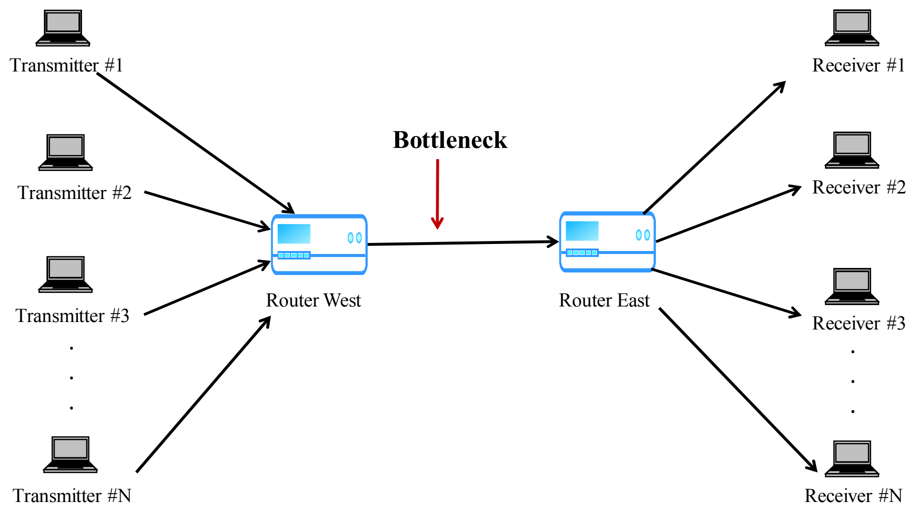


Figure 14 - Dumbbell network

A generic dumbbell network is made of N transmitters (the workstations on the left of the figure) connected to N receivers (the workstations on the right of the figure) by a bottleneck (the central link between the two routers). The presence of a bottleneck link in all the scenarios introduced so far allows us to use this simple model to study the performance of the introduced Cognitive Application Interface in a generic access network.

Moreover, the Dumbbell Network is recognized in literature as a good benchmark for testing new algorithms or new development in telecommunication (for example, see [Sh] and [Da]). For the sake of clarity, we hereinafter report a table highlighting the correspondences among the Dumbbell network elements shown in Fig. 9 (Workstations, Routers and wired link) and the devices relevant to the networks described in Chapter 10.

	Fixed Access Network	***Cellular Network***	***Ad-hoc Network***
Transmitters	Fixed Terminals	Mobile Terminals	Mobile Terminals
Router East	Gateway	Base Station	Cluster Coordinator Mobile
Router West-Bottleneck	Wired Link	Wireless Link	Wireless Link

It is worth stressing that, as highlighted in Chapter 9, when considering the "*uplink-side*" (communications from Terminals to the Gateway or Base Station), the Requirement Agents relevant to applications running in different Terminalshave to be placed in different physical positions so they cannot exchange information one another, thus justifying the adopted non cooperative Q-learning based solution.

10.2.2. QoS policy

OPNET controls the Quality of Service of a generic application by means of two correlated processes: firstly, to each packet relevant to the application is associated a value representing its Class of Service and secondly each router implements a scheduling policy that allows to manage with different priorities packets belonging to different Classes of Service.

The first task is accomplished by the IP layer of the workstation or server on which the particular application runs: the IP layer inserts into a proper field of the IP header a value representing the Class of Service of the packet. OPNET allows to define this value in two ways: the user can set the *Type of Service* (ToS) of the application (Best Effort, Background, Standard, Excellent Effort, Streaming Multimedia, Interactive Multimedia, Interactive Voice, Reserved) or the *Differentiated Service Code Point* (DSCP). In this thesis the latter method is used.

The DSCP architecture (see the following table) identifies five different classes: the first four classes are named Assured Forwarding (AF), while the last Expedited Forwarding (EF), dedicated to low-loss, low-latency traffic:

	Class 1	Class 2	Class 3	Class 4	Class 5
Low Drop	AF11	AF21	AF31	AF41	
Med Drop	AF12	AF22	AF32	AF42	EF
High Drop	AF13	AF23	AF33	AF43	

Packets assigned to the Class 5 (EF) have a greater priority than packets assigned to Class 4,3 etc.; moreover, within each class, packets are given a drop precedence (high, medium or low). The combination of classes and drop precedence yields twelve separate DSCP encodings from AF11 through AF43, plus the special class EF. In our implementation we decided to simulate only four possible Service Classes: AF11, AF21, AF31, AF41.

The scheduling policy implemented in network routers is in charge of manage packets with different priorities. As a matter of fact we can model a generic router as a set of queues, each associated to a specific Class of Service (in the DSCP case we can have a maximum of thirteen queues); the scheduling mechanism has to decide which queue has to transmit and for how long. OPNET offers different scheduling mechanisms: Priority Queuing, Weighted Fair Queuing, Modified Weighted Round Robin (see [Ku] for reference). In this thesis we decided to use the *WFQ scheduler*.

10.2.3. Supervisor and Requirement Agent algorithms implementation

In this paragraph the OPNET implementation of the Supervisor Agent and Requirement Agent described in Chapter 7 and 8 is illustrated.

<u>Supervisor Agent</u>

As stated in Chapter 8 the Supervisor is in charge of obtaining global information about the status of each Class of Service in the network. In our simulation scenario the modelled Supervisor can obtain these measures directly from the IP layer of the Router East; the following figure depicts the Node Model of the Supervisor Agent:

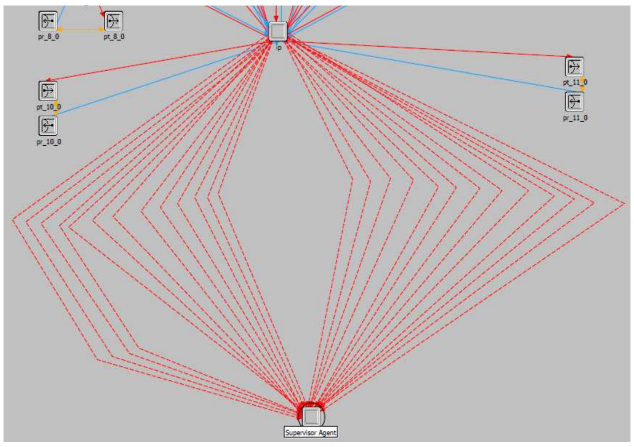


Figure 15 - Supervisor Agent: Node Model

The red links are called “statistic wire” and represent information exchanged by processes in the same node (in other words they do not represent a communication channel). Each of this link communicates to the Supervisor both the total traffic admitted and the delay experienced in the associated queue for each Class of Service. These global measures are then pre-processed by the Supervisor and sent to each Requirement Agent by means of the Status Signal. The Internal Model (or *Process Model*) of the Supervisor is depicted in the next picture:

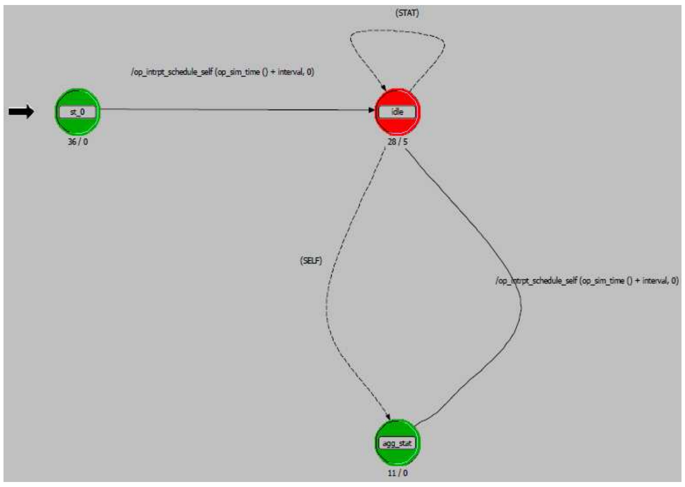

(STAT)
/op_intrpt_schedule_self (op_sim_time () + interval, 0)
st_0
36 / 0
idle
28 / 5
(SELF)
/op_intrpt_schedule_self (op_sim_time () + interval, 0)
agg_stat
11 / 0

Figure 16 - Supervisor Agent: Process Model

The pseudo-code representing the procedures encoded in the previous FMS is also given (this code is relevant to the i-th queue associated with the i-th Service Class):

```
/*Counter for number of packets arrived at the queue
packet_counter=0;
/*Delay experienced by packet transmitted in the queue
delay_counter=0;
```

```
/*Size of packet transmitted
traffic_counter=0;

/*Each $T_l$ seconds the supervisor updates the status signal
/* The computation of the Traffic Admitted and Delay is performed during an interval
/*ofduration $T_{monit-l}$
for t→[T; T+$T_l$)
        if (t< T+$T_{monit-l}$&& +packet_transmission==true)
                packet_counter++;
                delay_counter=delay_counter+current_delay;
                traffic_counter=traffic_counter+current_traffic;
        endif
endfor

/*Update traffic admitted and average delay (we consider also the overhead introduced by
mac level)
traffic_admitted=(traffic_counter+ 208*packet_counter)/$T_{monit-l}$;
delay=delay_counter/packet_counter;

/*Update status signal
put(traffic_admitted, i, status_signal);
put(delay, i, status_signal);

send_to_Agents(status_signal);
T= T+$T_l$;
```

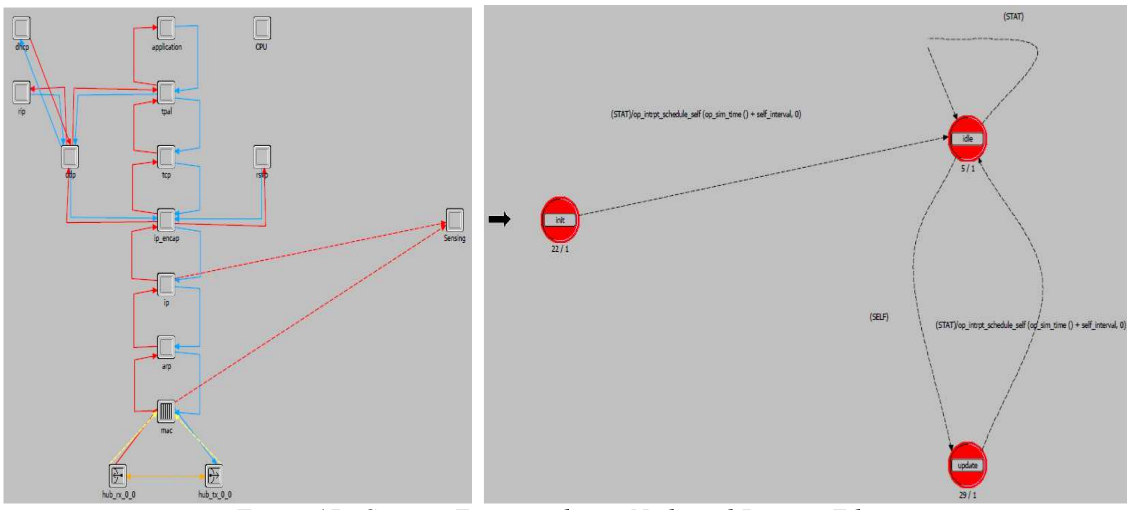
For the queue i, the Supervisor Agent counts the number of packets transmitted (variable *packet_counter*), the total delay experienced by each packet (*delay_counter*) and the total traffic admitted, in bit (*traffic_counter*) during the period of duration $T_{\text{monit-l}}$. Then, by using these values, the Supervisor computes the traffic admitted and the delay experienced by the *i*-th Service Class. It is worth stressing that, as highlighted in Chapter 8, the values relative to Traffic Admitted and Delay are computed by the Supervisor Agent by exploiting measurements taken in the time interval of duration $T_{\text{monit-l}}$, where $T_{\text{monit-l}}$ can in general be different from T_l. We made the reasonable hypothesis that the bigger part of the delay experienced by packets is due to the time they wait in these queues or, in other words, that the processing and transmission delay is not relevant.

It is worth reminding that, as described in Chapter 9, in real implementations, delay and bit rate of the admitted traffic can be computed by monitoring the performance of the so-called *probe applications*.

Requirement Agent

The modelled Requirement Agent is in charge of taking decisions about which Class of Service is more suitable for the corresponding application. It includes (i) the *sensing*and *elaboration*functionalities that allow to measure the QoEexperienced by the application, and (ii) the *control* algorithm that, on the basis of the above-mentioned measure and of the Status Signal received from the Supervisor Agent, has to select the appropriate Class of Service.

The *sensing* functionalities have been implemented in OPNET as shown in the following:


dhcp
application
CPU
rip
tpal
udp
tcp
rsvp
ip_encap
Sensing
ip
arp
mac
hub_rx_0_0
hub_tx_0_0
(STAT)
(STAT)/op_intrpt_schedule_self (op_sim_time () + self_interval, 0)
idle
5 / 1
init
22 / 1
(SELF)
(STAT)/op_intrpt_schedule_self (op_sim_time () + self_interval, 0)
update
29 / 1
Figure 17 - Sensing Functionalities: Node and Process Editor

The sensing process obtains from the MAC layer the bits admitted in the network and from the IP layer the delay experienced by packets. By using this information, the modelled Requirement Agent can compute the QoE of the application that is used by the control algorithm.

It is worth reminding, that in real implementations, the above-mentioned sensing functionalities will be provided by the Sensing functionalities of the Cognitive Managers, and the QoS parameters will be provided by the Elaboration functionalities of the Cognitive Managers (see Chapter 3).

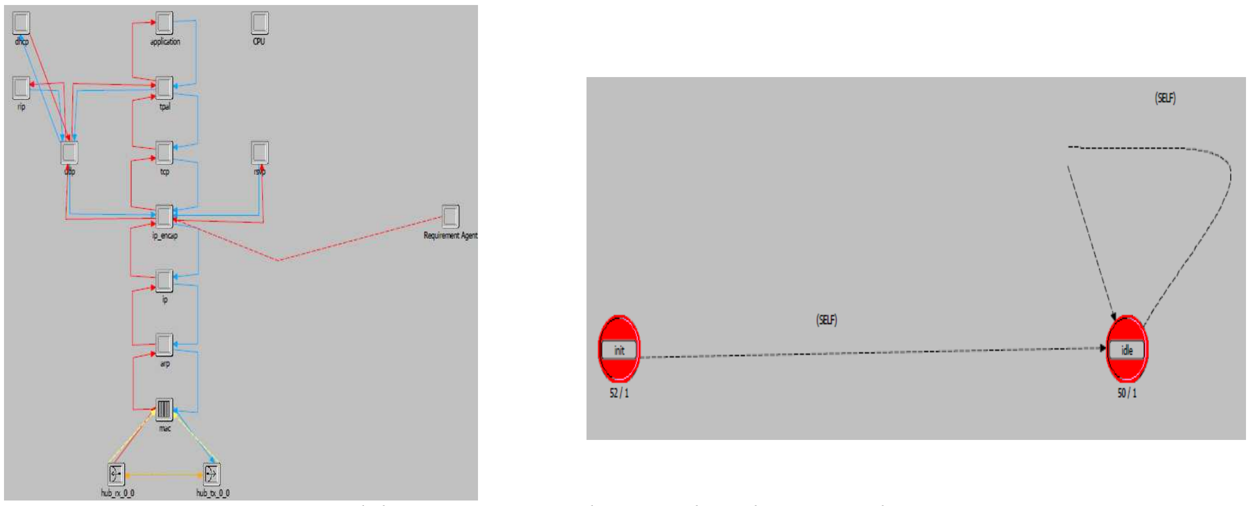


Figure 18 - Elaboration Functionalities: Node and Process Editor

Then, the selected *control* algorithm consists in a Q-learning algorithm (as illustrated in paragraph 5.5.6). By using such algorithm the Requirement Agent selects the most appropriate Class of Service; this control is then *enforced* to the IP layer changing the DSCP field relative to the Class of Service in the IP header (the red statistic wire in the former picture).

The procedures just introduced can be summarized in the subsequent pseudo-code:

```
/*The Agent computes QoE for each Service Class using the status signal
receive_from_Supervisor(status_signal);
for i→[1;number_CoS]
        QoE_super(i)=update_QoE(status_signal, i);
endfor
packet_counter=0;
delay_counter=0;
traffic_counter=0;

/*The Agent computes the QoE of its application by exploiting measurements taken in an
interval of duration $T_{monit-s}$
for t→[T; T+$T_s$)
        if (t< T+$T_{monit-s}$&& +packet_transmission==true)
                packet_counter++;
                delay_counter=delay_counter+current_delay;
                traffic_counter=traffic_counter+current_traffic;
        endif
endfor

traffic_admitted=(traffic_counter+208*packet_counter)/$T_{monit-s}$;
delay=delay_counter/packet_counter;
QoE=update_QoE(traffic_admitted, delay);

/*The Agent computes the current state and reward from QoE and update the Q-value
matrix
agent_state=create_state(QoE, QoE_super);
reward=compute_reward(QoE, QoE_target);
reinforcement_learning(agent_state, agent_state_past, action_past);

/*The Agent takes an action on the basis of an $\epsilon$-greedy policy
action_past=compute_next_action(agent_state);
agent_state_past=agent_state;
T=T+$T_s$;
```

During the period of duration $T_{monit-s}$ the Requirement Agent counts the number of packets transmitted (variable *packet_counter*), the total delay experienced by each packet (*delay_counter*) and the total traffic admitted, in bit (*traffic_counter*). Then, by using these values, the Requirement Agent computes the *admitted traffic* and the *delay* experienced by its associated application. It is worth stressing that, as highlighted in Chapter 8, the measures relative to Admitted Traffic and Delay are computed by the Requirement Agent by exploiting measurements taken in the time interval of duration $T_{monit-s}$.

