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MOBILE DATA OFFLOADING USING WIFI NETWORKS IN URBAN CONTEXT: A HOLISTIC ANALYSIS

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Resumo

A procura por conteúdos multimédia tem sofrido um crescimento incrivelmente acentuado, e as infraestruturas da rede celular estão sob grande pressão para lidar com esta volumetria de dados sem precedentes. A implementação massiva de redes WiFi em casas residenciais e estabelecimentos comerciais tem vindo a aumentar a cobertura da Internet em zonas urbanas, tornando este tipo de redes atrativas para aliviar a congestão na infraestrutura celular ou aceder a recursos de computação na *cloud/edge*.

Esta tese tem como objetivo melhorar o desenho, construção e avaliação de sistemas de *offloading* de dados móveis que possam tirar partido de pontos de acesso WiFi urbanos para enviar dados enquanto os utilizadores estão em trânsito. Para tal, dados reais de mobilidade e cobertura WiFi são utilizados para estudar as diferentes dimensões envolvidas no *offloading* de dados móveis.

A mobilidade humana num contexto de *offloading* de dados é extensivamente analisada, visando os períodos em que os utilizadores se encontram em trânsito. Uma metodologia inovadora, baseada em aprendizagem não supervisionada, é proposta e aplicada a dados de mobilidade provenientes de duas cidades distintas, Porto e Pequim, com o objetivo de perceber como se movem os utilizadores num cenário de *offloading* e como a mobilidade pode ditar janelas de conectividade. A previsibilidade da mobilidade é analisada usando múltiplos preditores teóricos e algorítmicos explorando diferentes atributos, como por exemplo, os períodos de aprendizagem e as propriedades da regularidade da mobilidade, que são cruciais para modelos preditivos. Os resultados indicam que padrões de mobilidade associados com *offloading* são primeiramente definidos pela forma como indivíduos se movem em meios urbanos, e não pelas características específicas de cada cidade. Assim sendo, as conclusões deste trabalho, derivadas da análise da mobilidade humana num cenário de *offloading* de dados, podem ser aplicadas a diferentes contextos urbanos, além dos explorados neste estudo.

A viabilidade e eficiência de redirecionar tráfego de dados móveis para pontos de acesso WiFi urbanos enquanto os utilizadores estão em trânsito é extensivamente analisada. Um simulador de *offloading* é proposto para avaliar o processo de *offloading* usando dados reais de mobilidade e cobertura WiFi em centros urbanos. Uma *framework* de conectividade WiFi é proposta e usada para modelar oportunidades de *offloading* em conexões WiFi, usando dados de cobertura WiFi. Diversas estratégias de *offloading*, que incluem abordagens oportunistas e determinísticas, foram desenvolvidas e usadas para investigar *offloading* com diferentes condições de WiFi e requisitos de tráfego de dados.

Finalmente, o impacto da utilização de diferentes tipos de informação durante a tomada de decisão é avaliado para perceber que aspetos fundamentais do processo de *offloading* são afetados quando dados do lado da rede e/ou do utilizador são usados na seleção dos pontos de acesso WiFi para *offloading*. O impacto da diminuição dos tempos de conexão das conexões de *offloading* é também explorado e uma solução para *offloading* capaz de tirar partido da mobilidade dos utilizadores para gerir o processo de *offloading* é proposta e avaliada.

Os resultados e conclusões desta tese permitem orientar e suportar o desenho de novos sistemas para *offloading* de dados móveis para que consigam tirar partido de pontos de acesso WiFi urbanos para enviar dados enquanto os utilizadores estão em trânsito.

Abstract

The demands for multimedia content are experiencing explosive growth, and the cellular network infrastructure is under pressure to cope with this unprecedented data overload. The massive deployment of WiFi networks in residential homes and businesses is increasing the Internet coverage in densely populated urban areas, making these networks attractive to offload mobile data or access computation resources in the cloud/edge.

This thesis aims to improve the design, building and evaluation of mobile data offloading systems that can leverage urban WiFi [APs \(Access Points\)](#) to offload data while users are in transit. For this, real-world data on users' mobility and urban WiFi coverage is used to study the different dimensions involved in mobile data offloading.

Human mobility from the offloading perspective is extensively analyzed, focusing on periods where users are in transit. A novel methodology, using unsupervised learning, is proposed and applied to mobility data collected from two different cities, Porto and Beijing, to understand how users move in an offloading scenario and how mobility can dictate connectivity windows to offload.

The offloading mobility predictability is analyzed using multiple theoretical and algorithmic predictors exploring different attributes, such as learning periods and mobility regularity properties, which are crucial for predictive models. The findings indicate that the mobility patterns associated with offloading are primarily shaped by how individuals move within urban environments, rather than by the unique characteristics of specific cities. Therefore, the results and conclusions of this work derived from examining human mobility in a data offloading scenario can be applicable to various urban contexts, beyond those specifically addressed in this study.

The feasibility and effectiveness of redirecting mobile data traffic through urban WiFi [APs](#) while users commute is extensively studied. A trace-driven offloading simulator is proposed to evaluate the offloading process using real-world data on mobility and WiFi coverage in urban centers. A WiFi connectivity framework was developed and used to model offloading opportunities using WiFi coverage data as WiFi connections. Various offloading strategies, employing both opportunistic and deterministic approaches, were developed and used to investigate offloading under various WiFi conditions and data traffic requirements.

Finally, the impact of using different context information during decision-making is evaluated to understand which fundamental aspects of the offloading process are affected when network-side and/or client-side data are used during the [AP](#) selection. The impact of reducing the link-setup time

of the offloading connections is also explored, and an offloading solution capable of leveraging the users' mobility to manage the offloading process is proposed and evaluated.

The findings and conclusions of this thesis guide and support the design of new mobile data offloading systems so that they can leverage urban WiFi [APs](#) to offload while users are on the move.

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I express my sincere gratitude to Professor Ana Aguiar and Professor Paulo Carvalho, my supervisors. The invaluable lessons derived from their distinctive and unique supervisory approaches have contributed significantly to my growth, both professionally and personally.

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I also express my appreciation to Dr. Aline Viana. She coauthored numerous papers developed during the creation of this thesis, but her impact extends further. My time at INRIA, Paris, under her guidance was truly enjoyable as she made me feel like an integral part of the team. I will always be grateful for her unparalleled empathy and her ability to consistently boost my confidence in the value of my work whenever doubts arise.

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Emanuel Lima

“The impossibility of constructing a complete, accurate quantitative description of a complex system forces observers to pick which aspects of the system they most wish to understand.”

Thomas Levenson

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Abbreviations

3GPP 3rd Generation Partnership Project. [12](#)

ACI Adjacent-Channel Interference. [51](#), [55](#), [57](#), [59](#), [130](#)

ACM Association for Computing Machinery. [6](#), [7](#)

AP Access Point. [iii](#), [iv](#), [xiii](#), [xiv](#), [3–8](#), [14](#), [16](#), [18](#), [22](#), [26](#), [29](#), [31](#), [32](#), [37–41](#), [43–53](#), [55–59](#), [63](#), [65](#), [66](#), [73](#), [75](#), [89–91](#), [93](#), [96–113](#), [115–120](#), [122–135](#)

API Application Programming Interface. [39](#), [40](#)

BS Base Station. [22](#), [25](#)

BSS Base Station Subsystem. [12](#)

C.I. Confidence Interval. [46](#), [47](#)

CCI Co-Channel Interference. [50](#), [55](#), [57](#), [59](#), [130](#)

CDMA2000 Code Division Multiple Access 2000. [12](#)

CDR Call Detail Record. [62](#)

CEMMO Cost-Effective Multi-Mode Offloading. [16](#)

CMM Community Based Mobility Model. [26](#), [27](#)

CSMA/CA Carrier Sense Multiple Access with Collision Avoidance. [50](#)

D2D Device-to-Device. [15](#), [16](#), [25](#), [26](#), [28](#), [32](#), [33](#)

DoS Denial of Service. [32](#)

DT Decision Trees. [82](#)

DTN Delay Tolerant Network. [20](#), [21](#), [31](#)

eNB eNode B. [22](#)

ESSID Extended Service Set Identifier. [41](#), [43](#), [48](#)

GPS Global Positioning System. [xiii](#), [28–31](#), [38–40](#), [44](#), [45](#), [63](#), [64](#), [66](#), [67](#), [71](#), [129](#), [134](#)

GSM Global System for Mobile Communications. [12](#), [40](#)

HeNB Home eNode B. [12](#)

HHW Heterogeneous Human Walk. [26](#)

HMM Human Mobility Model. [25](#), [26](#)

HNB Home Node B. [12](#)

IEEE Institute of Electrical and Electronics Engineers. [7](#), [8](#)

ISP Internet Service Provider. [xiii](#), [48–50](#), [119](#), [122](#)

LTE Long Term Evolution. [12](#), [23](#)

MAC Medium Access Control. [41](#), [43](#)

MC Markov Chain. [xiv](#), [xvii](#), [7](#), [63](#), [75](#), [76](#), [78–82](#), [84](#), [85](#), [90](#), [131](#)

MCC Mobile Cloud Computing. [16](#)

MIMO Multiple Input Multiple Output. [13](#)

MIT Massachusetts Institute of Technology. [28](#)

ML Machine Learning. [xiv](#), [7](#), [75](#), [82–84](#), [87](#), [90](#), [131](#)

MNO Mobile Network Operator. [1–3](#), [13–17](#), [21](#), [22](#), [34](#), [43](#), [49](#), [133](#)

MPTCP Multipath Transmission Control Protocol. [33](#), [34](#)

NN Neural Networks. [82](#)

OFDM Orthogonal Frequency Division Multiplexing. [13](#)

OLC Offloading Location Candidate. [65](#), [66](#), [68](#), [71](#), [122](#)

OR Offloading Region. [xiv](#), [xv](#), [xvii](#), [7](#), [8](#), [62](#), [65–90](#), [101](#), [122–128](#), [130](#), [131](#), [133](#), [134](#)

OS Operative System. 38–40, 43, 44

P2P Peer-to-Peer. 15

PoI Point of Interest. 4, 5, 7, 62, 63, 71, 76, 81, 90, 109, 131, 134

PSNR Peak Signal-to-Noise Ratio. 18

QoE Quality of Experience. 1, 2, 18, 30, 35, 61

QoS Quality of Service. 23

RAN Radio Access Network. 1

RDM Random Direction Model. 24, 25

RF Random Forest. 41, 63, 82, 84, 86, 87

RMM Random Mobility Model. 24, 25

RSSI Received Signal Strength Indicator. xiii, 43, 45–47, 50, 53, 55, 57–59, 96, 100, 101, 110, 112, 116, 117, 127, 130

RSU Road Side Unit. 93

RWM Random Waypoints Model. 24, 25

RWMM Random Walk Mobility Model. 24, 25

SCBS Small Cell Base Station. 12–14, 23

SCN Small Cells Network. 11–13

SGBMM Social Group Based Mobility Model. 26, 27

SINR Signal to Interference and Noise Ratio. 23

SLAW Self-similar Least Action Walk. 26, 27

SMS Short Message Service. 62

SNMP Simple Network Management Protocol. 31

TCP Transmission Control Protocol. 33, 119

TD-SCDMA Time Division-Synchronous Code Division Multiple Access. 12

V2I Vehicle-to-Infrastructure. [27](#), [93](#)

V2R Vehicle-to-RSU. [27](#)

V2S Vehicle-to-Sensor. [27](#)

V2V Vehicle-to-Vehicle. [27](#)

VoIP Voice over IP. [1](#)

W-CDMA Wide-Band Code-Division Multiple Access. [12](#)

WEP Wired Equivalent Privacy. [43](#)

WiMax Worldwide Interoperability for Microwave Access. [12](#)

WPA Wi-Fi Protected Access. [43](#)

WSS Within Sum of Squares. [53](#), [69](#)

Chapter 1

Introduction

In this chapter, the context, motivation, and research challenges addressed in this thesis are presented. The chapter concludes with the main contributions of this work and an overview of the structure of the document.

1.1 Context and Motivation

Due to the increasing popularity of mobile devices in people's daily lives, the demand for multimedia content is experiencing explosive growth. Smartphones, electronic tablets, and portable devices are constantly used to access services such as [VoIP \(Voice over IP\)](#), web browsing, streaming, social networks, and file downloading/upload. This is rapidly increasing the volume of mobile data traffic, causing unprecedented data overload in cellular networks that are under pressure to cope with this demand.

Since cellular networks are the most common data access method when users are on the move, supporting increased mobile traffic without degrading mobile users [QoE \(Quality of Experience\)](#) has become a challenge for [MNOs \(Mobile Network Operators\)](#). This is further worsened by the lack of available network resources, particularly in current [RANs \(Radio Access Networks\)](#) and backhaul networks [180, 88]. Therefore, to cope with the challenge of cellular network overload, the most straightforward approach is to update the network to the next-generation network, including the deployment of additional infrastructure to increase its capacity. However, this approach is expensive, takes time, and is not guaranteed to keep pace with the explosive increase of mobile data making [56, 81]. An alternative approach heavily discussed in the literature is to use complementary networks to offload mobile data originally planned for transmissions over the cellular network.

