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A Cognitive Mechanism for Vertical Handover and Traffic Steering to Handle Unscheduled Evacuations of the Licensed Shared Access Band

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"Effort, perseverance, and conviction, fundamental pillars to achieve great feats and continue despite stumbles."

— J.C.F.

ABSTRACT

There has been a steady growth in the traffic generated by Mobile Network Operators (MNOs), and by 2020 it is expected to overload the existing licensed spectrum capacity and lead to the problem of scarce resources. One method to deal with this traffic overload is to access unlicensed and shared spectrum bands using an opportunistic approach. The use of Licensed Shared Access (LSA) is a novel approach for spectrum sharing between the incumbent user (*i.e.,* the current owner of the shared spectrum) and the LSA licensee (*i.e.,* the temporary user of frequencies, such as an MNO). The LSA system allows the incumbent users to temporarily provide the LSA licensee with access to its spectrum resources. However, licensees must adopt vertical handover and traffic steering procedures to vacate their customers from the LSA band without causing interference, whenever this is required by the incumbent. These procedures should be carried out, de facto, before the base station is turned off as a part of a rapid release of unscheduled LSA band facing evacuation scenarios. Thus, in this dissertation, a cognitive mechanism is proposed to make decisions in advance to find the best target network(s) for evacuated customers in connected mode and with active traffic per class of service. On the basis of these decisions, the vertical handover and traffic steering procedures are carried out for the best target network(s), which are selected in advance and undertaken immediately to avoid interference between the licensee and incumbent services. Furthermore, this guarantees the seamless connectivity and QoS of evacuated customers and their traffic respectively, during and after the unscheduled evacuation scenarios. A performance evaluation conducted in a simulating scenario consisting of one LTE-LSA and three Wi-Fi networks, demonstrated that the proposed solution could be completed within the time required for the unscheduled evacuation, as well as, being able to ensure the QoS and seamless connectivity of the evacuees. The total execution time obtained during the performance evaluation of the proposed solution was around 46% faster than of two related works and could thus avoid interference between the licensee and incumbent services.

Keywords: Cognitive Mechanism. In-Advance Decisions. Vertical Handover. Traffic Steering. Spectrum Sharing. Mobile Network Operators. Licensed Shared Access. Unscheduled Evacuation. Long-Term Evolution Networks. Wireless-Fidelity Networks.

Uma Abordagem Cognitiva para a Transferência Vertical e Orientação do Tráfego em Cenários de Evacuação não Programada da Banda de Acesso Compartilhado Licenciado

RESUMO

O tráfego gerado pelas Operadoras de Rede Móvel (ORMs) está crescendo constantemente e se estima que no ano 2020 a capacidade do espectro licenciado estará sobrecarregado, levando ao problema de escassez deste recurso. Um método para lidar com essa sobrecarga de tráfego é acessar às bandas do espectro não licenciadas e compartilhadas usando uma abordagem oportunista. O Acesso Compartilhado Licenciado (ACL) é uma nova abordagem para o compartilhamento do espectro entre o usuário incumbente (*i.e.,* o atual proprietário do espectro compartilhado) e o licenciado ACL (*i.e.,* o usuário temporal da frequências compartilhado, como uma ORM). O sistema ACL permite que o(s) usuário(s) incumbente(s) forneçam temporariamente acesso ao seu espectro para o licenciado ACL. Além disso, devido ao fato de o usuário incumbente manter seus direitos sobre o espectro compartilhado, ele pode requisitar a desocupação da banda no momento e no lugar que precisar. Ademais, no caso de um usuário temporal (*e.g.*, ORM) estar utilizando o espectro no mesmo momento em que um usuário incumbente requisitar a banda AC, a ORM deve executar a transferência e a orientação do tráfego dos usuários que estejam na banda ACL para outras redes, em bandas diferentes. Além disso, é necessário garantir a conectividade com um determinado nível de QoS e ainda evitar a interferência entre os serviços do usuário incumbente e a ORM. Assim, nesta dissertação propõe-se um mecanismo cognitivo que toma antecipadamente decisões para encontrar a melhor rede de destino para os usuários, que estejam em modo conectado e com tráfego ativo por classe de serviço na evacuação. Com base nessas decisões, são executados a transferência vertical e a orientação do tráfego dos usuários evacuados para as melhores redes de destino selecionadas anteriormente. Estes processos são efetuados imediatamente para evitar a interferência entre os serviços do usuário licenciado e incumbente. Isso também permite garantir a conectividade contínua dos usuários evacuados e o QoS do tráfego, durante e após os cenários de evacuação não programados. Uma avaliação de desempenho realizada num cenário de simulação, composto por uma rede de Evolucao de longo termo na banda ACL e três redes Wi-Fi, demonstrou que a solução proposta cumpre o tempo exigido pela evacuação não programada, além de garantir o QoS e a conectividade sem interrupções dos usuários evacuados. O tempo total de evacuação obtido durante a avaliação de desempenho da solução proposta é cerca do 46% mais rápido do que o de dois trabalhos relacionados, evitando assim a interferência entre os serviços do usuário licenciado e incumbente.

Palavras-chave: Mecanismo cognitivo. Decisões Antecipadas. Transferência vertical. Orientação do tráfego. Acesso Compartilhado Licenciado. Operadoras de rede móvel. Redes de Evolução de longo termo. Redes Wi-Fi. Evacuação não programada.

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LIST OF ABBREVIATIONS AND ACRONYMS

AMR	*Adaptive Multi-Radio audio codec*
ASA	*Authorized Shared Access*
BS	*Base Station*
BES	*Best Effort Services*
CA	*Carrier Aggregation*
CFBP	*Cascade Forward Back Propagation*
CEPT	*European Conference of Postal and Telecommunication Administration*
CoS	*Class of Service*
CORE	*Cognitive Radio Trial Environment*
CRS	*Cognitive Radio System*
CTS	*Cognitive Traffic Steering*
CUS	*Collective Use of Spectrum*
C-VHO	*Cognitive Vertical Handover*
DFT	*Discrete Fourier Transformation*
DEF	*Ministry of Defense*
DL	*Downlink (BS to MS transmission direction)*
DSA	*Dynamic Spectrum Alliance*
EC	*European Commission*
ECC	*Electronic Communication Committee of the CEPT*
ECN	*Electronic Communication Networks*
ECS	*Electronic Communication System*
ECN&S	*Electronic Communication Networks & Services*
EIRP	*Effective Isotropic Radiated Power*
eNB	*Evolved Node B*
EPC	*Evolved Packet Core*
ETSI	*European Telecommunications Standards Institute*

E-UTRAN	*Evolved Universal Terrestrial Radio Access Network*
FDD	*Frequency-Division Duplexing*
FM	*Fourier Model*
HTTP	*Hypertext Transfer Protocol*
IMT	*International Mobile Telecommunications*
ITU	*International Telecommunication Union*
IP	*Internet Protocol*
LSA	*Licensed Shared Access*
LTE	*Long-Term Evolution*
MAPE	*Mean Absolute Percentage Error*
MCA	*Mobile Communication service on Aircraft*
MBB	*Mobile Broadband*
MIMO	*Multiple-Input and Multiple-Output*
MLR	*Multiple Linear Regression*
MNO	*Mobile Network Operator*
MFCN	*Mobile/Fixed Communication Networks*
MPEG	*Moving Picture Expert Group*
MS	*Multimedia Services*
MVNO	*Mobile Virtual Network Operator*
NN	*Neural Networks*
NMS/OSS	*Network Management Systems / Operations Support Systems*
NRA	*National Regulatory Authority*
NTFA	*National Table of Frequency Allocation*
OAM	*Operation, Administration and Maintenance*
OFDM	*Orthogonal Frequency Division Multiplexing*
OFDMA	*Orthogonal Frequency Division Multiple Access*
OFCOM	*Office of Communications*
PCAST	*President's Council of Advisors on Science and Technology*
PDF	*Probability Density Function*

PMSE	*Programme-Making and Special Events*
PAMR	*Public Access of Mobile Radio*
QoS	*Quality of Service*
QoSMet	*QoS Measurement*
QAM	*Quadrature Amplitude Modulation*
QPSK	*Quadrature Phase-Shift Keying*
RAN	*Radio Access Networks*
RSPG	*Radio Spectrum Policy Group*
RSS	*Radio Signal Strength*
RTM	*Regression Tree Model*
RTP	*Real-Time transport Protocol*
RTS	*Real-Time Services*
SAP	*Service Ancillary to Programme making*
SAB	*Service Ancillary to Broadcasting*
SINR	*Signal-to-Interference-Plus-Noise Ratio*
TCP	*Transmission Control Protocol*
TDD	*Time-Division Duplexing*
TLF	*Traffic Load Forecasting*
TS	*Traffic Steering*
UDP	*User Datagram Protocol*
UE	*User Equipment*
UL	*Uplink (MS to BS transmission direction)*
UMTS	*Universal Mobile Telecommunications System*
VHO	*Vertical Handover*
VoIP	*Voice over IP*
WiMAX	*Worldwide Interoperability for Microwave Access*
VTT	*Technical Research Centre of Finland*
Wi-Fi	*Wireless Fidelity*
WHNs	*Wireless Heterogeneous Networks*

CONTENTS

1 INTRODUCTION

Mobile Network Operators (MNOs) will have to tackle a huge growth of traffic in the near future. It is expected that mobile and wireless traffic volume increase a thousand-fold by 2020 (CISCO, 2016) (UMTS, 2011) (OSSEIRAN et al., 2014), leading to network congestion and spectrum scarcity. A promising solution to this problem is the new and emerging spectrum-sharing paradigm called Licensed Shared Access (LSA). LSA authorizes spectrum-sharing by allowing the incumbent user (*i.e.,* the current holder of the spectrum) to temporarily provide access to the LSA licensee(s) (*i.e.,* the temporary user of frequencies, such as an MNO) (PONOMARENKO-TIMOFEEV et al., 2016). For example, a Long-Term Evolution (LTE) operator can increase its bandwidth capacity for Mobile Broadband (MBB) services by obtaining access in an authorized manner within the additional spectrum (LSA band) of the incumbent. In Europe, the Programme-Making and Special Events (PMSE) of broadcasting or TV production companies is the most regular incumbent service within the band of 2.3 - 2.4 GHz (CEPT, 2015a). The National Regulatory Authority (NRA), incumbent user and LSA licensee define the technical and operational conditions as part of LSA-sharing framework to use the shared spectrum with a certain QoS and without harmful interference (ECC, 2011). Thus, the MNOs have obtained an additional spectrum bandwidth capacity that otherwise would not be accessible to cope with the network congestion and spectrum scarcity.

1.1 Research Problem

The LSA regime characterized by the incumbent user, employs the LSA spectrum band dynamically, as well as authorizing the LSA licensee to use it. This means that the incumbent is eligible to dynamically request the resources back at any time and from any geographical location. For instance, the incumbent' user can request the return of LSA band when and where the User Equipment (UE) of a certain MNO (*e.g.* the LTE operator) is operating. This compels the LSA licensee to evacuate the LSA spectrum promptly and thus avoid interference between the MBB and PMSE services of the MNO and incumbent users ((CEPT, 2015b)), respectively. Moreover, when the incumbent user requests the use of the LSA spectrum band in an emergency situation, the MNO triggers an unscheduled evacuation of the LSA band used by the base station(s) or cell sector(s) and UEs located in the requested area. Currently, the LTE operator has into the radio plan execution for turning off the air interfaces of the affected base station(s) or the cell sector(s) on the LSA band that have been evacuated in an unscheduled manner (CEPT, 2015b). The LTE operator also decides to disconnect the evacuated UEs from the LSA band for a period of time so that they can later be reconnected by themselves in a network that adopts the cell reselection procedure (ETSI, 2013). However, none of the current LTE procedures applied to LSA scenarios can be carried out because they require more time than the fast turning off time of the base station(s) or cell sector(s) on the LSA band to evacuate it in unscheduled manner. This causes that the current solutions can not guarantee the QoS and seamless connectivity of the UEs during and after an unscheduled evacuation of the LSA band. The drawbacks of the current procedures for dealing with unscheduled evacuation scenarios, are described as follows:

- The current LTE procedures applied to LSA scenarios are only corrective approaches because they are adopted after the disconnection of the evacuated UEs. The non-connection period causes the total degradation of the QoS provided to the UEs during and after the evacuation of the LSA band;
- According to the CEPT Report 56 (CEPT, 2015b), one Evolved Node B (eNB) with one sector can be turned off in average 20.62 seconds. As well as this, an eNB with five sectors turns off with an average delay of 33.27 seconds. Thus, the fast turning off time of the eNB prevents the current LTE procedures from ensuring QoS and seamless connectivity to all the evacuated UEs in unscheduled evacuation scenarios.

Various solutions have been proposed to address the question of the evacuation of the LSA band, and attention should be drawn to that of the VTT Technical Research Centre of Finland and European Telecommunications Standards Institute (ETSI) ((MATINMIKKO et al., 2013) (ETSI, 2013) (PALOLA et al., 2014a) (PALOLA et al., 2014b) (PALOLA et al., 2014c) (MUSTONEN et al., 2015b)). However, these solutions are not concerned with the implementation of the handover procedures in unscheduled evacuation scenarios since their performance time is higher than the turning off time of the eNB and involved sector(s). The principal procedures and their shortcomings for ensuring QoS and the connectivity of UE during and after an unscheduled evacuation of the LSA band, can be listed as follows:

- The cell reselection procedure is a corrective measure taken by the UEs after they have been disconnected from the LTE-LSA network because the air interfaces have been turned off. This procedure only takes note of the current measurement of Radio Signal Strength (RSS) and level of channel quality. This means the QoS and seamless connectivity of the UEs can not be guaranteed after being reconnected to some network in this area;
- The whole time of non-connection period and total QoS degradation of UEs depends on the alternative networks availability and decision-making time of the cell reselection procedure to reconnect the UE by itself in one of these networks;
- the VTT's forced handover is based on the cognitive decision, and takes more time than the eNB/sector to turn off the air interfaces on the LSA band. This is because the time for the QoS measurements, and decision-making on the fly is longer than what is required by the unscheduled evacuation, and thus restricts the forced handover execution.

The state-of-the-art about the procedures adopted to evacuate the users in scheduled and unscheduled cases can be summarized as involving inter-frequency handover, cell reselection and forced handover ((ETSI, 2013) (CEPT, 2015b) (MATINMIKKO et al., 2013) (PALOLA et al., 2014b). To the best of our knowledge, none of the current procedures have achieved the required time to avoid interference between the services of the incumbent and LSA licensee when faced with unscheduled evacuation scenarios. None of the current handover solutions for LSA scenarios can be carried out at the time of unscheduled evacuation because they are unable to ensure the QoS and seamless connectivity of the UEs before the eNB/sector(s) turn off the air interfaces. Besides the existing LTE procedures fail because do not consider into the decision-making process, the metrics such as *a)* the traffic load forecasting and *b)* the congestion status of overlapping networks.

1.2 Main Objectives

The purpose of this dissertation is to provide a cognitive mechanism to make decisions in advance and thus find the best target network(s) to carry out rapidly the vertical handover and traffic steering of UEs in unscheduled evacuation scenarios. The proposed cognitive mechanism periodically makes it possible to find the best target network(s) for the evacuated UEs per Class of Service (CoS) from the LTE network on the LSA band (LTE-LSA network). This provides the cognitive criteria for carrying out the vertical handover and traffic steering procedures immediately and thus guarantees the QoS and seamless connectivity of UEs. De facto, it is proposed a Cognitive Vertical Handover (C-VHO) to transfer the evacuated UEs as soon as an unscheduled evacuation request is received and thus keep their seamless connectivity in networks with less congestion. Furthermore, a Cognitive Traffic Steering (C-TS) procedure is designed to steer the UEs traffic per CoS taking into account the QoS requirements of UEs evacuated from the LTE-LSA network toward the best-overlapped Wi-Fi network(s) to guarantee their QoS in the long term. Both C-VHO and C-TS solutions enable the LSA licensee to create a list of potential target networks and traffic steering routes before an evacuation request is received, which considerably shortens the evacuation times of the UEs.

The architecture to support the proposed C-VHO and C-TS procedures is an extension of existing cognitive QoS-aware resources sharing architecture originally designed by Kunst *et al.* (KUNST et al., 2016a) (KUNST et al., 2016b). The original architecture is used to gather updated information on the resource usage of various operators in heterogeneous wireless network scenarios. The architecture of Kunst *et al.* (KUNST et al., 2016a) (KUNST et al., 2016b) allows different decision algorithms to be implemented. In contrast, we created a novel decision algorithm capable of selecting the best target network(s) for the evacuated UE traffic; this was in accordance with their CoS and based on the cognitive criteria. Moreover, it enabled the vertical handover and traffic steering of the UEs and traffic to transfer towards the best target network(s) in the shortest time when faced with the unscheduled evacuation of LSA band. More specifically, a scenario comprising one LTE-LSA and three Wi-Fi networks is chosen to evaluate the proposed solution. The evaluation conducted via Matlab simulations, was based on an analytical model system. The results show that the proposed solution is able to carry out an unscheduled evacuation of LSA band, which is *a)* achieved by the immediate vertical handover and traffic steering and *b)* takes into account the QoS requirements of the evacuating users. The key factors of this dissertation can be summarized as follows:

1. Enhancement of the network management procedures of MNOs to evacuate the customers in a shorter time while occurs an unscheduled evacuation of LSA band;
2. Creation of a cognitive in advance decision algorithm that can achieve a very fast evacuation of users on the LSA spectrum band;
3. Traffic load forecasting for wireless heterogeneous network scenarios, for LTE-LSA and Wi-Fi networks;
4. Anticipated selection of the best target networks (*e.g.,* Wi-Fi) considering the users' CoS in the LTE-LSA network;
5. Cognitive in advance decision-making to select the best target network(s) to execute the vertical handover and traffic steering procedures;
6. Immediate QoS-aware traffic steering in unscheduled evacuation scenarios;
7. Ensuring the QoS and seamless connectivity of evacuated users during and after an unscheduled LSA band evacuation;
8. Performance evaluation of the duration and QoS attained in comparison with current solutions for the unscheduled evacuation of the LSA band.

1.3 Dissertation Structure

This dissertation is structured as follows. Chapter 2 provides an overview of the main concepts in LTE and LSA scenarios that are needed to understand the proposed solution. In Chapter 3, there is a review of the related works found in the literature (both in the academic and industrial world) in the context of cognitive and non-cognitive approaches adopted in LTE and LSA scenarios. Chapter 4 examines the cognitive mechanism for the vertical handover and traffic steering which are carried out to ensure the QoS and seamless connectivity of the UEs during and after an unscheduled evacuation of LSA band. In Chapter 5, there is an evaluation of the vertical handover and traffic steering conducted by cognitive mechanism decisions made in advance to find the best target network(s) for the evacuated UEs. Finally, Chapter 6 provides the conclusion of this work with final remarks and makes suggestions for future work.

2 BACKGROUND

This chapter provides an overview of the fundamental concepts, features, and components involved in the proposed solution of this dissertation over Licensed Shared Access (LSA) scenarios. In Section 2.1, there is an explanation of MNOs in the context of LSA technology. Section 2.2 provides an overview of the Long-Term Evolution (LTE) architectural system which supports the vertical handover and traffic steering procedures. Section 2.3 gives a brief description of the concept and variants of resource sharing for MNOs. In Section 2.4 there is a description of heterogeneous wireless networks in LSA scenarios. Section 2.5 examines the type of spectrum licensing for MNOs, while Section 2.6 illustrates the main concepts, features, shared framework and, evacuation procedures of LSA technology. Section 2.7 investigates the concept and environment of the cognitive approach that is applied to LSA scenarios. Finally, Section 2.8 introduces the comparative models used in the Chapter 4 to carry out the traffic load forecasting of LTE-LSA and Wi-Fi networks.

2.1 Mobile Network Operators

A Mobile Network Operator (MNO) is simply a provider of Mobile Broadband (MBB) services in wireless and mobile communications to enable their customers to access the Internet. To achieve this, the MNO deploys a network infrastructure and services consisting of a wireless network, radio spectrum allocation, backhaul, customer care, the provisioning of computer systems, and marketing. Currently, the MNOs are working in the deployment of heterogeneous wireless networks that operate in different frequency bands such as licensed, LSA, and unlicensed frequencies in a harmonized and coordinated manner. For instance, an MNO on a licensed band from a particular region requests authorization to use the LSA frequency within the 2.3 - 2.4 GHz band in the same area. This usually occurs when an MNO is located in dense or overcrowded urban areas, and where the amount of traffic has overloaded the licensed band capacity. In this way, an MNO on LSA band can obtain a bandwidth expansion that otherwise would not be accessible.

Several research articles in the academic and industrial world such as (CISCO, 2016) (CHAPIN; LEHR, 2011) (HOSSAIN et al., 2014) (UMTS, 2011) (NADA, 2008) argue that the amount of traffic expected by 2020, exceeds the capacity of traditional spectrum resources used by the MNO. According to Hossain *et al.* (HOSSAIN et al., 2014) the existing wireless network of MNOs will not be able to deal with the thousand-fold increase in total mobile broadband data. By 2020, the wireless communications technologies are expected to have 1000 times higher volume of mobile data per unit area, and a 10-100 times greater number of connecting devices and user data rate (OSSEIRAN et al., 2014) (METIS, 2013).

LSA is a regulatory approach for the full control of spectrum sharing, where the incumbent user enables its unoccupied spectrum to be used by the LSA licensee (MNO) (ECC, 2011). The aim of the LSA spectrum sharing framework is to ensure the QoS level and avoidance of interference for the incumbent and LSA licensee (MATINMIKKO et al., 2014). The availability of LSA spectrum might be limited to a certain geographical location and time, although when it is available, the MNO can increase its spectrum bandwidth. Currently, the resources of the MNO cover heterogeneous wireless networks (*i.e.,* macro and small cells) operating in more than one spectrum frequency (*e.g.,* licensed, unlicensed and LSA). The MNO relies on technologies such as Frequency-Division Duplexing (FDD) and Time-Division Duplexing (TDD) to ensure there is an harmonious coexistence between the licensed and LSA spectrum frequencies, respectively.

In Europe, MNOs are currently planning to provide access at a frequency range of 2.3 - 2.4 GHz through the LSA technology. This band is designed for MBB services since it is subject to the International Mobile Telecommunication (IMT) and International Telecommunication Union (ITU) radio regulations. Moreover, it is suitable for the application of TDD into the LSA technology in which the base station applies the time-division multiplexing to separate outward and return signals. In contrast, the FDD is used by the base station on licensed bands (exclusively for the MNO) where the transceiver and receiver operate at different carrier frequencies. As well as this, recently the 3rd Partnership Project (3GPP) standardized the 2.3 - 2.4 GHz spectrum as LTE band 40 for TDD-LTE.

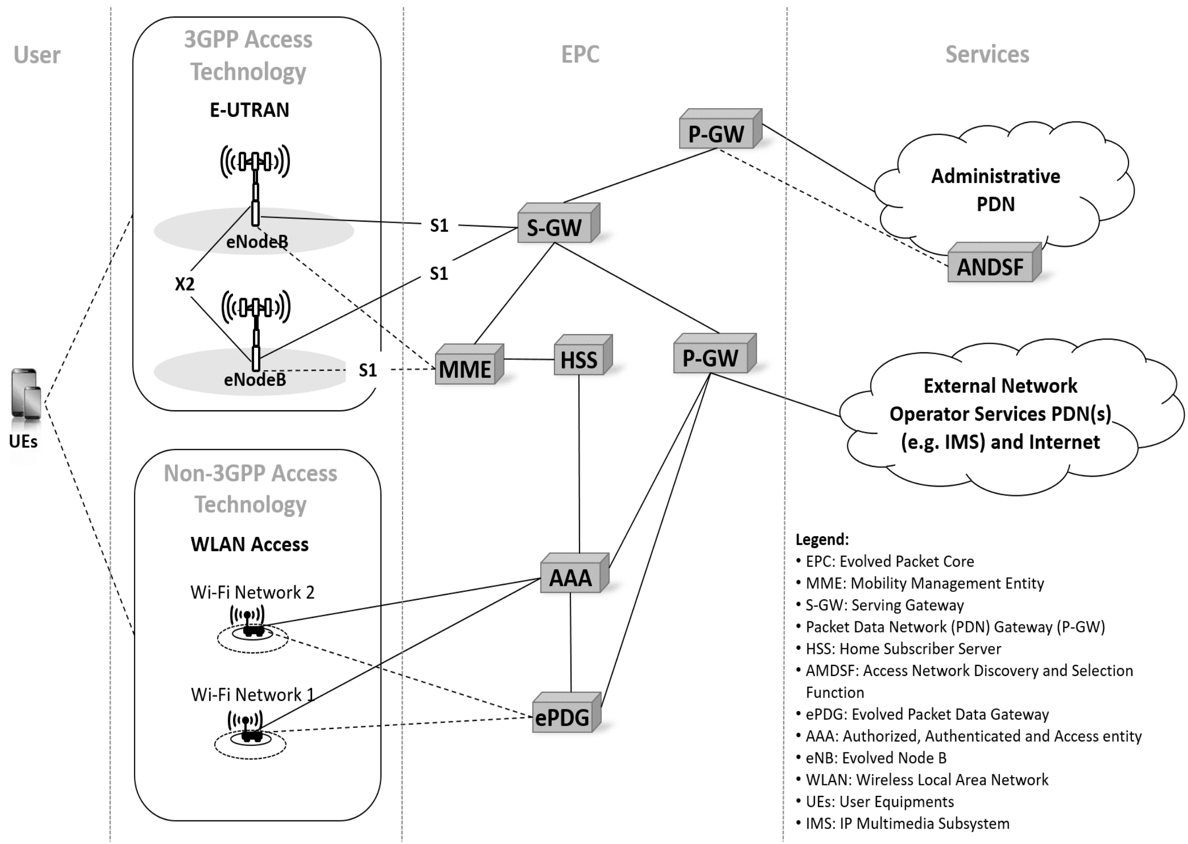
According to the ETSI document 103 113 (ETSI, 2013), the use of the LSA is recommended for small cells to leverage the bandwidth expansion of MNOs. Furthermore, the small cells make it easier to carried out the scheduled and unscheduled evacuations of users on LSA band, mainly because users allocate a different amount in macro cells than small cells. This explains the scenario evaluated in Chapter 5 which consists of one small-cell on the LSA band *i.e.,* 2.3 - 2.4 GHz. It should be taken into account that a small cell allow to MNOs to provide better service coverage and load distribution among the cells than using macro cells and femto cells. When evacuating the LSA band, small cells also simplify the handover of the users towards overlapped network(s). For this reason, this dissertation employs small cells for LSA scenarios.

2.2 Mobile Network Architecture

In this section, there is an examination of the Long-Term Evolution (LTE)/LTE-Advanced (LTE-A) network architecture. The 3GPP standardization incorporates the radio, core network and service architecture for LTE/LTE-A networks. The System Architecture Evolution (SAE), also known as Evolved Packet Core (EPC), is the core network architecture of the 3GPP' wireless communication standard. In addition, SAE has evolved from the General Packet Radio Service (GPRS) and supports the 3GPP' access systems (*e.g.,* 2G/3G/4G LTE) and non-3GPP technologies (*e.g.,* Wi-Fi and WiMAX). The main benefits of SAE include the following: *(i)* a simplified architecture, *(ii)* the All-IP Network (AIPN), *(iii)* support for higher throughput and lower latency in the E-UTRAN (Evolved Universal Terrestrial Radio Access Network).

Figure 2.1 displays the SAE architecture and illustrates where the User Equipment (UE), E-

Figure 2.1: System Architecture Evolution (SAE)



Source: (HOLMA; TOSKALA, 2011).

UTRAN, EPC and MNO services are operated. The EPC together with the E-UTRAN from the Evolved Packet System (EPS), are responsible for maintaining the end-to-end communication and Radio Access Network (RAN) operations. According to (HOLMA; TOSKALA, 2011) and (3GPP,), the principal management entities in current cellular networks are listed and explained as follows:

- Mobility Management Entity (MME) – this is a central control element that operates the control node of the LTE access network. The MME is also responsible for managing the mobility and authentication/security of UEs in the LTE network. Furthermore, paging and tagging procedures including retransmissions are carried out to reconnect the UEs in IDLE mode. One of the key functions of this entity is the authentication of UEs in the network through the subscription profile management (which covers the mobility issues). The MME provides the mobility management among the LTE and 2G/3G access networks through control plane function. This entity makes it possible to carry out the handover of UEs in connected or IDLE mode, in particular among the MMEs.
- Serving Gateway (SGW) – this is responsible for the routing and forwarding of user data packets when acting as the mobility anchor for the user plane during the handover

between inter-nodes and as the anchor for mobility between LTE and other 3GPP technologies. In the case of UEs in IDLE mode, the SGW terminates the downlink data path and triggers paging when the downlink data arrive. As well this, it manages and stores the network profile of UE, *e.g.,* the parameters of the IP bearer service, and internal network routing information. During the mobility between the eNBs, the SGW acts as the local mobility anchor. The MME commands the SGW to switch the tunnel from one eNB to another. The MME can also request the SGW to provide tunneling resources for data forwarding when there is a need to forward data from source eNB to target eNB while the UEs carriying out the radio handover. The mobility scenario also includes a shift from one SGW to another, and the MME controls this change accordingly, by removing tunnels in the old SGW and setting them up in a new SGW. This entity is also responsible for the indirect forwarding of downlink data during the handover and when the eNB connection is not available.

- Packet Data Network (PDN) Gateway (PGW) – this provides connectivity from the UEs to external packet data networks by being the point of entry and exit of their traffic. A UE can have concurrent connectivity with more than one PGW to access several PDNs. The PGW is responsible for policy enforcement, packet filtering for each UE, charging support, lawful interception and packet screening. Another key function of the PGW is to serve as the anchor for mobility between 3GPP *e.g.,* LTE and non-3GPP technologies *e.g.,* Wi-Fi.
- Home Subscriber Server (HSS) – this is a central database that contains information about the user and its subscription. The functions of HSS include mobility management, call and session establishment support, user authentication and access authorization.
- Access Network Discovery and Selection Function (ANDSF) – this provides information to the UE about connectivity to 3GPP and non-3GPP access networks *e.g.,* Wi-Fi. The purpose of the ANDSF is to assist UEs to discover overlapping or adjacent access network(s) and to provide rules (policies) to manage connections for these networks.
- Evolved Packet Data Gateway (ePDG) – this is designed to secure the data transmission with a UE connected to the EPC on an untrusted non-3GPP access. The ePDG operates as a termination node of IPsec tunnels established with UEs to achieve this.

The E-UTRAN is a collection of evolved Node B (eNB) interconnected via the interface (X2) and connected to the EPC through another interface (S1). The eNB represents a node for all radio protocols and is responsible for the control plane functions that monitor radio resource usage via the radio resource management. In addition, the mobility management has to evaluate the radio signal level measurements of both UE and eNB to carry out handover procedures. Owing to the large amount information, this section does not cover all the of components and features involved in the LTE/LTE-A architecture.

2.3 Resource Sharing

MBB services are increasingly covering more applications (such as content-rich multimedia and remote connection to the business network) for working and video conferencing which require more resource capacity (ETSI, 2013). According to the UMTS Report (UMTS, 2011), it is expected that mobile traffic demand increase 30-fold by 2020. With this future prospect, the MNO resources are tending to be more scarce for exclusive usage. The resource sharing solution between MNOs is a promising alternative in the face of resource scarcity and an expected high traffic load.

The vast amount of traffic expected by 2020 and scarcity of spectrum resources for the exclusive use of MNOs, will require resource-sharing among stakeholders. According to the 3GPP Report (22.951, 2012), the resources that can be shared by a stakeholder can be divided into five classes, which are listed and explained as follows:

- Core Networks: refers to multiple core networks sharing a network infrastructure. Infrastructural features can be shared to allow multiple frequency allocations. However, it is not feasible to share radio frequency resources and in this case, an MNO connects directly to its dedicated carrier.
- Radio Access Networks: in this case, multiple MNOs share a conventional core network. The MNO defines the deployment details, and this means that a different part of the network's radio infrastructure can be shared.
- Spectrum: corresponds to common spectrum resource-sharing when one MNO has a licensed frequency and shares the allocated spectrum with other MNOs.
- Network: a certain MNO "A" which covers a particular geographical area allows to the MNO "B" to use this coverage for its subscribers.
- Geographical Split: in this case, several licensed MNOs cover different geographical areas, *e.g.,* a part of a country, but cooperate to provide joint coverage. This means, a larger geographical area will be covered.

In contrast, the proposed solution in this dissertation refers to resource sharing that involves the radio access network, the network, and spectrum dealing with unscheduled evacuation scenarios of LSA band. On the one hand, the solution leverages the spectrum resources of the LSA band, and the unlicensed band can be accessed through the traditional spectrum access techniques. On the other hand, the multilevel architecture proposed by Kunst *et al.* ((KUNST et al., 2016a) (KUNST et al., 2016b)) is an essential support for the proposal and resource-sharing in LSA scenarios. The multilevel resource architecture proposed by Kunst *et al.* for resource allocation in wireless heterogeneous networks is under the control of a different MNO. This architecture obtains updated information with regard to the available network resources within the access systems, such as 3GPP and WLAN; this is explained more fully in Chapter 3.