The method *update_QoE* uses the *weighted QoE function* defined in chapter 8.2 to update the QoE both for the applications controlled by the Requirement Agent, named *QoE,* and both for the i-th Service Class (by means of the Status Signal transmitted by the Supervisor Agent), named*QoE_super,* using the measured Traffic Admitted and Delay. In this thesis we do not consider the Loss Rate for the reasons illustrated in the following Chapter.

The method *compute_reward* has the task of computing the reward, through the measured Quality of Experience *QoE* and the target one,*QoE_target,*using thefirst *reward function*defined in chapter 7.3.

The method *create_state* has the key role of creating an opportune state representation, named *agent_state,* from the measured QoE (both relative to the controlled application and the Service Classes), in order to apply the Q-learning algorithm. In particular, this method has to introduce a convenient *quantization* in the measured QoE. As stated in chapter 7.3, the state of the Requirement Agent is composed by: (i) the measured QoE associated with the controlled application *QoE* and (ii) the measured QoE associated with each Service Class, deduced by means of the Status Signal *QoE_super.* Hence, the state can be represented as a vector of K+1 components, where K is the number of Service Classes. The total number of possibile states in this representation is equal to N^{K+1}, where N is the number of possibile values the QoE can take.

As a matter of fact, the real measures relative to Quality of Experience can take all possible values in the interval [0;1]. In order to reduce the dimension of the Q-values matrixand the complexity of the implemented algorithm, se set N equal to 3, considering only three possible values for the measured QoE: *Low* (if $0 \leq QoE < 0,7$), *Medium*(if $0,7 \leq QoE < 9$), and *High*(if $0,9 \leq QoE \leq 1$).

In our implementation we use 4 different Service Classes: this means that the total number of possibile states is equal to $3^5=243$. Moreover, as far as the Q-values matrix is concerned, it is a matrix composed by 243 rows, the number of possible states, and 4 columns, the number of possibile actions (Service Classes).

The method *Q_learning* updates the Q-values matrix applying the Q-learning algorithm described in paragraph 5.5.6 by means of: the current agent state *(agent_state),* the agent state at the previous step *(agent_state_past)* and the action taken at the previous step *(action_past).*

The method *compute_next_action* returns the new action to be taken by the agent employing the current agent state and the Q-values matrix, following an*ϵ-greedy policy* (see chapter 5.5.5).

11.SIMULATION RESULTS

This chapter describes the simulated scenarios and illustrates the results obtained implementing the innovative QoE control framework introduced in this thesis.

11.1. Reference Scenario and key parameters

This chapter shows the performance of the approach described in this thesis highlighting the enhancements of a *dynamic* association between Applications and Service Classes(hereinafter this case will be referred to as *dynamic case*) with respect to the *static case*.

In the dynamic case each Application can dynamically change its Service Class, by means of the reasoning embedded in the Cognitive Application Interface as described in Chapters7 and 8, whilst in the static case the application interface just provides a static mapping between Applications and the most suitable Service Classes.

The simulated framework is the *Dumbbell network*described in Chapter 10.

We have considered two Application types: "Video Conference" and FTP, two built-in Opnet types.

In this respect, we have simulated the following scenarios:

- *Single-Application Scenario*: three "Video Conference" Applications transmit on a channel with capacity *C* equal to 7 Mbit/sec, for 700 seconds. We simulate both the static and the dynamic cases with different levels of network traffic;
- *Multi-Application Scenario*: two "Video Conference" applications and one FTP application transmit on a channel with capacity *C* equal to 7 Mbit/sec, for 700 seconds. We simulate both the static and the dynamic cases, with different levels of network traffic.

The following table, referring to the parameters introduced in Chapters 5,7 and 8, summarizes the selected values for Opnet implementation:

	Q-learning algorithm			***QoE Computation (weights)***			***T_l- $T_{monit-l}$ (sec)***	***T_s- $T_{monit-s}$ (sec)***
	Learning Rate	***Discount Factor***	***Exploring Factor***	α_1	α_2	α_3		
Requirement Agent	1/k	0.7	0.1	0.5	0.5	0	-	2
Supervisor Agent	-	-	-	-	-	-	40	-

The previous table shows that the coefficientα_3, related to the *Loss Rate* parameter in the QoE computation (see chapter 8.2), has been set to zero: this means that our simulations do not consider the *Loss Rate* in QoE computation. This choice can be justified by several evidences: (i) in wired networks the *BER*(Bit Error Rate) is negligible, while in wireless networks the most advanced physical link techniques (encoding, modulation, shadowing control, etc.) techniques allow a strict *BER* control (i.e. the measured BER is, in almost situations, lower than the maximum tolerated one), (ii) for *Loss rate* critical Applications the possible presence of the transport layer protocol TCP, in charge of retransmitting loss or damaged packets, further contributes to keep *Loss Rate* strictly controlled, (iii) traffic overflow at queue level is limited by proper dimensioning of queue lengths.

As shown in the previous table, both for the Supervisor and Requirement Agent,$T_{\text{monit-l}}$ and $T_{\text{monit-s}}$ have been chosen equal respectively to the periods T_l and T_s(see Chapter 8). This means that the *monitoring* period, during which the measurements to compute QoE are collected, and the *control* period, at the end of which the Service Class is selected, are equal.

As far as the Learning Rate is concerned, we chose a sequence that satisfies the *stochastic approximation conditions* described in paragraph 5.5.4. At this proposal, we have to point out that, in our scenario, it is recommended to *restart* the learning process if the performance obtained by the Requirement Agent is poor, since we are dealing with an Environment that can vary due to the presence of other Agents. For the same reason, in real implementations, the Agents have never to completely *stop* the learning process.

11.2. Single-Application Scenario

As previously introduced, this scenario considers three “Video Conference” Applications transmitting on a channel with capacity C equal to7 Mbit/sec.

Considering that, as stated in the previous chapter, we assume α_3=0, the measures used to compute QoE are the admitted traffic R_{adm} and the experienced delay D, or better the difference among these values and the corresponding thresholds, namely $R_{adm-min}$ (minimum guaranteed bit rate), and D_{max} (maximum transfer delay). We have assumed that these thresholds are equal for the three Video Applications: the only difference among them lies in the fact that we have assigned three different levels of QoE_{target}; note that, in the static case these three different levels correspond to the static mapping of the three Applications in three different Service Classes. In general, in the static case, no Service Class is able to guarantee the specific QoE target required by the relevant application: the only issue a Service Class is able to guarantee is a different priority among applications; for this reason the application associated with the highest QoE target will be assigned to the highest available Service Class and so on.

It is important to remark that in this thesis we do not implement the *Application Handler* described in Chapter x. For this reason, as far as the QoE targets are concerned, we assume the role of the Application Handler, setting up three different QoE targets (one for each application), in order to represent three possible users with different requirements.

In order to analyse the behaviour of our algorithm, we simulate five different *Traffic Scenarios*, ranging from a situation in which the bottleneck link is idle (Traffic Scenario #1), to a situation in which the bottleneck link is very congested:

- Traffic Scenario #1: the sum of the applications minimum guaranteed bit rate doesn’t exceed the link capacity ($3R_{adm-min} \approx 0.85C$);
- Traffic Scenario #2: the sum of the applications minimum guaranteed bit rate is slightly higher than the link capacity ($3R_{adm-min} \approx C$);
- Traffic Scenario #3: the sum of the applications minimum guaranteed bit rate exceeds the link capacity ($3R_{adm-min} \approx 1.3C$);

- Traffic Scenario #4 and #5: the sum of the applications minimum guaranteed bit rate greatly exceed the link capacity ($3R_{adm\text{-}min} \approx 1.5C$ in Scenario #4 and $3R_{adm\text{-}min} \approx 1.8C$ in Scenario #5).

11.2.1. Traffic Scenario #1

The following table illustrates the main parameters of the three Video Applications used to simulate traffic inScenario #1:

	***$R_{offered}$* (bits/sec)**	***$R_{adm\text{-}min}$* (bits/sec)**	***D_{max}* (sec)**	***QoE_{target}***	***Service Class***
Video #1	4300000	2000000	0.18	0.99	AF41
Video #2	4300000	2000000	0.18	0.94	AF31
Video #3	4300000	2000000	0.18	0.89	AF21

Figures19 and 20 refer to the static and dynamic cases, respectively. The simulations report the Measured QoE value as a function of the simulation time, and refer to the so-called *Averaged QoE*, which is deduced by averaging the QoE measured in the time interval ranging from the beginning of simulation till the current simulation time.

The graphs are relevant since we are primarily interested in achieving an *average* QoE that converges to the *target*QoE. As a matter of fact, the network operators policy has not the aim of providing to users a QoE value that is equal to the QoE target at each time instant; instead, the network operators policy's aim is that of guaranteeing to users an average QoE as far as possible close to the QoE target. The average is computed over a time slot that can change according to the user and/or the application type.

As stated at the beginning of the paragraph, in Traffic Scenario #1 the sum of the minimum guaranteed bit rates for the applications does not exceed the link capacity. For this reason, in the static scenario (Figure 19), the applications Video #1, Video #2 and Video #3 reach a value of QoE equal to one. This is due to the fact that, since the channel is not congested, the QoS policy implemented in Router East is always able to admit at least the minimum guaranteed bit rate for each application. Moreover, also the delay experienced by Video applications is always lower than the maximum admitted delay. Also in this circumstance, this is due to the fact that the channel is not congested and the waiting time inside the queues is negligible. This entails that, in the QoE computation with the formula 7.1, the value obtained in the static case is equal to one. In the dynamic case the aim of the algorithm is to reduce, as much as possible, the *error* between the obtained QoE and the target QoE. As Figure 20 depicts, Video #1 (the higher priority application) reaches the same average QoE of the static case. As far as Video #2 and Video #3 are concerned, the QoE values obtained are lower than the static case but closer to QoE target.

The following table reports the percentage errors (differences between the average QoE and the target QoE at the end of simulation, normalized with respect to the QoE target) obtained at the end of the simulation:

	Video #1	***Video #2***	***Video #3***
Static Case	1%	6%	12%
Dynamic Case	1%	3%	7%

Table 1: Scenario 1 - Percentage Error

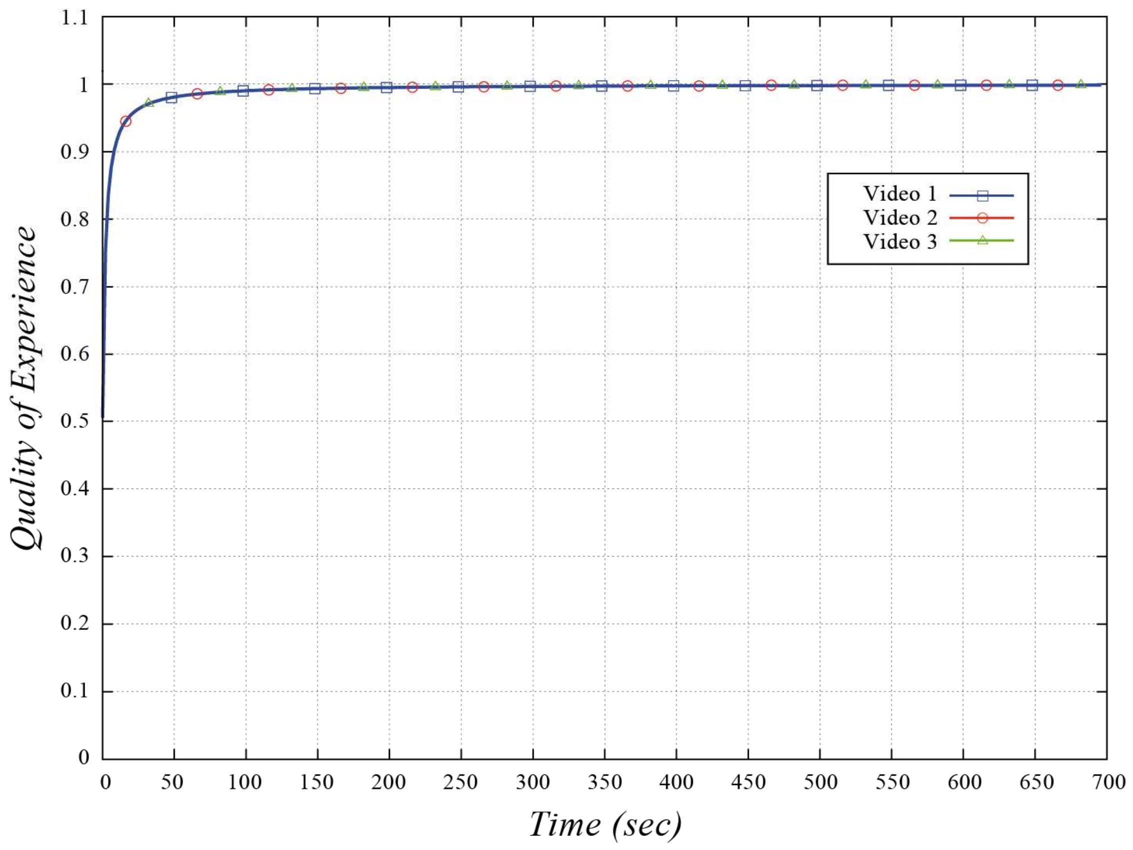


Figure 19 -Scenario 1: Average QoE- Static Case

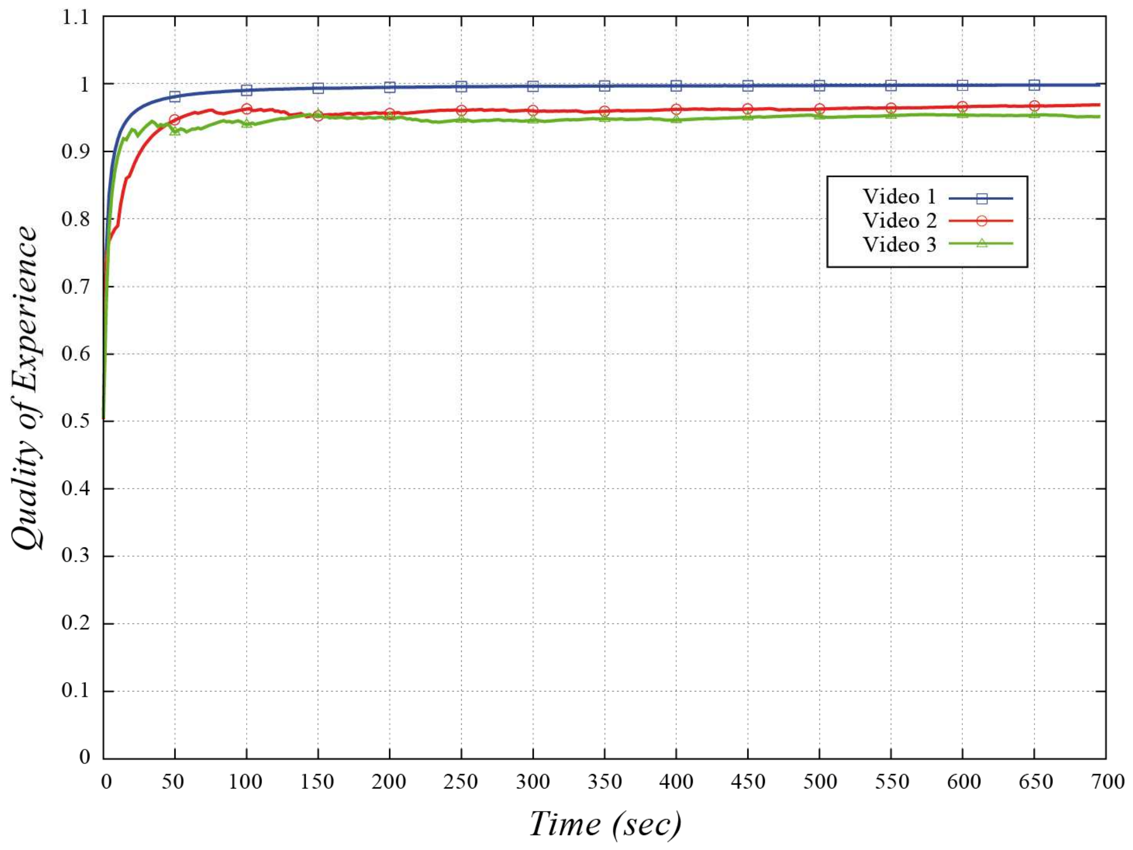


Figure 20 -Scenario 1: Average QoE- Dynamic Case

11.2.2. Traffic Scenario #2

The following table illustrates the main characteristics of the three Video applications used to simulate traffic in Scenario #2:

	***$R_{offered}$* (bits/sec)**	***$R_{adm\text{-}min}$* (bits/sec)**	***D_{max}* (sec)**	***QoE_{target}***	***Service Class***
Video #1	4300000	2500000	0.18	0.99	AF41
Video #2	4300000	2500000	0.18	0.94	AF31
Video #3	4300000	2500000	0.18	0.89	AF21

In this case we simulate the network at the limit of congestion, since the sum of the minimum guaranteed bit rate barely exceeds the link capacity.

In this Scenario it is evident that a dynamic choice of Service Classes entails better performance with respect to a static association. In the Static case (Figure 21) the different priority (due to different Service Classes) given to the Video applications is evident: Video #1 obtains the higher QoE, then respectively Video #2 and Video #3. Even in a low congestion scenario, a static approach is not able to guarantee a value of QoE close to the target, especially for Video #2 and #3 (see Table 2). The performance worsening with respect to Scenario #1 is mainly due to the network congestion. In Scenario #2, the sum of the minimum guaranteed bit rates exceeds the link capacity; this obviously entails that it is impossible to admit for all applications the required bit rate. Similarly, also the queuing time increases (the channel works as a bottleneck causing packets wait in the relevant queue until transmission) and this leads to a poor QoE, especially for low priority applications.