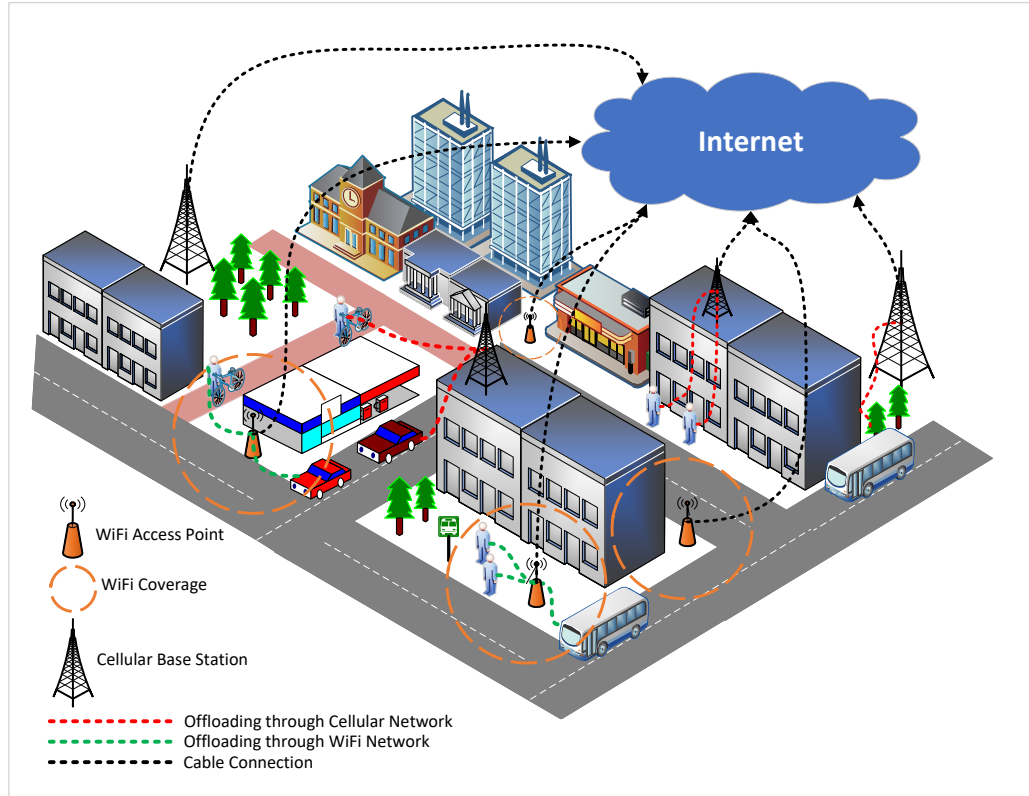


Figure 1.1: Mobile data offloading using WiFi networks.

This approach is commonly known as mobile data offloading, and considering the continuous and rapid increase in mobile traffic in the future, it is expected to play an important role in mobile networks in reducing MNOs capital and operational expenditure while maintaining or improving mobile users QoE [5].

Mobile data offloading has several benefits for both MNOs and users. From the MNOs perspective, mobile data offloading reduces network congestion, improves network efficiency, and reduces costs by shifting traffic from the cellular network to alternative networks. From the user's perspective, mobile data offloading enhances the user experience by providing more reliable and faster data transfer speeds, especially in areas where cellular coverage is weak. Mobile data offloading also reduces data usage costs by allowing users to leverage alternative networks that offer free or cheaper data plans. Finally, mobile data offloading reduces battery consumption, as it enables devices to use low-power networks when possible, prolonging battery life[178].

From all the different networks that can be exploited for mobile data offloading, WiFi networks

emerge as the perfect solution to alleviate cellular congestion by offloading data using WiFi APs [134]. In recent years, several research efforts have focused on improving the performance and reliability of mobile data offloading using WiFi networks. Currently MNOs are trying to increase the volume of traffic offloaded through WiFi networks by increasing the number of APs deployed in densely populated urban areas and ensuring that their clients can access the Internet using any of their APs. When a client subscribes to a MNO, he/she is no longer limited to its own AP but can use any AP from his/her MNO with the Internet sharing option enabled [123, 113]. Figure 1.1 illustrates a scenario for data offloading in mobile devices using urban WiFi networks. In this scenario, users on the move can use WiFi APs to offload data whenever they are inside an AP coverage.

The massive deployments of WiFi networks make these networks very attractive for offloading mobile data or to access computation resources in the cloud or at the edge. However, even though WiFi APs can be used as offloading surrogates, the design and implementation of mobile data offloading systems remains an open challenge due to the complexity of the problem. Mobile data offloading involves multiple layers of the network stack and requires the coordination of multiple network entities, including mobile devices, cellular networks, and alternative networks, such as WiFi. This makes the design and deployment of mobile data offloading solutions that are efficient and easy to use a crucial but very challenging task [178].

1.2 Thesis Claim and Research Challenges

Thesis Claim

Offloading mobile data through urban WiFi APs while users are in transit can significantly reduce the cellular network overload, specially if mobility information is leveraged to identify locations where strategies to improve the offloading conditions can be deployed.

The performance of mobile data offloading dictates the feasibility and adoption of an offloading solution. In Figure 1.2, the three main dimensions involved in mobile data offloading are represented, namely: *offloading infrastructure*, *offloading mobility* and *offloading decision*. These dimensions are mutually influential and all contribute to the overall performance of an offloading system.

The *offloading infrastructure* encompasses the WiFi APs that can be used as offloading surrogates to offload data while users are on the move. However, characterizing the capacity and availability of a densely deployed chaotic WiFi network, although crucial for the offloading process,

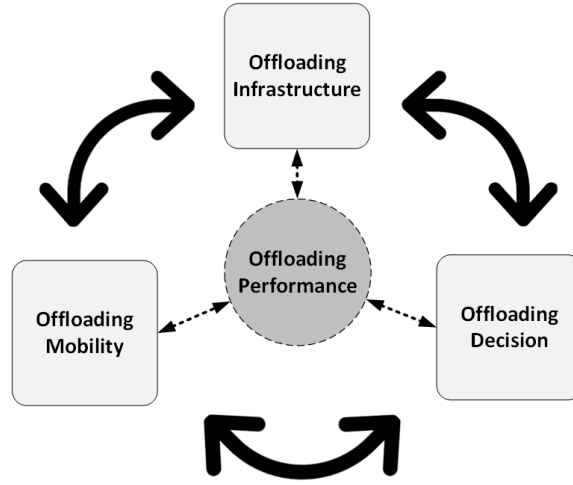


Figure 1.2: Mobile data offloading dimensions.

is a challenging task. This characterization can only be performed on the client side, which requires collecting large volumes of data on the available WiFi [APs](#) from a wide variety of providers in a wide geographic area. As expected, the implementation of a specialized infrastructure tailored for the sensing purpose has significant financial implications. Alternatives based on mobile crowdsensing [50, 100] have been used in the literature to collect large-scale data for urban WiFi characterization using smartphones as probes. However, given the nature of the collection process, the data collected is usually not ready to use, as the imprecision of the WiFi information needs to be addressed. In addition, to fully characterize an offloading infrastructure, it is necessary to inspect the characteristics of the offloading opportunities provided to users. This is not a trivial task, as it requires not only to define which attributes can be used to identify [APs](#) that can act as offloading surrogates, but also to characterize the offloading connectivity they can provide.

When focusing on the *offloading mobility* dimension, it is well known that most people spend their time in specific locations, known as personal [PoIs \(Points of Interest\)](#), e.g. home, work or favorite restaurant, which usually have WiFi networks that are used to offload data. Therefore, it can be argued that the overload of the cellular network is mainly caused by users in transit, since, during these periods, the cellular network is commonly the default option for Internet access. However, due to the limited coverage of WiFi [APs](#), the offloading opportunities offered to users are dependent on their mobility, and thus the mobility behavior and predictability of individuals.

Mobile data offloading systems need to rely on offloading mobility profiles that can provide detailed information about the users' mobility to assist mobile devices in deciding when and where to offload to WiFi networks. Several works have been proposed that study human mobility [140, 138, 38, 160, 98, 76], however, most of these works study human mobility between personal PoIs and not in offloading opportunities scenarios. Usually, PoIs are associated with a stay time, which confers its degree of importance, commonly on the order of several minutes. This time is suitable for detecting important locations but not for inferring offloading occasions, where short contacts with WiFi APs can be leveraged for mobile data offloading. How users move in an offloading scenario and how mobility can dictate connectivity windows to offload data or tasks is still an open challenge for the development of new offloading schemes.

The *offloading decision* dimension includes the decision process for offloading. Decision models can use different sources of information to assist in the decision-making of where and when to offload. Network or user-related information can be used to drive the decision to select the correct APs for the offloading or to decide whether the offloading should be performed immediately or delayed for a certain period. Given the wide range of parameters to be considered in decision-making, studying their impact on the performance of offloading is still an open issue. Several offloading schemes have been proposed that use different types of information during offloading decision-making [84, 65, 158, 31, 150]. However, most of these works focus on the analysis of the proposed solution and do not provide clarification on the impact that different information sources can have on the decision process and, consequently, the offloading performance. Moreover, due to the challenging nature of the analysis, most of the work that evaluates the offloading decision process is based on simulations and theoretical analysis, rather than real-world deployment and experiments.

Finally, research on mobile data offloading has focused on addressing specific aspects of data offloading, such as design, deployment, or management. However, the development of a comprehensive solution for mobile data offloading remains an open challenge. As the main objective, this thesis aims to provide clarification on the design and evaluation of mobile data offloading systems by seeking answers to the following research questions:

1. Which aspects do characterize an offloading infrastructure formed by a chaotic deployed WiFi network in urban scenarios?
2. How can individual offloading mobility profiles be established to improve mobile data offloading?

3. What are the expected performance outcomes for users in transit when using urban WiFi APs for offloading, and what are the key factors influencing the offloading process?

1.3 Contributions and Thesis Outline

In this thesis, different aspects related to mobile data offloading are studied to provide a thorough analysis of the performance and feasibility of using urban WiFi networks to offload. The context of offloading is analyzed using real-world data considering the periods where users are in transit, and the contributions of this work, as well as the outline of this document, can be summarized as follows:

Chapter 2

In this chapter, a review of related work on mobile data offloading is presented and discussed. The different approaches and main technologies used in mobile data offloading are categorized and detailed. The evaluation process of an offloading scheme is described with a summary of typical methodologies and offloading performance metrics used in the literature. Finally, an overview of the current issues and open challenges faced in mobile data offloading is presented at the end of the chapter.

Chapter 3

In this chapter, the datasets used in the work of this thesis are presented and details regarding the collection process are provided. The data quality regarding the WiFi indicators is analyzed and the data treatment steps to achieve high-quality information regarding the WiFi coverage using crowdsensed data are described. Finally, a comprehensive study of the characterization of APs is provided detailing how APs can be characterized as offloading surrogates. Part of the work presented in this chapter was peer reviewed and published in [ACM \(Association for Computing Machinery\) Workshop on Mobile Crowdsensing Systems and Applications \[91\]](#). The contributions of this chapter can be summarized as follows:

- a detailed analysis of the imprecision of crowdsensed WiFi data, both in terms of geo-referencing and reliability of WiFi signal indicators;
- an overview of the typical WiFi coverage achieved by open APs in a urban scenario;

- the identification and characterization of attributes that can define the quality and availability of an [AP](#) as an offloading surrogate using unsupervised learning;
- a detailed dataset containing both WiFi coverage and GPS mobility traces to be made available to the scientific community.

Chapter 4

In this chapter, an extensive analysis of human mobility is presented from the perspective of offloading. Mobility traces are extensively analyzed showing that offloading mobility profiles are feasible to differentiate user connectivity profiles during commutes. In addition, a data-based approach is used, using two granular data sets from the cities of Porto and Beijing, to measure the predictability of human mobility in an offloading scenario and to explore how this information can be used to help mobile devices decide when and where to offload to WiFi networks. The work on this chapter was peer reviewed and published in the [ACM Workshop on Challenged Networks \[92\]](#) and in [IEEE \(Institute of Electrical and Electronics Engineers\) Transactions on Network and Service Management \[93\]](#). The contributions of this chapter can be summarized as follows:

- the proposal of a new methodology that uses unsupervised learning to identify individual [ORs \(Offloading Regions\)](#) that reflect user habits and routines considering different time windows to offload;
- the categorization of [ORs](#) in terms of their relevance and spatial characteristics showing that, the laws driving users' mobility exhibit similar relevance and spacial characteristics even when considering data collected in different cities and time periods;
- the evaluation of the offloading opportunities offered to users at the [ORs](#) while travelling in terms of type, availability, time to offload and offloading delay that confirm opportunities to offload to limited coverage cells while the users are in transit;
- the analysis of the mobility predictability in an offloading scenario using theoretical and algorithmic evaluation of several mobility predictors that shows that mobility predictability for offloading purposes is far more challenging than mobility predictability between [PoIs](#), and that [ML \(Machine Learning\)](#) predictors outperform common [MC \(Markov Chain\)](#) predictors used in the literature, revealing the importance of context information in an offloading scenario;

- the proposal and discussion of further flavours that could impact ORs extraction and predictability, namely the *exploration phase length*¹, the *mobility regularity*, and *offloading locations*, as well as their impact on the design of offloading systems.