2.4 Heterogeneous Wireless Networks

One of the technological factors to be taken into account by the MNO, in the bandwidth expansion case, is the choice of topology for the network deployment of the 2.3 - 2.4 GHz band. The LSA regime is indeed applicable in the entire heterogeneous wireless network scenario. According to the ETSI Report (ETSI, 2013), the LSA regime in heterogeneous wireless networks can be applied as follows:

- Deployment of macro cells: In this scenario, the MNO determines its permitted portion of the 2.3 - 2.4 GHz frequency-based band, through a macro cell deployment using a high power base station tower. The MNO can either re-use the existing base station sites that have already been deployed to support the LTE operation in its licensed band, or it can decide to deploy high power base station towers to support the LTE operation in the allowed portion of the 2.3 - 2.4 GHz frequency band.
- Micro-, pico-, femto-, and another cell deployment: In these scenarios, the MNO determines its permitted portion of the 2.3 - 2.4 GHz frequency-based band through a deployment of low-power base station sites. An MNO may choose this kind of deployment topology to ensure it can satisfy the incumbent's protection requirements over a larger coverage area.
- LSA usage for small cells applies all the variants of deployment and results in a coverage area that is smaller than the typical area covered by a macro cell deployment but is not confined by, micro-, pico- and femto- cells.

The low transmission power of small cells, as well as their typical indoor and low-level outdoor deployments, have as a corollary, a smaller coverage area (compared with the coverage are of macro cells) which provide a smaller geographical granularity to the small cell. This allows a small cell deployment to cover an authorized geographic area under the LSA regime more fully, and thus create the opportunity for sharing in areas where macro cell deployments would be possible due to the need to protect the incumbent. The focus on heterogeneous wireless networks in the 3GPP, is an example of technologies that allow this type of deployment and are now being made available to the cellular industry. This local exploitation of spectrum will give rise to more spectrum sharing scenarios under the LSA regime.

It should be mentioned that the topology deployments outlined above, are not mutually exclusive and an MNO may deploy both or more topologies in different parts of the allowed region. An LSA can be applied in whole heterogeneous wireless networks through the LSA band usage and by the macro and small cells. When defining the cell size, the MNO takes into account the number of users in the deployment area, network load, and QoS requirements among other factors.

2.4.1 Wireless Fidelity Networks

Wireless Fidelity (Wi-Fi) is a technology for Wireless Local Area Networking (WLAN) based on the IEEE 802.11 standards. Wi-Fi is a popular wireless protocol that uses radio communication to provide high-speed Internet connections. Currently, Wi-Fi technology is working in cooperation with 3GPP systems (*i.e.* LTE networks) to deal with the plethora of mobile traffic expected by 2020. In fact, 3GPP systems and WLANs can be made interoperable through IP-based access networks. The principal objective an Interworking WLAN (IWLAN) is to extend the 3GPP functionality and services to have access to a WLAN environment. In particular, the IWLAN system provides the bearer services and allows a subscriber (*i.e.* UE) to use a WLAN to access 3GPP-based services (3GPP, 2011). In this dissertation, the SAE architecture contains the proposed solution, as one more entity or function that can support the IWLAN technology and thus the vertical handover and traffic steering procedures among LTE networks towards WLANs. To this extend, the WLAN can support additional traffic from an LTE network, especially when it encompasses more than, or equal to three overlapping Wi-Fi networks. The solution given in Chapter 4 comprises three overlapping Wi-Fi networks under the IEEE 802.11ac standard that are distributed throughout the coverage area of the LTE-LSA network.

The 802.11ac, also known as Gigabit Wi-Fi and 5G Wi-Fi, is a wireless networking standard of the 802.11 family, which is developed as a part of the IEEE Standards Association, and provides high-throughput WLANs on the 5 GHz spectrum band (SIDDIQUI; ZEADALLY; SALAH, 2015). Theoretically, the 802.11ac offers gigabit rates in a wireless connection. The new specification is based on the 802.11n standard, which expands the channel bandwidth to 80 MHz and adds optional 160 MHz channels. Furthermore, 802.11ac utilizes MIMO with up to 8 spatial streams and a higher order modulation scheme called 256-Quadrature Amplitude Modulation (256-QAM). This is achieved by extending the air-interface concepts covered by 802.11n: wider RF bandwidth (up to 160 MHz), more MIMO spatial streams (up to eight), downlink multi-user MIMO (up to four clients), and high-density modulation (up to 256-QAM).

2.5 Exclusive Spectrum Licensing

Exclusive licensing of the spectrum is the model that explains the success story of MNOs around the world. With this model, the MNO obtains exclusive access to a certain frequency range linked to MBB services and cellular communication, often on a national basis. The spectrum which has an exclusive usage model, is a concession for long-time periods (*e.g.* 15 - 30 years) by a certain MNO. The exclusive spectrum usage provides the licensee (*e.g.* an MNO) with an interference avoidance capability and warranty of QoS through policies granted by the NRA against unauthorized third-party services. Currently, the government-based NRAs is adopting a market-centric approach (*e.g.,* auctions) to reallocate scarce spectrum frequencies to the highest bidder, and this is leading to an exponential increase of prices based on exclusive spectrum usage rights (PONOMARENKO-TIMOFEEV et al., 2016).

In the band which gives priority to the allocation of mobile services, the MNO traditionally acquires an expensive license from an auction to operate in a particular spectrum band. The operation of this band is guaranteed to be long-term and is exempt from harmful interference from other radio communication services or other MNOs, which is alternative preferred by an MNO to ensure operational effectiveness and a return on a financial investment in the network infrastructure. The MNO can make an internal decision about the network deployments within the rules of the licensing agreement, which generally apply to large geographical coverage areas and enable high mobility. The traditional way for MNOs to acquire national spectrum resources is usually through an auction held by a government body. This spectrum is for the sole use of the MNO that makes the highest bid in the auction.

On the basis of the results of real tests ((MATINMIKKO et al., 2013) (PALOLA et al., 2014c)), the LSA spectrum can coexist with the exclusive frequency band in the same geographical area and time. A base station can operate in both bands *i.e.,* LSA and an exclusive spectrum can use the TDD and FDD technologies. This enables the MNOs to deploy base stations on both spectrum bands in accordance with the requirements of the users and mobile traffic demand. For instance, the scenario outlined by Palola *et al.* in (PALOLA et al., 2014a) shows the deployment of four base stations working on LSA (TDD) and exclusive (FDD) spectrum bands. However, in this dissertation, the exclusive spectrum has been disabled so that additional connections of UEs from the LTE-LSA network can be made during an unscheduled evacuation scenario. An exclusive band is not used because our simulated scenario addressed a highly dense area with a large number of users, for example the public, areas of a metropolitan city, airports, stadiums, etc. In this thesis, the main reason for using the LSA band is that there are areas where current mobile and wireless networks cannot satisfy a good level of QoS and seamless connectivity of UEs in the traditional exclusive spectrum bands. As a result, this avoids carrying out handover with additional UEs and their traffic steering, after an evacuation of LSA band towards the LTE network on the exclusive spectrum. Despite this, the proposed solution in Chapter 4 can include overlapping LTE networks on licensed bands in LSA band evacuation scenarios.

2.6 Licensed Shared Access

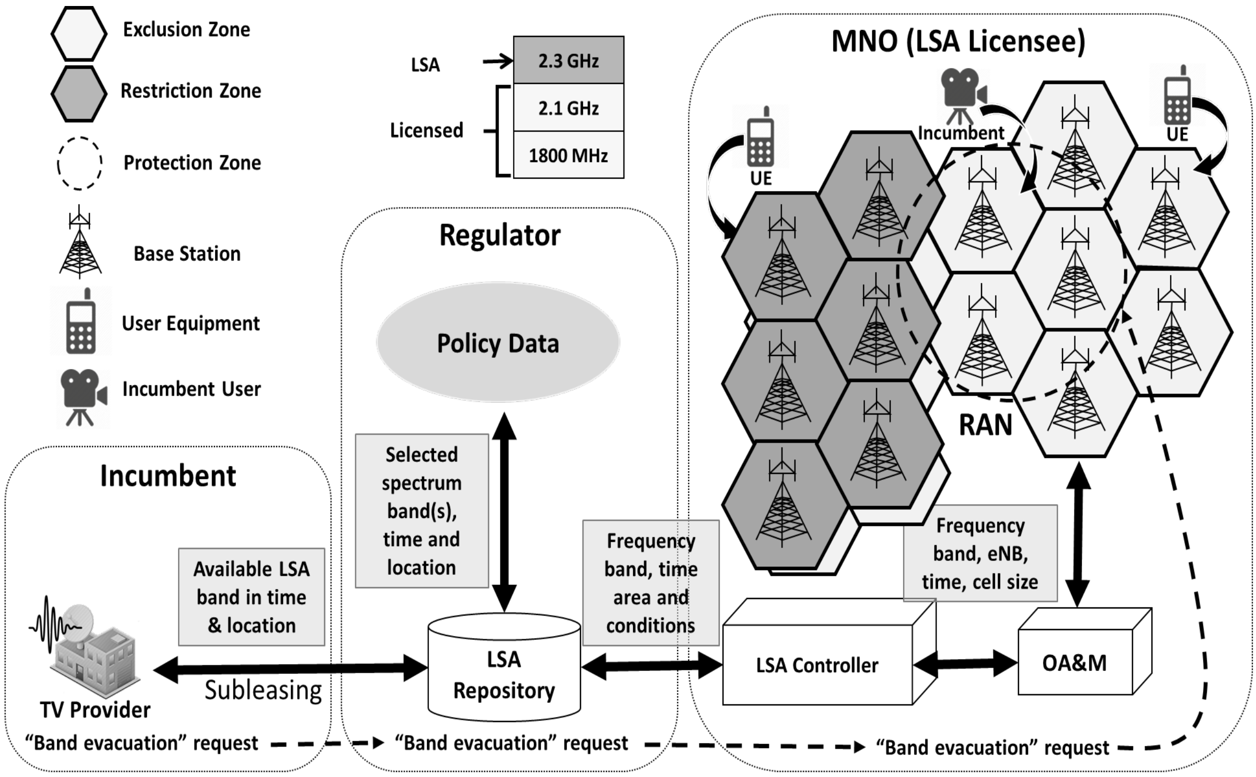
Licensed Shared Access (LSA) is the new paradigm and regulatory approach for spectrum sharing in a plenary controlled manner, where the incumbent allows the LSA licensee (MNO) the use of its spectrum, and emphasis is laid on avoiding interference and providing QoS guarantees (ECC, 2011) (MUSTONEN et al., 2015b). As opposed to the exclusive spectrum licensing, the LSA concept requires two additional entities on top of the existing MNO infrastructure and architecture: the LSA repository and LSA controller. These entities are displayed in Figure 2.2 and described in the following points which are based on the ETSI Report 103 113 (ETSI, 2013).

1. The LSA repository is the database that contains information about the spectrum usage of the incumbent and MNO. This database also includes information about policies, parameters, conditions, agreements and the rights to use the spectrum. The LSA repository is usually managed by the NRA, or the incumbent user or else is delegated to a trusted third party;
2. the LSA controller computes the LSA spectrum availability in spatial, frequency and time domains on the basis of the rules established by the agreements of the incumbent user and LSA licensee (MNO). The LSA controller can interface one or multiple networks of the MNO. The LSA licensee manages these elements for the top management entities of the MNO. The LSA controller signals the availability of LSA bands towards the OAM unit, and receives the LSA usage notification from it;
3. the Operation, Administrations and Maintenance (OAM) unit of MBB networks is responsible for handling the actual management of the LSA spectrum band. The OAM translates the de facto information of spectrum availability obtained from the LSA controller into commands of radio resource management, and then transmits this information to the base stations. On the basis of this information, the base stations can have access to the LSA spectrum and allocate UEs to it. The OAM can also reconfigure and update the system information of other networks on a licensed and unlicensed spectrum frequencies managed by the MNO.

Figure 2.2 display the LSA architecture where the LSA controller is under the purview of the MNO. Here the LSA controller interprets the information from the LSA repository, which is the interface of the MNO, to retrieve the information from the available LSA band. The controller also grants permission to the MNO network to access on LSA band, by interpreting the LSA band information and policies obtained from the LSA Repository (MUSTONEN et al., 2014). The LSA controller indicates if the LSA band is available and is given a notification of LSA usage by the OAM unit. According to Figure 2.2, the LSA Controller uses the information received from the LSA Repository together with the network plan, to obtain access to the LSA band. As result of network planning, the configuration sets out the parameters for the LSA band which are deployed in respective eNB(s)/sector(s) via the OAM unit of the LTE network. No changes are required in the LTE network, apart from the two functional blocks and their respective interfaces. As shown in Figure 2.2, the LSA implementation framework allows the incumbent user to request the LSA band on demand if the spectrum availability changes while the LSA licensee is using it. Otherwise, the incumbent request will generate the LSA band evacuation for the MNO infrastructure.

The LSA-sharing framework comprises the technical and operational conditions for entering, evacuation and releasing UEs to/from the LSA band. As shown in Figure 2.2, the sharing framework covers the exclusion, restriction and protection zones that maintain a certain level

Figure 2.2: Architecture of Licensed Shared Access (LSA)



Source: (MUSTONEN et al., 2014).

of QoS and ensure the avoidance of interference among incumbent and MNO services. In the following section, there is a brief definition and explanation of each zone based on the CEPT Report 56 (CEPT, 2015b):

- Exclusion Zone: a geographical area within which an MNO is not allowed to have active radio transmitters on the LSA band, especially when the incumbent is using this.
- Protection Zone: a geographical area within which incumbent services will not be subject to harmful interference caused by interferer transmissions. A protection zone is often applicable for a defined frequency band and period;
- Restriction Zone: a geographical area within which MNOs are allowed to operate radio transmitters, under restrictive conditions (*e.g.* maximum Effective Isotropic Radiated Power (EIRP) limits and constraints on antenna parameters). A restriction zone is usually applicable for a defined time and frequency band.

The spectrum-sharing framework is the main feature in the implementation of LSA because it defines the geographical areas for exclusion, protection, and restriction and can thus avoid harmful interference between the incumbent and MNO services (CEPT, 2015b). Thus, exclusion zones (or protection zones) are generally defined as a circular area of a few kilometers, with the incumbent being located in the center. A larger restriction zone can be defined when the incumbent is located near an interfering deployment area of potentially high density *e.g.,* a radio communication network of an MNO on the LSA band. The exclusion zone denotes the geographic area in which the incumbent is operating on the LSA band, and the MNO is restricted to the radio communication services on this band while the incumbent is there.

2.6.1 Procedures for LSA band Evacuation

Although the LSA-shared framework seeks to provide a certain level of QoS and avoid interference in the LSA licensee and incumbent services, the QoS level and seamless connectivity of UEs depends, to a great extent, on the evacuation procedures implemented by the MNO for handover and thus faces types of request by the incumbent to use the LSA band. In fact, the incumbent user can request the LSA band either in advance or in an emergency. This implies the LSA licensee (MNO) can carry out the evacuation of the LSA band in *(i)* a scheduled or *(ii)* an unscheduled manner depending on the type request made by the incumbent.

1. In the first, the MNO base stations execute a radio plan that is implemented in the Radio Access Network (RAN), to deactivate the LSA band usage in accordance with the requirements (*i.e.,* date, hour and area) scheduled by the incumbent via a manager web interface. In other words, the MNO executes a graceful shutdown of the base station in question or sector(s) on the LSA band, while the UEs are being transferred through the inter-frequency handover toward a network on the licensed spectrum (CEPT, 2015b).
2. In the second, the MNO performs an unscheduled evacuation in response to an emergency request by blocking the affected base station or sector(s) on the LSA band and thus turning off the air interfaces immediately (CEPT, 2015b). However, this has an adverse effect on the QoS and seamless connectivity of the UEs, during and after the unscheduled evacuation of the LSA band.

None of the current solutions carry out the handover and traffic steering of evacuated users towards another network in unscheduled evacuation scenarios since these take more time than what is required. Moreover, owing to the speed of the unscheduled evacuations, none of the LTE procedures have found a medium of ensuring the QoS and connectivity of the evacuated users after they have been reconnected in overlapping networks, without taking account their traffic congestion in the short term.

2.6.2 Activation and Deactivation of Radio Resources on the LSA band

During the stages of activating and deactivating the radio resources on the LSA band, the LSA controller reports changes in the availability of the LSA spectrum to the OAM unit and to the incumbent user. The degree of interference is estimated to optimize the size of the required area for the evacuation and adjust the LTE-LSA network configurations accordingly, so as to allow the incumbent to operate in the area (MUSTONEN et al., 2015b). If the radio resources are deactivated, the 3GPP standardization precludes the UEs from transmitting by means of the LSA band. The aim of the LSA controller is also to guarantee the QoS and avoidance of interference by the UEs on the LSA band, regardless of whether the radio resources have been deactivated. Thus deactivation is supported by LTE/LTE-Advanced techniques such as cell reselection, handover, and traffic steering of the evacuated UEs towards alternative network resources. As the radio resources on LSA are being deactivated, the same LTE/LTE-Advanced techniques distribute the traffic between them, and thus maximize the QoS of the UEs.

According to the CEPT Report 56 (CEPT, 2015b), the radio resources take the following steps to deactivate the air interfaces on the LSA band:

1. The incumbent user makes an evacuation request via the LSA Incumbent Manager. The LSA process starts when the incumbent spectrum user makes an evacuation request to the LSA Incumbent Manager. This manager submits the information to the LSA Repository which forwards the information to the LSA controller.
2. The LSA controller receives the incumbent information from LSA Repository. On the basis of this information, the LSA controller calculates which radio resource(s) must be deactivated by means of the OAM unit.
3. The OAM receives the deactivation command from the LSA controller. The OAM executes the radio plan deactivation of the radio resources on the LSA band. Two possible deactivation radio plans depend on the evacuation emergency.
   - In the case of an unscheduled evacuation of LSA band, the Mobile/Fixed Communication Network (MFCN) locks the affected eNB or sectors on the LSA band and in this way turns off their air interfaces. As a result, the UEs will automatically start a cell reselection procedure reconnect by itself into a network.
   - When the evacuation is scheduled or known beforehand, there can be a graceful shutdown. This involves gradually reducing the power of the eNBs or sectors on the LSA band. At the same time, the handover of UEs is carried out when the signal level of the eNB or sector on the LSA band drops bellow the signal level of another available network (on either licensed or unlicensed bands).
4. The eNB/sector on the LSA band is deactivated *i.e.,* the signal disappears. After this, the OAM finishes the radio plan execution and begins to check the status of the eNBs or sectors on the LSA band. As a result of the radio plan, the eNB or sector on LSA band has turned off its air interfaces. This information can be sent to the LSA controller.
5. The LSA controller receives confirmation of the eNB or sector on LSA band off-air status from the OAM. As soon as all the needed eNBs or sectors have reached the off-air status, the LSA controller ends the evacuation and submits the completed information to the LSA Repository.
6. The incumbent user receives the confirmation of the LSA band evacuation via the web or

mobile interface of the LSA Incumbent Manager.

The Finnish LSA trial environment followed each of these stages in the LSA band evacuation process, and initial performance measurement studies have been conducted to evaluate the involved time scales. The time measurements are listed in Table 2.1. The results concern the eNB or sector locking time for unscheduled evacuation. Graceful shutdown, which can be configured the decreasing time of the antenna power. This increases the scheduled evacuation time of the LSA band more than the unscheduled time.

Table 2.1: Time Measurements for Different Stages of the LSA Band Evacuation

Step	**Measurement Point**	**Evacuation using base station/sector Locking 1 sector**		**Emergency evacuation using single radio plan 3 base station/5 sectors**	
		Time [s]	St. Dev. [s]	Time [s]	St. Dev. [s]
1.	The incumbent makes an evacuation request via LSA Incumbent Manager	0		0	
2.	The LSA controller receives incumbent information from the LSA repository	1.135	0.0532	1.044	0.267
3.	OAM receives the deactivation command from the LSA controller	9.807	2.664	9.029	1.881
4.	LTE base station on the LSA band is deactivated	31.778	2.572	33.800	1.833
5.	The LSA controller receives confirmation of the off status of LTE base station on LSA band	59.360	3.457	73.059	1.493
6.	Incumbent user receives a confirmation of evacuation to the LSA Incumbent Manager	61.000	3.464	76.400	4.128

Sources: (CEPT, 2015b).

The results in Table 2.1 indicate that the deactivation of one sector takes a little over half a minute from the time when the evacuation request is made until the LSA band has been cleared. When making an evacuation request for all the sectors in the LSA trial environment, the clearance of the band takes 1.044 seconds what was required before the process. Two measurement points in Table 2.1 are relevant to demonstrate the efficiency of the proposed solution in Chapter 5. The LTE base station on the LSA with one sector delays in the average of 31.778 seconds, while three LTE base stations with five sectors take in average 33.800 seconds. It should be borne in mind that the incumbent user receives the confirmation of the evacuation to the LSA Incumbent Manager in the total of 61 seconds for the evacuation of an LTE base station with just one sector. Otherwise, the confirmation of the evacuation of tree LTE base stations with five sectors takes around 76 seconds to arrive at the LSA Incumbent Manager. Hence, the whole evacuation time comprising two stages. *i)* The evacuation request since that the incumbent user requests the LSA band usage, the LSA controller receives such request from the

LSA repository; the OAM receives the deactivation command from the LSA controller. *ii)* The LTE base station on the LSA band is deactivated, the LSA controller receives the confirmation of LSA band deactivation, and until the confirmation of the evacuation arrives at the incumbent.

Table 2.2: Total Delay of the Research Platform and Commercial Aspects of the LSA Trial

Area	**Evacuation Using Base Station/ sector Locking (1 sector) Average Delay [s]**	**Emergency Evacuation Using Single Radio Plan (5 sectors/ 3 Base Station) Average delay [s]**
LSA research platform delay	**20.620**	33.279
Commercial LTE OAM provision time deactivation radio plan	40.380	43.121

Source: (CEPT, 2015b).

With regards to the LSA research platform, the delay described in Table 2.2 includes the evacuation using an LTE base station with one sector which is locking in an average time of 20.620 seconds. This time is a threshold for all the current solutions to evacuate the users from one sector; else they are disconnected from the LTE base station on the LSA band to avoid interference with the incumbent services. The LSA research platform delay involves the system architecture-related delays as well as the network delay which consist of polling cases behind firewalls, publish /subscribe events delivery. Furthermore, the Table 2.2 details that the deactivation time of commercial radio plan conducted by the OAM unit of LTE networks. Indeed the commercial system takes 40.380 seconds to evacuate the LTE base station with one sector and 43.121 seconds in an average to evacuate three LTE base stations with five sectors. These times involve that the commercial system takes into account the LSA repository and the LSA Incumbent Manager as external entities leading to a considerable increase in evacuation time. Therefore, can be inferred that the time achieved to communicate the confirmation of the evacuation from the LTE base station to the OAM unit, LSA controller, LSA repository and the LSA Incumbent Manager delays more in commercial systems than in an research platform.

2.7 Cognitive Systems in Mobile Networks

Currently, the highly dynamic features of the incumbent user services makes it essential to the MNO on the LSA band to be reconfigured frequently and requires self-configurations and cognitive mechanisms. Similarly, the execution of the current UE handover procedures in accordance with cognitive criteria, represents a promising alternative to deal with these services.

The cognition applied to the radio communications systems of mobile and wireless networks refers to the concept of Cognitive Radio System (CRS) that has similarities with the definition of cognitive networks, mechanisms, and decision-making. According to the ITU-R Report SM.2152 (ITU, 2009), a CRS is a radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and internal state; to dynamically and autonomously adjust its operational parameters and protocols to its obtained knowledge and thus achieve its predefined objectives and to learn from the results obtained. ITU-R has noted in (ITU, 2009) that CRS techniques may offer improved efficiency and additional flexibility for spectrum use. Moreover, a CRS is not a radiocommunication service, but rather a system that employs technology that may in future be implemented in a wide range of applications in the land mobile service. According to Martinmikko *et al.* (MATINMIKKO et al., 2013) the CRS technology can help respond to the increasing traffic demand of mobile and wireless networks by improving the network resource usage and providing access to new shared spectrum *e.g.,* LSA band.

According to Thomas *et al.* (THOMAS; DASILVA; MACKENZIE, 2005) (THOMAS et al., 2006) a cognitive network is a network with a cognitive process (*i.e.* mechanism) that can take note of current network conditions, and then plan, decide, and act on them. The network can learn from these adaptations and use them to make future decisions, while taking into account end-to-end goals.

2.7.1 Cognitive Radio Trial Environment of LSA

This subsection examines the Cognitive Radio Trial Environment (CORE) from Technical Research Centre of Finland (VTT). CORE has a main part the Cognitive Engines (CEs) to control different radio systems (*e.g.,* LTE and Wireless Open-Access Research Platform (WARP)-based networks). The Finnish trial environment contributes for the creation of future experimental scenarios on the basis of CRS. The CORE project in the Finnish trial program in 2011–2012 established a test environment, which was later enhanced to include the CORE+ project in 2013–2014 (TEKES, 2013). The CORE+ project investigates CRS technology and carries out live trials with demonstrations. Currently, CORE++ is built the trial environment created for the preceding CORE/CORE+ projects in 2011-2014. The CORE++ seeks to establish a cross-industry end-to-end trial environment of new concepts/methods and to present results in research, regulation and business domains (TEKES, 2013). In particular, the CORE++ project examines the impact of new spectrum sharing ideas on the mobile communications networks and the required novel testing solutions from business, regulatory, and technological domains and trial-selected algorithms and concepts.

The first CORE enabled researchers to conduct experiments through cognitive decision-making which involves large-scale testing in both laboratory and field testing environments. The CORE consists of three components: A Cognitive Engine (CE), a live LTE network with eNBs, and a WARP-based network. The CORE trial environment of VTT is an environment for conducting experiments on cognitive decision-making. It allows the interfacing of new systems for data collection and makes adjustments through rule-based decision-making via a browser-based user interface.

In the first LSA trial, the CE interfaces LSA repository, eNBs, and end-user laptops use dedicated software components. The CE can make different adjustments using the software components, and this includes commanding the end-user laptops to carry out handover from the LTE to the Wi-Fi network and block the cell of the eNB. The CE processes decision rules defined by the CE management and produce of adjustment commands, which are routed to the software components by employing an event-based triggering mechanism called the cognitive application programming interface (API) for receiving information (MATINMIKKO et al., 2013). The CORE system uses the QoSMet (QoS Measurement) solution developed at VTT for the passive QoS monitoring of networking applications of individual users, to enable the QoS to be aware of cognitive decision-making (PROKKOLA et al., 2007) (TEKES, 2013). The live field trial environment can provide information and be controlled by the CE to optimize network resource usage and facilitate spectrum sharing between different systems. This allows load-balancing decisions to be tested so that they can perform handovers between different networks based on varying criteria (MATINMIKKO et al., 2013).

2.8 Traffic Load Forecasting Models

Enhancements in network management involve leveraging the existing networks through improved and efficient utilization of network resource capacity. This kind of improvements is a key driver of intelligent network traffic forecasting research: an accurate prediction of the network traffic is useful in the understanding of network dynamics, so it has great importance for the network plan deployment and the traffic management. Traffic load forecasting models are capable of identified predictors variables to estimate the trend patterns in the sampled network traffic. The purpose of traffic load forecasting models are intended to discover the future trend of the traffic as well as the availability and occupation of the medium capacity *e.g.* bandwidth. This enables to decide with the knowledge of future estimations that helps, for example, to ensure the QoS of users in the context of mobile and wireless networks. In this dissertation, to carry out the traffic load forecasting is considered some machine learning models, detailed in the following subsections.

2.8.1 Multiple Linear Regression Model

Multiple Linear Regression (MLR) model is based on previous measurements Y, which is related to a single predictor X for each observation. Therefore, the conditional mean function can be described as in (2.1), where α is the intercept, and β is the coefficient.

The general MLR model is detailed in the equation 2.1:

$$Y = X\beta + \varepsilon \tag{2.1}$$

Where Y is an $N \times 1$ vector of values of the response (dependent) variable, X is an $N \times p$ full-column rank matrix f known predictors (carrier, factors, regressors, explanatory variables) possible including one constant predictor, β is a $p \times 1$ vector of unknown coefficient (parameters) to be estimated, and ε is an $N \times 1$ vector of independent random variables each with zero mean and unknown variance σ^2.

Following standard notation such as that in Velleman and Welsh (1981), we use y_i and x_i yo denote the *i*th row of Y and R, respectively, and X_j to denote the jth column of X. By the *i*th observation we mean $x_i : y_i$, that is, the *i*th row in the matrix $(X : Y)$. We also use the subscript notation "(i)" or "$[j]$" to indicate the deletion of the *i*th observation or the *j*th variable, respectively. Thus, for example X_i is the matrix X with the *i*th row deleted, X_j is the matrix X with the *j*th column deleted, and $\widehat{\beta}_i$ is the estimated parameter vector when the *i*th observation is deleted. We reserve the symbols $\widehat{Y}$, e and SSE to denote the vector of residuals, and the residual sum od squares when Y is regressed on X, respectively, and the symbols R_j and W_j to denote the vectors of residual when Y and X_j, respectively. Finally, we use M^{-1}, M^T, M^{-T} to denote the inverse, transpose, and inverse of the transpose of a matrix M, respectively.

In fitting the MLR model 2.1 by the method of least squares, detailed as follows:

$$\widehat{\beta} = (X^T X)^{-1} X^T Y \tag{2.2}$$

$$Var(\widehat{\beta}) = \sigma^2 (X^T X)^{-1} \tag{2.3}$$

$$\widehat{Y} = X(\widehat{\beta}) = PY \tag{2.4}$$

$$P = X(X^T X)^{-1} X^T \tag{2.5}$$

$$Var(\widehat{Y}) = \sigma^2 P \tag{2.6}$$

$$e = Y - \widehat{Y} = (I - P)Y \tag{2.7}$$

$$Var(e) = \sigma^2 (I - P) \tag{2.8}$$

$$\widehat{\sigma^2} = \left(\frac{e^T e}{N - p} \right) \tag{2.9}$$

The $Var(\varepsilon) = \sigma^2$ estimates the residual mean square. It is well known that these quantities can be substantially influenced by observations; that is, not all the observations have equal importance in the least squares regression. In 1986, Chatterjee *et al.* (CHATTERJEE; HADI,

1986) concluded that results from the analysis are critical for an analyst to be able to identify such observations and evaluate their effect on various features of the analysis. In 1980, according to Belsley, Kuh, and Wlesh define the influence as a substantial observation is one which, either individual or together with several other observations, has a demonstrably larger impact on the calculated values of various estimates more than is the case for most of the other observations (LUKMAN; OSOWOLE; AYINDE, 2015).

The MRL model is broadly applied in areas such as trend line, telecommunications, finance, economy, environmental science, epidemiology. MLR model has many practical uses, among the most important applications, it can be used for forecasting through fitting the predictive model to an observed data set of Y and X values. The purpose of the MLR model is to establish a relationship among the group of predictors (*e.g.* historical mean traffic per second, minute, hour). MLR allows to understand which predictors have the greatest impact, and it aims to calculate the best fitting curve by minimizing the least squares errors. Papadoupli, Raftopoulus, and Shen (PAPADOPOULI; RAFTOPOULOS; SHEN, 2006) propose the short term traffic load forecasting in wireless networks. The authors propose and evaluate several traffic forecasting algorithms such as MLR algorithm which employs the recent traffic history and flow related information. According to Liu and Lee (LIU; LEE, 2015), the MLR algorithm and other six carry out the throughput prediction in mobile data networks. Further, they develop an information theoretic lower bound to define the prediction error. Niami *et al.* (NAIMI et al., 2014) apply the prediction over metrics such as the number of retransmissions needed and time expected to transmit a data packet to adjust the routing metrics in ad hoc wireless networks. In fact, the solution proposed in (NAIMI et al., 2014) anticipates the signal strength using linear regression over the historical measurements of the link quality. Noulas *et al.* (NOULAS et al., 2012) leverage the historical information on coarse granularity from the social platform Foursquare to predict the user mobility. The user, global, and temporal features sets are analyzed, then such features are trained in the supervised classification problem to predict the next check-in state. Linear regression and decision trees are used in this regard. Therefore, the application of the MLR model is intended to perform the prediction of scenario variables on the basis of the previous or historical information. In this dissertation, the MLR model is used to perform the traffic load forecasting of Wi-Fi and LTE-LSA networks. The output of this model is used by the proposed decision algorithm to carry out the vertical handover and traffic steering of evacuees as quickly and efficiently as possible in an unscheduled evacuation of the LSA band.

2.8.2 Neural Network Model

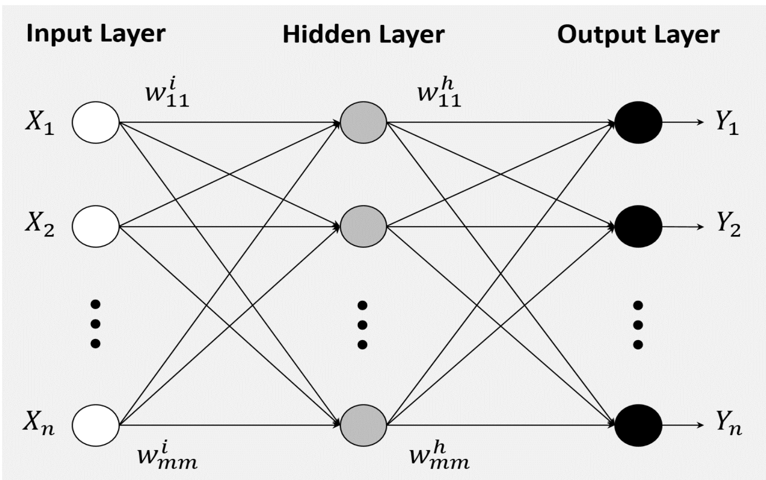
Neural Networks (NNs) are extensively used in computer science, which is based on a wide collection of simple neural units. Each neural unit is connected with several others, and such connections can improve or impede the activation status of adjacent neural units. Each neural unit computes using summation function. There may be a threshold function on each connection and on the unit itself, such that the signal must exceed the limit before propagating to other neurons. These systems are are trained and self-learning, in the place to be explicitly programmed in areas where the solution or feature detection is complicated to express in a traditional computer program.

