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Context-aware mechanisms for device discovery optimization

Aziza Ben Mosbah

► **To cite this version:**

Aziza Ben Mosbah. Context-aware mechanisms for device discovery optimization. Networking and Internet Architecture [cs.NI]. Institut National des Télécommunications, 2017. English. NNT : 2017TELE0018 . tel-01712303

HAL Id: tel-01712303

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THÈSE DE DOCTORAT CONJOINTE avec
TÉLÉCOM SUDPARIS et l'UNIVERSITÉ PIERRE ET MARIE CURIE

Spécialité

Télécommunications

École doctorale Informatique, Télécommunications et Électronique (Paris)

Présentée par

Aziza BEN-MOSBAH

Pour obtenir le grade de

DOCTEUR de TÉLÉCOM SUDPARIS

Sujet de la thèse :

**Mécanismes Sensibles au Contexte pour l'Optimisation
de la Découverte des Appareils**

soutenue le 28 Novembre 2017

devant le jury composé de :

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*A thesis submitted in fulfillment of the requirements
for the degree of Doctor of Philosophy in Telecommunications*

Subject

Context-Aware Mechanisms for Device Discovery Optimization

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Abstract

Research in communication networks aims to improve the capabilities and performance of network technologies, and to satisfy the ever increasing demand for instant information access and exchange. For example, work on Fifth Generation (5G) Wireless Systems aims to increase data rates and spectral efficiency while lowering latency and energy consumption. Within this context, proximity-based networking is being considered in order to improve the data sharing between nearby devices, regardless of the availability of additional infrastructure. An integral component of these solutions is the ability to quickly detect (or discover) other systems in the vicinity. While system and service discovery has been a concept used in networks for some time, its adoption by wireless networks has increased the importance and relevance of this type of mechanisms. Therefore, the goal of this thesis is to optimize the performance of the discovery process by using context-aware mechanisms.

First, we start by an introductory description of the challenges faced by network users and how current solutions (i.e. Long Term Evolution (LTE)) are unable to cover their needs. Second, we present the architecture we will use to evaluate our proposals, namely the device-to-device (D2D) architecture defined by the Third-Generation Partnership Program (3GPP) for use in LTE networks, with an emphasis on the description of the discovery process as defined in the standard specifications. Then, we present an analytical study, along with an implementation model to test and validate the performance of direct discovery. Building upon that analysis, we propose an adaptive transmission algorithm that optimizes the discovery process for static topologies. This contribution is used as the foundation for extended and enhanced algorithms targeting scenarios where the availability of historic data allows for predicting user density fluctuations, and fully dynamic situations without external infrastructure or support, showing how context-aware mechanisms can provide almost optimal performance.

All these contributions and analysis are supported and validated by simulation models and experiments that showcase the importance and correctness of our proposals in the optimization of the performance and reliability in D2D direct discovery.

Key words – Fifth Generation (5G), Proximity Services (ProSe), Long Term Evolution (LTE), Device-to-Device (D2D), D2D Discovery, public safety, reliability, performance, context-awareness, optimization, wireless, communications, networks, protocols.

Résumé

La recherche dans les réseaux de communication cherche à améliorer la capacité et les performances des technologies de réseaux tout en satisfaisant à la fois la demande croissante d'instantanéité des accès et des échanges d'information. Par exemple, les travaux sur les systèmes sans-fil de cinquième génération (5G) visent à augmenter le débit de données et l'efficacité spectrale mais aussi à réduire la latence et la consommation d'énergie. Dans ce contexte, la mise en réseau basée sur la proximité est envisagée afin d'améliorer l'échange d'information entre périphériques proches, même dans le cas où aucune infrastructure n'est disponible. Une composante essentielle de ces solutions est la capacité de rapidement détecter (ou découvrir) les autres systèmes à proximité. Bien que l'utilisation de la découverte des systèmes et de services ne soit pas à proprement parler une nouveauté dans les réseaux, son adoption dans les réseaux sans-fil a augmenté l'importance et la pertinence de ce type de mécanismes. Par conséquent, l'objectif de cette thèse est d'optimiser les performances du processus de découverte en utilisant des mécanismes contextuels.

Dans un premier temps, nous commençons par une description préliminaire des défis auxquels sont confrontés les utilisateurs du réseau et comment les solutions actuelles (c'est-à-dire Long Term Evolution (LTE)) ne peuvent pas couvrir leurs besoins. Dans un deuxième temps, nous présentons l'architecture utilisée pour évaluer nos propositions: l'architecture appareil-à-appareil (D2D) qui est définie par le programme de partenariat de troisième génération (3GPP) pour être utilisée dans les réseaux LTE. Nous mettrons tout particulièrement l'accent sur la description du processus de découverte tel qu'il est défini dans les spécifications. Finalement, nous présentons une étude analytique, avec un modèle de mise en œuvre pour tester et valider les performances de la découverte directe. En utilisant cette analyse, nous proposons un algorithme de transmission adaptatif qui optimise le processus de découverte pour les topologies statiques. Cette contribution sert de base à des algorithmes étendus et améliorés ciblant premièrement des scénarios où la disponibilité de données historiques permet de prédire les fluctuations de la densité des utilisateurs, et deuxièmement des situations entièrement dynamiques sans infrastructure

ou support externe, montrant comment les mécanismes contextuels peuvent fournir des performances presque optimales.

Toutes ces contributions et ces analyses sont supportées et validées par des modèles de simulation et des expériences qui montrent l'importance et l'exactitude de nos propositions dans l'optimisation de la performance et de la fiabilité dans le cadre de la découverte directe.

Mots Clés – cinquième génération (5G), Long Term Evolution (LTE), services de proximité (ProSe), communications appareil-à-appareil (D2D), découverte des appareils, sécurité publique, fiabilité, performance, mécanismes contextuelles optimisation, sans fil, communications, réseaux, protocoles.

Thesis Publications

International Journals

- **Aziza Ben-Mosbah**, Seif Eddine Hammami, Hassine MOUNGLA, Hossam Afifi, Richard Rouil, and Ahmed E. Kamal, *Enhancing Device-to-Device Direct Discovery Based on Predicted User Density Patterns*, submitted to Computer Networks, The International Journal of Computer and Telecommunications Networking.

International Conferences

- **Aziza Ben-Mosbah**, David Griffith, and Richard Rouil, *Enhanced Transmission Algorithm for Dynamic Device-to-Device Direct Discovery*, the 15th IEEE Consumer Communications and Networking Conference (CCNC), January 2018.
- **Aziza Ben-Mosbah**, David Griffith, and Richard Rouil, *A Novel Adaptive Transmission Algorithm for Device-to-Device Direct Discovery*, the 13th International Wireless Communications and Mobile Computing Conference (IWCMC Wireless Networking Symposium), June 2017.
- Richard Rouil, Fernando J. Cintr3n, **Aziza Ben-Mosbah**, and Samantha Gamboa, *Implementation and Validation of an LTE D2D Model for ns-3*, the Workshop on ns-3 (WNS3), June 2017.
- David Griffith, **Aziza Ben-Mosbah**, and Richard Rouil, *Group Discovery Time in Device-to-Device (D2D) Proximity Services (ProSe) Networks*, the IEEE International Conference on Computer Communications (INFOCOM), May 2017.
- Richard Rouil, Fernando J. Cintr3n, **Aziza Ben-Mosbah**, and Samantha Gamboa, *An LTE Device-to-Device module for ns-3*, the Workshop on ns-3 (WNS3), June 2016.

Other Publications

- Nada Golmie, Fernando Cintrón, Wesley Garey, Camillo Gentile, David Griffith, **Aziza Ben-Mosbah**, Richard Rouil, Ahmed Soua, *Public Safety Communications: How to Maintain Connectivity and Improve Resiliency?*, Public Safety Broadband Stakeholder Meeting, June 2015.

Acknowledgements

This dissertation would not have been possible without the help of so many people in so many ways.

I would like to express my gratitude towards my thesis director Prof. Hossam Afifi for his valuable guidance and supervision.

I am deeply grateful as well to my thesis supervisor Dr. Richard A. Rouil. Without his productive dedication and support, this work would hardly have been completed.

I would like to thank the members of the dissertation jury for accepting my invitation and honoring me with their presence. I particularly thank Prof. Enrico Natalizio and Prof. Ken Chen for reviewing this dissertation and providing me with their insightful feedbacks. I also thank this work's examiners Prof. Farid Naït-Abdesselam, Prof. Abderrezak Rachedi, Prof. Lynda Mokdad, and Prof. Samia Bouzefrane for their time and flexibility.

Many thanks go to the staff of Télécom SudParis and EDITE de Paris, particularly Mrs. Xayplathi Lyfoung, Mrs. Sandra Gschweinder and Mrs. Véronique Guy for their assistance and patience concerning the administrative procedures.

My special thanks go to the head of the Wireless Networks Division, Dr. Nada T. Golmie. She put her trust in me and offered me the possibility to join the Public Safety team at NIST. She made it possible to carry out this research by putting at my disposal adequate equipment and laboratory material.

I am also indebted to all my friends and my colleagues in the Wireless Networks Division and within NIST for their unlimited support and encouragement. They made my stay in the United States very pleasant and contributed to this thesis. Their knowledge and advices are highly appreciated. In particular, I express my warmest gratitude to Dr. Antonio Izquierdo Manzanares for his continuous optimism regarding this work, enthusiasm and jokes.

Last but not least, I would like to thank my beloved parents and my dearest sisters for being always there for me and for their unlimited understanding and unconditioned love. I would like also to thank my extended family and friends for their support.



Every challenging work needs self-efforts as well as guidance of those who are very close to our hearts. I dedicate this humble work to :

Afifa Ben-Mosbah, who was a second mother for me, may Allah bestow his mercy and grace on her soul.

Moufida Demni and **Faical Ben-Mosbah**, my precious parents.

Nahla Ben-Mosbah, the cutest sister ever.

Azza Ben-Mosbah, my amazing twin sister.

the **Ben-Mosbah** and **Demni** families.

Thank you for being part of my life. You nursed me with affection and love, and inspired me to succeed and excel.



Aziza Ben-Mosbah

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List of Abbreviations

-	
2G	2th Generation of Mobile Networks
3G	3th Generation of Mobile Networks
3GPP	3rd Generation Partnership Project
4G	4th Generation of Mobile Networks
5G	5th Generation of Mobile Networks
A	
ALUID	Application Layer User ID
C	
CDMA	Code Division Multiple Access
CDR	Call Detail Record
D	
D2D	Device-To-Device
DL	DownLink
E	
EMS	Emergency Medical Services
eNB	Evolved Node B
EPC	Evolved Packet Core
EPUID	EPC ProSe User ID
E-UTRAN	Evolved UTRAN
F	
FirstNet	First Responder Network Authority
G	
GIS	Geographic Information System
GSM	Global System for Mobile Communication
H	
HPLMN	Home Public Land Mobile Network
HSS	Home Subscriber Server
HTML	HyperText Markup Language
HTTP	HyperText Transfer Protocol

I	
ID	ID entifier
IMSI	I nternational M obile S ubscriber I dentify
IoT	I nternet o f T hings
IP	I nternet P rotocol
L	
LSB	L east S ignificant B it/ B yte
LTE	L ong- T erm E volution
M	
MAC	M edia A ccess C ontrol L ayer
MCC	M obile C ountry C ode
MNC	M obile N etwork C ode
MSE	M ean S quared E rror
MIC	M essage I ntegrity C heck
MME	M obility M anagement E ntity
N	
NPSBN	N ationwide P ublic S afety B roadband N etwork
NPSTC	N ational P ublic S afety T elecommunications C ouncil
ns-3	N etwork S imulator 3
P	
PCRF	P olicy and C harging R ules F unction
PDCP	P acket D ata C onvergence P rotocol L ayer
PDN	P acket D ata N etwork
PGW	P DN G ate W ay
PHY	P hysical L ayer
PLMN	P ublic L and M obile N etwork
PRB	P hysical R esource B lock
ProSe	P roximity S ervices
PSBCH	P hysical S idelink B roadcast C hannel
PSCCH	P hysical S idelink C ontrol C hannel
PSDCH	P hysical S idelink D iscovery C hannel
PSSCH	P hysical S idelink S hared C hannel
PSTN	P ublic S witched T elephonie N etwork
Q	
QoE	Q uality o f E xperience
QoS	Q uality o f S ervice
QPSK	Q uadrature P hase S hift K eysing
R	
RB	R esource B lock

RLC	R adio L ink C ontrol L ayer
RRC	R adio R esource C ontrol L ayer
RSRP	R eference S ignal R eceived P ower
RSSI	R eceived S trength S ignal I ndicator
S	
SF	S ub F rame
SGW	S erving G ate W ay
SIB	S ystem I nformation B lock
SL-BCH	S ide L ink B roadcast C hannel
SL-DCH	S ide L ink D iscovery C hannel
SL-SCH	S ide L ink S hared C hannel
SLP	S UPL L ocation P latform
SINR	S ignal-to- I nterference-plus- N oise R atio
SNR	S ignal-to- N oise R atio
SUPL	S ecure U ser P lane L ocation
SVR	S upport V ector R egression
T	
TB	T ransport B lock
TBS	T ransport B lock S ize
TETRA	T Errestrial T Runked R ADio
U	
UE	U ser E quipment
UL	U p L ink
UMTS	U niversal M obile T elecommunications S ervice
US	U nited S tates
UTC	U niversal T ime C oordinated
UTRAN	U MTS T errestrial R adio A ccess N etwork
W	
WiFi	W ireless F idelity
WLAN	W ireless L ocal A rea N etwork

Chapter 1

Introduction

1.1 Background

In recent years, the quality, capacity, and availability of networking technologies have experienced significant progress, as research and collaboration between the scientific community and the industry has led to cheaper and more reliable interconnection mechanisms, more efficient algorithms, and a wider range of devices to deploy according to the specific needs of each situation. All this is especially true for wireless network technologies, where more efficient devices and technologies have resulted in better coverage, throughput increases from 64 kb/s in the 1990s to 1 Gb/s nowadays [1], reduced deployment and acquisition costs, and an overall better user experience.

Simultaneously, the demand for ubiquitous high speed networks has increased exponentially, as multimedia and content-rich online applications have become not only feasible, but commonplace. Similarly, the number of mobile users is growing significantly. The emergence of the Internet of Things (IoT) means that more devices are connected than ever and most of them use wireless connection. Cisco predicts there will be 50 billion devices connected by 2020 [2]. Gartner, Inc. forecasts that 20.8 billion connected things, such as light bulbs, air conditioners, tracking devices and building management systems (not including phones, computers, and tablets) will be in use worldwide by 2020 [3]. Furthermore, there is the increase of data network adoption and uses, showcased, for example, in the upsurge of social media and related applications. For example, in the United States alone, when Pew Research Center began tracking social media adoption in 2005, just 5 % of American adults used at least one of these platforms. By 2011 that

share had risen to half of all Americans. Nowadays, more than 69 % of the public uses some type of social media [4].

As [5] shows, the usage of wireless networks is shifting towards data-centric content, from a voice-centric environment in the early 2000s. This produces a significant increase of the data demand, which consequently accelerates the saturation of the available spectrum, with projections for the next 10 years showing demands that range between 2 to 6 times the available radio resources. In this environment, there is a strong need for the design and implementation of solutions that mitigate these issues, either by proposing general case tools and techniques that can be applied in any situation, or by focusing on high-priority situations that demand specific solutions.

The Third Generation Partnership Project (3GPP) introduced the Long Term Evolution (LTE) technology in its Release 8 [6], and since then, multiple improvements (such as Multiple Input, Multiple Output (MIMO) and carrier aggregation) have been added throughout the following releases [7][8].

Although LTE-Advanced is considered the most prevalent mobile broadband communication technology worldwide, on its current form, 4G is showing to be incapable of satisfying the potential user's demands [9]. Some of the prime objectives that need to be targeted are increased capacity, improved data rate, decreased latency, and better overall Quality of Service (QoS), as shown in [10]. To meet these demands, drastic improvements need to be made in cellular network architecture, thus the transition to the fifth generation (5G) of mobile communications by standardization bodies [11]. It is planned to adopt key emerging technologies that are helpful in improving the architecture and meeting the demands of users, including Device-to-Device (D2D) communications, ultra dense networks, network virtualization, and millimeter waves [10]. It is assumed that a 5G system will be able to provide a seamless experience to the network users by reaching speeds of 10 Gb/s, a round-trip latency of 1 ms and a context-awareness built-in, which differs greatly from the first stages of the 4G LTE-Advanced [12][13].

The 5G research is progressing at a rapid pace and LTE constitutes an essential piece of the 5G picture. The standardization process within 3GPP has already started. In Release 12, the work has commenced on a new emerging technology: ProSe (Proximity

services) and Device-to-device (D2D) Communications where UEs rely on their geolocations and directly communicate with each other with or without the help of the core network [14]. These continuous improvements and additions to LTE networks constitute an integral component of next generation communication networks and will be carried on to future releases [15][16].

1.2 General Challenges

Any cellular network requires to take into account certain criteria for successful communications. The design and deployment of a network consider defined capabilities and potential. Congestion, delays, and data loss are assumed in high-speed, wireless and cell-based networks (like LTE), and mechanisms to manage them are incorporated in the architecture. LTE tried to mitigate those problems, but, due to the huge increment in the number of wireless mobile devices and services, there are still some challenges that cannot be accommodated even by 4G, such as the spectrum crisis, high energy consumption, and increasing demand for high data rates and mobility required by new wireless applications [17].

The network optimization is challenging because of the dynamic nature of its usage. In this section, we present few characteristics that define a cellular network. Because most of them are related and dependent, our work will focus on the following elements:

- **Scalability:** The network should be able to handle a growing number of users and to dynamically adjust to different configurations and topologies. This is important, especially in cases of large-scale events (i.e. presidential campaign, concert, sports gathering) or emergency situations (e.g. nature disaster, terrorist attack), where the use of mobile networks displays peaks of traffic.
- **Reliability and Resiliency:** The network should be available to all users at all times. Therefore the network has to maintain connectivity, to remain operable, and even to quickly recover and adapt after potential failures (infrastructure malfunction, natural disaster, targeted threats). Redundant or backup infrastructure (base stations) and powerful equipment (user terminals) should be considered in order to ensure the continuity of the network functionality.

- **Capacity:** The nature of the new applications and services means that demand spikes shall be expected, sometimes increasing the network traffic by orders of magnitude. The network must be designed to support and handle with minimal impact the additional traffic in these situations (e.g., by signaling applications to throttle down their sending rate, or diverting traffic with less stringent requirements of delay to neighbor cells).
- **Timeliness:** The response time is important in assessing the network performance. Delays and congestions are expected in actual systems, but more and more services are being defined and deployed that have strict requirements on the timeliness of the data exchange. Therefore, network users should be able to seamlessly establish communications and exchange information, so that their operations are not affected by network latency.

Other challenges may be considered but they are not addressed by our work. Some of them are listed below:

- **Coverage:** Network deployment is expensive and operators most likely only provide cellular coverage in the populated areas. But this does not radically exclude the necessity of extending the coverage to the less dense regions. A nationwide network is required to cover the entire country (even wilderness) and to serve as many users as possible, without increasing the cost.
- **Traffic Prioritization:** Traffic with different requirements and criticality must be differentiated, tagged, and processed accordingly, to provide adequate prioritization based on the use requirements. During some situations such as emergencies, when the maximum capacity of the network is reached and more resources are required, first responders should have priority over commercial users. Preemption should be considered if needed. Even among public safety users themselves, priority levels should be allocated. This will allow a better performance.
- **Interoperability:** Different technologies have been implemented differently by operators, as upgrades are costly and time consuming. Nevertheless, networks should be interoperable and functional despite their heterogeneity. For example,

some emergencies involve different public safety agents including police officers, firefighters, paramedics, and commanders from different jurisdictions. Because sharing one single nationwide platform would allow a more coordinated and effective response, during an incident, all first responders in place should be able to exchange information and operate successfully together, regardless of the operator that provides service in their home geographical area.

- **Battery Life:** Given the new connectivity pattern, users tend to permanently use the network. Applications and services are designed to keep working on the background, which is energy-consuming. Therefore, the communication devices (phones, tablets, etc.) need to conserve battery life, which can only be achieved when the network operations are performed in efficient and less complex ways.

1.3 Thesis Motivation

In the following subsections, we present a short overview of the centralized LTE architecture that showcases the effects of the spectrum scarcity. Then, we define some simulated scenarios of different natures to highlight some detected shortcomings of the LTE network.

1.3.1 Centralized LTE Architecture

Mobile networks have evolved through a series of innovations to meet the ever-growing user demands. As mentioned in [18], wireless services started with the analog cellular networks (i.e. First Generation) introduced almost 30 years ago, and kept evolving over the years: Second Generation (2G) mobile systems were characterized by digitization and compression of speech. Third Generation (3G) cellular networks introduced a packet data core network, while the access network was shared by circuit and packet domains. Fourth Generation (4G) systems eliminated the circuit-switched domain and used a simplified access network that was designed to support only packet-switched services. It aimed to provide seamless Internet Protocol (IP) connectivity between user equipment (UE) and the packet data network (PDN), without any disruption to the end users' applications during mobility.

Fig. 1.1 represents the LTE architecture as defined by 3GPP. Its first component is the air interface between the user terminal and the evolved node B (eNB). It uses an Orthogonal Frequency-Division Multiplexing (OFDM) technique, as opposed to the Code Division Multiple Access (CDMA) used in 3G systems. The other elements of the LTE network are the radio access network (called also Evolved UMTS Terrestrial Radio Access Network, i.e. E-UTRAN), the core network (named Evolved Packet Core, i.e. EPC) which a flat all-IP system, and the service network (e.g. Internet).

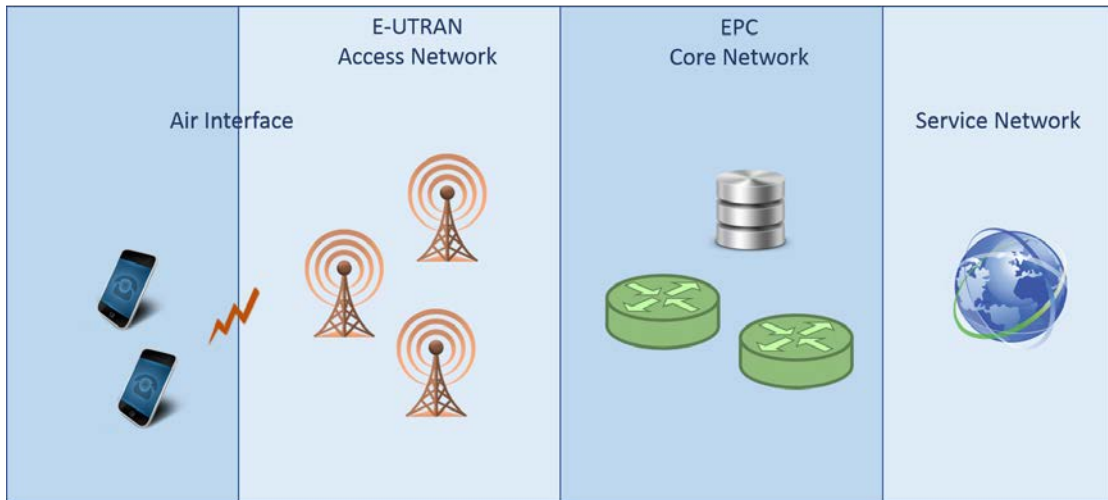


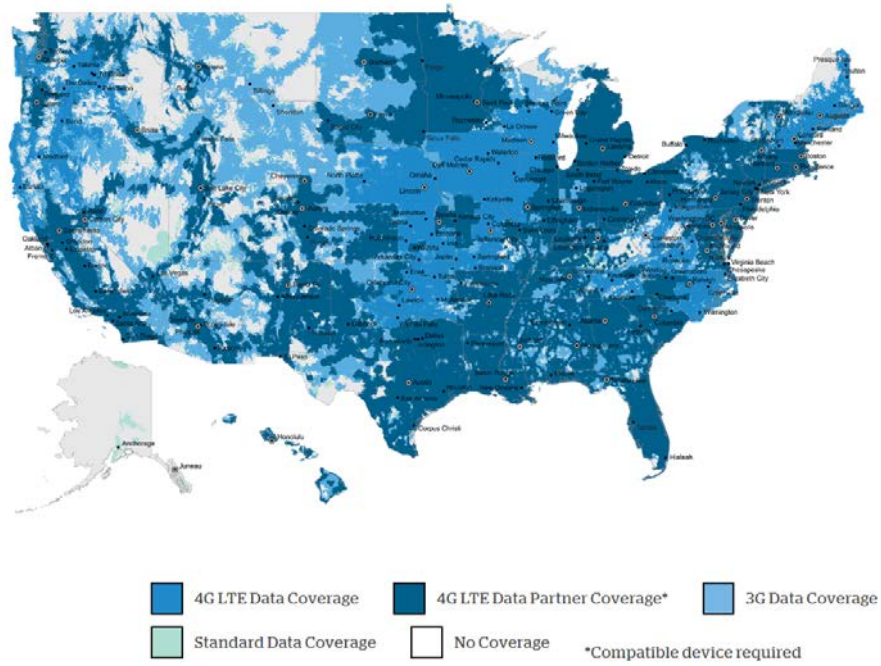
FIGURE 1.1: LTE Architecture

The E-UTRAN consists only of eNBs on the network side. It handles different features such as radio resource control (i.e. allocation, modification and release of resources for the transmission), radio mobility management (i.e. measurement processing and handover decision), detection and possibly correction of errors, modulation and de-modulation, and channel coding and de-coding. The EPC is composed of several functional entities:

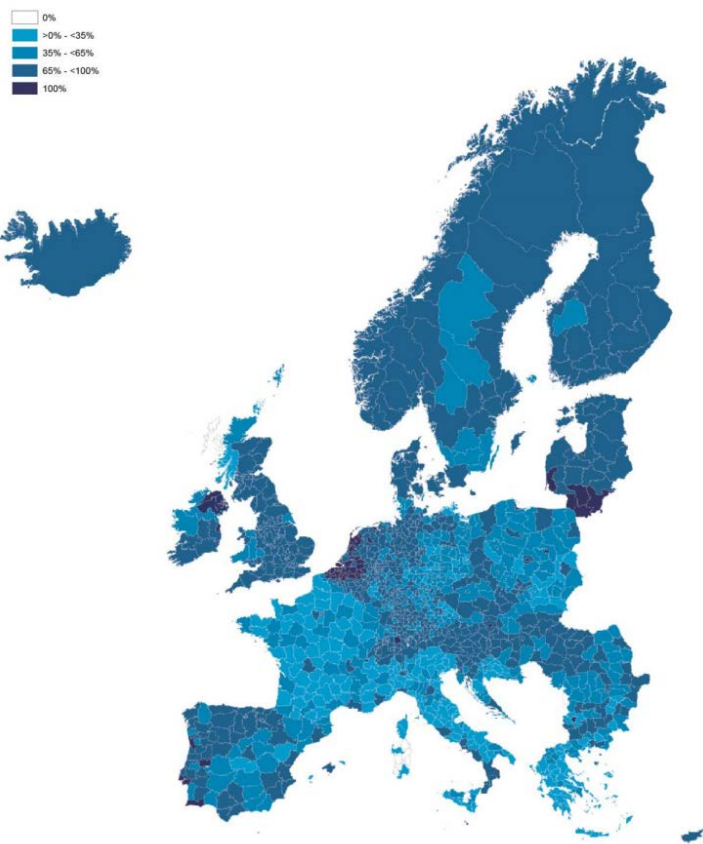
- **Mobility Management Entity (MME):** It is responsible for security procedures, session handling, and terminal location management.
- **Home Subscriber Server (HSS):** It contains all the user subscription information, and is in charge of generating security information from user identity keys.
- **Serving Gateway (SGW):** It serves as a local mobility anchor routing data packets through the access network.

- Proxy Gateway (PGW): It acts as the interface between the LTE network and other packet data networks; manages quality of service (QoS) and provides deep packet inspection.
- PCRF (Policy and Charging Rules Function) Server: It supports policy enforcement and flow-based charging.

Evolved nodes, interfaces, and protocol stacks have been defined building upon the 3G / UMTS architecture [19]. Thereby, although LTE presents different improvements in comparison with its predecessors of cellular communication networks, it is still an infrastructure-centric technology. For example, for one UE to send traffic to another UE, the data has to go all the way to the PGW and then back to the second UE, even if they are attached to the same eNB. Therefore, the network performance is very dependent on the deployment of expensive cell towers and management nodes, which usually leaves many areas without sufficient coverage, or any coverage at all. As shown in the reports [20] and [21], both maps in Fig. 1.2 show that even nowadays coverage is not guaranteed, especially in rural areas.



(A) Coverage map in the United States in 2017



(B) Coverage map in Europe in 2015

FIGURE 1.2: 4G LTE broadband coverage maps in the United States and Europe

1.3.2 Spectrum Scarcity

The radio frequency spectrum is a finite and increasingly precious world resource. It cannot be confined within national borders, and it is used and managed through international treaties and national policies. Fig. 1.3 from [22] shows the radio spectrum as it is allocated in the United States: Frequencies range from 3 kHz to 300 GHz and they are all used for wireless communications. Cellular communications uses frequencies allocated between 300 MHz and 3 GHz.

The use of the radio spectrum is not limited to the mobile communications. It also includes sound and television broadcasting, transport (e.g. aviation, railway and maritime), defense, remote control and monitoring, radio astronomy, and space research, as well as many other applications [23].

Due to the growing number of spectrum uses, its management is a growing problem. And as mobile-data demand continues to increase and as other desirable services arise, calls for an efficient and harmonized use of this limited resource are continuing.

Proposed solutions suggest that reallocating spectrum can solve the problem. While reallocation may offer some relief, the technical and political obstacles associated with spectrum reallocations will only deliver momentousness satisfaction [24]. Other solutions including reducing cell size, enabling spectrum sharing, and using higher frequencies are still under investigation [25]. However, these proposals come at a cost: Shrinking cell sizes increases spectrum capacity and enhances performance, the requisite infrastructure is more expensive and difficult to acquire, as coverage is still limited; while sharing spectrum with secondary users provides exclusive access to a channel whenever the primary user allows it, deployment of related techniques and hardware is costly; finally, higher frequencies have shorter wavelengths, which means that the waves do not travel as far before degrading. All these solutions are technically, politically, and economically challenging and each one alone cannot fulfill each country's increasing need for radio spectrum. However, expanding the availability of spectrum may be improved with smarter technologies and more adequate parameters for power control, interference mitigation, and service optimization.

1.3.3 Examples

In this section, we model and simulate two different scenarios in order to test and evaluate the performance of the LTE network, in order to showcase the effects of user saturation and infrastructure unavailability. Simulations were modeled in ns-3, an open source simulator that offers an LTE module [26].

1.3.3.1 Scenario 1: Large-scale Event

When a large-scale event happens, traffic loads and number of users involved increase significantly with respect to day-to-day network use. This can be illustrated by either a major professional sports game, a big music concert, or even an incident. One of the possible scenarios was defined and studied by the National Public Safety Telecommunications Council (NPSTC) in their report [27]: a gas leak incident in the Washington D.C. area.

Independently of the nature of the event, we define a common set of assumptions. It involves nearly 500 UEs including individuals and vehicles. All of them are deployed uniformly within 1 square mile of the event area. 11 sites are providing service to the area, 7 of which are actively used, with a single sector actually handling 60 % of the traffic. In addition, a number of standard applications are identified including video (ranging from high to low quality), voice and data, such as:

- Video streaming in high, medium and low quality,
- Web-based applications allowing access to local databases for example,
- Automatic location applications for both individuals and vehicles,
- Geographic Information Systems (GIS) in two levels of detail (street and detailed views),
- Third-party sensors such as security alarms,
- Public Switched Telephone Network (PSTN) voice applications,
- File and message transfer,

- Weather tracking (e.g. temperature, humidity),
- Emergency applications, such as telemetry data transfer.

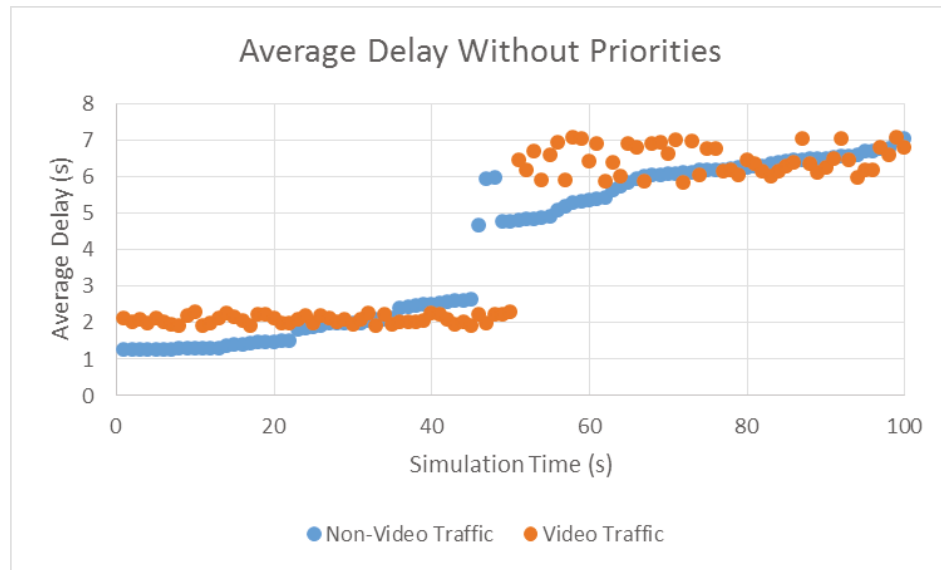
TABLE 1.1: Application throughput and usage parameters during a large-scale event

Application	Downlink Peak Throughput (Kbps)	Uplink Peak Throughput (Kbps)	Session Duration (s)	Number of Sessions per Hour	Percentage of Users per Application
Individuals					80
Medium Quality Video (DL) Traffic Camera	512	16	3600	1	1
Low Quality Video (DL) Situational	256	16	3600	1	2
Low Quality Video (UL) Situational	16	256	3600	1	2
High Quality Video (DL) Vehicle	1024	16	3600	1	0.5
High Quality Video (UL) Vehicle	16	1024	3600	1	0.5
Medium Quality Video (DL) Vehicle	512	16	3600	1	1.5
Medium Quality Video (UL) Vehicle	16	512	3600	1	1.5
Medium Quality Video (UL) Video conference	16	512	3600	1	0.5
Medium Quality Video (DL) Video conference	512	16	3600	1	0.5
Geographic Information Systems (GIS) Street View	560	56	1	5	2.5
Geographic Information Systems (GIS) Detailed View	683	68	1	60	1
Automatic Location (UL+DL)	0.04	0.04	1	240	75
File and Message Transfer UL	0.0016	0.016	1	4	7.5
File and Message Transfer DL	0.016	0.0016	1	4	7.5
PSTN Voice (Cell Phone)	10	10	3600	1	5
Third Party Sensors	0.025	0.0025	30	2	2
Weather Tracking	13.3	13.3	60	12	1
Emergency	0.454	32.53	30	120	26
Other	5	13	60	60	3
Vehicles					20
Automatic Location (UL+DL)	0.04	0.04	1	240	100
Vehicle Telemetry	0.027	2.7	300	4	100

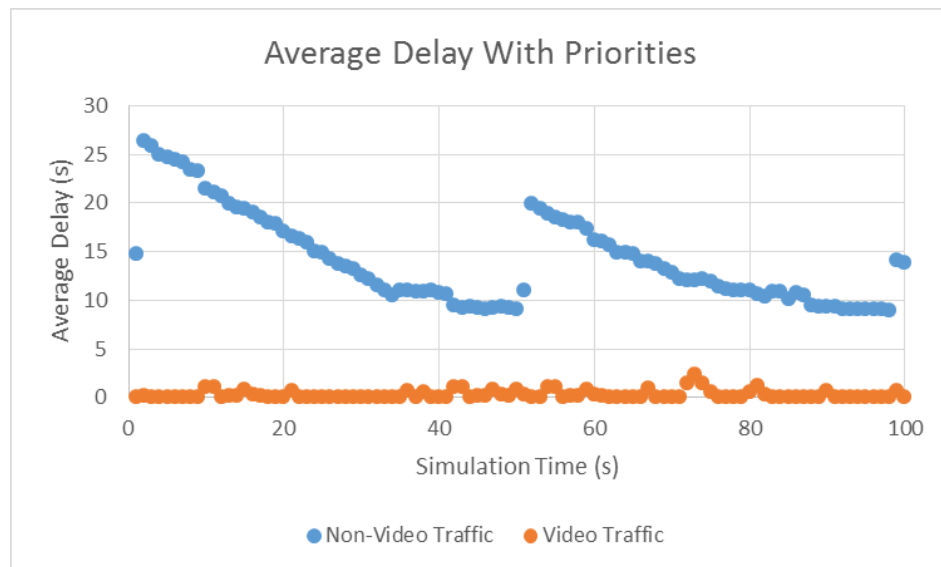
The Table 1.1 summarizes the application modeling in terms of peak throughput, session duration, and sessions per hour for each application. The number and type of users for each application was varied to match the demand described in the original report.

In our simulations, we measure the impact of network saturation due to a big event on the users' quality of service, and evaluate the efficiency of priorities in mitigating such impact. First, we compute the average delay and packet loss for both video traffic and other traffic. Then, we give video stream priority over the rest of traffic and compared the output results.