Chapter 5

In this chapter, the effectiveness of redirecting mobile data to urban APs while users are in transit is explored. The offloading performance achieved while users commute is analyzed considering different network conditions, offloading strategies, and user travel modes. The offloading decision process is inspected to draw conclusions about the impact on the offloading process when different context information is considered during offloading decision-making. Finally, different techniques and trade-offs are explored in order to provide insight on how offloading systems performance can be improved. The work in this chapter is under review for the IEEE Transactions on Mobile Computing with the title: *Mobile Data Offloading On-the-Move: Can we do it with WiFi?*. The main contributions of this chapter can be summarized as follows:

- the proposal of a WiFi connectivity model, along with different offloading strategies and a trace-driven simulator able to evaluate mobile data offloading using real-world data;
- the investigation of the offloading process when different context information is used during the AP selection stage showing that: using mobility information has marginal impacts on the offloading efficiency but, can double the time window to offload and significantly decrease the connection attempts; and that using network-side information can greatly improve the offloading efficiency, even though users can experience shorter time windows to offload;
- the exploration of different techniques and approaches to improve mobile data offloading performance using the users' mobility and network information showing that limiting offloading to a subset of locations and promoting soft-handover between APs can have the potential to greatly improve the overall offloading performance;
- the investigation of diverse aspects of the offloading process providing insights on the design and evaluation of data offloading system that can use urban APs to offload mobile data while users are in transit.

Chapter 6

¹Exploration phase is the time period required to visit each OR for the first time.

In this final chapter, an overview of the research conducted in this thesis is presented. The main conclusions and findings of this work are summarized, along with its limitations and key identified areas for future research. Finally, concluding remarks are provided addressing the overall contributions of this thesis.

Chapter 2

Background: Mobile Data Offloading

In this chapter, the broad topic of mobile data offloading is considered. The main offloading approaches and technologies presented in the literature are reviewed and categorized in Section 2.1. Section 2.2 details the evaluation of the performance of an offloading scheme, where the typical metrics, methodologies, and tools used to evaluate the offloading process are described. Section 2.3 provides an overview of the current issues and open challenges in mobile data offloading that need to be addressed to ensure the feasibility and adoption of offloading systems in the real-world. Finally, Section 2.4 presents the main remarks and a summary of the analysis presented in this chapter.

2.1 Offloading Technologies and Techniques

Mobile data offloading can be divided into three different approaches regarding the infrastructure used during the offloading process, namely, infrastructure-based, infrastructure-less and hybrid. Figure 2.1 shows the different offloading approaches compared to traditional offloading using cellular networks (Figure 2.1a).

2.1.1 Infrastructure-based Offloading

In infrastructure-based offloading solutions, some infrastructure with communication, computing, and storage capabilities is deployed to assist in data transmission. Here, SCNs (Small Cells Networks) and WiFi networks and are the main technologies used to support data offloading from the cellular network as represented in Figure 2.1b.

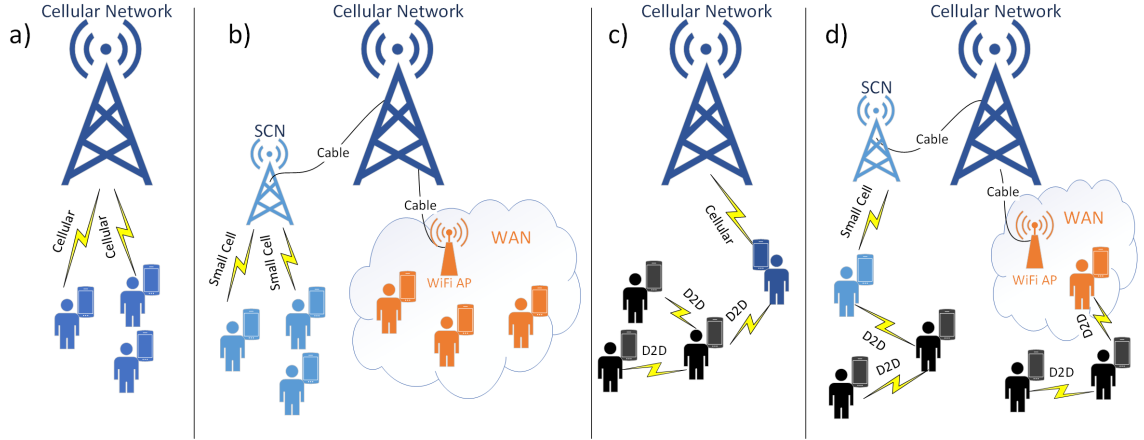


Figure 2.1: Typical offloading approaches: **a)** traditional offloading using cellular networks; **b)** infrastructure-based offloading; **c)** infrastructure-less offloading; and **d)** hybrid offloading.

2.1.1.1 Small Cells Networks

Data offloading through **SCNs** uses a variety of low-power **SCBSs** (Small Cell Base Stations), such as micro, pico, and femto **BSS** (Base Station Subsystem) to offload cellular traffic to **SCNs** [178]. **SCNs** can also be deployed with distributed radio technology by utilizing centralized base-band units and remote radio heads. The coverage of small cells can range from 10 meters within urban and in-building locations to 2 km for a rural location. Technologies such as beamforming, which aim to enhance the radio signal in a very specific region, can further improve the coverage of small cells.

Small cells are available for a wide range of wireless interfaces, e.g. **GSM** (Global System for Mobile Communications), **CDMA2000** (Code Division Multiple Access 2000), **TD-SCDMA** (Time Division-Synchronous Code Division Multiple Access), **W-CDMA** (Wide-Band Code-Division Multiple Access), **LTE** (Long Term Evolution), and **WiMax** (Worldwide Interoperability for Microwave Access). In **3GPP** (3rd Generation Partnership Project) terminology, a **HNB** (Home Node B) is a 3G femtocell while a **HeNB** (Home eNode B) is a **LTE** femtocell. **WiFi** is also a small cell but does not operate in licensed spectrum, thus cannot be managed as effectively and dynamically as small cells using licensed spectrum. The details and best practices associated with the deployment of small cells are always changing based on practical use cases and radio technologies employed. Several works have focused on studying how to use **SCNs** for mobile data offloading. In [14], the authors present a learning-based approach that involves predicting traffic demand and network resources to decide when and how to offload data from macro-to-small cells. In [27], a

multi-objective optimization approach is proposed for mobile data offloading in 5G small cell networks. The approach aims to maximize network throughput and minimize energy consumption by jointly optimizing the offloading decision and resource allocation. The simulation results show that the proposed approach can achieve a good trade-off between network throughput and energy efficiency. In [29], a joint optimization approach for both computation offloading and radio resource allocation is also proposed in small cell cellular networks. To solve the optimization problem, the paper proposes a heuristic algorithm based on the Lyapunov¹ optimization theory that involves two stages: i) the computation offloading decisions are made based on the estimated computation capacity of each mobile device; and ii) the radio resource allocation decisions are made based on the available radio resources and the quality of the wireless channel. The proposed approach is evaluated using simulations based on a realistic small cell network model and shows a significant improvement in the energy efficiency of the network while satisfying the constraints of the mobile devices and the network.

In summary, SCNs can constitute a great effective approach for offloading mobile data traffic carried by cellular networks. Due to the better radio conditions of the cellular links between mobile users and SCBSs, the performance on data transmission can be effectively improved.

2.1.1.2 WiFi Networks

WiFi stands for wireless fidelity, which is a wireless connectivity solution based on IEEE 802.11 standards [44]. It was designed to get Internet access in indoor environments. In 2007, by efficiently combining MIMO (Multiple Input Multiple Output) and OFDM (Orthogonal Frequency Division Multiplexing) technologies, the standard IEEE 802.11n (aka WiFi 4) improved the quality of wireless communication and the data rate to 600 Mbps [122]. More recently, the standards IEEE 802.11ac (aka WiFi 5) and IEEE 802.11ax (aka WiFi 6) allow data rates of up to 3.5 Gbps and 9.6 Gbps, respectively.

WiFi operates in free unlicensed frequency bands (2.4 GHz and 5 GHz) without causing interference to the cellular network, and therefore is an economical solution to expand the network capacity. Offloading part of cellular data traffic to WiFi networks is attractive to both mobile users and MNOs. From the perspective of mobile users, the use of offloading can effectively reduce the monthly bill incurred by the use of cellular data, or it can improve the battery life of mobile devices, since the energy consumption per bit of WiFi is one order of magnitude lower than that of using cellular connectivity [61]. However, the greatest benefits appear to be on the MNOs side, where

¹Lyapunov optimization refers to the use of a Lyapunov function to optimally control a dynamical system.

offloading cellular data through WiFi networks relieves cellular resources, which have higher deployment and maintenance costs.

Although WiFi is presented as a natural solution to mobile data offloading, its limited coverage due to its stationary position and finite transmit power [170] poses severe challenges to mobile data offloading systems. Most WiFi networks are in indoor environments; however, operators are continuously deploying outdoor WiFi **APs** in urban areas to meet the demand for ubiquitous access. Several works have been proposed that evaluate the economic trade-offs inherent in using the user's residential **APs** to offload. In [164], the authors reviewed the advances in the techniques and economics of two types of mobile data offloading: operator-initiated offloading and user-initiated offloading. In particular in [164], for operator-initiated offloading, mobile data can be offloaded by operators' **APs**, residential subscribers' **APs** and third-party **APs**. In [111], the authors proposed an iterative double-auction mechanism to ensure the efficient operation of the market where **MNOs** lease **SCBSs** that are already deployed for residential users, aiming to maximize the differences between the **MNOs**' offloading benefits and **SCBSs**' offloading costs, without global information about the **MNOs** and **APs**. The proposed scheme considers the coupling of **MNOs** offloading decisions and **SCBSs**' capacity constraints, and can create non-negative revenue for the market broker. In [149], a distributed market framework is proposed to price the mobile data offloading service. A detailed analysis of the incentives for the offloading of **MNOs** and the conflicts incurred by the interactions of different participants is performed. A Stackelberg game of multi-leader and multi-follower was used to model the interactions between the offloading of **MNOs** and the offloading service consumers. Extensive numerical results show that the Stackelberg equilibrium is close to the social optimum for both cases considered with/without the capacity limit.

Offloading using WiFi networks is considered one of the most promising techniques to deal with explosive data increase in cellular networks [68]. The work presented in this thesis uses this approach for the offloading process leveraging WiFi **APs** already deployed in an urban area.

2.1.2 Infrastructure-less Offloading

In the infrastructure-less offloading there is no need to deploy any dedicated infrastructure to assist the data transmission during the offloading process. Here, data is sent to other mobile devices where the offloading results from the combined mobility of a sequence of non-controllable entities [99, 175]. Data communication is ensured by opportunistic mobile networks created by neighboring mobile devices that can provide high data rates and low power consumption [176, 177]. For this reason, infrastructure-less offloading is often referred to as opportunistic offloading, as illustrated

in Figure 2.1c. **D2D (Device-to-Device)** technologies, such as Bluetooth and WiFi Direct, are typically used for data communications. As these technologies operate in the unlicensed 2.4GHz frequency band and are already available on the vast majority of mobile devices without additional equipment, they provide an extremely low-monetary-cost solution for **MNOs**.

Nowadays, a large number of mobile data, such as multimedia newspaper, popular videos and music, are of common interest among a set of users and most of these contents are not associated with strict real-time constraints. Content service providers can benefit from such delay-tolerant applications and only need to deliver the content to a small number of mobile nodes (i.e., initial seeds that will start the dissemination process) so as to save monetary cost. The initial seeds can then propagate to other subscribed nodes when they are in the communication range of each other using their equipped WiFi or Bluetooth interfaces [152].

Several solutions have been proposed to leverage opportunistic offloading to deliver content to users. The works [52, 53] were the first to take advantage of opportunistic mobile networks to remove mobile data traffic from cellular networks. These works explore the scenario where one message needs to be disseminated from a content service provider to all subscribers before a given deadline. They investigated how to select initial seeds to minimize mobile data traffic on cellular networks. The results of real trace-driven simulations show that the proposed solution can offload mobile data traffic up to 73%. In [26], the authors propose a content-centric routing scheme based on content name, which allows efficient content delivery through **D2D** communications. The scheme also considers the proximity of devices and their mobility patterns to determine the optimal route for content delivery. Performance evaluation using real-world mobility traces shows that the proposed approach can significantly reduce network traffic and improve content delivery performance compared to traditional approaches based on cellular networks. In [156], the authors introduce a subscribe-and-send architecture, which allows mobile devices to subscribe to content from nearby devices and to offload data through **P2P (Peer-to-Peer)** communication. The proposed architecture also takes into account the mobility of devices and dynamically adjusts the subscription and offloading process to ensure efficient data transfer, reduce network traffic, and improve data transfer performance.

Infrastructure-less offloading is very attractive for **MNOs** because there is little or no monetary cost associated with it. However, due to its opportunistic nature, there are also many factors that pose serious challenges to this offloading approach such as data with different delay constraints and different content size, different user demands and preferences for contents, incentives for initial seeds, battery and buffer constraints of the mobile devices, etc. [148, 179].

2.1.3 Infrastructure-hybrid Offloading

Data offloading through hybrid infrastructure uses heterogeneous networks interchangeably during the offloading process. Traffic offloading can be performed by exploiting infrastructure-based networks using small cells or WiFi networks, or can even be done using infrastructure-less approaches by leveraging opportunistic mobile networks, as shown in Figure 2.1d.