NNs can estimate almost any function in an efficient and stable manner when the underlying data relationships are unknown (RODRIGUES; NOGUEIRA; SALVADOR, 2010). The NN model is a nonlinear, nonparametric, adaptive modeling approach which is relied on the observed or historical data rather than on an analytical model (FENG; SHU, 2005). The architecture and parameters of the NN are determined solely by the dataset. NNs are characterized by nonlinear mapping and generalization ability, robustness, fault tolerance, adaptability, parallel processing ability.

NNs typically consist of multiple layers, and the signal path traverses from front to back. Back propagation is the use of forwarding stimulation to reset weights on the "front" neural units, and this is sometimes done in combination with training where the correct result is known. More modern networks are a bit more free flowing regarding stimulation and inhibition with connections interacting in a much more chaotic and complex fashion. Dynamic neural networks are the most advanced, in that they dynamically can, based on rules, form new connections and even new neural units while disabling others.

A NN regards of interconnected nodes, called neurons, each connection being characterized by weight. NN comprises several layers of neurons: *a)* an input layer, *b)* one or more hidden layers and *c)* an output layer. The most traditional NN architecture is feed-forward in which the information travels through the network only in the forward direction: from the input layer towards the output layer, as illustrated in Figure 2.3.

Figure 2.3: Neural Network Model



Sources: (PWASONG; SATHASIVAM, 2016) and (CAUDILL; BUTLER, 1994).

Using a NN as a predictor involves two phases: *a)* the training phase and *b)* the prediction phase (BARABAS et al., 2011). In the training phase, the training set is presented to the input layer, and the parameters of the NN are dynamically adjusted to achieve the desired output value for the input set. The most commonly used learning algorithm is the back propagation algorithm, based on the backward propagation of the error, where the weights are changed continuously until the output error falls below a predetermined value. In this way, the NN can learn correlated patterns between input sets and the corresponding target values. The prediction phase represents the testing of the NN. A new input (not included in the training set) is presented to the NN, and the output is calculated, thereby predicting the outcome of new input data.

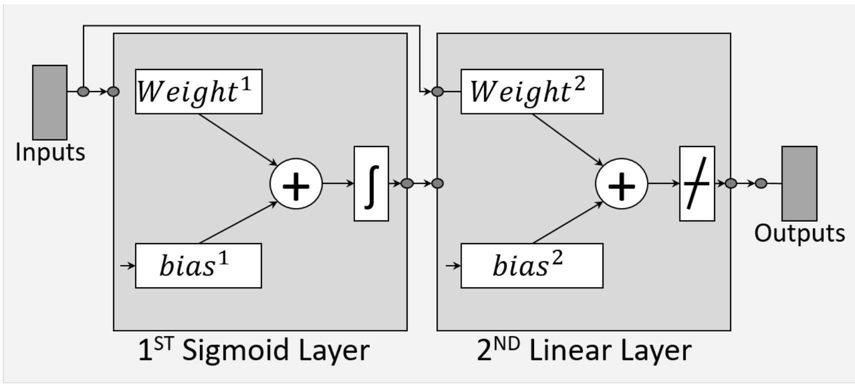
The number of hidden layers and the number of nodes in each layer is usually chosen empirically. NN must have at least one hidden layer to predict nonlinear values. Too many hidden layers slow down the training process and increase the complexity of the network. To improve the nonlinearity of the solution, the activation functions of neurons in the hidden layer are sigmoid functions, while the output nodes have linear transfer functions.

2.8.2.1 Cascade Forward Back Propagation Neural Network Model

Cascade-correlation neural network is "self-organizing" networks. The network starts with merely input and output neurons. It is designated a cascade due to the output from all of the neurons is already in the network that provides into new neurons. As new neurons are added to the hidden layer, the learning algorithm tries to increase the magnitude of the relationship among the new neuron’s output and the residual error of the network that it is seeking to reduce. The input, hidden, and output layers forms a cascade neural network, as depicted in Figure 2.3. The input layer is a vector of predictor variable values. The input neurons do no carry out any operation on the values other than distributing them to the neurons in the hidden and output layers. Furthermore to the predictor variables, there is a constant input of 1.0, called the bias that is fed into each of the hidden and output neurons; the bias is multiplied by weight and added to the sum going into the neuron. In the hidden layer, every input neuron is multiplied by a weight and added to the sum going into the neuron. In the hidden layer, every input neuron is multiplied by a weight, and the resulting weighted values are added together to produce a combined value. The weighted sum is fed into a transfer function, which then results in value. The output from the hidden layer is distributed to the output layer that receives values from all of the input neurons and all of the hidden layer neurons. Each value given to an output neuron is multiplied by a weigh, and the resulting weighted values are added together again to produce a combined value. The weighted sum is fed into a transfer function, which then results from the final value (PWASONG; SATHASIVAM, 2016) (CAUDILL; BUTLER, 1994).

The Cascade Forward Back Propagation (CFBP) is neural network model, which is used for the prediction of new output data and is applied as an independent model and in a hybrid neural network model (KASHYAP; BANSAL; SAO, 2015). Thatoi *et al.* (THATOI et al., 2014) asseverate that the CFBP network is equivalent to the feed-forward back propagation neural network, the input values are calculated after the every hidden layer is back-propagated to the input layer and the weights adjusted continuously. The input values are directly linked to the final output and relationship occurs among the values obtained from the hidden layers, and the values acquired from the input layers and weights are adjusted consecutively. Whilst in a feed forward propagation network, networks can potentially learn effectively any input relationship, such that feed forward networks with more layers might learn different relationships. Ai-Shayea and Bahia (AL-SHAYEA; BAHIA, 2010) affirm that the CFBP neural network has similarities with the feed forward back propagation network for applying the back propagation algorithm for weights updating, but the main symptom of this network is that each layer neuron communicates with all previous neurons. This type of modeling embraces the back propagation network because it is by far the most popular neural network model. The architecture of the neural network is mostly subject to out data representation decision. These selections determine the number of inputs and outputs The major architectural decision of CFBP deals with the number of hidden layer and hidden units.

Figure 2.4: Cascade Forward Back Propagation Model



Sources: (KASHYAP; BANSAL; SAO, 2015) and (THATOI et al., 2014).

The Figure 2.4 shows two basic layers, each one with variables such as weight and bias. The number of visible and hidden layers changes according to the system complexity. As with feed forward networks, a two-or-more layer of the CFBP network can learn any finite input-output relationship arbitrarily well given enough hidden neurons. The modeling process of a NN requires the disposal of an entry's number and the number of neurons in the output layer. The CFBP was found to be more efficient than the feed forwarding back propagation in terms of the accuracy and efficiency. In general, the work flow of neural network for traffic load forecasting can be divided in seven primary steps: *a)* collect the training data, *b)* create the network object, *c)* configure the network, *d)* initialize the weights and biases, *f)* train the network, *g)* validate the network (post-training analysis), and *h)* use the network.

Taking into consideration above steps and the implementation of CFBP neural network model of Matlab toolbox called "newcf function" (DEMUTH; BEALE, 2009), the CFBP algorithm is presented as follows:

1. Initialize the weights with small random values;
2. For each combination p_q, d_q in the learning sample:
    - Propagate the entries p_q forward through the neural network layers:

$$a^0 = p_q; a^k = f^k(W^k a^{k-1} - b^k), k = 1, ..., M \tag{2.10}$$

    - Back propagate the sensitivities through the neural network layers:

$$\begin{aligned} \delta^M =& -2F'^M(n^M)(d_q - a^M) \\ \delta^k =& F'^k(W^{k+1^T})\delta^{k+1}, k = M-1, ..., 1 \end{aligned} \tag{2.11}$$

    - Modify the weights and biases:

$$\begin{aligned} \varDelta W^k =& -\eta\delta^k(a^{k-1})^T, k = 1, ..., M \\ \varDelta b^k =& \eta\delta^k, k = 1, ..., M \end{aligned} \tag{2.12}$$

3. If the threshold criterion is reached, then stop; if not reached, they permute the presentation order of the combination built from the learning database, and Step 2 is performed again to achieve the desired threshold. Sometimes this threshold is related to an error limit which determined when the algorithm stop.

Xuefeng *et al.* (XUEFENG et al., 2006) applied the back propagation neural network model for forecasting final prices of online auction items, which is compared with results of multiple regressions models for forecasting with a continuous variable. Meantime the logistic regression for forecasting with a discrete variable in predicting the final prices online auction items. Khatib *et al.* (KHATIB et al., 2012) proposed assessment for solar radiation prediction to develop accurate models for predicting hourly solar radiation on the basis of the number of sunshine hours, day, month, temperature, humidity, and location coordinates. They regarded the neural network-based models such as feed-forward backpropagation, cascade forward backpropagation, and Elman backpropagation for the hourly solar radiation prediction. Chepati *et al.* (CHEEPATI; PRASAD, 2016) addressed the load forecasting of electricity generating plants can be predicted using the neural networks such as the CFBP model, among other algorithms such as multiple linear regression and regression tree in which CFBP is one the most accurate and efficient algorithm. In that case, the authors considered as input the historical data (average measurements of electrical load) from the last 24 hours for the neural network, which has as a result of the electrical load forecasting with a mean average percentage error of 2.9$\%$. Therefore, the CFBP model can be applied to perform the load forecasting of any system (*i.e.* traffic load forecasting of mobile and wireless networks) with a high accuracy and efficiency. In this sense, the CFBP model is used in Chapter 5 to carry out the traffic load forecasting in LTE-LSA and Wi-Fi networks.

2.8.3 Fourier Model

The curve fitting using the Fourier series model is defined in different ways in various fields of its application. Among these, the Fourier curve fitting can be applied to field ranging from engineering, seismology and economics (STRANG, 1994). Fourier model is named in honor of Joseph Fourier, who made important contributions to the study of trigonometric series, after preliminary investigations by Leonhard Euler, Jean le Rond d' Alembert and Daniel Bernoulli. Fourier applied this technique to find the solution of the heat equation. Furthermore, the Fourier analysis in forecasting overcomes certain limitations that other models have in capturing the seasonality phenomena (LYE; YUAN; CAI, 2009). Lye *et al.* (LYE; YUAN; CAI, 2009) decomposes the given time series (*i.e.* historical data) into a linear combination of sinusoids (*i.e.* frequency components) via an orthogonal transform method such as Fourier transform. In summary, they developed a new method demand for forecasting on the basis of the analysis in the frequency domain.

In this sense, the Fourier approach has been used for forecasting changes in load of electricity, traffic transportation, network traffic, and prices, which are variables that are clearly related to cyclic and recursive variations. The Fourier series can be applied considering the previous variables measurement repeat each season or each period that support to carry out the forecasting of the traffic load from the LTE-LSA and Wi-Fi networks, as detailed in Chapter 5.

The main principle behind the field of Fourier series analysis, in an infinite expansion of a periodic function in terms of sines and cosines or imaginary exponentials. It also makes use of the orthogonality relationships of the sine and the cosines (ASANTE-DARKO; ADABOR; AMPONSAH, 2016).

James Walker (WALKER, 1991) presented the Fourier series of a function as represented Equation 2.13.

$$f(x) = a_0 + \sum_{k=1}^{k} \left(a_k cos \frac{2\pi k}{n} x + b_k sin \frac{2\pi k}{n} x \right) \tag{2.13}$$

Where $f(x)$ is a periodic function, detailed in Equations 2.14 and 2.15.

$$a_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) cosnxdx, n = 1, 2, 3, ..., \tag{2.14}$$

$$b_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) sinnxdx, n = 1, 2, 3, ..., \tag{2.15}$$

The Fourier analysis applied to historical measurements of the formed returned a much more accurate forecast. The historical series included the calibration data set (traffic load measurements of the LTE-LSA and Wi-Fi networks in the last 15 minutes) and the validation data set (traffic load during the last minute) to carry out the traffic load forecasting of these networks, as demonstrated in Chapter 5.

2.8.4 Regression Tree Model

Regression Tree Model (RTM) makes use of the decision tree as a predictive model which outlines observations about a item to conclusions in the target of item value. It is one of the predictive models approaches used in the machine learning, statistics, and data mining. Tree models where the target variable can take a finite set of values are called classification trees; in this tree structure, leaves class and branches represent the labels and associations of features, respectively, that lead to those class labels. The RTM is often used to model the correlation of load consumption and other factors (*e.g.* number and priority of users) to apply the load forecasting regression method. In fact, the regression tree establishes the correlation among the predicator and response to built a fitting tree.

In regression trees, an entire data set, a binary tree is constructed with the repeated splits of the subsets according to independent variables. The goal is to produce subsets of the data which are as homogeneous possible in accordance with the response variables. According to Leland Wilkinson (WILKINSON, 2004) the classification and regression trees can be built by the growing and pruning of the tree. According to Strobl *et al.* (STROBL; MALLEY; TUTZ, 2009) the regression trees are simple nonparametric regression approach, which has as main characteristic the feature space, *i.e.* space spanned by all predictor variables are recursively splitting into a set of rectangular areas. They advocate that the splitting is created such that observations with similar response values are grouped. Thus, after the splitting is completed, a constant value of the response area is predicted within each area.

Qiang *et al.* (XU et al., 2013) proposed the network performance forecast for real-time, iterative mobile applications (PROTEUS). This solution is on the basis of a machine learning framework based on the regression tree to learn the trend of the network performance over short, fine-grained time windows using previously available observations.

Note that the resulting splitting is of the main differences between classification trees and linear regression models. In the case of linear regression, the information from different predictors that can be derived by means of recursive splitting - including multiple splits in the same variable. In specific, this involves nonlinear and even nonmonotone association rules, which do not need to be specified in advance but are determined in a data-driven way.

The RTM can be applied to carry out the traffic load forecasting in this dissertation, which has a scenario composed of an LTE-LSA and three Wi-Fi networks. The RTM takes into account the previous observations or measurements of the traffic load of these networks. *De facto*, the treatment of previous observations are the same for previously quoted forecasting models, by enabling the comparison of these since they have the same treatment of the observations (*i.e.* historical data). The RTM and rest of the forecasting models are compared in terms of accuracy and efficiency in Chapter 5.

3 RELATED WORK

This Chapter outlines the initial investigations of non-cognitive and cognitive solutions applied to LTE-LSA networks. Section 3.1 examines all the current non-cognitive solutions standardized and non-standardized LTE procedures to enter and vacate the UEs to/from the LSA band. Section 3.2 describes the current cognitive solutions to guarantee the QoS of users from LTE-LSA networks. In Section 3.3, there is an explanation of the multi-level architecture model used, adapted and extended for the purposes of this dissertation.

3.1 Current Non-Cognitive Solutions

Non-cognitive solutions encompass the current LTE/LTE-A procedures (standardized and non-standardized) that are adopted in LSA scenarios. These procedures involve operations without a cognitive mechanism for entering, evacuating and releasing the UE in/from the LSA band. For instance, the handover of UEs is carried out from a network "A" on the LSA band, toward a network "B" on licensed or unlicensed bands and vice-versa, with the aim of achieving a particular network objective.

3.1.1 Standardized LTE Procedures for LSA Support

The European Telecommunication Standards Institute (ETSI) has standardized LTE procedures for entering and vacating the UE to/from the LSA band (ETSI, 2013). In particular, we refer to cell reselection, inter-frequency handover (or vertical handover), and carrier aggregation. Moreover, the European Conference of Postal and Telecommunications (CEPT) in Report 56 adopted the handover and cell reselection procedures in the Finnish LSA trial environment (CEPT, 2015b). The execution of these procedures is subject to the type of operation on the LSA band. In the following section, there is a more detailed explanation of each standardized procedure.

3.1.1.1 Inter-Frequency Handover / Vertical Handover

Inter-frequency handover or vertical handover procedures use measurements calculated by the UE to determine when the Radio Signal Strength (RSS) or channel quality of the serving network (*e.g.,* LTE on LSA band) becomes significantly lower than that of another network (*e.g.,* LTE on licensed bands) (HÄMÄLÄINEN; SANNECK; SARTORI, 2012). Inter-frequency handovers between networks in LSA bands and exclusively licensed bands, assist in the optimization of the data rate and user experience (MUSTONEN et al., 2015b). When a scheduled evacuation of the LSA band is required, the MNO may gradually lower the transmission power of the base station before issuing the graceful shutdown command to allow the UEs to conduct inter-frequency handover in a controlled manner and without any break in connection.

The inter-frequency handover procedure carried out by the Radio Access Network (RAN) can be adopted for entering or evacuating the UEs (in connected mode) to or from the LSA band, respectively (ETSI, 2013). When the UEs enter the LSA band, this procedure assumes these users are only coming from an underlying band merely (*i.e.,* licensed spectrum). Furthermore, when the UE vacates the LSA band, the inter-frequency handover procedure includes the return them toward underlying networks on licensed spectrum. Likewise, the vertical handover is considered to transfer the UE, for example, from an LTE-LSA network towards one overlapping heterogeneous wireless network with the best signal strength *e.g.* Wi-Fi.

3.1.1.2 Carrier Aggregation

Carrier Aggregation (CA) allows scalable expansion of bandwidth through the use of radio resources across multiple component carriers (IWAMURA et al., 2010). CA provides a wider effective bandwidth for the UE by aggregating component carriers, either on the same or different bands (*i.e.,* licensed, LSA, and unlicensed). With the aid of CA, a carrier on the LSA band can be employed together with a carrier on a licensed band, to create another cell with almost the same coverage. The aim of this is to support macro cell capacity, or a cell with smaller coverage to increase the data rate and throughput in the local area. CA enables an MNO to use LSA resources to provide additional capacity for the UEs, without the risk of a connection break. A special case of CA is termed Supplemental Down-Link (SDL), which is the unpaired spectrum used for enhancing down-link capacity by bonding the downlink of an FDD channel (network on a licensed band) with the supplemental downlink of a TDD channel (network on an LSA band). Since LSA is currently being employed for TD-LTE bands, SDL might become one of the key enabling technologies for LSA scenarios. It should be notes that the RAN of MNO performs the CA, reconfiguring UEs either to start or stop operating in CA mode (due to the need to enter or vacate the LSA band (ETSI, 2013)). Despite the benefits of the CA procedure, this will see highly limited when the licensed spectrum is not available due to a high amount of users and the LSA spectrum is being evacuated by an incumbent user.

3.1.1.3 Cell Re-selection

UEs can reselect the serving network from heterogeneous wireless networks and spectrum frequencies, on the basis of measurements of the RSS and channel quality (ETSI, 2014). When the MNO has an additional cell on the LSA band, the reselection procedure enables the UE to connect it by itself, in an automatic and transparent manner (MUSTONEN et al., 2015b). If there is an unscheduled evacuation of the LSA band, the MNO locks the affected LSA cells, and the UEs will automatically start a cell reselection procedure.

When the UE in IDLE mode migrates in and out of the coverage area of the LSA frequency, it may make a reselection in this kind of frequency. After the UE in IDLE mode which is vacating from the LSA band has been disconnected from the LSA frequency, it adopts the cell reselection procedure by itself to reconnect, with the aid of the current measurements both of RSS and channel quality of underline networks on licensed spectrum (ETSI, 2013) (CEPT, 2015b). The disadvantage of this procedure is its dependence of the current measurement of the RSS and channel quality metrics to execute it and thus to evacuate the UE in idle mode from the LSA band in unscheduled scenarios.

3.1.2 Non-Standardized LTE Procedures for LSA Support

Within the context of heterogeneous wireless networks, the introduction of new shared bands must require the minimum modifications to the existing network infrastructure of the MNOs. Several procedures of the current LTE/LTE-A technology can facilitate the introduction of LSA bands. For the deployment of all the features of LTE/LTE-A technology is needed to optimize the use of spectrum resources in LSA scenarios and thus maximize the QoS provided for UEs, or assist in the planning of RAN under the LSA regime. In the next section, there is an explanation of the LTE procedures that can be adopted in the context of LSA scenarios.

3.1.2.1 Traffic Steering

Traffic steering is a current research topic in LTE and LSA network scenarios. According to Dryjanski *et al.* (DRYJANSKI; SZYDELKO, 2016), the goal of traffic steering is to find the most suitable evacuation route when vacating a frequency is necessary. According to Mustonen *et al.* (MUSTONEN et al., 2015a), traffic steering is based on the capability and load of heterogeneous wireless networks. Today, LTE procedures such as handover and traffic steering are designed to take account of algorithms which make cognitive decisions. This kind of decision-making brings intelligence to the allocation of radio and network resources, with the aim of increasing the overall network QoS (MATINMIKKO et al., 2013).

Traffic steering is also known as a self-optimization feature and refers to the ability to steer traffic to the most suitable network, cell layer, spectrum frequency, and heterogeneous wireless networks within any network governed by the MNO. Steering is undertaken to meet a set of optimization criteria such as network capacity and congestion, power consumption, or user experience. In LTE networks emphasis is laid on the application of traffic steering procedure owing to its coexistence with other heterogeneous wireless networks and multiple spectrum layers (HÄMÄLÄINEN; SANNECK; SARTORI, 2012). According to Mustonen *et al.* (MUSTONEN et al., 2015b), the use of LSA resources should be supported by traffic steering functions due to their varying availability.

Furthermore, since authorized access to the LSA band is available to the LTE network, the base station configures the radio parameters in accordance with the policies provided by the

LSA repository and established by the incumbent and LSA licensee. On this basis, the traffic steering can be planned to forward the UE traffic and handover from an overloaded LTE network on licensed bands towards other network on the LSA band or vice versa.

According to Mustonen *et al.* ((MUSTONEN et al., 2014) (MUSTONEN et al., 2015a) (MUSTONEN et al., 2015b)), LSA scenarios need the support of traffic steering functions because of the dynamic availability of the LSA band. A decision about load balancing for traffic steering can be made when the UEs are in connected or idle mode. In the connected mode, a UE may be dropped or directed to another cell via adjusting handover parameter configurations or forced handover. If redirected, the connected request from the UE is rejected in a session setup phase together with the redirection information. In the case of the UE in idle mode, load balancing is carried out by steering the UE decision to a certain cell (*e.g.,* taking account of the UE priority, and network load, among other factors).

When an LSA band is available, the base station configures the related parameters, sets up control channels, and starts provisioning services on this band. According to Mustonen *et al.* (MUSTONEN et al., 2014), since the LSA band provides extra capacity, traffic steering may be guided by predefined network optimization goals. The affected base stations notify neighboring cells of the change in their capacity. Traffic steering should give priority to the LSA band in the case of those UEs that support the LSA band for a more careful exploitation of the additional capacity. Traffic steering is treated differently among different UEs in connected status. In the connected mode, the base station performs the traffic steering by means of handover or redirection. According to Seppo *et al.* (HÄMÄLÄINEN; SANNECK; SARTORI, 2012), in the case of traffic steering, handover is only triggered when a cell overload is detected, and to keep the number of handovers and the related signaling fair. As soon as the information on the increased LSA band capacity arrives at the base station, the UEs in connected mode will be handed over from the LTE network on licensed band toward LSA bands through an inter-frequency handover.

3.1.2.2 Load Balancing

Load balancing is one of the LTE self-optimization procedures that evens out the load generated across the network by moving UEs from one cell to another via handover procedures (MUSTONEN et al., 2014). Base stations on LSA bands can be used as an additional network layer, and provide more capacity for the wireless broadband of UEs to balance the load. The variable availability of LSA resources raises the question about what kind of UEs (with regard to requested data rates, mobility, and priorities) can be best served and are least affected by the possible evacuation. According to the ETSI Report 103 113 (ETSI, 2013), the existing load balancing algorithms in RAN will make use of the newly available resources and transfer devices to the LSA band based on the need for a return to the underlying band.

3.1.2.3 Self-Configuration

The self-configuration can be regarded as a novel service procedure with a minimum manual intervention and more automated procedures at the network level (HÄMÄLÄINEN; SANNECK; SARTORI, 2012). According to Mustonen *et al.* (MUSTONEN et al., 2015b), self-configuration includes both, establishing connection and acquiring radio configuration parameters to adapt to the current state of the network deployment. With a dynamic radio configuration, the key radio configuration parameters of the new cell and its neighbors can be configured correctly on the fly. This kind of flexible deployment is particularly useful when deciding whether the LSA cells need to be switched off in response to evacuation requests, and then deciding on the reconfiguration when they have been switched on again.

Self-Configuration is still under investigation, and it is not a standardized process for LSA scenarios. However, it has recently been applied in some LSA research platforms with commercial equipment for testing in LTE networks and supported by the NOKIA company. According to the study conducted by Yrjola *et al.* (YRJÖLÄ et al., 2016), the Self-Organizing Network (SON) solution was introduced for the first time in 2016 to enhance power control concept algorithms that optimize protection zones to protect the incumbent's business while maximizing availability for the licensees and overall throughput for the end users. Despite this, this solution only focused on the ability of the algorithms to make decisions based on the current state of networks metrics which were implemented in the LSA controller.

3.1.2.4 Dual Connectivity

The Dual connectivity developed in the 3GPP standardization allows the UE to be connected to two base stations at the same time. It is mainly intended to be used by small cells under macro cell control. The macro cell acts as an aggregation point with the control channel. According to Mustonen *et al.* (MUSTONEN et al., 2015b), the UE can be connected to both the existing LTE network on licensed bands and the LTE network on LSA band or a Wi-Fi network at the same time, using dual connectivity.

This feature of the current 3GPP LTE system enables two network links to act as redundancy connections for signaling fairness to keep the connectivity in extreme situations *e.g.,* unscheduled evacuation scenarios of the LSA band. However, there is a drawback to dual connectivity which is that alternative networks must be constantly available, and only take account of the RSS and their channel quality of these. In the case of evacuation scenarios for the LSA band, the link to the LTE-LSA network is broken and the other link connected to the alternative network on licensed or unlicensed bands should be made available, Moreover, since the second network can be overloaded or congested this can lead to QoS degradation and even the disconnection of the UE.

3.2 Current Cognitive Solutions

The several portfolios included in current cognitive solutions make it possible to achieve the end-to-end objectives in the face of complicated scenarios that can impair the QoS provided to end-users. For instance, the question of handover has been a research topic that is widely explored because the importance of ensuring QoS and seamless connectivity for the UEs. At the present, investigations are geared to performing handover through cognitive solutions that rely on cognitive decisions. According to Martinnmikko *et al.* (MATINMIKKO et al., 2013) a cognitive decision provides intelligence for the use of resources such as the radio, spectrum, and network. This seeks to increase the QoS of end-users considerably, when compared with the standard systems. Martinmikko *et al.* also argue that a cognitive decision forms the bedrock of cognitive mechanisms because it is responsible for achieving the objectives of the end-to-end system *e.g.,* guaranteeing the QoS of end-users during the LSA band evacuation.

The cognitive engine designed by Martinmikko *et al.* (MATINMIKKO et al., 2013) is essential part of the first live trial of the LSA concept (*i.e.,* the CORE trial environment) and can control different radio systems with the aim of guaranteeing QoS while carrying out handover and traffic offloading procedures. In a similar way the CORE project form VTT in Finland carried out the forced handover that was based on a cognitive engine to guarantee the QoS of UEs, in the context of LSA (PALOLA et al., 2014b), (MATINMIKKO et al., 2013), (PALOLA et al., 2014c). In this way, the CORE analyzes alternative networks when high priority clients experience QoS degradation and when possible, carry out forced handover to deal with the problem. The QoS metrics (*e.g.,* delay, jitter, packet loss and throughput) are collected by the QOSMET tool (PROKKOLA et al., 2007). The cognitive engine performs the forced handover of the UE that has greatest priority *i.e.* the users with gold, silver, and bronze priorities. The cognitive decision-making is an essential functionality that is required to perform the forced handover of UE and guarantee the QoS in accordance with their priority, regardless of whether an evacuation of the LSA band takes place. For instance, the forced handover decides the traffic offloading of UE with the silver priority from the LTE network on the LSA band towards WLAN due to the current traffic congestion (MATINMIKKO et al., 2013).

According to Martinmikko *et al.* (MATINMIKKO et al., 2013), the duration of the cognitive cycle only takes 24.60 seconds, including the handover execution time. In unscheduled evacuation scenarios involving the LSA band, the average duration time of the cycle for carrying out the UE cannot be transferred to an alternative network before the eNB with one sector turned off, with an average delay of 20.62 seconds. In this view, when adopting the cognitive solution set out by Martinmikko *et al.*, the handover cannot be performed in unscheduled evacuation scenarios because the time needed for this is longer than the time when the eNB is locking with one sector. This can cause the QoS degradation and even disconnections for UEs, as well as interference between the MNO and incumbent services. Since a considerable amount of information must be gathered before the cognitive engine based decision (it is not suitable for time-sensitive decisions) such as those required for an unscheduled evacuation of the LSA band. The cognitive decision-making is not concerned with the time required for a forced handover in unscheduled evacuation scenarios of the LSA band. This means that unscheduled evacuations are required to perform faster handover to guarantee the QoS, seamless connectivity and the avoidance of interference with incumbent services before the radio resource turns off or locks the air interfaces on the LSA band. As well as this, previous researches have failed to take into account the problem of short-term congestion in the network when users make a reconnection by themselves or adopt third-party procedures to deal with the problem after the unscheduled evacuation. Accordingly, the users will suffer connection breaks and thus QoS degradation even under the management of a cognitive solution.

3.3 Multilevel Architecture

A multilevel resource architecture was designed by Kunst *et al.* for the allocation of QoS-aware resources in heterogeneous wireless networks (KUNST et al., 2016a) (KUNST et al., 2016b). This architecture relies on a broker which gathers together the updated information regarding the available network resources and them to be shared between the network operators. However, despite this benefit, the approach of the authors is not concerned with time-sensitive traffic steering and handover procedures.

With regard to the architecture of Broker, it can be divided into three levels: *(i)* updating, *(ii)* resources and *(iii)* decision-making. The first is responsible for collecting parameters from the networks which participate in the spectrum-sharing initiative. The second is responsible for providing information about the users currently operating in the geographical area, as well as about the available ranges of exclusive, shared and shared frequencies. The third level involves processing the requests of operators for spectrum resource renting. The broker architecture demonstrates that renting and provisioning the spectrum resources will make it possible to increase the frequency capacity of the stakeholders. Moreover, it shows that multilevel resource architecture can be easily adapted to perform LTE/LTE-A procedures that comply with cognitive criteria. Thus, this dissertation extends the architecture proposed by Kunst *et al.* in so far as it is able to carry out a vertical handover and traffic steering procedures that are in accordance with cognitive criteria.

4 COGNITIVE MECHANISM

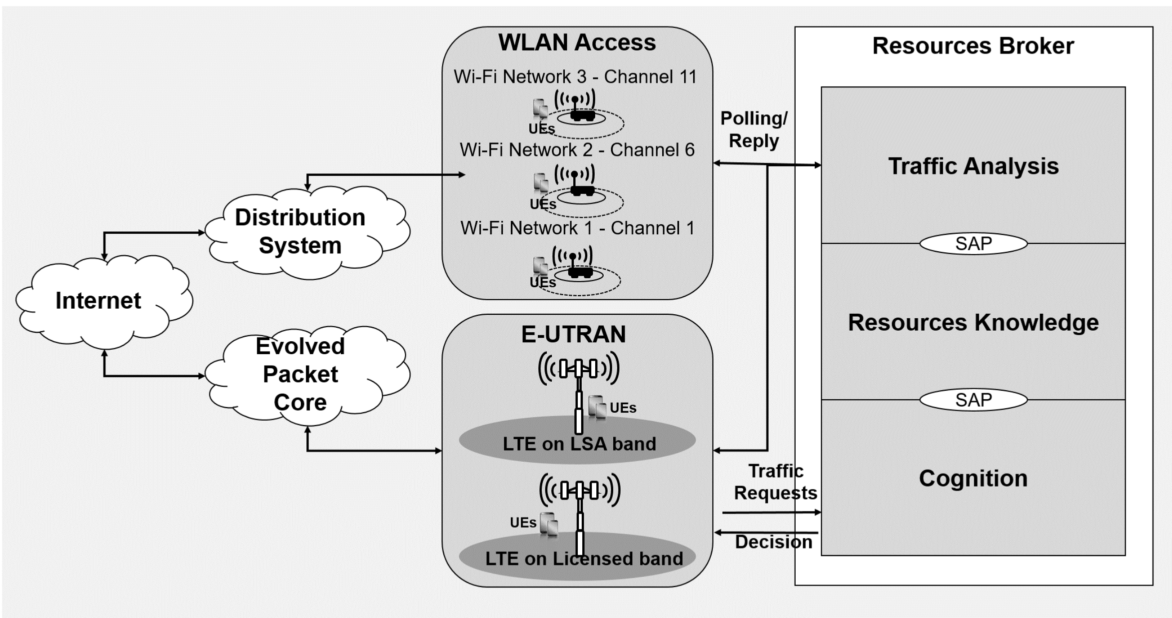
This Chapter present the architecture, components, and features of the proposed cognitive mechanism to take in advance decisions to find the best target networks for UEs in unscheduled evacuations scenarios. Based on these decisions, can be carried out the vertical handover and traffic steering of evacuated UEs towards the best target network. These procedures has the objective to guarantee the seamless connectivity and QoS of evacuated UEs during and after the unscheduled evacuation scenarios. In subsection 4.1.1 is presented the resource broker architecture of heterogeneous wireless networks. The subsections 4.2, 4.3, 4.4 introduce the components and features of each layer from the resource broker architecture.