Without priority management, all the applications are treated the same and the video quality is poor as shown in Fig. 1.4a. However, when the video stream is sent over a dedicated bearer with a higher priority, its average delay is reduced, as displayed in Fig. 1.4b. But higher transmission delays are observed for the rest of the traffic: Delay for all the applications, regardless of their nature, was uniform, with the delay growing steadily up to 8 seconds by the end of the simulation, for non-video applications when no priority is applied. But, now, after adding priority to video traffic over other traffic, delays for non-video applications oscillates between 9 seconds and 25 seconds. Given the burst nature of the traffic, even with high priorities allocated for the video, there are still bumps in the delay of the high priority traffic that reach more than 2 seconds, which has a negative impact on the jitter and the general Quality of Service (QoS) and Quality of Experience (QoE) for the user.



(A) Average delay without considering priorities

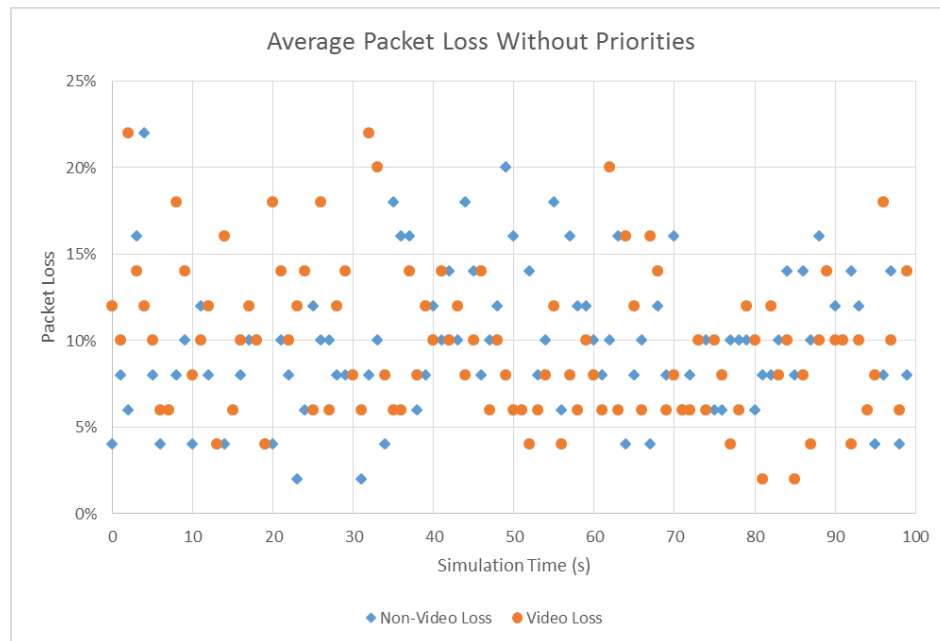


(B) Average delay after giving higher priority to video stream

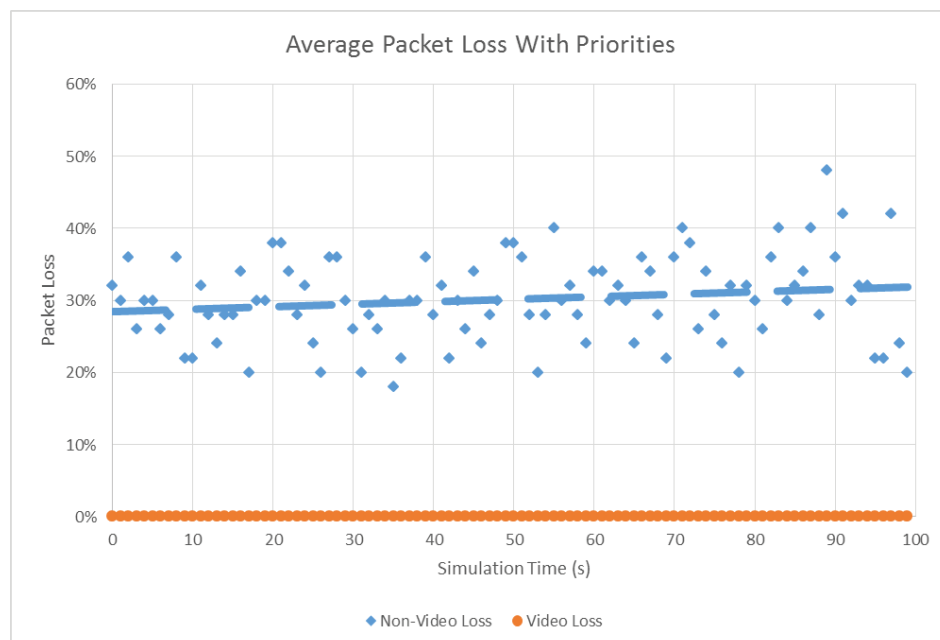
FIGURE 1.4: Average delay with and without considering priorities

Similar results can be observed for packet loss, represented in Fig. 1.5. Packets loss in first case was dispersed and ranged mostly between 5 % and 15 %. In the second case, although all video packets were successfully sent, other traffic suffered constantly of high packet loss rates orbiting around 30 %. So, if we use priorities, we can get acceptable metrics for the video applications, at the cost of having poor Quality of Service for the

rest of applications. In the long term, the situation is slowly deteriorating (the loss trend is ascending), which means applications will stop working at all.



(A) Average packet loss without considering priorities



(B) Average packet loss when giving video stream priority over other application

FIGURE 1.5: Average packet loss with and without considering priorities

This scenario shows that traffic and high number of close UEs inherent to incidents cannot be handled by the network without supporting mechanisms. Even the definition and use of priorities does not fully solve the problem, as the impact on the rest of the traffic is very significant.

1.3.3.2 Scenario 2: Site Failure

Another potential situation is a lack of infrastructure support, even in areas where the infrastructure has been deployed, for example due to extreme weather conditions or network breakdown. In the mildest cases, it will cause a cascade effect, as the neighboring infrastructure may also collapse under the extra load, in turn sending its users to other neighbors, with the whole process potentially leading to a local blackout in the whole area.

The following scenario [28] simulates the failure of one site during an incident in the Washington D.C. area, as shown in Fig. 1.6.

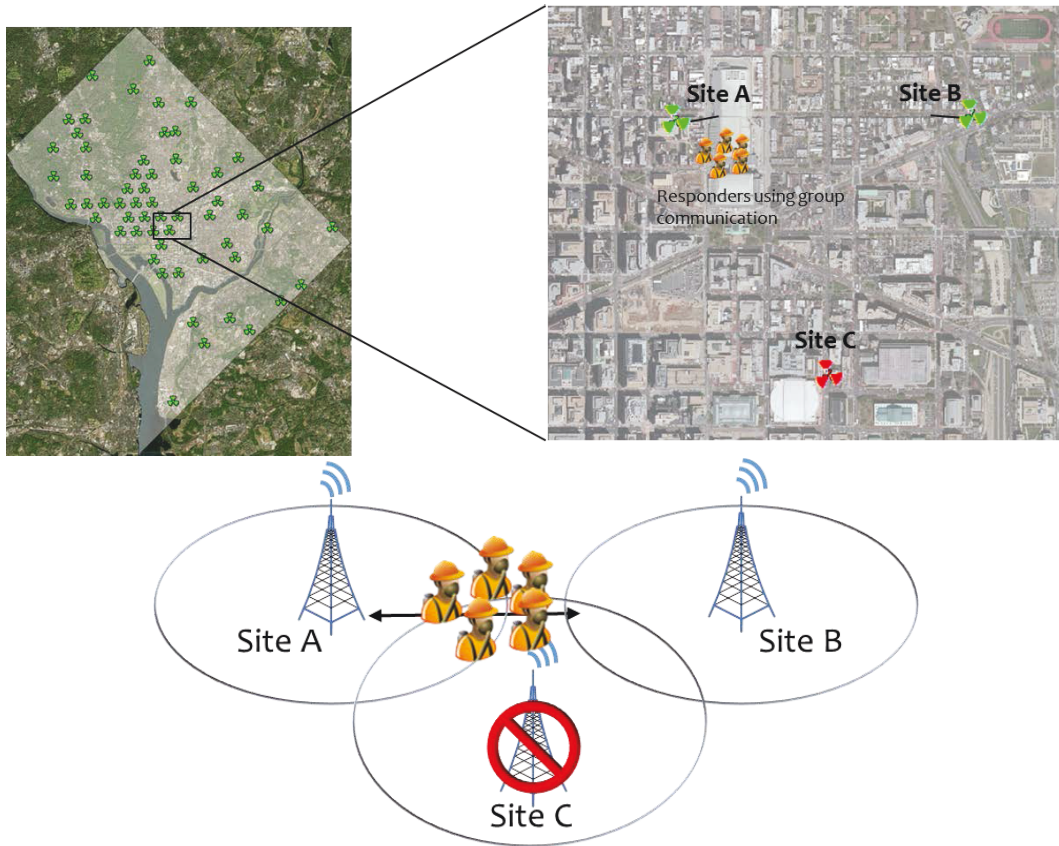


FIGURE 1.6: Illustration of the site failure

In the Baseline scenario, first responders are called to an incident area where there are 3 sites deployed, with one of the users (Site C) being not operational. Some of them are using voice calls with each other while moving from site A in direction of site B. At some point, users are out of coverage.

Public safety users are moving from site A to site B. So, when site C is down, the responders try to stay on the remaining sites (A and B) as long as possible. When located between 650 and 950 meters from site A, they are not able to detect any site. After 1000 meters, they connect to site B. First, we computed the Reference Signal Received Power (RSRP) in Fig. 1.7 as reported by the UEs. This metric is a Received Strength Signal Indicator (RSSI) type of measurement and represents the average received power of reference signals within certain frequency bands, expressed in decibels-milliwatts (dBm).

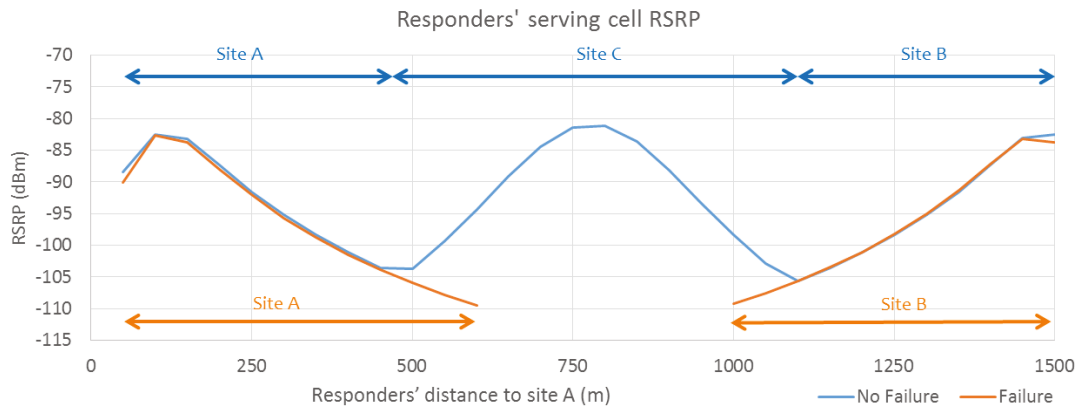


FIGURE 1.7: RSRP as function of the distance

Second, we calculated the packet loss rate for the two cases as represented in Fig. 1.8. Without failure, packet loss is perceived only at the cell edge where the signal strength is low: once when UEs are preparing to realize a handover between cells A and C, and then again when UEs change their attachment from cell C to camp on cell B as they get closer to the latter. In the case of site failure, a coverage gap of approximately 500 meters is identified, and responders experience a total loss of connectivity (100 % packet loss).

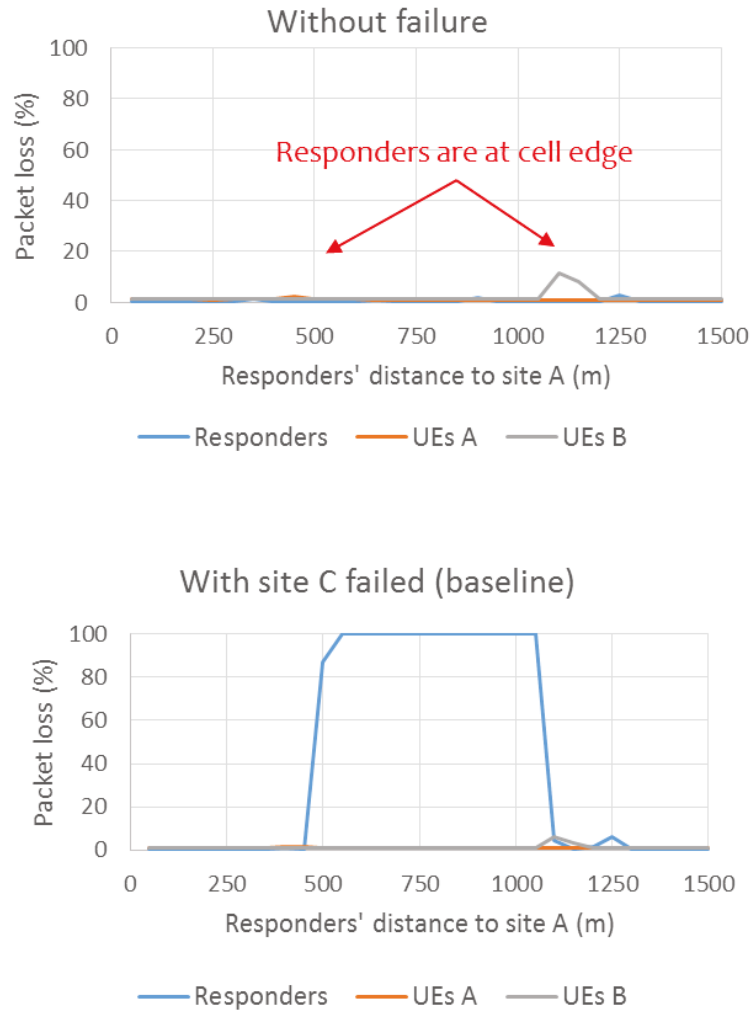


FIGURE 1.8: Packet loss as function of the distance

We also calculated the resource blocks (RBs) used for both cases (with and without failure). In LTE, a resource block is the smallest unit of resources that can be allocated to a user, and it is defined by the transmission bandwidth: for example, for 10 MHz we have 50 RBs, each of which consists of 12 consecutive sub-carriers, or 180 kHz, for the duration of one slot (0.5 milliseconds). In LTE, the amount of resources needed by the responders depend on their location in the cell and their throughput requirements. When responders are at the edge of a cell, more resources are needed to mitigate bad channel conditions, which is why an increase in the RBs utilization is perceived. As shown in Fig. 1.9, during Site C failure, the number of RBs used reached its maximum

value (no more available RBs) and congestion occurs. Therefore, high delays and packet loss happen.

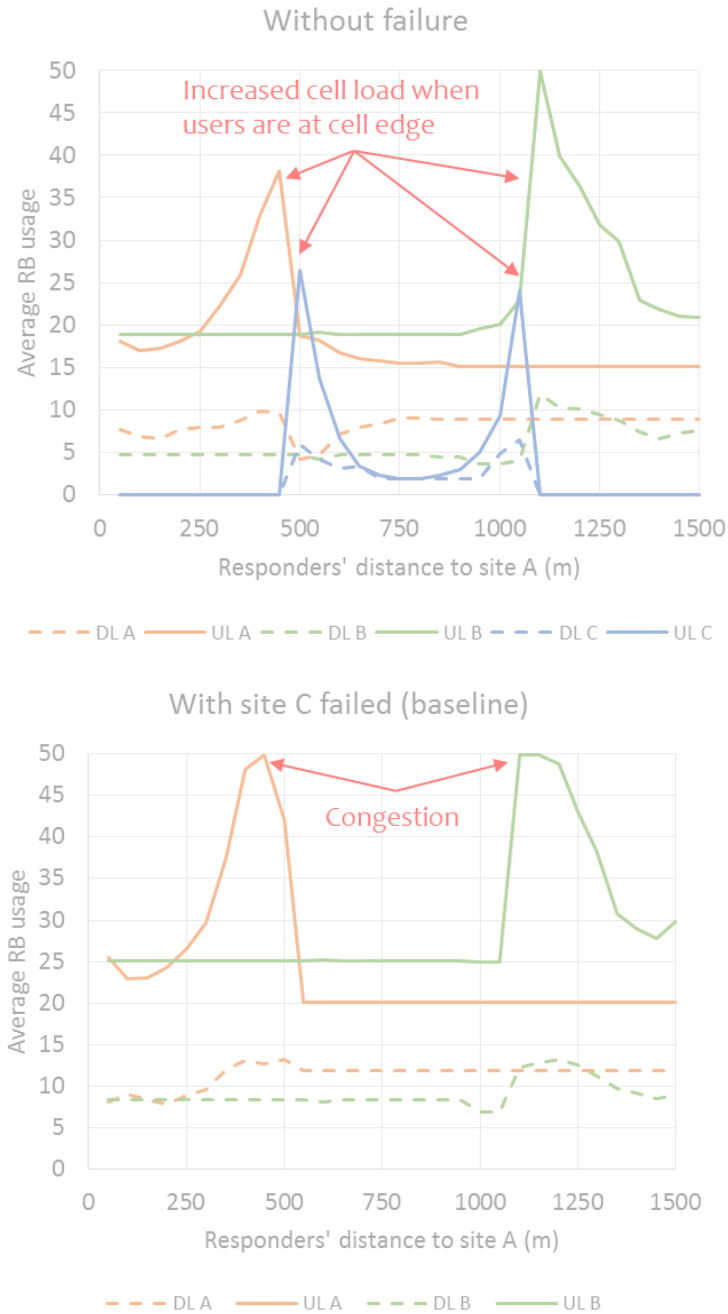


FIGURE 1.9: Average RB used as function of the distance

Based on this scenario, we conclude that, even in the areas with infrastructure deployed, we need to account for failures and maintenance downtime. This can significantly

reduce the network coverage and capacity. Congestions, delays and service shutdown are likely to happen, which affects network performance (QoS) and user experience (QoE). That is why we should offload the network whenever needed and extend the coverage if possible. It is also required that we have a communication solution that does not require an infrastructure to be provided.

1.4 Problem Statement

While the general approach aims to reduce costs and improve the adoption of novel applications and services, network users have very stringent requirements regarding service availability, resiliency, and quality of service. LTE, as designed currently, does not have the mechanisms to adequately support these requirements. The results of our several experiments showcase the shortcomings of the LTE centralized architecture in scenarios with high concentration of users or with infrastructure failures.

LTE offers multiple advantages, but also several concerns that need to be addressed. First, the coverage requirements, especially inside buildings or in densely populated areas are extremely hard to comply with. Second, increased number of users and traffic (such as those caused by big events) are difficult to handle without extreme over-provisioning the network because the fully network-controlled architecture introduces overhead and delays when communicating with nearby users. Besides, spectrum scarcity can be mitigated if resource optimization is considered. The system has to use less resource blocks (frequency channels) while efficiently delivering a guaranteed service. Therefore, there is a need for efficient tools and mechanisms that can work within the LTE existing framework, while satisfying the previous requirements: no dependence on infrastructure and optimization of resource utilization. In order to alleviate those problems and improve the network performance, we will focus on a new concept which is part of the next generation cellular communication 5G : LTE Device-to-Device (D2D) communications.

For the thesis, we will target one aspect of D2D communications which is D2D Discovery, more precisely direct discovery. We will optimize the discovery service for both in and out of coverage scenarios. Adaptive algorithms, with minimal modifications to the existing standards, will be designed in order to provide an efficient service. We will

focus on overcoming the limitations caused by the static design of LTE in D2D discovery, by means of adaptive algorithms, proactive parameter adjustment based on user density patterns, and enhanced detection mechanisms to learn of user mobility.

1.5 Proposals

Our main contributions of the thesis consists of the analysis, evaluation, and performance optimization of D2D discovery.

First, we studied and evaluated the D2D communications and their integration in the LTE architecture through simulation models [29] [30]. We extended the ns-3 LTE implementation to support D2D synchronization, discovery, and communication as defined by 3GPP. The behavior of the model has been verified using multiple scenarios.

Second, we validated the D2D discovery performance using both an analytical model and simulations results [31]. A Markov chain was developed to characterize the performance of Mode 2 (out-of-coverage) direct discovery. The resulting analytical model gives the distribution of the time for a UE to discover all other UEs in its group. This model was validated by our implementation of D2D discovery in ns-3.

Third, we proposed an adaptive algorithm which takes into account the available resources and the number of nearby users as they are being discovered, and adapts the transmission probability accordingly [32]. The algorithm improved the overall performance of the discovery process. It gives UEs the ability to dynamically adjust their transmission probabilities to reduce the time required to discover other UEs and optimize resource utilization.

Fourth, we proposed a D2D discovery algorithm that takes advantage of user density patterns extracted from real network traces [33]. Comparing it to the discovery mechanism defined in the Third Generation Partnership Project (3GPP) standards, we showed that the proposed algorithm struck a balance between network utilization and the time required to complete the discovery.

Finally, we proposed an enhanced version of the D2D discovery algorithm defined in [32]. It tuned the algorithm for more dynamic scenarios with groups of UEs causing bulk arrivals to and departures from the discovery group [34].

1.6 Outline

The remainder of this thesis is organized as follows. Chapter 2 describes D2D communications, with an emphasis on the discovery process. Chapter 3 includes an evaluation and validation of the D2D discovery performance based on mathematical and simulation models, followed by an optimization of the discovery process using an optimal value of the transmission probability for discovery messages. We use static topologies and introduce an adaptive algorithm to speed up the discovery process. In Chapter 4, we propose a combined use of predicted user densities along adaptive algorithms to improve the performance of D2D discovery. Chapter 5 enhances the adaptability of the algorithm shown in Chapter 3, by providing support for more dynamic environments and scenarios. Chapter 6 concludes the thesis and discusses further research opportunities.

Chapter 2

State Of The Art

2.1 Introduction

D2D communications were first investigated and defined by 3GPP, the standard body behind LTE network architecture in order to promote proximity awareness and communication. It is totally incorporated within the existing LTE Advanced services, networks and architecture.

D2D transmission and reception will be conjointly using the uplink LTE frequency bands, and resources would be assigned by the eNodeB or autonomously selected by the UE from a configured group of resources, called pool.

D2D communications are applied in different environments for both commercial and public safety use. This type of communications are expected to bring up some advantages like spectrum utilization and improvements in overall throughput and latency. 3GPP has already defined public safety use cases [35]. It should maintain communications in environments where we have little or no coverage (off-network) like on trains or underground. It would also be used when a partial or complete network shutdown occurs due to large scale natural disaster or power cuts. Extra capacity must be provided when needed, especially in large metropolitan areas.

2.2 D2D Communications

2.2.1 Overview

In order to support D2D communications, two main functionalities were added as standalones services: Discovery and Communication. Related key features have been

defined and 3GPP is still working on extending them:

- **Direct Discovery:** The UE is able to detect the presence of another UE in its vicinity without the need of external help (i.e. core network).
- **EPC-level ProSe Discovery:** The EPC determines the proximity of two ProSe-enabled UEs and informs them of their proximity.
- **Direct Communication:** UEs are capable of exchanging user traffic without going through the eNodeB (one-to-one, group or broadcast communication).
- **UE-to-Network Relay and/or UE-to-UE Relay:** A UE acts as a relay between either another UE and the eNB or between two other UEs.

Based on those features, devices will be able to discover each other and communicate either directly or using minimal network intervention. Unlike traditional LTE links, UEs in proximity of each other would not be forced to use the whole backbone network structure to exchange data. In addition, UEs will manage to communicate in areas lacking network coverage.

2.2.2 Applications

Various applications and services will be enhanced by the use of D2D. For commercial use, D2D would be mainly used for commercial advertising, social networking and gaming. For example, if you are in a shopping mall, passing by different stores, and you have a ProSe-Enabled mobile with open discovery added, those stores will be able to send you instantly their promotions, discounts and sales for the day via D2D services as presented in Fig 2.1.



FIGURE 2.1: D2D advertising

Similarly, Fig. 2.2 shows an example of D2D discovery: you may be walking around and receive an announcement to notify you that one of your friends is nearby too.

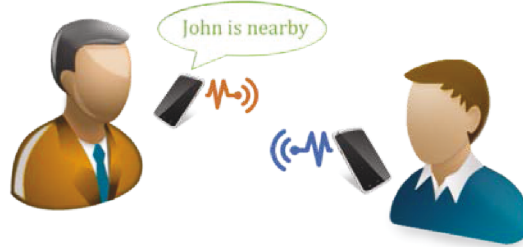


FIGURE 2.2: Discovering a nearby friend

For public safety usage, proximity detection and information sharing can be really efficient, as D2D services can be used as a notification service, and therefore alerts can be announced through the D2D network. For example, road users can be warned ahead of time if an accident just happened, so that they can be more careful or avoid the area. Also, during incidents, first responders can discover each other and start exchanging information directly without the need to use LTE core network, as symbolized in Fig. 2.3.



FIGURE 2.3: Alert notification among first responders using D2D communication

2.2.3 Modes

D2D communication and discovery can be performed in different situations depending on the UEs coverage status, i.e. connected or not to an LTE base station (eNB), as shown in Fig. 2.4:

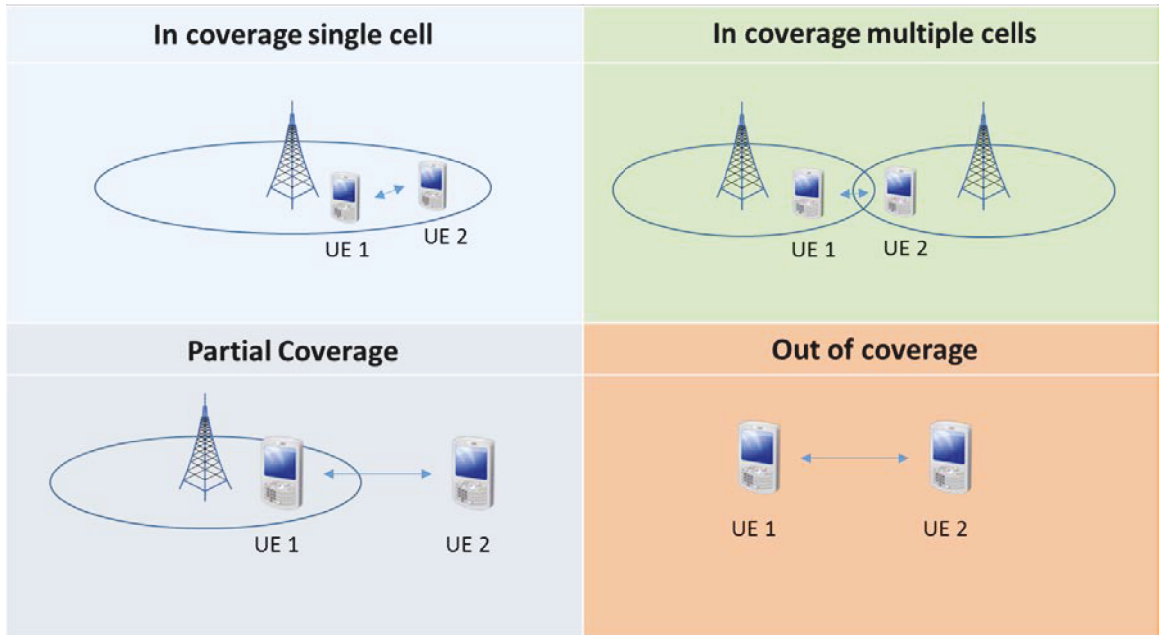


FIGURE 2.4: Illustration of possible D2D scenarios

- ***In-coverage***: In this case, both devices are basically attached to an eNB (not necessarily the same one) in an idle or a connected status. UEs are called in-coverage either of a single cell or multiple ones. In this context, users will be able to rely on LTE architecture and nodes to perform all D2D communications. For example, D2D synchronization is supported by the eNB.
- ***Partial coverage***: In this scenario, one UE is attached to one eNB (i.e. in-coverage), the other is not attached to any eNB (i.e. out-of coverage). At this point, the in-coverage UE acts as a relay to the other out-of-coverage UEs in order to maintain connectivity.
- ***Out-of-coverage***: In this case, none of the UEs are connected to any cell. The devices are no longer relying on the LTE infrastructure and nodes and perform D2D communications on their own using preconfigured D2D parameters.

In Release 12 [36], D2D communication is a group communication only, supported for both in coverage and out of coverage services, but for public safety usage exclusively. However, D2D discovery is mainly destined to commercial use and is only supported

when UEs are in-coverage[37]. Release 13 [36] provided the possibility of one-to-one communication along with out-of-coverage discovery [38].

2.2.4 Architecture

As defined in [39], Fig. 2.5 represents an advanced version of the LTE core network when supporting ProSe new entities and interfaces. This non-roaming architecture includes the following:

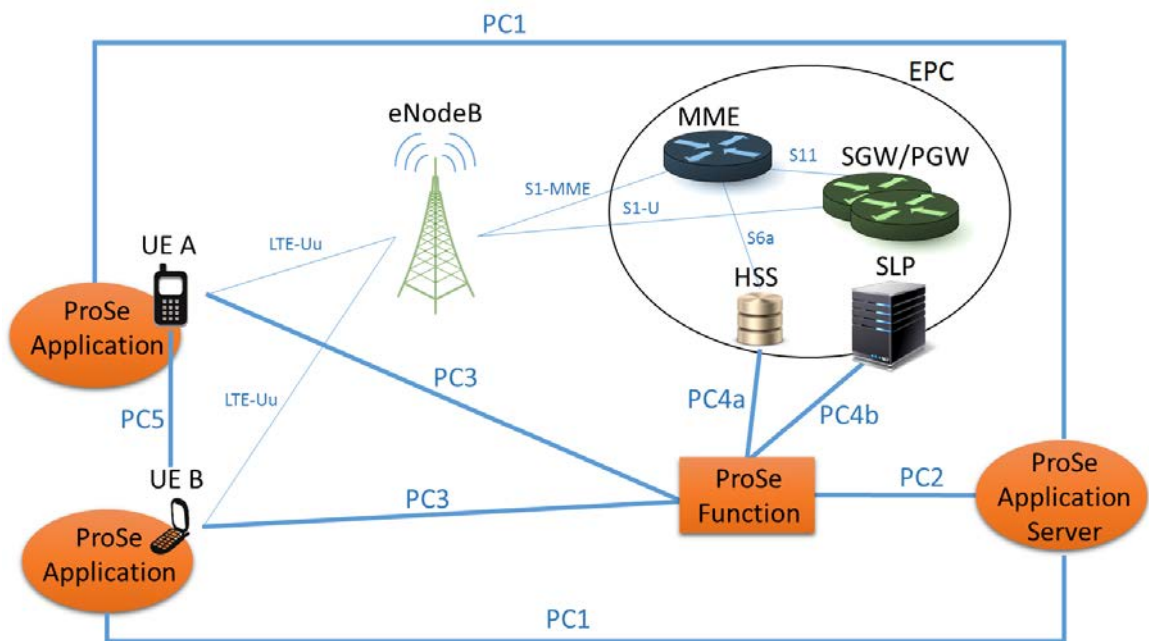


FIGURE 2.5: ProSe non-roaming reference architecture

- **Entities**

- ProSe Application running in the UEs.
- ProSe Function controlling services provided by the network.
- ProSe Application Server containing application information.

- **Interfaces**

- PC1: Application level signaling.
- PC2: Used for EPC-level discovery, between ProSe Function and ProSe Application Server.

- PC3 (between UEs and ProSe Function): Authorization and ProSe application code allocation.
- PC4a: Authorization interface between HSS and the ProSe Function.
- PC4b: Used for EPC-level discovery, between the SLP (SUPL (Secure User Plane Location) Location Platform) and the ProSe Function.
- PC5 (between UEs): Control/User data plane for Direct Discovery, Direct Communication, and Relay.
- S6a: Subscription information.

As shown above, different new reference points have been introduced to enable the standardization of Proximity Services. A more detailed definition of all those points is provided in [40]. However, in this work, we will focus on the interface between the two devices, PC5 and between each device and the so called Proximity Service (ProSe) Function, PC3. The ProSe Function is one of the most relevant functional entity. It controls the authentication, authorization and validation processes before starting Direct Discovery and Direct Communication.

2.2.5 Channels

New channels have been defined to handle D2D Communications, also known as sidelink communications for lower layers. The mapping between the MAC and physical layers is illustrated in Fig. 2.6 [41][42].

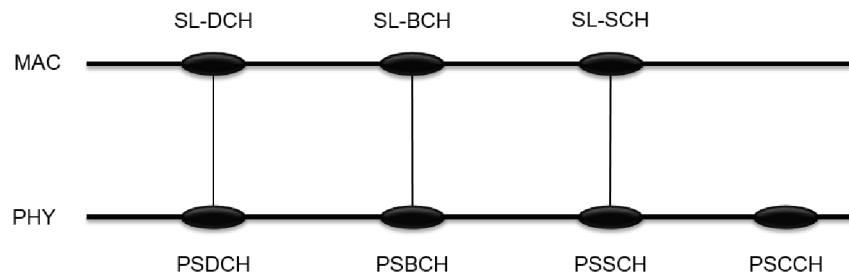


FIGURE 2.6: New Sidelink Channels

- Transport channels [43]:

- SL-SCH (Sidelink Shared Channel): It may bear a collision risk, depending on the resource assignment. The SL-SCH interfaces to the Physical Sidelink Shared Channel.
 - SL-BCH (Sidelink Broadcast Channel): It has a predefined transport format. It carries signaling information used for synchronization in the out-of-coverage or partial coverage scenarios. The SL-BCH interfaces with the Physical Sidelink Broadcast Channel.
 - SL-DCH (Sidelink Discovery Channel): It carries discovery messages at the MAC level. The SL-DCH interfaces with the Physical Sidelink Discovery Channel.
- Physical channels [44]:
 - PSSCH (Physical Sidelink Shared Channel): It is used to transport the communication data over the air.
 - PSBCH (Physical Sidelink Broadcast Channel): It is used to carry signaling information.
 - PSDCH (Physical Sidelink Discovery Channel): It contains the discovery information.
 - PSCCH (Physical Sidelink Control Channel): It contains the Sidelink Control Information (SCI), which carries the information the receiving UE requires in order to be able to receive and demodulate the PSSCH.

2.3 D2D Discovery

As mentioned above, D2D discovery is part of the ProSe functionality introduced by 3GPP in release 12 allowing a discovery-authorized UE to detect other discovery-supporting UEs in its vicinity. It is important because first it takes resources away from D2D communication, and since it usually precedes the communication, a slow discovery results on increasing the latency for the D2D communication. Therefore, the work in this thesis focuses on the performance evaluation and optimization of this service.

Fig. 2.7 shows a representation of direct discovery, where one UE (in blue) is sending discovery messages to nearby devices (in green). Some UEs (in red) are out of reach and they would not be able to receive nor detect the first UE (in blue).

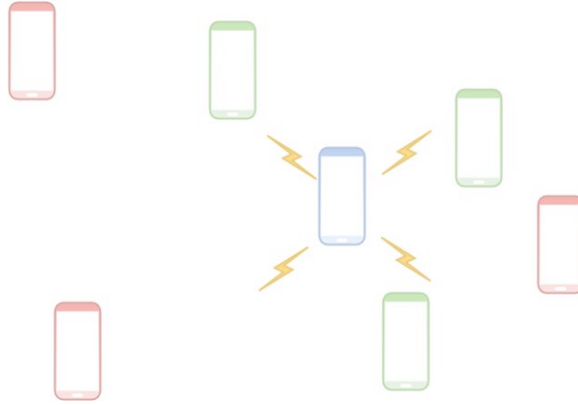


FIGURE 2.7: Representation of direct discovery

2.3.1 Resource Pool

When sending announcements, resources are picked from a defined resource pool. For in-coverage scenarios, the discovery radio resource pool is disseminated from the E-UTRAN within the System Information Block (SIB) Type 19 [45], providing information about whether the user device is allowed to announce (transmit) and/or monitor (receive) discovery messages. Based on the type of discovery and the network, the resources are either chosen randomly by the UEs, or requested by the users and assigned by the eNB. For in-coverage scenarios, discovery parameters (such as the pool information, the frequencies to be used and announcing and/or monitoring authorization) can be dynamically configured by the eNB to adjust them. However, for out-of-coverage cases, those parameters are pre-configured in advance in the user devices, and the UEs send discovery messages following a random uniform distribution and a threshold called “Transmission Probability”. For example, we have two UEs with their transmission threshold set to 0.5. We assume that UE_1 picks a value that is less than that transmission probability (e.g. 0.29) and the other UE_2 chooses a value that is greater than the defined transmission probability (e.g. 0.68). Then UE_1 will be able to transmit its discovery message in this period while UE_2 will defer transmission and will attempt to send its discovery message

during the next discovery period. The standard allows the use of four specific values: 0.25, 0.5, 0.75, and 1.

The discovery radio resource pool consists of multiple variables like the discovery offset, discovery period length, discovery bitmap to indicate which subframes (noted SF) could be used for discovery (where a bit set to "0" indicates not to be used for discovery and "1" means useable for discovery), number of repetitions (how often this bitmap is repeated within the discovery period), number of re-transmissions of the discovery message, resource block configuration (noted RB, including a start and an end numbers), the transmission and reception parameters, etc. [45]. The structure of the Discovery resource pool is shown in Fig. 2.8. The discovery available resources are computed based on equations defined in [46]. The total number of resources dedicated to discovery is the product of the number of subframes (N_t) and the number of resource block pairs (N_f).