Several works have proposed various traffic offloading schemes to leverage heterogeneous networks to offload. In [103], the authors propose a routing solution for the offloading of message exchange between end-users. The protocol initially attempts to transmit messages through opportunistic communications and switches to infrastructure-based offloading only when the probability of delivering the message within the deadline decreases. The work in [73] proposes a **CEMMO (Cost-Effective Multi-Mode Offloading)**, a mechanism that allows a peer node to play the role of relay between the source node and the **AP**. Three communication modes are allowed in **CEMMO**: cellular delivery, delay-tolerant delivery and peer-assisted delivery. **CEMMO** selects the most effective offloading mode by predicting the mobility and connectivity of the user with WiFi **APs**. Using information on user mobility and WiFi connectivity, **CEMMO** helps **MNO** select the best out of its three modes to reduce the total cost in terms of financial settlement, energy consumption and user satisfaction. In [102, 101], the authors propose a novel cooperative content dissemination strategy to offload cellular data traffic using **D2D** networks through ad-hoc connections that emerge opportunistically when mobile devices move and meet each other. The authors provided a detailed analysis for the content dissemination process and discuss the optimal parameter settings for the content dissemination strategy. Extensive simulation and numerical results show that the proposed strategy can offload a significant portion of data traffic from the cellular networks.

Finally, in [94] the authors investigate the mobile data offloading problem under the architecture of **MCC (Mobile Cloud Computing)** where mobile data can be delivered by cellular, WiFi and opportunistic mobile networks. They propose a model to offload a portion of mobile data to WiFi and opportunistic mobile networks to minimize the overall cost of data delivery tasks. The authors formulate the data offloading problem as a finite-horizon Markov decision process, and propose a hybrid offloading algorithm to solve this optimization problem. Extensive simulation results show that the proposed offloading scheme can achieve a minimal total cost compared to the other three offloading schemes.

2.2 Data Offloading Evaluation

Mobile data offloading can significantly improve the performance of mobile data services, such as web browsing, video streaming, and file transfer. However, in order to design effective offloading solutions, a well-defined evaluation process is required. In this section, key performance metrics and evaluation methodologies for evaluating mobile offloading performance are reviewed.

2.2.1 Offloading Performance Metrics

The implementation of offloading schemes can improve network performance in several ways. Both mobile users and [MNOs](#) benefit from mobile data offloading, but they focus on different offloading metrics, highlighting their essentially diverse perspectives [5]. Next, the main metrics used to evaluate mobile data offload performance in the [MNOs](#) and user perspectives are described.

2.2.1.1 Mobile Network Operators Perspective

From the perspective of operators, mobile data offloading is expected to reduce traffic load and alleviate cellular congestion. Therefore, the metrics of interest for [MNOs](#) are generally related to the impact that an offloading algorithm or framework has on overall infrastructure capacity. The main metrics used for this evaluation are described below:

- *Offloading Efficiency*: Some works may use the total offloading traffic amount to evaluate the effect of the proposed offloading strategies or algorithms. However, it lacks stringency on the efficiency, because different frameworks may generate traffic in different amounts. Generally, the larger amount of created traffic is, the more offloading amount can be achieved. Offloading efficiency is defined as the ratio of total amount of offloaded traffic, to total amount of generated traffic without implementing offloading, and therefore, is considered the fundamental parameter to evaluate the effectiveness of any offloading strategy from an operator perspective [125]. As expected, a higher offloading efficiency is desirable and the proposed offloading strategies try to maximize offloading efficiency.
- *Network Overhead*: this metric evaluates, in a broad sense, the amount of additional control data required by the offloading process. Some offloading strategies may required specific control message to be exchanged between the parts involved in the offloading in order to coordinate the offloading process. This overhead is dependent on the offloading strategy and may not be marginal, and therefore, it is an important metric for network operators.

- *Hop Count*: In the case of indirect data delivery, the average number of hops traveled by the data corresponds to the average number of entities that successively carried the data from its source to its destination. The strategies that compose the trajectories aim to minimize the hop count and to this end, the composition is done so as to find the entity that will carry the data to its destination with the fewest number of hops [11].

2.2.1.2 Users Perspective

Evaluation of offloading performance from the user perspective is associated with the overall satisfaction of the user. Commonly employed offloading metrics of interest used in the literature to evaluate the users' satisfaction in offloading are the following:

- *Energy Efficiency*: In some works, the concept of offloading is associated with the power savings that may be attained by the mobile devices. Searching for other devices or APs will consume a part of energy, however, the energy consumed in offloading process should be less than the consumed in a congested cellular network. In the case of offloading through WiFi networks, the energy consumed per bit is smaller than when using the cellular network [61], and therefore, offloading schemes will try to maximize the WiFi offloading to save energy.
- *Delivery Delay*: Although users can accept the existence of delivery delay, an infinite delay is not necessarily allowed. Data content is commonly associated with a certain deadline which represents the delay tolerance to the user's greatest extent. In most circumstances, the earlier that users are able to receive or send the desired content within the delay-tolerance threshold the better the offloading mechanism is.
- *QoE*: this metric is associated with the overall user satisfaction. For any offloading scheme, the total achievable throughput is a common but important metric. The QoE indicator is then made up of several sub-metrics that depend on the application and the type of offloading. For instance, video streaming QoE metrics are the PSNR (Peak Signal-to-Noise Ratio) and the amount of packet loss [125].

2.2.2 Performance Assessment and Tools

The performance of mobile data offloading is crucial to ensure seamless and efficient network operations. Researchers use different approaches to evaluate their proposed solutions. In this section, the typical methodologies and tools used to assess the performance of mobile data offloading are presented.

2.2.2.1 Analysis Methods

The goal of an offloading solution is to maximize or minimize one or more of the offloading metrics presented in Section 2.2.1. Different methodologies can be used to perform this evaluation, but they are usually categorized into three main groups: simulation-based, measurement-based, and hybrid.

Simulation-based methodologies involve creating a model of the mobile data offloading environment and testing it under various scenarios. This approach allows researchers to evaluate offloading performance by simulating a range of parameters from the network conditions, such as network topology and traffic patterns, to different users' mobility patterns. Network conditions are usually modeled as a set of discrete events, such as data transmission opportunities and their characteristics, that are then simulated over time. Although simulation allows to evaluate many different aspects, its effectiveness is intrinsically limited by the simplifications of the models used and the software complexity in order to allow processing in a reasonable time. Despite the fact that there is a large body of literature devoted to offloading, most of the evaluations are simulation-based [125].

Measurement-based methodologies involve collecting data from real-world environments and analyzing it to evaluate offloading performance. One common approach for this methodology is the usage of testbeds that can provide insights into the actual performance of mobile data offloading under real-world conditions. In testbed-based evaluations, a dedicated infrastructure can be deployed for evaluation purposes, allowing the evaluation of offloading performance using real user devices. Unlike simulation-based methodologies where network behavior is modeled, in real-world testbeds, it is possible to evaluate the impact of complex phenomena that occur on the wireless medium, such as interference, scheduling, and overhead, often inaccurately modeled in simulation. However, due to their nature, testbed-based experiments present several challenges related to their capacity to replicate real-world scenarios [55, 4]. Since most of the time a dedicated infrastructure is deployed for evaluation purposes, testbeds may not accurately replicate the complexity and variability of real-world scenarios, such as varying network conditions, user behavior, and device configurations. This can make it difficult to generalize the results to real-world scenarios. For the same reason, testbeds may not be able to accommodate large-scale experiments that involve a large number of mobile devices and users, which can limit the ability to evaluate the performance of mobile data offloading solutions at scale.

Finally, hybrid methodologies combine simulation-based and measurement-based approaches to evaluate the offloading performance, providing a balance between the advantages of simulation-based and measurement-based methodologies. A common hybrid methodology is emulation-based evaluation. In emulation-based evaluation, the network environment or the user's behavior are

emulated using a combination of simulation and real-world data. Different levels of emulation can be used to make the evaluation process flexible and scalable. For example, real-world mobility traces can be used in event-driven simulators, while the network component can be represented by simplified models and assumptions. In the present work, a hybrid methodology for studying the performance of mobile data offloading is adopted in Chapter 5.

2.2.2.2 Evaluation Tools

As mentioned above, simulations are the main way that authors use to assess and compare the performance of the proposed offloading strategies [134]. Multiple discrete-event simulators are available to simulate the mobility of mobile nodes and the packet-level interaction of data delivery protocols, such as MATLAB², ONE³, ns-2⁴, ns-3⁵, OMNeT++⁶ and SUMO⁷. MATLAB is usually used for the evaluation of radio signal propagation and queue-based models. ONE is used to simulate the mobility of mobile nodes with models already implemented. It is essentially an opportunistic network simulator for DTNs (Delay Tolerant Networks) already implementing typical DTN routing protocols. ONE also allows easy implementation of data delivery protocols by overriding primitives when nodes come into contact. However, due to its simplicity, ONE does not incorporate typical link-layer mechanisms such as wireless interference caused by buildings and other nearby communications, or bandwidth variation resulting from the distance between nodes. NS-2, its evolution NS-3, and OMNET++ are also popular simulators mainly used for packet-level analysis, as they can simulate realistic link-layer wireless protocols. However, they do not take into account an extensive range of mobility models for the nodes. On the other hand, SUMO is designed to simulate urban mobility, including modeling the mobility of vehicles traveling the roads and their interactions on a road network.

Despite the availability of these simulators, they can be inefficient when it comes to simulating the movement of nodes and their interaction with the network over large datasets. Their complexity and limited support for unusual modes of operation (as in the case of offloading) often lead to the development of custom simulators to evaluate offloading performance [11]. Here, programming languages such as R, Python, Java, and C are usually used to develop the tools needed to evaluate the performance of the proposed offloading solutions.

²<https://www.mathworks.com/products/matlab.html>

³<https://akeranen.github.io/the-one/>

⁴<https://www.isi.edu/nsnam/ns/>

⁵<https://www.nsnam.org/>

⁶<https://omnetpp.org/>

⁷<https://www.eclipse.org/sumo/>

2.3 Open Issues and Challenges

Despite the potential advantages for both [MNOs](#) and users, the adoption of offloading strategies may not be widespread among mobile users unless the associated challenges are effectively addressed. In this section, an overview of the main challenges encountered in mobile data offloading is presented. These challenges are highlighted as open research areas that need to be addressed to ensure the feasibility and adoption of mobile data offloading solutions.

2.3.1 Offloading Incentives and Expected Outcomes

Incentives for offloading can broadly be categorised in three categories, namely, cost, energy, and rate. These incentives have been investigated to stimulate [MNOs](#) and users to accept offloading solutions.

2.3.1.1 Cost

To be successful and widely adopted in a heterogeneous network, mobile data offloading must be economically beneficial to both users and operators. Therefore, it is crucial to explore ways in which both parties can benefit from offloading.

Previous studies such as [81] try to quantify the economic gain of delayed offloading by fully considering the interactions between [MNOs](#) and their subscribers. However, this work only focuses on the upper-bound of the benefits, while realistic scenarios between multiple providers and misinformation of user profiles are not solved yet. The authors of [183, 184] propose a novel incentive framework to motivate users to use traffic delay tolerance for cellular traffic offloading. To effectively capture the dynamic characteristics of users' delay tolerance, the proposed framework is based on reverse auction to let users proactively express their delay tolerance by submitting bids. For the evaluation scenario, two different models are used to assess the user offloading potential, one for the WiFi infrastructure and the other for the [DTNs](#). However, being separated models, it does not really represent a hybrid and complex offloading scenario. In [64], the authors study the trade-off between cost, throughput, and delay in making offloading decisions. In the study, aspects such as instantaneous variation of network conditions and support to cooperative network and prefetch mechanism have not received sufficient attention. In [80], the authors considered the poor coverage of current WiFi networks by a tethering-based cooperative approach, but the impact on the complexity of the computation on the implementation is unclear.

In general, more research is still required to fully evaluate the trade-offs between the cost incentive and the expected outcome for users and **MNOs**. Future directions are to improve all existing mechanisms within seamless experience and concurrent connections with dynamic traffic and infrastructure behavior [56].

2.3.1.2 Energy

In recent years, green communication has garnered increased attention due to the growing popularity of energy-saving initiatives. It is crucial to explore methods for reducing energy consumption in heterogeneous networks for operators. Additionally, users may be inclined to embrace offloading if it enables to extend devices' battery life by conserving energy.

Several works have been carried out to try to address the challenge of energy consumption in the offloading of mobile data from the **MNOs** and user perspectives. Works such as [118, 54] that offer solutions to lease WiFi **APs** deployed by a third party to offload can reduce **BSs (Base Stations)** energy consumption. However, it is challenging to minimize energy consumption and achieve optimal traffic offloading. In [8], the authors propose to lease WiFi mesh networks and introduce an analytical framework that determines which mobile users should be offloaded. This decision is based on the energy cost that cellular base stations (**eNB (eNode B)**) incur to service their demands. However, the final operator's revenue from users is not clear. In [143], an experimental approach is conducted to identify the main components that impact energy consumption in mobile devices connected to cellular and WiFi networks. However, the goal of dynamically switching between network interfaces was not fully accomplished as this process was manual. Continuing on the trend of concurrent connections in mobile devices, in [107, 108] the author extended the state-of-the-art of the uplink scenario with a fair bandwidth allocation algorithm. Despite this, the impact of computational complexity on users' mobile devices is not fully addressed. Similarly, in [137], the authors exploited the prediction of mobility and prefetching and well evaluated the energy consumption and throughput, but no prototype was presented.