4.1 Cognitive Mechanism: An Overview

The proposed architecture for cognitive mechanism support is presented in Figures 4.1 and 4.2. The illustration is divided into two parts which communicate through a polling and reply mechanism. In the left side, the resources users coexist in a geographical area considering a scenario that allows communication among them. In the right side of the figure, the structure of a resource broker of heterogeneous wireless networks is represented. The proposed broker is based on the architecture designed by Kunst et al. (KUNST et al., 2016a) (KUNST et al., 2016b) which is liable to coordinate the resources sharing among different network operators.

4.1.1 Architecture

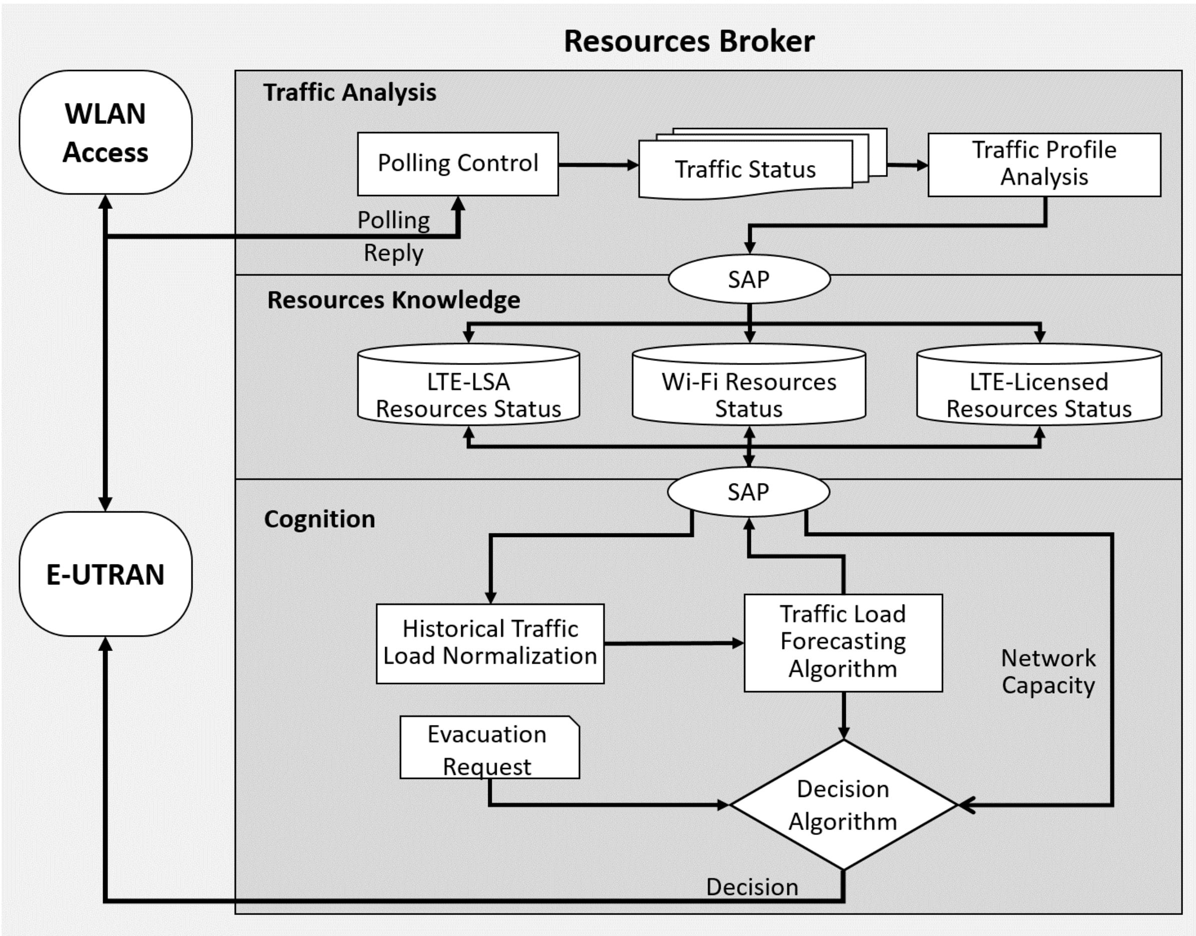
Figure 4.1: General Architectural Design of Resource Broker



Source: by author (2017).

The general and specific characteristics of the proposed architecture is presented in Figures 4.1 and 4.2, respectively. The illustration is divided into two parts which communicate using the polling and reply mechanism. The architecture is composed of heterogeneous wireless networks such as LTE and Wi-Fi. These networks have the full connection using the WLAN interworking standardization (3GPP, 2011) which enables the traffic offloading, in both network directions, on demand. In the left side of Figures 4.1 and 4.2 illustrate the coexistence of LTE-LSA and Wi-Fi operators within the same geographical area and each one connected to its network core and finally to the Internet. On the right side of Figures 4.1 and 4.2, the structure of resource broker is divided into three layers. The resource broker is an entity which is capable to provide all the required information to the cognition layer in order to decide which of the overlapped Wi-Fi networks is most convenient in terms of less congestion to use for the short-term future.

Figure 4.2: Specific Architectural Design of Resource Broker



Source: by author (2017).

The resource broker is responsible for coordinating resources sharing. The resource broker plays the role of a centralized entity which keeps track of the network resources availability. Three layers are defined to provide independent and simultaneous control of different tasks of resources sharing management. These layers communicate with each other via Service Access

Points (SAP). Each layer is named accordingly to the function executed by each one: *(I)* Traffic Analysis Level, *(II)* Resources Knowledge Level, and *(III)* Cognition Level.

4.2 Traffic Analysis Layer

The first layer of the broker is responsible for controlling the polling mechanism used to gather updated information on the resources conditions of the WLAN and E-UTRAN access systems. The information received from each Wi-Fi operator contains a tuple composed of its identification, current average delay, jitter, and throughput. This tuple is received and pre-processed by a Traffic Status analyzer and then relayed to the Traffic Profile Analysis block, which is responsible to keep track of both current and historical values of the QoS parameters, which will feed the Resources Knowledge layer.

4.2.1 Polling Control

This block allows the interval time configuration of polling monitoring technique. The correct definition of such interval is crucial to deal with the trade-off to obtain the required QoS information without generating network overloads. Here, the objective is to reduce the overhead generated during the control and collection of parameters over the traffic load of each wireless network. This block has also the function to translate the heterogeneous wireless networks update data into useful information for the architecture.

4.2.2 Traffic Status

This block allows the configuration of the interval between polls. The precise definition of such interval is crucial to deal with the trade-off between having accurate information about the current resources usage profile of each network operator and the overhead generated by the control information transmitted to update the resource broker. Another important function performed by the Traffic Status block is the translation of the raw update data into useful information to allow the architecture to take proper decisions regarding resources sharing. Therefore, the definition of the structure detailed in Table 4.1 is used as a critical function by the MNO to update the resource broker.

Over receiving the raw update data structured according to the presented organization, the Traffic Status block performs an SINR estimation in the wireless channel and collects the timestamp of the instant when the raw update information was received. In summary, the load of throughput and delay are calculated using the SINR, average throughput, and average delay measurements. After being calculated each average load of each metric is sent to the Resource Knowledge layer to record the historical load assessment of the each QoS parameter.

Table 4.1: Framework for Raw Update of Data

Field	Size	Description
Wireless Network SSID	1 byte	Uniquely identifies the network operator in the spectrum sharing architecture
Average Throughput (Mbps)	8 bytes	Updated assessment of the average throughput. Performed by the network operator
Average Delay (ms)	8 bytes	Updated assessment of the average delay. Performed by the network operator

Sources: (KUNST et al., 2016a) and (KUNST et al., 2016b).

4.2.3 Traffic Profile Analysis

The pre-translated update data of heterogeneous wireless networks (LTE and Wi-Fi) is received by the assessment of Traffic Load Profile block, which is responsible for keeping track the historical information captured by each heterogeneous wireless network. This historical information is taking into account to define the current usage profile of the network in order to minimize the effect of abnormal behaviors of the traffic on wireless networks that is common in real scenarios.

This block take into account the tracking of historical information about QoS parameters of network traffic status block. This historical information allows to predict future status of QoS parameters about network traffic. The proposed mechanism can find the best target networks(s) for the users with different CoS and thus to carry out the vertical handover and traffic steering the evacuees to cope an unscheduled evacuation of the LSA band.

4.3 Resource-based Knowledge Layer

Databases are organized within the Resources Knowledge, which is the second layer of the resource broker. This layer implements three databases to store information regarding the resources available in E-UTRAN and WLAN Access systems respectively. The E-UTRAN resources comprises the LTE network on licensed frequencies and LTE network on LSA band. In the database for each of these networks are store the traffic information such as throughput and delay of each Class of Service (CoS) In addition, the WLAN Access database stores the traffic information of each Wi-Fi network overlapped to the coverage area of the LTE-LSA network. This layer plays a crucial role in the traffic classification because it provides the required knowledge about all resources available that can serve as target network(s) facing unscheduled evacuation scenarios. Afterward to have obtained the throughput and delay information within each database, respectively, these data can be sent toward the Cognition layer.

4.3.1 Wi-Fi Resources Status

This database stores the historical, updated and predicted information of total traffic load of each Wi-Fi network which is overlapped to the LTE-LSA network. Specifically, this database contains the historical and updated information about current average delay, jitter, throughput, and traffic load of each Wi-Fi network overlapped to the LTE-LSA network that can be used as target network in unscheduled evacuation scenarios. In addition, this database contains the record information about the capability, occupation, and availability of the bandwidth of each Wi-Fi network for the future 15 minutes. It was determined and fixed the traffic load forecasting for the next 15 minutes due to the accuracy of the prevision for each model after to repeat 30 times the simulation obtains around 95% of confidence degrees. The predicted information calculated by the traffic load forecasting model is valid for 15 minutes. For that time the predicted values are stored in the database to be used by the decision-making process at the Cognition layer.

4.3.2 LTE-LSA Resources Status

This database stores the historical, updated and predicted information of traffic load in LTE networks on LSA band. This database stores information regarding the resources availability of LTE-LSA networks. Specifically, this database contained the historical, updated and predicted information of the delay, jitter, throughput, and traffic load of LTE-LSA networks. This database of LTE-LSA resources is characterized due to it records each CoS traffic type (HTTP, Video, and VoIP) from the LTE-LSA network. Furthermore, this database is responsible for providing the required information to carry out the traffic load forecasting model and decision algorithm. The predicted traffic load has available for next 15 minutes, stored each time the prediction model is performed for each CoS of the LTE-LSA network. At the cognition layer, the predictions of the occupation and availability from the bandwidth of the LTE-LSA network are stored in this database.

4.3.3 LTE-Licensed Resources Status

This database stores the historical, updated and predicted information of traffic load in LTE networks on licensed band which is located in the same area of the LTE-LSA network. The LTE-licensed resource status contains the throughput, delay, and traffic load of LTE networks on the licensed bands. Besides, when this database is activated, it will record the predicted capability, occupation, and availability of the bandwidth of LTE-licensed networks. This database provides to the Cognition layer the traffic parameters information about the current and historical measurements of the networks on licensed bands. This database is not enabled for our proposed scenario because it does not consider any LTE network on the licensed bands such as a possible alternative for sending evacuated UEs with their traffic in LSA scenarios. However, this and one more database can be activated for future works as an extension of the resource knowledge layer of proposed architecture to support more networks.

4.4 Cognition Layer

This is the most important layer of the resource broker architecture due to it joins all the knowledge learned in above layers to carry out cognitive decisions. In this sense, machine learning models for traffic load forecasting and QoS-aware associations are using by the decision algorithm to find the best target networks among all overlapped Wi-Fi, by the analysis of the traffic load forecasting in the future short-term *e.g.* next 15 minutes. This layer is constantly running, with the goal of taking in advance decisions required to guarantee the QoS and connectivity of UEs during and after a quick evacuation of the LSA band in unscheduled scenarios. By means of the decisions in advance can be carried out the vertical handover and traffic steering procedures from cognitive criteria to achieve a fast evacuation of UEs, guaranteeing their QoS and seamless connectivity when the incumbent user request the LSA band.

In accordance with the above description, this dissertation embraces merely two LTE/LTE-A procedures carried out under cognitive criteria to guarantee the QoS and connectivity of UE in unscheduled evacuation scenarios. In this sense, a Cognitive Vertical Handover (C-VHO) is proposed to transfer all evacuated UE toward the best networks selected in advance by the proposed cognitive decision algorithm. C-VHO has the aim to ensure the seamless connectivity of evacuees by reconnecting them immediately or in a very short time into the best overlapping Wi-Fi networks. The cognitive decisions in advance making for C-VHO are used to carry out the Cognitive Traffic Steering (C-TS). C-TS is responsible for steering the traffic of evacuated UEs according to their CoS, with the aim to guarantee the QoS of them into the best Wi-Fi networks with less congestion in the short-term future. Thanks to the C-TS association in advance, it is possible to ensure the throughput and delay of all evacuated UEs as well as to carry out a kind of load balancing procedure based on the next 15 minutes forecasts of overlapped networks avoiding the future traffic congestions. In this sense, the C-VHO and C-TS procedures are required to guarantee the QoS and seamless connectivity of evacuated UEs, respectively, during and after an unscheduled evacuation of LSA band.

4.4.1 Historical Traffic Load Normalization

The historical traffic load normalization is crucial for achieving a high accuracy predictions and a good time performance with the help of the traffic load forecasting. Thereby, the normalization of historical traffic load embraces two major phases. The first phase is the time series extraction of data traffic from LTE-LSA and Wi-Fi networks. The second phase consists of the polynomial curve fitting of each traffic.

In the former, the data points obtained from the traffic load simulations in the LTE-LSA network were divided into three data sets: training, validation, and testing. The training data set comprises the traffic load measurement corresponding to the first 900 seconds or 15 minutes of the time series. The validation data set consists of a 10 percent of testing data. This enabled to compare the forecasting data with the current data of simulated traffic. In accordance with (ARLOT; CELISSE et al., 2010), the cross-validation method is the preferred manner of measuring the predictive performance of a statistical model. That using the 10 percent of training data set to find the difference among the prediction and current values. Further, the testing data set is used to obtain the performance features of prediction such as accuracy and time processing. Alike, the traffic of each Wi-Fi network was divided into training, validation and testing data sets. Therefore, the total time series consists of all simulated data points values for each CoS demand in LTE-LSA network and traces in Wi-Fi networks. The first time series comprise the simulated traffic for LTE-LSA network and real traffic traces for Wi-Fi networks.

The simulated traffic in LTE-LSA network and the trace in Wi-Fi has as the standard time unit in seconds because the traffic load forecasting is more accurate than in minutes. In the second phase, we perform the polynomial curve fitting to smooth peaks and noise of overall traffic *i.e.,* for training, validation and testing data sets. The polynomial was fixed in 10 degrees for fitting the all collected traffic of each network. Over the new data points obtained from the polynomial of ten degrees are used for the classification of the training, validation and testing data sets again.

Therefore, the measurement of historical traffic load comprises the time series extraction, and polynomial curve fitting of each traffic load correspond to the LTE-LSA (source network) and all traffic of Wi-Fi (target network). Based on this normalized information, in the next section 4.4.2 is performed the traffic load forecasting using the Multiple Linear Regression (MLR) model.

4.4.2 Traffic Load Forecasting Algorithm

The traffic load forecasting algorithm has as input the obtained traces to describe the behavior of the Wi-Fi operators. The traffic traces were obtained from CRAWDAD database (SCHULMAN; LEVIN; SPRING, 2009) to forecast the traffic behavior using the Multiple Linear Regression (MLR) model implemented using Matlab. This model is based on a traffic measurement Y, which is related to a single predictor X for each observation. Therefore, the conditional mean function can be described as in (4.1), where α is the intercept, and β is the coefficient.

$$\mathrm{E}[Y \mid X] = \alpha + \beta X \tag{4.1}$$

Considering that multiple predictors (n) are available from the traces, the MLR model is considered, according to (4.2).

$$\mathrm{E}[Y \mid X] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{4.2}$$

The variability of the ith measurement Y around its mean value is specified in (4.3).

$$\mathrm{E}[Y \mid X_i] = \alpha + \beta_1 X_{i,1} + \beta_2 X_2 + \cdots + \beta_n X_{n,i} + \epsilon_i \tag{4.3}$$

In this case, the error assumptions for ϵ_i are that $\mathrm{E}[\epsilon_i] = 0$ and var$(\epsilon_i) = \sigma^2$. The accuracy of the forecast can be measured by the mean absolute percent error (η), which is given by (4.4). In this equation, e_t represents the actual network occupation based on network traces and y_t is the forecast occupation of the same network in a given instant of time.

$$\eta = \frac{1}{n}\left(\sum_{t=1}^{n}\left|\frac{e_{(t)}}{y_{(t)}}\right|\right) \tag{4.4}$$

The resulting forecast points compose a continuous traffic function, $f(x)$, which describes the occupied area of each analyzed network. In this context, let $f : D \to R$ be a function defined on a subset D of R and let $I = [a, b]$ be a closed interval contained in D. The closed interval represents the start and the end time of the forecast. Finally, let $P = \{[x_0, x_1], [x_1, x_2], \cdots, [x_{n-1}, x_n]\}$ be a partition of I such as $P = \{a = x_0, x_1, \cdots, x_n = b\}$. Thus, a Riemann sum (S) of f over I with partition P is defined in (4.5).

$$S = \sum_{i=1}^{n} f(x_i^*)(x_i - x_{i-1}) \tag{4.5}$$

When the number of points in P increases indefinitely, it is possible to apply (4.6) to calculate the occupied area of each network, which can be related to the occupied network capacity.

$$A_{occupied} = \int_a^b f(x)dx = \lim_{x\to\infty}[s^*(P, f)] \tag{4.6}$$

This value is normalized considering the total capacity (A_{total}) area of each network operator. Its complement, therefore, represents the percentage of available resources of a given network. Let $\Theta = \{o_0, o_1, \cdots, o_{n-1}, o_n\}$ be a set of network operators. Thus, the free capacity percentage of the network operators is given by (4.7).

$$\forall o \in \Theta, A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right) \tag{4.7}$$

4.4.3 Cognitive Decision Algorithm

In this dissertation is proposed a novel decision algorithm capable of selecting the best target networks for the evacuated UE and their CoS traffic based on the cognitive criteria. Moreover, this algorithm enables the execution of the vertical handover and traffic steering procedures toward the best target networks in the shortest time when faced with the unscheduled evacuation of LSA band. To evaluate the proposed decision algorithm, it is used a scenario comprising one LTE-LSA and three Wi-Fi networks.

Three CoS are defined to accommodate different types of traffic regarding the QoS requirements. *(I)* Real Time Services (RTS), to support delay and jitter sensitive real-time transmissions, *(II)* Multimedia Services (MS), comprehending real-time services with high throughput but no strict delay and jitter and *(III)* Best Effort Services (BES), designed to support best effort transmissions without strict QoS requirements. On the basis of the amount of free resources of each operator, calculated in advance by the traffic forecasting algorithm, a decision algorithm is implemented, as defined in the algorithm (1).

In the proposed algorithm, the decision is relied on in advance information obtained, on the basis of the traffic load forecasting model, which stores this in advance decision information in the databases of the Resources Knowledge layer. Whenever an Evacuation Request is received, the decision algorithm queries the database in order to obtain the most updated forecast of best target networks. Such predictions are then considered along with the CoS of the request to search for a traffic steering route which guaranteed the QoS of the requesting client. The decision algorithm was designed based on the equations and variables presented in Section 4.4.2, by regarding each CoS, QoS metrics and overlapped networks to make the decisions. Therefore, the most significant contribution of this dissertation is the Algorithm 1, presented as follows:

Algoritmo 1 Decision Algorithm

Entradas: r ▷ A structure containing a cognitive evacuation request
Entradas: $A_{total}(o)$ ▷ The total amount of resources of each operator
Entradas: $A_{occupied}(o) = \int_a^b f(x)dx = \lim_{x\to\infty}[s^*(P, f)]$ ▷ The amount of occupied resources of each operator

$selected\_operator = 0$
$c \leftarrow r.CoS$; $d \leftarrow r.Delay$; $t \leftarrow r.Throughput$
switch c **do**
    case RTS:
        for all $o \in \Theta$ **do**
            $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
            $delay(o) = get\_knowledge\_layer(Wi - Fi, delay)$
            if $A_{free}(o) \geq t$ & $delay(o) \leq d$ **then**
                return o
            end if
        end for
    case MS:
        for all $o \in \Theta$ **do**
            $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
            if $A_{free}(o) \geq t$ **then**
                return o
            end if
        end for
    case else:
        for all $o \in \Theta$ **do**
            $max\_operator = 0$
            $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
            if $A_{free}(o) \geq max\_operator$ **then**
                $max\_operator = A_{free}(o)$
                return $selected\_operator = o$
            end if
        end for
        return $selected\_operator$

5 PERFORMANCE EVALUATION

In this Chapter, an evaluation of the traffic steering and vertical handover procedures are conducted that involves cognitive in advance decisions-making. This includes conducting an analysis of accurate decisions, processing time, and QoS requirements. The simulation scenario is discussed in Section 5.1 and the performance of the proposed solution is analyzed in Section 5.2 with regard to three keys factors: *(I)* traffic load forecasting, *(II)* the accuracy of cognitive decisions, *(III)* the effectiveness of cognitive vertical handover, and *(IV)* the efficiency of cognitive traffic steering.

5.1 Simulation Scenario

At the moment, there is no specific traffic demand modeling for an LTE network in an LSA band. However, an LTE network in a licensed frequency can represent a scenario in a LSA band. Thus, the behavior of the proposed solution is simulated on the basis of the traffic demand from the LTE network operator. The traffic model includes the connection arrival rate and the amount of traffic demanded per connection. The traffic model used in the simulated LTE scenario implemented in Matlab is based on the System Evaluation Methodology document, published by WiMAX Forum specifications (NADA, 2008), UMTS forum (UMTS, 2011), and the report of Cisco Visual Networking Index (CISCO, 2016). These documents were chosen because are based on realistic measurements and provides a solid basis to estimate the current and future traffic demanded by different users in a LTE network.

In terms of the hardware used to perform the Matlab simulations. Basically, it was used a computer with an Intel Core 5 processor, 8 GB DDR4 of RAM with 2400 GHz speed. In order to leverage all the processor capacity, it was also activated the virtual processors to obtain eight processors running during the simulations execution of traffic load generation, the traffic load forecasting and execution of proposed algorithm, vertical handover and traffic steering.

Table 5.1: Traffic Simulation Parameters

Parameter	**Values for LTE-LSA Network**
Channel Bandwidth	10 MHz
LTE Frame Length	10 ms
Duration of Simulation	1800 s
HTTP Traffic %	40%
VoIP Traffic %	30%
Video Traffic %	30%

Sources: (NADA, 2008), (UMTS, 2011) and (CISCO, 2016).

In the simulation, three different types of traffic (HTTP, Video, and VoIP) are generated and examined in accordance with each CoS defined in the architecture outlined in the Chapter 4. The amount of traffic generated by each CoS is a parameter of the simulation tools. On the basis of the UMTS Forum (UMTS, 2011) and the Report of Cisco Visual Networking Index (CISCO, 2016), the distribution of the traffic load was estimated to be 40% for BES, 30% for MS, and 30% for RTS. The remaining simulation parameters are summarized in Table 5.1. The characteristics and parameters of the traffic models for each CoS are described as follows.

5.1.1 Traffic Model for Best Effort Services

The Best Effort Service (BES) is characterized by the HTTP traffic type, which is one of the most widely used protocols on the Internet. For example, Dynamic Adaptive Streaming over HTTP (DASH) is an adaptive bitrate standard that enables high-quality streaming of media content over the Internet, delivered from traditional HTTP web servers (SODAGAR, 2011). Currently, YouTube and NetFlix companies have already implemented DASH open standard for adaptive video streaming. Although the proposed scenario for BES does not in practice conform to the DASH standard, in theory, DASH is included in the HTTP traffic load percentage of Table 5.1 due to its current and future impact on video streaming.

HTTP is used to model BES traffic when the DASH standard is included. The HTTP transmissions comprise the main page, which has a given number of embedded objects, such as images, scripts, and other sorts of attached files. After requesting and receiving the files, the browser parses the page to make it readable to the user. The user then reads the page before making a new request. The values of each phase of the HTTP statistical model are given in Table 5.2.

5.1.2 Traffic Model for Real-Time Services

The Real-Time Service (RTS) traffic is modeled to include VoIP transmissions, and Adaptive Multi-Rate (AMR) codec, which has ON/OFF behavior. This behavior is modeled to cover the activity of speech in conversations using this codec system. For simulation purposes, AMR codec was used to model conversations and the duration of each period modeled was modeled on the basis of an exponential distribution with an average of 1026 ms of talk (ON period) and 1171 ms of silence (OFF period). The parameters of the simulation are shown in Table 5.3. These parameters are the same as those defined in the System Evaluation Methodology document, published by the WiMAX Forum (UMTS, 2011).

Table 5.2: HTTP Traffic Parameters

Component	**Distribution**	**Parameters**	**PDF**
Main Page Size	Truncated Lognormal	Mean = 10710 bytes SD = 25032 bytes Min = 100 bytes Max = 2 Mbytes	$\sigma = 1.37$ $\mu = 8.37$
Embedded Object Size	Truncated Lognormal	Mean = 7758 bytes SD = 126168 bytes Min = 50 bytes Max = 2 Mbytes	$\sigma = 2.36$ $\mu = 6.17$
Number of Embedded Objects	Truncated Pareto	Mean = 5.64 Max = 53	$\sigma = 1.1$ $\mu = 55$
Reading Time	Exponential	Mean = 30 s	$\mu = 0.033$
Parsing Time	Exponential	Mean = 0.13 s	$\mu = 7.69$

Sources: (KUNST et al., 2016a) and (KUNST et al., 2016b).

5.1.3 Traffic Model for Multimedia Services

When modeling the Multimedia Service (MS), a traffic model was used for the transmission of on-demand video clips encoded using MPEG-4 method, since this coding system is one of the most widely accepted and efficient for video encoding. The parameters of a video clip transmission may differ from one trace to another. In view of this, for simulation purposes, a trace was selected from a talk show. In this trace, two resolutions are available with 176x144 pixels and 320x240 pixels.

Each of the videos has a variable length, ranging exponentially from 15 to 60 seconds. The selected display size of the video clip leads to an average frame size of 2.725 Kbytes after the video is compressed. Each transmission requires an average channel capacity of 7.6 Mbps due to the 8 bits of color depth in a standard video clip. The parameters used for the simulations are summarized in Table 5.4 (NADA, 2008).

Table 5.3: VoIP Traffic Parameters

Parameter	Value
Call Holding	Exponential: μ = 210s
Codec	AMR
Frame Duration	20ms
Talk Duration (ON)	Exponential: μ = 1026ms
Silence Duration (OFF)	Exponential: μ = 1071ms
Silence Suppression	ON
Embedded Protocols	RTP/UDP/IP
Speech Activity	47.17%
MAC Header (ON)	42 bytes
MAC Header (OFF)	16 bytes

Sources: (KUNST et al., 2016a) and (KUNST et al., 2016b).

Table 5.4: Video Clip Traffic Parameters

Parameter	Value
Video Length	Truncated Exponential: 15-60s
Video Resolution	176x144 pixels
Codec	MPEG-4
Protocol	TCP
Direction	Downlink
Color Depth	8 bit
Mean Uncompressed Frame Size	38.016 kbytes
Compression Ratio	13.95
Mean Compressed Frame Size	2.725 kbytes
Frames per Second	25

Sources: (KUNST et al., 2016a) and (KUNST et al., 2016b).

The simulation was performed in Matlab with the above models and parameters for traffic in the LTE-LSA network. Our solution is deployed and evaluated on the basis of that simulation. The LTE-LSA network consists of one TDD-LTE base station transmitting in the band range of 2.3 to 2.4 GHz. Since the traffic models are stochastic, there is a confidence interval of 95% for traffic generation. The confidence interval of 95% was obtained after the 30 repetitions of simulation, after that the interval does not change sufficiently for the next simulation of traffic generation. Thus, the simulation of traffic generation was fixed for 30 fold to obtain a good enough of confidence interval. The SINR parameter is fixed in 5 dB with an antenna gain of 17 dBi (ETSI, 2013). The frame duration is 10 ms, and the transmissions are carried out in a channel bandwidth of 10 MHz. The number of connections during the simulation was fixed at 100 for BES, 300 for MS and 100 for RTS. The overall simulation duration was set at 30 minutes for the traffic load forecasting.

In general, the scenario can be formed of any heterogeneous wireless networks overlapping the LTE-LSA network *e.g.* Wi-Fi networks. For this reason, the proposed solution is based on historical and current measurements of the traffic load of each overlapping network to carry out the cognitive decision-making.

5.1.4 Wi-Fi Network Traffic Traces

Our scenario consists of one simulated LTE-LSA network *i.e.* a small cell represented by an LTE base station with one sector on the LSA band. In addition, it contains three overlapping Wi-Fi networks in the geographical area which is covered by the sector signal of the small cell on the LSA band. The traffic load of each Wi-Fi is not separated per CoS as in the LTE-LSA network. In the scenario employed in this dissertation, the real traces obtained from the CRAWDAD database (SCHULMAN; LEVIN; SPRING, 2009) represent the aggregate of real Wi-Fi networks. These traces contain the aggregate traffic of each Wi-Fi without discriminating the CoS. The traces were classified strategically to represent the traffic congestion in certain Wi-Fi networks. Congestion is an important factor in demonstrating our solution because of its call to cognition in the management of traffic and resources. The scenario is composed of three Wi-Fi networks operating in no interfering channels and one LTE network operator using LSA frequencies. Hence, this heterogeneous wireless network scenario can coexists with harmony operation and no interference at spectrum level. In this case, the Wi-Fi networks 1, 2, and 3 are operating on the non-overlapping channels 1, 6, and 11, respectively (as depicted in Figure 4.1). As a result, avoidance of interference among the Wi-Fi networks and its users can be guaranteed. During the simulation period of the proposed solution, the Wi-Fi 1 represents a highly congested network, Wi-Fi 2 has medium congestion, and the Wi-Fi 3 has low congestion. On the basis of the different traffic load of each Wi-Fi network, the proposed solution can show the intelligent decisions of the proposed cognitive mechanism and efficient resource broker architecture. Thus, the evaluation of the proposed cognitive mechanism and the components of the resource broker, are carried out on the basis of the simulated traffic per CoS for the LTE-LSA network and the traces of aggregate traffic for each Wi-Fi network.

5.2 Performance Evaluation

In this section, the first stage of the performance evaluation of the proposed solution involves assessing of the traffic load forecasting models. In the second stage, there is an evaluation of the cognitive decision algorithm. In the third stage, an evaluation is made of the vertical handover and in the fourth stage of the traffic steering. On the basis of these evaluations, it can demonstrated that the performance and efficiency of the proposed solution can ensure the QoS and connectivity of UE in unscheduled evacuations of the LSA band.

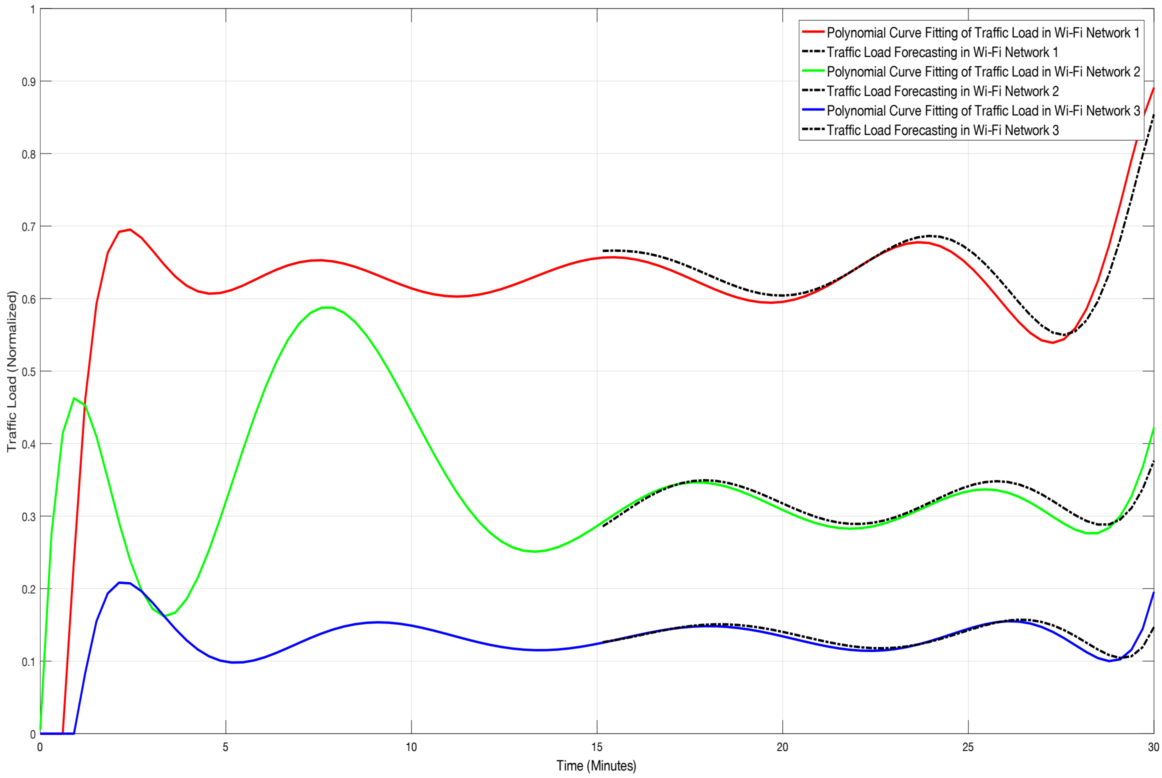
5.2.1 Evaluation of Traffic Load Forecasting Models

With regard to the performance of the proposed solution, the first factor to analyze is the accuracy of the traffic load forecasting for each model. The forecasting procedure follows three key phases. The first is the time series extraction of traffic data from LTE-LSA and Wi-Fi networks. The second consists of fitting the polynomial curve of traffic data of both LTE-LSA and Wi-Fi networks. In the third phase, the forecasting is carried out by means of the machine learning models, as outlined in the following sections.