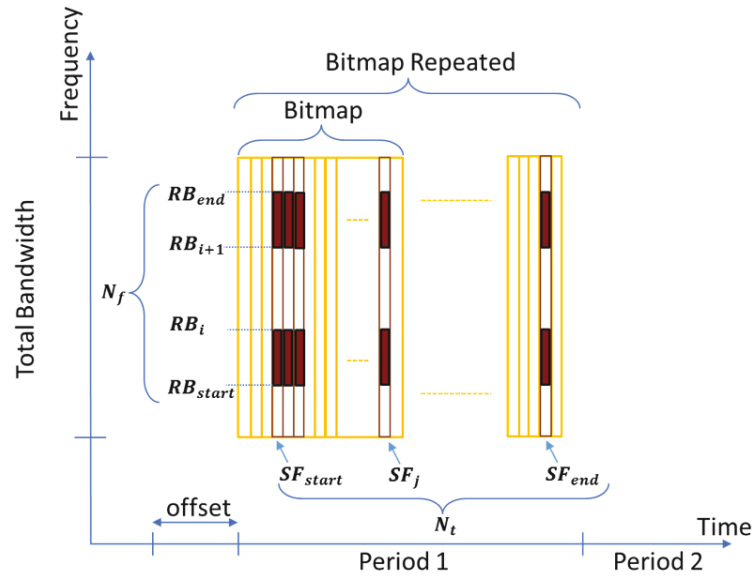


FIGURE 2.8: Structure of Discovery Resource Pool

2.3.2 Types, Models and Options

Different types, models and options are presented in [35], depending on how physical resources are allocated for the discovery process, the protocol model to use, and the availability and security of the advertised functions.

- Type 1 (**UE-Selected**): Resources for discovery signal transmission are allocated on a non-UE specific basis (for all users). The UE is provided with resource pool configuration that can be used for discovery. This is the only type valid for out-of-coverage.
- Type 2: Resources for discovery signal transmission are allocated on a per-UE specific basis.
 - Type 2A: Resources are allocated for each specific transmission instance of discovery signals.
 - Type 2B (**Scheduled**): Resources are semi-persistently allocated for discovery signal transmission using a transmission pattern.

So, for in-coverage scenarios, the network is able to control the resources used for D2D communications. It may assign specific resources to a transmitting UE (i.e. benefiting from the *Scheduled* mode), or may assign a pool of resources the UE selects from (i.e. based on the **UE-Selected** mode). This way, interferences with the cellular traffic is avoided and the D2D communication may be optimized. However, for the out-of-coverage case such a control is not possible: The UEs choose independently from preconfigured resources, that are not specific to a certain UE, using only the *UE-Selected* mode.

The models of discovery defines whether the discovery protocol uses a PUSH or PULL process:

- Model A: "*Here I am!*" The device broadcasts information about itself (Announcement).
- Model B: "*Who is out there?*" / "*I am here!*" The device requests a certain information (Solicitation and Response).

Finally, the options address the availability of the discovery:

- Open discovery: any nearby UE can discover this UE/application.
- Restricted discovery: a permission is required from the discovered-to-be device.

2.3.3 Protocol Stack

D2D communications define new interfaces: one for signaling, called PC3, and the other for data sharing, PC5. PC3 is the control signaling interface between the UE and the ProSe Function where HTTP 1.1 is used as transport protocol [40]. The PC5 interface is established between two UEs and is used to transport actual discovery announcements and communication packets.

2.3.3.1 PC3 Interface

The PC3 interface is used when UEs are within cell coverage in order to request a ProSe Application Code when announcing or match one when monitoring. As shown in Fig. 2.9, for the UE, the PC3 control is sitting on top of the LTE protocol stack and the IP layer. The LTE interfaces between the UE and the eNB (i.e. Lte-Uu), between the eNB and the SGW (i.e. S1-U), and between the SGW and the PGW (i.e. S6/S8) are not used. In order to contact the ProSe Function, the device has to establish an Radio Resource Control (RRC) connection with the network. RRC protocol layer exists in both UE and eNodeB, It is part of LTE air interface control plane. It follows a state machine defining certain specific states that a UE may be present in. The device uses IP messages (i.e. HTTP Request and Response message) for an information exchange between the UE and the ProSe Function. Therefore, the discovery request or response messages are inserted in the body of the HTML request or response message.

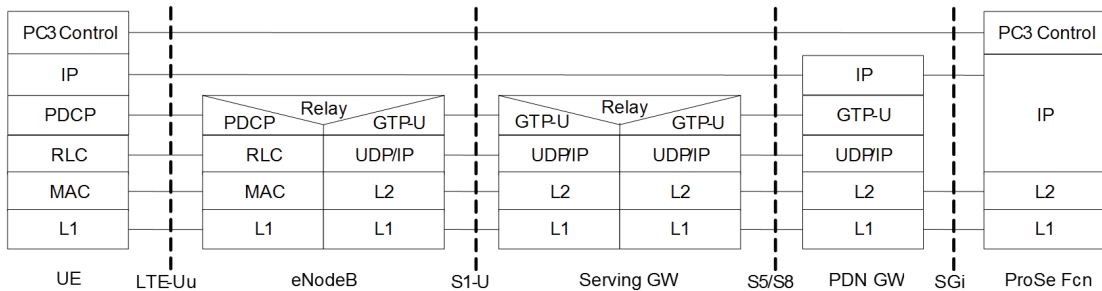


FIGURE 2.9: ProSe Control Signaling between UE and ProSe Function

Different messages can be exchanged depending on the discovery procedure:

- Direct Discovery:

- **Announce Request Procedure:** The purpose of the announce request procedure is for the UE to obtain a ProSe Application Code to be announced over the PC5 interface.
 - **Monitor Request Procedure:** The purpose of the monitor request procedure is to allow a UE to receive and process discovery messages.
 - **Match Report Procedure:** The Match Report procedure allows a UE to send a ProSe Application Code that was matched during the monitoring operation and to receive the corresponding ProSe Application ID, when there is no such mapping stored locally.
- EPC-level Discovery:
 - **UE Registration:** The UE would ask to get registered for a specific service and to have an EPC ProSe User ID (EPUID).
 - **Application Registration:** It is used to generate an Application Layer User ID (ALUID).
 - **Proximity Request:** The UE requests to be notified when it enters proximity with another UE in which it may be interested. Different ranges are supported.
 - **Location Reporting:** The locations of the UEs are provided to the ProSe Functions (periodically/triggered) by the Secure User Plane Location (SUPL) Location Platform (SLP)
 - **Proximity Alert:** The network triggers this procedure when UEs are in proximity.

The overall procedure for direct discovery model A can be captured in Fig. 2.10 [39]. In the first step, the ProSe Function determines if the UE is allowed to perform D2D communications and more specifically discovery. The UE may initiate the authorization procedure if the UE has something to announce or monitor and has no valid authorization. Unless the UE receives a response from the ProSe function for service authorization, the UE can not consider that the request has been authorized.

If the UE is planning on announcing a service/application, an announce request is sent to the ProSe function. The Discovery Request message includes a Transaction ID, the command is set to “Announce”, the UE’s identity in form of its International Mobile Subscriber Identity (IMSI), the ProSe Application Identity (ID) and the Application ID, both are coming from higher layers. The Application ID is a unique identifier for the application that has triggered the transmission of the Discovery Request message. An announce response is sent back to the UE with either an acceptance or a denial. If the announce request was accepted, the network assigns a ProSe Application Code plus a validity timer for this specific code to be included in the future discovery messages, while the announce request procedure may be denied due to errors such as UE/application authorization failure, or application violations.

For a monitoring UE, a monitor request procedure is required. The UE sends a discovery request to the ProSe function soliciting to monitor (i.e. receive) discovery messages.. The Discovery Request message contains the very same information as for announcing, with the difference that the command is set to “Monitor”. After running a discovery authentication with the network, the ProSe function sends the discovery response. As a result of the monitor request procedure completing successfully, the UE obtains one or more discovery filters with the needed ProSe Application Code. A denied monitor request is caused by similar errors as the announce request.

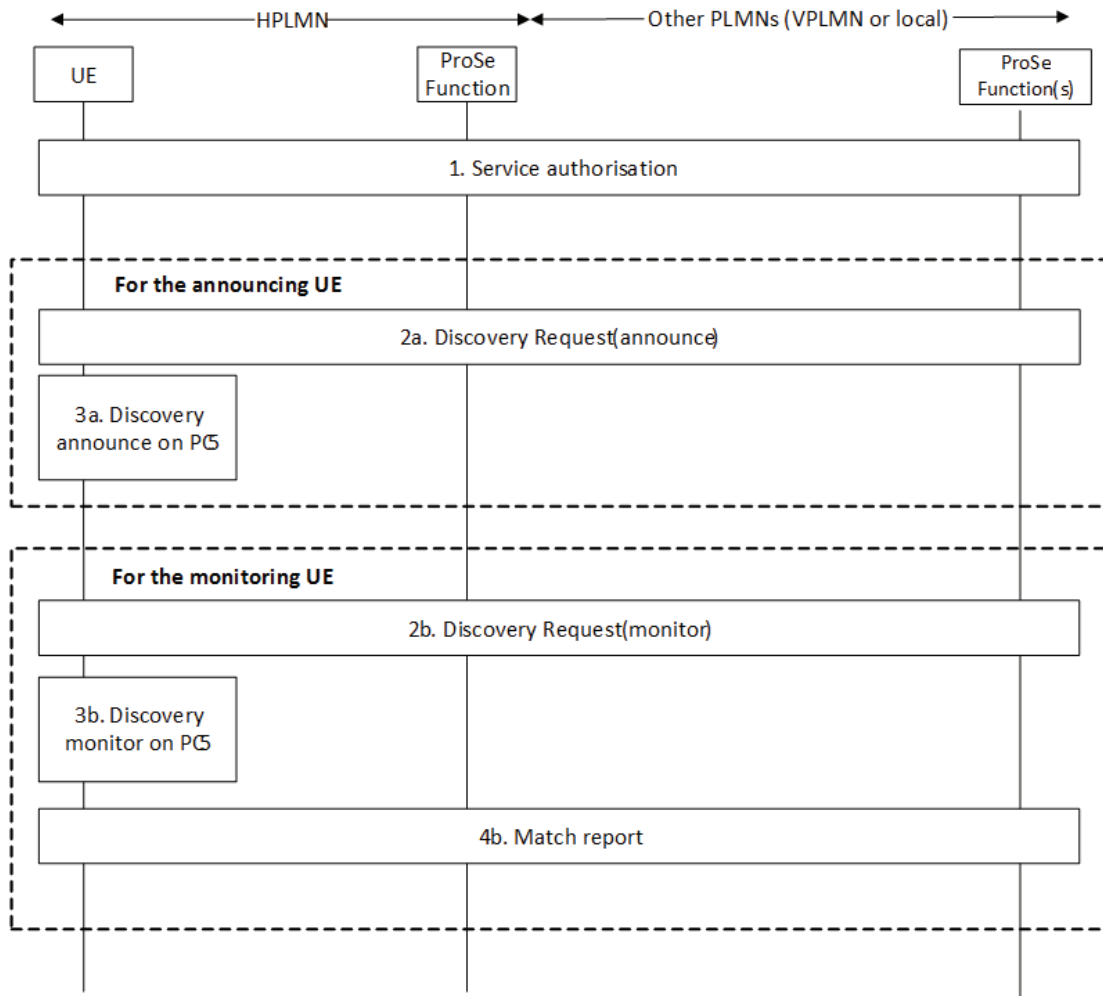


FIGURE 2.10: Overall Procedure for ProSe Direct Discovery (Model A)

For direct discovery, the authorization and request/response procedures, defined above, are only performed when the UE is connected to the network. Otherwise, the UEs are pre-authorized to use D2D services and ProSe Application Codes are preconfigured in their devices.

The overall call flow for EPC-level ProSe discovery is different from the direct discovery as illustrated in Fig. 2.11 [39]. The UE performs both UE and application registration with the ProSe Function to take advantage of the EPC-level discovery where UEs ask to get notified when other UEs are in proximity through Proximity requests and proximity alerts. They also exchange new or updated location reports with the Prose function.

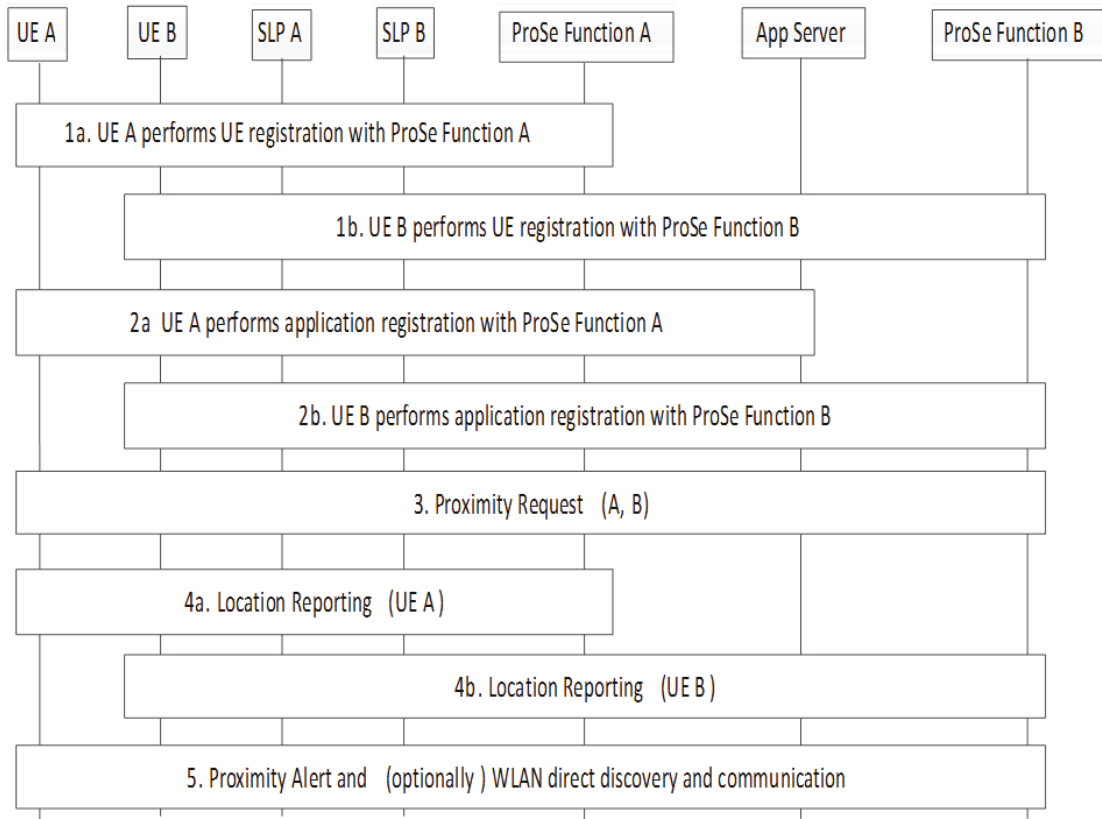


FIGURE 2.11: Overall call flow for EPC-level ProSe Discovery

2.3.3.2 PC5 Interface

The radio protocol stack for D2D direct discovery is shown in Fig. 2.12. The discovery messages do not use the RLC - PDCP queuing system that the communication messages use, and instead, they are passed to the MAC directly. Therefore, on the air interface, D2D communication is connectionless. Messages are created on the application level of the UE and transmitted on the next opportunity to the MAC. If a connection is required, it has to be done within the application. In the sending node, the MAC layer received the discovery information from the upper layer and determines the required radio resources for transmitting it. Afterwards, the resulting message (with the added headers and fragmented as needed) is passed to the PHY layer for transmission. In the receiving node, the PHY layer decodes the radio resources available for discovery, and forwards their content to the MAC layer, which assembles them (and if needed, discards them due to errors or duplications) and processes their contents.

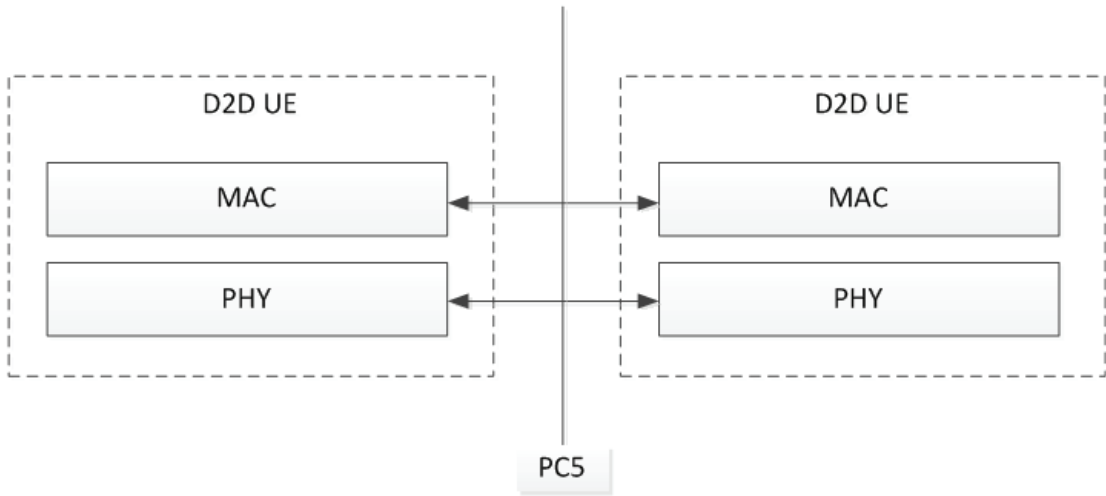


FIGURE 2.12: ProSe protocol stack for D2D direct discovery

2.3.4 Discovery Message

The discovery message is the information transmitted on specific Discovery Resources (allocated by the network or selected by the UE) by the announcing UE. The monitoring UE would look into those resources and filter what information he is interested in. The total size of a discovery message is 232 bits, which is equal to the Transport Block (TB) Size (TBS) of 2 resource blocks (RBs). The modulation scheme that is used is Quadrature Phase Shift Keying (QPSK) and the message is mapped to two contiguous RB per time slot. The MAC layer receives the discovery message (e.g. announcement) directly from higher levels and uses the Sidelink Discovery Channel (SL-DCH) to map the discovery message to the the Physical Sidelink Discovery Channel (PSDCH). A discovery message can be transmitted several times depending on the number of retransmissions (i.e. 1, 2 or 3) configured in the discovery resource pool. The content of a discovery message is defined as shown in Table 2.1 [40]. The Discovery Message is comprised of the ProSe Application Code combined with some supporting information.

TABLE 2.1: Discovery message content

Information Element	Type/Reference	Presence	Length (bits)
Message Type	Message Type	M	8
ProSe Application Code	Binary	M	184
MIC	Binary	M	32
UTC-based Counter LSB	Binary	M	8

2.3.4.1 Message Type

It is used to indicate the model (unconditional announcement, request/response) and option (open, restricted) of the direct discovery.

2.3.4.2 ProSe Application Code

This is the more important part of the discovery message. The ProSe Application Code can be considered as a discovery message identifier. For the announcing UE, the Prose Application Code is obtained from the Home Public Land Mobile Network (HPLMN) ProSe Function using the Announce Request procedure. It is contained in the message that is actually transmitted over the radio interface (on PC5) by a UE engaged in the ProSe Direct Discovery procedure to UEs performing direct discovery monitoring. The Prose Application Code is allocated per announcing UE and application and has an associated validity timer that runs in both the ProSe Function and the UE.

Each ProSe Application Code is represented in Fig. 2.13 and composed of the following parts [39]:

- The public land mobile network **PLMN ID** of the ProSe Function that assigned the ProSe Application Code, i.e. Mobile Country Code (MCC) and Mobile Network Code (MNC).
- A temporary identity that corresponds to the **ProSe Application ID Name** [40]. The ProSe Application ID consists of two parts: the PLMN ID and ProSe Application ID Name. In contrast to the way in which the PLMN ID is used for the ProSe Application Code, here the PLMN ID is purely comprised by the MCC and MNC. Each ProSe Application ID can be associated with various temporary identities

that contains as many identifiers as there are levels in the corresponding ProSe Application ID Name. The very first label is always named “ProSe App”. Labels are separated by dots as represented in the examples below:

- *mcc345.mnc012.ProSeApp.Food.Restaurants.Italian*
- *mcc300.mnc165.ProSeApp.Shops.Sports.Surfing*
- *mcc320.mnc050.ProSeApp.Sports.AmericanFootball.Teams.DallasCowboys*

The internal structure for the temporary identity of the ProSe Application ID Name is not within the scope of the 3GPP specification and may be specified by the service provider and is therefore network operator specific.

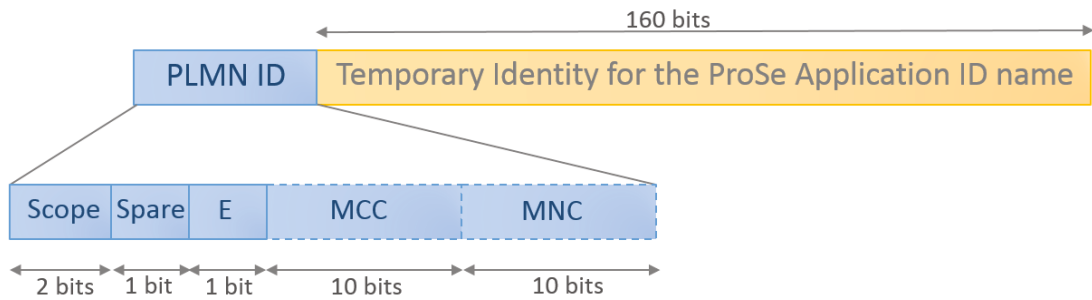


FIGURE 2.13: Representation of the ProSe applications code

2.3.4.3 MIC

It is a Message Integrity Check associated with the ProSe Application Code, computed by the terminal and included in the discovery message [47].

2.3.4.4 UTC-based Counter LSB

It contains the four least significant bits of the UTC-based counter associated with the discovery transmission opportunity used by the UE performing direct discovery announcing.

2.4 Related Work in Scientific Literature

As mentioned before, the Third Generation Partnership Project (3GPP) introduced the notion of Proximity Services (ProSe) to LTE in its Release 12 in order to enable Device-to-Device (D2D) communications services in nearby User Equipments (UEs) [14].

Although the idea of integrating peer-to-peer communications and cellular networks was proposed by some early works on ad hoc relaying technologies [48][49], the concept of enabling the (re)use of cellular spectrum resources simultaneously with ongoing cellular traffic is relatively new [50].

Recently, D2D communications have received much attention due to different considerations [51], [52], [53], [54]. Several services have been defined within ProSe umbrella including D2D communication, D2D discovery and D2D synchronization [55]. In [56], a feasibility analysis was established and D2D is proved to perform efficiently under full load in terms of throughput, especially when a dynamic interference coordination mechanism is applied.

Unlike unlicensed-band technologies such as WiFi and Bluetooth where the device has total control over the resource allocation using a contention-based access, D2D transmission and reception use part of the LTE licensed band and core network. This makes it less vulnerable to interference. Besides, WiFi and Bluetooth need manual pairing to enable the communication which takes time, personal effort, and additional focus. However, using D2D network, users are dynamically and transparently connected to each other without further manipulation. For example, when trying to offload a cellular network in case of extra traffic, a WLAN communication can be handed over to a D2D connection and the user will not perceive any difference, thanks to either the eNB assistance or the pre-configuration implemented in the terminals. Moreover, D2D network is expected to have lower delays and more efficient energy savings compared to other short-range communications such as WiFi [57]. Furthermore, this approach is confirmed to significantly achieve better performance in terms of throughput, power efficiency, and spectral utilization compared to infrastructure-based communications (i.e. routing through the LTE core network) as shown in [58], [59], and [60]. Additionally, coverage can be extended if some users' equipment acted as relays to others [61].

Although research work related to Device-To-Device (D2D) communications started a while ago, most of the work on D2D has focused on the communications aspect, and how to mitigate interference, avoid collisions, and improve power control. In [62] and [63], radio resources were simultaneously used by cellular as well as D2D links, thereby saving bandwidth. Also, in [64], a model for a joint optimization of mode selection, resource assignment, and power allocation was developed for D2D communications under network control. It helps to protect the cellular layer from interference from D2D links and reduces the overall power consumption in the network.

In [65] and [66], new interference management and interference cancellation strategies were proposed to enhance the overall capacity of cellular networks and D2D systems. In [67], a resource allocation scheme was proposed to maximize the spectrum efficiency and to protect the cellular users interference, guaranteeing the QoS of D2D links. In [68], the authors compared two other resource allocation methods with conventional ones and showed higher throughput and significant energy savings. Furthermore, in both [69] and [70], new power control algorithms for network-assisted D2D communication scenarios were evaluated. In [71], the authors proposed a new network model for a D2D underlaid cellular system. In this system, both centralized and decentralized power control algorithms were defined. A trade-off between supporting reliable communication for the uplink cellular user and improving the cellular network throughput was identified.

Similarly, the existing research on D2D discovery has mainly focused on evaluating and enhancing the performance of network-assisted discovery. The throughput of network-assisted discovery was evaluated in [72] and power control strategies were investigated in [73]. In [74] and [75], eNBs were used to improve the discovery process in order to allocate resources and prevent contention. Authors from [76] took advantage of the availability of network infrastructure to speed up the discovery process.

In [77], an analytical study of the number of UEs in a network-assisted D2D discovery group was provided, where the authors analyze the statistical behavior of the distance between two D2D peers using the core network knowledge, assuming that the base stations follow a Poisson distribution. Based on that, they identify conditions to maximize the D2D discovery probability. Additionally, in [78], Goa et al. present an evaluation of

how the user behavior (i.e. user density and mobility, traffic load) impacts the D2D communication performance in the network, consisting of millimeter-wave small cells based on their proposed centralized scheduling scheme. In [79], Li et al. develop a theoretical analysis for the D2D discovery performance over single and multiple discovery periods. Different static UEs densities and data load were evaluated. The analysis showed that the discovery retransmission scheme behaves better with low transmit UE density while probability-based transmission scheme behaves better with high density.

Those works are limited to in-coverage scenarios. Regarding the D2D discovery process without network intervention, few contributions are found in the literature. Out-of-coverage discovery was considered in [80] and a static scheme was proposed in order to control interference. However, this model is rigid and cannot react to changes in the size of the discovery group or in the transmission conditions, which results in a very stagnant discovery. Also, in [81], the authors propose an alternate framework to that of 3GPP's that extends the services available for the UEs. In [82], Chour et al. presents a new D2D discovery scheme for vehicular users by exploiting the Road Side Units (RSUs) in highways. The proposed scheme offloads a portion of the D2D discovery traffic to the Vehicle Ad hoc Network (VANET). The results show a low discovery latency. In addition, in [83], the authors studied the interconnection between the D2D nodes and 5G networks, and propose new architectural enhancements in the Evolved Packet Core (EPC) in order to facilitate inter-cell D2D communication in 5G network.

For our thesis, we study D2D direct discovery, focusing on out-of-coverage scenarios, although our contributions are also applicable for in-coverage cases.

2.5 Conclusion

In this chapter, LTE Device-to-Device communications was identified as a promising approach to overcome the previous limitations identified in Chapter 1. LTE technologies were introduced as baseline for D2D communications. We defined the D2D architecture and protocols as presented in the 3GPP specifications. The provided mechanisms for out-of-coverage scenarios are completely static and pre-configured. However, the D2D parameters should depend on the environment, the user density, and the traffic load.

Therefore, we need efficient mechanisms to avoid both the pitfalls a network-centric LTE and the lack of adaptability when out-of-coverage. We showed how the discovery process is of capital importance, as if it is performed inefficiently, it will cause delays and shortage of resources, by taking longer to complete the discovery and consuming a lot of resources that can no longer be used for communication. The research on this area was also reviewed, and it was shown that it has mainly focused on in-coverage discovery. Henceforth, in our work, we will focus on out-of-coverage D2D direct discovery, type 1 (UE-selected), model A (announcements broadcast). Our main goal is to amplify the advantages of this type of communications while minimizing the limitations, thus ensuring their suitability for next generation networks.

In the next chapter, we present our work in extending and validating simulation tools that are used in testing the efficiency of our proposals.

Chapter 3

Novel Adaptive Transmission Algorithm for Device-to-Device Direct Discovery

3.1 Introduction

Device-to-Device (D2D) communications rely on discovery, which is the process that UEs use to exchange information regarding the D2D related applications and capabilities that they support. In scenarios that use model A and type 1, where there is no infrastructure support, discovery parameters are configured in advance, thus not taking into account the different potential scenarios, nor the dynamism introduced by the user mobilities.

In order for the discovery process to be executed efficiently and without requiring a large number of resources, a flexible and adaptive discovery algorithm is needed. Allocating more resources to the discovery process reduces the collision rate, but it also reduces the bandwidth that is available for data transmission. On the other hand, allocating too few resources slows down the discovery, and devices take longer to identify UEs in proximity because of the high contention risk. In order to dynamically adjust the configuration of the parameters that govern the discovery process, it is important to develop models that allow operators to accurately understand the performance impact of each of the parameters involved.

In this chapter we first present and validate through simulations an analytical model

that allows direct computation of the distribution of the time for a UE in a group to discover all other UEs in the group. Later, using that model as a base, we propose an algorithm that allows UEs performing discovery to dynamically tune the transmission probability according to the available pre-configured resources and the number of UEs already discovered. This allows convergence to the optimal transmission probability by the time each UE has discovered every other UE in the group, resulting in faster and more efficient discovery.

In the next sections, we review the related work and literature, followed by a description of the D2D discovery resource pool model, and the development of an expression that allows for the analytical modeling of the number of periods required for any given UE to discover all the other UEs in the group. These analytical models will be validated using system-level simulations. Then, our novel adaptive algorithm is presented and its performance evaluated through further system-level simulations. Finally, we provide a summary of the contributions and analysis of the results.

3.2 Related Work

Research on the performance of D2D services has mainly focused on modeling and evaluating the communication service. In [84], Asadi et al. define utility functions to model resource allocations and energy consumption when using jointly LTE and WiFi technologies. The formulated problem aims to maximize the sum of utilities over all possible combinations of users and modes et to minimize interference generated by both D2D and LTE users. In [85], ElSawy et al. develop an analytical framework for D2D-enabled uplink cellular networks, with two important design parameters: a bias factor, which accounts for both the D2D link quality and the cellular link quality and controls the extent to which the D2D communication is enabled in the network, and a power control cutoff threshold, which controls the tradeoff between the SINR outage and truncation outage. In [86], Hakola et al. generate some numerical equations, used to evaluate the system performance and to find out the optimal and practical system capacities when D2D communication is performed alongside with conventional cellular network.

Until very recently, most of the existing work on D2D discovery was part of larger works describing and analyzing all the D2D services defined in the 3GPP specifications, like [55] where Sun et al. provide a summary on synchronization, discovery, and communication, as stated in the 3GPP specifications at the time (March 2014).

In the context of the D2D discovery, there has been some work on modeling the effect of SINR on the discovery process, notably the works by Kang and Kang [87] and Bagheri et al. [88]. Kang and Kang base their analysis on the average number of devices discovered in a given number of periods, without further analysis of the time required to discover all the devices in the group, and Bagheri et al. do not consider the half-duplex effect in their analysis. Regarding the discovery process itself, we can find contributions like Xu et al.'s [74], where the authors realize that if UEs are using scheduled mode and are within cell coverage, it is possible to avoid collisions and improve discovery by using the eNB to gain knowledge of the UEs that want to participate in D2D, and allocate the resources for discovery based on the position and number of UEs in the network. Similarly, Choi et al. [75] propose another network-assisted model where the eNB efficiently allocates resources for discovery as it is aware of all the discovery traffic going on in the cell. Also using the infrastructure, to improve the discovery process, Ngo et al. [76] use two eNBs to calculate the relative distance between UEs, and presume that this knowledge can be used to accelerate the discovery process. However, these proposals focus only on network-assisted discovery where the eNB is in control, therefore limiting their improvements to in-coverage scenarios.

The most significant contribution in the literature to discovery in out-of-coverage scenarios is Li et al.'s proposal of a static scheme to control interference [80] where instead of basing the transmission of discovery messages on a transmission probability, they propose using a scheme that replaces the randomness of the probability with predictable "equivalent" transmissions (i.e. instead of a transmission probability of 0.25 each period, they propose one transmission every 4 periods). However, this model is static and cannot react to changes in the size of the group or in the transmission conditions.

Finally, Griffith and Lyons. [89] propose a theoretical model that calculates the optimized value of the probability of transmission for a given set of parameters (i.e. number

of UEs and resources). In this chapter, we build upon that research and use the mathematical model to design an adaptive algorithm where the UEs keep track of the optimized transmission probability over time. The algorithm dynamically adjusts to different environments and resource configurations while improving the overall discovery performance.

3.3 D2D Discovery Resource Pool Model

3.3.1 Assumptions

We assume that UEs transmit discovery messages during every occurrence of the PSDCH discovery resource pool for each discovery period [35]. A resource pool is composed of a pair of adjacent Physical Resource Blocks (PRBs) that occupy the same subframe. Discovery messages can be repeated in a given period up to four times (i.e., one original transmission followed by a number of retransmissions, varying between zero and three). This retransmissions number is given by the parameter N_{SLD}^{TX} [46]. The resource pool's effective dimensions in the frequency and time domains are respectively $N_f = \left\lfloor \frac{M_{RB}^{PSDCH}}{2} \right\rfloor$ and $N_t = \left\lfloor \frac{L_{PSDCH}}{N_{SLD}^{TX}} \right\rfloor$, where M_{RB}^{PSDCH} is the number of PRBs in the pool and L_{PSDCH} is the number of subframes. Therefore, the total number of resources in the pool is $N_r = N_f \times N_t$. We assume that all UEs are half-duplex, so that a UE that sends a discovery message during a given subframe is incapable of receiving any discovery messages transmitted by other UEs during that subframe. We also consider discovery type 1.

3.3.2 Analysis

In each period, every UE, independently of every other UE, generates a uniformly random resource index $n_{PSDCH} \in \{0, 1, \dots, N_r - 1\}$, which maps to a unique set of PRB and subframe indices via the following equations [46]:

$$a_j^{(i)} = (j - 1) \left\lfloor \frac{N_f}{N_{SLD}^{TX}} \right\rfloor \quad (3.1)$$

$$b_j^{(i)} = n_{PSDCH} \bmod N_t \quad (3.2)$$

where i is the period index and j indexes the transmission attempts in the i^{th} period, ensuring that $1 \leq j \leq N_{SLD}^{TX}$.

In general, a UE can transmit using different transmission probabilities, by generating an additional random variate that is uniform over the unit interval and comparing this result to a threshold; the UE sends its message if the variate is less than the threshold [43]. In this chapter, we only consider the case where the value of that probability is equal to 1, which means the UE is transmitting discovery messages at every opportunity.

The result of this mapping scheme is that when $N_{SLD}^{TX} > 1$, two UEs that pick resource indices that cause them to produce identical values for $b_j^{(i)}$ in a given period, i , will transmit in the same subframes for all N_{SLD}^{TX} transmissions during that period. This effect allows us to conceptualize the discovery resource pool as shown in Fig. 3.1. We depict the pool using a rectangular grid, where each element of the grid is associated with a unique value of n_{PSDCH} and corresponds to a particular PRB pair and set of $N_{SLD}^{TX} > 1$ subframes.

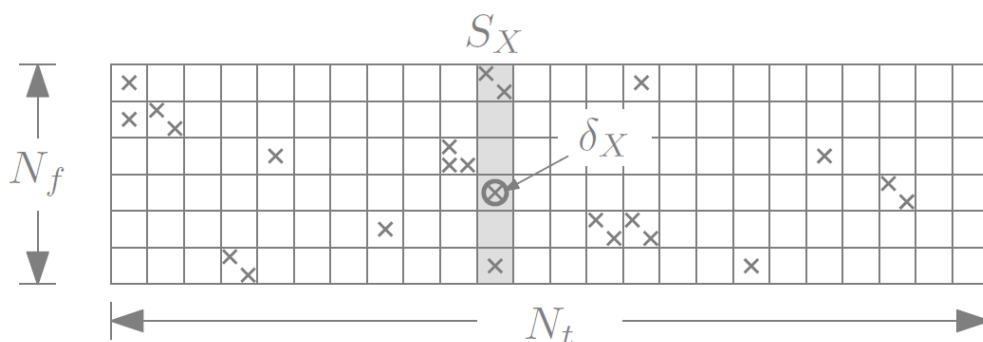


FIGURE 3.1: Discovery resource pool model, showing transmissions from UEs in the D2D group

We assume that we have a group of UEs, participating in D2D communications; the number of UEs in the group is N_u . We assume that N_u is constant. We also assume that every UE in the group is able to receive transmissions from every other UE in the group. We assume that when two or more UEs pick the same resource in the pool, the interference will prevent any collided message's being received by other UEs. This gives us a conservative performance estimate.

In practice, some collided messages may be received by some UEs if the Signal to Noise and Interference Ratio (SINR) is high enough. In the subsequent analysis, we will focus on a single UE, which we denote as UE_X , and we will develop a mechanism for computing the cumulative distribution of the time for UE_X to discover the other $(N_u - 1)$ UEs in the group.