In conclusion, there are still open research challenges that do not allow to fully understand the limits of the energy savings that can be achieved through mobile data offloading. Not only is it necessary to investigate how **MNOs** can reduce energy consumption but also how users can benefit from it, since they dictate the adoption of a certain offloading scheme.

2.3.1.3 Offloading Rate

The offloading rate can be regarded as the average completion time of the required data transmissions in the offloading. Several factors can influence offloading rate such as transmission rate of a radio access network, congestion, switching delay, etc. Due to the wide variables space and their complexity, these conditions are often simplified or ignored in the literature. The work in [33] claims to be the first study to focus on congestion-aware network selection and data offloading problems with multiple heterogeneous users. However, the scenario used is very optimistic, as it assumes that the cellular network is available to all the users, at all possible locations, and at any given time. In [135], a distributed cross-system traffic steering framework is proposed in which SCBSs leverage WiFi to autonomously optimize long-term performance in the licensed spectrum band as a function of traffic load and user QoS (Quality of Service) requirements. Although the proposed solution outperforms several benchmark algorithms and traffic steering policies, it was only applied to users with reduced mobility. In addition, interference management and the interaction between mobility and cell association are not considered.

Regarding more theoretical approaches, the authors of [136] perform a theoretical analysis of cell load coupling for LTE networks. They utilize the load coupling equation obtained from a SINR (Signal to Interference and Noise Ratio) model, which considers the load of each cell, taking into account that the load of one cell affects the load of other cells in a non-linear manner. This load coupling model provides a reliable estimate for complex load models. However, their research only focuses on addressing the demand to be met within cellular networks. To extend this idea to WiFi offloading and achieve load coupling in heterogeneous networks, the authors of [57, 58] formulated a utility maximization problem where the demand to be served in a heterogeneous network is optimized, maximizing the utility function. Considering practical implementation, the authors also propose a strategy to constrain the load to a maximum value. However, more work is still needed to consider additional factors such as energy savings and the association between the user and the network.

Although several works have been proposed to improve the offloading rate, factors such as network congestion and load balancing are still not well understood. More research is needed to ensure that mobile data offloading is feasible in nonideal scenarios.

2.3.2 Mobility of Nodes

The mobility of nodes can be explored for communication opportunities for offloading in infrastructure-less and infrastructure-based offloading. However, this is not a simple task, as mobility creates a

communication instability problem resulting from a non-stable end-to-end path guarantee between mobile users and the network infrastructure. The critical challenge is how to effectively manage and use mobile users' mobility to maximize offloading performance. Most of existing works focus on characterizing the mobility pattern of mobile nodes with history mobility, to predict when and where to initiate communication. These works use mobility models or mobility traces that have been adopted and studied in different fields of wireless communication [21, 12].

In this section, the various mobility models proposed and the wide range of mobility traces collected by the research community are summarized.

2.3.2.1 Mobility Models

Mobility models are designed to realistically represent various real-life mobility scenarios, such as emulating movement patterns. These mobility models allow researchers to focus on the influence of different parameters of mobility, such as speed, waypoints (destination), location, contact⁸ time, inter-contact⁹ time, encounter frequency, etc. Mobility models have been widely categorized in the literature [21, 12, 153]. Next, the main categories of mobility models used in mobile data offloading are summarized:

RMMs (Random Mobility Models): In these models, nodes move freely and without restriction. All mobility attributes such as speed, direction, and destination are selected randomly and independent of previous selection. Therefore, these mobility models are generally termed memoryless, as speed (or direction) at time instant t is independent of speed (or direction) at instant $t - \Delta t$. These models can be further divided into **RWMs (Random Waypoints Models)**, **RDMs (Random Direction Models)** and **RWMMs (Random Walk Mobility Models)** [115, 79, 85].

- **RWMs:** these models are frequently used mobility models due to its simplicity [114, 78, 154, 165, 157, 116]. Here, mobile nodes move within a known dimensional area, and the average speed of users is distributed uniformly between minimum and maximum speeds. The velocities and directions of users are chosen independently. When mobile nodes come into contact, their movements stop for certain duration of time, known as pause-time. The maximum velocity and pause-time are the two basic parameters that determine the mobility of users. Small maximum speed and long pause-time result in high stability, while fast user movement and small pause-time produce highly dynamic behaviours of the users, and communication may become unstable. Thus, **RWMs** may fail to achieve a steady state,

⁸contact time captures the frequency of encounters and time length

⁹inter-contact time captures the length of the time interval between contacts

in terms of average user speed, and as a result, the speed may constantly decrease as the simulation progresses [162, 36]. Moreover, it is observed that the spatial user distribution of **RWMs** is transformed from uniform distribution to non-uniform distribution as it reaches a steady state [13, 15]. However, in the steady state, the maximum density of nodes occurs at the center area whereas it is almost zero around the boundary of the simulated area (e.g. edge of the coverage area of a **BS**). This makes difficult to use **RWMs** to model the user distribution in **D2D** communication underlying cellular network within the coverage area of a **BS**;

- **RDMs**: these sort of models were proposed to resolve the problem of non-uniform spatial distribution of user density associated with **RWMs** [131]. In **RDMs**, a user randomly and uniformly selects a direction between $[0, 2\pi]$ until it reaches the edge of the simulation area. Then, after stopping with a pause-time, it randomly and uniformly chooses another direction to move [9, 77, 34]. Attending to its characteristics, this mobility model may not be applicable in certain communication applications where the simulation area represents the coverage area of a network and the goal is to use relay nodes that need to go in and out of the coverage scenario;
- **RWMMs**: these models emulate the unpredictable movements of the particles in the field of physics. They are often adopted by the wireless communication community because it is assumed that mobile users may also move in unpredictable ways [166, 59, 96, 167, 168]. **RWMMs** have certain similarity to **RWMs**, as node movements are random in the both models. However, in **RWMMs**, the nodes movements are purely random, and nodes have zero pause-time when they come into contact. Therefore, the difficulty of applying **RWMMs** to offloading communications is that in offloading scenarios users do not have any information about the past state when they come into contact, because the present velocity is independent of the past velocity. This completely extreme randomness may not fit the real-life offloading communication scenario, as, in reality, the velocities at which two mobile nodes establish a link for communication may be dependent on their previous velocity [153].

HMMs (Human Mobility Models): the aforementioned **RMMs** are not particularly suited for modeling human mobility, as they are unable to produce patterns and statistical properties required to mimic real-life human mobility patterns [69]. The definition of **HMMs** is based on physical space, temporal properties, and connectivity. In physical space, proximate users generally travel in a close vicinity to their home and office environments [12]. Regarding temporal properties, users

are most likely to return to a previous location with an encounter frequency that is proportional to the rank of popular location. Thus, a high success probability can be achieved in finding the current location of users by knowing the history of user movements. The connectivity properties related with the contact duration can be measured by the inter-contact time and the contact time. Real-life human mobility traces are often used to find spatial and temporal properties of users in establishing a communication link between D2D users, or users and the network infrastructure [17, 46, 139, 24]. Human mobility also explores the contact duration, contact frequency, community structure, and mobile user centrality from mobility traces in the real world [62, 92, 93]. The HMMs models can be further classified into SLAW (Self-similar Least Action Walk), HHW (Heterogeneous Human Walk), SGBMMs (Social Group Based Mobility Models) and CMMs (Community Based Mobility Models) [153].

- **SLAW**: is one of the primary mobility models for emulating human walk behaviors [62, 82], and it has been shown that the model can capture the users mobility patterns for offloading [69, 6]. It is particularly effective in emulating the mobility patterns of users having common interest for offloading, transmitting or caching popular contents within the same geographical location, e.g. university campus, office or home. Moreover, **SLAW** can also express spontaneous trip patterns present in the daily mobility of users. People typically keep a routine of visiting the same places every day, e.g. going to office, but at the same time, maps irregular trips caused by unexpected events of daily live, which can be represented by **SLAW**. However, **SLAW** may not necessarily capture all the important statistical features of human mobility, such as the temporal features. People meet because they are in the same place and also at the same “time”. Moreover, people move to a certain location at a certain time because they have to be there at that time. A WiFi **AP** may become popular only at a certain time, e.g. at dinner time at a restaurant area, and therefore, real mobility patterns must be a result of representing these spatial and temporal correlations. When generating mobility traces, **SLAW** chooses randomly a set of destinations to be visit from a given set of locations, and the visits to a certain location are determined by a function of distance from the current location. While this decision process may capture some realism in spatial constraints, it does not represent temporal tendencies of human mobility. The drawback is the exponential cut-off that appears every twelve hours in the **SLAW** mobility model, which impacts on people’s daily routines [48];
- **HHW**: aims to generate realistic and more general human mobility patterns, including the heterogeneity of human popularity. It also tries to capture the spatio-temporal regularity of

human mobility. The heterogeneous popularity can be global or local. A node has a local popularity within its community and a global popularity across the whole network. Since a node can belong to multiple communities, it can have multiple local popularities [12]. Unlike [SLAW](#), this model can describe the overlapping community/group structure which contributes to human heterogeneous popularity. Therefore, a user can initiate the contact time with destination users according to their contact history to leverage mobility prediction. As some users are more popular in the community, they have more chances of encountering others, being therefore, more suitable for relaying data than non-popular users [159, 70];

- [SGBMMs](#): this sort of models, found on social network theory, allow a number of users to form a group collectively based on social relationships among the users [110, 90]. The grouping of users is then mapped onto a topographical space, and user movements are influenced by the strengths of social ties among users, which may change in space and time. In [SGBMMs](#) models, users mobility is modeled assuming that users can cooperate or communicate with each other as a group in a social network [109, 60, 151];
- [CMMs](#): these models are proposed as a scheme for peer discovery in social networks. It captures the social nature of humans and is heavily dependent on the structure of relationships among people. Although similar to [SGBMMs](#), [CMMs](#) differ in terms of the definition of the central user. In [CMMs](#), the central user of a group is static, while in [SGBMMs](#) the central user is also moving along with other users in the group [165, 34].

In the literature, other types of mobility models were also proposed focusing on vehicular networks, including [V2S \(Vehicle-to-Sensor\)](#), [V2V \(Vehicle-to-Vehicle\)](#), [V2I \(Vehicle-to-Infrastructure\)](#), and [V2R \(Vehicle-to-RSU\)](#) communications. These models try to emulate the locomotion of vehicles along the road or highway with respect to the speed and movement, in queues, stopping at traffic signals, etc. [32, 141, 147],

Mobility models work reasonably well for situations where the mobility patterns of mobile users exhibit a sufficient degree of regularity. However, the mobility of irregularly moving nodes is unpredictable and, therefore, challenging. Continuous efforts on new and more robust mobility models that take into account more complex scenarios are needed to allow the full design and evaluation of mobile data offloading schemes.

2.3.2.2 Mobility Traces

In order to create a realistic mobility model that accurately emulates the mobility patterns of a real-life application, it is highly effective to directly infer or derive key mobility parameters from real-life mobility data. Therefore, considerable attention has been given on collecting real-life mobility traces. Some researchers capture mobility traces from devices equipped with [GPS \(Global Positioning System\)](#) and some exploit traces from opportunistic networks. Table 2.1 summarizes the most used mobility datasets in the literature, namely:

- *mit/reality* [39]: this dataset captures communication, proximity, location and activity information from 100 [MIT \(Massachusetts Institute of Technology\)](#) staff and students over the 2004-2005 academic year (9 months). Because this dataset captures real-life human mobility patterns, which are inherently connected with social networks, it is particularly useful for investigating offloading communication involving human mobility;
- *cambridge/haggle* [132]: this dataset includes contact information and data transfer opportunities for the users at locations such as office and conferences from a group of users who carry iMote devices in office and city environments. The duration of the dataset is up to 6 days, and has been utilized to help solving different technical problems of [D2D](#) communication;
- *Sigcomm2009* [121]: this dataset was collected during the Sigcomm 2009 conference at Barcelona. Around 100 smart devices were used where each device was initialized with the users' social profile, including the information of the user's home city, country and affiliation. Each user is advised to log on to the Facebook profile, which helps the user to find friends and interest in the mobile social network. The traces present opportunistic data transmission, encounter frequency and social profiles of proximate users in the scenario of [D2D](#) communication;
- *roma/taxi* [16]: the dataset comprises the mobility traces of around 320 taxis in the central Rome, Italy, collected over 30 days. The data collected includes the taxis current locations, speeds, heading angles, status, etc., every 7 sec;
- *umass/diesel* [19]: the dataset contains data traces of 30-40 buses equipped with WiFi capabilities, which are sparsely covering almost 150 miles. It measures the intermittent connectivity between buses and the bus mobility itself using [GPS](#);

- *dartmouth/campus* [75]: the dataset was collected for a period of 5 years at Dartmouth College, a large college campus with 190 buildings and a large number of students. There are 450 APs installed with ranges of about 130-150 feet indoors, serving several thousands of users. The dataset records the mobility traces of users whose mobile devices can access the wireless APs. The estimated movements of mobile users between APs may be erroneous due to the relatively long distance between APs. Thus, the data traces are not entirely satisfactory for explaining the detailed human mobility trajectories due to uneven granularity [126];
- *Shanghai Taxi* [182]: this dataset contains mobility traces from approximately 2019 operational taxis carrying GPS devices in Shanghai, China, for the duration of one month. The dataset contains the information of taxis' current location, time duration, speed, heading angle, and status;
- *Beijing Taxi* [89]: this dataset contains the mobility traces of 27000 taxis in Beijing, China, for the duration of one month. This large vehicular mobility dataset is widely utilized to study large-scale vehicular systems in large urban environments;
- *upb/hyccups* [35]: this dataset contains information regarding mobile users' interactions with their smartphones, e.g., statistical usage, activities of users, battery usage and sensor data. In addition, it also contains information regarding the encounters between users. The mobility traces of this dataset include wireless contacts, social connections and users' interests;
- *oviedo/asturies-er* [20]: the dataset contains GPS traces generated by GPS devices embedded mainly in cars and trucks, but also in a helicopter and a few personal radios. A total of 229 devices reported 19,462,339 locations, being a new location reported with an interval of approximately 30 seconds whenever the GPS device detects movement;
- *copelabs/usense* [42]: this dataset was collected using the open-source middleware NSense¹⁰. A first dataset was collected relying on a first NSense version in 2015. Then, a second dataset was collected in 2016, with a refined version of NSense. In all datasets, devices were carried around by people sharing the same affiliation during their individual daily routines (24 hour periods). Data such as relative distance to the WiFi APs, social strength (based on Bluetooth contact duration), sound activity level and motion type (stationary, walking and running) was collected from a maximum of 9 participants during 12 days;

¹⁰<https://github.com/COPELABS-SITI/NSense>

- *Geolife* [171]: this dataset contains **GPS** traces collected in the GeoLife project by 182 users for a period of over three years. It contains 17,621 traces with a total distance of about 1.2 million kilometers and a total duration of 48,000+ hours. These traces were recorded by different **GPS** loggers and **GPS**-phones, and have a variety of sampling rates – 91% of the trajectories are logged in a dense representation, e.g. every 1-5 seconds or every 5-10 meters per point.