The normalization of the traffic load for each CoS of the LTE-LSA network and the aggregate traffic of each Wi-Fi network is based on time series with treatment effect. According to Hamilton (HAMILTON, 1994) the time series is a sequence of data points, that generally consists of successive measurements made in a time interval. These data points are divided into three datasets: training, validation, and testing. The training dataset comprises the traffic load measurement that corresponds to the time series of 900 seconds which represent the half of the total simulation time used for the training dataset. That time is equivalent to 30 minutes of simulation to generate each CoS *i.e.,* HTTP, Video, and VoIP traffic behavior for LTE networks. In fact, the total traffic generation simulation time is equivalent to 1800 seconds, in which the second half time serves to compare the forecasting with the simulating traffic load. The validation dataset consists of 10 percent of the testing dataset which is used to analyze the outcomes of the prediction, by taking into account metrics such as accuracy and processing time (ARLOT; CELISSE et al., 2010). The cross-validation process of machine learning models is usually defined as the 10 percent of the total dataset to evaluate the accuracy of each traffic load forecasting model (NGUYEN; ARMITAGE, 2008). Once the traffic load forecasting model is ready to perform the predictions, need to verify if it is accurate sufficiently. For this is compared it with the actual values. Also, the confidence interval of 95% was obtained after the 30 repetitions of simulation, after that, the interval does not change sufficiently for the next simulation of traffic load forecasting. Thus, the simulation of traffic load forecasting was fixed for 30 repetitions to obtain a good enough of the confidence interval.

5.2.1.1 Traffic Load Forecasting with the Multiple Linear Regression Model

Figure 5.1: Current vs. Predicted Traffic Load for each Wi-Fi Network with the Multiple Linear Regression Model



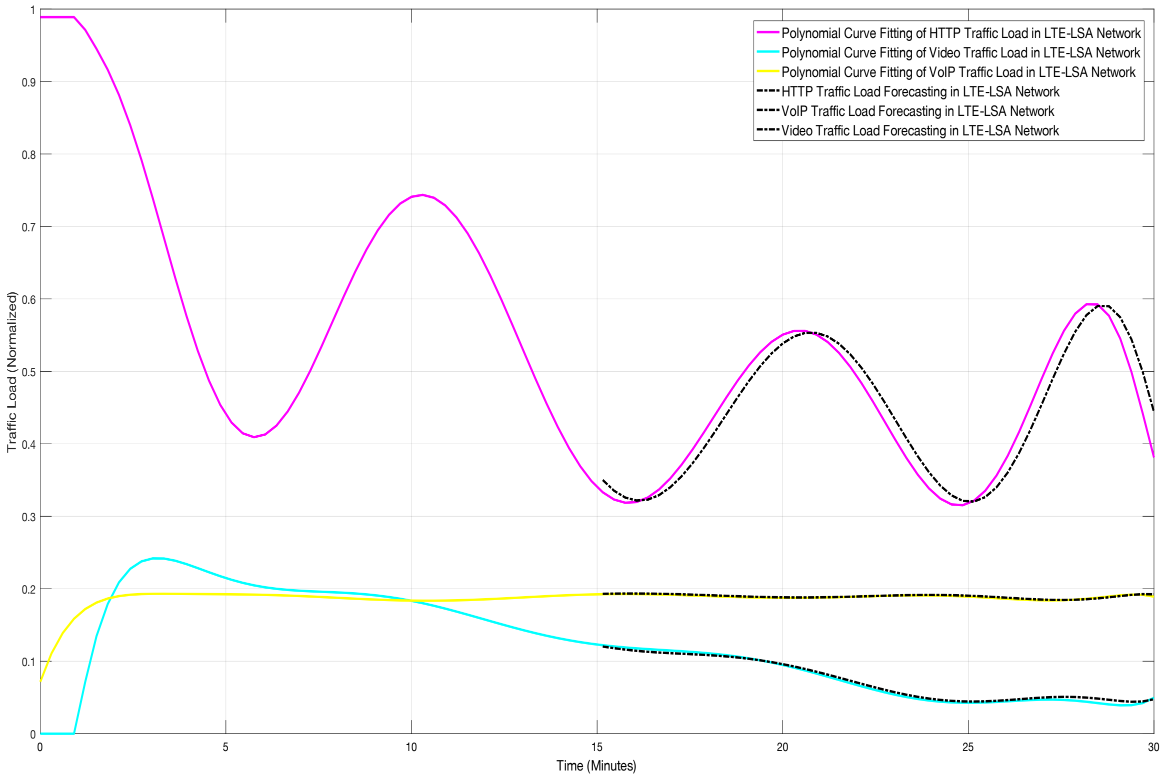
Source: by author (2017).

The Multiple Linear Regression (MLR) model processes the trained dataset of each simulated traffic demand per CoS *i.e.,* Video, VoIP, and HTTP from the LTE-LSA network, as well as the aggregate traffic of Wi-Fi networks. The simulated traffic in the LTE-LSA network and the traces in Wi-Fi are computed in units of seconds to improve the accuracy of the model. The first step of the analytical methodology involves calculating the polynomial curve fitting for the smoothing out the peaks and noise of overall traffic *i.e.,* it is used for training, validation and testing datasets. The polynomial was fixed at 10 degrees for curve fitting analysis of the traffic of each network. The classification is then performed again and includes the new data points obtained from the ten degrees polynomial for the training, validation, and testing datasets. After this, the MLR model is applied to carry out the traffic load forecasting and the validation dataset is used to evaluate its accuracy for each network.

The accuracy of MLR model is evaluated by the cross-validation method which involves comparing the forecasted values with the current values. At this point, the MLR model can be adjusted to improve the accuracy of the upcoming predictions. The MAPE Equation 4.4 is also used to measure the accuracy of the MLR model.

The MLR accuracy is evaluated by the cross-validation method which involves comparing the forecasted values with the current values. At this point, the MLR model can be adjusted to improve the accuracy of the upcoming predictions. The MAPE Equation 4.4 is also used to measure the accuracy of the MLR model. The results of the Figure 5.1 enables the analysis of the accuracy of the traffic load forecasting of the three overlapping Wi-Fi networks in relation to current traffic load. As can be seen in the graph, the traffic load forecasting was very accurate, and reached levels of 96.179%, 93.607%, and 94.197% degrees of accuracy, for Wi-Fi networks 1, 2, and 3, respectively. Another analysis that is conducted for traffic load forecasting concerns the LTE-LSA frequencies. This analysis is needed to forecast the behavior of the incumbent user, which may request an evacuation. The outcomes of the simulation related to this scenario are shown in Figure 5.2 which shows the traffic load forecasting of VoIP, Video, and HTTP in the LTE-LSA network. In this case, the levels of accuracy are up to 95.724%, 98.473%, and 94.764% respectively, for each class of service.

Figure 5.2: Current vs. Predicted Traffic Load for each CoS in the LTE-LSA Network with the Multiple Linear Regression Model



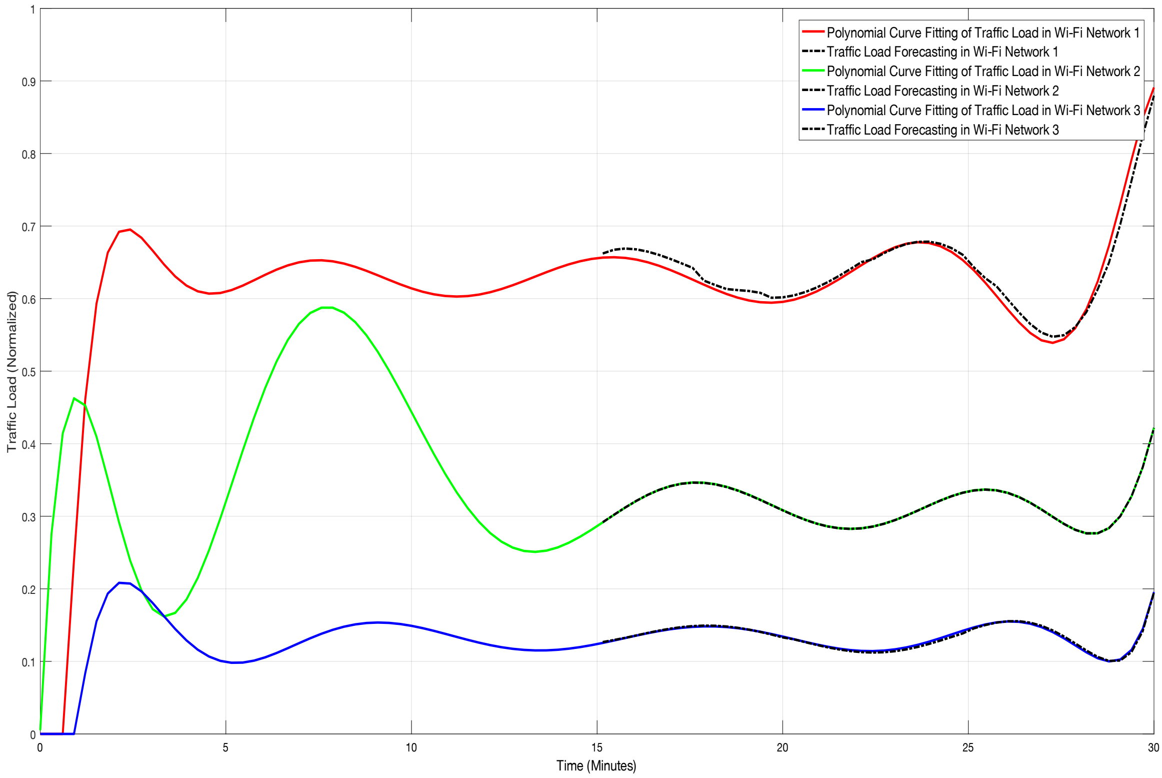
Source: by author (2017).

5.2.1.2 Traffic Load Forecasting using the Neural Network Model

The Neural Network Model (NNM) by the Cascade Forward Back Propagation (CFBP) model carry out the following steps for traffic load forecasting of each CoS in the LTE-LSA network, and the aggregate traffic of each Wi-Fi network. As depicted in Figure 5.4, the forecasting of HTTP, Video, and VoIP traffic load changes according to the historical traffic load of each network. The trained data of the NN model is collected by previous stages of the resource broker architecture. The first step involves the normalization of the training, validation, and testing datasets in time series. The second step consists on carry out the current implementation of CFBP model in Matlab NN toolbox for traffic load forecasting.

The CFBP model processes the trained dataset of each simulated traffic demands *i.e.,* Video, VoIP, and HTTP from the LTE-LSA network, as well as of the aggregate traffic of Wi-Fi networks. The simulated traffic in the LTE-LSA network and the traffic traces of Wi-Fi are computed in units of seconds to improve the accuracy of the results. The first step of the analytical methodology implicates calculating the polynomial curve fitting for smoothing out the peaks and noise of the traffic in the LTE-LSA and Wi-Fi networks. The polynomial was also fixed at 10 degrees to achieve the best curve fitting of the traffic load of each network. The second step consists in the classification for the training, validation, and testing datasets which are composed by the new data points obtained from 10 degrees polynomial. The third step regards the CFBP model carrying out the traffic load forecasting. Then, the prediction accuracy of each network is evaluated by means of the validation dataset.

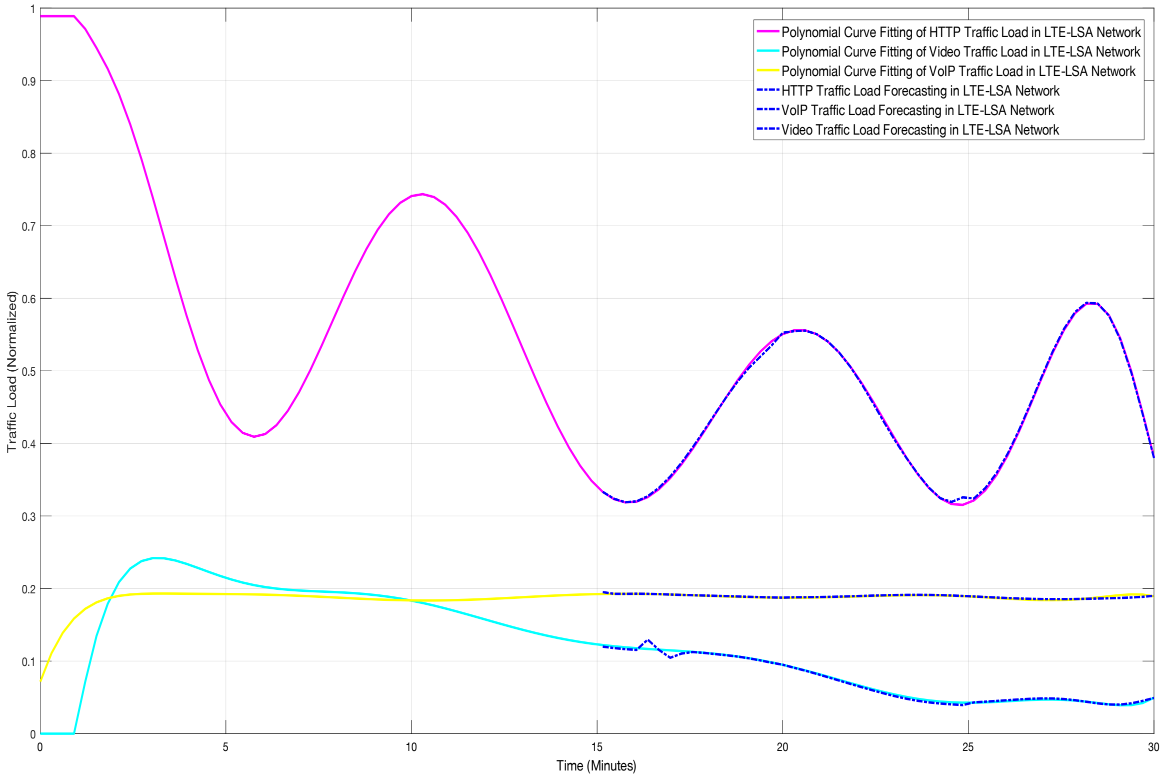
Figure 5.3: Current vs. Predicted Traffic Load for each Wi-Fi Network using the Neural Network Model



Source: by author (2017).

The predictions accuracy of CFBP model are calculated by means of the MAPE Equation (4.4). As well as, the cross-validation method enables to compare the current values with the

Figure 5.4: Current vs. Predicted Traffic Load for each CoS in the LTE-LSA Network using the Neural Network Model



Source: by author (2017).

predicted ones. Thus, the CFBP model can be auto adjusted to improve the accuracy of the future predictions. Figure 5.7 shows the analysis of the accuracy degree of the traffic load forecasting which examines three Wi-Fi networks as possible best target network(s) for vertical handover and traffic steering procedures. Such analysis is on the basis of the relation among the current and predicted traffic load for each network. In fact, the traffic load forecasting for Wi-Fi networks 1, 2, and 3 achieved the degree average accuracy of 96.727%, 95.924%, and 98.633%, respectively. Also, the traffic load forecasting of each CoS from the LTE-LSA network is used by the proposed decision algorithm to estimate the load of traffic that will be steered towards overlapping Wi-Fi networks and thus prevent future network congestions. Figure 5.4 depicts the traffic load forecasting of VoIP, Video, and HTTP in the LTE-LSA network. In this case, the average accuracy degree achieved by the CFBP prediction model is 99.547% (VoIP), 98.559% (HTTP), and 98.249% (Video), respectively.

Whenever the CFBP model carry out the traffic load forecasting, the updated data points values of the time series prediction can be used as input to the cognitive decision algorithm. This algorithm is responsible for finding the best network for vertical handover and traffic steering procedures. Thus, the cognitive decision has as first action to estimate the availability and occupation of the bandwidth for each targeted network on the basis of previous forecasting carried out by the CFBP model. The second action entails selecting the Wi-Fi network(s) which is able to guarantee the same level of QoS as that offered in the LTE-LSA network. This kind of decision is taken on the basis of the predicted availability of network resources. The main resource, in this case, is the network capacity for next 15 minutes. However, in order to guarantee the same QoS level, the proposed solution also considers the delay metric. The third action which is performed by the decision algorithm consists on the association of the CoS to the decision process.

5.2.1.3 Traffic Load Forecasting using the Regression Tree Model

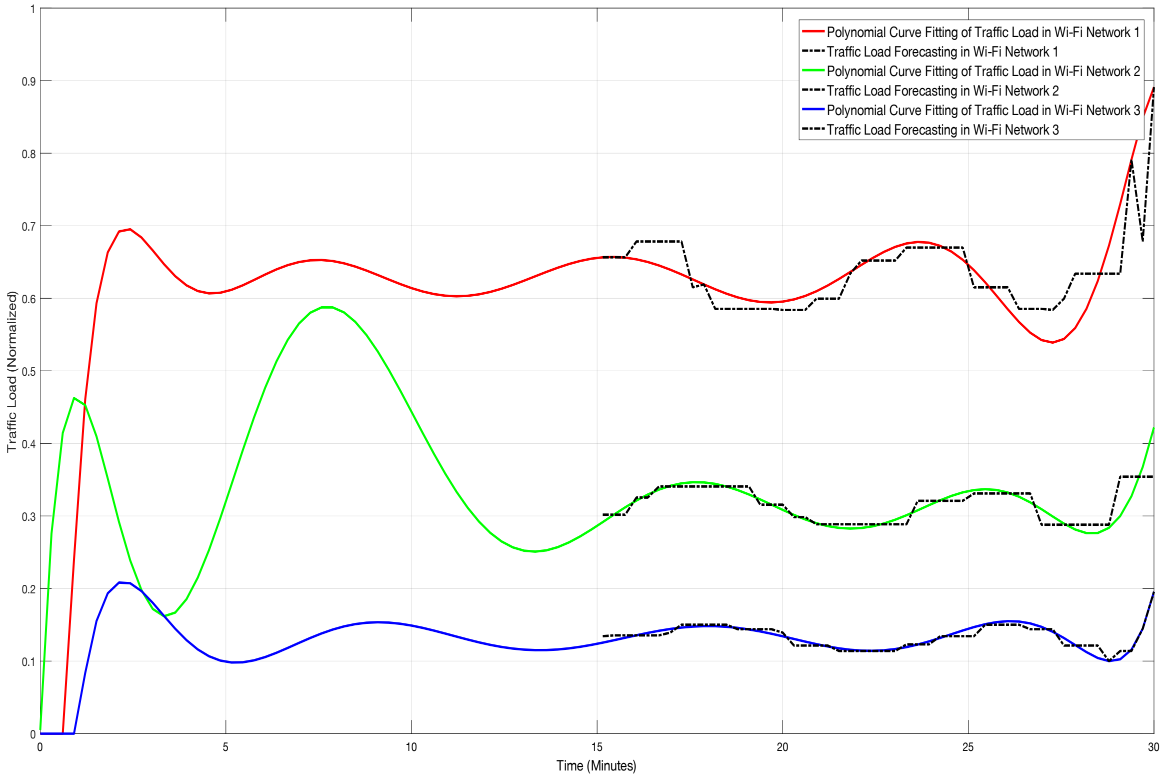
The traffic predictions carried out by the Regression Tree Model (RTM) are also evaluated through MAPE Equation (4.4) to calculate the prediction accuracy degree, as well as to compare the current values with the predicted by means of the cross-validation method. Figure 5.5 shows the analysis of the accuracy degree of the traffic load forecasting which examines three Wi-Fi networks as possible best target network(s) for vertical handover and traffic steering procedures. Such analysis is on the basis of the relation among the current and predicted traffic load for each network. Indeed the traffic load forecasting for Wi-Fi networks 1, 2, and 3 achieved the degree average accuracy of 96.549%, 28.305%, and 94.830%, respectively. Also, the traffic load forecasting of each CoS from the LTE-LSA network is used by the proposed decision algorithm to estimate the load of traffic that will be steered towards overlapping Wi-Fi networks and thus prevent future network congestions. The outcomes of the simulation related to this scenario are depicted in Figure 5.6 which shows the traffic load forecasting of VoIP, Video, and HTTP in the LTE-LSA network. In this case, the forecasting accuracy degree was in average around to 89.394% (VoIP), 97.025% (HTTP), and 96.064% (Video), respectively.

Whenever the RTM carry out the traffic load forecasting, the data points values of time series prediction are updated and entered as input to the cognitive decision algorithm, which is responsible for finding the best target network(s). For this, the first action taken by the cognitive decision is to estimate the availability and occupation of bandwidth for each targeted network on the basis of the previous forecasting carried out by the RTM. The second action involves selecting the Wi-Fi networks(s) which can ensure the same level of QoS as that offered in the LTE-LSA network. This kind of decision is taken on the basis of the predicted availability of network resources. The main resource, in this case, is network capacity for the short-term future. However, to ensure the same QoS level, the proposed solution also considers the delay metric. The third action performed by the decision algorithm is also related to the QoS and association of the CoS to the decision process.

5.2.1.4 Traffic Load Forecasting using the Fourier Model

The traffic predictions carried out by the Fourier Model (FM) are evaluated using the MAPE Equation (4.4) to calculated the accuracy degree, as well as to compare the current values with

Figure 5.5: Current vs. Predicted Traffic Load for each Wi-Fi Network using the Regression Tree Model

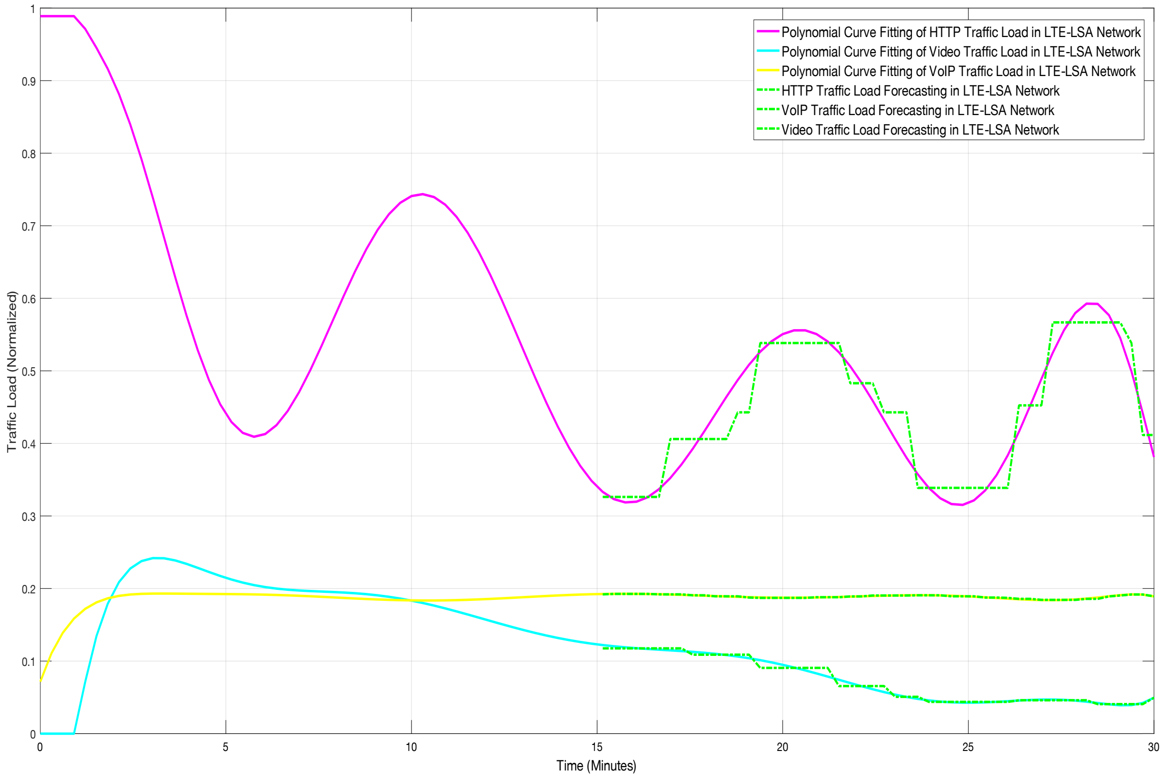


Source: by author (2017).

the predicted is used the cross-validation method. Figure 5.7 shows the analysis of the accuracy degree of the traffic load forecasting which examines three Wi-Fi networks as possible best target network(s) for vertical handover and traffic steering procedures. Such analysis is on the basis of the relation among the current and predicted traffic load for each network. In fact, the traffic load forecasting achieved an average accuracy degree of 96.327%, 94.936%, and 92.310% for Wi-Fi networks 1, 2, and 3, respectively. The traffic load forecasting of each CoS of the LTE-LSA network is used by the decision algorithm to estimate the load of traffic that will steer toward the overlapped Wi-Fi networks and thus prevent future network congestions. The outcomes of the simulation related to this scenario are depicted in Figure 5.8 which shows the traffic load forecasting of VoIP, Video, and HTTP in the LTE-LSA network. In this case, the degree of forecasting accuracy is in average to 91.015% (VoIP), 99.198% (HTTP), and 90.091% (Video), respectively.

Whenever the FM carry out the traffic load forecasting, the updated data points values of the time series prediction can be used as input to the cognitive decision algorithm, which is responsible to find the best target network(s). For this, the first action taken by the cognitive decision is to estimate the availability and occupation of bandwidth for each targeted network on the basis of previous forecasting carried out by the FM. The second action entails selecting the Wi-Fi network(s) which can guarantee the same level of QoS as that offered in the LTE-LSA network.

Figure 5.6: Current vs. Predicted Traffic Load for each CoS in the LTE-LSA Network using the Regression Tree Model



Source: by author (2017).

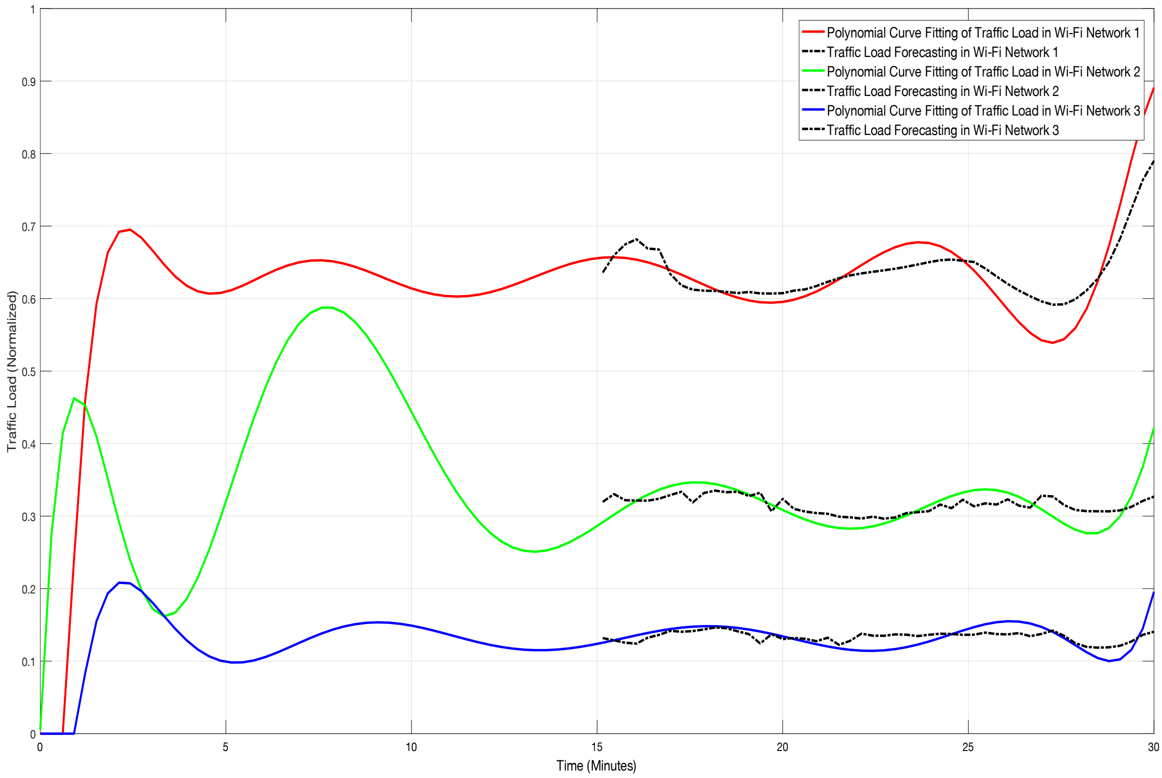
This kind of decision is taken on the basis of the predicted availability of network resources. In this case, the main resource is the network capacity in the short-term future. However, to guarantee the same QoS level, the proposed solution also considers the delay metric. The third action performed by the decision algorithm is also related to the QoS and association of the CoS to the decision process.

5.2.1.5 Comparison Table of Performance Metrics for each Traffic Load Forecasting Model

The evaluation of traffic load forecasting performance in time and accuracy metrics are fundamental for the proposed solution. The comparison models addressed make use of the same input parameters based on the polynomial curve fitting values of the traffic of each network of the scenario. In this sense, after applying each of the models for the traffic load forecasting, we present at following the results of performance metrics *i.e.,* time and accuracy for each network.

According to Table 5.5, the RTM depicted to be faster than others models to predict the future 15 minutes of traffic load for the Wi-Fi 1 and 2. However, the MLR is the fastest model to predict the next 15 minutes of traffic load for Wi-Fi 3. In the case of Table 5.5, the results obtained represent the average time for each model that carry out the prediction of aggregate traffic load for each Wi-Fi network. Furthermore, the Table 5.6 contains the output of the mean

Figure 5.7: Current vs. Predicted Traffic Load for each Wi-Fi Network using the Fourier Model



Source: by author (2017).

absolute percentage error for each Wi-Fi network, through these results can be estimated the accuracy rate of the prediction.

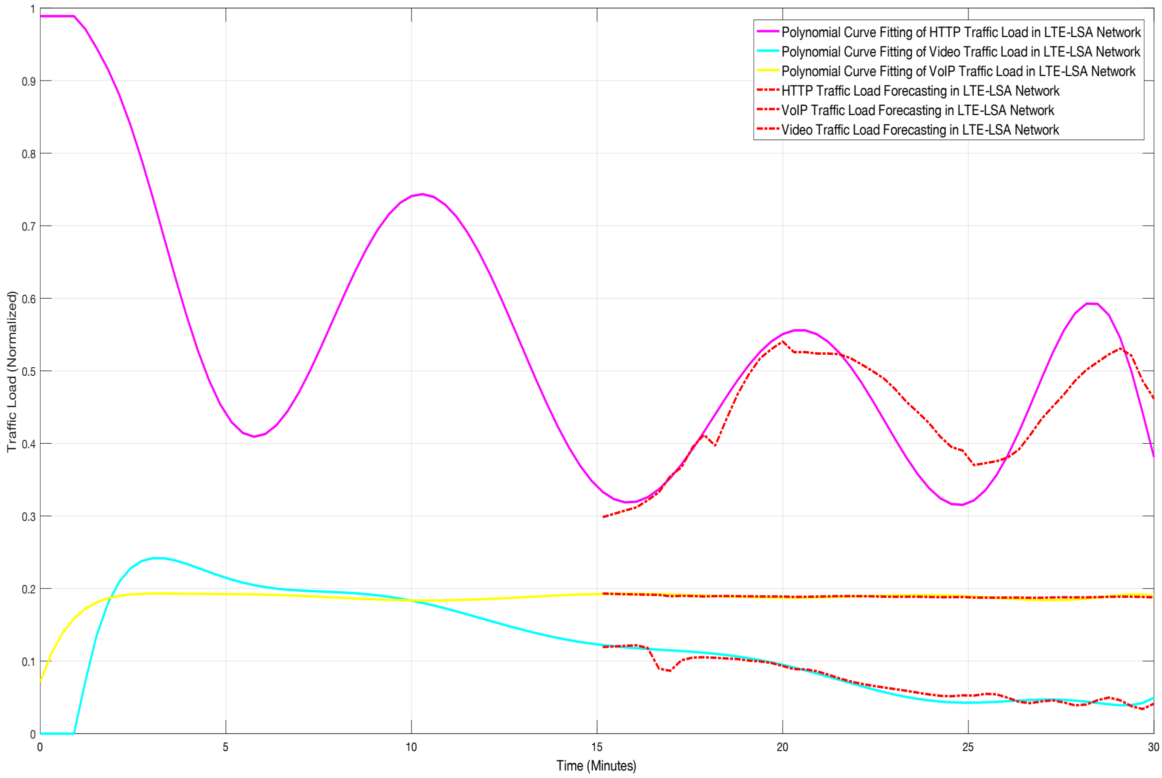
Table 5.5: Average Time for Traffic Load Forecasting in Wi-Fi Networks

Forecasting Model	**Wi-Fi Network 1 [s]**	**Wi-Fi Network 2 [s]**	**Wi-Fi Network 3 [s]**
Multiple Linear Regression	6.525	0.072449	0.04258
Neural Network	12.289	383.088	5.564
Regression Tree	0.024	0.02478	0.106
Fourier	4.909	0.696	0.733737

Source: by author (2017).