Analogous considerations are valid also in the dynamic case (Figure 22). Despite that, even though the QoE does not converge to the target, the QoE values obtained in the dynamic case are higher than the values reached in the static one. This is due to the opportunity for applications to dynamically change their Service Class according to the congestion level of the network. Both from Figure 22 and Table 2 can be noted that the algorithm is very effective especially for Video #2 and Video #3, while Video #1 obtains similar outcome both in static and dynamic case. This result is caused by the fact that in the static case Video #1 is associated to the highest priority class and consequently it obtains the highest bit rate and the lowest delay achievable in the network. For this reason, the QoE attained in the static case by Video #1 represents a sort of “upper limit”, that is very challenging to overcome. Nevertheless, also in the dynamic case, the same value of QoE with respect to the static case is reached (the % error is the same), thus highlighting the effectiveness of our approach. The following table reports the percentage errors obtained at the end of the simulation:

	Video #1	***Video #2***	***Video #3***
Static Case	-4%	-12%	-20%
Dynamic Case	-4%	-5%	-3%

Table 2 - Scenario 2: Percentage Error

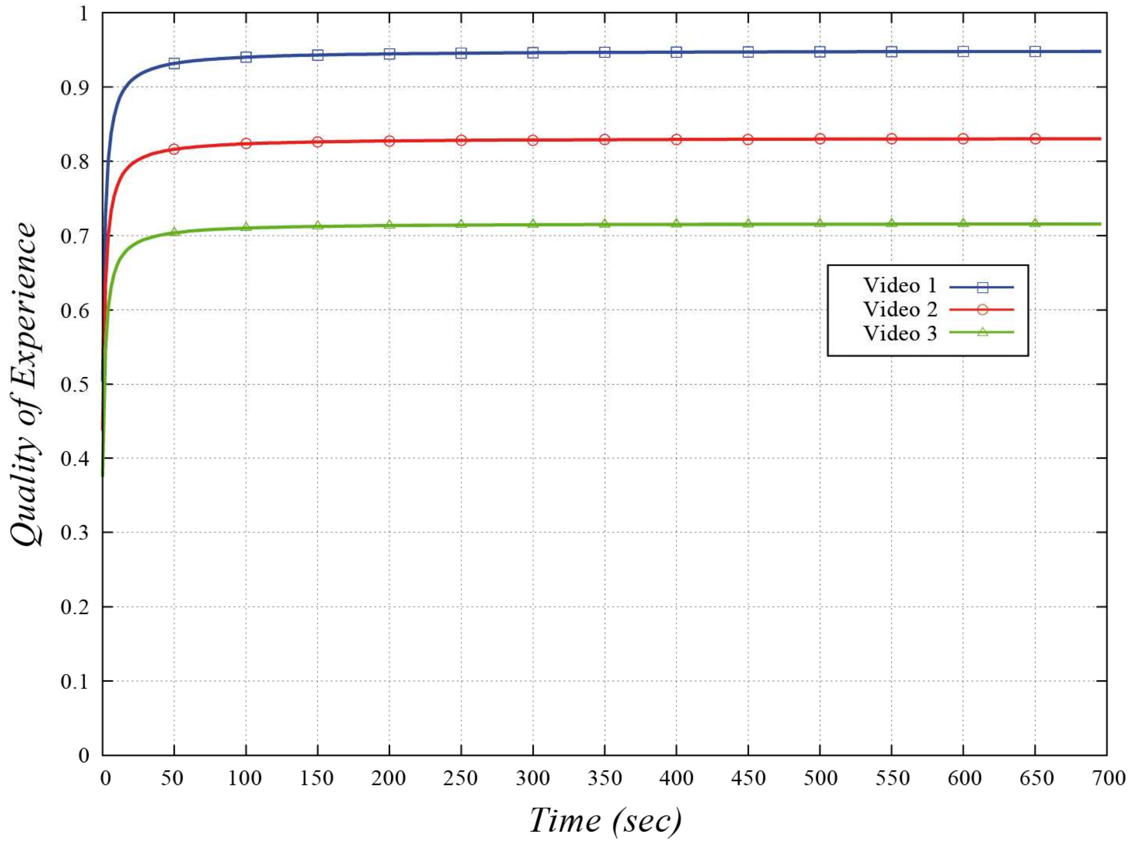


Figure 21–Scenario 2: Average QoE- Static Case

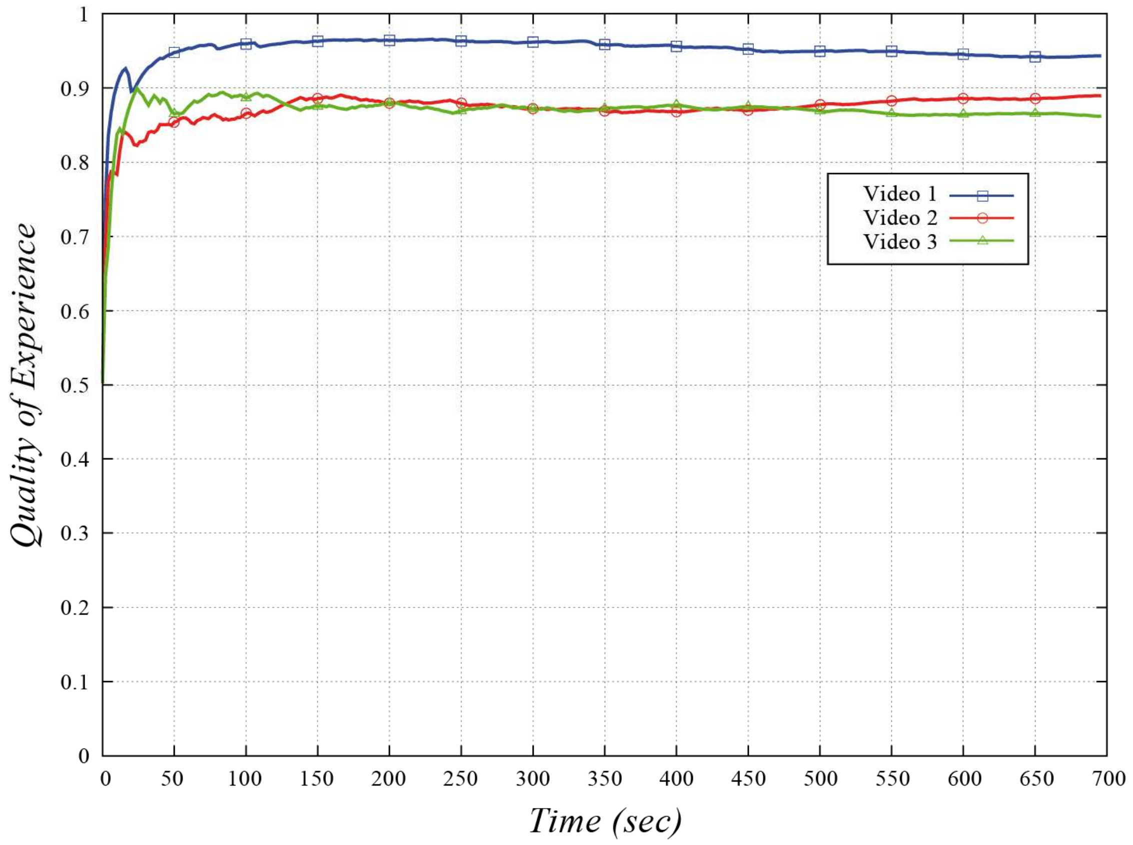


Figure 22–Scenario 2: Average QoE- Dynamic Case

11.2.3. Traffic Scenario #3

The following table illustrates the main characteristics of the three Video applications used to simulate traffic in Scenario #3:

	$R_{offered}$ *(bits/sec)*	$R_{adm\text{-}min}$ *(bits/sec)*	D_{max} *(sec)*	QoE_{target}	***Service Class***
Video #1	4300000	3000000	0.18	0.99	AF41
Video #2	4300000	3000000	0.18	0.94	AF31
Video #3	4300000	3000000	0.18	0.89	AF21

As expected, as the traffic increases, the performance deteriorates, especially in the static case (similar considerations with respect to Scenario #2 can be repeated). Even in this scenario, a dynamic approach performs better than a static association, and an improvement can be noted also for Video #1 (see Figure 24 and Table 3). Another aspect to highlight is the convergence time toward stable QoE values, that is always in an interval of sixty seconds. This value seems acceptable also from a real implementation point of view. The following table reports the percentage errors obtained at the end of the simulation:

	Video #1	***Video #2***	***Video #3***
Static Case	-12%	-20%	-27%
Dynamic Case	-11%	-11%	-9%

Table 3 -Scenario 3: Percentage Error

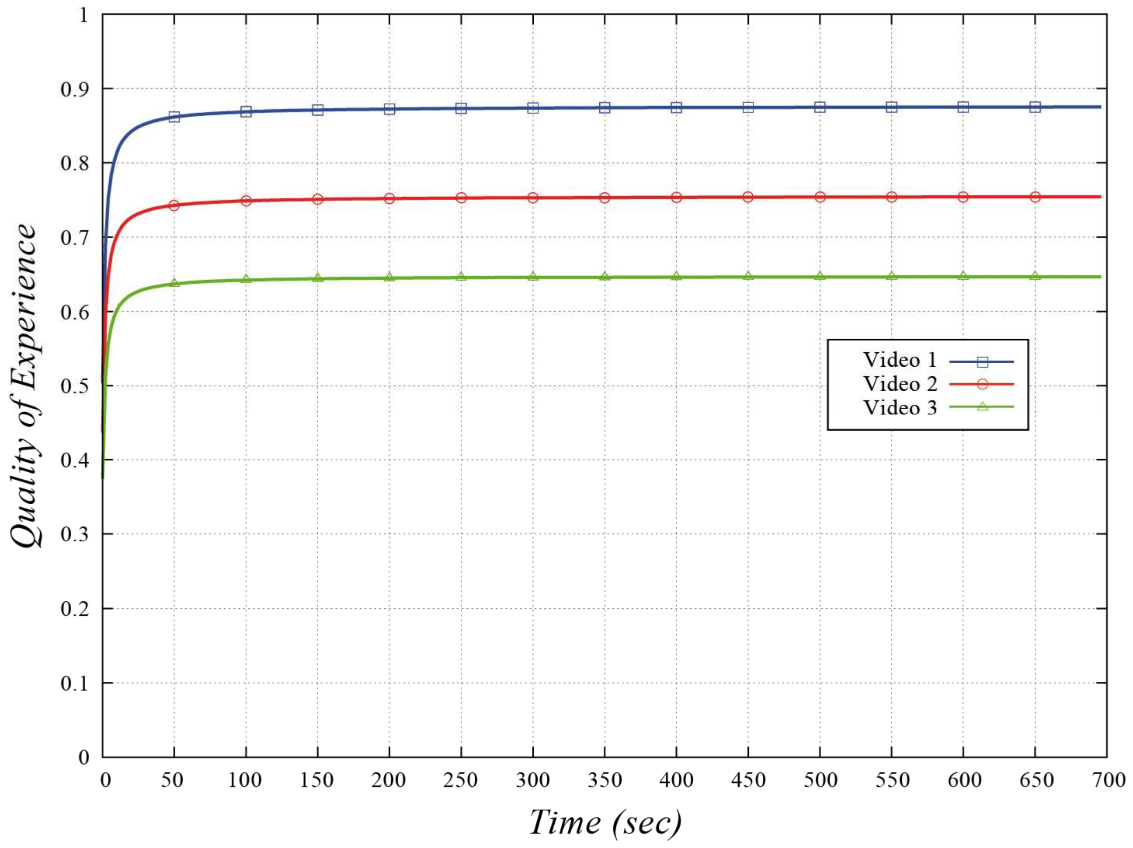


Figure 23–Scenario 3: Average QoE- Static Case

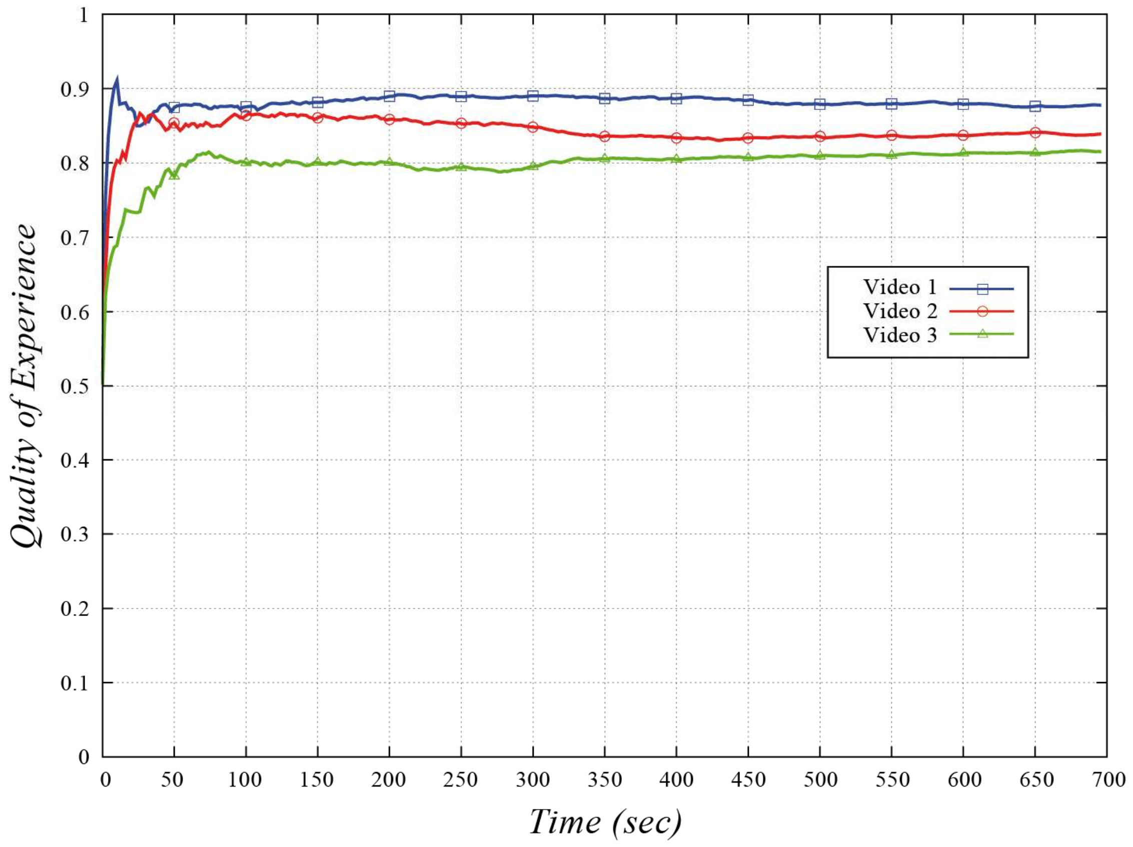


Figure 24–Scenario 3: Average QoE- Dynamic Case

11.2.4. Traffic Scenario #4 and #5

The following table illustrates the main characteristics of the three Video applications used to simulate traffic in Scenario #4 and #5:

	$R_{offered}$ *(bits/sec)*	$R_{adm\text{-}min}$ *(bits/sec)*		D_{max} *(sec)*	QoE_{target}	***Service Class***
		Scenario #4	*Scenario #5*			
Video #1	4300000	3500000	4200000	0.18	0.99	AF41
Video #2	4300000	3500000	4200000	0.18	0.94	AF31
Video #3	4300000	3500000	4200000	0.18	0.89	AF21

These are very demanding scenarios since the sum of the applications minimum guaranteed bit rates greatly exceed the link capacity. As Figure 25 and 27 show, even the highest priority application Video #1 achieves a low QoE in the static case. Better results are accomplished in the dynamic case (figures 26 and 28), especially for Video #2 and #3; an improvement is evident also for Video #1, in both scenarios, thus underlining that the performance of the dynamic approach versus the static one improves as more as the network is congested. Tables 4 and 5 report the percentage errors for Scenario #4 and #5.

Graphs 26 and 28(dynamic case) show an initial phase where Video #2 and Video #3 achieve similar values of QoE or Video #3 performs better than Video #2, even though the latter has a higher QoE target. This behaviour can be caused by: (i) the high level of congestion: the applications are trying to admit an amount of traffic that greatly exceed the capacity *C* and this makes the task of the Requirement Agents very difficult, (ii) the learning process embedded in the Requirement Agents, that, starting without an a priori knowledge on Environment dynamics and state-action value matrix, entails an initial phase of exploration and learning, and (iii) a lack of coordination among agents since, as already mentioned, Q-learning is not a multi-agent algorithm. This entails that it is possible for low priority applications to perform better than high priority applications.

Despite that, after the transitory phase, the agents are autonomously able to restore the correct hierarchy.