Real-world mobility traces have been crucial in developing mobility models and supporting the evaluation of mobile data offloading. However, there are still many limitations in the majority of the mobility datasets presented above, which pose serious challenges to the study of human mobility and consequently impact on the design and evaluation of offloading schemes. One of these limitations is the lack of heterogeneity of the participants. Most datasets contain mobility information from a specific set of participants, e.g. conference attendees, students, researchers, etc., which not permits to generalize some of the mobility characteristics in the dataset to different types of participants that may present a distinct mobility behavior. Another typical limitation is related to the size of the individual data. Most datasets do not provide sufficient data from the same participant to extract more complex mobility patterns, since they only provide a small number of consecutive days with data. Moreover, a high sampling rate of the participant location information, although ideal, is often a challenge due to the energy constraints in the measurement device (e.g. smartphone). This leads to datasets with sparse location information that can limit the dataset potential for analysis.

As a contribution of the work in this thesis, a rich mobility dataset containing high-sampled **GPS** trajectory traces for more than 380 participants will be made available to the research community. This dataset is presented and detailed in Chapter 3.

2.3.3 Operational Challenges

There are several operational challenges that need to be solved in order to make mobile data offloading feasible in the real-world. Improving users **QoE** by making the offloading process secure and seamless for users is crucial to ensure that users adopt offloading solutions.

2.3.3.1 Security and Privacy

Mobile data offloading raises various security and privacy concerns, as it involves sharing of sensitive user data and network resources between different networks and devices. As such, offloading

Table 2.1: Mobility traces datasets in the literature.

Name	Year	Size	Collection Period	Collected Data
mit/reality [39]	2004	100 SmartPhones	9 months	Communication, proximity, location, and activity information
cambridge/haggle[132]	2009	8-78 iMotes	several days	Bluetooth sightings in office, conference environments and city environments
sigcomm2009 [121]	2009	76 Smartphones	5 days	Bluetooth sightings, opportunistic message creation and dissemination, and user's social profiles
roma/taxi[16]	2014	320 taxis	30 days	GPS data
umass/diesel[19]	2005	30-40 buses	3 years	GPS data and real transfers of the bus-based DTNs testbed
dartmouth/campus[75]	2001	450 APs	5 years	Connection between users and APs obtained from syslog events, SNMP (Simple Network Management Protocol) polls and network sniffers (tcpdump)
Shanghai Taxi[182]	1991	2019 taxis	1 month	GPS data
Beijing Taxi [89]	2010	27000 taxis	1 month	GPS data
upb/hyccups[35]	2012	72 Smartphones	63 days	Usage statistics, user activity, battery and sensors data and devices' encounters with other devices or with APs
oviedo/asturies-er [20]	2011	229 GPS devices	1 year	GPS data
copelabs/usense [42]	2016	9 Smartphones	12 days	Relative distance to WiFi APs; social strength (based on Bluetooth contact duration), sound activity level and motion type.
Geolife [171]	2007	182 Smartphones	3 years	GPS data

solutions are vulnerable to various types of attacks, such as eavesdropping, man-in-the-middle, replay, and [DoS \(Denial of Service\)](#).

In infrastructure-less offloading, the mobile devices, which are resource-constrained by nature, usually take care of functionalities such as authorization, authentication, auditing, and logging, which are usually managed by a centralized entity. This makes security enforcement a serious challenge [152]. Cross-layer security frameworks, such as the one presented in [181], could improve reliability of [D2D](#) communications. Here, the physical layer provides wireless link security, whereas, the application layer ensures authentication through watermarking. Together, both layers can ensure the confidentiality and integrity of data as it passes through the wireless channel.

Privacy is another challenge in mobile data offloading. Although voluntary sharing of personal information has become a daily habit, many disapprove of companies using their data to create profiles. Mobile devices are typically associated with a single person and, therefore, communication patterns such as location, time, duration of communication, device type, etc., can be used to identify a particular user and anticipate its decisions. Standards and procedures must be studied to enforce user privacy, data anonymity, and an adequate level of security for information storage [18].

Taking into account the broad scope of security issues faced by mobile data offloading solutions, the main challenges can be categorized into four categories, namely:

- *Data Security*: when data is transferred over alternative networks, it becomes susceptible to interception, eavesdropping, and data theft. Attackers can exploit vulnerabilities in the network, such as weak authentication mechanisms and insecure data transfer protocols, to gain unauthorized access to user data;
- *Network Security*: alternative networks used in mobile data offloading, such as WiFi and Bluetooth, are susceptible to security attacks such as man-in-the-middle, [DoS](#), and rogue [APs](#). Attackers can exploit these vulnerabilities to intercept user data, compromise the integrity of the network, or launch attacks against the user's device;
- *Device Security*: mobile devices are susceptible to security attacks such as malware, spyware, and phishing attacks. Besides, security issues in the mobile terminal can still come from the mobile users themselves, since mobile users usually lack security awareness or can mishandle the devices. These issues can compromise the user's device and enable attackers to gain access to sensitive data such as login credentials, financial information and personal data [142];

- *Privacy*: mobile data offloading raises privacy concerns as data can be transferred over public networks that are not secure. Attackers can use information gathered from mobile data offloading to conduct targeted attacks or obtain sensitive information about users.

Security and privacy issues in mobile data offloading are crucial factors that need to be addressed to ensure the safety and secure deployment of the offloading systems in the real-world. Various security and privacy solutions and measures have been proposed and investigated; however, further research is needed to develop more effective and efficient solutions that can increase user confidence and adoption.

2.3.3.2 Managing Seamless Communication

When using heterogeneous networks, such as WiFi and D2D networks, to offload data, it is expected that the mobile device will be constantly switching between different network interfaces. This may lead to disruptions to ongoing communications that affect users' satisfaction. Therefore, it is crucial to investigate how to alleviate disruptions and maintain continuous communications during the offloading process.

Different approaches have been proposed to provide seamless communication to users while offloading. Network selection in the mobile terminal is proposed to make a decision and switch wireless interfaces in heterogeneous networks to reduce handovers and interruptions. Smart terminals or wireless systems can initiate a decision mechanism based on the status of these interfaces. However, simply switching between multiple interfaces is not an option for ongoing TCP (Transmission Control Protocol) sessions, as it is bound to cause data interruption and loss. In order to address the continuity issue, several research groups [25, 146, 155] attempted to deal with interruptions while switching between wireless interfaces. However, their approaches either need to extend the current infrastructures or require novel protocols instead of existing ones. Moreover, to optimize the performance of services, handover schemes need to take into account more information, such as the status of network access and the type of applications running on the mobile device [86].

Instead of focusing on the handover process to provide seamless communication, other approaches focus on using multiple paths through several networks to simultaneously transmit the data [66, 72]. Since multipaths cannot be handled in TCP, MPTCP (Multipath Transmission Control Protocol) is devised as a multipath protocol in the transport layer to extend TCP and address this issue [163]. With MPTCP, there is no need to update the hardware to be able to manage several simultaneous connections through multiple networks. MPTCP has a congestion control mechanism to balance traffic on each path to avoid congestion. Evaluations have shown that more than 50%

of channel waiting time can be saved by WiFi by [MPTCP](#) [124, 47]. However, in terms of energy efficiency, only the transmission of data blocks can show satisfactory performance unless a better activation control scheme is devised to determine when to utilize [MPTCP](#) [30]

2.4 Concluding Remarks

In this chapter, the literature on mobile data offloading was reviewed, providing an overview of the main concepts and works in the field. In Section 2.1, the offloading approaches were categorized according to the infrastructure used during the offloading process, namely, infrastructure-based, infrastructure-less and hybrid, providing an overview of the state-of-the-art for each approach. The work presented in this thesis is focused on infrastructure-based offloading using WiFi networks, since it is considered one of the most promising techniques to deal with the explosion growth of mobile data [68].

The evaluation of the performance of the offloading was discussed in Section 2.2. The main metrics used in evaluating the performance of the offloading from the perspective of [MNOs](#) and the user were presented, as they may not share the same interests in the offloading. The three main methodologies used in the literature to evaluate offloading performance were also discussed, which can be simulation-based, measurement-based, or hybrid, highlighting their strengths and weaknesses. As discussed in Section 2.2, hybrid methodologies provide a balance between the advantages of simulation-based and measurement-based methodologies. In the context of this thesis work, an event-driven simulator was developed to study offloading performance; that is detailed in Chapter 5.

In Section 2.3, an overview of the open issues and challenges currently faced in mobile data offloading was provided. The main concerns on finding the best trade-off in terms of cost, energy, and offloading rate that need to be tackled to satisfy both [MNOs](#) and users were highlighted. Since user mobility is one of the main challenges in mobile data offloading, an overview of the main mobility models and mobility datasets available to study mobile data offloading was provided. Mobility models work reasonably well for simple mobility patterns but struggle to model human behavior in more complex scenarios. For this reason, real-world mobility datasets are preferred in the field of mobile data offloading. However, finding datasets that have a large number of diverse participants and a substantial amount of data collected per participant over numerous days, all at a high sampling rate, poses a significant challenge. In Chapter 3, the dataset used in this work is presented, which possesses unique advantages compared to the mobility datasets available in the literature.

Finally, this chapter was concluded with an overview of some of the operational issues related to security and privacy of the offloading process, as well as the QoE provided to the user that need to be solved to allow mass adoption of an offloading scheme by end users.

Chapter 3

Urban WiFi Offloading Infrastructure: Datasets and Characterization

To study the feasibility of using WiFi [APs](#) to offload data while users are on the move, it is first required to characterize a typical WiFi deployment on a city scale. In this chapter, the first research question presented in the introduction of this thesis is addressed: Which aspects do characterize an offloading infrastructure formed by a chaotic deployed WiFi network in urban scenarios?

To answer this question, the datasets used in this work are presented. The data collection process is detailed, and the imprecision of crowdsensed WiFi data is addressed to achieve high-quality information on the WiFi coverage at the city scale. Furthermore, the characteristics that can be used to identify [APs](#) as possible offloading surrogates are explored by using multidimensional attributes to classify the quality and availability of [APs](#) for offloading.

The chapter outline is organized as follows. Section [3.1](#) describes the sources of information and the data collection process used to build the datasets that contain information on the mobility of users and the WiFi coverage of the city. In Section [3.2](#) the impression of the WiFi indicators is addressed, both in terms of geo-referencing and reliability of the WiFi signal indicators. The characterization of [APs](#) as possible offloading surrogates is studied in Section [3.3](#). Finally, Section [3.4](#) presents an overview of the main findings and conclusions presented in this chapter.

3.1 Information Sources

Mobile crowdsensing applications make use of the sensing and wireless communication capabilities provided by billions of smart mobile devices to collect data. This sensing paradigm has been

Table 3.1: Crowdsensed dataset details.

Total Area	25km ²
Collection Period	2016 to 2018
Participants	401
Mobility Traces Dataset	
Car Trips	8635
Foot Trips	5460
Bus Trips	528
Metro Trips	180
Bike Trips	139
WiFi Coverage Map	
Total WiFi Scans	1.2M
Distinct <i>APs</i>	154k
Distinct Open <i>APs</i>	40k (26%)

thoroughly surveyed in recent literature [49, 28, 1] where efforts have been made to define taxonomies that consider aspects such as engagement strategies, privacy policies, and participant involvement and awareness.

In this thesis, the data collected from a mobile crowdsensing application is utilized. However, it is important to note that the development of the crowdsensing application itself was not in the scope of this thesis. In this section, the data collection process is described to provide the necessary background to understanding the data collected and the consequent analysis.

Two main sources of information were considered to build the datasets used in the present work, namely: *GPS* traces and WiFi data. This data was collected from multiple crowdsensing campaigns, resulting from the participation of more than 400 participants who were using smartphones with Android *OS (Operative System)* as sensing probes. Most of the participants were related to academia, for example, researchers, students, and professors; however, a significant portion of them were not, as the crowdsensing application was publicly available through the Google Play Store¹.