According to Table 5.6, the NNM demonstrated to has the lowest MAPE and thus the most accurated prediction model for the aggregate traffic load of each Wi-Fi network in the proposed scenario. In addition, the MLR and FM models can be considered for traffic load forecasting in

Figure 5.8: Current vs. Predicted Traffic Load for each CoS in the LTE-LSA Network using the Fourier Model



Source: by author (2017).

Wi-Fi networks due to the MAPE outputs are very closed to the NNM.

Table 5.6: Mean Absolute Percentage Error of Wi-Fi Traffic Load Forecasting Models

Forecasting Model	**Wi-Fi Network 1 [%]**	**Wi-Fi Network 2 [%]**	**Wi-Fi Network 3 [%]**
Multiple Linear Regression	3.821%	6.393%	5.803%
Neural Network	3.273%	4.076%	1.367%
Regression Tree	3.451%	71.695%	5.170%
Fourier	3.673%	5.064%	7.690%

Source: by author (2017).

According to Table 5.7, the MLR model has the fastest average time for traffic load forecasting for each CoS in the LTE-LSA network. Despite this, the FM is almost faster than the MLR model. Accordingly, the FM can be considered as a second model with better time performance to predict the traffic load of each CoS in the LTE-LSA network.

Table 5.7: Average Time for Traffic Load Forecasting for Each CoS in the LTE-LSA Network

Forecasting Model	HTTP [s]	VoIP [s]	Video [s]
Multiple Linear Regression	0.0118	0.0156	0.0170
Neural Network	12.289	383.088	5.564
Regression Tree	7.6403	211.350	82.013
Fourier	0.7579	0.18967	0.1223

Source: by author (2017).

Table 5.8: Mean Absolute Percentage Error of Traffic Load Forecasting Models for each CoS in the LTE-LSA Network

Forecasting Model	HTTP [%]	VoIP [%]	Video [%]
Multiple Linear Regression	4.276%	1.527%	5.236%
Neural Network	0.453%	1.441%	1.751%
Regression Tree	10.606%	2.975%	3.936%
Fourier	8.985%	0.802%	9.909%

Source: by author (2017).

According to Table 5.8, the NNM demonstrated the better MAPE for each CoS in the LTE-LSA network, despite the FM just has better MAPE for HTTP prediction. In addition, for traffic load forecasting of each CoS in the LTE-LSA network can also be considered the MLR model due to it showed a stable MAPE results after these are shown by the NNM.

According the results in the above tables, can be concluded that the best traffic load forecasting model among all the tested is the MLR model because it achieves the best accuracy and fastest time in average.

5.2.2 Evaluation of the Cognitive Decision Algorithm

Whenever the traffic load forecasting is performed and the best model achieves the most accuracy and fastest prediction, the data points values are updated and entered as input to the cognitive decision algorithm. This algorithm is responsible for finding the best target network(s) to carry out the vertical handover and traffic steering procedures in unscheduled evacuations of the LSA band. The first step taken by the cognitive decision is to estimate the availability and occupation of bandwidth for each targeted network on the basis of previous traffic load forecasting models. Where the multiple linear regression model demonstrates to be the most accurate and fastest among all evaluated. The second step involves selecting the Wi-Fi network(s) which can guarantee the same level of QoS as that offered by the LTE operator. This kind of decision is made on the basis of the predicted availability of network resources. In this case, the main resource is network capacity. However, the same QoS level can only be ensured if the proposed solution is also able to include other QoS metrics, such as delay and jitter. The third step performed by the decision algorithm is also related to QoS and entails the association of the CoS with the decision-making by taking into account this information.

The analysis of the future bandwidth capacity of each overlapping Wi-Fi network is conducted by the cognitive decision algorithm by relying on the trapezoidal numerical integration to calculate the area under the curve of the best traffic load forecasting model. In this case, the area under the MLR curve is equivalent to the percentage of occupied bandwidth for each Wi-Fi network. The same process is repeated for Wi-Fi 1, 2 and 3, as well as for each CoS in the LTE-LSA network. These values are predicted as the average occupied bandwidth for the next 15 minutes and serve as inputs for the decision algorithm. In light of the evaluated network scenario and an analysis of Figure 5.1, the percentage of forecasted occupied bandwidth for Wi-Fi 1 is 63.8%, for Wi-Fi 2 is 31.6%, and for Wi-Fi 3 is 13.4%, as is outlined in Table 5.9. In light of these values, the in advance decision algorithm selects Wi-Fi network 1 as a low priority route for traffic steering because of its very high traffic load. On the other hand, the cognitive decision defines Wi-Fi networks 2 and 3, as high-priority traffic steering routes. After this initial analysis, when an evacuation is requested, the decision algorithm associates the CoS with the previously obtained information to perform the traffic offloading while taking into account of the QoS requirements of the evacuees.

Table 5.9: Average Percentage of Future Occupation and Availability of Wi-Fi Networks Bandwidth for the next 15 minutes

Network	% of Occupation	% of Availability
Wi-Fi Network 1	63.8%	36.2%
Wi-Fi Network 2	31.6%	68.4%
Wi-Fi Network 3	13.4%	86.6%

Source: by author (2017).

On the basis of each CoS load (Video, HTTP, and VoIP), the future bandwidth capacity of the LTE-LSA network, is required to provide more knowledge about what occurs in the next 15 minutes, to the cognitive decision algorithm. The trapezoidal numerical integration is carried out at this level to calculate the area under and above the curve of the MLR prediction. The area above the MLR curve is equivalent to the average percentage bandwidth availability of the LTE-LSA network for each CoS. The area under the MLR curve is equal to the average percentage bandwidth occupation of the LTE-LSA network for each CoS. With regard to Figure 5.2, the percentage of predicted bandwidth occupation of 7.14% for Wi-Fi 1, 57.5% for Wi-Fi 2 and 19.4% for Wi-Fi 3, as shown in Table 5.10. The results shows that the in advance decision algorithm has as output the HTTP traffic offloading for the target network with more available bandwidth for next 15 minutes. Furthermore the output decision of the proposed algorithm is the VoIP traffic offloading in the target network with available medium access bandwidth for the next 15 minutes. Finally, with regard to the video traffic offloading, the algorithm makes the decision for one targeted network with almost congested bandwidth for the next 15 minutes to guarantee the QoS and connectivity of the evacuated UEs.

Table 5.10: Average Percentage of Future Occupation and Availability of LTE-LSA Network Bandwidth for the next 15 minutes

Network	% of Occupation	% of Availability
LTE-LSA Network (Video)	7.14%	92.86%
LTE-LSA Network (HTTP)	57.5%	42.3%
LTE-LSA Network (VoIP)	19.4%	80.6%
Aggregate Traffic in the LTE-LSA Network	84.4%	15.6%

Source: by author (2017).

5.2.3 Evaluation of the Cognitive Vertical Handover of Evacuees

Whenever the incumbent user requests an unscheduled evacuation of the LSA band, a decision will be made in advance with the best targeted network(s) for the vertical handover of the evacuees. The first assessment of the vertical handover performance involves measuring the time needed to transfer the UE from the LTE-LSA network to the Wi-Fi networks. The second stage is to evaluate the QoS of UEs in targeted network(s) after these have been evacuated, by measuring the delay, traffic load and bandwidth status of networks with the additional traffic of the LTE-LSA network.

When carrying out an unscheduled evacuation of the LSA band, it is necessary to make decisions in advance with a predictive QoS guarantee. In this sense, the vertical handover procedure carried out under the decisions in advance from the proposed cognitive mechanism is denominated Cognitive Vertical Handover (C-VHO). The C-VHO with the above characteristics, takes 3.55 milliseconds to calculate the best Wi-Fi networks for each evacuee depending on its CoS traffic. For this reason, the result of the cognitive decision is the same for both procedures *i.e.,* vertical handover and traffic steering, because they are based on the CoS traffic. Specifically, the sum of each CoS of the LTE-LSA and the aggregate traffic of each Wi-Fi is regarded by the C-VHO to transfer the UEs according to their CoS and QoS requirements. The results demonstrated that Wi-Fi network 1 was rejected in advance so that additional traffic and connections of the evacuated UEs could not be received for the next 15 minutes because of traffic congestion on it. Otherwise, the in advance decision selects the Wi-Fi network 2 to carry out the C-VHO to transfer the video and VoIP traffic load from the LTE-LSA network. Furthermore the decision algorithm selects the Wi-Fi network 3 as the best for evacuated UEs with HTTP traffic from the LTE-LSA network. This is owing to the high traffic load predicted for HTTP CoS, and the low traffic load predicted for the Wi-Fi network 3. On the basis of previous predictions, the proposed decision algorithm carries out the C-VHO of evacuees with HTTP traffic towards the Wi-Fi network 3.

The traffic steering works hand-in-hand with mobility management indeed, to ensure a reasonable number of handovers and avoid disconnections. This means that, the C-VHO decision-making is closely related to that of the traffic steering because both have the same target network(s) for transferring evacuated UEs and their traffic according to the CoS. Thus, Figures 5.10 and 5.11 illustrate the results after the evacuees have been connected to the target network(s) selected previously by the proposal cognitive decision algorithm. In the case of C-VHO, the time to carry out the handover for all the evacuated UEs from the LTE-LSA network toward each Wi-Fi, is previously selected in accordance with their CoS. Table 5.11 describes the time taken by the C-VHO for the handover of the UEs with HTTP traffic towards the Wi-Fi network 3, and to transfer the UE with VoIP and video traffic toward the Wi-Fi network 2.

Table 5.11: Average Time for the C-VHO of UE from the LTE-LSA Network

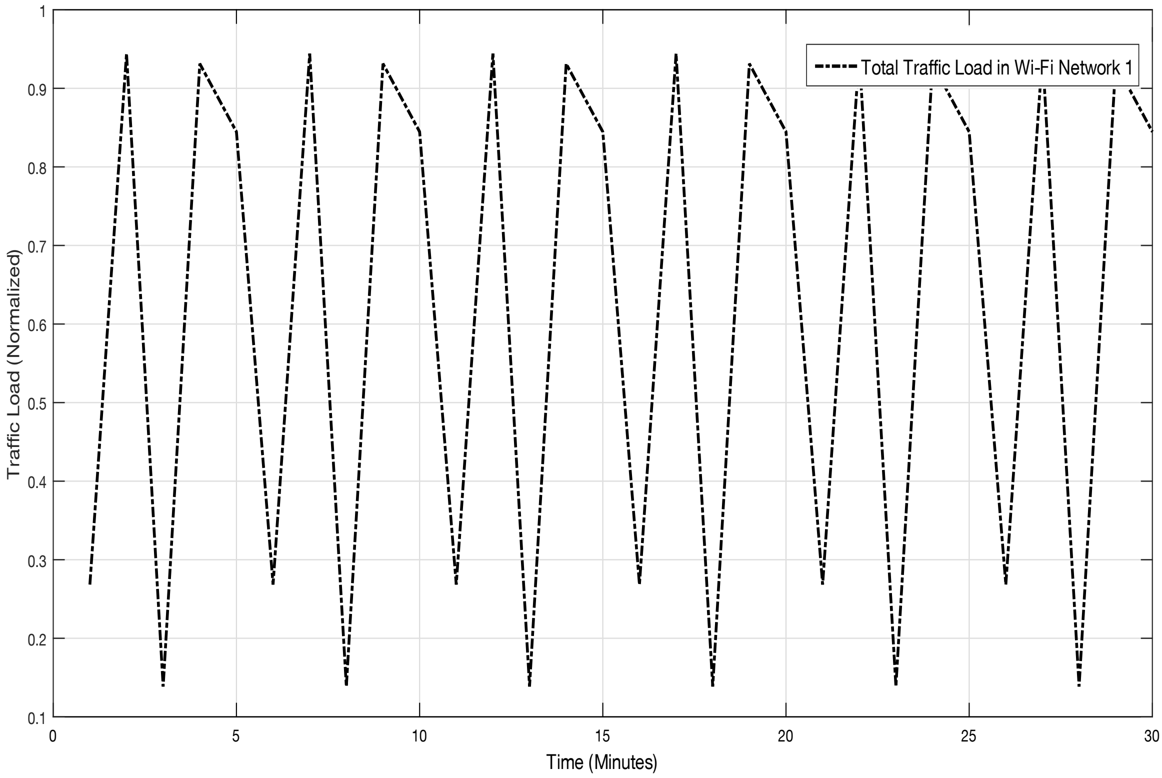
Process	**UEs w/ HTTP [s]**	**UEs w/ VoIP [s]**	**UEs w/ Video [s]**
C-VHO	0.012	0.016	0.018

Source: by author (2017).

5.2.4 Evaluation of Cognitive Traffic Steering of CoS

Whenever the incumbent user requests an unscheduled evacuation of the LSA band, a decision will be made in advance with the best target network(s) for traffic steering. The first assessment of the traffic steering performance involves measuring the time needed to offload the traffic of the UE from LTE-LSA network toward Wi-Fi networks. The second stage involves evaluating the QoS of the evacuated UE by measuring the traffic load and bandwidth status of the network with the additional traffic of the LTE-LSA network.

Figure 5.9: No Additional Traffic Steering from LTE-LSA to Wi-Fi 1



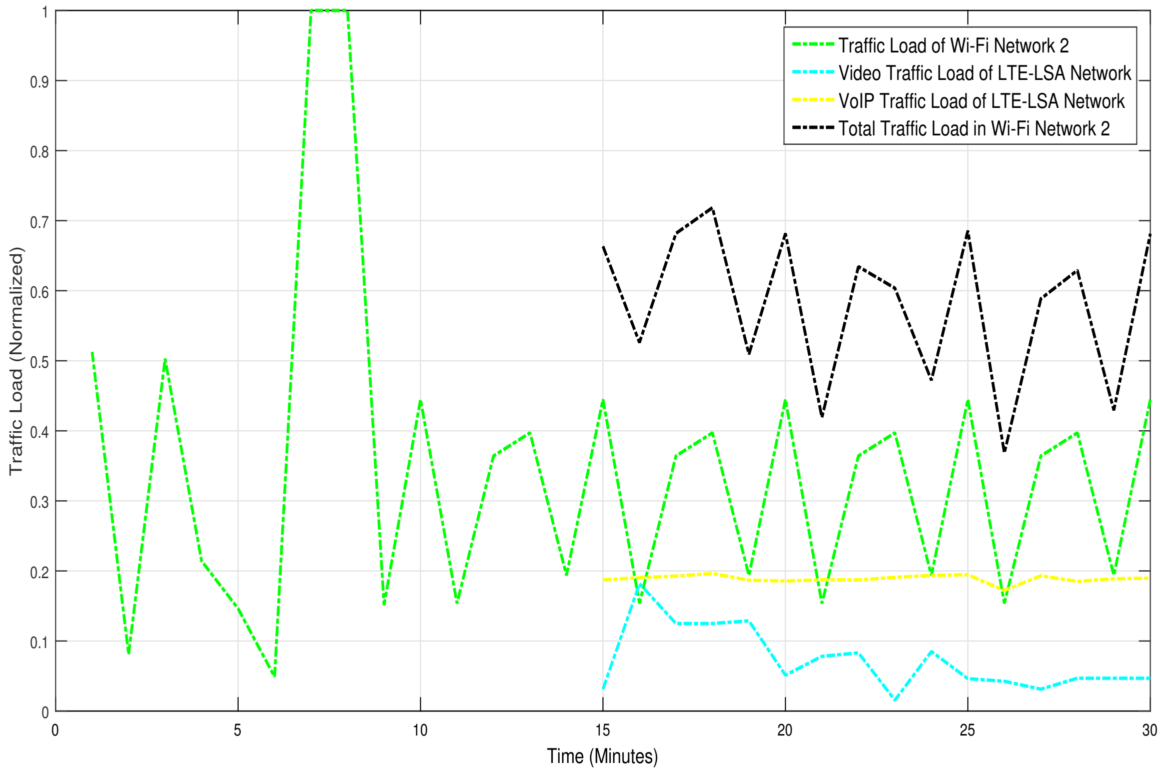
Source: by author (2017).

Figures 5.9, 5.10, and 5.11 show the occupation and capacity of Wi-Fi networks 1, 2 and 3, respectively, after the traffic steering, and this allows an analysis to be conducted over the QoS of the evacuees. The results show that Wi-Fi network 1 is rejected in advance to receive additional traffic from evacuated UEs for at least the next 15 minutes since it will be highly congested. The occupation of the bandwidth in Wi-Fi network 2 is almost 40% and 60% respectively, after the offloading of video and VoIP traffic from the LTE-LSA network. The bandwidth of Wi-Fi network 3 has an occupation of 80% and an availability of almost 20% after the HTTP traffic offloading. These results show that all the traffic was accommodated in the target networks without overloading them. Thus, the QoS can be guaranteed owing to the network capacity.

Another important QoS metric is delay. Figure 5.12 shows the behavior of this metric when there are a wide range of connections received by each Wi-Fi network. As can be seen in the graph, Wi-Fi 1 has the smallest delay value because it is a low-priority traffic steering route and thus the cognitive decision algorithm does not eligible to receive traffic from delay-sensitive applications. Wi-Fi networks 2 and 3, on the other hand, receive QoS sensitive traffic and are capable of keeping the average delay below 30ms. This value is sufficient to guarantee the QoS of multimedia traffic, which generally requires the delay to be between 100 and 200 ms.

Another crucial factor that must be covered by the traffic steering algorithm is to avoid interfering with the turning off of an LTE base station with one sector, to release the LSA band, as part of an unscheduled evacuation. For this reason, the traffic steering must occur as fast

Figure 5.10: Video and VoIP Traffic Steering from LTE-LSA to Wi-Fi 2



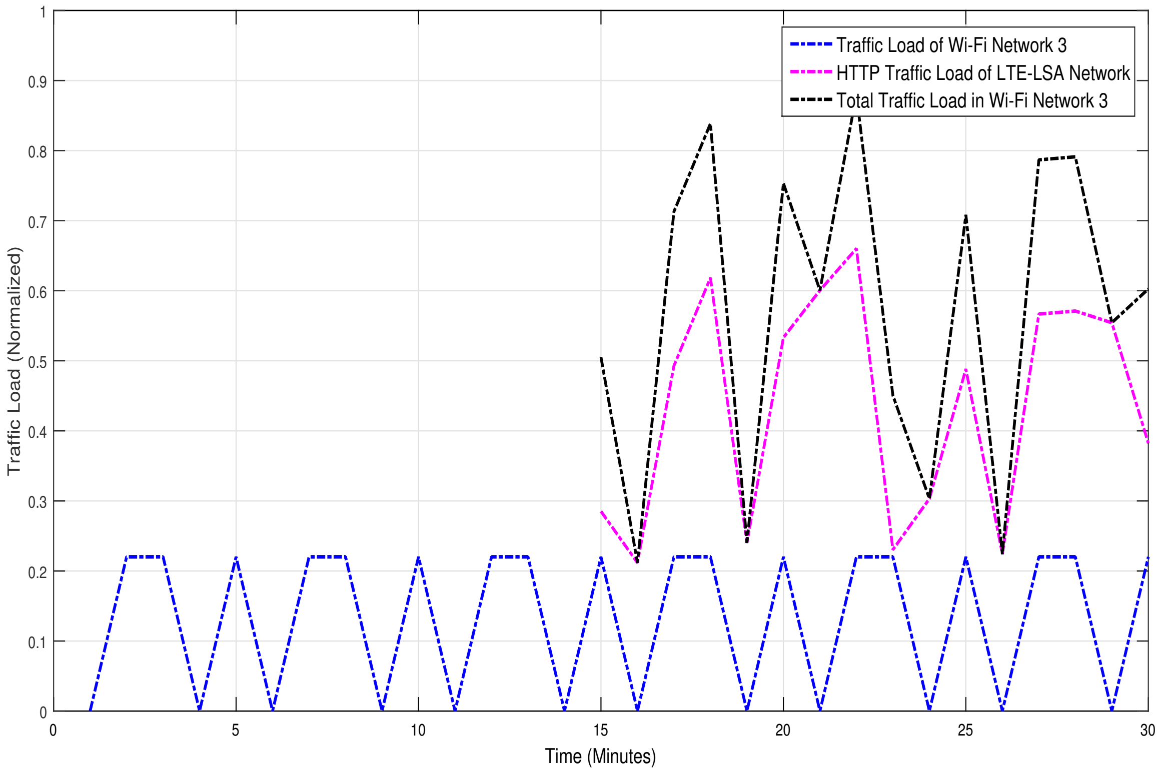
Source: by author (2017).

as possible. However, the traffic steering has been already under investigation and it is not used in the related work proposed by Martinmikko *et al.* (MATINMIKKO et al., 2013) and Palola *et al.* (PALOLA et al., 2014b). These works merely proposed the execution of handover procedures under a cognitive engine to transfer the evacuees toward the most suitable network at the moment of an evacuation. Thus, the proposed time of the traffic steering procedure is the first one in the context of simulated scenarios of the unscheduled evacuation of LSA band.

The processes related to the overall time required by the proposed solution to evacuate the LSA band and hence to offload the traffic toward Wi-Fi networks, are outlined in Table 5.12. Since the proposed approach involves making decision in advance, the duration of both the decision process and the overall evacuation can be reduced. The CEPT Report 56 (CEPT, 2015b) stated that the duration for turning off an LTE base station with one sector delay, lasts 20.620 seconds on average. This time limit constraints the ability of the traditional procedures to evacuate the UEs at a lower time to avoid interfering with the incumbent services in the LSA frequency and ensure the QoS of the evacuees. The results of the simulation show that the proposed solution allows the overall evacuation to be conducted in about 11.274 seconds, which represents a value that is around 46% below the specified limit.

Matinmikko *et al.* (MATINMIKKO et al., 2013) achieve 24.6 seconds for total cognitive cycle time as is detailed in Table 5.13. Palola *et al.* (PALOLA et al., 2014b) obtain 20.259 seconds for total handover cycle, described in Table 5.14.

Figure 5.11: HTTP Traffic Steering from LTE-LSA to Wi-Fi 3



Source: by author (2017).

Table 5.12: Duration of Evacuation

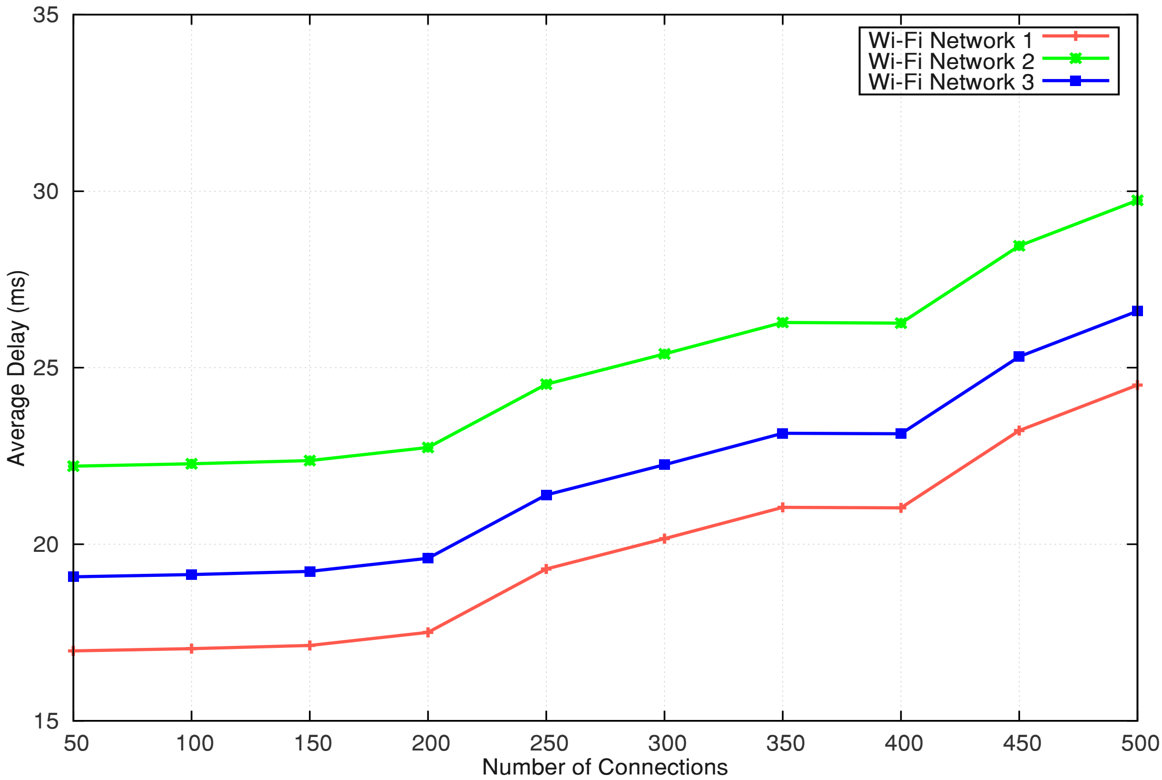
Process	**Average Duration [s]**	**Standard Deviation [s]**
Traffic Load Forecasting	3.826	0.2161
Cognitive Decision	0.037	0.0051
Vertical Handover	0.015	0.0027
Traffic Steering	7.396	0.9477
Total Duration	**11.274**	3.0167

Source: by author (2017).

Alike, the proposed solution can achieve a duration of 11.274 seconds which represents almost the half time of the related work, as outlined in Table 5.15. The advantage of shortening the decision time is to steer the traffic of the evacuated UEs quickly and before the LTE base station and sector(s) have been turned off to release the LSA band for the incumbent user who may need to operate on it in an emergency.

Indeed, the results of the proposed algorithm obtained after the 30 fold execution are faster than those found in the related work of LSA scenarios. Hence, can be inferred that the proposed

Figure 5.12: Average Delay in Wi-Fi Network



Source: by author (2017).

Table 5.13: Cognitive Cycle Timing Proposed by Matinmikko *et al.* (MATINMIKKO et al., 2013)

Process	**Average Duration [s]**	**Standard Deviation [s]**
Information delivery delay	0.5	0.2
Cognitive Engine decision delay	0.4	0.3
Total decision delay	0.9	0.3
Handover command delivery (Client 1)	6.0	4.0
Handover command delivery (Client 2)	6.0	3.8
Blocking command delivery	6.3	3.1
Blocking duration	17.4	1.7
Total cognitive cycle duration	**24.6**	3.6

Source: (MATINMIKKO et al., 2013).

Table 5.14: Cognitive Cycle Timing Proposed by Palola *et al.* (PALOLA et al., 2014b)

Handover Process	**Average Duration [s]**	**Standard Deviation [s]**
Decision delay (LSA Controller)	0.624	0.193
Handover command delivery (LSA Controller)	7.144	1.168
Handover command duration (UE)	11.086	3.850
Network info delivery (LSA Controller)	2.448	0.515
Total handover cycle (LSA Controller)	**20.259**	3.855

Source: (PALOLA et al., 2014b).

Table 5.15: Comparison between Cognitive Approaches Times

Cognitive Approaches	**Average Duration [s]**	**Standard Deviation [s]**
Total time of proposed approach	**11.274**	3.0167
Total handover cycle (PALOLA et al., 2014b)	20.259	3.855
Total cognitive cycle duration (MATINMIKKO et al., 2013)	24.6	3.6

Source: by author (2017).

decision algorithm is the fastest in the context of LSA scenarios. Furthermore, the times obtained during the simulation experiments of the vertical handover and traffic steering change in a real testbed. In this sense, it is highlighted that the comparison is unfair among the execution time of the real testbed detailed in Tables (5.13 and 5.14) and the times of the simulated scenario detailed in Table 5.12. However, the timing comparison among the decision algorithm of the proposed solution and the related work is fair and valid because these algorithms run on a similar computer.

Table 5.16 illustrates the speed of the proposed algorithm in relation with the related work, which is fundamental to deal with unscheduled evacuation scenarios of LSA band. Matinmikko *et al.* (MATINMIKKO et al., 2013) was able to perform the decision-making in approximately 0.9 seconds on average, and Palola *et al.* (PALOLA et al., 2014a) designed an algorithm which was able to carry out the decision in 0.624 seconds. Owing to the cognitive in advance decision mechanism, which is based on accurate forecasts, the proposed solution reduces the average decision time to values as low as 37.1 milliseconds. Whilst the proposed decision algorithm

Table 5.16: Comparison between Cognitive Decision Times

Cognitive Approaches	Average Duration [s]	Standard Deviation [s]
Total time of proposed decision algorithm	**0.037**	0.0051
Total time of decision proposed by (MATINMIKKO et al., 2013)	0.9	0.3
Total time of decision proposed by (PALOLA et al., 2014b)	0.624	0.193

Source: by author (2017).

runs, after of 30 executions, with an average of 0.037 seconds, becoming it in the fastest algorithm in the context of unscheduled evacuation of LSA band. Therefore, it is concluded that the proposed algorithm is the main proposal of this dissertation because it guarantees the QoS and seamless connectivity of each CoS used by the evacuated UE during and after an unscheduled evacuation of LSA band.

Other factors related to the overall time required by the proposed solution to evacuate the LSA band and hence to offload the traffic to the selected Wi-Fi network, are shown in Table 5.12. Since the proposed approach makes in advance decisions, the total duration of both the decision process and the overall evacuation process are reduced. A CEPT report (CEPT, 2015b), published in March 2015 stated that the total duration of an evacuation must not exceed 20.620 seconds to avoid interfering with the incumbent services to be placed in the LSA frequency. Simulation results show that the proposed solution allows the overall evacuation to be conducted in about 11.274 seconds, what represents a value around 46% below the specified limit. Therefore, it is possible to conclude that the proposed approach can avoid interfering with the services of the incumbent user.

5.2.5 Experiments and Discussion

In this dissertation, several issues and topics have been discussed in the light of the proposed approach and the results obtained after the performance evaluation that are based on the evaluation of the traffic load forecasting models. It is remarkable how many algorithms and models can be used for traffic load forecasting. The aim of these is to find the best time and degree of accuracy and thus enable the next steps of the cognitive decision algorithm to handle an unscheduled evacuation of the LSA band. By replacing the algorithms or models by better versions for traffic load forecasting, there can be a slight improvement in the accuracy and reduction of the time performance metrics. Despite this, the traffic load forecasting model used in this dissertation achieved the time and accuracy required to handle an unscheduled evacuation scenario and the shutdown time of the base station needed to release the LSA band.

It was also noted in the results of the experiments that traffic load forecasting can be made for longer time periods. However, this requires older historical information to train the prediction algorithm, mainly for a first stage of the forecasting. We found that the time granularity and recent traffic history have dominant impact on the prediction accuracy. That is, the finer the time granularity (15-minutes vs. 30 minutes or 1 hour intervals) and more recent the historical traffic data is, the larger their impact on the prediction error. The accuracy is reduced and time performance is longer when the traffic load forecasting extends the time of prediction. For this reason, the prediction model should carry out a new forecast for each network every 15 minutes to maintain the current forecasting configuration.

The proposed solution has the objective to guarantee the QoS and connectivity of evacuated users using the vertical handover and traffic steering procedures under cognitive criteria addressing a critical scenario. This scenario comprises a small cell with one sector that is evacuated, depending on the urgency of the incumbent user. It should be stressed that a small cell with one sector, delays turning off on average 21 seconds and thus limits the vertical handover and traffic steering procedures carried out by traditional decision-making. In addition, the scenario in question is formed of three overlapping Wi-Fi networks located in an overcrowded area, that require QoS-aware and in advance cognitive decision-making to ensure the QoS and connectivity in these networks. The LTE networks that are currently on licensed bands are not included in the scenario of this dissertation. However, in a future scenario, there will be overlapping LTE networks on licensed bands, as an alternative target network in unscheduled evacuation scenarios.

Another important factor that should be discussed is the average duration of an unscheduled evacuation, although there are no precedents for this, and the fact that this time should not exceed approximately 30 minutes. For this reason, the proposed solution seeks to guarantee the QoS and connectivity of the evacuated UEs for the next 15 minutes and after that for a further 15 minutes until the LTE-LSA network is available again to return the UEs. In addition, the service type of the incumbent user should be taken into account within the duration of an unscheduled evacuation. This led to the choice of PMSE which is the most common service in Europe and uses the spectrum band of 2.3 - 2.4 GHz. PSME provides video links through the wireless cameras from a certain broadcasting company that might be required for the LSA band in cases of emergency *e.g.* to cover a sudden news item by the reporting team and journalists. For the scenario used in this dissertation, the incumbent user is assumed to be a broadcasting provider who request in unscheduled manner the LSA band for Video Services Ancillary to Broadcasting/Services Ancillary to Programme making (SAB/SAP). It is considered in specific the case of the traditional usage scenario where a camera crew goes a new spot with wireless camera equipment for live broadcasting. This means that the proposed solution aims to avoid interference with the PMSE services through the rapid release of the LSA band, as well as to guarantee the QoS and connectivity of UEs as long as any kind evacuation (both scheduled and unscheduled) may be occurring.

This dissertation can be applied to LTE-LSA network with one or more base stations with one or more sectors, Wi-Fi networks with an access point or small cell, among another kind of network operators. However, these networks require having similar modulation and channel bandwidth characteristics to support the replication of the traffic load forecasting per CoS of the evacuated LTE-LSA network into the Wi-Fi networks. In this sense, we considered three overlapping Wi-Fi networks under the standard 802.11AC to support the traffic steered from the LTE-LSA network. In fact, the proposed cognitive mechanism was designed to support more networks from different operators to achieve a resource spectrum sharing in an opportunistic manner. Despite as more cell sectors and evacuated users have the LTE-LSA network, the proposed solution will need more time to handover the evacuees toward the best target networks while the base station or sectors on LSA band are turning off. Even thus, the proposed in advance cognitive algorithm is envisioned to carry out the evacuation of a high number of evacuated users from the LTE-LSA network toward the best target networks of different operators in the time required, *i.e.,* before the cell sectors turned off the air interfaces (CEPT, 2015b).