The following tables report the percentage errors obtained at the end of the simulations:

	Scenario #4		
	Video #1	***Video #2***	***Video #3***
Static Case	-18%	-25%	-32%
Dynamic Case	-15%	-16%	-12%

	Scenario #5		
	Video #1	***Video #2***	***Video #3***
Static Case	-25%	-30%	-38%
Dynamic Case	-22%	-21%	-20%

Tables4 and 5 -Scenarios 4 and 5: Percentage Error

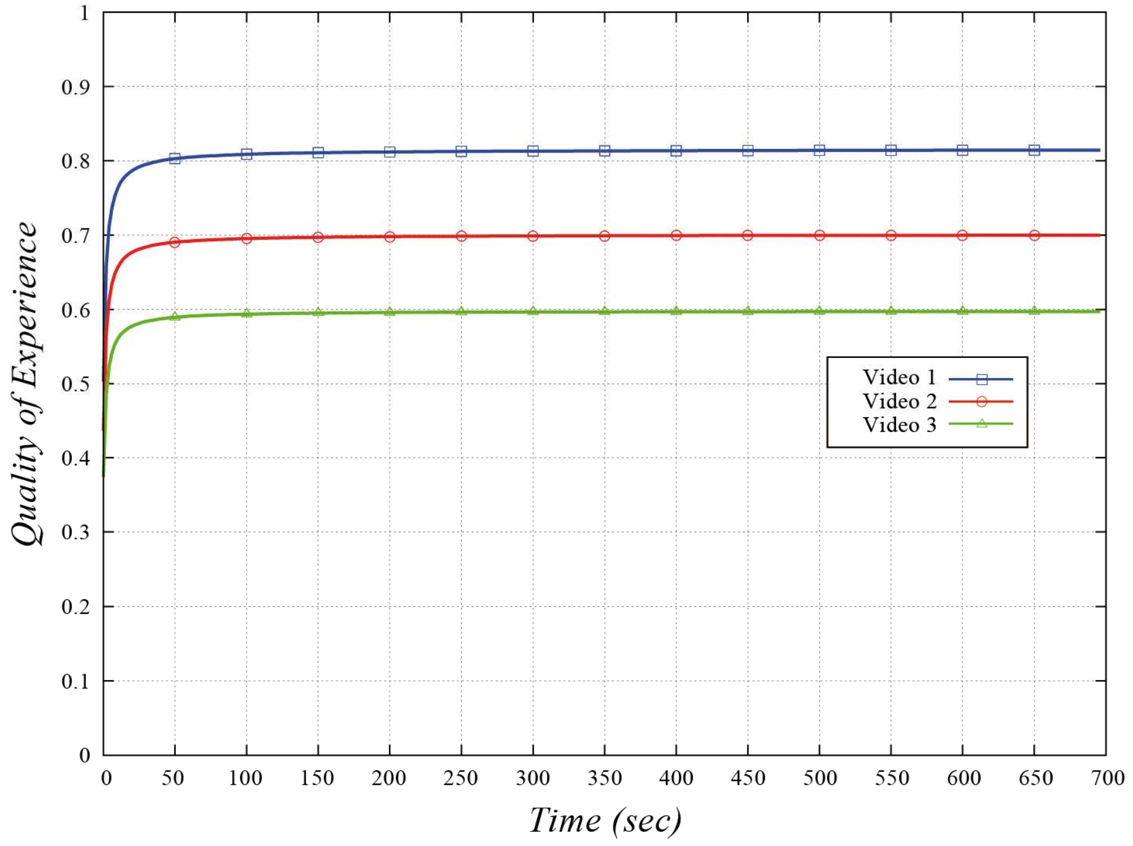


Figure 25–Scenario 4:Average QoE- Static Case

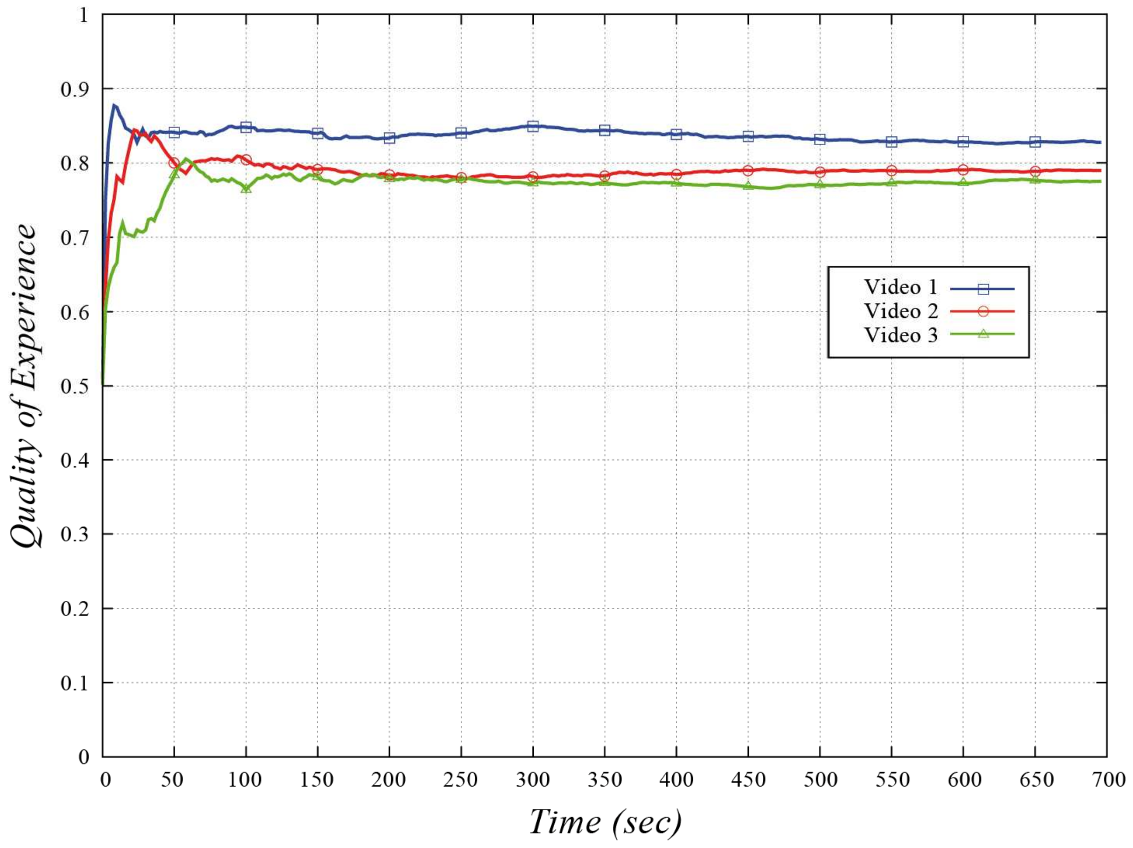


Figure 26–Scenario 4: Average QoE- Dynamic Case

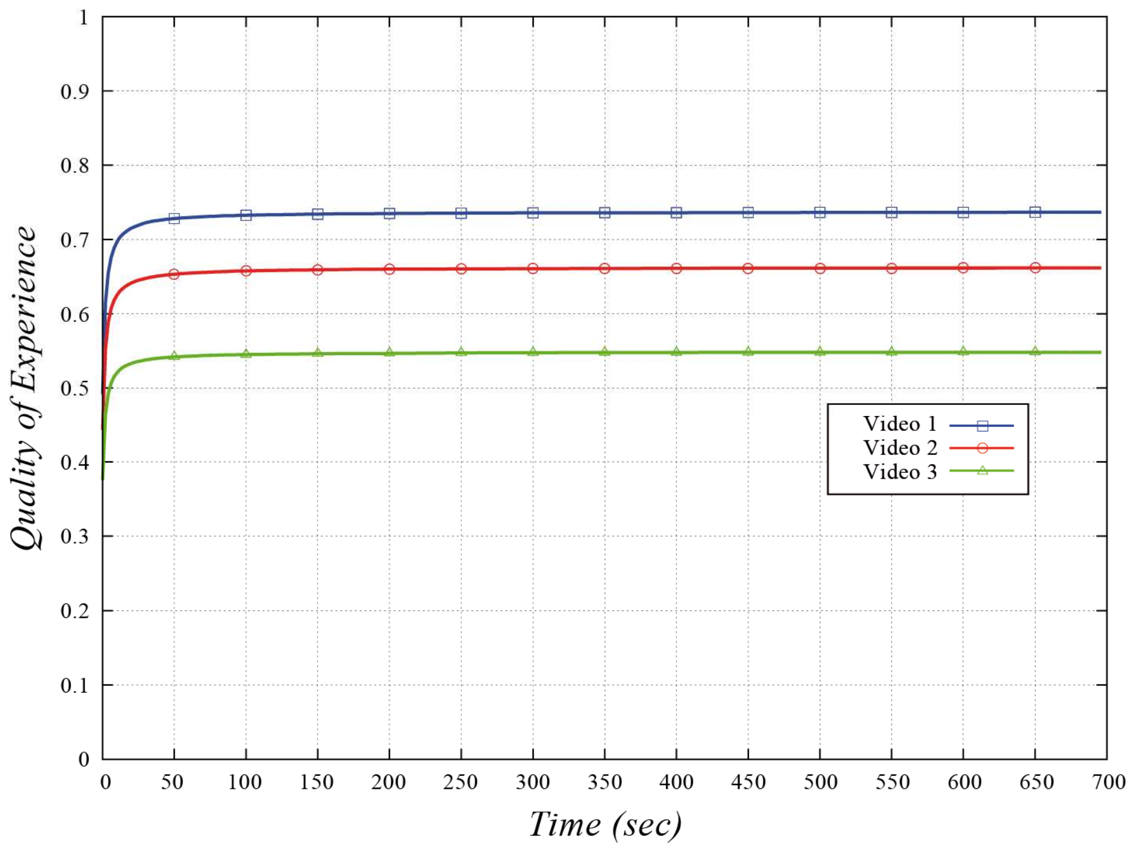


Figure 27–Scenario 5:Average QoE- Static Case

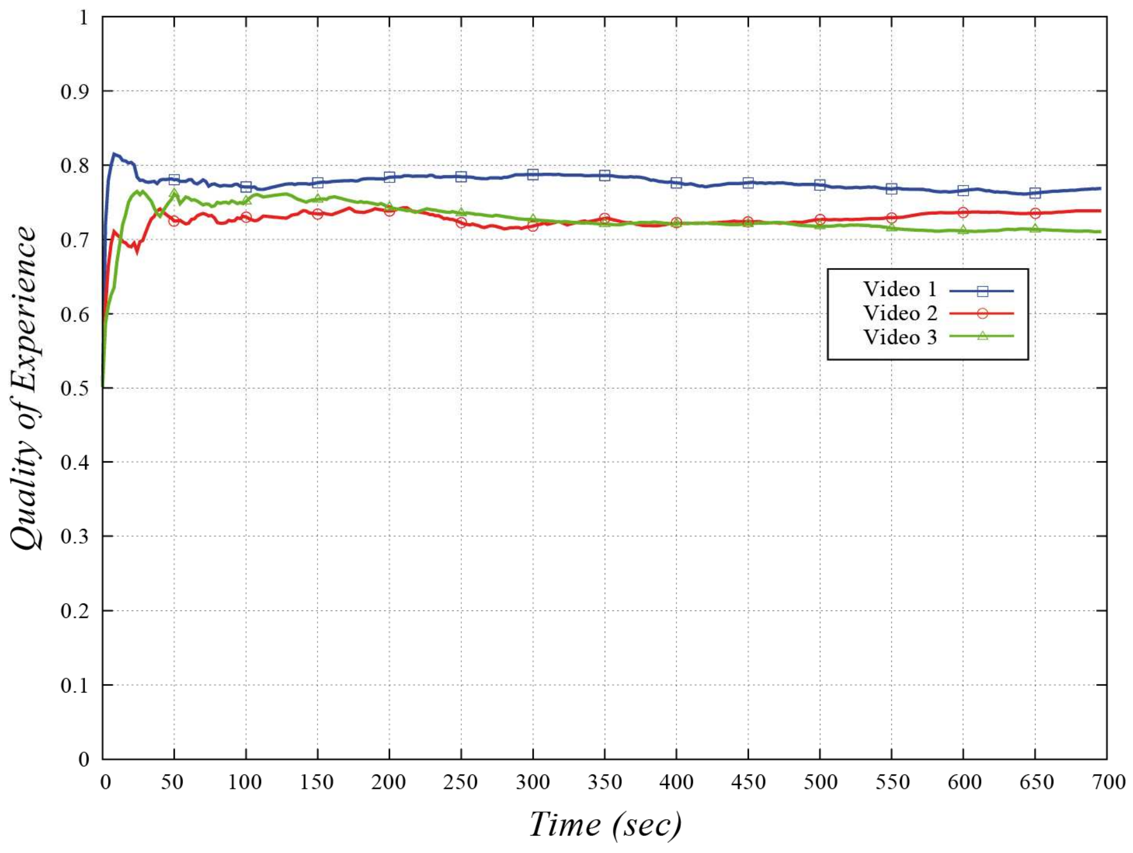


Figure 28–Scenario 5: Average QoE- Dynamic Case

In conclusion, the following table summarizes the steady state percentage errors obtained in the precedent scenarios:

	Scenario #1		***Scenario #2***		***Scenario #3***		***Scenario #4***		***Scenario #5***	
	Static	*Dynamic*	*Static*	*Dynamic*	*Static*	*Dynamic*	*Static*	*Dynamic*	*Static*	*Dynamic*
Video #1	1%	1%	-4%	-4%	-12%	-11%	-18%	-15%	-25%	-22%
Video #2	6%	3%	-12%	-5%	-20%	-12%	-25%	-16%	-30%	-21%
Video #3	12%	7%	-20%	-3%	-27%	-9%	-32%	-12%	-38%	-20%

Table 6 -Scenarios 1 to 5: Percentage Error

It is evident that, especially in congested scenarios, a dynamic choice of the Service Classes entails better performances with respect to a static association. The applications that attain more benefits from a dynamic approach are Video #2 and Video #3, even though also Video #1 attains better results with respect to a static case in particular in very congested scenarios (Scenario #4 and Scenario #5). As stated previously this is due to the fact that, in the static case, Video #1 is associated with the highest priority class and can exploit at the maximum the network resources. In consideration of the above, we believe the results obtained are very significant: a dynamic selection of Service Classes always allows to reduce the QoE error both for Video #2 and Video #3, without damaging Video #1, and, in the most congested scenarios, also to reduce the error for Video #1.

It is also remarkable that the percentage errors at the end of simulation in the dynamic case are similar for the three applications thus entailing that, even though there is not an explicit coordination among agents, we are able to achieve a sort of "fairness" among them.

11.3. Multi-Application Scenario

This scenario has the purpose of demonstrating the effectiveness of our approach also when applications with different requisites (in terms of minimum guaranteed bit rate and maximum delay) transmit on a channel of capacity *C* equal to7 Mbit/sec. We simulate two applications of the "Video Conference" type and one application of FTP Opnet type.

In order to analyse the behaviour of our algorithm, we simulate two different *Traffic Scenarios*, similar to Scenario #2 and #3 of the previous section as far as the total minimum admitted bit rate is concerned:

- Traffic Scenario#1: the sum of the applications minimum guaranteed bit rate is slightly higher than the link capacity ($\sum R_{adm\text{-}min} \approx C$);
- Traffic Scenario#2: the sum of the applications minimum guaranteed bit rate exceeds the link capacity ($\sum R_{adm\text{-}min} \approx 1.4C$);

11.3.1. Traffic Scenario #1

The following table illustrates the main characteristics of the three applications used to simulate traffic in Scenario #1:

	$R_{offered}$ (bits/sec)	***$R_{adm\text{-}min}$ (bits/sec)***	***D_{max} (sec)***	***QoE_{target}***	***Service Class***
Video #1	2850000	2200000	0.15	0.99	AF41
Video #2	2850000	2200000	0.15	0.89	AF21
FTP	4200000	3700000	0.5	0.97	AF31

The main difference with respect to the Single-Application scenarios is the presence of two type of applications with different requisites: Video Applications require a low delay and a minimum guaranteed bit rate that is smaller than the minimum guaranteed bit rate of FTP application. On the contrary, the FTP Application has not a demanding constraint on the delay, but requires a high guaranteed bit rate.

In this scenario the network is congested and this explains why, also in the static case, the QoE obtained is very low, especially for Video #2 (equivalent considerations with respect to the Single-Application Scenario are valid also for this case). Both Figure 30 and Table 7 show that a dynamic association between applications and Service Classes entails better performance with respect to a static association. The QoE error is reduced for every application, especially for Video #2 and FTP.

It can be observed from Figure 30 that, in the dynamic case, there is a transitory phase during which Video #2 performs better than FTP. This behaviour can be due to causes similar to those illustrated in paragraph 11.2.4 for the Single-Application case, in particular a lack of coordination among agents. In the following Chapter a different Reinforcement Learning Algorithm (Friend or Foe algorithm) will be introduced aiming at reducing this problem. Despite that, also a simple Q-learning algorithm, after an initial learning phase, is able to recover the correct priority among applications.