Figure 3.1 shows the distribution of the smartphone of the participants per manufacturer/vendor. Although a total of 27 different manufactures/vendors were found in the pool of smartphones used during data collection, the majority (51.2%) of the participants were using smartphones from three well-known smartphones manufacturers, namely: Samsung, HUAWEI and Xiaomi.

¹Google's place for downloading Android applications – <https://play.google.com/store>

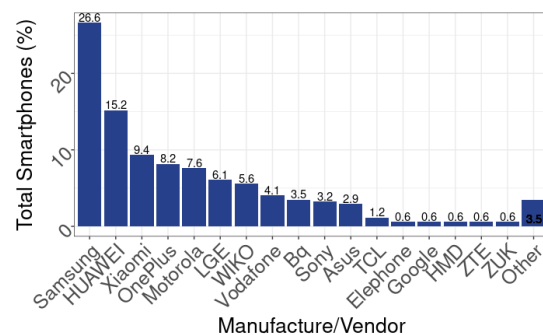


Figure 3.1: Participants' smartphones manufacturers.

3.1.1 Mobility Traces

Mobility traces were collected using the participants' smartphones **GPS** receiver. This receiver is able to provide location data, including longitude, latitude, altitude, speed, heading, and estimated accuracy. Each of these measurements is timestamped with the highly accurate atomic clock of the satellites. However, **GPS** requires a non-negligible amount of energy to operate and can provide very low accuracies when tracking positions underground, indoors or near high buildings with limited line-of-sight to satellites.

In order to make location sensing more reliable and less expensive for smartphones' battery life, Android **OS** provides a location service that can be accessed through Fused Location² **API** (**Application Programming Interface**). This service allows for simplified management of the trade-off between location accuracy, sampling rate, and energy consumption and was used by the crowdsensing application. This service can either provide location information when the **GPS** signal is not available or present large errors, e.g. inside buildings or underground, by combining location estimations from multiple sources. Therefore, complementary to the **GPS** receiver, which has a high energy consumption, works poorly indoors, but can have a 1Hz sampling rate and an accuracy of a few meters outdoor, network information is also used to support location estimation. In this case, if an Internet connection is available, the list of nearby towers of the cellular network and WiFi **APs** is sent to the online **API**³, which returns a location and accuracy estimation that works indoors, with a varying sampling rate from 1 to 5Hz.

The crowdsensing application was designed to ensure location with the highest available **GPS** sampling rate, and whenever a **GPS** signal was not available, or for battery saving purposes, Fused

²Fuse Location API: <https://developer.android.com/training/location>

³<https://developers.google.com/maps/documentation/geolocation>

Location [API](#) was used to provide a network-aided estimated location. When inspecting the location data samples provided by the crowdsensing application, the results show that $\approx 85\%$ of the collected locations were obtained directly from [GPS](#), and the remaining $\approx 15\%$ were estimated from nearby WiFi [APs](#) and [GSM](#) cell towers. More details on the data collection process can be found in [127, 128].

3.1.1.1 Trips Detection

A key feature of the crowdsensing application was its ability to detect movement, which allows the automatic gathering of mobility data from the daily trips of the participants in a non-intrusive way. This was possible due to an algorithm that uses three different sensor streams to detect movement, namely activity recognition, location updates, and geofencing. These sensor streams were running as background services respecting the Android [OS](#) power saving limitations and provide a wide range of configurations regarding the frequency of updates, required accuracy and allowed power burden. These configurations allow to define the trade-off between saving battery or quickly detecting a trip [3].

Combining the different sensor streams through the usage of a fuzzy function, the algorithm was able to detect the beginning and the end of a total of 14942 trips. Figure 3.2 shows the distribution of the number of trips per participant. As shown, the number of trips vary significantly from participant to participant. While 25% of the participants have less than 3 trips in the dataset, 10% have more than 93. This difference is mainly correlated with the amount of time participants used the crowdsensing application. Figure 3.3 shows that 50% of the participants used the application for less than a month, while 12.5% used it for more than three months.

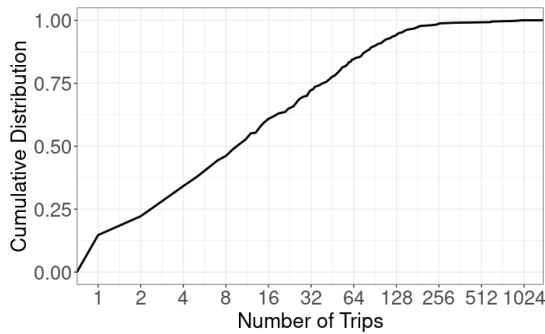


Figure 3.2: Number of trips per participant.

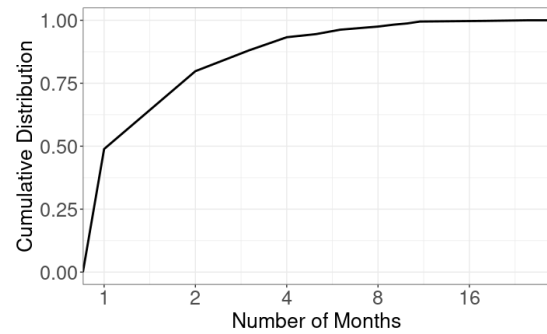


Figure 3.3: Total duration of application usage by participants in the crowdsensing study.

3.1.1.2 Transportation Mode Labeling

At the end of each trip, transportation mode questionnaires were delivered to the participants to indicate the transportation mode used on the trip, namely, foot, car, bus, metro and bike. Most trips were not annotated by participants or were annotated with multiple transportation modes. So, in order to determine the transportation mode used by the participants, the authors of [129] developed a machine learning classifier to annotate trip segments that uses as ground truth the annotated trips with a single transportation mode. The developed algorithm was shown to achieve an accuracy and precision of 85% when using the **RF (Random Forest)** algorithm to classify the transportation mode used in each trip, and therefore it was used to classify trips that were not manually classified by participants. Table 3.1 presents the transportation mode labeling of the trips in the dataset accounting for a total of 8635 car trips, 5460 foot trips, 528 bus trips, 180 metro trips, and 139 bike trips. Figure 3.4 shows a heatmap with the number of trips per 20x20m cell in the city for each mode of transport.

3.1.2 WiFi Beacon Frames

In addition to mobility-related data, the crowdsensing application also collected beacon frames from participants nearby WiFi **APs**. Figure 3.5 shows the typical **MAC (Medium Access Control)** frame structure where the first two octets correspond to the Frame Control field. Different types of 802.11 frames are defined by the combination of the Type and Sub-Type bits from the Frame Control field, see Appendix A. There are three main frame types, namely, management, control, and data. The management frames allow the stations to establish and maintain communication, while the control frames are used to assist the delivery of data frames between the stations. Finally, data frames are used to carry high-level protocol data.

Beacon frames are a sub-type of management frames and are used by **APs** to advertise their networks and capabilities to devices in range (assuming that the network is in infrastructure mode). These frames contain information such as the **ESSID (Extended Service Set Identifier)**, the **APs'** supported rates, operating frequency, authentication mode, among others. There are two possibilities for a device, such as a smartphone, to receive network advertisements: (i) passive scanning, where the device listens to beacon frames on each channel by continuing to change channels at a set interval, or (ii) active scanning, where the device actively searches for an **AP** by sending a management frame of sub-type probe request (see Appendix A) on each channel that the device is configured to use, and waits for probe responses from **APs**.

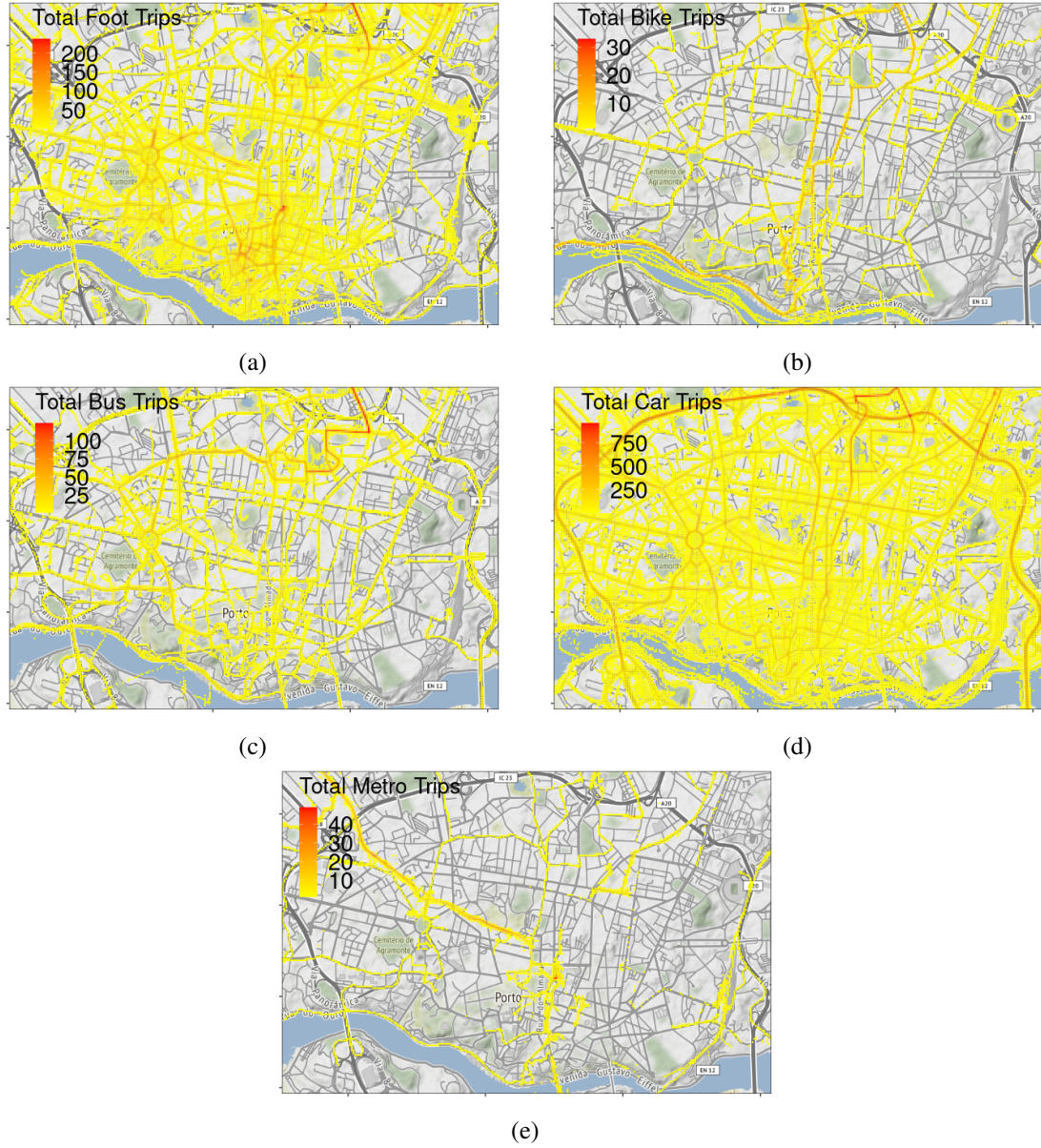


Figure 3.4: Heatmap displaying the number of trips per 20x20m cell in Porto.

The crowdsensing application used for data collection was configured to save the information from both passive (regularly performed by Android OS itself) and active (initiated by the participant) WiFi scans. Therefore, the APs information extracted and saved from the beacon frames received consisted of: MAC address, RSSI (Received Signal Strength Indicator), ESSID, operating channel, type (AP, Repeater, Ad-Hoc, etc.) and protection mode (Open, WEP (Wired Equivalent Privacy), WPA (Wi-Fi Protected Access), etc.). This information was then analyzed and treated to build a WiFi coverage map of the city of Porto described in the next section (Section 3.2).

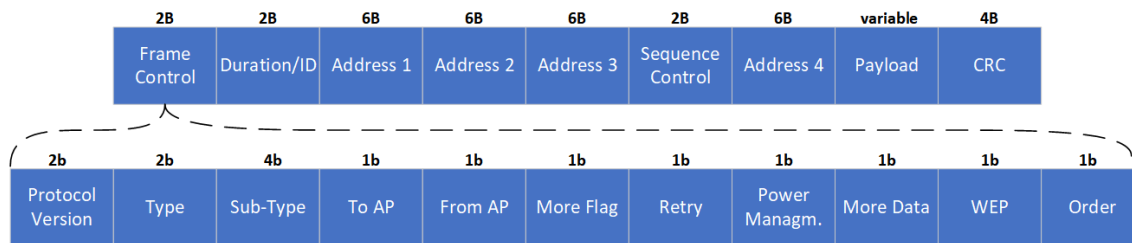


Figure 3.5: Typical 802.11 frame.

3.2 WiFi Coverage Map

In order to build a dataset with detailed information on the city's WiFi coverage, the WiFi information collected through beacon frames was analyzed and treated. For this process, only open APs (APs that do not require authentication) were considered. These APs are usually deployed by MNOs to allow their customers to access the Internet using a WiFi connection while outside, making them ideal for offloading while outside. Moreover, only beacon frames received with a RSSI greater than -82 dB were considered, as this ensures a minimum signal power to establish a WiFi connection between a mobile device and an AP.