Previous studies and trials in Finland have already established the technological feasibility of LSA (PALOLA et al., 2014b). These studies have provided valuable knowledge for the regulatory body (CEPT) in defining the LSA recommendations. They have involved technical trials which have raised justifiable hopes among the scientific community about the deployment of dynamic spectrum access networks. In Europe, Finland is leading the research on the standardization of LSA (ETSI). In the United States, the Federal Communications Commission (FCC) is responsible for the Spectrum Access System (SAS) based on LSA technology (COMMISSION et al., 2014). In the case of Brazil, the LSA spectrum-sharing model can be exported as means of increasing the bandwidth capacity of MNOs in overcrowded areas.

In Brazil, a recent public consultation report issued by the Brazilian Ministry of Communications (MiniCom) about the review of the telecommunication services model in Brazil, made some recommendations about the efficient use of electromagnetic spectrum by means of the LSA technology. The report released by Agência Nacional de Telecomunicações (ANATEL) and MiniCom group, examined several measures that could be adopted to increase spectrum efficiency, including an LSA spectrum-sharing regime (MARTINHãO et al., 2016). Furthermore, ANATEL announced that there would be a public consultation about the clearance of the 2.3 – 2.4 GHz band by the incumbents (PMSE) which could be used by MNOs. Other bands identified by the ITU for IMT services, (standardized for LTE by 3GPP, and not used in Brazil for IMT services) are 3.4 - 3.6 GHz and 3.6 - 3.8 GHz. Contacts with ANATEL are expected to provide access to the real spectrum opportunities for LSA paradigm in these bands (QUALCOMM, 2015). As a result, there are plans for proposed solution in this dissertation to be used in a future testbed developed in Brazil or the current LSA testbeds from Europe or United States. Thus, the proposed cognitive mechanism aims to provide an enhancement in the network management procedures for MNOs so that they can evacuate their customers in a very short time during unscheduled scenarios, by ensuring a suitable QoS level and seamless connectivity of evacuees continuously.

To conclude, the proposed algorithm demonstrates to find the best target networks on the basis of traffic load forecasting and in advance decision. This kind of decision enables also in advance association of each available overlapping Wi-Fi networks with the UEs depending of their CoS to carry out the vertical handover and traffic steering procedures. Moreover, through the application of the proposed cognitive mechanism, other LTE/LTE-A procedures such as load balancing, cell-reselection, carrier aggregation, self-configuration, and dual connectivity procedures can be carry out. In fact, the proposed solution ensures the load balancing is embedded in the traffic steering procedure which carries out the traffic offloading per CoS from the LTE-LSA network toward each Wi-Fi network, and is thus able to avoid future traffic congestion. In this dissertation is demonstrated that the vertical handover and traffic steering procedures can guarantee a suitable QoS level and seamless connectivity of users for the next 15 minutes by means of the in advance decisions of the proposed cognitive mechanism. Likewise, we envision that above LTE/LTE-A through the use of the proposed solution can also guarantee the QoS and seamless connectivity of evacuees in long-term to handle scheduled and unscheduled evacuation scenarios.

6 CONCLUDING REMARKS

This dissertation has proposed a QoS-aware cognitive algorithm that is designed to make in advance decisions in the context of the unscheduled evacuation of LSA bands. This algorithm makes decisions in advance to find the best target network(s) based on the traffic load forecasting of target networks to evacuate all the customers in connected mode and with active traffic per class of service. On the basis of these decisions, the vertical handover and traffic steering procedures can be carried out for the best target network(s), which are selected in advance and undertaken immediately to avoid interference between the licensee and incumbent services. As well as, the proposed algorithm finds the target networks to transfer there immediately the evacuated customers and creates a list of candidate traffic steering routes taking into account the class of service and QoS requirements of evacuees. This kind of in advance decision-making allows a very fast evacuation. The results show that the decision algorithm is faster than those in two related works and that the overall time consumed during the evacuation process is 46% faster than the maximum time allowed to avoid interfering with the incumbent user. Moreover, the outcomes of the simulations show that the proposed solution is able to guarantee QoS by including metrics such as throughput and delay. It is concluded that the vertical handover and traffic steering procedures executed under a cognitive mechanism based mainly in make decision in advance guarantee the QoS and seamless connectivity of customers during and after an unscheduled evacuation of LSA band.

6.1 Summary of Contributions

In this work, a cognitive mechanism was proposed to perform the vertical handover and traffic steering of evacuated customers in unscheduled evacuation scenarios. The focal point of this dissertation is that it ensures the QoS and seamless connectivity of evacuated users during and after the evacuation of the LSA band. As well as this, the proposed solution avoids interference among the incumbent and licensee services. In particular, it guarantees the QoS of users according to the classes of services used just before the evacuation. As a result of the performance evaluation, the proposed solution has guaranteed *a)* QoS and seamless connectivity during and after the vertical handover and *b)* traffic steering of evacuees towards the best target Wi-Fi networks with lower traffic congestion in the short-term future.

The resource broker architecture used by the proposed cognitive mechanism is a standalone entity on top of MNO management architecture. However, the broker entity and the proposed solution are not integrated into the LSA system, or in the LSA controller, although this is a part of the MNO domain. The proposed solution can be incorporated in either the LSA controller or in the LSA management unit of the current LSA system, which can reduce even more the time to perform the vertical handover and traffic steering in unscheduled evacuation scenarios. However, integrating the proposed solution in the LSA controller or LSA management unit, requires carrying out the responsibilities of the resource broker. Among the most important of these, are the polling and reply techniques which are carried out in an authorized manner to measure the QoS metrics of the heterogeneous wireless networks. For this reason, it is worth analyzing the incorporation of all (or almost all) the functions of the resource broker within the LSA controller.

An additional issue that should be explored in deeper manner in the future work, is the time needed for the proposed solution when it is carried out in real commercial LTE base stations, core networks, and network management systems (formed of the LSA system and the resource broker entity). This raises the question of the communication delay time in the whole LTE commercial infrastructure and the time needed to confirm the release of the LSA band as well as to perform vertical handover and traffic steering in compliance with the cognitive criteria. In fact, the proposed cognitive mechanism found the best target networks to carry out the vertical handover and traffic steering in around 11.274 seconds. However, the execution time of these procedures in commercial and real environments can increase a little more in the relation of the time achieved in the Matlab simulations. This means that in future work there is a need to analyze the time performance of the proposed solution in commercial LTE base stations, core networks, and network management systems.

6.2 Final Remarks and Suggestions for Future Work

Future investigations should conduct an in-depth analysis of the performance of the proposed solution. This analysis could include the execution of the cognitive algorithm and the resource broker in realistic testbeds. For instance, the proposed solution could be tested in the Cognitive Radio Trial Environment (CORE) from VTT Technical Research Centre of Finland where the principal and first testbed of LSA technology around the world is located.

Moreover, other QoS metrics, such as jitter and packet loss could be taken into account during the decision process. Finally, the proposed algorithm can be extended so that it can be executed in scenarios with a larger number of network operators which are able to implement different technologies, leading the application of the proposed solution to more heterogeneous scenarios.

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AppendixA SUBMITTED PAPER – WCNC 2017

The paper submitted in the WCNC conference titled Cognitive Vertical Handover for LTE-LSA Networks. This research presents the cognitive vertical handover of users and traffic offloading against an unscheduled evacuation of LSA band. This mechanism is based on the machine learning algorithms to carry out the traffic load forecasting used for the cognitive decision in advance to handover the evacuated users and offload their traffic. The wireless network traffic is expected to overload the existing licensed spectrum by 2020. One solution to deal with this traffic overload is to access opportunistically in LSA and unlicensed spectrum bands. LSA allows incumbent users to temporarily provide access to its resources. However, licensees must vacate the band without causing interference, whenever the incumbent requires. Unscheduled evacuation is therefore performed by the LSA licensee. In the paper, a cognitive vertical handover was proposed to deal unscheduled evacuations in the time required to avoid interference. This solution aims at guaranteeing the QoS and seamless connectivity of evacuees by means of cognitive decisions to find the target network with least congestion in short term. A performance evaluation conducted in a scenario composed of one LTE-LSA and three IEEE 802.11ac networks, demonstrates that the proposed solution fulfills the time required by the unscheduled evacuation as well as guarantees the QoS and seamless connectivity of evacuees in long term. Results depicted the proposed solution achieves 3.64 seconds for vertical handover and traffic offloading under the cognitive mechanism based on traffic load forecasting.

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Cognitive Vertical Handover for LTE-LSA and Wi-Fi Networks

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Abstract—**The wireless network traffic is expected to overload the existing licensed spectrum by 2020. One solution to deal with this traffic overload is to access opportunistically in the shared and unlicensed spectrum bands. Licensed Shared Access (LSA) allows incumbent users to temporarily provide access to its spectrum. However, licensees must vacate the band without causing interference, whenever the incumbent requires. Unscheduled evacuation is thus performed by the LSA licensee. In this paper, a cognitive vertical handover is proposed to deal unscheduled evacuations in the time required to avoid interference. This solution aims to ensure the QoS and seamless connectivity of evacuees by cognitive decisions to find the target network with least congestion to the short term. A performance evaluation conducted in a scenario composed of one LTE-LSA and three IEEE 802.11ac networks, demonstrates that the proposed solution meets the time required by an unscheduled evacuation and guarantees the QoS and seamless connectivity of evacuees.**

I. Introduction

The traffic generated by mobile network operators is constantly growing and by 2020 it is expected to overload the existing licensed spectrum [1], leading to resource scarcity problem. Licensed Shared Access (LSA) is an emerging solution to deal with this kind of problem, due to it enables authorized spectrum sharing by allowing the incumbent user (*i.e.,* the current holder of spectrum rights) to temporarily provide access to LSA licensees (*i.e.,* temporary user of the spectrum) [2]. However, the incumbent user has the right to request the resources back at any time. Such request compels the LSA licensee to promptly evacuate the spectrum to avoid interference among mobile broadband and incumbent services.

The main motivation of this paper is to provide a solution to perform the handover in shortest possible time and ensuring the QoS of end-users during and after an unscheduled evacuation of LSA band. The proposed approach considers a Cognitive Vertical Handover (C-VHO) solution to transfer the User Equipment (UE) and offload its traffic from the LTE-LSA to a IEEE 802.11 WLAN network. Many solutions have been proposed to addressed the evacuation of LSA band [3] [4] [5] [6] [7]. These solutions are generally not concerned on the implementation of the handover procedures necessary during an unscheduled evacuation of LSA band. Consequently, the UE are simply disconnected from LTE-LSA network, before offloading the whole traffic, causing a severe QoS degradation.

Considering that current solutions of LSA literature are not concerned on executing handover due to the time required to calculate the best target network, in this paper, an extension of a multilevel resource architecture [8] [9] is proposed to perform handover based on cognitive decisions.This architecture intends to guarantee the QoS and seamless connectivity of UEs by prioritizing the traffic based on the Class of Services (CoS) such as real-time, multimedia and best effort. Unlike other solutions, the handover decision is based on forecasting of the short-term network congestion.

The proposed architecture extension obtains updated traffic information regarding to two wireless heterogeneous networks *i.e.,* LTE-LSA and WLAN (IEEE 802.11ac) controlled by the same network operator. A multilevel broker is used to obtain updated information and to implement the decision algorithm, which selects in advance the most suitable WLAN networks to implement C-VHO based on the CoS priorities.

The proposed C-VHO scenario is modeled and simulated using Matlab to assess its behavior in a wireless heterogeneous networks scenario. The scenario is formed by three WLAN and one LTE-LSA network. The C-VHO is conducted based on the traffic load forecasting of each network respectively. Then the resources availability is estimated in the short-term for each target network (WLAN). The main contribution of this paper are listed at following:

- Handover optimization in the operator network management for unscheduled evacuation of LSA band;
- Forecasting of aggregated traffic load;
- Anticipated selection and association of the best WLAN network considering the CoS of the UE which is performing C-VHO;
- Immediate traffic offloading;
- Guaranteeing the QoS and connectivity of evacuated UEs.

The remainder of this paper is organized as follows. Related work about current solutions for LSA band evacuations is presented in Section II. The system model architecture and the proposed solution is detailed in Section III. Performance evaluations are discussed in Section IV. Finally, conclusions and future work are presented in Section V.

II. Related Work

The handover scheme has been a research topic widely explored due to the importance to guarantee the QoS and seamless connectivity of UEs. Nowadays, investigations are oriented to perform handover under the cognitive decision. The cognitive decisions bring intelligence to the usage of the radio and network resources and considerably increases end users QoS [7]. However, the time required for this can be higher due to algorithm complexity, the number of metrics, and the network objectives. In the context of LSA, the forced handover is the unique solution based on a cognitive decision-making concerned to guarantee the QoS of UEs.

The Cognitive Radio Trial Environment (CORE) project from VTT in Finland develops the forced handover to guarantee the QoS of UE in the context of LSA [3] [7] [10]. The forced handover is based on the QoS measurements and UE's priority. The QOSMET tool measures the QoS metrics *e.g.,* delay, jitter, packet loss and traffic load. Further, the priority for each UE is classified in gold, silver, and bronze. Cognitive decision-making is the key functionality to perform the forced handover of UE, guaranteeing the QoS according to their priority, regardless if occurs an evacuation of LSA band. For instance, makes the offloading decision to handover UE with silver priority from LTE network to the WLAN [7]. In addition, the NEMO tool allows recording the time when forced handover is completed. However, the forced handover solution is not addressed to cope an unscheduled evacuation of LSA band. This is due to the time spent for QoS measurement, decision making and forced handover execution is more than required. According to Matinmikko et, al. [7] merely the cognitive cycle duration takes 24.6 seconds to be performed, including the handover execution time.

Currently, in the literature to optimize the use of LSA spectrum is regarded several LTE-A features. Among these, the cell re-selection, inter-frequency handover, carrier aggregation, load balancing, traffic aggregation, load balancing, self-configuration, dual connectivity can be selected for particular cases. Despite the cell re-selection, inter-frequency handover and carrier aggregation procedures are the only ones standardized by ETSI to deal with evacuations of LSA band [11] [6]. For scheduled evacuation, the MNO performs a graceful shutdown, reducing the signal power of an LTE network *i.e.,* eNB(s)/sector(s) on LSA band. As well, the Radio Access Network (RAN) of LTE-LSA network performs the inter-frequency handover to transfer the evacuated UEs from LSA band toward licensed bands. Unlike in unscheduled evacuations, the MNO responses immediately turning off the air interfaces of eNB(s)/sector(s) on LSA band [6]. Accordingly, the UE are disconnected from LTE-LSA network, causing a total QoS degradation of them. For this, the cell re-selection is the unique standardized procedure deemed to reconnect the UE by itself measuring the signal power of networks in scope.

Multilevel resource architecture was proposed by Kunst et, al. for resources allocation in wireless heterogeneous networks under control of different operators [8] [9]. This architecture obtains updated information regarding the available network resources. Further, the architecture of Broker is divided into three levels: *(i)* update, *(ii)* resources and *(iii)* decision. The former is responsible for collecting parameters from the networks which participate in the spectrum sharing initiative. The later is responsible for providing information regarding the users currently operating in the geographical area as well as about the available ranges of exclusive, shared and exclusively shared frequencies. At the third level, is processed the requests of operators for spectrum resource renting. The broker architecture demonstrates by renting and provisioning the spectrum resources to increase the frequency capacity of stakeholders. Further to show that multilevel resource architecture can be easily adapted to perform LTE-A features under cognitive criteria. In this sense, we argue that our extended architecture is also extensible to perform a cognitive vertical handover.

Among all investigated solutions in the context of LSA, the forced handover is the unique that perform cognitive decisions to guarantee the UE's QoS. Nevertheless, this solution do not regard the congestion of target networks and takes more time than 33.08 seconds to deactivate the eNB/sector on LSA band [6]. Accordingly, is required a solution that consider the future congestion of target network(s) and perform the handover before that the LTE antenna on LSA band turns off to guarantee the QoS and seamless connectivity of UE during and after an unscheduled evacuation of LSA band. Thereby, we propose a cognitive vertical handover solution as part of an adaptation of multilevel resource architecture. We leverage the architecture adaptation to control wireless heterogeneous networks *i.e.,* LTE-LSA and Wi-Fi networks. Our proposal relies on cognitive decisions in advance with machine learning algorithms for traffic load forecasting. The proposed solution is better detailed in the following section.

III. Cognitive Mechanism Architecture

The design of the proposed architecture is presented in Fig. 1. The illustration is divided in two parts which communicate through a polling and reply mechanism. In the left side, the resources users coexist in a geographical area considering a scenario that allows communication among them. In the right side of the figure, the structure of a heterogeneous network broker is represented. This broker is based on the proposal of Kunst *et al.* [8] [9] liable for coordinating resources sharing.

In the illustration, the simulated scenario is presented considering the coexistence of two kinds of networks. The first one is a LTE-LSA E-UTRAN based network operator and the second one is a cloud composed of three IEEE 802.11 WLAN networks which operate in different channels. The proposed architecture allows resources sharing in two ways, *i.e.* each network operator can dynamically assume the role of a resources provider or the role of a resources renter. In this paper, the direction of the C-VHO will always be from the LTE-LSA to the IEEE 802.11 cloud.

The broker plays the role of a centralized entity which keeps track of the network resources availability. Three levels were defined to provide independent and simultaneous control of different tasks of resources sharing management. These levels were named accordingly to the function executed by each one: (I) Traffic Analysis Level, (II) Resources Knowledge Level, and (III) Cognition Level. These levels are interconnected by Service Access Points (SAP) which implement the flow of information among the different levels of the broker.

The first level of the broker is responsible for controlling the polling mechanism used to obtain updated information on the resources conditions of the WLAN/IEEE 802.11 cloud. The received information contains a tuple composed of the WLAN

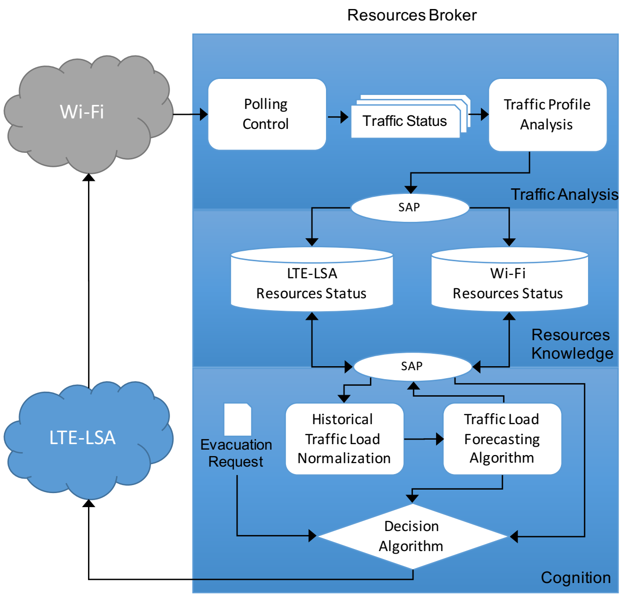

Fig. 1. Architecture Design

Operator ID, its average Delay, Jitter, and Throughput. This tuple is processed by a Traffic Status analyzer and relayed to the Traffic Profile Analysis block, which is responsible to keep track of the historical value of the QoS parameters. And then, stored it on the databases at the Resources Knowledge Level.

Databases are organized withing the Resources Knowledge, which is the second level of the Broker. This level implements two databases to store information regarding to the resources available in E-UTRAN and WLAN Access respectively. The E-UTRAN database stores the traffic information of each LTE-LSA network, *i.e.,* throughput and delay of different Class of Service (CoS). In addition, the WLAN Access database stores the traffic information of each Wi-Fi network overlapped to the LTE-LSA network converge area. This level plays a crucial role on the traffic classification to allow the unscheduled evacuation of LSA band. This feature is a requirement to implement traffic offloading from E-UTRAN to WLAN.

The Cognition Level accesses information on the second level of the Broker in order to take decisions when a handover is requested. This level is constantly running, with the goal of taking in advance decisions, which are used to promptly implement C-VHO when required. This in advance decision demands this layer to forecast the traffic of the WLAN cloud. Such forecast requires knowledge about the historical traffic load, which is stored in the WLAN Resources Status Database and is processed and normalized in the Cognition Layer and serve as a parameter to a Traffic Load Forecasting Algorithm.

The Traffic Load Forecasting algorithm takes into account previously obtained traces to describe the behavior of the IEEE 802.11 WLAN users. These traces were obtained from CRAWDAD database [12]. In order to forecast the traffic behavior, a multiple linear regression model was implemented using Matlab. This model is based on a traffic measurement Y, which is related to a single predictor X for each observation. Therefore, the conditional mean function can be described as in (1), where α is the intercept and β is the coefficient.

$$\mathrm{E}[Y \mid X] = \alpha + \beta X \tag{1}$$

Considering that multiple predictors (n) are available from the traces, in this paper, a multiple linear regression model is considered, according to (2).

$$\mathrm{E}[Y \mid X] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{2}$$

The variability of the ith measurement Y around its mean value is specified in (3).

$$\mathrm{E}[Y \mid X_i] = \alpha + \beta_1 X_{i,1} + \beta_2 X_2 + \cdots + \beta_n X_{n,i} + \epsilon_i \tag{3}$$

In this case, the error assumptions for ϵ_i is that $\mathrm{E}\,\epsilon_i = 0$ and $\mathrm{var}(\epsilon_i) = \sigma^2$. The accuracy of the forecast can be measured by the Mean Absolute Percent Error (MAPE), which is given by (4). In this equation, e_t represents the actual network occupation based on network traffic traces and y_t is the forecast occupation of each network.

$$MAPE = \frac{1}{n}\left(\sum_{t=1}^{n}\left|\frac{e_{(t)}}{y_{(t)}}\right|\right) \tag{4}$$

The resulting points compose a continuous function $f(x)$ which describes the occupied area of each IEEE 802.11. This occupied area represents to the network capacity with traffic. The Riemann sum is used to obtain an approach of the area.

In this context, let $f : D \to R$ be a function defined on a subset D of R and let $I = [a, b]$ be a close interval contained in D. In this paper this closed interval represents the start and the end time of the forecast. Finally, let $P = \{[x_0, x_1], [x_1, x_2], \cdots, [x_{n-1}, x_n]\}$ be a partition of I such as $P = \{a = x_0, x_1, \cdots, x_n = b\}$. Thus, a Riemann sum of f over I with partition P is defined in (5).

$$S = \sum_{i=1}^{n} f(x_i^*)(x_i - x_{i-1}) \tag{5}$$

When the number of points in P increase indefinitely, it is possible to obtain the definition presented in (6) to calculate the occupied area of the network capacity. This value is normalized considering the total available area to be used at the decision process. Its complement represents, therefore, the percentage of available resources of a given network.

$$A_{occupied} = \int_a^b f(x)dx = \lim_{x \to \infty} [s^*(P, f)] \tag{6}$$

The most recent calculated available area of each WLAN is converted to the unit of available capacity and serves both as a feedback to the Decision Algorithm, which is executed when a C-VHO request is received. This algorithm performs a fast response due to time restrictions imposed by an unscheduled evacuation. Therefore, the decision algorithm compares the QoS requirements and offloads the traffic to WLAN.

IV. Performance Evaluation

This Section carried out the evaluation of the Cognitive Vertical Handover (C-VHO) solution. We analyze the accuracy and efficiency of the decisions-making of C-VHO to guarantee the QoS and connectivity of UE during and after an unscheduled evacuation of LSA band. The performance evaluation of the proposed solution, is divided in the analysis of the *(i)* traffic load forecasting; *(ii)* cognitive decision; and *(iii)* cognitive vertical handover.

A. Simulation Scenario

To design and simulate the behavior of the proposed solution embedded in the HetNet Broker architecture is necessary to model suitably the traffic load of the LTE-Advanced operator on LSA band. The traffic model considers the connection arrival distribution and the traffic load per connection. We take into account [1] [11] [13], for traffic model and parameter in LTE-Advance network on LSA band. These models were used due to the high accuracy in long-term predictions about the traffic load in mobile wireless networks. Based on it, during the simulation of HTTP, Video, and VoIP traffic types for the LTE-LSA network. The values of simulation traffic parameters for each CoS are presented in the table I.

TABLE I
Simulation Traffic Parameters

Parameter	Values for LTE-LSA Network
Operating Frequency Range	$2.3 - 2.4$ GHz
Duplex Mode	Time Division Duplex (TDD)
Cell Sizes	500 to 1000 m
BS Antenna Gain	17 dBi
LTE power control parameters (for LSA)	α = 1, SINR$_{tgt}$ = 5 dB
Propagation model	ITU urban micro
Channel Bandwidth	10 MHz
LTE Frame Length	10 ms
Duration of Simulation	1800 ms
Total Number of Users	500
VoIP Traffic %	20%
Video Traffic %	20%
HTTP Traffic %	60%

For the Best Effort Services (BES), the first kind of traffic models the HTTP packets. The transmission are composed of a main page, which has a given number of embedded objects, such as images, scripts, and other sorts of attached files. After requesting and receiving the files, the browser parses the pages to make it readable to the user. Later, the users reads the pages before making a new request. For the Real-Time Services (RTS), the VoIP transmissions are modeled according to Adaptive Multi Rate (AMR) codec, which presents ON/OFF behavior. The duration of each period regards an mean exponential distribution of 1026 ms for ON period of conversations and 1171 ms for OFF period (silence). For the Multimedia Services (MS), are generated Packet Data Unit (PDU) of 42 bytes long and every 20 ms. The traffic model deemed video clips encoded with MPEG-4. Every video changes the length from 15 to 60 seconds. The display size of the video clip is 176x144, resulting on a mean frame size of 2.725 bytes after the video clip is compressed.

The simulation was performed in Matlab with above models and parameters of traffic in the LTE-LSA network. Based on these simulations was evaluated the C-VHO solution. The LTE-LSA network is composed by one TDD-LTE base station (eNB) transmitting in the band range of 2.3 to 2.4 GHz. Since the traffic models are stochastic, it is considered a confidence interval of 95% for traffic generation. The SINR parameter is fixed in 5 dB with an antenna gain of 17 dBi [11]. The frame duration is 10 ms and the transmissions are carried out in a channel bandwidth of 10 MHz. The number of connections were fixed in 300 for BES, 100 for MS and 100 for RTS during the simulation. The overall simulation duration was set in 30 minutes to also perform the traffic load forecasting.

To add Wi-Fi networks in our scenario, we make use of real traces of traffic obtained from CRAWDAD database [12]. Such traces were classified strategically to represent the traffic congestion of peak times. The congestion is an important factor to demonstrate our solution, besides being an active investigation as indicated in [3]. Thus, we leverage both the simulated traffic of LTE-LSA and traces traffic of Wi-Fi networks to perform the traffic load forecasting of each one, evaluated in the next section.

B. Traffic Load Forecasting Evaluation

In this section, we demonstrate the operation of the traffic load forecasting model for Video, VoIP, and HTTP loads in the LTE-LSA network and for the traffic of each Wi-Fi network. We evaluate the accuracy and performance of traffic load forecasting model for each network of the scenario.

The traffic load forecasting process embraces three major phases. The first phase is the time series extraction of data traffic from LTE-LSA and Wi-Fi networks. The second phase consists of the polynomial curve fitting of each traffic. In the third phase is performed the traffic load forecasting using the Multiple Linear Regression (MLR) model of machine learning as detailed in equation 2. Considering the time series is a sequence of data points, typically consisting of a successive measurements made over a time interval [14]. The data points obtained from the traffic load simulations was divided in three data sets: training, validation, and testing. The trained data set comprises the traffic load measurement corresponding to a time series of first 900 seconds. The validation data set consists of a 10 percent of testing data. This enables to compare the forecast data with the current data of simulated traffic. Further, the testing data set is used to obtain the performance features of prediction such as accuracy and time processing. Another important aspect to highlight is that the data points of traffic of each Wi-Fi network was also divided in training, validation and testing data sets. Therefore, the total time series consists of all simulated data points values for each CoS load in LTE-LSA network and the correspond traces of Wi-Fi networks.

The MLR model processes as an input the trained data set of each simulated traffic, *i.e.,* Video, VoIP, and HTTP loads of LTE-LSA network as well as the aggregate traffic of

Wi-Fi networks. The simulated traffic in LTE-LSA network and the trace in Wi-Fi has as standard time unit in seconds because the traffic load forecasting is more accurate than in minutes. Afterwards, was executed the polynomial curve fitting to smooth peaks and noise of overall traffic *i.e.,* for training, validation and testing data sets. To achieve the better curve fitting, the polynomial was fixed in 10 degree for the traffic of each network. Over the new data points obtained from polynomial of degree 10 is performed again the classification of the training, validation and testing data sets. Once to have the training data set of 10^{th} polynomial traffic, the MLR model is applied for traffic load forecasting. Then, the validation data set is used to evaluate the accuracy of the traffic load forecasting for each network. In fact, the MLR uses the cross validation to compare the forecast values with the current values and thus adjust the MLR model for the next predictions. Finally, the testing data set is used to evaluate the accuracy of the algorithm using the MAPE Equation 4.

According to the figure 2, the accuracy results performed by MAPE over traffic load forecasting were 5.485%, 14.447%, and 6.867% for Wi-Fi network 1, 2, and 3 respectively.

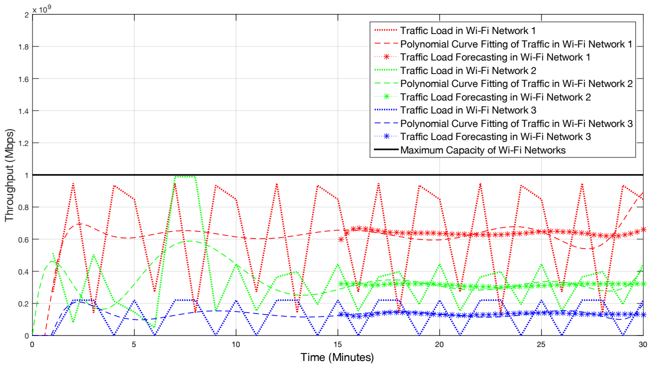

Fig. 2. Actual vs Predicted Traffic Loads for each Wi-Fi Network

According to the figure 3, the accuracy results performed by MAPE traffic load forecasting of VoIP, Video, and HTTP loads from the LTE-LSA network were 0.17%, 17.806%, and 1.571% respectively.

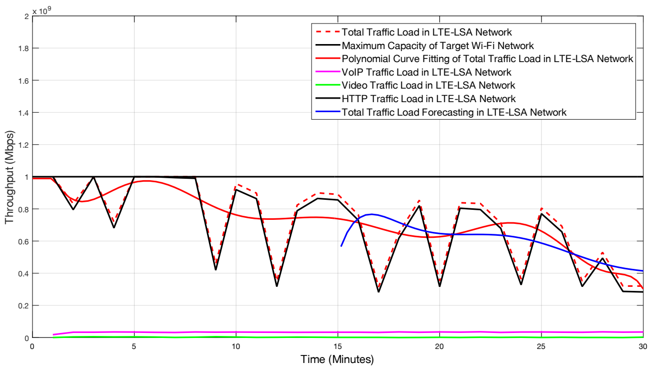

Fig. 3. Actual vs Predicted Traffic Loads for each CoS in LTE-LSA Network

The MLR model demonstrates to have better accuracy and efficiency for predictions than other models such as the neural network and least square support vector machine. Consequently, we leverage the MLR model as a bedrock of the C-VHO solution. Further, to deal with an unscheduled evacuation of the LSA band, the traffic load forecasting of 10^{th} degree polynomial has a projection for the future next 15 minutes and is performed every 15 minutes. However, the decision-making on the basis of the forecasted values enables selecting in advance the target network for handover and traffic offloading of evacuated UE in a shortest time.

C. Cognitive Decision Evaluation

Each time the traffic load forecasting is performed, the values of time series data points prediction are updated and entered as input of the cognitive decision algorithm of the C-VHO. The first action taken by the cognitive decision is to estimate the availability and occupation of bandwidth for each target network based on the previous forecasting. The second action consists in the advance selection of the best Wi-Fi network based on the occupation and availability of future bandwidth status. The third action performed by the decision algorithm associate in advance of each CoS from LTE-LSA network with the Wi-Fi networks selected as the best for the predicted time. Above steps are required for each CoS traffic that can be offloaded when occurs an unscheduled evacuation.

To estimate the future availability and occupation of bandwidth for each target network, the proposed solution considers the maximum bandwidth capacity of each Wi-Fi. The trapezoidal numerical integration is carried out by the cognitive decision algorithm to calculate the area under the curve of MLR forecast model. The area under the MLR curve is equivalent to the percentage occupation of each Wi-Fi network in the predicted time series. The cognitive decision algorithm can found the percentage of future occupation and availability of the bandwidth of the Wi-Fi 1, 2, and 3, as well as for each CoS traffic of the LTE-LSA network. This algorithm made a fictitious simulation where the predicted mean values of each CoS is added to the average traffic load expected of each target network. Thereby, the algorithm finds the best Wi-Fi network(s) in term of congestion for each CoS in the next 15 minutes even with the traffic offloaded from LTE-LSA network as soon as occurs an unscheduled evacuation.