	Video #1	***Video #2***	***FTP***
Static Case	-10%	-22%	-16%
Dynamic Case	-7%	-4%	-9%

Table 7: Scenario 1: Percentage Error

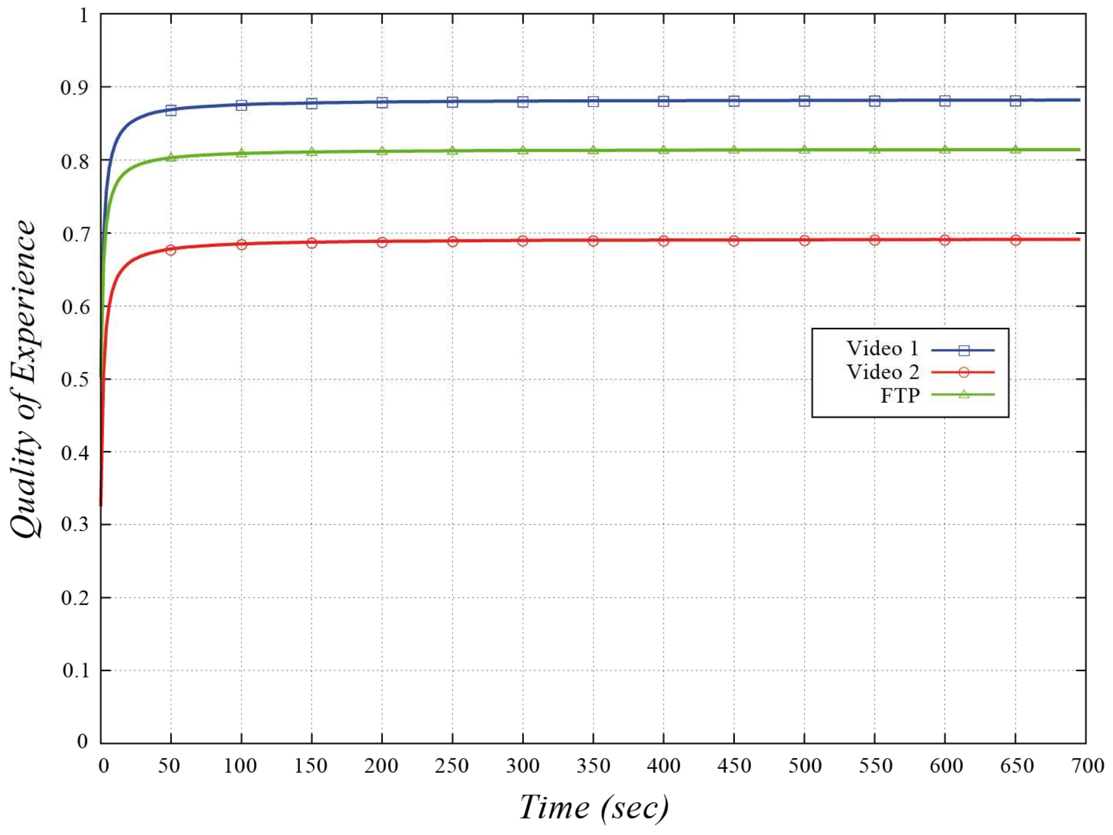


Figure 29 - Scenario 1: Average QoE - Static Case

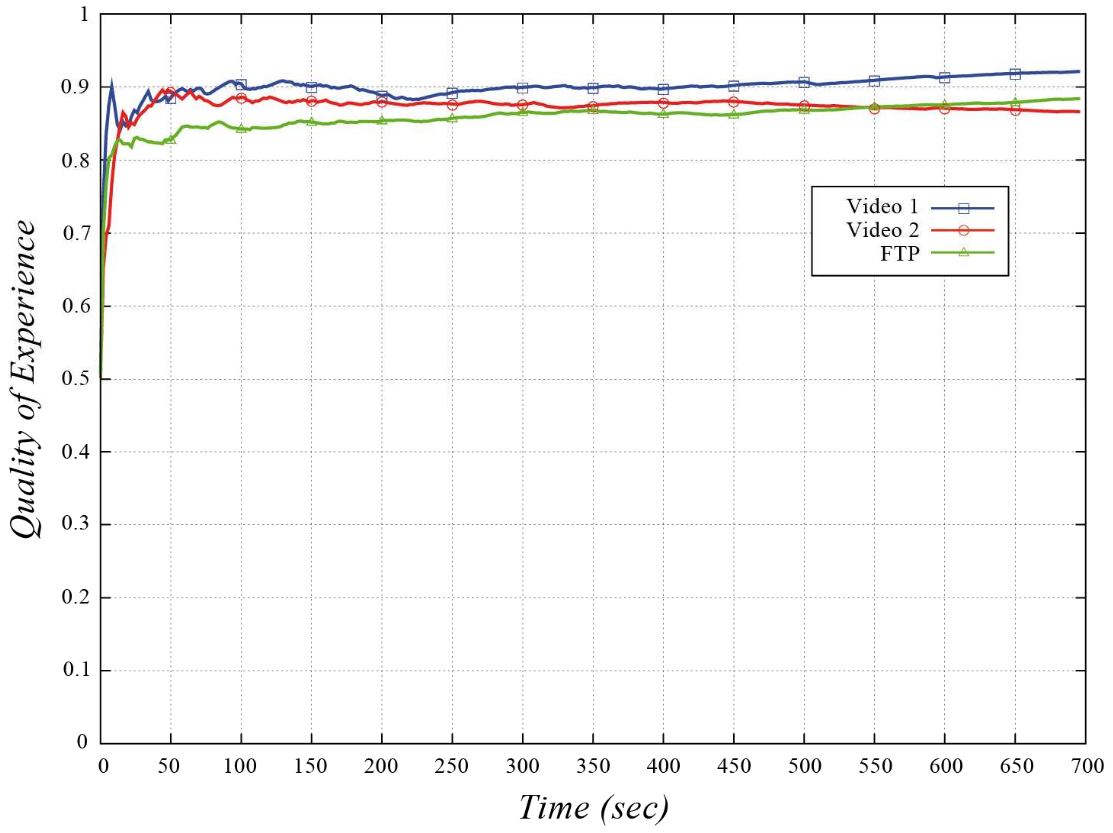


Figure 30 - Scenario 1: Average QoE - Dynamic Case

11.3.2. Traffic Scenario #2

The following table illustrates the main characteristics of the three applications used to simulate traffic in Scenario #2:

	***$R_{offered}$* (bits/sec)**	***$R_{adm-min}$* (bits/sec)**	***D_{max}* (sec)**	***QoE_{target}***	***Service Class***
Video #1	2850000	2700000	0.15	0.99	AF41
Video #2	2850000	2700000	0.15	0.89	AF21
FTP	4200000	4200000	0.5	0.97	AF31

As expected, the performance worsens, bothin the static and dynamic case, due to the high level of congestion. Nonetheless, in confirmation of the results presented in the previous paragraphs, the dynamic case performs better than the static one, both in terms of percentage error reduction and in terms of "fairness" among applications (the percentage errors for the three applications are similar).

It is also evident from Figure 32 that the applications reach a stable value of QoE nearly after sixty seconds, a value that seems acceptable also as far as an implementation on real devices is concerned.

Table 8 shows the QoE percentage errors obtained both in static and dynamic case:

	Video #1	***Video #2***	***FTP***
Static Case	-14%	-32%	-20%
Dynamic Case	-12%	-10%	-14%

Table 8 -Scenario 2: Percentage Error

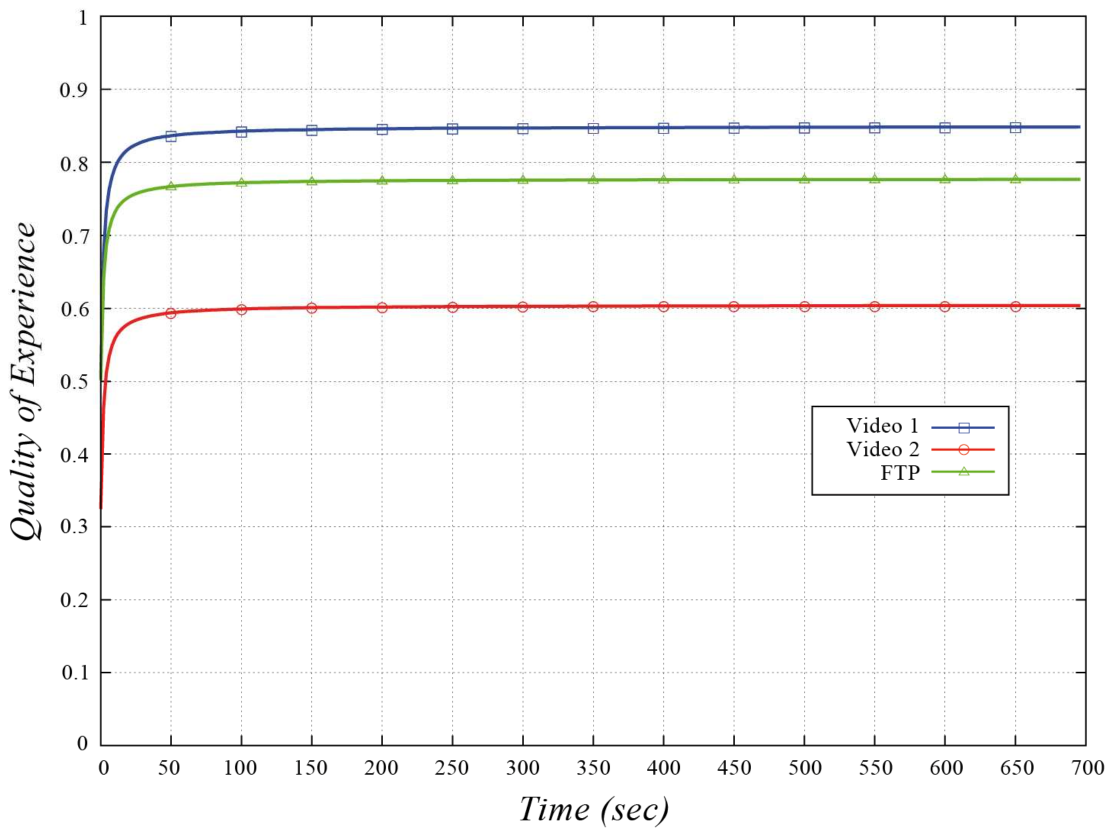


Figure 31 - Scenario 2: Average QoE - Static Case

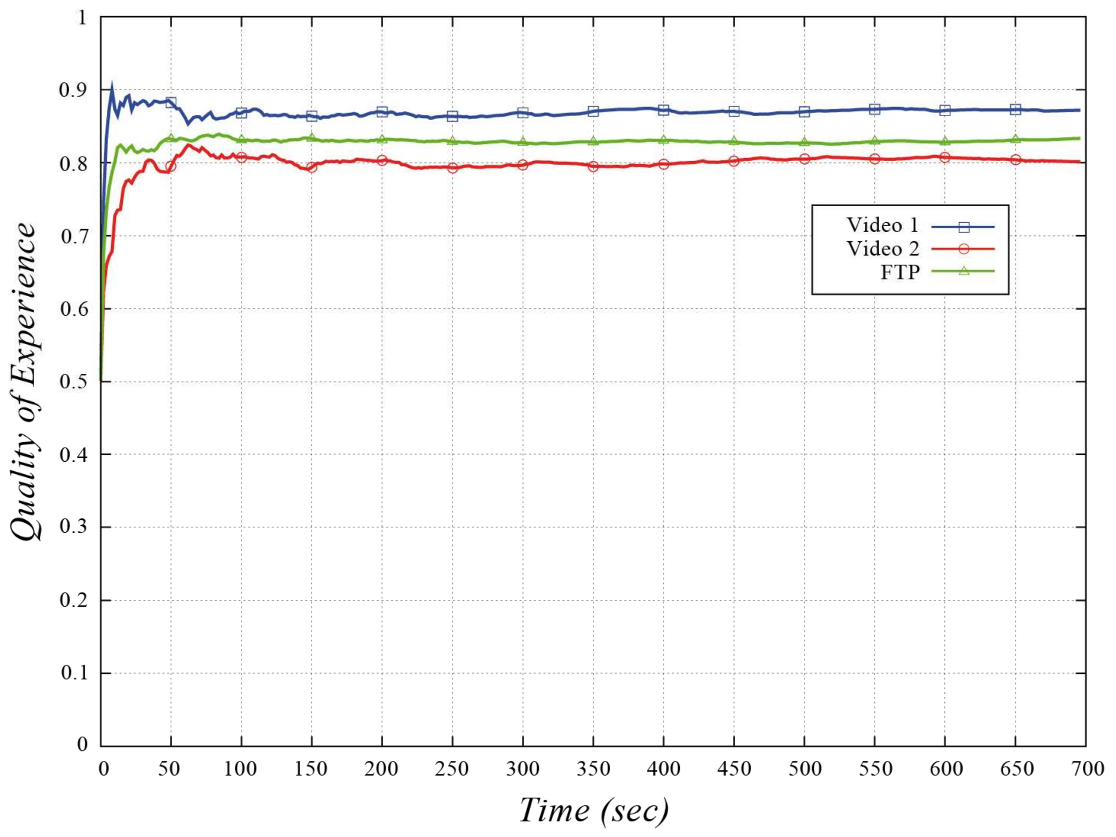


Figure 32 - Scenario 2: Average QoE - Dynamic Case

11.4. Conclusions

The results presented in this chapter clearly show that a *dynamic* control of Service Classes allows to reduce, especially in congested scenarios, the error (difference between the average QoE and the target QoE)and to guarantee higher “fairness” among applications with respect to a *static* association between applications and Service Classes.

This is mainly due to the capability of the Requirement Agents (provided with a Q-learning algorithm) to learn and adapt their behaviour according to: (i) the *local* status of the controlled application and (ii) the *global* status of the network, encoded into the Status Signal and transmitted by the Supervisor Agent.

Moreover, it is worth stressing that the results illustrated in this thesis have been obtained implementing a standard *Q-learning* algorithm, without any explicit coordination signalling among agents with the exception of the Status Signal. This issue is important especially as far as an implementation on real devices is concerned: (i) the only overhead is introduced by the Status Signal and (ii) the Q-learning algorithm is very simple, scalable, distributed and easily implementable in real devices.

12.AN ALTERNATIVE RL APPROACH: PROPOSED SOLUTION AND PRELIMINARY RESULTS

In chapter 6.3 a proposal for overcoming some limitations of the Q-Learning approachhas been introduced,based on the Friend-or-Foe Q-learning algorithm. In this chapter a preliminary proposal of implementation of a Friend or Foe based solution is presented and preliminary simulation results are illustrated.

12.1. Friend-or-Foe algorithm

The Friend-or-Foe Q-learning (FFQ) is a particular Reinforcement Learning algorithm able to deal with Multiagent environments. This section illustrates the *two-players version* of FFQ from the perspective of Agent 1.

As in a common Q-learning algorithm each agent has to choose an action, observe the reward and update a table of Q-values. In FFQ-learning this update is performedaccording to the following expression:

$$Q_1(s,a_1,a_2) = Q_1(s,a_1,a_2) + \alpha\left(r - Q_1(s,a_1,a_2) + \max_{a_1\in A_1, a_2\in A_2} Q_1(s,a_1,a_2)\right)$$

if the opponent is considered a friend and:

$$Q_1(s,a_1,a_2) = Q_1(s,a_1,a_2) + \alpha\left(r - Q_1(s,a_1,a_2) + \max_{\pi\in\prod(A_1)} \min_{a_2\in A_2} \sum_{a_1\in A_1} \pi(a_1) Q_1(s,a_1,a_2)\right)$$

if the opponent is considered a foe.

As stated in chapter 6.3, in FFQ-learning it is assumed that the opponents are *friends* (they work together to maximize agent's value) or *foes* (they work together to minimize agent's value). To be able to update its Q-table each Agent has to know the state *s*, the reward *r*, its action a_1 but also the action a_2 chosen by the other agent. This obviously entails a sort of observation of the Agent 1 with respect to the Agent 2, and vice versa, or a communication between the Agents. In our setting this is not feasible, since communication among Agents is totally excluded: the only allowed signalling can be from the Supervisor Agent to the Requirement Agents. For this reason, in the following paragraph we illustrate a possible modification of the Supervisor Agent and Requirement Agent to deal with this aspect.

It is worth stressing that a complete explanation of the FFQ-learning is beyond the aim of this thesis and can be found in [Vi] and [Li-2].

12.2. Cognitive Application Interface implementation

In our setting each application is associated with a Requirement Agent, in charge of dynamically selecting the most appropriate Service Class to guarantee the specific QoE target. An explicit signalling among Agents is not allowed, consequently an Agent cannot detect the actions selected by the other Agents and a standard implementation of FFQ-learning is not possible. For this reason, in an implementation with FFQ algorithm, the Supervisor Agent has the key roleof modelling a "Macro-Agent" representing the entire cloud of Requirement Agents (and associated applications), as depicted in the following figure (the figure refers to a Cellular Network, but similar considerations can be repeated also for Fixed Access and Ad-hoc Networks):

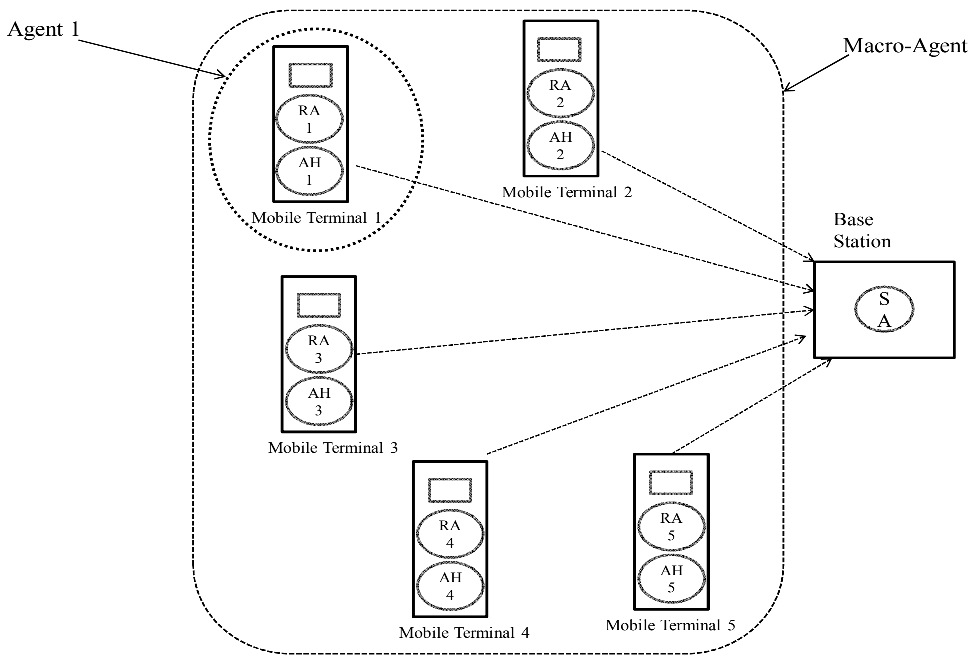


Figure 33- Friend or Foe approach: The Macro-Agent

The Supervisor Agent has the key role of analysing the behaviour of the Requirement Agents cloud and modelling the Macro-Agent. In this way, each Requirement Agent can implement a FFQ algorithm in the two players case, where the two players are itself and the Macro-Agent. We also suppose that that the traffic admitted by a single application is a small fraction of the total traffic in the network, i.e. that a single application does not have significant effects on the Macro-Agent. This supposition seems trustworthy in real networks, where many devices transmit at the same time.