3.3.3 Analytical Study

We characterize the time required for a randomly chosen UE, which we denote as UE_X , to discover all other UEs in its group. We use a discrete-time Markov chain whose time index indicates the number of PSDCH periods that have elapsed since the starting time, and whose single state variable, $N_D[t]$, is the number of UEs that have been discovered by UE_X at the end of the t^{th} period. Also, we denote the number of undiscovered UEs at the end of the t^{th} period as $N_U[t] = (N_u - 1) - N_D[t]$. The range of possible values for $N_D[t]$ is $0 \leq N_D[t] \leq N_u - 1$; the starting state is $N_D[0] = 0$ (because UE_X has not yet discovered any of the other $(N_u - 1)$ UEs in the group) and the Markov chain's eventual ending state is $\lim_{n \rightarrow \infty} N_D[t] = N_u - 1$, which is the Markov chain's sole absorbing state. More details about this theoretical study can be found in [31].

3.3.4 Validation Model

We will now validate the theoretical results shown previously with a D2D communication and discovery simulation model we developed using ns-3: [29] and [30]. We examined two resource pool configurations: $N_f = 5$ PRB pairs and $N_f = 10$ PRB pairs, with $N_t = 10$ subframe sets in both cases. For each resource pool configuration, we considered three D2D group sizes: 10 UEs, 20 UEs, and 30 UEs. For each scenario, we performed 10 runs, with 500 trials per run. In each trial, we generated a set of uniformly distributed UEs within an area sufficiently small to that each UE could receive messages from every other UE (e.g., a 100 m \times 100 m). Each UE transmitted a discovery message in every period using a randomly chosen pool resource, and we recorded the number of periods required for the UE to discover all of the other UEs in the group. We used these results to generate a sample CDF for each run, and we averaged the ensemble over all

runs to produce our estimate of the CDF of the number of periods for UE_X to discover all other UEs.

We show the results for the six cases in Fig. 3.2 and Fig. 3.3, in which we show 95 % confidence envelopes for each case, and we plot the corresponding theoretical CDF in each subfigure for comparison. Fig. 3.2 and Fig. 3.3 also show the confidence envelope based on Massart's refinement of the Dvoretzky-Kiefer-Wolfowitz (DKW) inequality, which states that, given a set of random variates $\{X_i\}_{i=1}^N$ that are drawn from a distribution with CDF F_X and that produce an empirical CDF \hat{F}_X , the probability that the true and empirical CDFs are separated by more than $\varepsilon \in \mathbb{R}^+$ over their entire support has the following upper bound [90].

$$Pr \left\{ \sup_{x \in \mathbb{R}} \left| \hat{F}_X(x) - F_X(x) \right| > \varepsilon \right\} \leq 2e^{-2N\varepsilon^2} \quad (3.3)$$

Note that the upper bound on the excursion probability in Eq. (3.3) decreases to zero for any $\varepsilon > 0$ as N increases, and we can easily extend the inequality to discrete random variables, since the resulting CDF is still defined over the whole real line. The 95 % confidence interval associated with the DKW inequality is actually a confidence envelope over the entire domain of interest, whose upper and lower bounds are defined by the empirical CDF plus or minus the error offset ε . Since we are interested in interval bounds that result in the theoretical curve lying entirely within the confidence envelope with 95 % probability, we can set the upper bound in Eq. (3.3) equal to 0.05, the probability that the theoretical CDF deviates from the empirical CDF by more than ε , and then solve for ε , giving

$$\varepsilon = \sqrt{\frac{\log\left(\frac{2}{0.05}\right)}{N_{runs} \times N_{trials}}} \quad (3.4)$$

since the empirical CDF is constructed from $N = N_{runs} \times N_{trials}$ variates. We plot the resulting confidence envelope $\hat{F}_X[n] \pm \varepsilon$ in both Fig. 3.2 and Fig. 3.3 using dark gray bars. Note that the pointwise 95 % confidence intervals are contained within the 95 % confidence envelope, which is a looser interval because it covers the entire domain. Note also that the pointwise confidence intervals are widest near the median and become narrower in the distribution's tails.

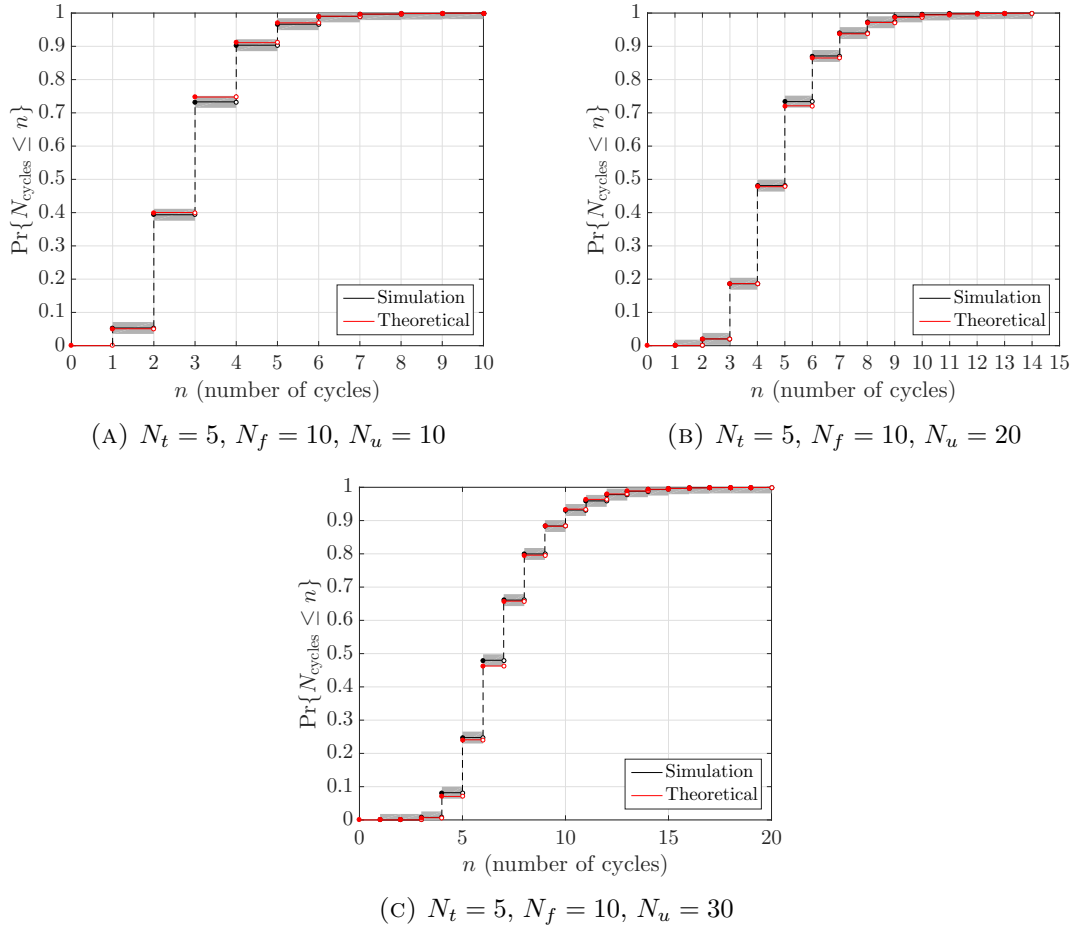


FIGURE 3.2: Cumulative distribution function plots and corresponding ns-3 simulation results, with envelope 95 % confidence intervals shown, plotted versus n , the number of PSDCH periods: 5 subframes and 10 RB pairs

The resulting plots in Fig. 3.2 and Fig. 3.3 show excellent agreement between the theoretical and simulation results, with the theoretical curve lying entirely within the confidence intervals over the entire domain. The results also illustrate the effect of increasing the size of the discovery resource pool. Comparing Fig. 3.2 and Fig. 3.3 shows that doubling the resource pool size produces a noticeable shift (i.e. a shorter time completing discovery) in the CDF for each group size, and that the CDFs for the various group sizes are closely spaced when $N_r = 100$ resources, while the CDF associated with $N_u = 30$ UEs indicates degraded performance due to increased collisions by UEs using the smaller pool.

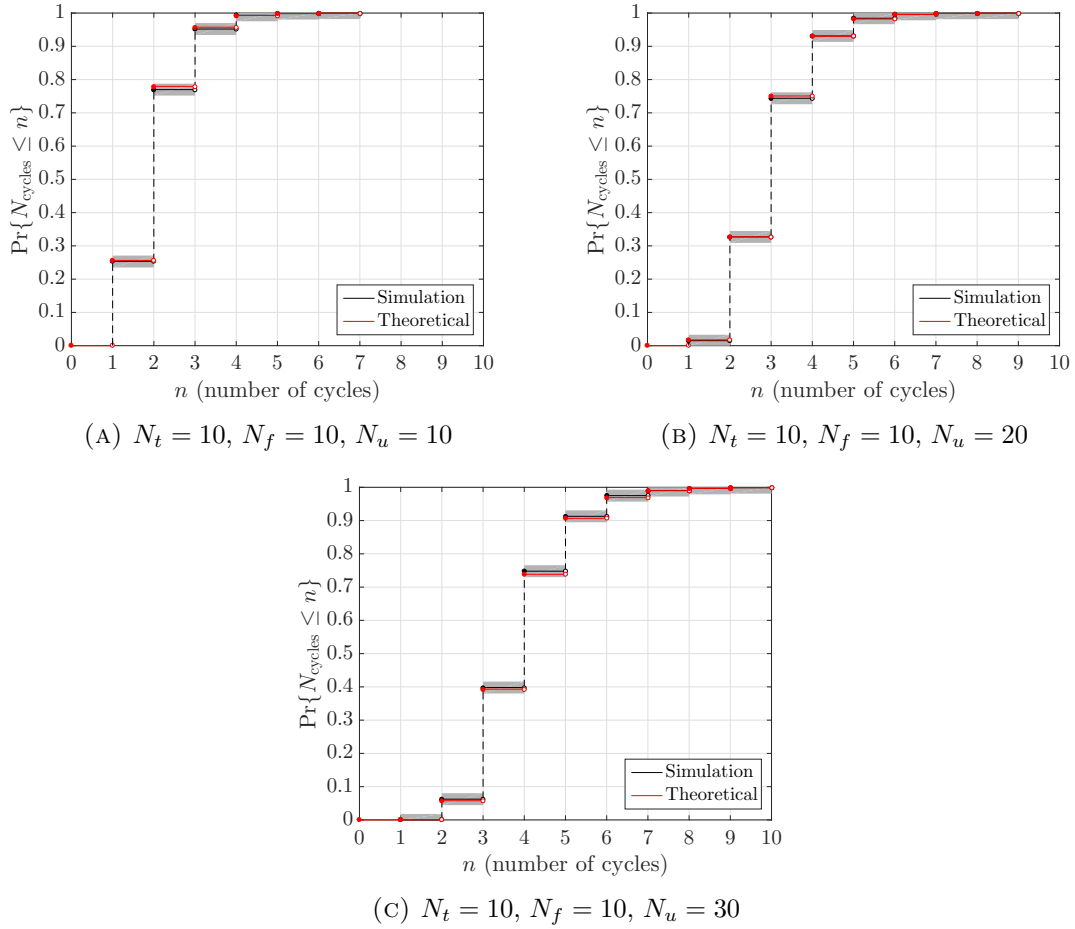


FIGURE 3.3: Cumulative distribution function plots and corresponding ns-3 simulation results, with envelope 95 % confidence intervals shown, plotted versus n , the number of PSDCH periods: 10 subframes and 10 RB pairs

3.4 Adaptive Algorithm

After validating the theoretical model with system-level simulations, we can now build and propose an adaptive discovery algorithm that makes use of the knowledge obtained so far. We will first describe the modeling of the discovery process that makes use of the analytical model, followed by the detailed description of the proposed algorithm.

3.4.1 System Model

In table 3.1, we provide a list of symbols we will use to describe the discovery process and our contributed algorithm.

TABLE 3.1: List of Symbols

Symbol	Definition
N_f	Number of resource block pairs available for discovery
N_t	Number of subframes available for discovery
N_r	Total number of resources in discovery pool
UE_X	Randomly chosen UE
n	Number of UEs discovered by UE_X
N_n	Number of new UEs discovered by UE_X
N_o	Number of UEs previously discovered by UE_X
N	Total number of UEs in the scenario
N_u	Number of UEs discovered by UE_X plus UE_X itself
θ	Optimal transmission probability for UE_X
UE_n	late arrival UE

In our model for the discovery process, we assume that each UE sends one discovery message (i.e. one announcement) each time it is supposed to do discovery after checking its transmission probability threshold. For clarity, and without loss of generality, we will consider that the number of applications is equal to the number of UEs. For analysis and simulation purposes, we also consider that all UEs are interested in announcing their own application and in monitoring all other applications within the group (i.e., UEs not participating in the discovery process will not be accounted for).

When sending announcements, UEs choose the resources to do so from a defined resource pool. The latter consists of given numbers of subframes (SF) N_t (time-wise) and resource block (RB) pairs N_f (frequency-wise). As described in Fig. 2.8 and 3.1, the total number of resources N_r is:

$$N_r = N_t \times N_f \quad (3.5)$$

According to the 3GPP working assumptions [35], the channel to be used for discovery is half-duplex. So, if a UE transmits a discovery message in one subframe, it cannot receive any other discovery message transmitted by any other UE in that same subframe. Taking this into account, in [89], Griffith et al. developed an analytical model proving that D2D direct discovery performance can be enhanced using an optimal value of the transmission probability θ , defined by Eq. (3.6):

First step is to check the number of subframes N_t defined in the discovery resource

pool. If $N_t = 1$, UEs will never get to discover each others because of the half duplex constraint. That's why that case is specifically checked for, and if met, we know that discovery would not happen. Then, we examine if the number of devices performing discovery are way smaller than the numbers of subframes and resources (N_t and N_r respectively). For this case, the UEs choose to announce all the time because of the low probability of collisions. If the previous checks fail, we compute the optimal value of the transmission probability θ .

$$\theta = \begin{cases} 1, & \text{if } N_u < \frac{N_r(N_t-2)+N_t}{N_t-1} \\ \frac{2N_r+N_t(N_u-1)-\sqrt{4N_r(N_r-N_t)+N_t^2(N_u-1)^2}}{2N_u} & \text{otherwise} \end{cases} \quad (3.6)$$

As we can see, the computation of the optimal transmission probability requires prior knowledge of the number of UEs in the group (N_u), which means that in a changing environment the UEs need to learn that information dynamically.

If the UEs know the PSDCH dimensions (N_r and N_t), then they can use the formula below to get the value for N_u since:

$$N_u = \frac{N_r \times N_t - (2N_r - N_t) \times \theta}{(N_t - \theta) \times \theta} \quad (3.7)$$

3.4.2 Adaptive Discovery Algorithm

We consider a group of N users that decide to start using D2D communication at the same time (e.g. when a group of emergency responders arrives at an incident). They hold D2D direct discovery-capable equipment, so in order to discover each other, they start sending discovery messages using a pre-configured transmission probability and allocated resources N_f , N_t , and N_r .

Depending on the number of repetition defined in the discovery pool, each UE may end up with multiple versions of the same discovery message. After discarding duplicated information, each UE (noted as UE_X) successfully receive discovery messages from n different UEs.

At any point of the discovery process UE_X will have detected N_o UEs, and only N_n of those n received discovery messages have never been received before. $N_u - 1$ represents

the total number of UEs that UE_X succeeded to discover.

$$N_u = N_o + N_n + 1 \quad (3.8)$$

where $N_o < N$, $N_n \leq n < N$ and $N_u < N$.

The new transmission probability of UE_X will be an approximation to the nearest non-zero multiple of 0.25 less than or equal to 1 (to conform to the values allowed by 3GPP) of the final result of Eq. (3.6). For the following period, the UE will start announcing using the new value of computed transmission probability.

For any given UE_X , the computation of the adjusted transmission probability will follow Algorithm 3.1.

Algorithm 3.1: Adjusted Transmission Probability

```

1 for any given  $UE_X$  that starts the discovery process do
2   UE receives discovery messages from  $n$  UEs;
3    $N_n = 0$ ;
4   for  $i$  in  $[1, n]$  do
5     if  $UE_i$  was never discovered before then
6        $\lfloor$  increment  $N_n$ ;
7    $N_u = N_o + N_n + 1$ ;
8   if  $N_u > 1$  then
9     calculate  $\theta$  (Eq. 3.6) ;
10    approximate  $\theta$  to the nearest multiple of 0.25;
11    use the approximate value of  $\theta$  to transmit discovery message;
12   $N_o = N_u - 1$ ;

```

We assume that a UE_X has already discovered N_o UEs in the discovery group ($N_o = 0$ at the beginning of the discovery process). UE_X will start the discovery the process with the initial transmission probability it retrieved from the resource pool. At the end of each discovery period, UE_X will count the number of new UEs discovered N_n (based on received announcements). Taking into consideration Eq. 3.6 and replacing N_u by $N_o + N_n + 1$, we compute the new value of the transmission probability, and we use its approximation to transmit discovery messages for the next periods. This operation is repeated at each discovery period.

3.5 Performance Evaluation

3.5.1 Simulation Design

Once we have defined our proposed algorithm, we need to validate its expected behavior and actual performance, and we will do so by using simulations with the discrete event simulator ns-3. In this simulator, we implemented D2D direct discovery type 1 according to both 3GPP specifications and our improved algorithm.

We considered a simple topology of a group of N_u stationary UEs. We examined different group sizes varying from 10 to 60 UEs while fixing the resource pool configuration, consisting of 4 resource blocks pairs ($N_f = 4$) and 5 subframes ($N_t = 5$), which provides a total of 20 discovery resources ($N_r = 20$). According to Eq. 3.6, the fluctuation of the optimal transmission probability depends on the number of UEs and the resource pool configuration, mainly the N_r and N_f . Fig. 3.4 shows the exact computed value of θ and its approximate (i.e. nearest multiple of 0.25). The chosen numbers of UEs, in the discovery group, covers the whole range of effective values of θ (i.e. from 0.25 to 1).

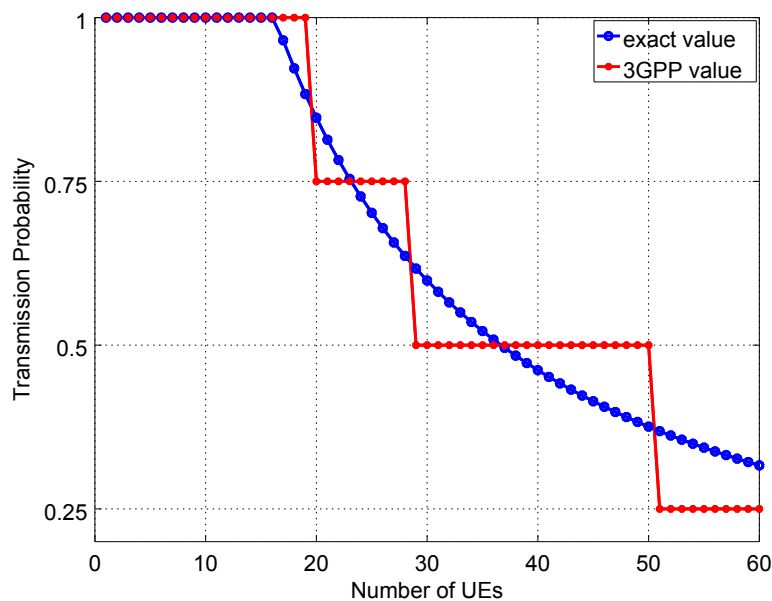


FIGURE 3.4: Optimal transmission probability for different number of UEs, 4 resource block pairs and 5 subframes

Table 3.2 outlines the individual scenarios based on UE populations used, their corresponding optimal θ and the transmission probability for that optimal value, and Table 3.3

summarizes a list of simulation parameters and their default values.

TABLE 3.2: Scenarios

Scenario	Number of UEs	Optimal θ	Approximate θ
A	10	1.4105	1.00
B	20	0.84703	0.75
C	40	0.46184	0.50
D	60	0.31644	0.25

TABLE 3.3: Simulation Parameters and Values

Parameters	Values
UE transmission power	23 dBm
Propagation model	cost231
Available bandwidth	50 Resource Blocks (RB)
Carrier frequency	700 MHz
Discovery period	0.32 s
Number of retransmission	0
Number of repetition	1
Number of resource block pairs	4
Number of subframes	5
Total number of resources	20
Total number of UEs	10, 20, 40, 60
Area Size	$200 \times 200 m^2$
Discovery start	2 s
Total simulations per scenario	100

In each simulation, we randomly deployed users so that all UEs are within range of each other and therefore every UE can discover all other UEs in the group. Every UE is able to send announcements using a randomly chosen pool resource.

We will be comparing the 3GPP discovery algorithm and our improved algorithm. Initially, we set the transmission probability to a defined value. As the 3GPP discovery algorithm is static, this initial value will be used for the whole simulation when that algorithm is used. However, when using our proposed algorithm all UEs will eventually compute and update their own transmission probability.

3.5.2 Simulation Results

3.5.2.1 Stationary Scenario: Baseline

We define a baseline configuration where we discard all colliding discovery messages, and we use a simple propagation model with minimal propagation errors as assumed in [89].

The metrics we will use to compare the performance of these algorithms are the time (measured in number of periods) required for all UEs in the group to discover each other, and the time required for one random UE to discover everyone else.

Results from Fig. 3.5 correspond to a fixed number of resources ($N_r = 20$) and different group sizes: 10 UEs (Scenario A, Fig. 3.5a), 20 UEs (Scenario B, Fig. 3.5b), 40 UEs (Scenario C, Fig. 3.5c) and 60 UEs (Scenario D, Fig. 3.5d). We also plotted the confidence interval of 95 %.

Through simulations, we validated that the theoretical optimal θ gives the best overall discovery performance. The line corresponding to the adaptive algorithm performance fits a flat plot, which means that, independently of the used initial transmission probability, the number of periods needed to complete discovery is roughly the same. We also noticed that the number of periods needed for all UEs to discover all other UEs show trends similar to the number of periods needed for one random UE to discover everyone else.

We can see from these results that the ratio of total number of UEs to total number of resources determines the shape of the plot, which was expected from the theoretical model: the smaller the ratio, the faster the discovery process and our algorithm is doing much better compared to the 3GPP case. However, if that ratio is closer to 1, the algorithm does not improve the results that much, but we can see how it does not make them worse either.

We can observe how, for each scenario, without prior knowledge of the size of the group, there is a chance of 25 % of starting the discovery process with the optimal transmission probability value. For that case, the 3GPP discovery algorithm would present better results giving that the discovery process used, since the beginning, the optimal transmission probability. However, we proved that the adaptive algorithm succeeds to

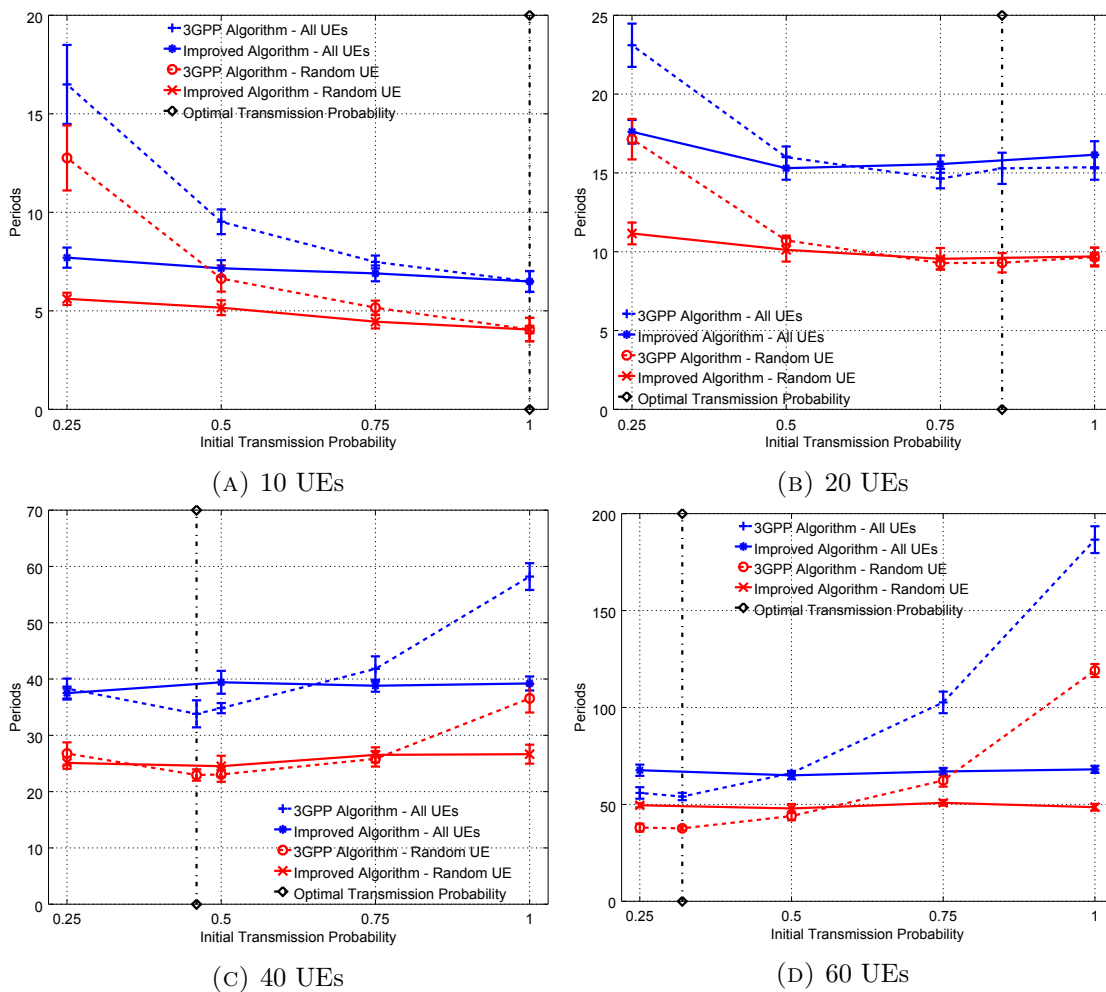


FIGURE 3.5: Stationary Topology: Number of periods needed for all UEs in the group and for one random UE to discover everyone else in the group (Baseline)

catch up for scenarios A and B, with the difference in number of periods less than 10 for scenarios C and D. For the rest 75 % of the possible cases, using the pre-configured transmission probability, the UEs take longer to discover each other using a static algorithm. Our adaptive algorithm allows the UEs to complete the discovery faster, independently of their initial transmission probability, with performance increase being really significant for scenarios A and D. As we can see in Fig. 3.5d, using 1 as the value for the transmission probability makes the 3GPP discovery to take almost 3 times longer than our adaptive algorithm. This is due to our algorithm succeeding to acknowledge the presence of more UEs in the vicinity and adapting the transmission probability to the optimal value, saving time compared to the 3GPP algorithm. In general, the 95 % bracket is

smaller for the proposed algorithm than for 3GPP, which means the results are more consistent and therefore, predictable.

3.5.2.2 Stationary Scenario: Collisions and Recovery

While the baseline scenario showed promising results for our algorithm, we needed to evaluate the performance when the channel is not ideal. For this purpose, we modified our scenario by removing the simplistic assumptions. First, we were able to retrieve at most one discovery message when there are collisions: discovery messages can be decoded during collision if the SINR is high enough. Then, we used a more realistic propagation model (cost231 [91]). Results of those simulations, along with a confidence interval of 95 %, are shown in Fig. 3.6.

As expected, using a more stringent propagation model means that the discovery process takes longer, even though the recovery process manages to save some of the announcements. We can still observe that our algorithm manages to perform the whole discovery process faster than the 3GPP algorithm in general, and at least as efficiently when starting the simulation with the optimal transmission probability. We can also observe how the theoretical optimal value of the transmission probability is still valid even when a message recovery procedure and a more realistic error model are in place. A final point to notice is that the difference in the size of the 95 % brackets is even more significant.

To appreciate the difference that our algorithm makes in the performance of the discovery process, we plotted the Cumulative Distribution Function (CDF) of UEs discovered over time for two specific cases. Fig. 3.7 shows the plots for two of the scenarios shown before. We have validated that the rest of the cases also show similar behaviors, with the distance between the curves being proportional to the differences shown in Fig. 3.6. In Fig. 3.7, we compare the number of UEs discovered in the group using the 3GPP algorithm and our adaptive algorithm. Fig. 3.7a represents scenario A using an initial transmission probability equal to 0.25, while Fig. 3.7b describes scenario D for an initial transmission probability equal to 1. As we can see, our algorithm provides faster discovery. For example, for scenario D, when using the 3GPP algorithm, 95 % of the UEs are discovered in 263 periods. However, the latter value is reduced by more than

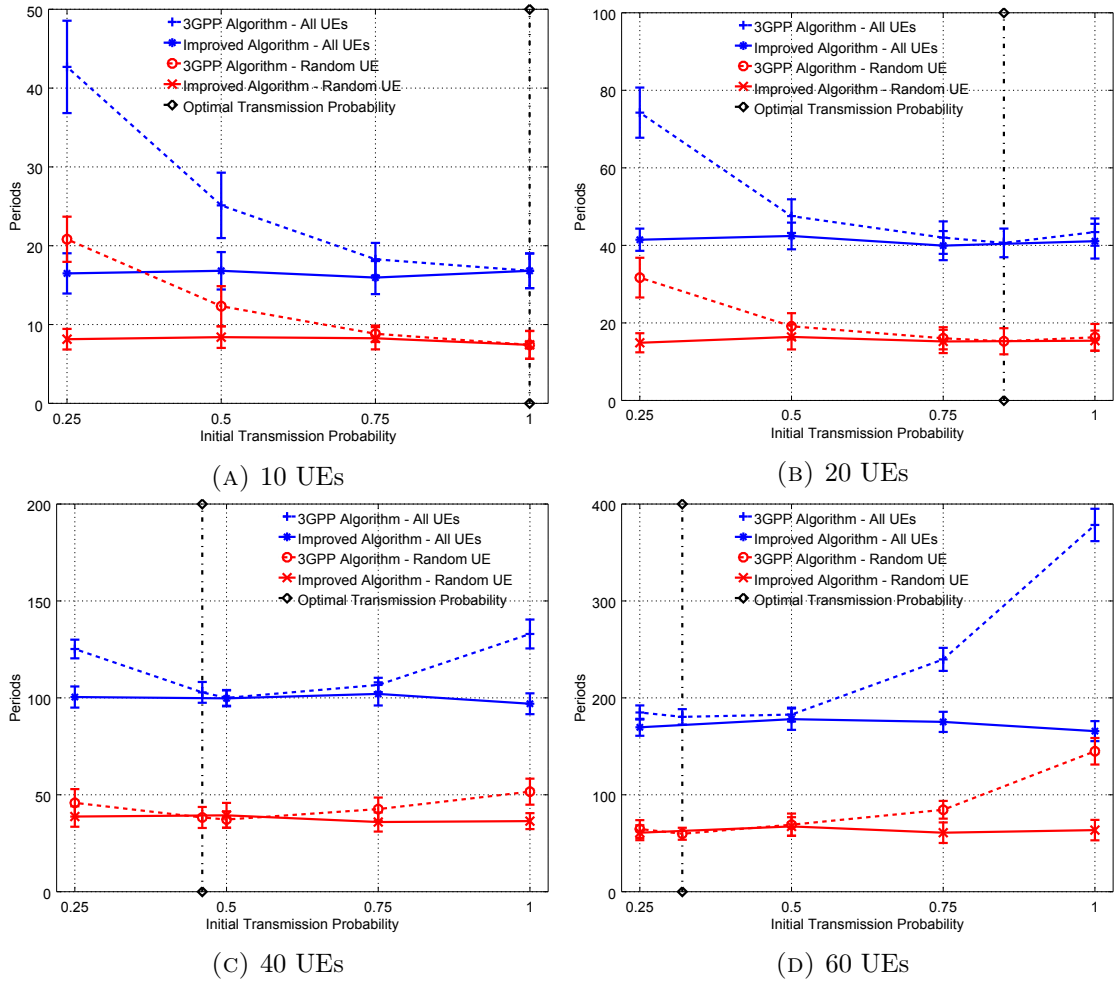


FIGURE 3.6: Stationary Topology: Number of periods needed for all UEs to discover all other UEs in the group and for one random UE to discover everyone else in the group (Loss and Recovery)

half (115 periods) when our algorithm is applied, which is a significant improvement in the overall performance.

Fig. 3.7 highlights the difference in average. However, looking through the CDF, we can see how the differences are even bigger for 95 % of the UEs. Increasing the number of UEs creates more collisions and congests the half-duplex channel. Our algorithm behaves better for a significant number of UEs (in comparison with available discovery resources), thanks to its adaptability.

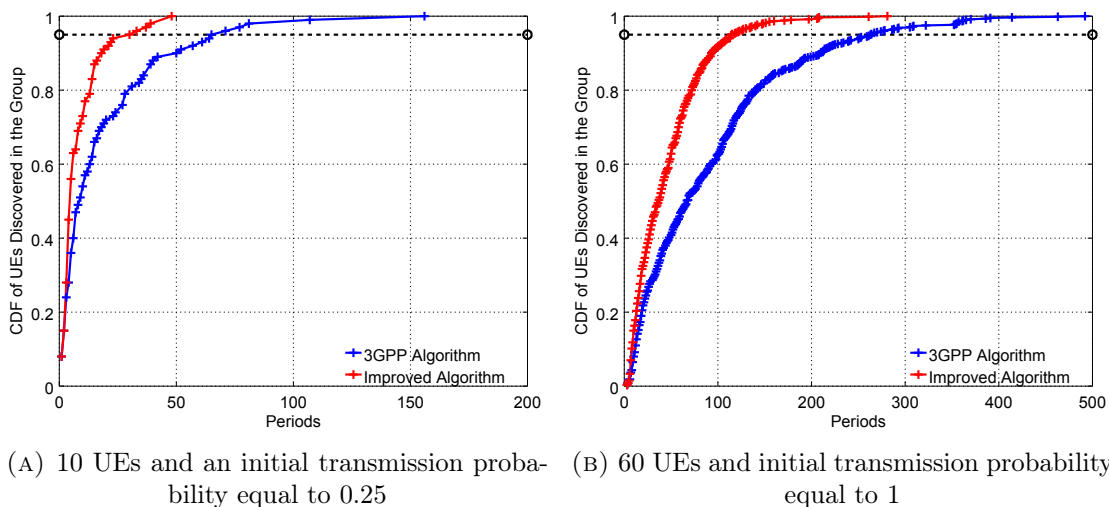


FIGURE 3.7: Stationary Topology: CDF of UEs discovered versus number of periods (Loss and Recovery)

3.5.2.3 Dynamic Scenario

For further evaluation of our adaptive algorithm, we assume that one UE, noted UE_n , is joining the discovery group at a later time. Using its preconfigured transmission probability, UE_n will initiate discovery after the discovery process has already been completed for the existing UEs.

We verified that, for validation and testing purposes, the introduction of this additional UE does not change the optimal transmission probability in each scenario (shown in Table 3.2), despite increasing the number of UEs in each group.

This scenario allows us to evaluate the effect of new arrivals on the UEs' synchronization to the optimal transmission probability timewise. We will be interested in assessing how long it takes the UE_n to discover the rest of the UEs in the group and how long it takes other UEs to detect UE_n 's presence.

In Fig. 3.8, we compute the percentage change for UE_n (or all UEs, including UE_n) discovering the rest of the group (or all other UEs, respectively). Let $P_{Improved}$ be the total number of periods needed when applying our dynamic improved algorithm, and P_{3GPP} the total number of periods needed when using the 3GPP static algorithm. We plot the result of Eq. (3.9). A confidence interval of 95 % is also computed.

$$\Delta = \left(\frac{P_{Improved} - P_{3GPP}}{P_{3GPP}} \right) \times 100 \% . \quad (3.9)$$

The results are matching and as expected, it shows that the late arrival UE_n is the one driving the completion of the discovery. Besides, when we use the optimal value of the transmission probability since the beginning of the simulations, the difference can be positive (percentage increase) but close to zero (and within our 95 % confidence interval). But it is negative (percentage decrease) when using other initial transmission probabilities (i.e., 75 % of the possible cases), which means a reduction in the maximum number of periods needed to complete discovery.

In scenario B, the optimal transmission probability is equal to 0.75. If the discovery process starts using that value as its initial transmission probability, we record for Fig. 3.8a a delay of less than 2 % of the time needed to complete the whole discovery process. This constitutes the worst case. The best registered amelioration is displayed in Fig. 3.8, for scenario A, when starting with an initial transmission probability equal to 0.25. Our algorithm helped reduce the maximum number of periods reached by more than 17 %.

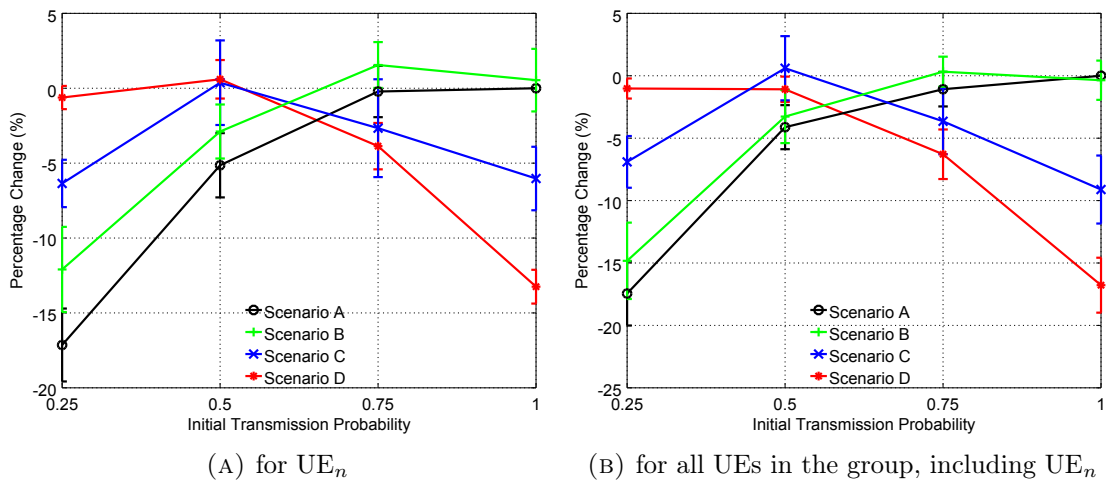


FIGURE 3.8: Dynamic Topology: Percentage change of the number of periods needed to complete discovery

Overall, those results show significant improvement, by just taking into account the number of UEs discovered to adjust the transmission probability. There is little cost associated with our simple but efficient proposal.