We argue that the parameters considered in the cognitive decision algorithm to perform the vertical handover of evacuated UE and traffic offloading from the LTE network, resemble those seen in real environments. The percentage of future bandwidth occupation for Wi-Fi 1 is 63.8%, for Wi-Fi 2 is 31.6% and for Wi-Fi 3 is 13.4%. On the basis of the results, the Wi-Fi 1 will be almost congested with their own users and will not support additional traffic over the available capacity. Thus, the cognitive decision algorithm discarded in advance it for handover and traffic offloading. Also, the cognitive decision algorithm selects in advance the Wi-Fi 2 and 3 for traffic offloading. This kind of decision carry out the traffic load forecasting of each CoS in the next 15 minutes to balance the future traffic load and avoid the congestion in target networks.

D. Cognitive Vertical Handover Evaluation

It is true to address an unscheduled evacuation of the LSA band is necessary to perform the fast, accurate and efficient decision in terms of QoS. The C-VHO achieves 0.003555 of a second to calculate the best Wi-Fi networks for each CoS traffic. To evaluate the C-VHO was compared the sum traffic of validation data set of each CoS and each Wi-Fi. The results showed that Wi-Fi 1 is discarded in advance to receive additional traffic of evacuated UE at least for next 15 minutes. Unlike, the Wi-Fi 2 was selected and associated by C-VHO for traffic offloading the video and VoIP from the LTE-LSA network. In addition, the C-VHO selects the Wi-Fi 3 as the best for offload the HTTP traffic from the LTE-LSA band.

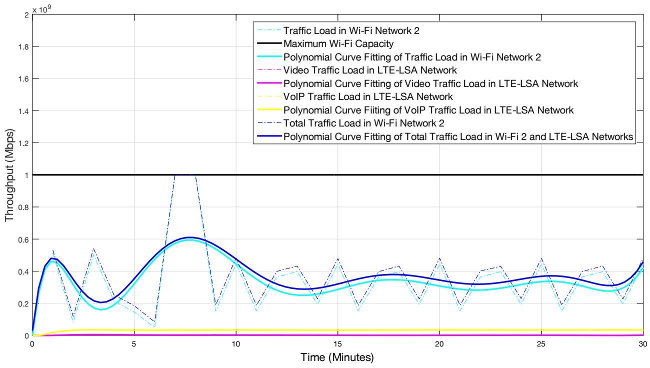

Fig. 4. Offloading of Video and VoIP Traffic in Wi-Fi 2

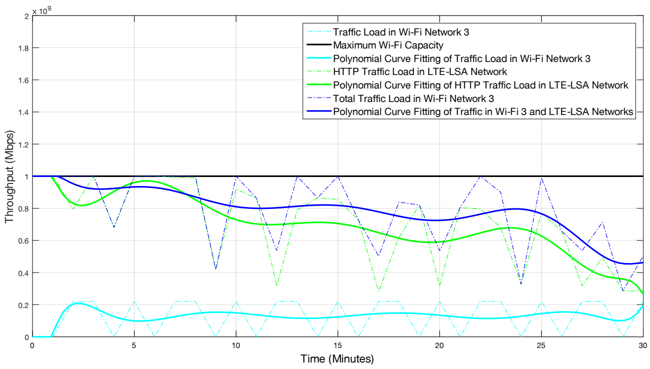

Fig. 5. Offloading of HTTP Traffic in Wi-Fi 3

According the results, the request of an unscheduled evacuation of LSA band arrives to the HetNet broker in the minute 15 of simulation. In the figures 4 and 5 are depicted the traffic sum after each CoS has been offloaded from the LTE-LSA network to the best Wi-Fi networks. The traffic offloading from the evacuated LTE-LSA network toward the selected Wi-Fi(s) by C-VHO was performed in 3.632249 seconds. This includes the offloading of the Video and VoIP traffic to Wi-Fi 2 and HTTP traffic to Wi-Fi 3. To conclude, we prove in our simulated scenario the feasibility of the C-VHO to guarantee the QoS and seamless connectivity of UE after an unscheduled evacuation of LSA band.

V. Conclusion

This paper dealt with the implementation of C-VHO in a scenario where LTE-LSA and WLAN networks coexist in the same geographical area. The results show that the implementation of a multilevel broker allows the resources sharing. Through this is possible to perform LTE-Advanced features such as the vertical handover from a cognitive criteria. Our C-VHO solution attains the handover optimization in time processing and decision to guarantee the QoS provided to the network customers. Directions for future work include the use other LTE-Advanced features to guarantee the QoS of customers in long-term by the cognitive decisions basis.

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AppendixB ACCEPTED PAPER – ICC 2017

This paper presented an improvement of solutions definition, system and results in relation to the previous article submitted on WCNC conference. This research focused on the cognitive decision in advance for traffic steering the CoS after an unscheduled scenario of LSA band. This approach was based on traffic load forecasting for each CoS from LTE-LSA network and target network(s) as Wi-Fi. The cognitive decisions are conducted by an top cellular management entity called resource broker that enable the network and spectrum sharing. Results show that the decision algorithm is faster than two related work and that the overall time consumed during the evacuation process is 46% faster than the maximum time allowed to avoid interfering with the incumbent user. Moreover, the outcomes of the simulations show that the proposed solution is able to guarantee QoS considering metrics such as throughput and delay.

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  Paris, France

A Cognitive Algorithm for Traffic Steering in LTE-LSA/Wi-Fi Resource Sharing Scenarios

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***Abstract*—The wireless network traffic is expected to overload the existing licensed spectrum by 2020. One method to deal with this traffic overload is to access unlicensed and shared spectrum bands using an opportunistic approach. Licensed Shared Access (LSA) allows incumbent users to provide temporary access to its spectrum resources. However, licensees must perform traffic steering to vacate the band without causing interference, whenever the incumbent requires. In this paper, a cognitive algorithm is proposed to take in advance decisions to promptly create a list of traffic steering routes whenever an unscheduled evacuation is demanded. This solution aims at guaranteeing the QoS and seamless connectivity during traffic steering. A performance evaluation conducted in a scenario composed of one LTE-LSA and three Wi-Fi network operators demonstrates that the proposed solution fulfills the time required by the unscheduled evacuation as well as guarantees the QoS and seamless connectivity of evacuees.**

I. Introduction

The traffic generated by mobile network operators is constantly growing and by 2020 it is expected to overload the existing licensed spectrum [1], leading to a resource scarcity problem. Licensed Shared Access (LSA) is an emerging solution to deal with this kind of problem, since it authorizes spectrum sharing by allowing the spectrum rights holder (*i.e.,* the incumbent user) to temporarily provide access to the LSA licensees [2]. However, the incumbent user is eligible to dynamically request the resources back at any time. Such request compels the LSA licensees to promptly evacuate the spectrum to avoid interfering with the incumbent services. In order to vacate the resources in a timely manner, the LSA licensees must implement fast handover strategies and consequently manage to steer the traffic of evacuees to available portions of the spectrum.

The main goal of this paper is to provide a cognitive mechanism to perform in advance decisions to allow traffic steering in unscheduled evacuation of LSA bands. Various solutions have been proposed to address this kind of evacuation ([3] [4] [5] [6] [7]). The main contribution of the proposed approach in comparison with these related works is to take decisions beforehand. In other words, the proposed approach enables the LSA licensee to create a list of potential traffic steering routes before an evacuation request is received, which considerably shortens the evacuation duration. An additional important contribution of the proposed solution is the in advance association of the Quality of Service (QoS) metrics considering different classes of service during the decision process. Thus, the traffic steering decision aims at maintaining the QoS of the evacuated users.

A novel traffic steering solution is proposed by extending an existing cognitive QoS-aware resources sharing architecture originally proposed by Kunst *et al.* ([8] [9]). The original architecture is used to gather updated information regarding resources usage of various operators in heterogeneous network scenarios. Since this architecture allows the implementation of different decision algorithms, in this paper, the original algorithm is replaced by one which is capable of taking in advance decisions. This kind of decision allows the selection of alternative routes for traffic steering in unscheduled spectrum evacuation scenarios. Specifically, a scenario composed of LTE-LSA and Wi-Fi network operators is considered to evaluate the performance of the proposed solution. Such evaluation is conducted via Matlab simulations based on an analytical system model. Results show that the proposed solution is able to allow fast spectrum evacuation and traffic steering, taking into account the QoS requirements of the evacuating users.

The main contributions of this paper are summarized as follows:

1) Proposal of a cognitive in advance decision algorithm to allow fast evacuation of LSA spectrum bands;
2) Fast traffic steering in unscheduled evacuation of LSA bands;
3) Performance and viability analysis (in terms of evacuation duration) of the proposed solution in heterogeneous network scenarios composed of LTE-LSA and Wi-Fi network operators.

The remainder of this paper is organized as follows. Current solutions for LSA spectrum evacuation are analyzed in Section II. The proposed solution is described in Section III. The performance evaluation is presented in Section IV. Finally, conclusions and directions for future work are presented in Section V.

II. Related work

Traffic steering is a current topic of research in LTE and LSA network scenarios. The goal of traffic steering is to find the most suitable evacuation route when vacating a frequency is necessary [10]. According to Mustonen *et al.* [11], the traffic steering is carried out on the basis of the capacity and load of heterogeneous networks. Nowadays, LTE features such as handover and traffic steering are oriented to be performed considering algorithms which provide cognitive decisions. This kind of decision brings intelligence to the allocation of radio and network resources, aiming at increasing the overall network QoS [7].

The cognitive engine designed by Martinmikko *et al.* [7] is the essential part of the cognitive radio trial environment to control different radio systems with the aim of guaranteeing QoS while carrying out handover and traffic offloading procedures. In fact, the cognitive engine analyzes alternative networks when high priority clients experience QoS degradation and when possible, carry out forced handover to deal with the problem. The cognitive decision making is an essential functionality to perform the forced handover of users and thus guarantee the QoS in accordance with their priority, regardless an evacuation of the LSA band takes place.

A Multilevel resource architecture was designed by Kunst *et al.* for the allocation of QoS-aware resources in heterogeneous wireless networks [8] [9]. This architecture relies on a broker which gathers together the updated information regarding the available network resources and them to be shared between the network operators.

Despite very relevant, related works are not concerned with time-sensitive traffic steering and handover procedures. Considering this limitation, in this paper is proposed a cognitive algorithm to carry out a fast traffic steering procedure. Our proposed solution takes into account both the QoS requirement of the evacuees and the time limit set by an LTE base station to release the LSA band ([6]) and thus avoid interference with the incumbent services. Details on the proposed approach are presented in next section.

III. Cognitive Traffic Steering Algorithm

An adaptation of Kunst *et al.* architecture ([9]) is presented in Fig. 1. The architecture allows communication among diverse network operators through a polling based mechanism. The left side of the figure illustrates the coexistence of LTE-LSA and Wi-Fi operators within the same geographical area. In the right side of the figure, the structure of the resources broker is represented. This Broker is responsible for coordinating resources sharing in heterogeneous networks scenarios and it is also adapted from Kunst *et al.* proposal.

The Broker plays the role of a centralized entity which keeps track of the network resources availability. Three levels are defined to provide independent and simultaneous control of different tasks of resources sharing management. These levels communicate with each other via Service Access Points (SAP) and are named accordingly to the function executed by each one: (I) Traffic Analysis Level, (II) Resources Knowledge Level, and (III) Cognition Level.

The first level of the Broker is responsible for controlling the polling mechanism used to gather updated information on the resources conditions of the Wi-Fi access cloud. The information received from each Wi-Fi operator contains a tuple composed of its identification, current average Delay, Jitter, and Throughput. This tuple is received and pre-processed by a Traffic Status analyzer and then relayed to the Traffic Profile Analysis block, which is responsible for keeping track of both current and historical values of the QoS parameters, which will feed the Resources Knowledge Level.

Databases are organized in the Resources Knowledge, which is the second level of the Broker. In the approach proposed in this paper, the Resources Knowledge level implements two databases to store information regarding the resources availability of LTE-LSA and Wi-Fi networks, respectively. This level plays a crucial role both on the traffic forecast and on the cognitive decision process which allows the unscheduled evacuation of the LSA band whenever necessary.

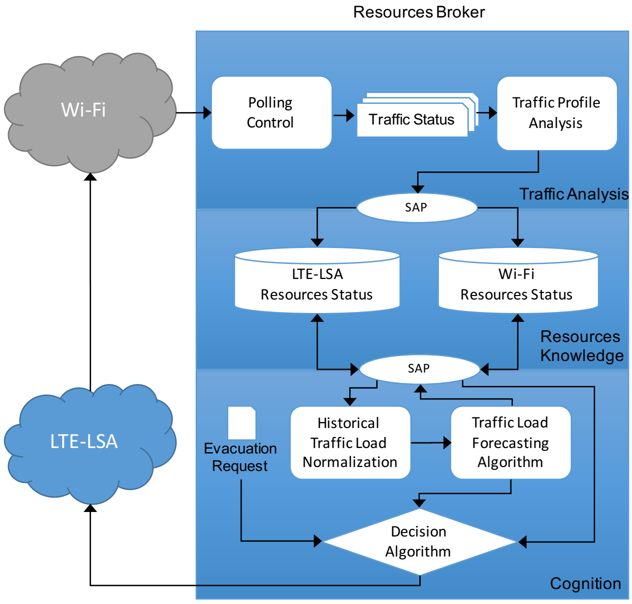

Fig. 1. Architecture Design

The Cognition Level accesses information on the second level of the Broker to take decisions when an evacuation is required. The evacuation request is composed of a struct which informs the CoS and the QoS requirements of the client. This level is constantly running, with the goal of taking in advance decisions regarding the traffic steering, which is used to promptly vacate the LSA band when required. This in advance decision demands the Cognition Level to forecast the traffic of the LTE-LSA and Wi-Fi operators in order to identify the best evacuation route. Such forecast requires knowledge about the historical traffic load, which is stored in the Resources Status Database of the LTE-LSA and Wi-Fi networks, respectively. Later, the historical traffic load is processed and normalized in the Cognition Layer. The resulting values serve as inputs to the Traffic Load Forecasting Algorithm.

In order to forecast the traffic behavior, a Multiple Linear Regression (MLR) model is implemented using Matlab. This model is based on a traffic measurement Y, which is related to a single predictor X for each observation. Therefore, the conditional mean function can be described as in (1), where α is the intercept and β is the coefficient.

$$\mathrm{E}[Y \mid X] = \alpha + \beta X \tag{1}$$

Considering that multiple predictors (n) are available from the traffic traces, in this paper, the MLR modeled according to (2).

$$\mathrm{E}[Y \mid X] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{2}$$

The variability of the ith measurement Y around its mean value is specified in (3).

$$\mathrm{E}[Y \mid X_i] = \alpha + \beta_1 X_{i,1} + \beta_2 X_2 + \cdots + \beta_n X_{n,i} + \epsilon_i \quad (3)$$

In this case, the error assumptions for ϵ_i are: $\mathrm{E}[\epsilon_i] = 0$ and $\mathrm{var}(\epsilon_i) = \sigma^2$. The accuracy of the forecast can be measured by the mean absolute percent error (η), which is given by (4). In this equation, e_t represents the actual network occupation based on network traffic traces and y_t is the forecast occupation of the same network in a given instant of time.

$$\eta = \frac{1}{n}\left(\sum_{t=1}^{n}\left|\frac{e_{(t)}}{y_{(t)}}\right|\right) \quad (4)$$

The resulting forecast points compose a continuous traffic function, $f(x)$, which describes the occupied area of each analyzed network. In this context, let $f : D \to R$ be a function defined on a subset D of R and let $I = [a, b]$ be a close interval contained in D. In this paper, this closed interval represents the start and the end time of the forecast. Finally, let $P = \{[x_0, x_1], [x_1, x_2], \cdots, [x_{n-1}, x_n]\}$ be a partition of I such as $P = \{a = x_0, x_1, \cdots, x_n = b\}$. Thus, a Riemann sum (S) of f over I with partition P is defined in (5).

$$S = \sum_{i=1}^{n} f(x_i^*)(x_i - x_{i-1}) \quad (5)$$

When the number of points in P increase indefinitely, the equation (6) calculates the occupied area of each network, which can be related to the occupied network capacity.

$$A_{occupied} = \int_a^b f(x)dx = \lim_{x\to\infty}[s^*(P, f)] \quad (6)$$

This value is normalized considering the total capacity area (A_{total}) of each network operator. Its complement therefore represents the percentage of available resources of a given network. Let $\Theta = \{o_0, o_1, \cdots, o_{n-1}, o_n\}$ be a set of network operators. Thus, the free capacity percentage of the network operators is given by (7).

$$\forall o \in \Theta, A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right) \quad (7)$$

Three CoS are defined to accommodate different types of traffic regarding the QoS requirements. (I) Real-Time Services (RTS), to support delay and jitter sensitive real-time transmissions, (II) Multimedia Services (MS), comprehending real-time services with high throughput but no strict delay and jitter, and (III) Best Effort Services (BES), designed to support best effort transmissions without strict QoS requirements. Based on the CoS requirements and on the amount of free resource of each operator calculated beforehand by the traffic forecasting algorithm, a decision algorithm is implemented, as defined in Algorithm 1.

In the proposed algorithm, the decision is based on information gathered from the Traffic Load Forecasting Algorithm. The outcomes of this algorithm are stored in the databases of the Resources Knowledge Level of the Resources Broker.

Algorithm 1 Decision Algorithm

Require: r ▷ A struct containing a cognitive evacuation request
Require: $A_{total}(o)$ ▷ The total amount of resources of each operator
Require: $A_{occupied}(o) = \int_a^b f(x)dx = \lim_{x\to\infty}[s^*(P, f)]$ ▷ The amount of occupied resources of each operator

$selected\_operator = 0$
$c \leftarrow r.CoS$; $d \leftarrow r.Delay$; $t \leftarrow r.Throughput$
switch c **do**
  case RTS:
    for all $o \in \Theta$ **do**
      $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
      $delay(o) = get\_knowledge\_level(Wi - Fi, delay)$
      if $A_{free}(o) \geq t$ & $delay(o) \leq d$ **then**
        return o
      end if
    end for
  case MS:
    for all $o \in \Theta$ **do**
      $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
      if $A_{free}(o) \geq t$ **then**
        return o
      end if
    end for
  case else:
    for all $o \in \Theta$ **do**
      $max\_operator = 0$
      $A_{free}(o) = 1 - \left(\frac{A_{occupied}(o)}{A_{total}(o)}\right)$
      if $A_{free}(o) \geq max\_operator$ **then**
        $max\_operator = A_{free}(o)$
        return $selected\_operator = o$
      end if
    end for
    return $selected\_operator$

Whenever an evacuation request is received, the decision algorithm queries the referred databases to obtain the updated forecast. This forecast is then considered along with the class of service of the request to search for a traffic steering route which is able to guarantee QoS of the evacuees.

IV. Performance Evaluation

In this section, an evaluation of the traffic steering is conducted that involves cognitive in advance decisions. This includes conducting an analysis of accurate decisions, processing time, and QoS requirements. The simulation scenario is discussed in Subsection IV-A, and the performance of the proposed solution is analyzed in Subsection IV-B with regard to three key factors: (I) traffic load forecasting, (II) cognitive decisions accuracy, and (III) cognitive traffic steering efficiency.

A. Simulation Scenario

Modeling the traffic demand of the LTE network operator is important to simulate the behavior of the proposed solution. The traffic models consider the arrival distribution and the traffic demanded per connection. This model is based on the WiMAX forum specification [12] and simulates three kinds of traffic: HTTP, Video, and VoIP. The remaining simulation parameters are summarized in Table I.

HTTP are used to model BES traffic. The transmissions comprise the main page, which has a given number of embedded objects, such as images, scripts, and other sorts of attached files. After requesting and receiving the files, the browser

TABLE I. TRAFFIC SIMULATION PARAMETERS

Parameter	Values for LTE-LSA Network
Channel Bandwidth	10 MHz
LTE Frame Length	10ms
Simulation Duration	1800s
% of HTTP Traffic	40%
% of VoIP Traffic	30%
% of Video Traffic	30%

parses the page to make it readable to the user. The user then reads the page before making a new request. The values of each phase of the HTTP statistical model are described in Table II.

TABLE II. HTTP TRAFFIC PARAMETERS

Component	Distribution	Parameters	PDF
Main Page Size	Truncated Lognormal	Mean = 10710 bytes SD = 25032 bytes Min = 100 bytes Max = 2 Mbytes	$\sigma = 1.37$ $\mu = 8.37$
Embedded Object Size	Truncated Lognormal	Mean = 7758 bytes SD = 126168 bytes Min = 50 bytes Max = 2 Mbytes	$\sigma = 2.36$ $\mu = 6.17$
Number of Embedded Objects	Truncated Pareto	Mean = 5.64 Max = 53	$\sigma = 1.1$ $\mu = 55$
Reading Time	Exponential	Mean = 30 s	$\mu = 0.033$
Parsing Time	Exponential	Mean = 0.13 s	$\mu = 7.69$

RTS are modeled to include VoIP transmissions, and Adaptive Multi-Rate (AMR) audio codec, which has ON/OFF behavior. This behavior is modeled to cover the activity of speech in conversations using this codec system. The duration of each period was modeled on the basis of an exponential distribution with an average of 1026 ms for ON period of (conversation) and 1171 ms for OFF period (silence). Finally, MS are modeled by video transmissions encoded using the MPEG-4 format.

The simulations are performed in Matlab considering the architectural model presented in Section III, the above traffic models, as well as the realistic traces obtained from CRAWDAD database to model Wi-Fi networks traffic [13]. The scenario consists of three Wi-Fi networks operating in no interfering channels and one LTE network operator using the LSA spectrum band.

B. Performance Evaluation

With regard to the performance of the proposed solution, the first factor to analyze is the accuracy of the traffic load forecasting model. The forecasting follows three key phases. The first is the time series extraction of traffic data from LTE-LSA and Wi-Fi networks. The second consists of fitting the polynomial curve of traffic data of both LTE-LSA and Wi-Fi networks. In the third phase, the forecasting is carried out by means of the MLR model as detailed in equation 2.

Considering that the time series is a sequence of data points, that generally consists of successive measurements made in a time interval [14]. These data points are divided into three data sets: training, validation, and testing. The training data set contains the traffic load measurement that corresponds to the first 15 minutes of the time series. The validation data set consists of 10 percent of the testing data set which is used to analyze the outcomes of the prediction, by taking account of metrics such as accuracy and processing time.

The MLR model processes the trained data set of simulated traffic demands for the LTE-LSA network, as well as the aggregate traffic of the Wi-Fi networks. The simulated traffic in the LTE-LSA network and the traffic traces of Wi-Fi are computed in units of seconds to improve the accuracy of the model. The first step of the analytical methodology involves calculating the polynomial curve fitting for smoothing out the peaks and noise of the network traffic. The polynomial was fixed at 10 degrees for curve fitting analysis of traffic of each network. The classification is then performed again and includes the new data points obtained from the ten degrees polynomial for the training, validation, and testing datasets. After this, the MLR model carries out the traffic load forecasting and the validation data set is used to evaluate its accuracy for each network.

The MLR accuracy is evaluated by the cross-validation method which involves the comparing the forecasted values with the current values. At this point, the MLR model can be adjusted to improve the accuracy of the upcoming predictions. The MAPE equation (4) is also used to calculate the accuracy of the MRL model. Fig. 2 shows the analysis of the accuracy of traffic load forecasting, which examines three Wi-Fi networks as possible traffic steering routes. As can be seen in the graph, the traffic load forecasting was very accurate and reached levels of 96.18%, 93.61%, and 94,20% degree of accuracy, for Wi-Fi networks 1, 2, and 3, respectively.

The traffic load forecasting is also correlated to the classes of service to analyze the QoS support feature of decision algorithm in terms of selecting the traffic steering route which presents the higher probability of preventing future network congestion. The outcomes of the simulation related to this scenario are depicted in Fig. 3 which shows the traffic load forecasting of VoIP, Video, and HTTP in the LTE-LSA network. In this case, the levels of accuracy are up to 95,72%, 98,47%, and 94,76%, respectively.

Every time the traffic load forecasting is performed, the values of the time series data points prediction are updated and input into the cognitive decision algorithm, which is responsible for selecting the traffic steering routes. The first step taken by the decision algorithm is to estimate the availability and occupation of bandwidth for each target network on the basis of the previous forecasting. The second step involves selecting the Wi-Fi networks which can guarantee the same level of QoS as that offered in LTE-LSA network. This kind of decision is made on the basis of the predicted availability of network resources. However, the same QoS level can only be ensured if the proposed solution is also able to include the delay metric. The third step performed by the decision algorithm is also related to the QoS and entails association of the CoS to the decision process.

The traffic load forecasting starts from the 15 minutes in Figs. 2 and 3 because it requires the historical traffic load measurements of the last 15 minutes to train the MLR model and predict the next 15 minutes traffic load trend with an accuracy close to 95% and to guarantee a fast response.

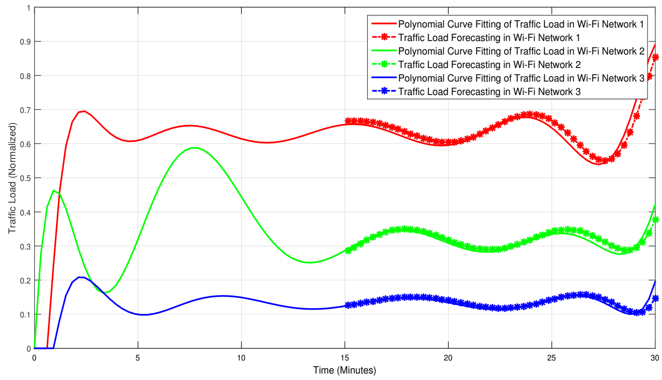

Fig. 2. Actual vs. Predicted Traffic Load for each Wi-Fi Network

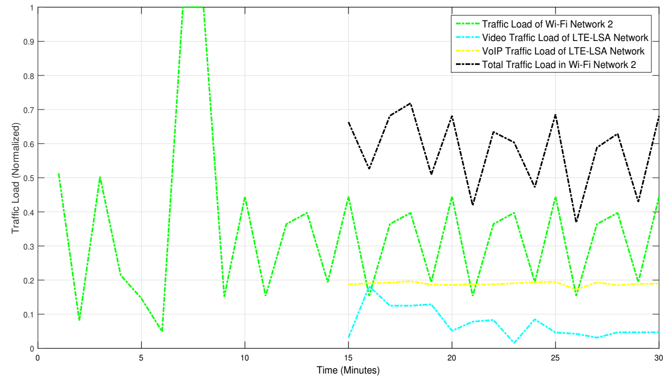

Fig. 4. Video and VoIP Traffic Steering from LTE-LSA to Wi-Fi 2

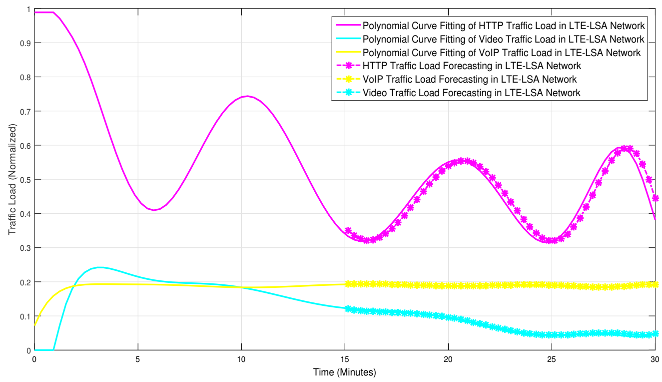

Fig. 3. Actual vs. Predicted Traffic Load for CoS in the LTE-LSA Network

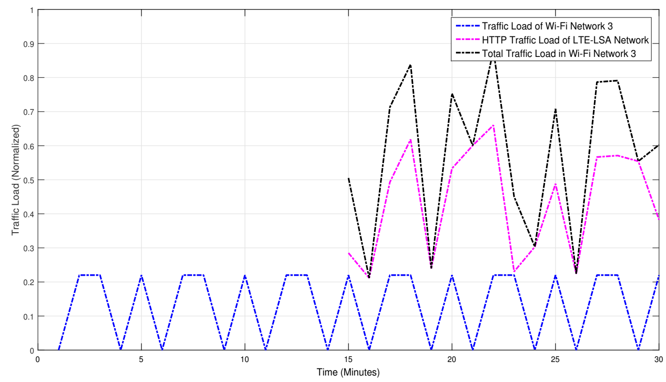

Fig. 5. HTTP Traffic Steering from LTE-LSA to Wi-Fi 3

The cognitive decision algorithm conducts the analysis of future bandwidth capacity of each overlapping Wi-Fi network by relying on the trapezoidal numerical integration to calculate the area under the curve of the MLR forecast. The area under the curve is equivalent to the percentage of occupied bandwidth resources for each Wi-Fi. As stated of the evaluated network scenario and an analysis of Fig. 2, the percentage of forecasted occupied bandwidth for Wi-Fi 1 is 65.8%, for Wi-Fi 2 is 31.6% and for Wi-Fi 3 is 15.4%. Based on these values, the in advance decision algorithm determines Wi-Fi 1 as a low priority route for traffic steering because of its very high traffic load. On the other hand, the cognitive decision defines Wi-Fi 2 and 3, as high-priority traffic steering routes. After this initial analysis, when an evacuation is required, the decision algorithm associates the class of services with the previous information to perform the traffic offloading while taking account of the QoS requirements of the evacuees.

The bandwidth occupation in Wi-Fi 1 oscillates close to 95% with its original users, making this network unavailable. Figs. 4 and 5 show the occupation of Wi-Fi 2 and 3 after the traffic steering. The bandwidth occupation in Wi-Fi 2 fluctuates between 40% and 70% after the offloading of Video and VoIP traffic demands from the LTE-LSA network, while Wi-Fi 3 network bandwidth occupation is around 80%. These results show that all the traffic was accommodated in the destination networks without overloading them. Thus, the QoS of the evacuees can be guaranteed without interfering with the original Wi-Fi users in terms of network capacity.

Another important QoS metric is the delay. Fig. 6 shows the behavior of this metric considering a variable amount of connections accommodated by each Wi-Fi network. As can be seen in the graph, Wi-Fi 1 has the smallest delay value because it is a low-priority traffic steering route and thus the cognitive decision algorithm does not make it eligible to receive traffic from delay-sensitive applications. Wi-Fi networks 2 and 3, on the other hand, receive QoS sensitive traffic and are capable of keeping the average delay below 30ms. This value is sufficient to guarantee the QoS of multimedia traffic, which generally requires the delay to be between 100 and 200 ms.

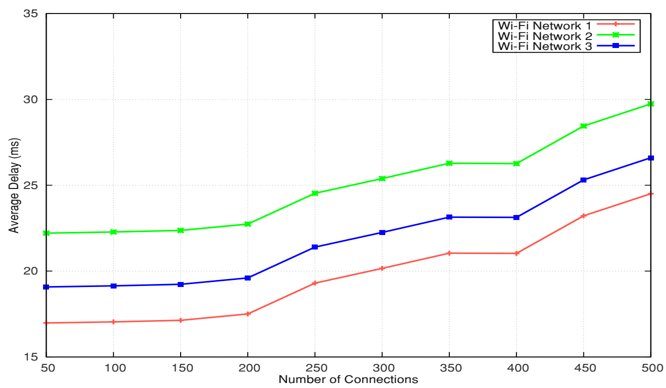

Fig. 6. Average Delay in Wi-Fi Networks

Another crucial factor that must be covered by the decision algorithm is to avoid interfering with the incumbent services in the event of an unscheduled evacuation. For this reason, the traffic steering must occur as fast as possible. The outcomes of this approach are similar to those of related work in the literature. Matinmikko *et al.* [7] was able to perform the decision in approximately 0.9 seconds on average, while Palola *et al.* [3] designed an algorithm which was able to carry out the decision in 0.624 seconds. Owing to the cognitive in advance decision mechanism, which is based on accurate forecasts, the proposed solution reduces the average decision time to values as low as 0.0371 of a second.

The processes related to the overall time required by the proposed solution to evacuate the LSA band and hence to offload the traffic to the selected Wi-Fi network, are outlined in Table III. Since the proposed approach involves making decisions in advance, the duration of both the decision process and the overall evacuation can be reduced. The CEPT Report 56 [6] stated that the duration for turning off an LTE base station with one sector delays 20.620 seconds on average. This limit of time constraints the ability of the traditional procedures to evacuate the UEs at a lower time to avoid interfering with the incumbent services in the LSA frequency and ensure the QoS of the evacuees. The results of the simulation show that the proposed solution allows the overall evacuation to be conducted in about 11.3 seconds, which represents a value that is around 46% below the specified time limit.

TABLE III. DURATION OF EVACUATION

Process	Average Duration [s]	Standard Deviation [s]
Traffic Load Forecasting	3.8267	0.2161
Cognitive Decision	0.0371	0.0051
Traffic Steering	7.3962	0.9477
Total Duration	11.2698	3.0163

V. CONCLUSIONS

This paper proposed a QoS-aware cognitive algorithm designed to take in advance decisions in the context of the unscheduled evacuation of LSA bands. This algorithm creates a list of candidate traffic steering routes taking into account the CoS and consequently the QoS requirements of the evacuating users. This kind of in advance decision allows a very fast evacuation to take place. The results show that the decision algorithm is faster than those in two related works and that the overall time consumed during the evacuation process is 46% faster than the maximum time allowed to avoid interfering with the incumbent user. Moreover, the outcomes of the simulations show that the proposed solution is able to guarantee QoS by including metrics such as throughput and delay.

Directions for future investigation include a deeper analysis of the performance of the proposed solution. This analysis can include the execution of the cognitive algorithm and the resources broker in realistic testbeds. Moreover, other QoS metrics, such as jitter and packet loss can be taken into account during the decision process. Finally, the proposed algorithm can be extended so that it can be executed in scenarios with a larger number of network operators which are able to implement different technologies, leading the application of the proposed solution to more heterogeneous scenarios.

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