In order to implement the FFQ algorithm, we propose to consider the Macro-Agent as a "*foe*". This assumption is realistic since the applications, and the related Requirement Agents, transmit on the same limited channel. This entails the consumption of a limited common resource by the i-th application to the detriment of the other applications (and vice versa) or, in other words, that the i-th application operate damaging the other applications (and vice versa). Since the Macro-Agent is the representation of the other Requirement Agents, the hypothesis that it is an opponent seems reasonable.

Another important aspect to highlight is that the signalling among the Supervisor and the Requirement Agents has to occur at every time step t_s the Requirement Agents take an action. This is a necessary conditions in the FFQ-learning in order to update the Q-value table, because also the action chosen by the other Agent has to be known (see chapter 6.3) when the update is performed. This entails that the action selected by the Macro-Agent has to be communicated to the Requirement Agents each time they chose an action and update the Q-table, i.e. every t_s seconds. For this reason, differently from the Q-learning implementation, in this case the parameters T_l, $T_{monit\text{-}l}$ and $T_{monit\text{-}s}$ have to be chosen equal to T_s, in order to evaluate the two actions' effect in the period of duration T_s.

<u>*Supervisor Agent*</u>

In order to make possible the implementation of the FFQ algorithm in the Requirement Agents, the Supervisor Agent has the key role of modelling the Macro-Agent and communicating the action chosen by the Macro-Agent to the Requirement Agents. As stated previously, the Macro-Agent is a global representation of the applications supported by the network and it is not a real operating agent. The actions it can take are similar to those of the Requirement Agents, i.e. to move the traffic from one Service Class to another; but differently from the Requirement Agents, that have to move the entire traffic from one Service Class to another, the Macro-Agent can choose to assign a fraction of the entire traffic to different Service Classes. In other words, each t_s seconds, the Macro-Agent can assign a percentage equal to $\alpha(t_s,1)$ of the whole traffic to the Class 1, equal to $\alpha(t_s,2)$ of the whole traffic to the Class 2 and so on; with the constrain that $\alpha(t_s,1)+\alpha(t_s,2)+\ldots+\alpha(t_s,K)=1$ (where K is the total number of Service Classes).

In order to pursue this task, at each time t_s, we propose that the Supervisor Agent computes, for each Service Class k (from 1 to K), the admitted traffic $R_{adm}(t_s,k)$. The parameter $R_{adm}(t_s,k)$ is computed by the Supervisor Agent by exploiting measurements taken in the time interval $[t-t_s;\ t]$, where t is the current time. At each time t_s the Supervisor Agent broadcasts to the Requirement Agents a proper message, hereinafter referred to as *Action Signal* and indicated as $as(t_s)$, i.e. a string of LK bits as the following:

$$as(t_s) = [\ \alpha(t_s,1),\ \alpha(t_s,2),\ldots,\ \alpha(t_s,K)]$$

where L is the number of bits necessary to code $\alpha(t_s,k)$ and K is the total number of Service Classes. The parameter $\alpha(t_s,k)$ is defined as the percentage of traffic admitted by the Class of Service k and is computed as:

$$\alpha(t_s,k) = \frac{R_{adm}(t_s,k)}{\sum_{i=1}^{K} R_{adm}(t_s,i)}$$

The signalling overhead introduced by the Action Signal consists in broadcasting LK bits every T_s seconds, where T_s is the duration of the period between the broadcast of a given status signal and the next one, i.e. $T_s=t_{s+1}-t_s$.

The Action Signal represents for the Requirement Agents the action chosen by the Macro-Agent and is interpreted as the percentage of traffic the Macro-Agent has moved into the different Service Classes.

<u>*Requirement Agent*</u>

The Requirement Agent, at each time t_s, based on the action signal received by the Supervisor Agent, has to select a Service Class.In order to perform the Service Class selection, each Requirement Agent is provided with a Friend-or-Foe Q-learning algorithm. In particular we refer to the *foe* version of the algorithm.Respect to the Q-Learning based solution (see chapter 7.3), the Reinforcement Learning model will be modified as follows:

State and action spaces

For the state variables s, a suitable selection, at time t_s, is the measured QoE $QoE_{meas}(t_s,a)$, as defined in chapter 8.2 (“QoS case”).

Concerning the action space, the action a_1 is the action selected by the Requirement Agent (the proper Service Class), and the action a_2 is the action selected by the Macro-Agent, i.e. the Action Signal $as(t_s)$.

Reward function

The proposed reward function $r(t_s)$ is the first function asdescribed in chapter 7.3, that is:

$$r(t_s) = - [QoE_{meas}(t_s,a)–QoE_{target}(a)]^2$$

12.3. Preliminary simulation results

The Figure 34 illustrates a preliminary simulation result obtained implementing the proposed solution using a FFQ-learning algorithm.

The simulation refers to the Multi-Application Scenario#1 described in paragraph 11.3.1, highlighting the presence of a transitory phase during which Video #2 performs better than FTP. In this case, the use of a FFQ-learning avoids this behaviour. The results obtained in terms of QoE are similar to those obtained with a Q-learning implementation, even though an improvement both for Video #1 and #2 can be noticed (see Table 9).

	Video #1	***Video #2***	***FTP***
Static Case	-10%	-22%	-16%
Dynamic Case (Q-learning)	-7%	-4%	-9%
Dynamic Case (FFQ-learning)	-5%	-3	-9

Table 9 – Scenario 1 – Q-Learning versus FFQ: Percentage Error

Future experimentations are recommended in order to further investigate the advantages of the alternative approach presented in this Chapter.

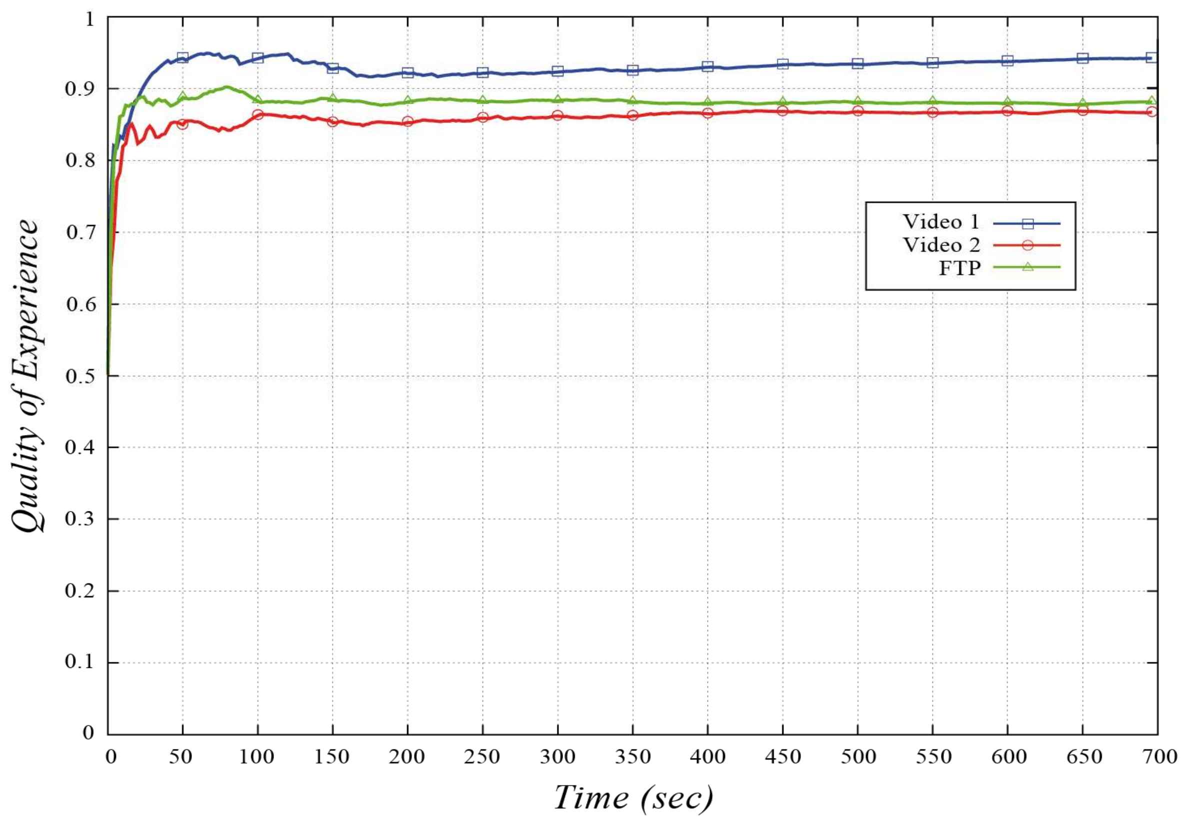


Figure 34 -Traffic Scenario #1- Dynamic Case with FFQ-learning

13.CONCLUSIONS

This workis aimed at defining an innovative*Application Interface* able to manage "cognitive" Application Requirements, to be defined in terms of *Quality of Experience* (QoE) Requirements.

The proposed Interface is based on three basic elements: the *Application Handler*, the *Requirement Agent* and the *Supervisor Agent*.

The main element, from the "cognitive" point of view, is the so called *Requirement Agent*. The Requirement Agent is in charge of dynamically selecting the most appropriate *Class of Service* to be associated to the relevant application in order to "drive" the underlying networks elements to satisfy the application QoE Requirements, that is reaching (or approaching) the *target QoE* level. The *QoE function* is defined considering all the relevant factors influencing the quality of experience level as it is perceived by the final users for each specific Application (including Quality of Service, Security, Mobility and other factors).

The Requirement Agent must be able to "learn",based oninteraction with the environment, to take optimal decisions regarding the Class of Service, in other words, the agent must to solve a "*Reinforcement Learning problem*":the key idea followed in the thesis is modelling the Requirement Agent as a "Reinforcement Learning Agent".

After a documentation regarding, on the one hand,different control, optimization, multi-agent systems and machine learning theories and, on the other hand,availableSW platforms and tools, the Author decided to adopt a *model-free* Reinforcement Learning approach, based on the *Q-Learning algorithm*.

The Q-learning algorithm seems to be a really "cognitive" and "adaptive" solution to the QoE problem, especially in the considered scenario, where the following key assumptions and constraints must be considered: no a priori knowledge aboutthe network/system model and dynamics, no coordination/communication among agents, limited agent signalling, power, memory and computation capabilities.

Once defined the *action* space(in terms of Service Classes),in order to define the RL model several *state* variables and *reward* functions were considered andanalysed.

The selected *state* variables (the measured QoE of the relevant Application and the measured QoE of each Class of Service) allow to describe the current network situation to the RL agent, while the proposed *reward* function is able to guarantee that the Class of Service will be selected aiming at reaching the target QoE, meaning thatthe *action* (Class of Service selection) will be changed (improved)aiming at reducing the difference between the measured and target QoE (the *quadratic error* is considered).

For implementation and simulation purposes, the *QoS case* was considered: this is a special case, where the Application QoE is defined in term of *Quality of Service* metrics. In the QoS case*, throughput*, *delay* and *loss rate*parameters were considered: the proposed *QoE function* assigns different *weights* to the QoS *parameters* and allows to guarantee a satisfactory granularity in defining Application QoE requirements.

The proposed RL based solution was implemented and tested using *OPNET*, a license-based network and traffic simulation platform widely used in the ICT field; the proposed Supervisor and Requirement algorithms were implementedon OPNET using the supported version of C^{++} *language*.Several *simulations*were run in order to test functionality and performance of the proposed Cognitive Application Interface and algorithms, considering single and multiple application*scenarios* with different network congestion levels.

The proposed solution demonstrated to be effective: theinnovative *dynamic*RL-based approach performs better than the traditional *static* approach, especially in case of medium-high network congestion levels, both in terms of percentage error (difference between measured and target QoE) reduction and in terms of “fairness” among applications.

A different RL approach, based on a *two-agent* scenario, was also investigated in the final part of this work: in this approach, each Requirement Agent plays against a “Macro-Agent”, incorporating the Environment and all the Requirement Agents, and the RL problem is solved implementing a *Friend or Foe algorithm*(Foe version).

Some *preliminary tests*were run on this Friend or Foe based solution, considering one of the scenariosalready implemented for the Q-Learning solution (in particular: multi-application scenario with medium congestion level): the results seem promising in terms of improving the RL algorithm performance, overcoming some limitations of the Q-Learning solution when adopted in multi-agent scenarios.

Considering the main advantages and limitations of the proposed approaches,further developments and *future research* should address:

- the definition of more general *QoE functions*, considering additional information and metrics (such as Security and Mobility parameters and QoE feedback directly sent by the final users),
- possible refinements of the proposed *Reinforcement Learning*based solutions,
- the investigation of *alternative solutions*, considering Multi Agent System theory and statistical modelbased approaches,
- the implementation of *more complex network scenarios*, considering topology and traffic events and their possible impacts on the system properties and dynamics.

Finally, regarding possible *usages*and *applications*, this thesis work representsa preliminary contribution to the *FI-WARE project* activities, regarding the architectural chapter "*Interface to Network and Devices*" and, in particular, the definition of an innovative *Application Interface* and the proposal of a "cognitive" solution for the *Application QoEmanagement* problem(see Annex A, par. A.3).

References

A) References on Future Internet

[Ca] Castrucci, Cecchi, Delli Priscoli, Fogliati, Garino and Suraci, "*Key concepts for the Future Internet Architecture*", Future Network and Mobile Summit 2011, Warsaw, Poland, June 2011

[Da] DARPA Research, Active Networks, http://www.sds.lcs.mit.edu/darpa-activenet

[De-1] Delli Priscoli, Suraci and Castrucci, "*Cognitive Architecture for the Internet of the Future*", Sixth international workshop on next generation networking middleware, October 2009

[De-2] Delli Priscoli, "*A Fully Cognitive Approach for Future Internet*", Special Issue on "Future Network Architectures of Future Internet", Molecular Diversity Preservation International (MDPI), Vol. 2, January 2010

[Ch] Chu, Popa, Tavakoli, Hellerstein, Levis, Shenker and Stoica, "*The Design and Implementation of a Declarative Sensor Network System*", in Proceedings of the 5th ACM Conference on Embedded Networked Sensor Systems, Sydney, Australia, 2007

[Ge] Global Environment for Network Innovations, http://geni.net

[Ga] Galis, Abramowicz and Brenner, "Management and Service-aware Networking Architectures (MANA) for Future Internet, Position Paper, 2009

[Eu-1] *The EUROPEAN FUTURE INTERNET INIZIATIVE (EFII): White paper on the Future Intern PPP Definition*, January 2010

[Eu-2] *FI-WARE final submission*, April 2011

[Eu-3] *FI-WARE High-level Description*, August 2011

[Te] Terziyan, Zhovtobryukh and Katasonov, "*Proactive Future Internet: Smart Semantic Middleware for Overlay Architecture*", Fifth International Conference on Networking and Services, 2009

[Va] Van Der Meer, Strassner and Phelan, "*The Design of a Novel Autonomic Management Methodology and Architecture for Next Generation and Future Internet Systems*", Sixth IEEE Conference and Workshop on Engineering of Autonomic and Autonomous Systems, 2009

[Ve] Ventre, "*Future Internet and Net Neutrality*", Seminary, AGCOM Authority, Naples, October 2011

References on State of the Art

[Da] Das, Pung, Lee and Wong, "*NETWORKING 2008: Ad hoc and Sensor Networks, Wireless Networks, Next Generation Internet*", Springer, 2008

[Ka] Karagiannis, Papagiannaki and Faloutsos, "*BLINC: Multilevel Traffic Classification in the Dark*", Conference on Special Interest Group on Data Communication, 2005

[Ku] Kurose and Ross, "*Computer Networking: A Top-Down Approach Featuring the Internet*", Pearson, 2000

[No] Nokia Corporation, "*Quality of Experience (QoE) of mobile services: Can it be measured and improved*?", 2004

[Ro] Roughan, Sen, Spatscheck and Duffield, "*Class-of –Service Mapping for QoS: A Statistical Signature based Approach to IP Traffic Classification*", Internet Measurement Conference, 2004

[Sc] Van der Schar, Turaga and Wong, "*Classification-Based System For Cross-Layer Optimized Wireless Video Transmission*", IEEE Transaction on Multimedia, Vol. 8, No. 5, October 2006

[Sh] Shin, Kim and Kuo, "*Dynamic QoS Mapping Control for Streaming Video in Relative Service Differentiation Networks*", European Transactions on Telecommunications, Vol. 12, No. 3, 2001