Our improved algorithm outperforms the 3GPP algorithm, even in situations where we have UEs joining the discovery group at a later time. It adjusts dynamically to a growing topology, thanks to its adaptive nature.

3.6 Conclusion

In this chapter, we have described the discovery process for UEs using D2D communications, and based on that process, a model based on a Markov chain model was developed. This model allows exact computation of the distribution of the number of periods required for one random UE to discover all of the other UEs in its group, while accounting for the effect of half-duplex UEs. Using this theoretical model, we were also able to prove the correctness of our D2D direct discovery implementation in ns-3.

Based on the results observed from the validation of the analytical mode, we proposed a novel adaptive discovery algorithm that improves the performance of the discovery process in out-of-coverage scenarios, by dynamically adjusting the transmission probability based on vicinity awareness. The algorithm gives UEs the ability to change their transmission probabilities as needed to reduce the time required to discover other UEs. The efficiency of our proposal was validated with simulations and the results proved that our algorithm reduces the time required for the discovery process in a group of UEs for several different configurations.

Several scenarios with different premises, both accounted for and not accounted for in the analytical model's assumptions, were used for evaluation. The results were consistent across the board, regardless of whether we look at the group results or at single UEs. It consistently showed performance improvements that ranged from matching the performance of the ideal case within the 95 % confidence, to gains of 50 % in terms of time and resources used.

In the analysis and simulations, we assumed that all UEs were announcing and discovering (i.e., we ignored other UEs). However, having UEs that only announce, only monitor, or do none of those operations does not change the results. They would be incorporated in the algorithm if they announce, and if they do not, they would discover UEs at a slightly faster rate (as they do not have collisions), but they wouldn't change the results significantly. In the second part of our simulations, although the addition of the new UE did not change the optimal transmission probability, no significant penalty would have incurred if it changed. As we have seen in the results, the algorithm allows UEs to converge extremely quickly to new optimal value of the transmission probability

θ , even when all of them are using a non-optimal value (i.e., the results when 3GPP starts with the optimal θ , and the algorithm shows that the “convergence” overhead is very small, almost negligible). So even, in those cases, the analysis and conclusions are still valid.

In the next chapter, we will use our adaptive transmission algorithm and use it in environments where traffic patterns based on real-trace user densities are available. It will allow us to have a novel proactive discovery algorithm by anticipating the number of users in the cell.

Chapter 4

Enhancing Device-to-Device Direct Discovery Based on Predicted User Density Patterns

4.1 Introduction

D2D communications, as introduced by 3GPP in Release 12, are based on geographical proximity. UEs are able to detect and communicate with other UEs in their vicinity [14].

D2D communications are applied in different environments for both commercial and public safety use. It is already expected to bring up advantages like spectrum utilization optimization and improvement in throughput and latency. 3GPP has already defined public safety use cases, as these users need to maintain communications in environments where we have little or no coverage like underground. It would be also used to provide service during a partial or complete network shutdown occurring due to large scale natural disaster or power power disruptions, as it can provide extra capacity when needed, especially in large metropolitan areas [35].

Mobile users tend to consume resources in significantly different ways, depending on the time at which they use network services and the location where they do. This results in large variations of network usage profiles or even different daily users' density profiles according to each location. We propose an online prediction framework, based on Support Vector Regression (SVR) [92] and trained with real network traces, that is able

to predict these instant densities. SVR is known to be more efficient with large dataset processing since it uses only few samples (support vectors) from the training dataset, which reduces notably the processing time, in addition to their minimal computational requirements.

In this chapter, we use SVR to generate user density predictions that allow the anticipation of the number of users for different types of areas and traffic classes, and based on that, we propose an adaptive algorithm to enhance the discovery process in dynamic environments. However, the main challenge for D2D discovery is the high volume of messages sent during announcing and monitoring procedures. In particular, announcing UEs would consume a lot of energy for permanent periodic transmission of discovery messages. This chapter addresses such an efficient direct D2D discovery procedure challenges enabling energy saving. We validate our model with real traces of spatio-temporal UEs density patterns, which allow us to evaluate the feasibility of our approach.

The rest of this chapter is organized as follows. In Section 4.2, we discuss the related work in D2D discovery and existent user density models. In Section 4.3, UEs density prediction using cell tower traces is introduced, and in Section 4.4, a transmission algorithm for D2D direct discovery that takes into account those user density patterns is proposed. Then, Section 4.5, shows the evaluation performance of the algorithm and results analysis. Finally, we conclude and discuss future work in Section 4.6.

4.2 Related Work

Although literature work related to D2D communications has been available for some time, existing research on D2D has focused on the direct communication and how to mitigate interference and to control power. In [62] and [63], radio resources were simultaneously used by cellular as well as D2D links, thereby saving bandwidth. In [65] and [66], new interference management and interference cancellation strategies were proposed to enhance the overall capacity of cellular networks and D2D systems. In [71], the authors proposed a new network model for a D2D underlaid cellular system. In this system, both centralized and decentralized power control algorithms were defined and trade-off

between supporting reliable communication for the uplink cellular user and improving the cellular network throughput.

Most papers on D2D discovery have mainly focused on evaluating and enhancing the performance of network-assisted discovery. For example, throughput of network-assisted discovery was evaluated in [72] and power control strategies were investigated in [73]. In [74] and [75], the eNBs were used to improve the discovery process in order to allocate resources and prevent contention. Authors from [76] took advantage of the network availability as well to speed up the discovery process. Therefore, for scenarios with infrastructure failures, such work can not be considered, as discovery needs to be independent of the network core.

Additionally, UEs are carried by subscribers that commute between different places throughout the day (from home to work, for example), which induce a specific time-dependent patterns of daily UE density within each base station. Few recent works investigate the impact of users' density on the process of D2D discovery. In [79], the authors propose a performance analysis for D2D discovery for multiple periods and show the impact of both high and small transmitting users density cases. The analysis showed that the discovery retransmission scheme behaves better with low transmit UE density while probability-based transmission scheme behaves better with high density. In [82], Chour et al. exploit the Road Side Units (RSUs) of the Vehicle Ad hoc Network (VANET) to propose a VANET-aided discovery protocol. The authors test different traffic volumes (vehicle per hour per lane), only in highways, and the results show a low discovery latency. In [77], an analytical study of the number of UEs in a network-assisted D2D discovery group was provided. The authors analyze the statistical behavior of the distance between two D2D peers using the core network knowledge, assuming that the base stations follow a Poisson distribution. Based on that, they identify conditions to maximize the D2D discovery probability. Even for D2D communication services, few works address the issue of studying D2D adaptation for different users' density patterns. In [78], an evaluation of the UEs density and traffic load impact on a proposed transmission scheduling scheme is made. The model is evaluated in a static network by using different levels of user densities, then it is evaluated in a dynamic networks use-case by adopting

a realistic human mobility model (SLAW) proposed in [93]. In the context of prediction-based D2D discovery algorithms, an adaptive discovery scheme is proposed in [94], which is based on predicting the inter-contact time intervals of users supposing that they follow a power-law distribution. Although the authors claim to use real mobile mobility trace, the corresponding study is old (2006, before smartphones became widespread) and accounts only for traces of Bluetooth sightings by groups of users carrying small devices in office environments, conference environments, and city environments.

The main shortcoming of the previous works evaluating D2D discovery performance that they use either simulated users' density pattern or theoretical models which may deviate from the real-world users' density behavior and ignore the daily fluctuation of UEs numbers. In our work, we validate our model with real BS load profiles and this allows us to evaluate the reactivity of the model in different environments, and enhance the algorithm derived from analytical models with predictions based on actual traffic. The advantage of using real traces is that it guarantees the model reliability and enhances its efficiency. To the best of our knowledge, no previous contributions propose an adaptive D2D direct discovery algorithm based on realistic UEs' density traces and take advantage from a learning-based UEs' density prediction model to anticipate and accelerate the discovery process.

4.3 Online User Density Prediction

We propose a model based on support vector regression (SVR) algorithm [92] for cell users' density prediction. Given a time-series training sample with N size (the history of cell UEs density), $(x_i, y_i)^N$, SVR aims to find a linear function f which maps x_i with y_i in a feature space \mathbf{F} (usually with higher dimension). The function is formulated as follows:

$$f(x) = W^T \phi(x) + b \quad (4.1)$$

where W is a vector in \mathbf{F} space and ϕ is the transformation function corresponding to \mathbf{F} .

The function is obtained by solving the following primal problem:

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N (\xi_i + \xi_i^*). \quad (4.2)$$

$$\begin{aligned} \text{s.t. } & ((w \bullet x_i) + b) - y_i \leq \varepsilon + \xi_i, i = 1, 2, \dots, N \\ & y_i - ((w \bullet x_i) + b) \leq \varepsilon + \xi_i, i = 1, 2, \dots, N \\ & \xi_i^* \geq 0, i = 1, 2, \dots, N \end{aligned}$$

where ξ_i and ξ_i^* are slack variables introduced to deal with prediction errors higher than the insensitive loss parameter ε and C is the penalty parameter.

To solve the quadratic programming of the primal formulation, Lagrange multipliers are introduced and the following dual formulation is obtained:

$$\min_{\alpha, \alpha^*} \frac{1}{2} \sum_i^N \sum_j^N K(x_i, x_j) (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) + \varepsilon \sum_i^N (\alpha_i + \alpha_i^*) - \sum_i^N y_i (\alpha_i - \alpha_i^*) \quad (4.3)$$

$$\begin{aligned} \text{s.t. } & \sum_{i=1}^N (\alpha_i - \alpha_i^*) = 0, \\ & \leq \alpha_i, \alpha_i^* \leq \frac{c}{N}, i = 1, 2, \dots, N \end{aligned}$$

The optimal prediction function is found after introducing Lagrangian multipliers (α_i) and it is as follows:

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (4.4)$$

where $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the Kernel function and its equation is as follows:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

Table 1 depicts some examples of kernel functions that are used in the literature.

TABLE 4.1: Examples of SVR kernel functions

Kernel function	equation
Linear	$K(x_i, x_j) = \langle x_i, x_j \rangle + b$
Polynomial	$K(x_i, x_j) = \langle x_i, x_j \rangle^d + b$
Sigmoid	$K(x_i, x_j) = \tan(\langle x_i, x_j \rangle) + b$
RBF	$K(x_i, x_j) = \exp(-\gamma \ x_i - x_j\)^2$

In our contribution, we use the radial basis function (RBF) as kernel function because it is more efficient with non-linear time-series (as our case) due to its generalization ability and non-linear mapping ability into an infinite feature space.

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|)^2$$

The prediction is performed in two steps: training, in which we use the history of users' density, and testing steps, in which model parameters are optimized. We model the training data with a set of four pertinent features for each base station. Each training vector $X_i \in \mathbb{R}$ is described as follows, $X_i = \{x_i^1, x_i^2, x_i^3, x_i^4\}$, where:

- $x_i^1 \in \{1, 2 \dots 144\}$ stands for the chronological order of the ten-minute time interval within a day.
- $x_i^2 \in \{1, 2 \dots 24\}$ indicates the hour of the corresponding training sample. The choice of this feature is based on the daily cycles inferred from the data.
- $x_i^3 \in \{1, 2 \dots 7\}$ indicates the weekday standing for the training data. We choose this feature because we noticed that the data has weekly cycles.
- $x_i^4 \in \{1, 2 \dots 52\}$ represents the chronological order of training data week. We choose this feature because some yearly behavior can occurred like holidays or seasonal periods, etc.

The choice of these features is made based on the periodicity analysis where we find daily and weekly cycles.

Each vector X_i must be trained with its corresponding label y_i which stands for the base station UEs' density at the time interval x_i^1 . To find the optimal value of the model

parameters C , ϵ and γ for RBF kernel function, we used the cross-validation technique and we fix the optimal parameter which minimizes the error as depicted in fig 4.1.

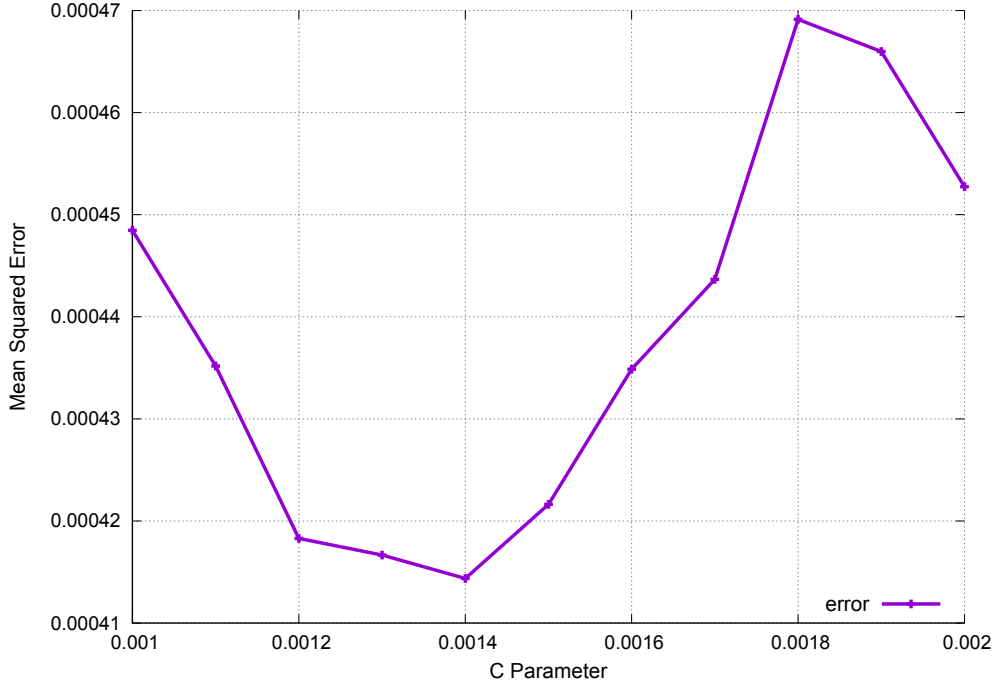


FIGURE 4.1: Performance measurement of the SVR-based load prediction

SVR prediction efficiency is validated by using testing data extracted also from Dakar dataset, which represents anonymous patterns of Orange’s mobile phone users in Senegal, on an hourly basis. The datasets are based on Call Detail Records (CDR) of phone calls and text exchanges, between more than nine million of Orange’s customers in Senegal for a whole year [95].

Fig. 4.2 shows a comparison between a predicted and real base station data and we can see that the prediction is very close to the real load.

The accuracy of the load SVR-based prediction is evaluated by two major indicators: The Mean Squared Error (MSE) measurement and the squared correlation coefficient. MSE gives an overall idea of the errors which occurred during forecasting and measures the average squared deviation of predicted values from the real data. Its mathematical expression is as follows:

$$MSE = 1/n \sum_{1 \leq k \leq n} (y_k - f_k)^2 \quad (4.5)$$

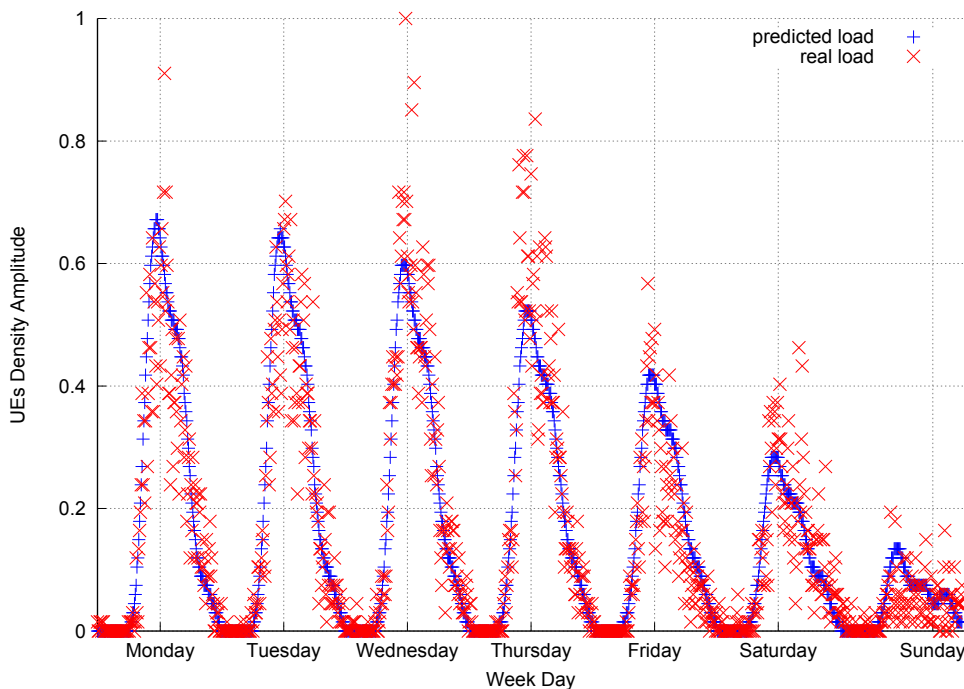


FIGURE 4.2: Predicted versus real traffic profiles

where y_k corresponds to the real load value at time k , f_k represents the predicted value, and n is the total number of points constituting the load (real and predicted) time series.

The model MSE average reaches a minimal value 21.6 with large testing history data and this value is very acceptable for long time-series forecasting. On the other hand, the squared correlation coefficient (or the coefficient of determination R^2) is a statistical measurement of how close the real data is to the prediction. For our model, this performance measurement reaches a value equal to 0.91. Thus, these metrics prove that our prediction model has a good accuracy.

In this contribution, we trained our model with realistic UEs' density profiles that we extracted previously during network CDR analysis and that we integrated in ns-3 to build a realistic traffic generator. In fact, in a previous study [96], we inferred and classified from a large dataset of CDRs, provided by Orange Senegal, three profile classes of base stations UEs' density. Each base station profile belongs to a specific pattern of network usage and load fluctuation, which depend on the nature of its location. The profile classification of base station installed into Dakar city is shown in Fig. 4.3. As depicted in the figure, Dakar city is divided into different areas according to their installed base

station profile. Fig. 4.4 shows a simple illustration of these load profile shapes.

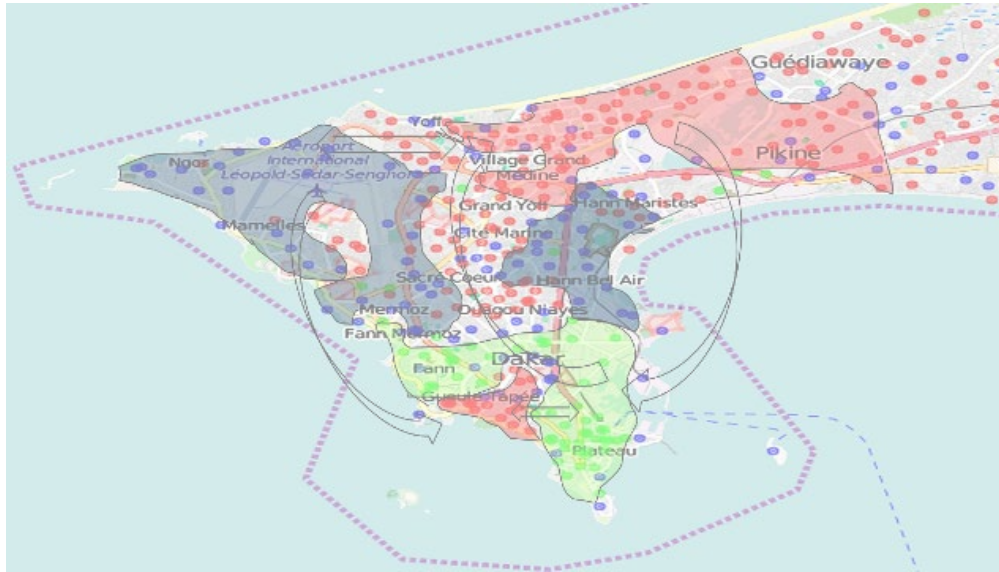


FIGURE 4.3: Dakar Base station load profile classification

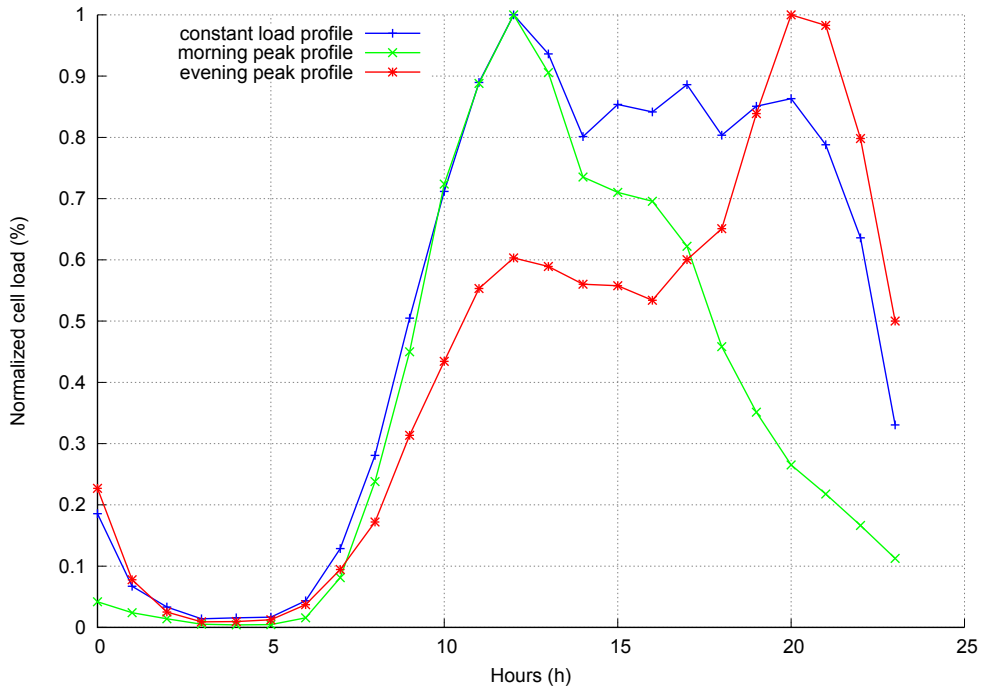


FIGURE 4.4: Base station load over time profile illustration

The red curve belongs to the “Night peak profile” and represents residential areas, the green curve corresponds to areas with “Day peak profile” where most of business areas

and activities are located, and the blue curve with a “constant load profile” corresponds to mixed areas. A set of UEs density patterns are extracted from Dakar data and integrated in ns-3 to implement a realistic traffic generator tool. The tool is then used to generate realistic pattern to train SVR model in order to make a prediction of the UEs density evolution within each area and then use the predicted values for the D2D Direct discovery algorithm.

4.4 Proposed Algorithm

4.4.1 Discovery Characteristics

For this work and as described in the previous two chapters, we consider half-duplex channel and D2D discovery performed by out-of-coverage UEs, which implies no network intervention.

As mentioned in chapter 3, section 3.4, D2D direct discovery in mode 2 lacks adaptivity to the changing communication environments, because it relies on fixed pre-defined parameters, including the transmission probability. Griffith and Lyons developed an analytical model to calculate the optimal value of the discovery message transmission probability that minimizes the mean number of periods required for a successful discovery message transmission [89].

We assume that we have N_u UEs in a discovery group, N_r and N_t are the discovery parameters as defined in 2.8. A discovery message is successfully received between two specific UEs when several conditions are satisfied:

- the transmitter is allowed to announce in the current period after checking its threshold: θ .
- the receiver should not be announcing at the same time slot (i.e. subframe): $1 - \frac{\theta}{N_t}$, otherwise it would miss the transmitter’s discovery message due to the half-duplex channel.
- none of the other UEs pick the same resource in the same time slot as the transmitter: $(1 - \frac{\theta}{N_r})^{N_u-2}$, in order to avoid any collisions.

Accounting for those requirements, the final expression of success probability is determined by Eq. (4.6).

$$P_{success} = \theta \left(1 - \frac{\theta}{N_t}\right) \left(1 - \frac{\theta}{N_r}\right)^{N_u-2}. \quad (4.6)$$

The value of θ that maximizes the success probability is determined by differentiating Eq. (4.6). Therefore, taking into account the half-duplex nature of UE transmissions and assuming that the number of users interested in discovery is equal to N_u , the optimal value of the transmission probability θ is defined by Eq. (3.6) (as shown in chapter 3, section 3.4).

The authors show that there is a small impact to performance when quantizing θ to multiples of $1/4$ ($0 < \theta \leq 1$), as allowed by the 3GPP standard. The model presented in [89] assumes an ideal environment with minimalistic propagation errors. It also considers a pessimistic approach of discovery messages handling: all colliding discovery messages are dropped and their respective applications and UEs are not discovered. However, in [32] and chapter 3, we use simulations to prove that adding interference and retrieving discovery message with the strongest signal don't affect the quantized value of the transmission probability (i.e. the discovery performance is better using that specific value).

4.4.2 Algorithm Description

Our proposed algorithm (i.e. Algorithm 4.1) makes use of Eq. (3.6) and the predicted user density patterns in order to determine the transmission probability value providing the best discovery performance. It is executed every hour and takes into consideration the number of predicted users for that area during that time of the day. It computes the optimal value of the discovery transmission probability accordingly.

At the beginning of each hour, the algorithm takes into account the geographical area to determine the traffic type. It checks its saved real database of similar traffic, calculates the average and gets the number of predicted users in the area for that hour and for that specific traffic. The user density patterns utilized during this process are extracted from real network traces. Therefore, it gives a close idea of the actual number

of UEs present in the network. Based on this information, the optimal transmission probability θ is calculated in order to get the best discovery performance. This value will be used throughout the whole hour, until the next period of time where the predicted number of UEs may change.

Algorithm 4.1: Hourly Adjusted Transmission Probability

Data: Total number of discovery resources (N_r) and number of subframes dedicated to discovery (N_t)

Result: Probability of transmission to be used (θ)

```

1 for each hour of the day do
2   get the total number of predicted users in the area for that hour based on the
   predicted user density pattern ( $N_u$ );
3   for any given UE performing D2D discovery do
4     compute  $\theta$  (using Eq. (3.6));
5     round  $\theta$  to the nearest multiple of 0.25;
6     use the resulting value of  $\theta$  for the rest of the hour;

```

4.5 Simulation Results

In this section, we present the test and evaluation of our algorithm based on ns-3 simulations [30]. We use a scenario extracted from Orange Senegal traces study [96] and integrate it in ns-3 as realistic UEs' density patterns, to study the efficiency of the proposed algorithm.

UE density patterns, which are extracted from Dakar dataset, were added to ns-3 to create a realistic traffic generator tool. The tool is then used to train SVR model in order to make a prediction of the UE density evolution within each area and then use the predicted values for the D2D Direct discovery algorithm.

4.5.1 Assumptions

We consider a morning traffic scenario in an area characterized by user fluctuation due to the presence of high education institutions. Under normal conditions the area would be served by 3 eNBs, but in this scenario they have been rendered unusable (e.g.,

due to backhaul connectivity losses). The UEs are randomly deployed in 3 different areas where the eNBs are located, as represented in Fig. 4.5.

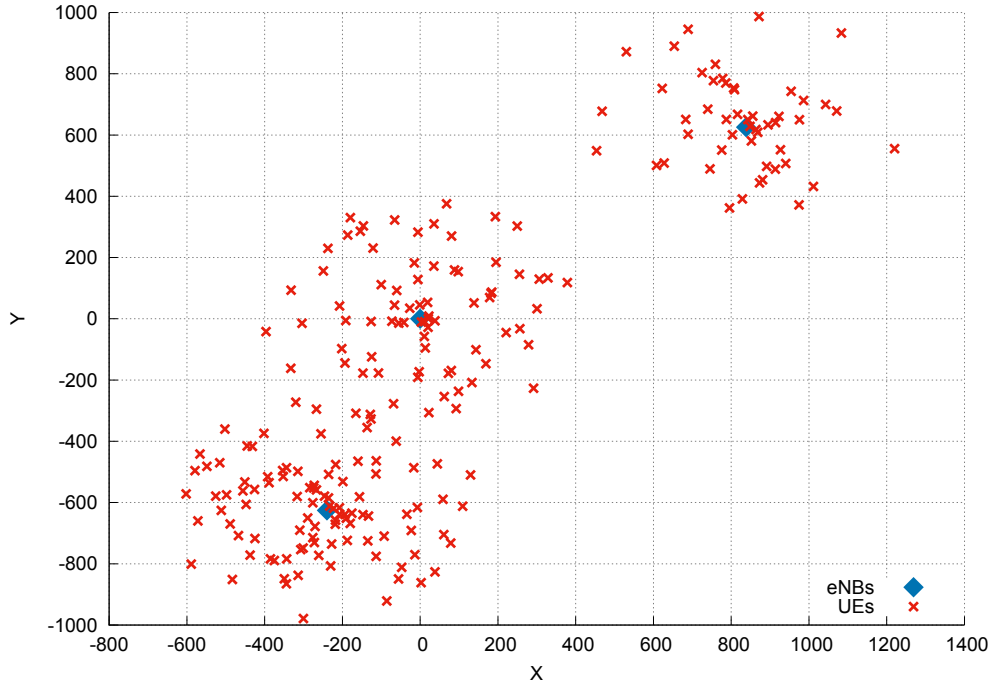


FIGURE 4.5: Example of nodes' position for the morning traffic scenario

In this scenario, we are interested in comparing the performance (in terms of messages sent and time required to complete discovery) of our discovery algorithm with that of the discovery mechanism defined in the 3GPP standard (with different operational parameters). The number of messages sent will let us know how much spectrum is being used for the discovery operations, and the time to perform discovery will provide an indication of the impact on the user experience. In order to provide an upper bound of the time metric, the discovery process can only run for 60 seconds, giving up on discovering more UEs after that amount of time. The results shown in this Section are the outcome of running the scenario 100 times in the simulator. For each metric we show the average value and 95 % confidence interval.

In each simulation, every UE is able to send announcements using a randomly chosen discovery resource. A UE uses discovery resources to send discovery but there is no guarantee that its discovery message would make it to the receivers because of potential collisions with other UEs choosing the same resources, or the fact that the receiver is

TABLE 4.2: Simulation Parameters and Values

Parameters	Values
UE transmission power	23 dBm
Propagation model	Cost231 ([91])
Available bandwidth	50 RBs
Carrier frequency	700 MHz
Discovery period	0.32 s
Number of retransmission	0
Number of repetition	1
Number of resource block pairs	4
Number of subframes	5
Total number of resources	20
Total number of eNBs	3
Maximum number of users at peak hours	50, 75, 100
Discovery start	2 s
Total simulations per scenario	100

transmitting too.

Table 4.2 summarizes the list of network parameters and their values used for our simulations.

4.5.2 Results

Fig. 4.6a, 4.7a, and 4.8a show the number of messages until all the UEs in the area were discovered. Fig. 4.6b, 4.7b, and 4.8b represent the time (measured in periods) until the 60-second discovery period expired.

For the 3GPP algorithm, the transmission probability is invariable throughout the simulation and can be either 0.25, 0.5, 0.75, or 1. However, our algorithm uses the information about the predicted number of users to adjust the correspondent transmission probability dynamically. UEs are able to compute their own transmission probability over time.

A significant energy savings and packets loss avoidance can be ensured using the considered discovery mechanism, which is the immediate consequence of reduced number of transmitted messages as shown in Fig. 4.6a, 4.7a, and 4.8a.

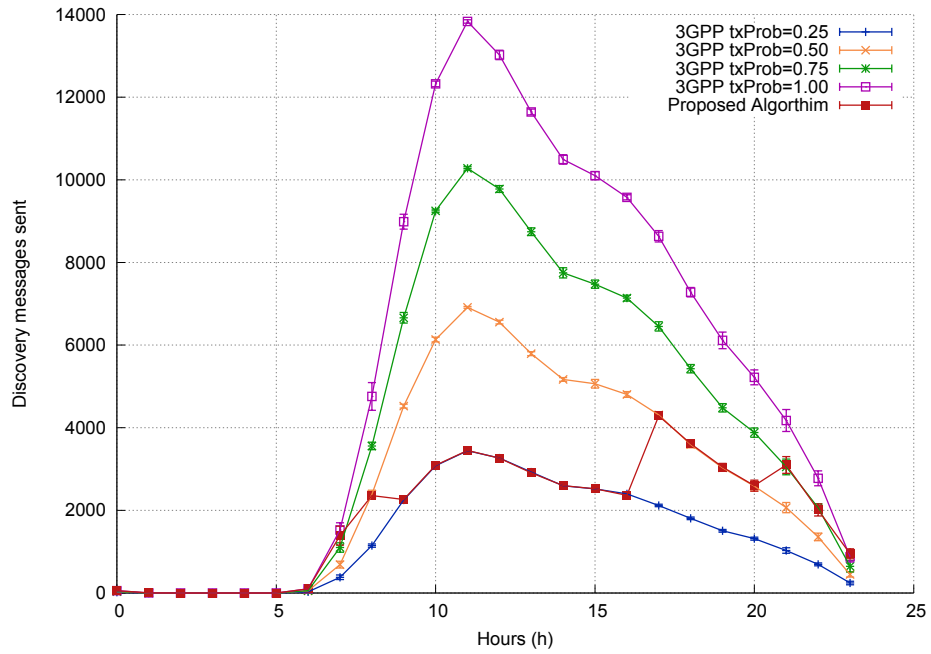
In Fig. 4.6b, 4.7b, and 4.8b, the discovery performance is very similar among all areas. We can observe an increase in the network activity that reaches a peak around noon. The curves validate the fact that we are simulating a morning-based traffic. We

can also notice that during the hours with low number of UEs, there is a direct trade-off between the time required to complete discovery and the number of messages sent. This information is highly valuable, as it can be used by the devices to adjust their operational parameters depending on the situation. For example, they can aim for a faster discovery process at the expense of spectrum utilization when minimizing the delay is the top priority, but switch to a longer process that requires sending less messages when the batteries are low. We can see how our proposed algorithm strikes a balance between both metrics. For the number of messages, only the configuration with a transmission probability of 0.25 provides better performance at certain times, and at those points the time metric shows better results for our algorithm. What may be more important, our algorithm shows a more predictable behavior (with more consistent values for number of messages and time required) than the 3GPP algorithms.

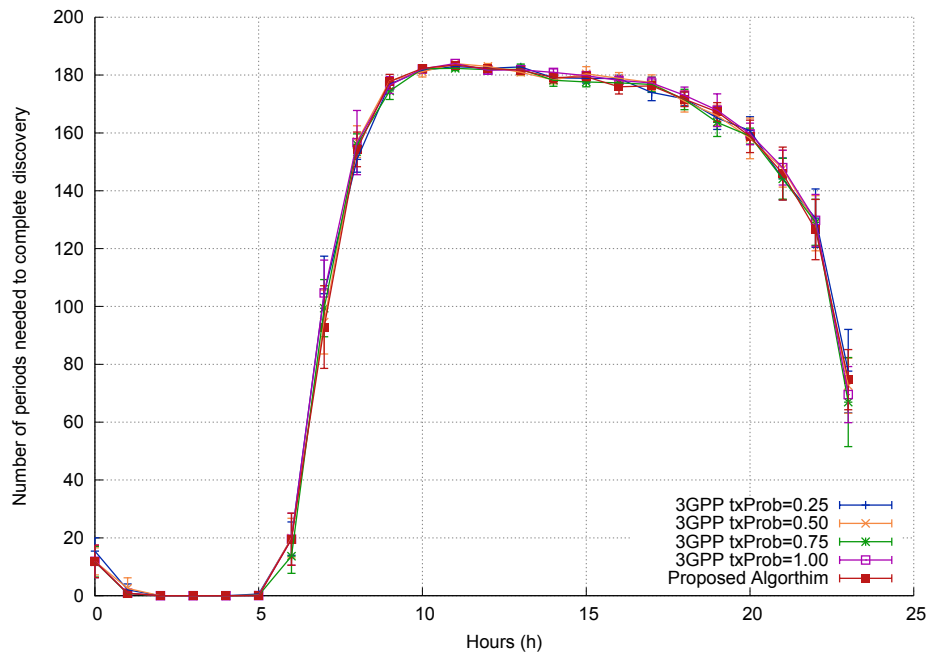
4.6 Conclusion

In this chapter, we proposed the combined use of predicted user density values along adaptive algorithms to improve the performance of D2D discovery. We showed how adaptive algorithms that use the predicted values as their baseline and adaptively account for deviations from that expected value can significantly improve the overall performance, not just in a specific subset of scenarios. We also show how an algorithm derived from an analytical model, without further tuning, can strike a balance between channel utilization and time required for discovery. So that a significant energy consumption savings can be achieved by reducing overall discovery messages signaling in the network, and further optimize network resource utilization for the discovery procedure.