B) References on Reinforcement Learning and Multi Agent Systems

[Ba] Barto and Mahadevan, "*Recent Advances in Hierarchical Reinforcement Learning*", Discrete Event Dynamic Systems, Vol. 13, No. 4, pp. 341-379, 2003

[Bo] Boutilier, "*Sequential Optimality and Coordination in Multiagent Systems*", International Joint Conference on Artificial Intelligence, 1999

[Ca] Castrucci, "*Fault-tolerant routing in Next Generation Home Networks*", PhD Thesis, 2009

[Cr] Crites and Barto, "*Elevator Group Control Using Multiple Reinforcement Learning Agents*", Machine Learning, Vol. 33, pp. 235-262, 1998

[Cl] Claus and Boutilier, "*The Dynamics of Reinforcement Learning in Cooperative Multiagent Systems*", Proceedings of National Conference on Artificial Intelligence, 1998

[Do] Dowling, Curran, Cunningham and Cahill, "*Using Feedback in Collaborative Reinforcement Learning to Adaptively Optimize MANET Routing*", IEEE Transactions on Systems, Man, and Cybernetic- Part A: Systems and Humans, Vol. 35, No. 3, 2005

[Jo] Jong and Stone, "*Compositional Models of Reinforcement Learning*", European Conference on Machine Learning, 2009

[Kae] Kaelbling, Littman and Moore, "*Reinforcement Learning: A Survey*", Journal of Artificial Intelligence Research, Vol. 4, pp. 237-285, 1996

[Kap] Kapetanakis and Kudenko, "*Reinforcement Learning of Coordination in Cooperative Multi-agent Systems*", Proceedings of the 18th National Conference on Artificial Intelligence, 2002

[La] Lauer and Riedmiller, "*An Algorithm for Distributed Reinforcement Learning in Cooperative Multi-Agent Systems*", Proceedings of the 17th International Conference on Machine Learning, 2000

[Li-1] Littman, "*Markov games as a framework for multi-agent reinforcement learning*", Proceedings of the 11th International Conference on Machine Learning, 1994

[Li-2] Littman, "*Friend-or-foe Q-learning in General-Sum Games*", Proceedings of the 18th International Conference on Machine Learning, 2001

[Ma] Manfredi and Mahadevan, "*Hierarchical Reinforcement Learning Using Graphical Models*", Proceedings of the ICML'05 Workshop on Rich Representations for Reinforcement Learning, 2005

[Man] Mannor, Menache, Hoze and Klein, "*Dynamic Abstraction in Reinforcement Learning via Clustering*", Proceedings of the 21th International Conference on Machine Learning, 2004

[Mi] Mignanti, "*Reinforcement Learning Algorithms for Technology Independent Resource Management in Next Generation Networks: Connection Admission Control Procedures*", PhD Thesis, 2008

[Mu] Murphy, "A *Survey of POMDP Solution Techniques*", 2000

[Ru] Russel and Norvig, "*Artificial Intelligence: A modern Approach - Third Edition*", Prentice Hall, 2009

[Se] Sen, Sekara and Hale, "*Learning to coordinate without sharing information*", Proceedings of 1989 Conference on Neural Information Processing, 1989

[Sch] Schneider, Wong, Moore and Riedmiller, "*Distributed Value Functions*", Proceedings of the 16th International Conference on Machine Learning, 1999

[Su] Sutton and Barto, "*Reinforcement Learning: An Introduction*", The MIT Press, 1998

[Vi] Vidal, "*Fundamentals of Multi-Agent Systems with NetLogo Examples*", March 2010

[Wo] Wolpert, Wheeler and Tumer, "*General Principles of Learning based Multi-Agent Systems*", Proceedings of the 3rd International Conference on Autonomous Agents, pp. 77-83, 1999

ANNEXA–The Future Internet PPP (FI-PPP) Programme

A.1 Future Internet PPP Programme

On 3 may 2011, the *Public-Private Partnership on the Future Internet(FI-PPP)* was officially launched in Brussels by EC Vice-President Neelie Kroes and representatives of the European ICT Industry.

The 600 mln€ initiative runs for *five years* and aims to address the challenges that hold back Internet development in Europe.

The projects launched after the first call of the FI-PPP (*FI-PPP 2011 Call*, deadline december 2011) will together receive 90 mln€ in EU funding.

As known, the FI-PPP Programme refers to four *Objectives* in the *Seventh Framework Programme* (7FP):

- Objective 1.7 - Technology Foundation: Future Internet Core Platform
- Objective 1.8 - Use Case scenarios and early trials
- Objective 1.9 - Capacity Building and Infrastructure Support
- Objective 1.10 - Programme Facilitation and Support.

For about two decades, the Internet infrastructure has been increasingly used for applications it was not designed for. The avalanche of user-generated content in the wake of Web 2.0, the increased usage for commercial applications and particularly the rise of connected mobile devices have pushed the Internet towards its limits.

The Future Internet PPP aims to overcome these limitations and create benefits for European citizens, businesses and public organisations.

As part of the EC's Innovation Union strategy, the FI-PPP has been created to support innovation in Europe and help businesses and governments to develop a novel Internet architecture and solutions that will provide the desired *accuracy*, *resilience* and *safety*, which the current Internet is more and more lacking, while the data volumes and the application demands are increasing exponentially.

The ***FI-PPP Programme*** is structured in three phases.

The ***first phase*** started on 1 April 2011 and has a duration of *two years*. In the first phase the *architecture* will be defined, requirements from *usage areas* will be captured and potential test infrastructures will be evaluated.

In ***phase two*** the *Core Platform* will be developed and instantiated on the test infrastructure, while early trials of all usage areas will be run.

Finally in ***phase three*** large-scale trials will be run to "challenge" the overall platform as a *proof of concept*. Small and medium sized enterprises (SMEs) are expected to play a large role in this by developing and providing *applications*.

A main activity that runs throughout the five years is the *Technology Foundation,* often referred to as *Core Platform.* Its goal is design and develop a *generic* and *open* network and service *platform* that is capable of supporting *application requirements* from the usage areas, e.g. transport, health or energy.

"FI-WARE", coordinated by *Telefonica*, has started as a *three-year project* to commence this activity.

Furthermore, two *support actions* have started:

CONCORD will provide the overall programme coordination, complementing the administrative procedures of the Commission.

INFINITY's task is to identify potential experimental infrastructures that can be used for later trials, and maintain this information in a web-based repository.

The eight *use cases projects* play an important role: they will define *scenarios* from various usage areas to be trialled later, and define their *use case specific requirements* that the core platform will need to support.

The use cases are intended to make sure that the Core Platform is fully suited for running applications from any potential application area.

The list below provides an overview of the eight *usage area projects,* started on 1 April 2011:

FINEST – Future Internet enabled optimisation of transport and logistics business networks. Coordinator: *Kuehne + Nagel Management AG.*

INSTANT MOBILITY – In the Instant Mobility vision, every journey and every transport movement is a part of a fully connected and self-optimising ecosystem. Coordinator: *Thales*.

SMART AGRIFOOD – Smart food and agribusiness: Future Internet for safe and healthy food from farm to fork. Coordinator: *DLO*.

FINSENY – Future Internet for smart energy: foster Europe's leadership in ICT solutions for smart energy, e.g. in smart buildings and electric mobility. Coordinator: *Nokia System Networks.*

SafeCity – Future Internet applied to public safety in Smart Cities: to ensure people feel safe in their surroundings. Coordinator: *Isdefe*.

OUTSMART – Provisioning of urban/regional smart services and business models enabled by the Future Internet: water and sewage, waste management, environment and transport. Coordinator: *France Telecom*.

FI-CONTENT – Future media Internet for large scale content experimentation e.g. in gaming, edutainment & culture, professionally and user-generated content. Coordinator: *Technicolor.*

ENVIROFI – The environmental observation Web and its service applications within the Future Internet: to reliably provide the large & growing volumes of observation data across geographical scales, e.g. on air pollutants, biodiversity and marine data. Coordinator: *Atos Origin.*

A.2 The FI-WARE project

FI-WARE project is a three-year large-scale Integrated Project (IP), launched in the context of the "*ICT"* themefor R&D under the specific program "*Cooperation*" implementing the *Seventh Framework Program* (7FP, 2007-2013) of the European Community.

The 66mln€project, started on 1 May 2011, was proposed under the 7FP *FI-PPP 2011 Call,* referring to the Challenge 1 "*Pervasive and Trusted Network and Service Infrastructures*" and the FI-PPP *Objective* "*Technology Foundation: Future Internet Core Platform*".It will receive 41mln€ in EU funding,

The project involves 26 Partners, including the main European ICT operators and manufacturers, together with Universities and Research Institutes.

In particular, the European TLC Operators involved in the Project are:

- *Telefonica Investigacion* (Project Coordinator),
- *Deutsche Telekom.*
- *France Telecom*
- *Telecom Italia.*

The Universities and Research Institutes involved in the Project are:

- *Institut National de Recherche en Informatique et en Automatique*
- *Universidad Politecnica de Madrid*
- *Universitaet Duisburg-Essen*
- *Università "La Sapienza" di Roma*
- *University of Surrey.*

The high level *goal* of the FI-WARE project is to build the *Core Platform* of the Future internet.

This Core Platform, also referred to as the *FI-WARE Platform*, will dramatically increase the global competitiveness of the European ICT economy by introducing an innovative infrastructure for cost-effective creation and delivery of versatile digital services, providing high quality and security guarantees.

As such, it will provide a powerful foundation for the Future Internet, stimulating and cultivating a sustainable ecosystem for:

- innovative *service providers* delivering new applications and solutions meeting the requirements of established and emerging usage areas
- *end users and consumers* actively participating in content and service consumption and creation.

Creation of this *ecosystem* will strongly influence the deployment of new wireless and wired infrastructures and will promote innovative *business models* and their acceptance by final users.

FI-WARE will be *open*, based upon elements, called *Generic Enablers (GE)*, which offer reusable and commonly shared functions serving a multiplicity of usage areas, across various sectors. Generic enablers differ from *Specific Enablers (SE)*, that are common to multiple applications but specific to one particular usage area, or a very limited set of usage areas.

Key goals of the FI-WARE project are the *identification* and *specification* of GEs, together with the development and demonstration of reference implementations of identified GEs.

Any *implementation* of a GE comprises a set of components and will offer capabilities and functionalities which can be flexibly customised, used and combined for many different usage areas, enabling the development of advanced and innovative Internet applications and services.

The FI-WARE architecture comprises the description of GEs, relations among them and relevant properties.

Specifically, the Core Platform to be provided by the FI-WARE project is based on GEs linked to the following main ***architectural chapters*** or *technical foundations*:

Cloud Hosting – the *fundamental layer* which provides the computation, storage and network resources, upon which services are provisioned and managed. It enables application providers to host their applications on a cloud computing infrastructure so that ICT resources are elastically assigned as demand evolves, meeting SLAs and business requirements and they only pay for actual use or ICT resources; it supports both IaaS(Infrastructure as a Service)-oriented and PaaS (Platform as a Service)-oriented provisioning of resources. The cloud computing infrastructure linked to a Core Platform instance can be *federated* with that of another Core Platform instance or external Clouds, through standard APIs/protocols.

Data/Context Management Services – the facilities for effective accessing, processing and analysing massive streams of data and semantically classifying them into valuable *knowledge*. They are based on a collection of enablers supporting Access to Context information (including user profile and preferences) to ease development of context-aware applications, Storage of large amounts of data, Processing, correlation and distribution of large amounts of events and Processing of multimedia contents. They are accessible through a standard set of APIs.

Applications/Services Ecosystem and Delivery Framework – the infrastructure to create, publish, manage and consume *FI services* across their life cycle, addressing all *technical* and *business* aspects. It enables applications to be accessible by end users from any device and within and across domain-specific Core Platform instances, enables applications "mash-up" and the exploitation of user-driven innovation and incorporates open Application/Services marketplace capabilities and the publication of applications through different channels (Facebook, AppStores, ….)

Internet of Things (IoT) Services Enablement – the bridge whereby FI services interface and leverage the ubiquity of heterogeneous, resource-constrained *devices* in the IoT. It enables an uniform access to the "Internet of Things": universal (unique) identification of "things", standard information model, standard management APIs and standard APIs for gathering data: it is implemented as a common layer which mediates with the different types of sensor and device networks.

Interface to the Network and Devices – *open interfaces* to networks and devices, providing the *connectivity needs* of services delivered across the platform. Interfaces wrapping access to network enablers that would be published to application programmers and Interfaces required for development of Platform components (such as Interfaces to control QoE/QoS and Network Resources allocation, Gateway communication middleware and hosting interfaces) are considered.

Security – the mechanisms which ensure that the delivery and usage of services is trustworthy and meets *security* and *privacy* requirements.

In order to illustrate the concept of GEs, GEs linked to the *Data/Context Managed Services* can be defined, for example, such as GEs:
- allowing compilation and storage of massive data from different sources (e.g. connected things, user devices, users or applications),
- processing the stored data, enabling generation and inference of new valuable data that applications may be interested to consume
- supporting a well-defined API, enabling FI Applications to subscribe to data they are interested in, making them capable of receiving in real time.

To a large degree, the functionalities of the GEs will be driven by requirements from Use Case projects. Therefore, FI-WARE will closely collaborate with the *Use Case projects* and the *Capacity Building project* in the FI-PPP Programme.

However, it will also be driven by additional requirements extrapolated for any other future services: these requirements may be brought by *partners* of the FI-WARE project (based on inputs from their Business Units) or gathered from *third parties* external to the PPP projects.

The FI-WARE project will introduce a *generic* and *extensible* ICT platform for Future Internet Services.

The Platform aims to meet the demands of key *market stakeholders* across many different sectors, strengthen the innovation-enabling capabilities in Europe and overall ensure the long term success of European companies in a highly dynamic market environment.

Strategic goals of the FI-WARE project are the following:

- To specify, design and develop a *Core Platform*, meant to be a generic, flexible, trustworthy and scalable foundation.
- Design *extension mechanisms* so as to enable support for yet unforeseen usage areas non being addressed in the context of the FI-PPP, extrapolating current technology and business trends and translating them into specific design and implementation principles of the Core Platform
- To liaise between the project and the relevant *standardisation bodies*, in order to keep the project up-to-date with respect to the activities in the standardisation bodies and to ensure active and coordinated contribution of specifications from the project, leading to open standardised interfaces.

- To implement and validate the FI-WARE approach in *trials* together with Use Case projects in order to develop confidence for large scale investments in solutions for smart future infrastructures, on national and European level.
- To enable established and emerging players in the services and application domains to tap into *new business models*, by providing components, services and platform allowing them to innovate.
- To support the development of *a new ecosystem*, including agile and innovative service providers consuming components and services from FI-WARE and thereby building new business models based on FI-WARE and associated usage areas.
- To stimulate *early market take-up*, by promoting results jointly with the other projects in the FI-PPP.

R&D activities in FI-WARE project will comprise:

- *Evolving components already existing*, provided by partners of the project or by or third parties, incorporating *new features* (required to implement GEs in the context of the FI) and allowing GEs implemented through these components to be *integrated* (pluggable) with other GEs in the FI-WARE architecture
- Creating *new components* required to cover gaps in the FI-WARE architecture.

The FI-WARE project will draw upon the wealth of results already achieved through earlier European research, not only within the FP's, but also at national - or corporate -funded levels, and leverage them further through *a systematic integration*, with a complete system's perspective.

A list of terms that are "key" to the FI-WARE vision is provided below, with a concise definition:

FI-WARE GE: a functional building block of FI-WARE. Any implementation of a GE is made up of a set of components which together supports a concrete set of functions and provides a concrete set of APIs and interoperable interfaces that are in compliance with *open specifications* published for that GE.

FI-WARE compliant product: a product which implements, totally or in part, a FI-WARE GE or composition of FI-WARE GES, therefore implementing a number of *FI WARE Services*. The *open* and *royalty-free* nature of FI-WARE GE Specifications allows the existence of alternative implementations of a GE.

FI-WARE GE Provider: any implementer of a FI-WARE GE or a FI-WARE compliant product. Implementers can be *partners* of FI-WARE projects or *third parties*.

FI-WARE Instance: the result of the integration of a number of FI-WARE compliant products and, typically, a number of *complementary products* (proprietary products), therefore comprising a number of FI-WARE GEs and supporting a number of FI-WARE Services, such as Infrastructure as a Service (Iaas) and Context/Data Management Services. While specifications of FI-WARE GEs define FI-WARE Platform in functional terms, FI-WARE Instances are built integrating a concrete set of FI-WARE compliant Products.

FI-WARE Instant Provider: a company or organisation that operates a FI-WARE Instance.

Future Internet Application: an application that is based on APIs defined as part of *GE Open Specifications.* A FI Application should be *portable* across different FI-WARE Instances that implement the GEs that the application relies on, no matter if they are linked to different FI-WARE Instance Providers.

FI-WARE Application/Service Provider – a company or organisation which *develops* FI applications and/or services based on FI-WARE GE APIs and *deploys* those applications/services *on top* of FI-WARE Instances. The open nature of FI-WARE GE specifications enables *portability* of FI applications and/or services across different FI-WARE Instances.

FI-WARE testbed: a concrete FI-WARE Instance operated by *partners* of the FI-WARE project that is offered to *Use Case projects* within the FI-PPP Program, enabling them to test their poof-of-concept *prototypes*.