In the next chapter, we will keep working on enhancing our adaptive algorithm to meet more requirements, such as changing topologies. This will help us optimize the discovery performance without any prior knowledge of the area and/or traffic, by spreading location-based awareness.

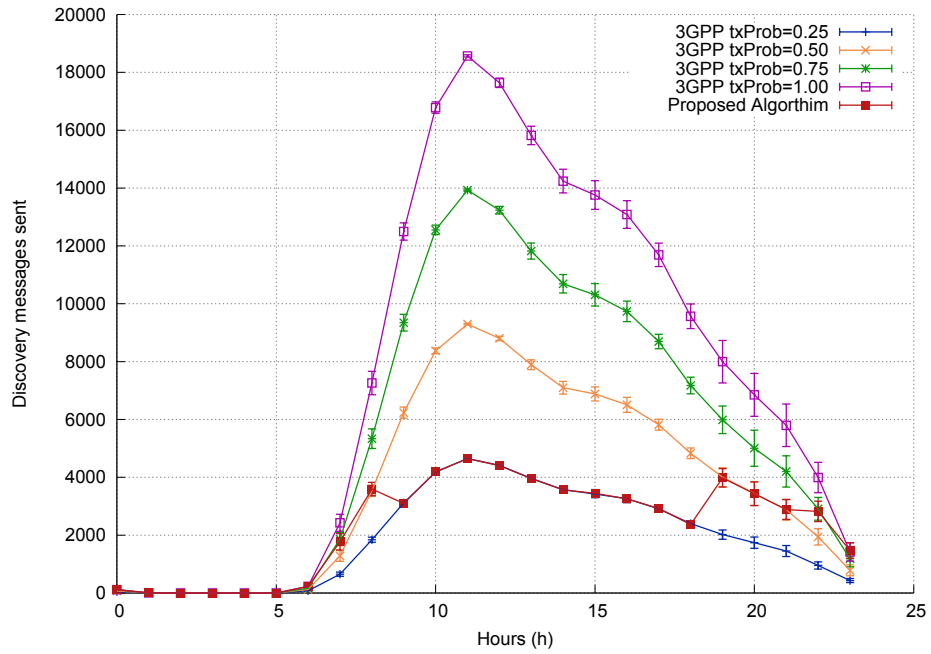


(A) Number of discovery message sent

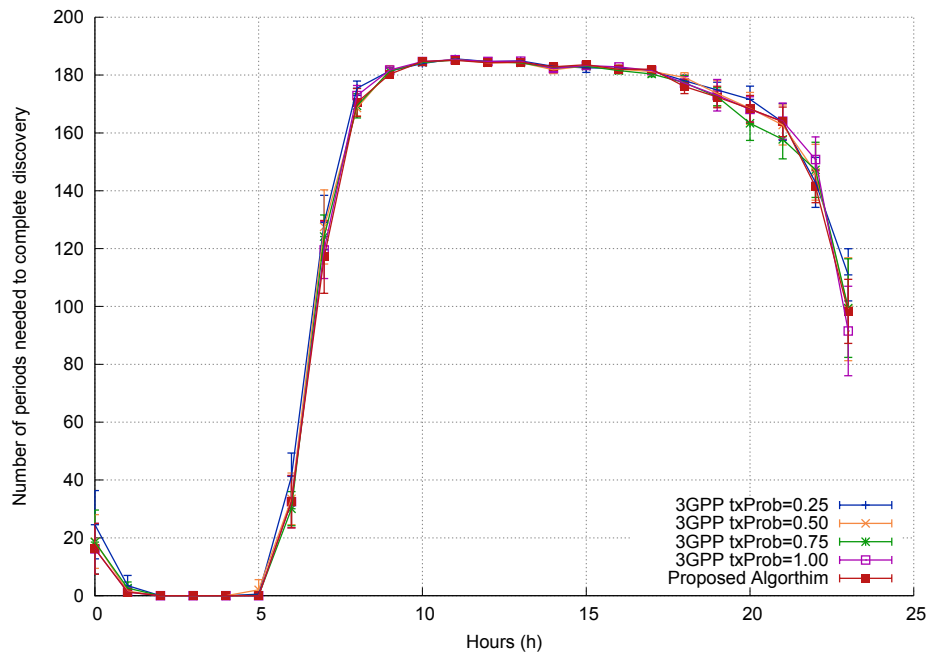


(B) Number of periods needed to complete discovery

FIGURE 4.6: Morning Traffic Scenario: Area 1

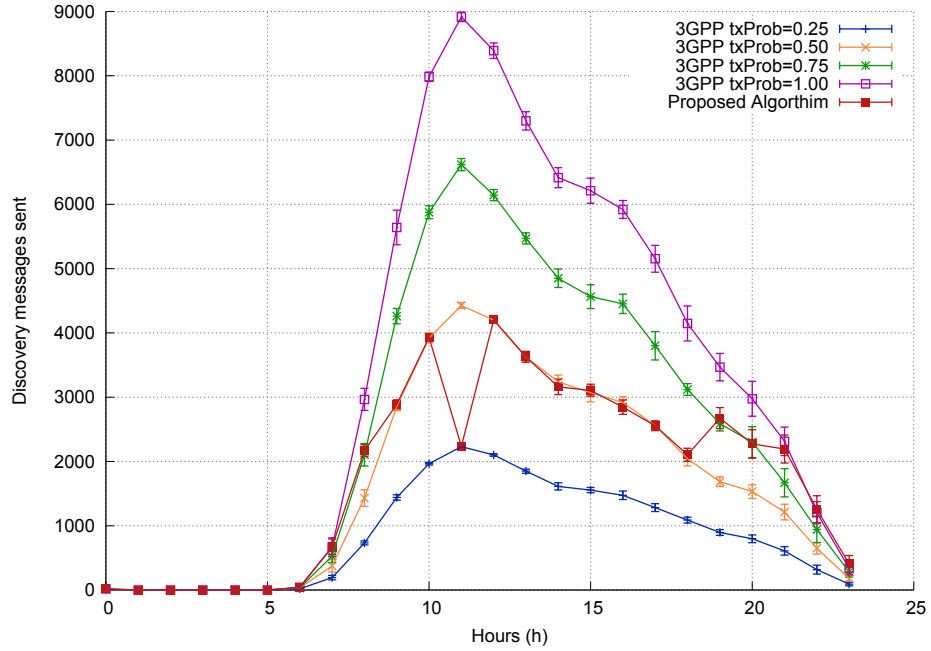


(A) Number of discovery message sent

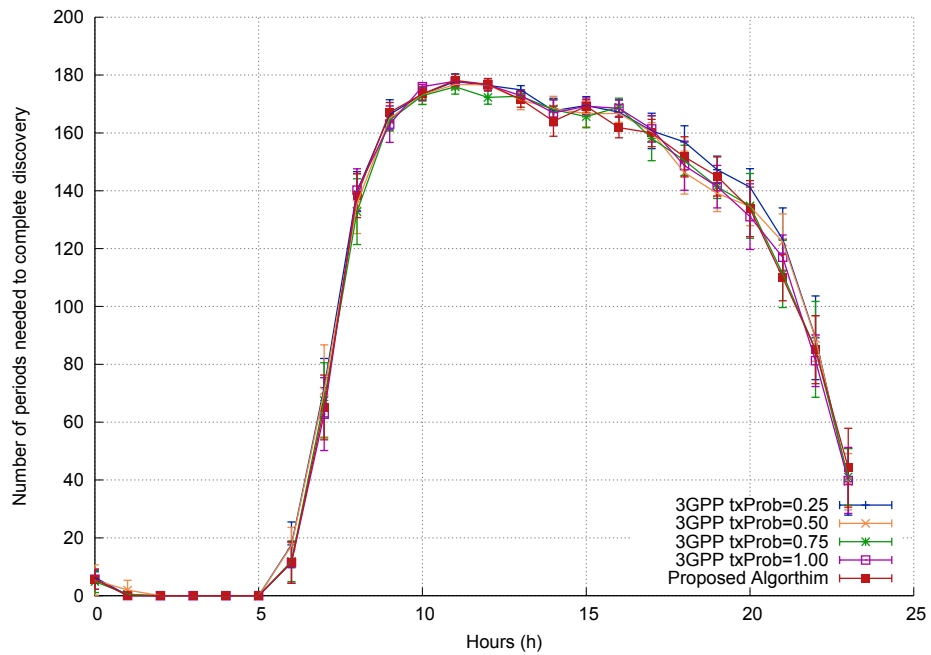


(B) Number of periods needed to complete discovery

FIGURE 4.7: Morning Traffic Scenario: Area 2



(A) Number of discovery message sent



(B) Number of periods needed to complete discovery

FIGURE 4.8: Morning Traffic Scenario: Area 3

Chapter 5

Enhanced Transmission Algorithm for Device-to-Device Direct Discovery

5.1 Introduction

LTE cellular networks rely on infrastructure nodes (e.g. eNBs, MME, SGW, and PGW) to manage the communication and network access by the users. This architecture simplifies the administration of the resources and allows for a more accurate understanding of the status of the network as a whole by the entities managing access. This means that coverage and service quality are dependent on the existence of supporting infrastructure. That is why D2D communications were introduced to increase coverage, provide service in areas without access to infrastructure, and improve the quality of service in saturated areas. As mentioned in the last chapters, for out-of-coverage scenarios, communication parameters are preconfigured in the devices and are not modified during operation, meaning that the devices can not adapt to the actual network conditions to make an efficient use of the available resources.

In this chapter, we make the UEs aware of the network conditions (e.g. number of UEs) using the messages from the discovery service. This in turn allows us to improve the use of resources and reduce the time required to complete the discovery of all the UEs in the group. The proposed algorithm allows UEs performing discovery to detect the presence and the withdrawal of other UEs in the discovery group.

The rest of this chapter is organized as follows. In Section 5.2, we discuss the related work in D2D discovery. In Section 5.3, we present our proposed transmission algorithm that takes into account success probabilities and recognizes both UE arrivals and departures. Performance evaluations and simulation results are described in Section 5.4. Finally, we conclude our work in Section 5.5.

5.2 Related Work

Existing research on D2D Discovery has focused on the modeling and performance of network assisted discovery (that is, D2D discovery for in-coverage scenarios, where the eNB controls the process). For example Madhusudhan et al. study the performance in terms of throughput of network-assisted discovery in [72]. Xenakis et al. [77] study and provide analytical models for the number of UEs and their deployment in a group for discovery to perform optimally. Similarly, Chour et al. in [82] offload the discovery process from the LTE UEs to Vehicular Ad-hoc Network (VANET) nodes (like roadside units (RSU)), and Albasry and Ahmed in [73] propose power control strategies to minimize interference and noise.

Regarding the D2D discovery process without network intervention (D2D direct discovery), we can find some works in the literature exploring the architecture design: Sharmila et al. in [81] propose an alternate framework to that of 3GPP's that extends the services available for the UEs, and Murzak et al. in [83] look into the potential of direct D2D discovery for interconnecting LTE and 5G networks.

There has been some work on optimizing the D2D direct discovery, in particular the work by Griffith and Lyons [89]. These authors computed the optimal value of the discovery message transmission probability that minimizes the mean number of periods required for all members of a group of UEs to discover each other.

Based on the work that we presented in chapter 3, an adaptive algorithm is proposed [32]. The discovery process in LTE D2D out-of-coverage scenarios is improved by dynamically adjusting the transmission probability to the optimal value as defined in [89]. Therefore, the algorithm gives the UEs the ability to change their transmission probabilities as needed to reduce the time required to discover other UEs. However, that

algorithm is able to detect UEs joining the group at any time of the discovery process, but it does not take into account UEs leaving. In this chapter, we enhance that algorithm using probabilities of success to learn how long a UE should wait before assuming that another UE has left the group, enabling the devices to fully adapt to dynamic scenarios. To the best of our knowledge, this is the only research available that allows the UEs to learn and adapt the size of the discovery group over time, and adapt the transmission parameters accordingly.

5.3 Enhanced Transmission Algorithm

In Table 5.1, we provide a list of symbols we use in this chapter.

TABLE 5.1: List of Symbols

Symbol	Definition
N_f	Number of resource block pairs available for discovery
N_t	Number of subframes available for discovery
N_r	Total number of resources in discovery pool
N_u	Total number of UEs in the scenario
UE_X	Randomly chosen UE
θ_i	Received transmission probability of UE_i
θ_{tx}	Transmission probability of the transmitter UE_{tx}
θ_{rx}	Transmission probability of the receiver UE_{rx}
θ_{ini}	Initial transmission probability for the 3GPP algorithm
n_{min}	Minimum number of periods before assuming a UE is gone
p	Success criteria (i.e. confidence) value
t_i	Time of the last reception of UE_i

5.3.1 Optimal Transmission Probability

According to the standardized architecture by 3GPP, all UEs announce using the same preconfigured transmission probability defined in the discovery resource pool for UE-Selected mode. However, based on [89], the use of specific transmission probability values selected according to the size of the group improves the performance of the whole process significantly. The optimal transmission probability θ^* is calculated as shown in Eq. (3.6).

Although the computed value θ^* is not necessarily a multiple of $1/4$ (as recommended by 3GPP), we mentioned in chapter 4 that rounding up to the nearest allowed value (i.e. 0.25, 0.5, 0.75, and 1) does not alter the discovery performance. That is why, from now on, we will be using θ as the approximation of θ^* to the nearest non-zero multiple of 0.25 less than or equal to 1. This work anticipates the number of discovery users (N_u) and computes the optimal value accordingly, which is not always the case. So, to take advantage of the previous equations, we consider that each UE will dynamically compute its optimal transmission probability based on the number of UEs it discovered throughout the time.

5.3.2 Success Probability

A discovery message is successfully received between two UEs if several conditions are satisfied. First, the transmitter UE_{tx} is allowed to announce in the current period after checking its transmission probability θ_{tx} . Secondly, the receiver UE_{rx} shouldn't be announcing at the same time slot (i.e. subframe) or it would miss UE_{tx} discovery message, as the discovery messages are sent over a half-duplex channel, which prevents the UEs from sending and receiving data in the same time slot (half-duplex constraint). Finally, none of the other UEs pick the same resource in the same time slot as the transmitter to avoid any collisions. Accounting for those requirements, the success probability of UE_{rx} discovering UE_{tx} for a **single period** is defined by Eq. (5.1) for the 3GPP-defined behavior, and by Eq. (5.2) for the adaptive algorithm presented in chapter 3 and [32].

According to the 3GPP behavior, all the UEs use the initial transmission probability θ_{ini} throughout the whole discovery process. So, the probability of a discovery message being successfully received is:

$$P_{success3gpp} = \theta_{ini} \times \left(1 - \frac{\theta_{ini}}{N_t}\right) \times \left(1 - \frac{\theta_{ini}}{N_r}\right)^{n-2}; \quad (5.1)$$

However, using the adaptive algorithm, we know that each UE_i has its own transmission probability θ_i computed using Eq. (3.6), and from them we derive the probability

of success:

$$P_{success_{algorithm}} = \theta_{tx} \times \left(1 - \frac{\theta_{rx}}{N_t}\right) \times \prod_{i \neq tx, i \neq rx} \left(1 - \frac{\theta_i}{N_r}\right); \quad (5.2)$$

The resource pool parameters N_r and N_t are known and constant. Knowing that, we use Eq. (5.1) and Eq. (5.2) to calculate the probability of a successful reception within \mathbf{n} periods, which is:

$$p = 1 - (1 - P_{success})^n; \quad (5.3)$$

Eq. (5.3) allows us to determine the minimum number of periods for a UE to receive an announcement from another UE, given a success criteria equal to \mathbf{p} .

$$n_{min} = \frac{\ln(1 - p)}{\ln(1 - P_{success})}; \quad (5.4)$$

Using these models it is possible for the receiver to know how long it should wait before learning that a transmitter has turned off or moved away, according to the confidence (i.e. the success criteria) on that learning that is desired or required.

5.3.3 Redesigned Discovery Message

In order to be able to make use of those analytical models in the discovery process, we need to announce each UE's transmission probability. To do so, we will introduce a minor modification in the discovery message format. The most significant component of the discovery message is the ProSe Application Code (with a size of 184 bits [97]). This code is allocated per announcing UE and application, and has an associated validity timer. Discovery messages are limited in size (only 232 bits) to allow their transmission in a single subframe and a pair of resource blocks, even in bad channel conditions. Increasing its size is not a practical option because that will be resource-consuming and shrink the available bandwidth. To overcome this limitation and to avoid unnecessary overhead, our proposal allocates 3 bits of the ProSe Application ID Name to carry the value of the probability of transmission in the form of two coded bits for the four allowed values (i.e. 0.25, 0.5, 0.75, 1). While the use of that extra bit is marginal, you reserve it to improve the algorithm and enable more complex and sophisticated algorithms in the future.

Using this approach, we maintain the size of the ProSe Application Code, as shown in Fig. 5.1. A mapping example of the 3-bit values is presented below:

- 000 for $\theta = 1$
- 001 for $\theta = 0.75$
- 011 for $\theta = 0.5$
- 010 for $\theta = 0.25$

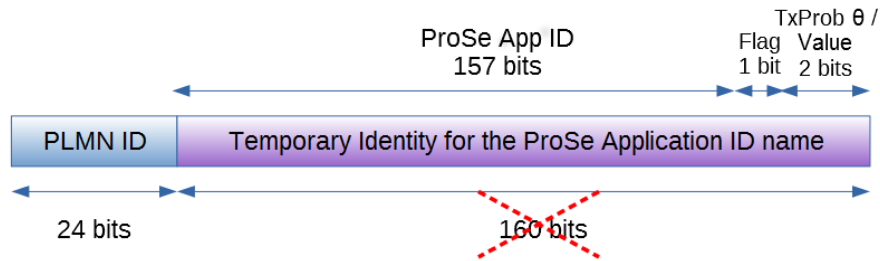


FIGURE 5.1: Modified ProSe Application Code

5.3.4 Proposed Algorithm

Given that 3GPP does not define how the detection of departing UEs should happen, we will be testing an implementation similar to the one in our enhanced algorithm. Therefore, the only differences between both implementations (static, i.e. 3GPP defined with our departure detection mechanism, and dynamic, i.e., our proposed enhanced algorithm) will be the use of the optimal theta and keeping track of the individual values of θ .

For any given UE_X , the transmission process for D2D direct discovery in UE-Selected mode will follow either Algorithm 5.1 or Algorithm 5.2 depending on whether we are using the 3GPP-defined transmission probability or the enhanced algorithm. The discovery period length, the number of subframes and resource blocks dedicated to discovery, and the considered success probability are the inputs to both algorithms.

Using the modified version of the 3GPP algorithm (Algorithm 5.1), each UE (e.g. UE_X) will keep track of UEs it discovered and the time they were discovered. If the discovery message received is sent from a UE that UE_X did not discover before, UE_X

will create a record for this UE with the discovery message timestamp. Otherwise, UE_X will update the previously-created UE's record with the new timestamp of the received announcements. Then, based on both Eq. (5.1) and Eq. (5.4), the UE looks at the registered UEs records and computes, for each UE, the minimum time needed to consider that the UE left the group. If the timer did not expire yet, the UE is still performing discovery, otherwise it is assumed to be gone. Finally, UE_X updates the number of UEs discovered. This will be referred to as static configuration because θ does not change throughout the simulation.

Algorithm 5.1: 3GPP transmission algorithm (Static) using success probabilities for D2D Discovery

Data: d is the discovery period length in seconds and p is the considered success criteria

```

1 for any given  $UE_X$  performing D2D discovery do
2    $UE_X$  receives discovery messages from  $n$  UEs;
3   Record current time as  $TimeNow$ ;
4   for  $i$  in  $[1, n]$  do
5     if  $UE_i$  was never discovered before then
6       Create record for  $UE_i$ ;
7       Set  $t_i = TimeNow$ , where  $t_i$  is the time of most recent reception from
          $UE_i$ ;
8     else
9       Update  $UE_i$ 's record: set  $t_i = TimeNow$ ;
10   $N_u = 1$ ;
11  for each  $UE_j$  received so far do
12    calculate  $n_{min}$  based on all the received transmission probabilities
      (Eq. (5.4));
13    if  $n_{min} < \frac{TimeNow - t_j}{d}$  then
14      Delete  $UE_j$ 's record;
15    else
16      Increment  $N_u$ ;

```

For the enhanced algorithm (Algorithm 5.2), each UE (UE_X) will be able to process the received announcements, check which ones are new or contained a different transmission probability. UE_X will either create a new record (identifier, timestamp and transmission probability) for the newly-discovered UE or update its old record with the

new received values. After that, similarly to Algorithm 5.1, for each discovered UE, UE_X calculates the number of periods to wait according to Eq. (5.2) and Eq. (5.4) and decides whether to consider that the UE is still there (but unable to successfully get discovered because of collisions) or gone (e.g. due to its mobility pattern). Based on the number of the remaining UEs (i.e. after discarding UEs that may have left the discovery group), UE_X computes its own transmission probability using Eq. (3.6). This algorithm will be referred to as dynamic configuration because of the continuous update of the value of θ .

Algorithm 5.2: Enhanced transmission algorithm (Dynamic) using success probabilities for D2D Discovery

Data: d is the discovery period length in seconds and p is the considered success criteria

```

1 for any given  $UE_X$  performing D2D discovery do
2    $UE_X$  receives discovery messages from  $n$  UEs;
3   Record current time as  $TimeNow$ ;
4   for  $i$  in  $[1, n]$  do
5     if  $UE_i$  was never discovered before then
6       Create record for  $UE_i$ ;
7       Set  $t_i = TimeNow$ , where  $t_i$  is the time of most recent reception from
          $UE_i$ ;
8       Set the transmission probability  $\theta_i$ ;
9     else
10      Update  $UE_i$ 's record: set  $t_i = TimeNow$  and  $\theta_i$ ;
11    $N_u = 1$ ;
12   for each  $UE_j$  received so far do
13     Calculate  $n_{min}$  based on all the received transmission probabilities
       (Eq. (5.4));
14     if  $n_{min} < \frac{TimeNow - t_j}{d}$  then
15       Delete  $UE_j$ 's record;
16     else
17       Increment  $N_u$ ;
18   if  $N_u > 1$  then
19     Calculate  $\theta$  based on the new  $N_u$  value, and the pool configuration ( $N_t$ 
       and  $N_r$ ) (Eq. (3.6)) ;
20     Round  $\theta$  to the nearest multiple of 0.25;
21     Add the encoded value to next announcements;
22     Use the resulting value of  $\theta$  to announce;

```

5.4 Simulation and Results

In this section, we provide the parameters for the scenarios, and the simulation results. To obtain the results presented here we used the discrete event simulator ns-3 [26] with the LTE D2D models from [29] and [30], extended to include the described algorithms.

We define arrival and departure scenarios where UEs join and leave the discovery group throughout the simulations. Users are deployed randomly within an area of $200 \text{ m} \times 200 \text{ m}$, where all UEs are able to discover each other. Each UE sends discovery messages by independently choosing a resource from a discovery resource pool using the procedure in [43]. Table 5.2 contains a list of simulation parameters and their default values.

TABLE 5.2: Simulation Parameters and Values

Parameters	Values
UE transmission power	23 dBm
Propagation model	Cost231 [91]
Available bandwidth	50 RBs
Carrier frequency	700 MHz
Discovery period	0.32 s
Number of retransmission	0
Number of repetition	1
Number of resource block pairs	6
Number of subframes	5
Total number of resources	30
Area size	$200 \text{ m} \times 200 \text{ m}$
Success criteria	0.99, 0.95, 0.90
Total simulations per scenario	100

Based on this scenario parameters and according to Eq. (3.6), the optimal transmission probability depends on the number of UEs as represented in Fig. 5.2.

5.4.1 Arrival Scenario

First we will look at a scenario with UEs only arriving to the group. With this scenario we will validate that the modifications introduced in the discovery algorithm do not alter the behavior observed in the previous proposal from chapter 3 ([32]). We assume that we have X initial UEs in the area. Their number vary from 10 to 90.

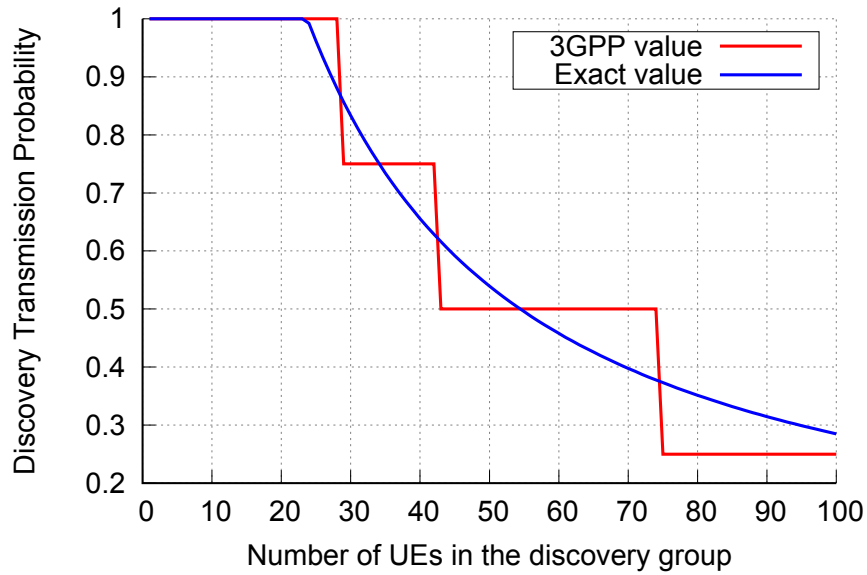


FIGURE 5.2: Optimal transmission probability associated with the number of UEs

After 100 seconds, Y UEs start joining the initial group, such as $X + Y = 100$. In the rest of this section, the number of UEs indicated in the legends for the plots will be the number of UEs initially in the group (i.e. X). Using 3GPP algorithm, the discovery performance varies based on the pre-configured (3GPP-defined) transmission probability used. Using our algorithm, the UEs start announcing using a transmission probability equal to 1 (i.e. 100 %) until they start monitoring discovery messages and use the adaptive algorithm to evaluate the optimal transmission probability value. The second group starts discovery at 100 s (i.e. when all the UEs in the first group have discovered everyone else in that group). We consider a success criteria of 99 % and we compute the number of periods needed for all UEs to discover all other UEs in their own group and the second group, along with a confidence interval of 95 %. Because of the nature of our adaptive algorithm, the number of periods needed to complete discovery is independent of the initial transmission probability used.

We will look at the results of UEs in group 1 discovering the UEs in group 1, UEs in group 1 discovering the UEs in group 2, UEs in group 2 discovering the UEs in group 2, and the UEs in group 2 discovering everyone.

5.4.1.1 Group 1 discovering group 1

We start by evaluating the discovery process for the first group as shown in Fig. 5.3. As expected, the more UEs in the group, the longer it takes to discover all of them. Besides, our algorithm outperforms the 3GPP algorithm for most cases, and provides close results when the 3GPP algorithm starts using the optimal transmission probability value. For example, for 90 UEs, the optimal transmission probability is 0.25. Using the adaptive algorithm, it takes less than 60 periods to discover all UEs in the group as represented by the blue mark at the far west end of the plot. However, using the 3GPP algorithm and a pre-configured transmission probability equal to 0.75 or 1 (i.e. 50 % of the possible cases), we have an increase of over 100 % for an initial transmission probability of 1, and over 50 % for an initial transmission probability of 0.75, in terms of number of periods needed to complete discovery.

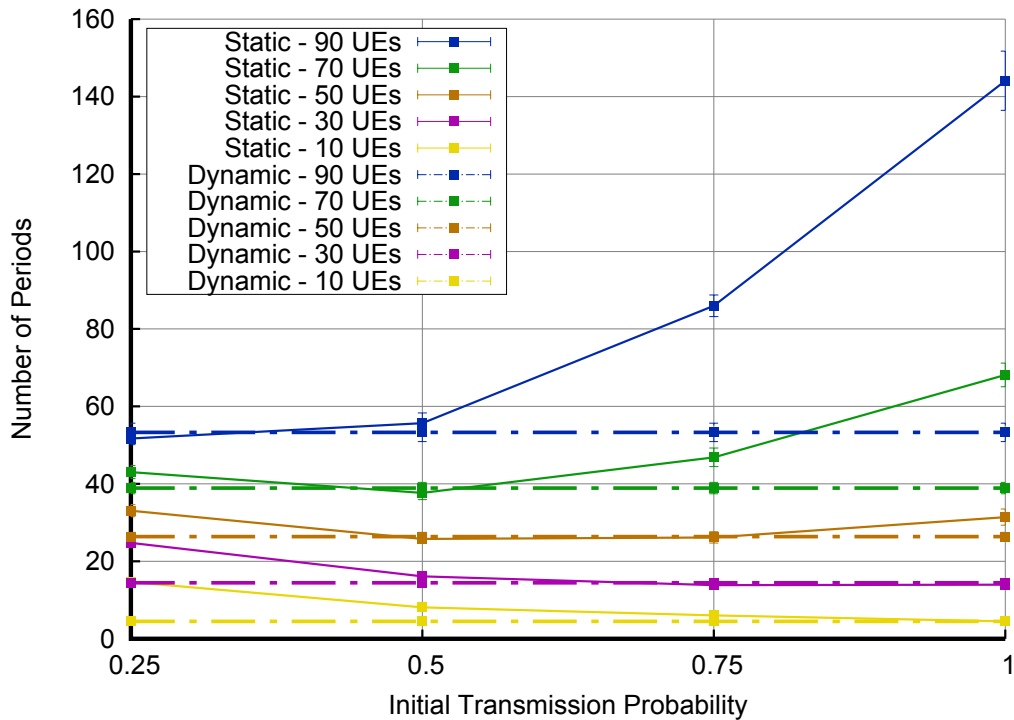


FIGURE 5.3: Number of periods needed to complete discovery within group 1

5.4.1.2 Group 1 discovering group 2

We compute the number of periods needed for group 1 to complete the discovery of group 2 in Fig. 5.4 with 95 % confidence intervals. The UEs in group 1 start discovering UEs in group 2 after 306 periods (approximately 100 s). The results show that the discovery performance is better when using the enhanced algorithm (dashed lines) in comparison to the 3GPP algorithm (solid lines), independently of the initial transmission probability.

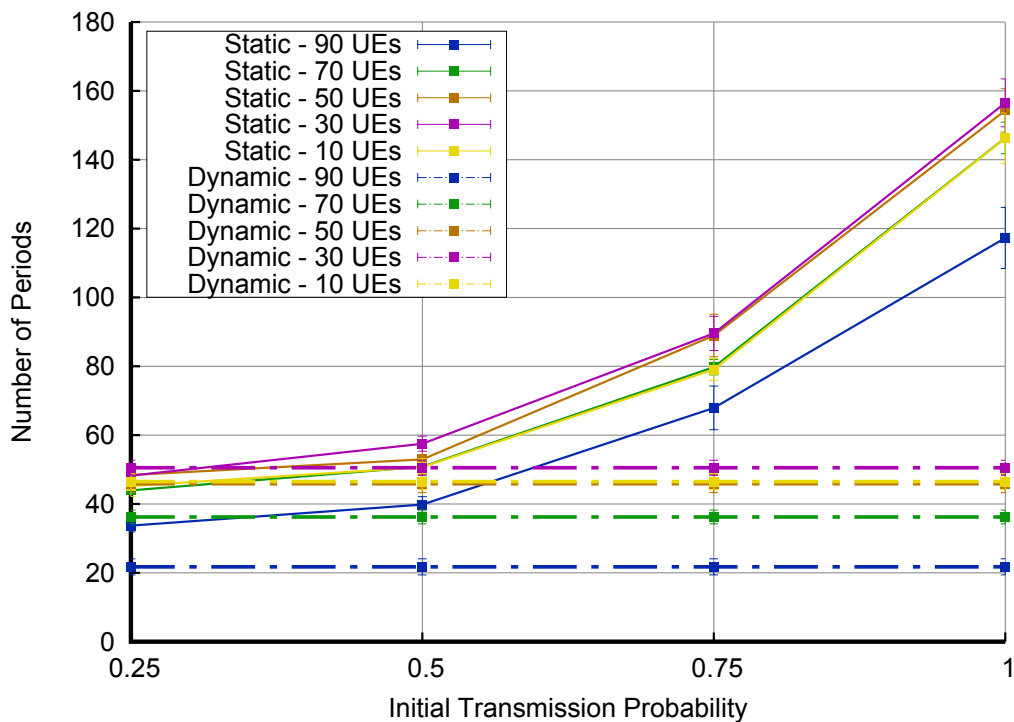


FIGURE 5.4: Number of periods needed for group 1 to complete discovery of group 2

For the 3GPP algorithm, all UEs (from both groups, i.e. 100 UEs) are transmitting at the same initial transmission probability. Based on Fig. 5.2, the discovery performance is optimal for a transmission probability of 0.25. Therefore, the higher the transmission probability used, the more periods are needed to finish the discovery. X/Y refers to the scenario where there are X UEs in the first group and Y UEs in the second group. So, we have X UEs discovering Y UEs. The least time needed to finish discovery is when we have 90/10, i.e. 90 UEs in group 1 and only 10 UEs to be discovered (group 2) by

those 90 UEs (blue solid line). However, 70/30 (green solid line) and 10/90 (red solid line) take less time than 50/50 (orange solid line) and 30/70 (pink solid line). In those cases, all UEs in both groups send announcements simultaneously to discover each other, which creates collisions and delays the discovery completion. The delay is related to the number of UEs performing the discovery and the number of UEs to be discovered. The 50/50 and 30/70 UEs results are worse than in the other cases, as the UEs in group 1 were already at a low transmission probability θ , with a few UEs coming in with $\theta = 1$ initially, which reduced collisions, or the UEs in group 1 were a few UEs with $\theta = 1$, so when group 2 joined, a large number of UEs were discovered in that first period (as everyone is transmitting, all the RBs will be used), and that triggered a quick drop in the value of θ , improving the performance. The results for 50/50 and 70/30 UEs show how the “intermediate” values are the ones most likely to be penalized the most by collisions, due to similarly sized groups of UEs having different values of transmission probability (but not 1 or 0.25).

For the enhanced algorithm, as expected, we can see how the initial θ is irrelevant for the results, and only the optimal value of θ for the initial group is a factor that provides different performance. The first group is already using its computed optimal transmission probability. Similarly to the 3GPP algorithm, 90 UEs discovering 10 UEs takes the least number of periods. The UEs in group 2 start using $\theta = 1$ and then adjust it according to the number of UEs they are discovering, thus the yellow and green dashed lines are superimposed and close to the performance for the last two cases. Finally, the discovery performance for the last two cases (10/10 and 30/70) is close.

5.4.1.3 Group 2 discovering group 2

The performance of group 2 discovering group 2 is basically the same behavior of group 1 discovering group 1, but the discovery process takes longer, because UEs from group 2 are, at the same time, discovering UEs from the existing group (e.g. collisions, half-duplex), for both 3GPP and the adaptive algorithms.

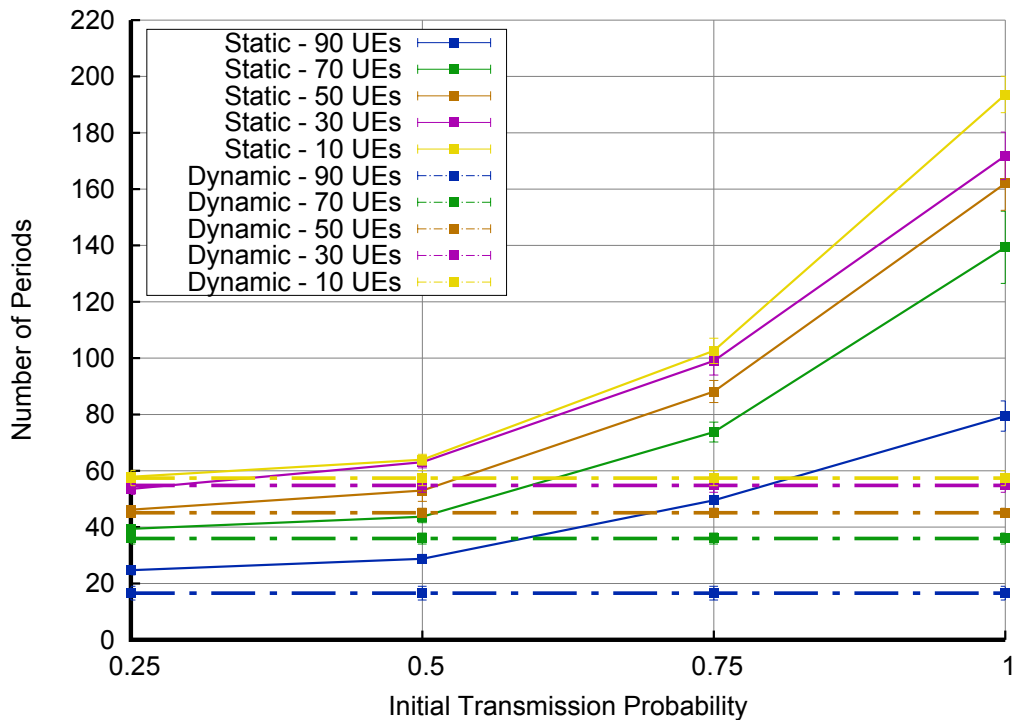


FIGURE 5.5: Number of periods needed to complete discovery within group 2

5.4.1.4 Group 2 discovering everyone

We compute the number of periods needed to complete the discovery by group 2 in Fig. 5.6 with 95 % confidence intervals. The enhanced algorithm outperforms the 3GPP algorithm. The UEs in the second group finish discovery (including the first group) later than the first group, because they are simultaneously discovering UEs from the first group and their own group. We notice that, for both algorithms, the number periods needed to finish the discovery for group 2 is inversely proportional to the number of UEs in the first group, as fewer UEs in group 2 means fewer UEs to discover the whole group, thus saving time.