FI-WARE Instance in production: A FI-WARE instance run by a *FI-WARE Instant Provider* in the context of a *trial* (e.g. trials in the phase 2 of the FI-PPP) or as a part of its *offering* to the market. FI-WARE Instances in production will typically have their *own* certification and developers community support environments, but may establish alliances to set up common certification or support environments.

Products implementing FI-WARE GEs can be picked and plugged together with *complementary products* in order to build *FI-WARE instances*, operated by so called *FI-WARE Instance Providers.*
Complementary products are *proprietary products* that allow FI-WARE Instant Providers to *differentiate* their offering and implement their desired *business models.*Complementary products can be integrated to allow a better integration with products already used by one company, making operations more efficient (e. g. proprietary monitoring/management tools), but also for supporting the commercialisation/monetisation of the services delivered through the FI-WARE Instance they operate (e. g. proprietary billing or advertising Support Systems).

FI-WARE GEs are classified into *core* GEs and *optional* GEs: core GEs are required to be deployed in every FI-WARE instance.

Many different stakeholders will be part of the *business ecosystem* creating Future Internet based applications and services. They are likely to have differentiated business objects and offerings and therefore will take one or more of the *roles* defined above (FI-WARE GE, Instant or Application/Service Providers).

Relevant *stakeholders* include:

- established *TLC Industry* (such as TLC Operators, Network equipment manufacturers, mobile terminal manufacturers and TLC solution providers),
- *IT Industry* (such as SW vendors, service providers and IT solution providers),
- emerging FI *solution aggregators* (e.g. SME),
- various *usage areas* stakeholders,
- *end users* and *prosumers*.

A.3The role of “La Sapienza” University

The growing number of heterogeneous devices which can be used to access a variety ofphysical networks, contents, services, and information provided by a broad range of network,application and service providers has clearly created the conditions required for an increasingnumber of users to be always in touch with what is going on in the world, both for personaland work-related purposes.
In the attempt to differentiate the offer, device manufacturers, service and contentproviders are continuously introducing new and more sophisticated features in their products, however the drawback of difficult communication among devices due to low or even absentstandardization is often an issue for successful connectivity. Moreover, users, contentproviders and third-party service providers call for basic network services such as Quality ofExperience/Quality of Service, Mobility and Security.

FI-WARE envisions that the concept of *Intelligent Connectivity* is at the basis of theFuture Internet. The Intelligent Connectivity concept will connect users to the network byintelligently leveraging the features of the network.

The “La Sapienza” University is involved in *Work Package 7 (WP7): Interfaceto the Network and Devices*, whose main objective is to provide of a set of open andstandardized Interfaces to the Network and to the Devices, each virtualizing a particularnetwork infrastructure or device features and addressing a distinct intelligent connectivityneed of the Core Platform components and the future internet services.

In particular, LaSapienza University is involved in:

(i) *Task 7.1- Interface to connected devices*: this Task develops the enablers that providethe interfaces related to connected devices; the work will identify and develop thosegeneric enablers which will provide advanced capabilities (e.g. related to sensorintegration and context awareness) to be easily portable across multiple device classes.The set of interfaces will give access in a uniform and standardised way to features of theconnected devices.

(ii) *Task 7.3- Interface to open networking entities*: this Task developsuniforminterfaces for the configuration and programming of network elements that provide intelligent network connectivity by packet and/or circuit switching. The interfaces are expected to dynamically enable customized network functions for cloud computing, network virtualization, resource reservation and also potentially a certain level of programmability of the network. The interfaces will be generic and technology independent as far as possible (e.g., packet switching vs. circuit switching), andspecifically take into account the requirements of carrier-grade operation.

The University of Rome will participate in the specification and development of innovative interfaces, focusing on Quality of Experience/Quality of Servicemanagement issues.

ANNEXB – OPNET Code

B.1 Supervisor Agent Code

```
/*Global status signal definition*/
Vvec_Vector ss;
int num_CoS=4;
int num_quantization=3;
int num_stazioni=3;

typedef struct frequency_class_of_service
        {
        double station[10][4];
        } frequency_class_of_service;

frequency_class_of_service class_of_service;

static void reset_variables(Vvec_Vector sent,Vvec_Vector del,Vvec_Vector
pk_count,Vvec_Vector tr_sent,Vvec_Vector average_del,int dim)
        {
        int i;

        for (i = 0; i < dim; i++)
                {
                /*Set the value in i-th position to zero*/
                op_vvec_value_set (sent, i, 0.0);
                op_vvec_value_set (del, i, 0.0);
                op_vvec_value_set (pk_count, i, 0.0);
                op_vvec_value_set (tr_sent, i, 0.0);
                op_vvec_value_set (average_del, i, 0.0);
                }
        }

static void reset(frequency_class_of_service class_service,int dim)
        {
        int i;
        int j;

        for (i = 0; i < 4; i++)
                {
                for (j=0; j< dim; j++)
                        {

                        class_service.station[i][j]=0;

                        }
                }
        }

static void counters_update(int pos,Vvec_Vector sent,Vvec_Vector del,Vvec_Vector
pk_count)
        {
        double sent_counter;
        double delay_counter;
        double pk_counter;
        /*Get the value of current packets and delay*/
        op_vvec_value_get (sent, pos, &sent_counter);
        op_vvec_value_get (del, pos, &delay_counter);
        op_vvec_value_get (pk_count, pos, &pk_counter);

        /*Update values*/
        sent_counter=sent_counter+op_stat_local_read(pos);
        delay_counter=delay_counter+op_stat_local_read(pos+20);
        pk_counter++;

        /*Update vectors*/
        op_vvec_value_set (sent, pos, sent_counter);
        op_vvec_value_set (del, pos, delay_counter);
        op_vvec_value_set (pk_count, pos, pk_counter);
        }

static void update_final_variables(int inter,Vvec_Vector sent,Vvec_Vector del,Vvec_Vector
pk_count,
        Vvec_Vector tr_sent,Vvec_Vector average_del,int dim)
        {
        int i;
        double sent_counter;
        double delay_counter;
        double pk_counter;

        for (i = 0; i < dim; i++)
                {
                /*Get the value of total packets and delay*/
                op_vvec_value_get (sent, i, &sent_counter);
                op_vvec_value_get (del, i, &delay_counter);
                op_vvec_value_get (pk_count, i, &pk_counter);

                /*Calculate average traffic sent and delay and update the vectors*/
                op_vvec_value_set (tr_sent, i, (sent_counter+208*pk_counter)/inter);
                if (pk_counter!=0)
                        op_vvec_value_set (average_del, i, delay_counter/pk_counter);
                else op_vvec_value_set (average_del, i, 0.0);
                }
        }

static void status_signal(Vvec_Vector s_signal,Vvec_Vector sent,Vvec_Vector
del,frequency_class_of_service c_service,int dim)
        {
        int i;
        int j;
        double av_sent;
        double av_del;

        for (i = 0, j=0; i < dim; i++, j=j+2)
                {
                /*Get the average traffic sent and delay for the i-th class*/
                op_vvec_value_get (sent, i, &av_sent);
                op_vvec_value_get (del, i, &av_del);

                /*class_number=0;
                for (k=0; k<3; k++)
                        {
                        class_number=class_number+c_service.station[k][i];
                        }

                if (class_number>0)             class_number=class_number/20;
                if (class_number==0) class_number=1;*/

                /*Update the status signal*/
                op_vvec_value_set (s_signal, j, av_sent);
                op_vvec_value_set (s_signal, j+1, av_del);
                }
        }

static void update_statistics(Vvec_Vector sent,Vvec_Vector del,Stathandle s11,
        Stathandle d11,Stathandle s21,Stathandle d21,Stathandle s31,Stathandle d31,
        Stathandle s41,Stathandle d41,Stathandle sef,Stathandle def)
        {
        double s;
        double d;

        op_vvec_value_get (sent, 0, &s);
        op_vvec_value_get (del, 0, &d);

        op_stat_write(s11,s);
        op_stat_write(d11,d);

        op_vvec_value_get (sent, 1, &s);
        op_vvec_value_get (del, 1, &d);

        op_stat_write(s21, s);
        op_stat_write(d21, d);

        op_vvec_value_get (sent, 2, &s);
        op_vvec_value_get (del, 2, &d);

        op_stat_write(s31, s);
        op_stat_write(d31, d);

        op_vvec_value_get (sent, 3, &s);
        op_vvec_value_get (del, 3, &d);

        op_stat_write(s41, s);
        op_stat_write(d41, d);
        }
```

B.2 Requirement Agent Code

```
typedef struct frequency_class_of_service
        {
        double station[10][4];
        } frequency_class_of_service;

/*Global variables*/
extern Vvec_Vector ss;
extern Vvec_Vector link_availability;
extern frequency_class_of_service class_of_service;
extern int num_CoS;
extern int num_quantization;
extern int num_stazioni;

/*Matrix of comparison (each row is a comparison vector, associated to a service class)*/
typedef Vvec_Vector Comparison_Supervisor [13];
typedef Vvec_Vector Q_values_matrix [243];

static double max_r(int state, Vvec_Vector super_state, Q_values_matrix Q, int CoS, int
quantization);

static void reset_vector_zero (Vvec_Vector comp, int dimension)
        {
        int i;
        for (i=0; i<dimension; i++)
                {
                op_vvec_value_set (comp, i, 0);
                }
        }

static void init (Vvec_Vector Q, int dimension, double value)
        {
        int i;

        /*Initialize the elements of Q matrix with 'value'*/
        for (i=0; i<dimension; i++)
                {
                op_vvec_value_set (Q, i, value);
                }
        }

static void reset_Q (Q_values_matrix Q, double r, int quantization, int CoS)
        {
        int i;

        /*Initialize the elements of Q matrix with 'value'
        The initialization proceeds from the first to the last row of Q matrix*/
        for (i=0; i<pow(quantization, CoS+1); i++)
                {
                Q[i]=op_vvec_create(OpC_Type_Double);
                init(Q[i],CoS,r);
                }
        }

static void reset_learning_rate (Vvec_Vector l_rate, int quantization, int CoS)
        {
        int i;

        for (i=0; i<pow(quantization, CoS); i++)
                {
                op_vvec_value_set(l_rate, i, 1.0);
                }
        }
```

```
static void get_QoE (Vvec_Vector comp,double tr_adm,
        double av_delay,double min_tr,double max_del,double* lk_av)
        {

        /*Compute QoE 0*/
        if (tr_adm>=min_tr && av_delay<=max_del)
                *lk_av=1;

        else if (tr_adm>=min_tr && av_delay>max_del)
                *lk_av=0.5+0.5*(1-((av_delay-max_del)/max_del));

        else if (tr_adm<min_tr && av_delay<=max_del)
                *lk_av=0.5+0.5*(1-((min_tr-tr_adm)/min_tr));

        else if (tr_adm<min_tr && av_delay>max_del)
                *lk_av=0.5*(1-((min_tr-tr_adm)/min_tr))+0.5*(1-((av_delay-
max_del)/max_del));
        }

static void get_QoE_super (Comparison_Supervisor comp,
        Vvec_Vector ind,Vvec_Vector s_signal,double min_tr,double max_del,
        Vvec_Vector lk_av_super, int dimension, frequency_class_of_service c_service, int
num)
        {
        int i;
        int j;
        int k;
        double tr_sent;
        double av_del;
        double lk_av;
        double ind_super;
        double class_number;

        /*For each row of the matrix comparison we compute the QoE*/
        for (i=0, j=0; i<dimension; i++, j=j+2)
                {
                op_vvec_value_get (s_signal, j, &tr_sent);
                op_vvec_value_get (s_signal, j+1, &av_del);

                /*If the i-th service class doesn't send packets than
                it is free*/
                if (tr_sent==0)
                        op_vvec_value_set (lk_av_super, i, 1.0);
                else
                        {
                        /*Assign to local variable the QoE*/
                        op_vvec_value_get (lk_av_super, i, &lk_av);

                        class_number=0;
                                for (k=0; k<num; k++)
                                        {
                                        class_number=class_number+c_service.station[k][i];
                                        }

                        if (class_number>0)             class_number=class_number/19;
                        if (class_number==0) class_number=1;
```

```
                    tr_sent=tr_sent/class_number;

                    /*Compute QoE for the i-th service class*/
                    get_QoE (comp[i],tr_sent,av_del,min_tr,max_del,&lk_av);

                    /*Update QoE*/
                    op_vvec_value_set (lk_av_super, i, lk_av);
                    }
            }
    }

static void compute_agent_state(double lk_av, int* state, int quantization)
    {
    double lk_av_100;

    /*Compute the agent state from QoE*/
    lk_av_100=lk_av*100;
    /*A quantization is introduced that divides the interval [0;1]
    into a finite set of sub-intervals*/

    if (lk_av_100<=100)   *state=2;
    if (lk_av_100<=90)    *state=1;
    if (lk_av_100<=30)    *state=0;
    }

static void compute_ss_state(Vvec_Vector lk_av_super, Vvec_Vector s_state, int CoS, int
quantization)
    {
    int i;
    double lk_av;
    int state;

    /*Compute the state of each Class of Service, from the status signal*/
    for (i=0; i<CoS; i++)
            {
            op_vvec_value_get(lk_av_super, i, &lk_av);
            op_vvec_value_get(s_state, i, &state);

            compute_agent_state(lk_av, &state, quantization);

            op_vvec_value_set(s_state, i, state);
            }
    }

static void compute_reward(double lk_av, double lk_av_target, double *r)
    {
    /*Compute the reward of the agent*/
    *r=-1000*(lk_av-lk_av_target)*(lk_av-lk_av_target);
    }

static void reinforcement_learning(int state_past, Vvec_Vector super_state_past, int
act_past, int state,
    Vvec_Vector super_state, double r, Q_values_matrix Q, int CoS, int quantization,
double alpha_0, double gamma)
```

```
        {
        int i;
        int s;
        int row;
        double q_val;
        double long_reward;

        /*From the global state of the agent (agent_state+supervisor_state)
        we compute the correspondent row of the Q_matrix (we consider the global state
        as a string of number expressed in base-val, with val equals to 'quantization')*/
        row=0;
        for (i=0; i<CoS; i++)
                {
                op_vvec_value_get(super_state_past, i, &s);
                row=row+s*pow(quantization,i);
                }

        row=row+state_past*pow(quantization,CoS);

        /*Obtain the past value of the Q_matrix*/
        op_vvec_value_get(Q[row], act_past, &q_val);

        /*Apply the Q_learning algorithm (past value+ increment)*/
        long_reward=max_r(state,super_state,Q,CoS,quantization);

        q_val=q_val+alpha_0*(r+gamma*long_reward-q_val);

        if (q_val<-1000)        q_val=-1000;

        /*Write the new value*/
        op_vvec_value_set(Q[row], act_past, q_val);
        }

static void get_learning_rate(Vvec_Vector l_rate, Vvec_Vector super_state, int
quantization, int CoS, double* alpha_0)
        {
        int i;
        int s;
        int row;
        double app;

        row=0;
        for (i=0; i<CoS; i++)
                {
                op_vvec_value_get(super_state, i, &s);
                row=row+s*pow(quantization,i);
                }

        op_vvec_value_get(l_rate, row, &app);

        *alpha_0=app;

        op_vvec_value_set(l_rate, row, 0.98*app);
        }
```

```
static double max_r(int state, Vvec_Vector super_state, Q_values_matrix Q, int CoS, int
quantization)
        {
        int i;
        int s;
        int row;
        double max_reward;
        double app;

        /*From the global state of the agent (agent_state+supervisor_state)
        we compute the correspondent row of the Q_matrix (we consider the globalstateas
a string of number expressed in base-val, with val equals to 'quantization')*/
        row=0;
        for (i=0; i<CoS; i++)
                {
                op_vvec_value_get(super_state, i, &s);
                row=row+s*pow(quantization,i);
                }

        row=row+state*pow(quantization,CoS);

        /*Compute, for the current state, the higher possible reward*/
        op_vvec_value_get(Q[row], 0, &max_reward);

        for (i=1; i<CoS; i++)
                {
                op_vvec_value_get(Q[row], i, &app);
                if (app>max_reward)  max_reward=app;
                }

        return max_reward;
        }

static void next_action(int* a, int state, Vvec_Vector super_state, Q_values_matrix Q,
double eps, int CoS, int quantization,

int ide)
        {
        int i;
        int s;
        int row;
        double max_reward;
        int greedy_action;
        double app;

        /*From the global state of the agent (agent_state+supervisor_state)
        we compute the correspondent row of the Q_matrix (we consider the global state
        as a string of number expressed in base-val, with val equals to 'quantization')*/
        row=0;
        for (i=0; i<CoS; i++)
                {
                op_vvec_value_get(super_state, i, &s);
                row=row+s*pow(quantization,i);
                }
```

```
          row=row+state*pow(quantization,CoS);

          /*Compute, for the current state, tha higher possible reward; the
          action associated with this reward is the greedy action*/
          greedy_action=0;
          op_vvec_value_get(Q[row], greedy_action, &max_reward);

          for (i=1; i<CoS; i++)
                    {
                    op_vvec_value_get(Q[row], i, &app);
                    if (app>max_reward)
                              {
                              max_reward=app;
                              greedy_action=i;
                              }
                    }

          /*With probability 'eps' we choose a random action*/
          app=((double) (rand() % 1000 +1))/1000;

          if (app>=eps)  *a=greedy_action;
          else                     *a=rand() % CoS;
          }

static void action_to_class (int a, int* c)
          {

          /*This method translates the action into a value correspondent to
          a real Class of Service. This number will be written into the
          IP header of the packet*/
          if (a==0)        *c=40;
          if (a==1)        *c=72;
          if (a==2)        *c=104;
          if (a==3)        *c=136;
          }
```