5.4.2 Departure Scenario

This second scenario will serve to analyze and validate our algorithm in scenarios with UEs departing the group. We assume that we have a group with 100 UEs. Y (with $0 \leq Y < 100$) UEs leave the group after 100 seconds (i.e. after the discovery for

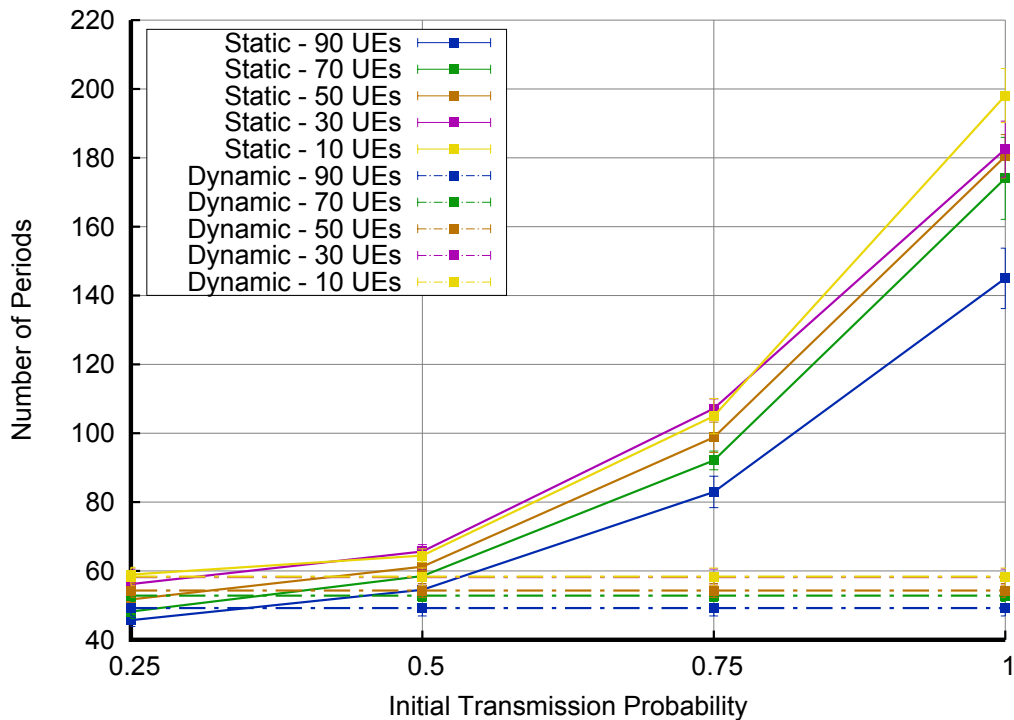


FIGURE 5.6: Number of periods needed to complete discovery by group

2

the group has been completed). We implemented the departure detection logic to the 3GPP algorithm as described in Algorithm 5.1, but, instead of considering the different transmission probability values for each UE as in our adaptive algorithm, in 3GPP case, UEs use the initially-defined value θ_{ini} . From that point onward, the 3GPP results will be about the modified 3GPP, unless explicitly stated otherwise. We will first focus on the beginning when the 100 initial UEs start discovering each other. Then, later on, we will evaluate the departure process and how UEs react to the changes in the discovery group. We will vary the success criteria (99 %, 95 %, 90 %, 85 %, 80 %, and 75 %) and assess how that affects the number of UEs discovered and its reliability.

5.4.2.1 The discovery process at the beginning

We will evaluate the discovery process at the beginning of the simulation, when all UEs are in the group. The results for different success criteria values are represented in Fig. 5.7. In the 3GPP case, starting with a transmission probability equal to 1 makes the discovery take the most time. For values of 0.25 and 0.5, the performance is

close and the best. The enhanced algorithm, although less efficient than starting with the optimal transmission probability, succeeds to catch up with that ideal case, with minimal overhead. Varying the success criteria value affects the discovery process in different ways. For the enhanced algorithm (i.e. dynamic), values lower than 99 % make the algorithm oscillate, as it assumes that some UEs left the group after not hearing from them for a while, due to the fact that most UEs are changing their transmission probabilities simultaneously. This is more obvious for values of the success criteria lower than 99 % (specifically for 75 %). The number of UEs is increasing and the optimal transmission probability is switching from 1 to 0.25. UEs are tuned to wait less according to Eq. (5.4), and when they do not hear from other UEs after the time period they originally computed, they consider them gone and the mean estimated group size decreases.

For low success criteria values, we have an unreliable judgment which impacts the accuracy of the computed wait time. However, those UEs may have changed their own θ values to accommodate the UEs discovered and thus they are announcing less frequently. Once this new information is propagated, the actual number of UEs discovered increases back to what it is expected. We do not observe those oscillations for the modified 3GPP algorithm because it uses a constant transmission probability (Eq. (5.1)).

For both the enhanced and the 3GPP algorithms we see that, with success criteria lower than 99 %, it is not possible to acknowledge the total number of UEs in the discovery group, with the difference between the “discovered” amount of UEs and the total increasing as the success criteria decreases. This inaccuracy is due to the fact that some UEs do not wait long enough before assuming another UE has departed the group.

5.4.2.2 The discovery process after 100 seconds

At this time, some UEs leave the group (for simulation purposes, this happens instantly). We assess the behavior of both the enhanced and modified 3GPP algorithms. First, we evaluate the effect of the change of the initial value of θ . Then, we study the impact of different success criteria values on both algorithms. In Fig. 5.8, we consider a 3GPP transmission probability of 1 and we vary the success criteria. In this case, the

modified 3GPP algorithm is using $\theta = 1$. Based on Eq. (5.1) and Eq. (5.4), the probability of success is low and the UEs wait longer before deciding to discard other UEs from the discovery group because of the potential collisions and the half-duplex feature. The wait time is greater when the accuracy required is high.

For the enhanced algorithm, the departure process starts with $\theta = 0.25$. We notice a stair effect generated by the change of the transmission probability based on the number of UEs discovered over time, which affects the pace of the discovery process as well. The concavity is smoother as the success criteria is smaller.

Like the 3GPP algorithm, the enhanced algorithm drops UEs faster and the wait time is reduced for low success criteria values. However, the impact of the success criteria on the reduction of the wait time is more perceptible for the 3GPP algorithm than for the enhanced algorithm.

We also notice how, even though lower success criteria reduces the time required to assume that UEs have left the group, this also makes the algorithms to miscount some UEs as departed, thus reducing estimated total group size. The gap between the computed number of UEs leaving and the “expected” group size gets wider for lower success criteria.

Similar conclusions can be drawn when considering initial transmission probabilities of 0.75, 0.5, and 0.25, (respectively Fig 5.9, 5.10, and 5.11) with a narrower gap between the performance of both the enhanced and the 3GPP algorithms.

In Fig. 5.12, we fix the success criteria to 99 % while varying the initial transmission probability. The discovery performance and the number of UEs left does not change in the enhanced algorithm case. At that point, the UEs transmit using the optimal θ (i.e. 0.25), and the initial θ value does not affect its behavior. The change occurs for the modified 3GPP case. We notice that it takes less time to start considering some UEs gone. For example, the system reaches a stable state after 330 periods for an initial transmission probability of 0.25, compared to 460 periods for an initial transmission probability of 1. That is when the modified 3GPP algorithm behaves the worst, with the performance penalty represented as the longer time required to learn that UEs left the group.

For $\theta = 1$ initially, the enhanced algorithm outperforms the 3GPP algorithm and

succeeds to reach a stable state faster. For $\theta = 0.75$ initially, the enhanced algorithm reaches a stable state at approximately the same time as the 3GPP algorithm, although the enhanced algorithm drops more UEs over time. Less congestion and contention are recorded, which delays the convergence to the actual number of UEs in the discovery group.

For $\theta = 0.5$ initially, the discovery performance is close to the optimal case. The enhanced algorithm starts detecting more UEs leaving the discovery group at the beginning of the process. But, the modified 3GPP succeeds to catch up and reaches a stable state faster.

For $\theta = 0.25$ initially, the modified 3GPP and the enhanced algorithms have the same starting point. This is shown through the graphs for the first 20 periods after the actual UE departures (i.e. 306 periods). However, the modified 3GPP algorithm drops the number of UEs discovered faster than the enhanced algorithm, because UEs in the enhanced algorithm take time adjusting θ based on the number of UEs.

Although the 3GPP algorithm behaves better than the enhanced algorithm with $\theta = 0.25$, we showed in chapter 3 that a low transmission probability with small groups may increase the time required for discovery significantly, making it 3 times longer than needed. That is the strength of the enhanced algorithm: while fixed values of the transmission probability may provide better results for specific group sizes, that knowledge of the group size and channel conditions is generally not known a priori, and in that case, the enhanced algorithm consistently provides near-optimal and very consistent results for groups of any size, regardless of UE arrivals and departures.

5.5 Conclusion and Future Work

In this chapter we presented an enhanced discovery algorithm for LTE D2D to be used in out-of-coverage scenarios. The enhanced algorithm builds on previous proposals that identified the optimal transmission probability depending on the group size, and extends them enabling the discovery process to fully be aware and react to dynamic changes in the network. We have shown how the algorithm can be tuned depending on whether the primary concern is fast adaptation or accuracy, making the process more

suitable to be used in a wide variety of scenarios. From this contribution we can foresee several research possibilities, such as the automation of the tuning parameters depending on the group size volatility.

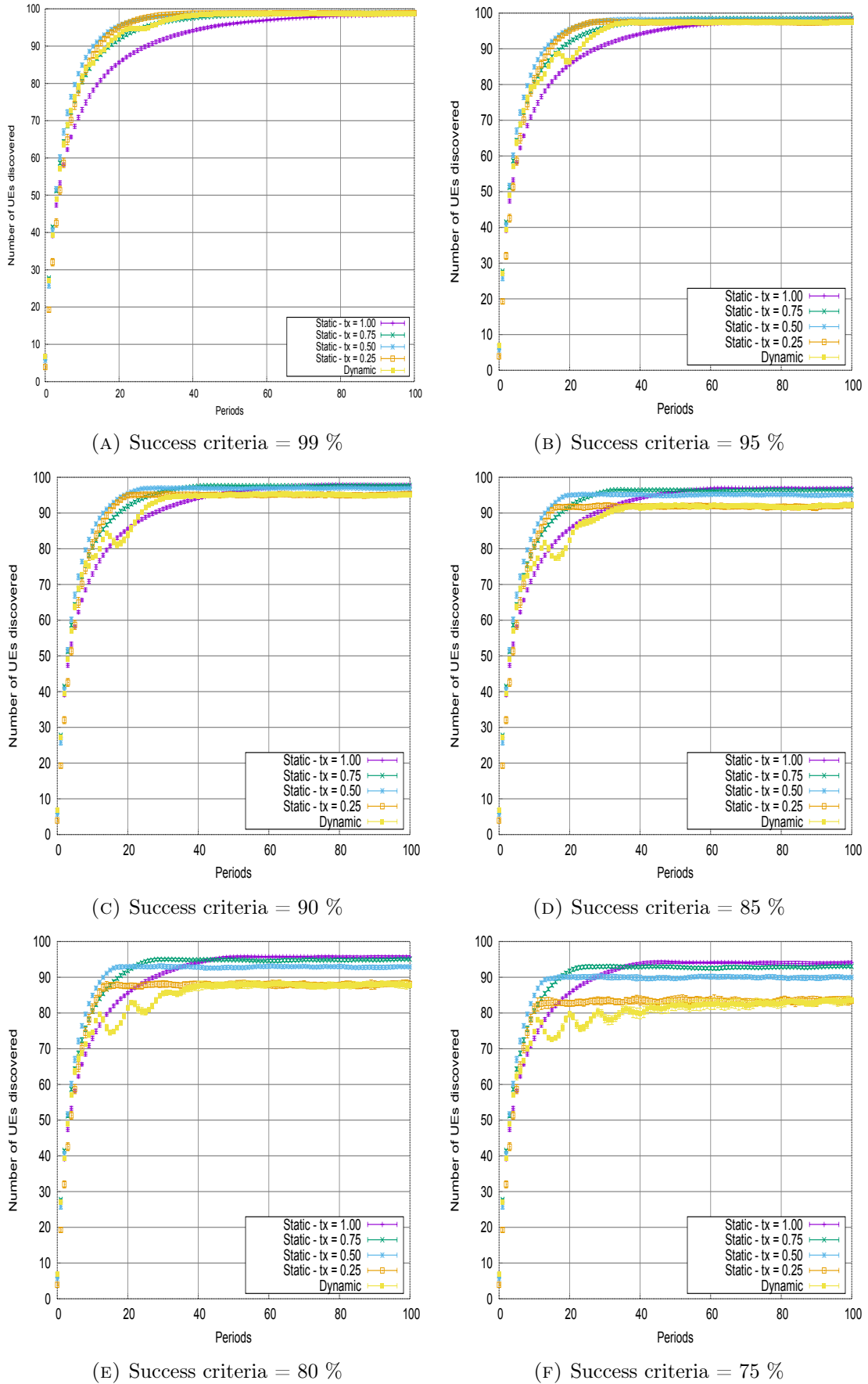


FIGURE 5.7: Number of periods needed for all UEs to discover all other UEs in the group for different success criteria values (3GPP transmission probability = tx)

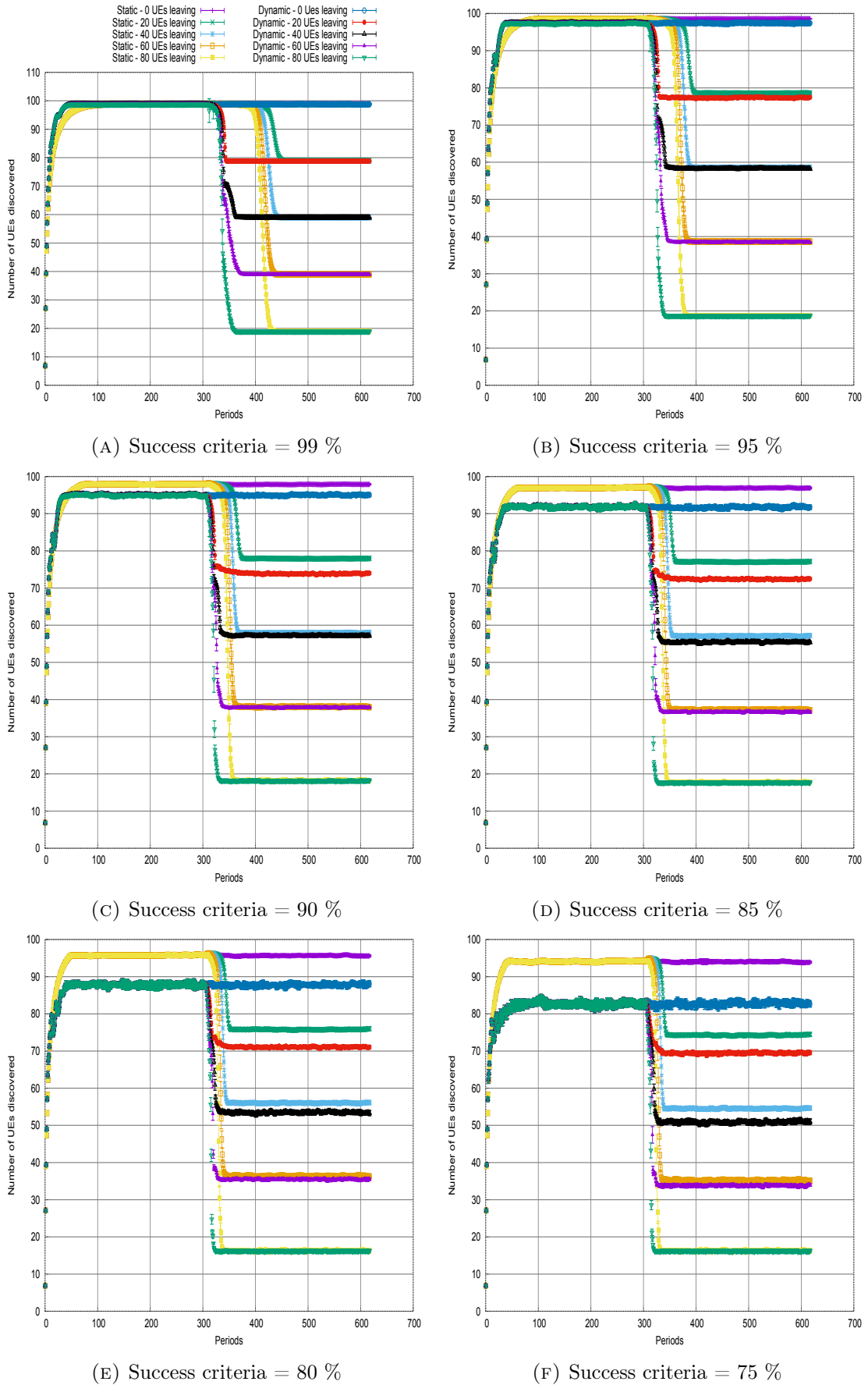


FIGURE 5.8: Number of UEs acknowledged to be in the group over time for different success criteria values (3GPP transmission probability = 1)

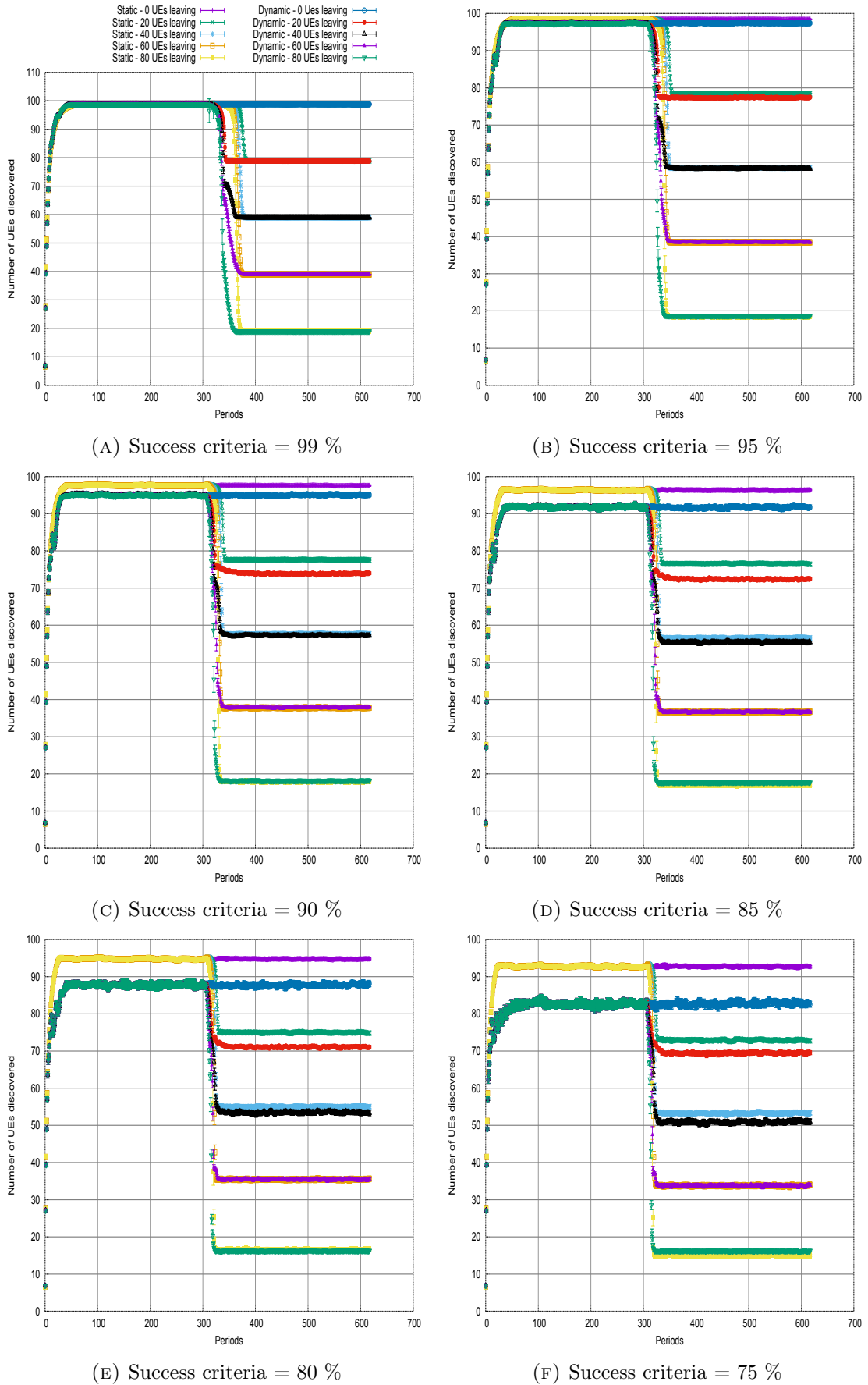


FIGURE 5.9: Number of UEs acknowledged to be in the group over time for different success criteria values (3GPP transmission probability = 0.75)

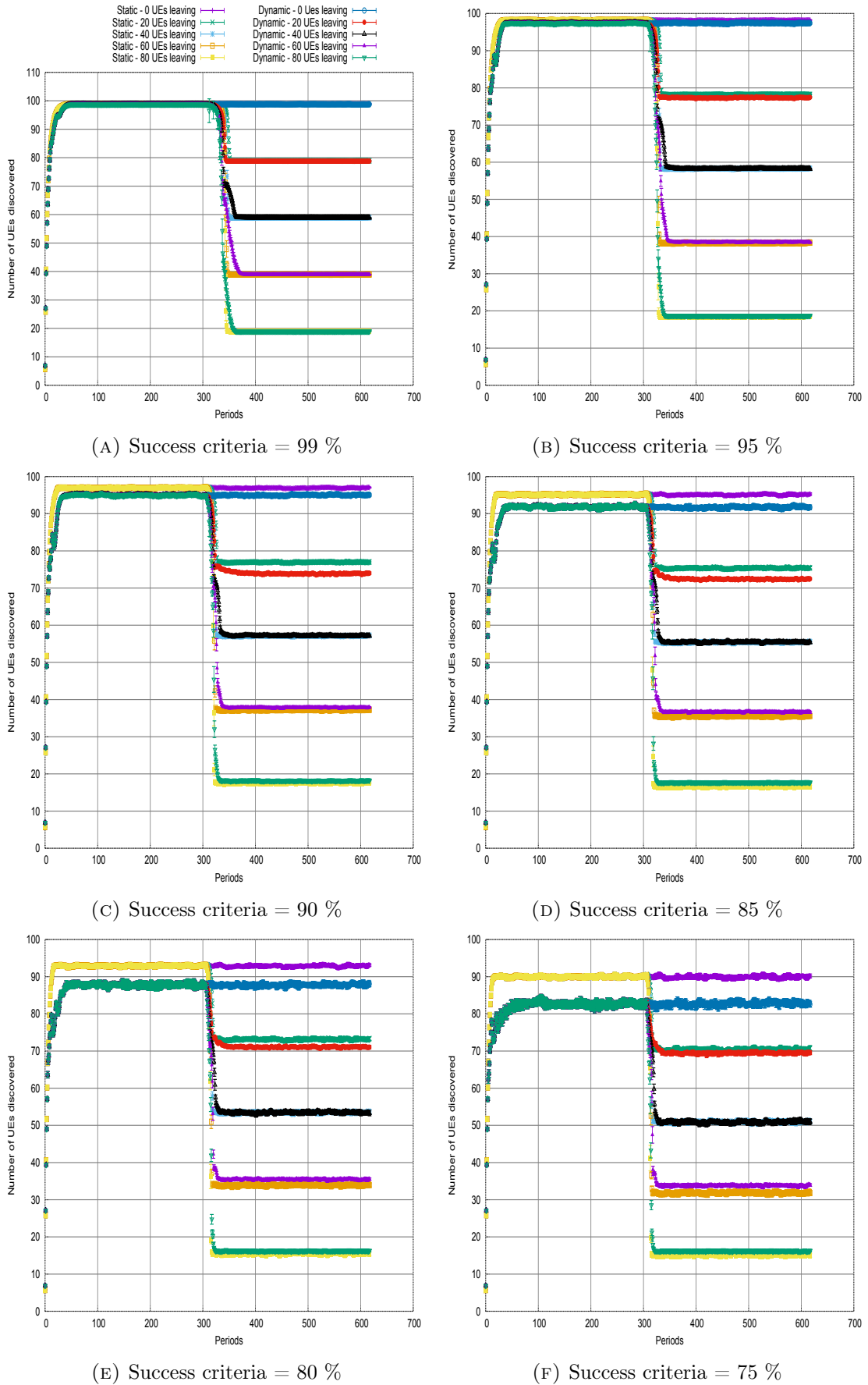


FIGURE 5.10: Number of UEs acknowledged to be in the group over time for different success criteria values (3GPP transmission probability = 0.5)

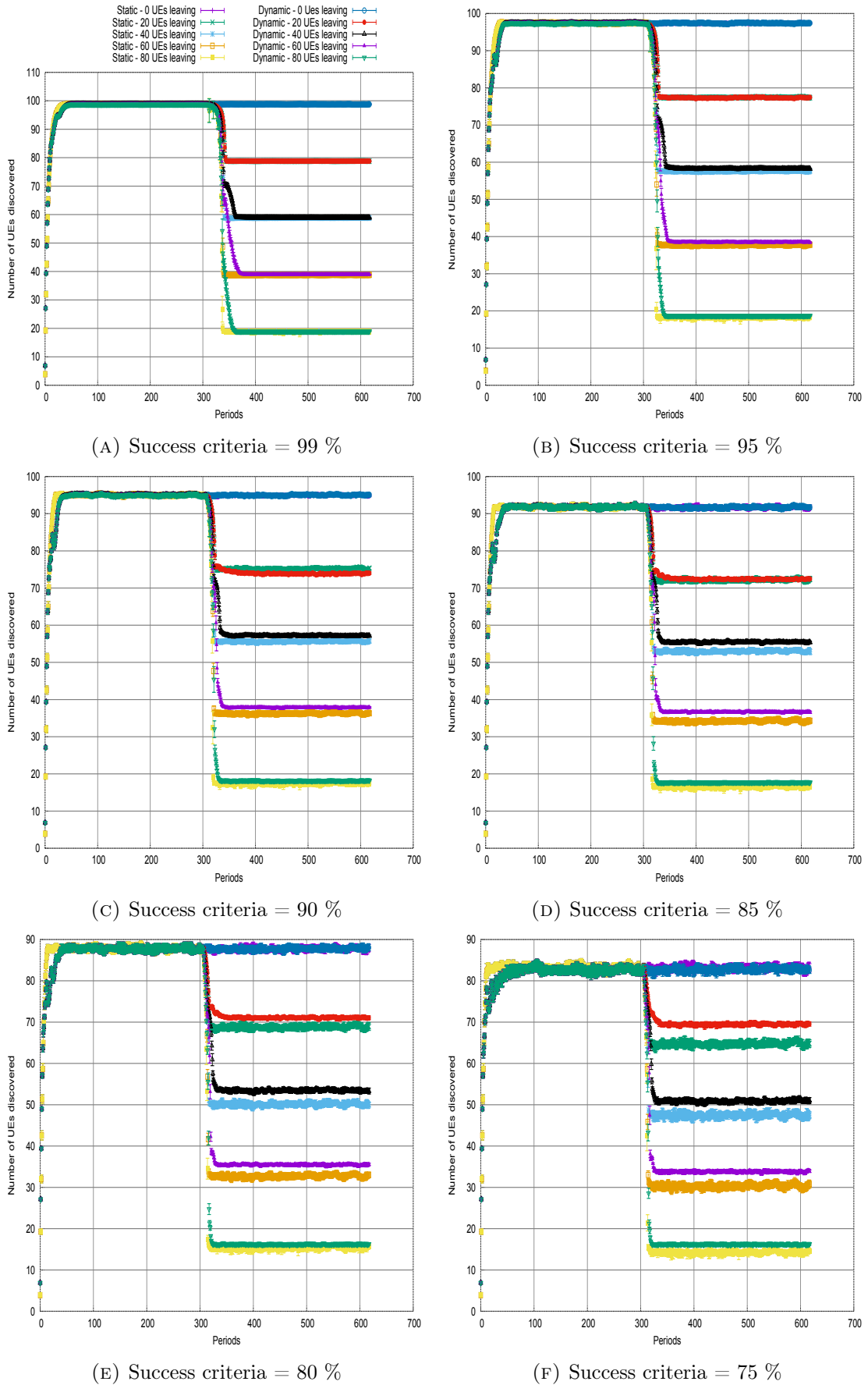


FIGURE 5.11: Number of UEs acknowledged to be in the group over time for different success criteria values (3GPP transmission probability = 0.25)

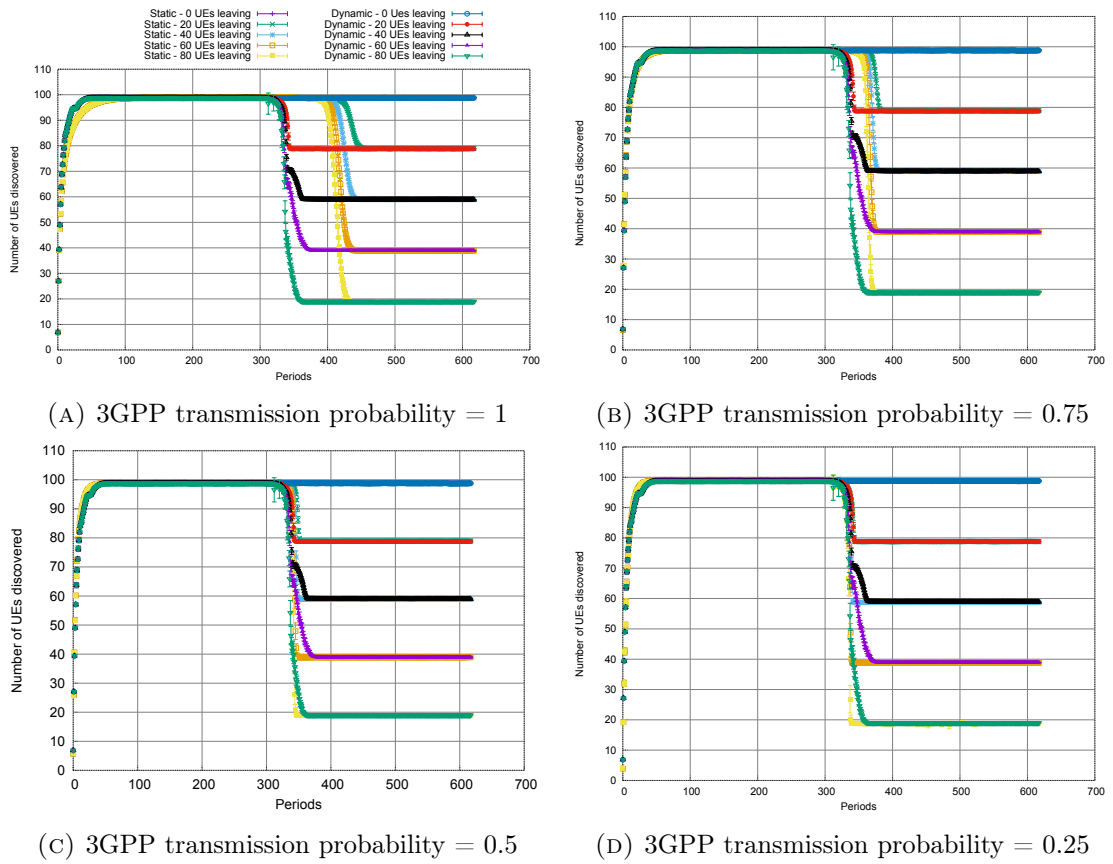


FIGURE 5.12: Number of UEs acknowledged to be in the group over time for different initial transmission probabilities and a success criteria of 99 %

Chapter 6

Conclusions and Perspectives

6.1 Conclusions

Given the explosive growth in mobile broadband traffic and new applications requirements, novel mechanisms are involved in order to improve the current network architecture and to optimize spectrum utilization. Cellular networks have always used a centralized design, reliant on network infrastructure. The new approach aims to reduce this dependency and ensure the efficiency of a distributed network where the nodes take control and operate based on their local knowledge. Context-aware mechanisms are much needed in those situations. In this thesis, we are focused on providing such mechanisms in the context of device-to-device communications and more specifically device discovery.

Initially, we started by specifying a non-exhaustive list of requirements to preempt network failures and fulfill successful communications such as scalability, reliability, capacity, coverage, and timeliness. We also examined the spectrum scarcity and expressed the need to have more efficient and smarter technologies in order to optimize the use of the available resources. Then, we studied and evaluated the current centralized LTE network, its capabilities, and how it reacted in case of emergencies, big events, and failures. It was proven that, in case of large-scale events, congestions and network saturation were inescapable. High delays and packet losses were observed, which affected the users' Quality of Service. Even the introduction of priorities did not fully resolve the problem, as the overall impact was very significant. Similarly, in case of site failures and network breakdown, both the network coverage and capacity were reduced, which resulted in congestions, delays, and service shutdown, and affected network performance (QoS) and user experience (QoE). We concluded that, even in areas where infrastructure was

deployed, we needed to address such misfortunes and provide adequate solutions. Therefore, although LTE is the newest deployed technology for cellular networks and offers multiple advantages compared to its predecessors, it also presents several concerns that need to be resolved in order to keep up with the emergent demands and ever increasing number of connected devices, applications, and users.

Next, we studied the D2D communications from both the standards (i.e. 3GPP) and the research perspectives. These services are totally incorporated within the existing LTE network and architecture, and can operate with or without the assistance of the LTE nodes, in and out of the network coverage. Although the idea of peer-to-peer communications has been already treated by the introduction of ad-hoc technologies, the concept of reusing licensed bands of the spectrum and taking advantage of the cellular network infrastructure is new. This approach has already shown significant performance improvements in terms of throughput, power efficiency, and spectral utilization compared to infrastructure-based communications. However, most research works focused on the D2D network from a communication point of view. They tried to handle the interference issues and provide power control mechanisms in order to allow a better co-existence between traditional cellular links (i.e. LTE) and direct communications (D2D). Even the existing research on D2D discovery has primarily revolved around evaluating and enhancing the performance of network-assisted discovery. We focused our thesis work on a discovery process than can work both on and off-network, and how to improve spectral efficiency and network performance by proposing novel context-aware mechanisms.

As part of the evaluation and validation of our proposals, we extended the LTE module in the discrete-event network simulator ns-3 in order to include the D2D discovery functionality as described in the standards. In addition to that, we used an analytical study of the discovery resource pool to model and evaluate the D2D discovery. The mathematical expressions were validated by the network simulations, and allowed us to determine, for a given topology and resource configuration, the maximum number of periods needed for one random UE to discover all the other UEs in the discovery group. This gave us an idea about the discovery performance for a more comprehensible discovery configuration and a static group of users trying to discover each other.

Then, we took into account a mathematical study aiming to optimize the discovery

process by defining an optimized transmission probability for each discovery configuration. The transmission probability for direct discovery is defined by the discovery resource pool, and for out-of-coverage context, it is predefined in the devices. So, the UEs are able to transmit discovery messages using that static threshold. The study demonstrated that the suggested values did not always provide the best discovery performance and that for a given number of users performing discovery and allocated resources there was an optimized value to use. The study also considered a fixed number of UEs, simplified propagation models, and the discard of all colliding discovery messages, which, while not usually the case for real communications, proved to be a solid foundation. We tried to make use of the generated equations and developed an adaptive algorithm that updated the number of UEs discovered through time and calculated the optimized transmission probability at each point of time. The UEs used the new computed value and transmitted discovery messages accordingly. For validating this mechanism, we first simulated the discovery process using the same assumptions as the analytical model, and we showed that the discovery process ended faster using our proposed algorithm, compared to the traditional discovery process defined in 3GPP standards. Then, we considered more realistic assumptions (i.e. propagation loss and attempts of recovery in case of collisions). Although the UEs took longer to finish the discovery process (given the increased number of collisions and errors), our proposed algorithm still behaved better than the standard-defined discovery process. We also validated that adding UEs to already discovered groups, and observed that the algorithm succeeded in better accounting for the change in the group's topology, which translated in the UEs detecting the newcomer faster than the discovery according to the 3GPP specifications. Therefore, our proposed algorithm was dynamic and adaptive, and it managed to save transmission resources by striking a balance between the benefits of saturating the channel with messages and the cost of message collisions.

Subsequently, based on the previous algorithm and making use of real network traces, we proposed a proactive algorithm which predicted the number of users in a specific area and adjusted in advance the transmission probability accordingly, in order to provide better efficiency. The algorithm managed to accomplish this by taking into account data provided by actual network operator. As a first step, predicted user density patterns

were extracted and synthesized, varying between different areas depending on their geographical locations and traffic types (i.e. residential, industrial, and mixed). They were used to create a history of the numbers of users located around the area during each hour of the day. Then, those density patterns were integrated in our algorithm to compute the corresponding optimized transmission probability. We were interested in evaluating the discovery performance in terms of time required to complete discovery, and messages sent. We witnessed a huge reduction in the number of transmitted discovery messages using our discovery mechanism, which resulted in significant resource economy, compared to the 3GPP discovery.

Finally, we proposed an enhanced transmission discovery algorithm which accounted for message reception success probabilities to adjust the number of users in the discovery group when more dynamic scenarios are considered. Having multiple arrivals and departures affecting the discovery group caused a variation in the number of UEs performing discovery. This value is important in computing the optimized transmission probability. Prior to our contribution there was no way of knowing the actual number of UEs in highly fluctuating environments. Our proposed enhanced algorithm makes use of the transmission probability used by each UE, along with the probability of successfully receiving a discovery message, to determine how long we should wait before considering that one UE left the discovery group. This allowed us to update the transmission probability used based on the likelihood of a UE presence, and consequently, we were able to detect UEs joining or leaving the group at any time of the discovery process thanks to the adaptability of our algorithm. A success criteria was defined to determine the accuracy of those assumptions, thus enabling us to tune the algorithm depending on our primary goal, either a faster discovery or a more accurate group size. The proposed departure detection mechanism also worked good with the 3GPP algorithm, although with the limitations and performance imposed by the fixed transmission probability.

6.2 Perspectives

This thesis has mainly focused on evaluating the novel context-aware mechanisms proposed to improve device discovery for D2D communications.

From the work presented here, several major lines of future work are available: First, while the proposals in this thesis work in the general case, specific users (e.g. vehicles) may have constraints that require the algorithms proposed here to be adapted to account for them. Second, more advanced algorithms may be designed based on Machine Learning or Big data analysis, so that the algorithm itself evolves over time to reflect changes in the behavioral patterns of the users.

Furthermore, D2D communications are still under standardization. Vehicle-to-everything (V2X) communications has been introduced lately (3GPP Release 14) as part of D2D communications to allow vehicles to communicate with fixed or moving parts of the traffic system around them (e.g. other vehicles, road infrastructure, and pedestrians). This may entail more stringent requirements in terms of delays and loss due to the high mobility related to vehicular networks. The mechanisms proposed in this thesis would need to be examined in order to assess their applicability in such environments. It is essential to evaluate their resiliency and sustainability when vehicular mobility is considered.

Additionally, the fifth next generation cellular networks (5G) are estimated to be deployed around 2020, although there is pressure from some operators to launch earlier. The 5G networks, as planned right now, will operate in a high-frequency band of the wireless spectrum, between 30 GHz and 300 GHz, in what is known as the millimeter wave spectrum. These millimeter waves can transfer heaps of data at very high speeds, but they do not travel as far as the lower-frequency waves used in 4G networks. High-frequency millimeter waves also have difficulty getting around walls, buildings, and other obstacles. It would be interesting to test our proposals in such stringent propagation models.

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Appendix A

Résumé de la Thèse

A.1 Introduction Générale

A.1.1 Contexte

Au cours des dernières années, la qualité, la capacité et la disponibilité des technologies de réseau ont connu des progrès considérables, car la recherche et la collaboration entre la communauté scientifique et l'industrie ont conduit à des mécanismes d'interconnexion moins coûteux et plus fiables, des algorithmes plus efficaces et une gamme plus large de périphériques se déployant selon les besoins spécifiques de chaque situation. Simultanément, la demande des réseaux omniprésents à grande vitesse a augmenté de façon exponentielle, car les applications riches en multimédia et en contenu sont devenues non seulement réalisables, mais banales. De même, le nombre d'utilisateurs mobiles a augmenté énormément.

L'utilisation de réseaux sans fil évolue vers un contenu centré sur les données, par contraste avec un contenu axé sur la voix au début des années 2000. Cette augmentation de la demande a eu pour effet d'accélérer la saturation du spectre disponible, les projections pour les 10 prochaines années montrant des demandes allant du double des ressources radio disponibles, jusqu'à 6 fois ce montant.

Le projet de partenariat de troisième génération (3GPP) a introduit la technologie à long terme (LTE) dans sa version 8. Et depuis lors, plusieurs améliorations ont été ajoutées dans les versions suivantes. Bien que LTE soit considérée comme la technologie de communication large bande mobile la plus répandue dans le monde entier, la quatrième génération (4G) se révèle incapable de satisfaire les demandes potentielles de l'utilisateur.

A.1.2 Défis

Tout réseau cellulaire doit tenir compte de certains critères pour une communication réussie. Nous présentons quelques caractéristiques qui définissent un réseau cellulaire. Parce que la plupart d'entre elles sont liées et dépendantes, notre travail se concentrera sur les éléments suivants: scalabilité, fiabilité/résilience, capacité, et rapidité.

A.1.3 Motivation

A.1.3.1 Architecture Centralisée de LTE

La première composante de l'architecture LTE est l'interface aérienne entre le terminal utilisateur et le noeud évolué B (eNB). Elle a utilisé une technique de multiplexage par répartition en fréquence orthogonale (OFDM) en comparaison à l'accès multiple par division de code (CDMA) pour les systèmes 3G. Les autres éléments du réseau LTE sont le réseau d'accès radio (appelé réseau d'accès à la radio terrestre UMTS évolué, c'est-à-dire E-UTRAN), le réseau de base (nommé Evolved Packet Core, c'est-à-dire EPC) qui est un système IP tout plat et le Réseau de service (par exemple, Internet). De nouveaux noeuds, interfaces et piles de protocoles ont été définis.

Ainsi, bien que LTE présente différentes améliorations par rapport à ses prédécesseurs de réseaux de communication cellulaire, il s'agit encore d'une technologie centrée sur l'infrastructure. Par conséquent, elle est très dépendante du déploiement de tours de cellule coûteuses et de noeuds de gestion, ce qui laisse souvent de nombreuses zones sans couverture suffisante, voir même aucune couverture du tout. Même aujourd'hui, la couverture n'est pas garantie, particulièrement dans les zones rurales. Le réseau doit toujours être raffiné pour répondre aux besoins des utilisateurs.

A.1.3.2 Rareté du Spectre

Le spectre des fréquences radioélectriques est une ressource mondiale finie et de plus en plus précieuse. Il n'est pas limité aux frontières nationales, et il est utilisé et géré par des traités internationaux et des politiques nationales. Le spectre radioélectrique, tel qu'il est attribué aux États-Unis, s'étend en fréquence de 3 kHz à 300 GHz et est utilisé

pour les communications sans fil. Les communications cellulaires utilisent des fréquences comprises entre 300 MHz et 3 GHz.

L'utilisation du spectre radioélectrique n'est pas limitée aux communications mobiles. Elle comprend également la radiodiffusion sonore et télévisuelle, les transports (par exemple, l'aviation, le chemin de fer et maritime), la défense, la télécommande et le suivi, la radioastronomie et la recherche spatiale, ainsi que de nombreuses autres applications. En raison du nombre croissant d'utilisations du spectre, la gestion du spectre est un problème croissant. Et comme le trafic de données mobiles continue d'exploser et que d'autres services apparaissent, les appels à une utilisation efficace et harmonisée de cette ressource limitée se poursuivent.

Les solutions proposées suggèrent que la réaffectation du spectre peut résoudre le problème. Bien que la réaffectation puisse offrir un certain soulagement, les obstacles techniques et politiques associés aux réallocations du spectre apporteront une satisfaction temporaire. D'autres solutions, y compris la réduction de la taille des cellules, permettant le partage du spectre, et l'utilisation de fréquences plus élevées sont encore à l'étude. Mais, ils ont un coût.

A.1.3.3 Exemples

Nous modélisons et simulons deux scénarios différents pour tester et évaluer les performances du réseau LTE. Les simulations que nous avons menées ont été modélisées dans ns-3, un simulateur open source qui offre un module LTE.

A.1.3.3.1 Scénario 1: Événement à Grande Échelle

Lorsqu'un événement à grande échelle se produit, les charges de trafic et le nombre d'utilisateurs impliqués augmentent considérablement en fonction de l'utilisation quotidienne du réseau. Cela peut être illustré par un jeu de sport professionnel majeur, un grand concert de musique ou même un incident.

Ce scénario montre que le trafic et le nombre élevé d'UE proches inhérents aux incidents ne peuvent être gérés par le réseau sans mécanismes de support. Même la définition et l'utilisation des priorités ne résolvent pas complètement le problème, car l'impact sur le reste du trafic est très important.

A.1.3.3.2 Scénario 2: Échec du Site

Une autre situation potentielle est le manque de soutien d'infrastructure, même dans les domaines où l'infrastructure a été déployée, par exemple en raison de conditions météorologiques extrêmes ou d'une panne de réseau. Dans les cas les plus doux, cela entraînera une surcharge de l'infrastructure voisine, alors que dans le cas le plus défavorable, il risque de mettre la vie des individus en danger, par exemple en ne fournissant pas de services aux premiers intervenants ou en empêchant les personnes de contacter les numéros d'urgence.

Sur la base de ce scénario, nous concluons que, même dans les domaines où l'infrastructure est déployée, nous devons tenir compte des pannes et des temps d'arrêt de la maintenance. Cela peut réduire considérablement la couverture et la capacité du réseau. Les congestions, les retards et l'arrêt du service sont susceptibles de se produire, ce qui affecte la performance du réseau (QoS) et l'expérience de l'utilisateur (QoE). C'est pourquoi nous devrions décharger le réseau chaque fois que cela est nécessaire et étendre la couverture si possible. Il est également nécessaire de disposer d'une solution de communication qui ne nécessite pas d'infrastructure.

A.1.4 Énoncé du Problème

La LTE, tel qu'elle est conçue actuellement, ne dispose pas des mécanismes permettant de soutenir adéquatement ces exigences. Les résultats de nos expériences montrent les faiblesses de l'architecture centralisée de la LTE dans des scénarios avec une forte concentration d'utilisateurs ou des pannes d'infrastructure. Pour cette thèse, nous ciblons un aspect des communications D2D qui est la découverte D2D, plus précisément la découverte directe. Nous optimiserons le service de découverte pour les scénarios de couverture et de hors couverture. Les algorithmes adaptatifs, avec des modifications minimales aux normes existantes, seront conçus pour fournir un service efficace. Nous nous concentrons sur la résolution de la conception statique de LTE dans la découverte de D2D, au moyen d'algorithmes adaptatifs, d'une base de réglage de paramètres proactif sur les modèles de densité des utilisateurs et de mécanismes de détection améliorés pour apprendre la mobilité des utilisateurs.

A.2 Algorithme Adaptatif de Transmission pour la Découverte Directe Appareil-à-Appareil

A.2.1 Modèle de Ressources

Nous supposons que les UEs transmettent des messages de découverte pendant chaque occurrence du pool de ressources de découverte pour chaque période de découverte. Une ressource de pool est composée d'une paire de blocs de ressources physiques adjacents (PRB) qui occupent la même sous-trame. Les messages de découverte peuvent être répétés dans une période donnée jusqu'à quatre fois (c'est-à-dire une transmission originale suivie d'un certain nombre de retransmissions, variant entre zéro et trois); Il est donné par le paramètre N_{SLD}^{TX} .

Les dimensions effectives du pool de ressources dans les domaines de la fréquence et du temps sont respectivement: $N_f = \left\lfloor \frac{M_{RB}^{PSDCH}}{2} \right\rfloor$ et $N_t = \left\lfloor \frac{L_{PSDCH}}{N_{SLD}^{TX}} \right\rfloor$, où M_{RB}^{PSDCH} est le nombre de PRB dans le pool et L_{PSDCH} est le nombre de sous-frames. Par conséquent, le nombre total de ressources dans le pool est:

$$N_r = N_t \times N_f \quad (\text{A.1})$$

Nous supposons que tous les UEs sont semi-duplex, de sorte qu'un UE qui envoie un message de découverte pendant une sous-trame donnée est incapable de recevoir des messages de découverte transmis par d'autres UEs pendant cette sous-trame. Nous considérons également la découverte du type 1 où l'UE choisit ses propres ressources de transmission.

Sur la base de ce processus, un modèle de chaîne de Markov a été développé. Ce modèle permet un calcul exact de la répartition du nombre de périodes requises pour un UE aléatoire pour découvrir tous les autres UEs dans son groupe, tout en tenant compte de l'effet des UEs semi-duplex. Nous caractérisons le temps requis pour un UE choisi au hasard, que l'on appelle UE_X , pour découvrir tous les autres UEs dans son groupe. Nous utilisons une chaîne de Markov à temps discret dont l'indice de temps indique le nombre de périodes de PSDCH qui se sont écoulées depuis le début et dont la variable d'état unique, $N_D[t]$, est le nombre de UEs qui ont été découverts par UE_X à la fin

de la t^{th} période. En outre, nous désignons le nombre d'UEs non découverts à la fin de la t^{th} période comme $N_U[t] = (N_u - 1) - N_D[t]$. L'intervalle des valeurs possibles pour $N_D[t]$ est $0 \leq N_D[t] \leq N_u - 1$; l'état de départ est $N_D[0] = 0$ (car UE_X n'a pas encore découvert les autres $(N_u - 1)$ UEs dans le groupe) et l'état final final de la chaîne de Markov est $\lim_{n \rightarrow \infty} N_D[t] = N_u - 1$, qui est le seul état absorbant de la chaîne de Markov.

En utilisant ce modèle théorique, nous avons également pu prouver l'exactitude de notre implémentation de découverte directe D2D dans ns-3.

A.2.2 Algorithme Proposé

Sur la base des résultats observés à partir de la validation du mode analytique, nous proposons un nouvel algorithme de découverte qui améliore la performance du processus de découverte dans des scénarios hors couverture réseau, en ajustant dynamiquement la probabilité de transmission en fonction de leur voisinage. L'algorithme donne aux UE la possibilité de modifier leurs probabilités de transmission au besoin pour réduire le temps requis pour découvrir d'autres UEs.

Dans la norme, le canal à utiliser pour la découverte est à mi-duplex et tous les UEs annoncent l'utilisation de la même probabilité de transmission préconfigurée définie dans le pool de ressources de découverte pour le mode sélectionné par l'UE. Cependant, l'utilisation de valeurs de probabilité de transmission spécifiques sélectionnées en fonction de la taille du groupe améliore considérablement la performance de l'ensemble du processus. La probabilité de transmission optimale θ^* est ainsi calculée.

$$\theta = \begin{cases} 1, & \text{if } N_u < \frac{N_r(N_t-2)+N_t}{N_t-1} \\ \frac{2N_r+N_t(N_u-1)-\sqrt{4N_r(N_r-N_t)+N_t^2(N_u-1)^2}}{2N_u} & \text{otherwise} \end{cases} \quad (\text{A.2})$$

Bien que la valeur calculée θ^* ne soit pas nécessairement un multiple de $1/4$ (comme recommandé par le 3GPP), il était démontré que l'arrondi jusqu'à la prochaine valeur autorisée (c'est-à-dire, 0.25, 0.5, 0.75, 1) ne modifie pas la performance de la découverte. C'est pourquoi, à partir de maintenant, nous utiliserons θ comme approximation de

θ^* pour le multiple le plus proche non nul de 0.25 inférieur ou égal à 1. Ce travail anticipe le nombre d'utilisateurs de la découverte (noté N_u) et calcule la valeur optimale en conséquence, ce qui n'est pas toujours le cas. Ainsi, pour tirer parti de l'équation précédente, nous considérons que chaque UE va calculer dynamiquement sa probabilité de transmission optimale en fonction du nombre d'UEs découverts tout au long du temps.

Notre algorithme propose que, à tout moment du processus de découverte, la nouvelle probabilité de transmission de l'UE $_X$ sera calculée suivant l'équation (A.2) où N_u est le nombre de UEs découverts jusqu'ici. Pour la période suivante, l'UE commencera à annoncer en utilisant la nouvelle valeur de la probabilité de transmission évaluée.

L'efficacité de notre proposition est validée avec des simulations et les résultats prouvent que notre algorithme réduit le temps requis pour le processus de découverte dans un groupe d'UE pour plusieurs configurations différentes.

Plusieurs scénarios avec des différents environnements, en prenant en compte ou pas les hypothèses du modèle analytique, ont été utilisés pour l'évaluation et les résultats ont été réguliers dans tous les domaines, que nous examinions les résultats du groupe ou dans des UEs individuels, montrant constamment des améliorations de performance. Cela correspond à des gains de 50 % en termes de temps et de ressources utilisés, pour la performance du cas idéal dans la confiance de 95 %.

Dans l'analyse et les simulations, nous avons supposé que tous les UEs annonçaient et découvraient (c.-à-d., nous avons ignoré d'autres UEs). Cependant, avoir des UEs qui annoncent seulement, ou surveillent seulement ne modifient pas les résultats. Ils seraient incorporés dans l'algorithme s'ils annoncent, et s'ils ne le font pas, ils découvriront les UEs à un rythme légèrement plus rapide (car ils n'ont pas de collisions), mais ils ne modifieront pas les résultats de manière significative). Dans la deuxième partie de nos simulations, bien que l'ajout du nouvel UE n'a pas changé la probabilité de transmission optimale, aucune pénalité significative n'aurait été engagée si elle a changé. Comme nous l'avons vu dans les résultats, l'algorithme permet aux UEs de converger extrêmement rapidement vers de nouvelles valeurs de theta, même si elles utilisent toutes une valeur non optimale (c'est-à-dire les résultats lorsque le 3GPP commence par le θ optimal, et l'algorithme montre que les frais généraux de "convergence" sont très faibles, presque négligeables). Donc, même dans ces cas, l'analyse et les conclusions sont encore valables.

A.3 Amélioration de la Découverte Directe Appareil-à-Appareil basée sur des Modèles Prévisibles de Densité d'Utilisateur

A.3.1 Prédiction en Ligne de la Densité des Utilisateurs

Nous proposons un modèle basé sur l'algorithme de régression de vecteur de support (SVR) pour la prédiction de densité des utilisateurs de cellules. Compte tenu d'un échantillon de formation de séries temporelles avec une taille de N (l'histoire de la densité de l'UE des cellules), $(x_i, y_i)^N$, SVR vise à trouver une fonction linéaire f qui mappe x_i avec y_i dans un espace de fonctionnalité \mathbf{F} (généralement avec une dimension plus élevée).

Dans notre contribution, nous utilisons la fonction de base radiale (RBF) comme fonction du noyau car elle est plus efficace avec les séries temporelles non linéaires (comme dans notre cas) en raison de sa capacité de généralisation et de sa capacité de cartographie non linéaire dans un espace infini de fonctionnalité. La prédiction se déroule en deux étapes: l'entraînement, dans laquelle nous utilisons l'historique de la densité des utilisateurs et le test, dans lesquelles les paramètres du modèle sont optimisés. L'efficacité de la prédiction SVR est validée en utilisant des données de test extraites également à partir de l'ensemble de données de Dakar. La précision de la prédiction basée sur la SVR est évaluée par deux indicateurs majeurs: la mesure de l'erreur quadratique moyenne (MSE) et le coefficient de corrélation au carré.

En fait, dans une étude antérieure, nous avons déduit et classé à partir d'un grand ensemble de données fourni par Orange Senegal, trois classes de profil de densité d'UE des stations de base. Chaque profil de la station de base appartient à un modèle spécifique d'utilisation du réseau et de fluctuation de charge, qui dépend de la nature de son emplacement. La classification de profil de la station de base installée dans la ville de Dakar est également prise en considération. Le "profil de charge de nuit" représente les zones résidentielles, le "Profil de charge du jour" représente la plupart des secteurs d'activité et des activités, et le "profil de charge constante" correspond à des zones mixtes. Un ensemble de modèles de densité des UEs est extrait des données de Dakar pour être intégré dans ns-3 pour implémenter un outil de générateur de trafic réaliste. L'outil est ensuite utilisé afin de prévoir l'évolution de la densité de l'UE dans chaque zone et ensuite utiliser les valeurs prédites pour l'algorithme de découverte directe.

A.3.2 Algorithme Proposé

La découverte directe D2D en mode 2 manque d'adaptabilité aux environnements changeants de communication, car elle repose sur des paramètres fixes pré-définis, y compris la probabilité de transmission.

Nous proposons un algorithme qui utilise les diagrammes de densité d'utilisateur prédits afin de déterminer la valeur de probabilité de transmission fournissant la meilleure performance de découverte. Il est exécuté toutes les heures et tient compte du nombre d'utilisateurs prédits pour cette zone pendant cette période de la journée. Il calcule la valeur optimale de la probabilité de transmission découverte en conséquence suivant l'équation (A.2) où N_u est le nombre d'utilisateurs prédit. Au début de chaque heure, l'algorithme prend en compte la zone géographique pour déterminer le type de trafic. Il vérifie sa base de données réelle enregistrée de trafic similaire, calcule la moyenne et obtient le nombre d'utilisateurs prédits dans la zone pour cette heure et pour ce trafic spécifique. Les profils de densité d'utilisateur utilisés pendant ce processus sont extraits de traces réelles du réseau. Par conséquent, il donne une idée précise sur le nombre réel d'UEs présents dans le réseau. Sur la base de cette information, la probabilité de transmission optimale θ est calculée afin d'obtenir les meilleures performances de découverte. Cette valeur sera utilisée pendant toute l'heure jusqu'à la prochaine période où le nombre prévu d'UEs pourrait changer.

Nous avons montré comment cet algorithme qui utilise les valeurs prédites comme base et qui représente de manière adaptative des écarts par rapport à cette valeur attendue peuvent considérablement améliorer la performance globale, pas seulement dans un sous-ensemble spécifique de scénarios. Nous montrons également comment un algorithme dérivé du modèle analytique peut trouver un équilibre entre l'utilisation des canaux et le temps requis pour la découverte. Cela permet d'obtenir des économies significatives en matière de consommation d'énergie en réduisant la signalisation globale des messages de découverte dans le réseau et en optimisant davantage l'utilisation des ressources réseau pour la procédure de découverte.

A.4 Algorithme Amélioré de Transmission pour la Découverte Directe Appareil-à-Appareil

Dans cette partie, nous proposons une amélioration de la contribution présentée dans la section A.2.

A.4.1 Modèle du Système

Nous utilisons la liste des symboles suivante tout le long de cette partie:

TABLE A.1: Liste de Symboles

Symbole	Définition
N_f	Nombre de paires de blocs de ressources disponibles pour la découverte
N_t	Nombre de sous-trames disponibles pour la découverte
N_r	Nombre total de ressources dans le pool de découverte
UE_X	UE sélectionné au hasard
n	Nombre d'UEs découverts par UE_X
N_n	Nombre de nouveaux UEs découverts par UE_X
N_o	Nombre d'UEs précédemment découverts par UE_X
N_u	Nombre total d'UEs dans le scénario
N_X	Nombre d'UEs découverts par UE_X plus UE_X lui même
θ	Valeur de probabilité de transmission optimale de UE_X
θ_i	Valeur de probabilité de transmission reçue de UE_i
t_i	Temps de la dernière réception de UE_i

A.4.1.1 Probabilité de Transmission Optimale

Le modèle analytique tel qu'il est défini dans la section A.2 prouve que la performance de découverte directe D2D peut être améliorée en utilisant une valeur optimale de la probabilité de transmission θ , définie par l'équation (A.2).

A.4.1.2 Probabilité de Réussite

Selon le comportement 3GPP, tous les UEs utilisent la probabilité de transmission initiale θ_{ini} tout au long du processus de la découverte. Ainsi, la probabilité qu'un message de découverte soit reçu avec succès soit:

$$P_{success_{3gpp}} = \theta_{ini} \times \left(1 - \frac{\theta_{ini}}{N_t}\right) \times \left(1 - \frac{\theta_{ini}}{N_r}\right)^{n-2}; \quad (\text{A.3})$$

où:

θ_{ini} est la probabilité de transmission initiale définie par le 3GPP,
 N_r et N_t sont définis par l'équation (A.1), et
 n est le nombre d'UEs détectés jusqu'ici.

Cependant, en utilisant l'algorithme adaptatif, nous savons que chaque UE_{*i*} à sa propre probabilité de transmission θ_i , et nous déduisons la probabilité de succès:

$$P_{success_{algorithm}} = \theta_{tx} \times \left(1 - \frac{\theta_{rx}}{N_t}\right) \times \prod_{i \neq tx, i \neq rx} \left(1 - \frac{\theta_i}{N_r}\right); \quad (\text{A.4})$$

où:

θ_{tx} est la probabilité de transmission de l'émetteur UE_{*tx*},
 θ_{rx} est la probabilité de transmission du récepteur UE_{*rx*}, et
 N_r et N_t sont définis par l'équation (A.1).

Les paramètres du pool de ressources N_r et N_t sont connus et constants. En sachant cela, nous calculons la probabilité qu'une réception soit réussie dans \mathbf{n} périodes, qui est:

$$p = 1 - (1 - P_{success})^n; \quad (\text{A.5})$$

Cela nous permet de déterminer le nombre minimum de périodes pour qu'un UE reçoive une annonce d'un autre UE, compte tenu du critère de réussite \mathbf{p} .

$$n_{min} = \frac{\ln(1 - p)}{\ln(1 - P_{success})}; \quad (\text{A.6})$$

Avec ces modèles, il est possible pour le destinataire de savoir combien de temps il devrait attendre avant de considérer qu'un émetteur s'est éteint ou éloigné, selon la confiance (c'est-à-dire les critères de réussite) souhaitée ou requise.

A.4.1.3 Message de Découverte Redessiné

Afin de pouvoir utiliser ces modèles analytiques dans le processus de découverte, nous devons annoncer la probabilité de transmission de chaque UE. Ainsi, nous introduisons

une modification mineure dans le format du message de découverte. Le composant le plus important du message de découverte est le code d'application ProSe (avec une taille de 184 bits). Ce code est attribué pour chaque pair de UE et application, et a une temporisation de validité associée. Les messages de découverte sont de taille limitée (seulement 232 bits) pour permettre leur transmission dans une seule sous-trame et une paire de blocs de ressources, même dans de mauvaises conditions du canal. L'augmentation de sa taille n'est pas une option pratique, car elle consomme beaucoup de ressources et réduit la bande passante disponible. Pour surmonter cette limitation et pour éviter les frais généraux inutiles, notre proposition remplace 3 bits du nom de l'identifiant de l'application ProSe pour porter la valeur de la probabilité de transmission sous la forme de deux bits codés pour les quatre valeurs autorisées (c'est-à-dire, 0.25, 0.5, 0.75, 1). Le bit supplémentaire sert à indiquer si la probabilité de transmission a changé ou est toujours la valeur initiale tout au long du processus de découverte.

En utilisant cette approche, nous maintenons la taille du code d'application ProSe. Un exemple de correspondance des valeurs de 3 bits est présenté ci-dessous:

- 000 pour $\theta = 1$
- 001 pour $\theta = 0.75$
- 011 pour $\theta = 0.5$
- 010 pour $\theta = 0.25$
- 100 quand θ ne change pas

A.4.2 Algorithme Proposé

Pour l'algorithme amélioré, chaque UE (UE_X) peut traiter les annonces reçues, vérifier celles qui sont nouvelles ou contiennent une probabilité de transmission différente. UE_X crée un nouvel enregistrement (identifiant, horodatage et probabilité de transmission) pour l'UE nouvellement découvert ou met à jour son ancien enregistrement avec les nouvelles valeurs reçues. Ensuite, pour chaque UE découvert, UE_X calcule le nombre de périodes à attendre et décide s'il est toujours là (mais qui ne peut pas être découvert avec succès en raison de collisions) ou disparu (par exemple en raison de son modèle

de mobilité). Sur la base du nombre des UEs restants (c'est-à-dire après avoir éliminé les UEs qui ont quitté le groupe de découverte), UE_X calcule sa propre probabilité de transmission. Cet algorithme sera appelé configuration dynamique en raison du calcul continu de θ .

Ainsi, nous examinons et simulons deux scénarios: arrivée et départ. Tout d'abord, nous allons regarder un scénario avec les UEs qui arrivent en groupe. Avec ce scénario, nous validons que les modifications introduites dans l'algorithme de découverte ne modifient pas le comportement précédemment observé. Nous examinons les résultats des UEs dans le groupe 1 découvrant les UEs dans le groupe 2 et les UEs dans le groupe 2 découvrant tout le monde. Le deuxième scénario sert à analyser et à valider notre algorithme dans des scénarios avec des UEs partant du groupe. Nous évaluons d'abord le processus de découverte au début de la simulation, lorsque tous les UEs sont dans le groupe. Ensuite, nous inspectons les résultats après 100 secondes, quand certains UEs quittent le groupe existant.

Comme l'algorithme proposé s'appuie sur des propositions précédentes qui ont identifié la probabilité de transmission optimale en fonction de la taille du groupe, il permet au processus de découverte de bien connaître et de réagir aux changements dynamiques du réseau. Par conséquent, l'algorithme peut être réglé selon que l'intérêt principal, qui est soit l'adaptation rapide, soit la précision, ce qui rend le processus plus approprié pour être utilisé dans une grande variété de scénarios.

A.5 Conclusions et Perspectives

A.5.1 Conclusions

Les réseaux cellulaires ont toujours été centralisés et dépendent de l'infrastructure et des nœuds du réseau. La nouvelle approche vise à réduire cette dépendance et à assurer l'efficacité d'un réseau distribué où les nœuds prennent le contrôle et agissent en fonction de leurs connaissances du voisinage. Des mécanismes contextuels sont très nécessaires dans ces situations. Dans cette thèse, nous nous concentrons sur la proposition de tels mécanismes dans le contexte des communications entre périphériques et plus particulièrement de la découverte des périphériques.

Dans un premier temps, nous avons commencé par spécifier une liste non exhaustive d'exigences pour des communications réussies. Ensuite, nous avons étudié et évalué le réseau LTE, ses capacités et sa réaction en cas d'urgence et de grands événements. Il a été prouvé que, en cas d'événements à grande échelle ou de défaillance de réseau, les congestions et la saturation du réseau étaient incontournables. Des retards élevés et des pertes de paquets ont été observés, ce qui a affecté la qualité de service des utilisateurs (QoS). Nous avons conclu que, même dans les domaines où l'infrastructure était déployée, nous devons faire face à de tels incidents et fournir des solutions adéquates. Par conséquent, bien que LTE soit la plus récente technologie déployée pour les réseaux cellulaires et offre de multiples avantages par rapport à ses prédécesseurs, elle présente également plusieurs préoccupations qui doivent être résolues afin de suivre les applications émergentes et le nombre toujours croissant d'appareils et d'utilisateurs connectés.

Ensuite, nous avons étudié les communications entre périphériques (D2D). Ces services sont intégrés dans l'architecture LTE et peuvent fonctionner avec ou sans l'aide du réseau. La plupart des travaux de recherche se concentrent sur le réseau D2D du point de vue de la communication. Ils ont essayé de gérer les problèmes d'interférence et de fournir des mécanismes pour contrôler la puissance de transmission afin de permettre une meilleure coexistence entre les liaisons cellulaires traditionnelles (c'est-à-dire LTE) et les communications directes (D2D). Et même les recherches existantes sur la découverte de D2D ont principalement porté sur l'évaluation et l'amélioration des performances de la découverte assistée par le réseau. Cela dit, nous avons concentré notre travail de thèse sur un processus de découverte qui peut fonctionner à la fois sur et hors réseau, et comment améliorer l'efficacité spectrale et améliorer les performances du réseau en proposant de nouveaux mécanismes contextuels.

Par la suite, nous avons étendu le module LTE dans le simulateur de réseau ns-3 afin d'inclure la fonctionnalité de découverte D2D comme décrit dans les normes. Nous avons utilisé une étude analytique du pool de ressources de découverte pour modéliser et évaluer la découverte D2D. Les simulations mathématiques ont été validées par les simulations de réseau et nous ont permis de déterminer, pour une topologie et une configuration de ressource donnée, le nombre maximal de périodes nécessaires pour un utilisateur aléatoire pour découvrir tous les autres utilisateurs dans le groupe de découverte.

Ensuite, nous avons tenu compte d'une étude mathématique visant à optimiser le processus de découverte en définissant une probabilité de transmission optimisée pour chaque configuration de découverte. Pour le contexte hors couverture, cette probabilité est prédéfinie dans les périphériques. L'étude a démontré que les valeurs proposées ne fournissaient pas toujours les meilleures performances de découverte et que, pour un nombre donné d'utilisateurs effectuant des découvertes et des ressources allouées, il y avait une valeur optimisée à utiliser. Nous avons utilisé les équations générées et nous avons développé un algorithme adaptatif qui a mis à jour le nombre d'UE détectés au fil du temps et calculé la probabilité de transmission optimisée à chaque instant. Premièrement, nous avons validé le modèle analytique en utilisant les mêmes hypothèses que le modèle analytique, et nous avons montré que le processus de découverte était plus rapide en utilisant notre algorithme proposé, par rapport au processus de découverte traditionnel défini dans les standards 3GPP. Ensuite, nous avons considéré des hypothèses plus réalistes (affaiblissement de propagation et tentatives de récupération en cas de collisions). Bien que les UEs aient pris plus de temps pour terminer le processus de découverte (compte tenu du nombre accru de collisions et d'erreurs), notre algorithme proposé s'est encore mieux comporté que le processus de découverte défini par la norme. Nous avons également testé l'ajout d'un utilisateur à des groupes déjà découverts et nous avons observé que l'algorithme a réussi à mieux reconnaître la modification de la topologie du groupe que la découverte selon les spécifications 3GPP. Par conséquent, notre algorithme proposé était dynamique et adapté, et il a réussi à économiser les ressources de transmission.

Par la suite, sur la base de l'algorithme précédent et en utilisant des traces de réseaux réelles, nous avons proposé un algorithme proactif qui a prédit le nombre d'utilisateurs dans une zone spécifique et réglé en avance la probabilité de transmission afin de fournir une meilleure efficacité. Dans une première étape, les diagrammes de densité d'utilisateur prédits ont été extraits et synthétisés, variant entre différentes zones en fonction de leurs emplacements géographiques et de leurs types de trafic (c'est-à-dire résidentiel, industriel et mixte). Ils ont été utilisés pour créer un historique du nombre d'utilisateurs situés autour de la zone pendant chaque heure de la journée. Ensuite, ces patrons de densité ont été intégrés dans notre algorithme pour calculer la probabilité de transmission optimisée

correspondante. Nous étions intéressés à évaluer les performances de découverte en termes de temps requis pour compléter la découverte et les messages envoyés. Nous avons assisté à une énorme réduction du nombre de messages de découverte transmis en utilisant notre mécanisme de découverte, ce qui a entraîné une économie ressource importante, par rapport à la découverte du 3GPP.

Enfin, nous avons proposé un algorithme de découverte de transmission amélioré qui a permis de vérifier les probabilités de réussite de la réception des messages pour ajuster le nombre d'utilisateurs dans le groupe de découverte lorsque des scénarios plus dynamiques sont considérés. Les arrivées et les départs des UEs sont affecté le groupe de découverte et entraîné une variation du nombre d'utilisateurs exécutant la découverte. Ce nombre est important dans le calcul de la probabilité de transmission optimisée. Nous avons réussi à mettre à jour la probabilité de transmission utilisée en fonction de la probabilité d'une présence d'un utilisateur et, par conséquent, nous avons pu détecter les utilisateurs qui joignent ou quittent le groupe à tout moment du processus de découverte grâce à l'adaptabilité de notre algorithme. Un critère de succès a été défini pour déterminer la précision de ces hypothèses, ce qui nous permet de régler l'algorithme en fonction de notre objectif principal, soit une découverte plus rapide, soit une taille de groupe plus précise.

A.5.2 Perspectives

Cette thèse a principalement porté sur la proposition et l'évaluation de nouveaux mécanismes contextuels proposés pour améliorer la découverte des périphériques pour les communications D2D.

Du travail présenté ici, deux grandes lignes de travail futur sont disponibles: d'une part, alors que les propositions dans cette thèse fonctionnent dans le cas général, les utilisateurs spécifiques (par exemple, les véhicules) peuvent avoir des contraintes qui exigent que les algorithmes proposés ici soient adaptés pour les prendre en compte. D'autre part, des algorithmes plus avancés peuvent être conçus en fonction de l'apprentissage par machine ou d'une grande analyse de données, de sorte que l'algorithme lui-même évolue au fil du temps pour refléter les changements dans les comportements des utilisateurs.

En outre, les communications entre périphériques (D2D) sont toujours sous la standardisation. Les communications véhiculaires (V2X) ont été introduites récemment (3GPP, version 14) dans le cadre des communications D2D pour permettre aux véhicules de communiquer avec des parties fixes ou mobiles du système de circulation autour d'elles (p. Ex. Autres véhicules, infrastructures routières et piétons) . Cela peut entraîner des exigences plus strictes en termes de retards et de pertes en raison de la forte mobilité liée aux réseaux de véhicules. Les mécanismes proposés dans cette thèse devraient être examinés afin d'évaluer leur applicabilité dans de tels environnements. Il est essentiel d'évaluer leur résilience et leur durabilité lorsque la mobilité des véhicules est envisagée.

En outre, on estime que la cinquième génération (5G) de réseaux cellulaires seront déployés vers 2020, bien qu'il y ait une pression de certains opérateurs pour lancer la technologie plus tôt. Les réseaux 5G, comme prévu en ce moment, fonctionneront dans une bande à haute fréquence du spectre sans fil, entre 30 GHz et 300 GHz. Ces ondes millimétriques peuvent transférer des tas de données à des vitesses très élevées, mais elles ne se déplacent pas autant que les ondes de fréquence inférieure utilisées dans les réseaux 4G. Les ondes millimétriques à haute fréquence ont également du mal à se déplacer autour des murs, des bâtiments et d'autres obstacles. Il serait intéressant de tester nos propositions dans des modèles de propagation aussi restreints.