3.2.1 Addressing WiFi Data Imprecision

Due to the challenges of having harsh data collection scenarios comprising the usage of a wide variety of hardware and software versions, a detailed inspection of the data quality is required to ensure the fidelity of the WiFi coverage information. In this section, the WiFi data imprecision is addressed by inspecting issues related to georeferencing of WiFi scans, mismatching coverage information, and the reliability of WiFi signal indicators.

3.2.1.1 Georeferencing Passive WiFi Scans

The WiFi dataset contains independent timestamps added at the application layer for every [GPS](#) position and WiFi scan. However, while the first is sampled at 1Hz, the latter has variable duration, which can take several seconds. In Android [OS](#), a scan consists of three phases: i) scan initialization, ii) channel scan, and iii) returning scan results to the application layer. Each phase can have a different duration depending on the hardware and version of Android [OS](#) in use [87]. As a consequence, a WiFi scan to location matching using timestamps introduces an additional location error, which may lead to erroneous conclusions concerning the WiFi coverage for a specific location.

To characterize the scanning duration of a smartphone, the duration of a WiFi scan, S_D , is defined as the difference between the timestamps of consecutive scans, since the crowdsensing applications were scanning in loop. Figure 3.6 shows that 92% of all scans had a duration lower than 5 seconds, and a long tail of the distribution starts beyond that. Therefore, 5 seconds is considered a reasonable maximum scan duration for a smartphone in our dataset. When the time between scans is longer than 5 seconds, it is considered a consequence of the lack of WiFi coverage in the neighborhood of the participant.

Figure 3.7 shows the distribution of the error associated with all the scans, computed as the mean [GPS](#) accuracy for the duration of each scan, S_{acc} . As shown, 85% of all scans present a [GPS](#) error lower than 20m. Figure 3.8 shows the distribution of the WiFi scan to the location matching error associated with all scans, computed as the distance traveled during each scan duration. As shown, for 30% of the scans with [GPS](#) error lower than 20m, the smartphone collecting data moved more than 20m during the scan. In these cases, the matching error can be larger than the [GPS](#) error. This has two consequences for the analysis: (i) the WiFi scan to location matching is improved by using the centroid of all available positions for the duration of a scan; and (ii) the georeferencing error, i.e., the maximum of [GPS](#) and matching errors, is used when filtering the samples.

3.2.1.2 Location Mismatches and Representativeness

The exact location of [APs](#) is naturally unknown as smartphones were just collecting beacon frames. However, it was noticed that some [APs](#) appeared in scans collected in locations far from each other, for example, more than 500m. These outliers were mainly caused by large [GPS](#) errors or unexpected software malfunctions. To solve this problem, unsupervised learning was used to infer the location of [APs](#). The k-medoids clustering algorithm was used as it is more resilient to outliers than the k-means. Then, beacon frames received from distances higher than 44m from the [APs](#)'

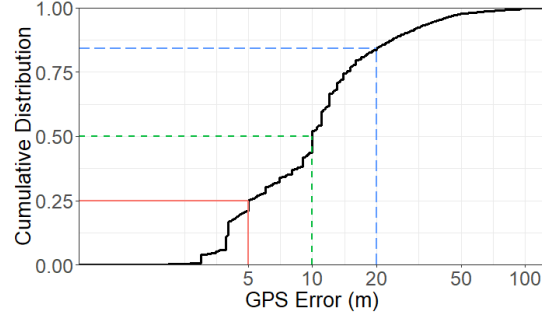
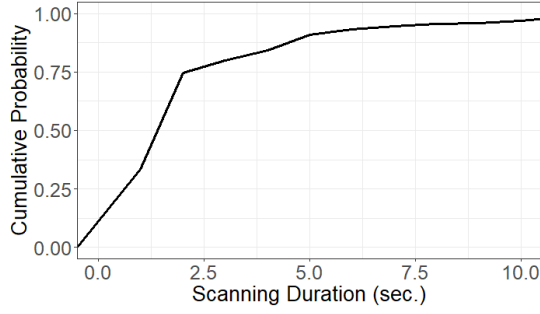


Figure 3.6: Scans' duration from all smartphones. Figure 3.7: GPS error (S_{acc}) from all scans.

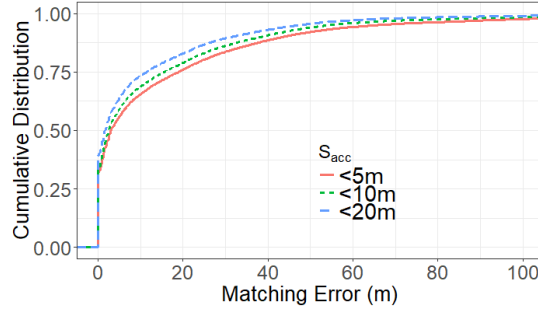


Figure 3.8: WiFi scan to position matching error for different S_{acc} .

estimated locations were discarded. Figure 3.9 shows an example of this filtering process for one AP.

It was also observed that a large number of APs were present in a small set of WiFi scans. In order to ensure enough data per AP, only APs that appeared in at least five different WiFi scans were considered. This simple filter reduced the total number of APs in the dataset by almost 45% (from $\approx 24k$ to $\approx 14k$), however, it had a negligible impact on the overall coverage of WiFi in the city. In other words, this heuristic reduced the density of APs per location but not the total number of locations with at least one AP.

3.2.1.3 Reliability of WiFi Signal Indicators

Due to the fact that the RSSI data is being collected as a spatial-temporal random process, assessing the quality of each measurement needs to be carried out by looking at how much it varies along time and between measurement probes (smartphones). For this, the space was discretized by applying

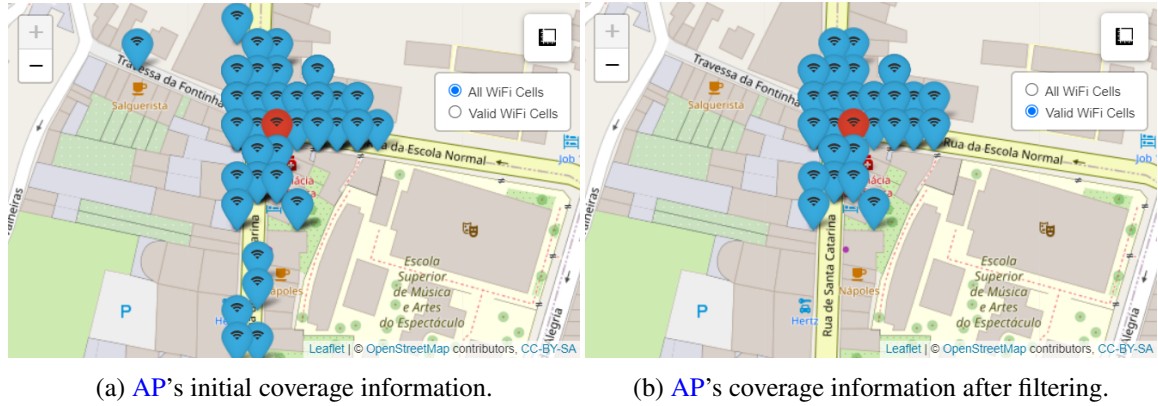


Figure 3.9: Example of WiFi scans with mismatch location.

a square tessellation with a grid with 11mx11m grid squares (cells), all WiFi scans inside a cell mapped to its center. Only samples with a low georeferencing error ($<10\text{m}$) were considered.

To assess the **RSSI** variability across time, the variation of the **RSSI** values is evaluated for each **AP**-cell pair, for the same smartphone, in different days. For each smartphone with data from more than 5 days in relation to an **AP** cell pair, the 90% **C.I. (Confidence Interval)** of the average **RSSI** for those days is computed.

To evaluate the **RSSI** variability across smartphones, the 90% **C.I.** of the mean **RSSI** from all smartphones in an **AP**-cell pair is computed. In this case, only **AP**-cell pairs with information from more than 5 smartphones were considered.

As baseline, the 90% **C.I.** of the mean **RSSI** collected by a smartphone on multiple consecutive scans (at least 10) for an **AP**-cell pair is used. The width of the baseline **C.I.** is a reference of the expected **RSSI** variations when the smartphone is in a cell, and consequently, listening to beacons from an **AP**.

Figure 3.10 shows that the median width of **C.I.** when data is collected from different smartphones is 6 dBm (**C.I.** width is twice the value in the curves), just 4 dBm more than for the baseline. Work on vehicular WiFi access suggests 2dBm as the margin of error in estimating the mean signal strength to be used in handoff decisions [45]. In our dataset, only the baseline can ensure this stability, denoting that mapping **RSSI** using smartphones as probes to access handoff decision is still an open issue. More interestingly, it is observed that the **RSSI** variability is more affected by the position of the smartphone itself than by the fact that the smartphones differ. In the first case, the increase on the **RSSI** variability may come from the smartphone being in a pocket, bag, in the hand, etc. In the second case, it is due to different hardware. This is observed in the larger distance

between the C.I. curves when comparing the baseline with the across time curve (1.32 dBm between medians) than between the across time curve with across smartphones curve in Figure 3.10 (0.84 dBm between medians).

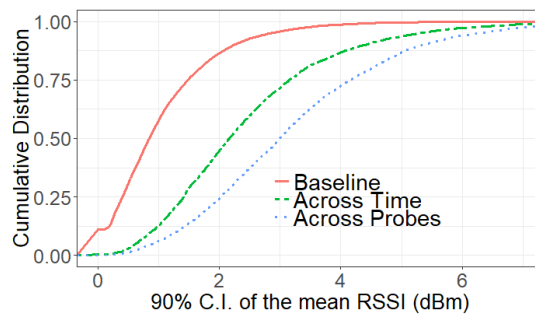


Figure 3.10: RSSI variability expressed as the confidence interval width of the mean RSSI for each AP-cell pair.

3.2.2 WiFi Coverage Overview

After tackling the data issues mentioned in the previous sections, the city of Porto was divided into 20x20m cells applying a square tessellation and the WiFi coverage information mapped to the center of each cell. The result was the dataset presented in Figure 3.11 – warmer colors indicate a higher number of APs at that location. The dataset contains WiFi information from more than 14k open APs for a total of 41974 different cells that correspond to 71% of the total area of the city. In this section, an overview of the information in this dataset is provided focusing on the availability of APs, the use of the spectrum and the ownership of the infrastructure.

3.2.2.1 Access Points Availability

The density of APs per location was computed as the total number of different APs detected in the same cell. Figure 3.12 shows the distribution of the density of APs per location in two scenarios: i) when considering all locations in the dataset (depicted by the red distribution); and ii) when considering only the locations in the dataset with WiFi coverage (depicted by the blue distribution). The results show that most of the locations are not covered by open APs – only 37% has WiFi coverage provided by open APs as shown by the red distribution. These locations are mainly located on the main streets of the city (see Figure 3.11), which are associated with higher population densities and therefore are more likely to have APs deployments. When focusing on the locations

that have WiFi coverage (blue distribution), it can be seen that the density of APs is not uniformly distributed – while 35% of these locations have less than 2 APs, 25% have more than 8.

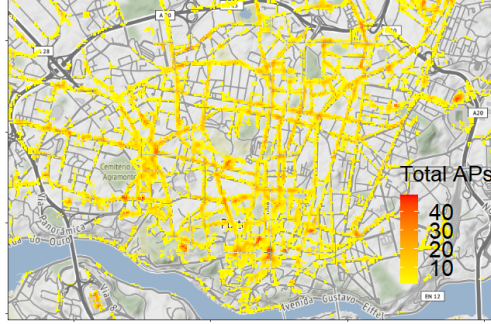


Figure 3.11: WiFi coverage map of Porto.

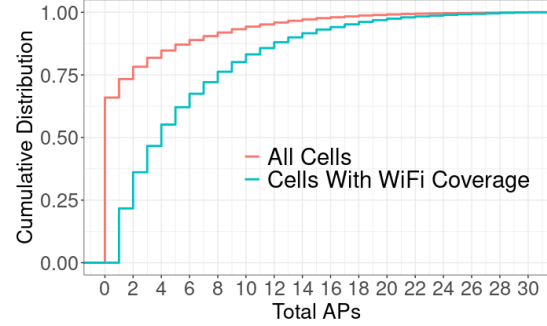


Figure 3.12: Density of APs per location (20x20m cell).

3.2.2.2 Spectrum Usage

Figure 3.13 shows the spectrum usage of the 14k open APs in the dataset. As shown, most of the APs operated in the 2.4GHz band, especially in channels 1, 6, and 11, which are the orthogonal channels set as default channels from the majority of the APs' manufacturers. Although 5GHz was already available from 2016 to 2018, it was not present in most APs. In fact, the coverage challenges associated with higher frequencies make the number of APs operating in the 5GHz band residual.

The high density of APs in the same location can affect the overall quality of the WiFi connection due to interference caused by APs operating in the same channel, also known as co-channel interference. To investigate this factor, the number of APs operating in the same channel at the same location (20x20m cell) was computed. Figure 3.14 shows that for 37.5% of these locations there can be more than 3 APs operating in the same channel indicating that co-channel interference can play an important role in the quality of the WiFi connection.

3.2.2.3 Infrastructure Ownership

The ownership of the infrastructure can be estimated based on the ESSID broadcast by APs. Figure 3.15 presents the total number of APs per ESSID collected and shows that $\approx 70\%$ of the open APs in the dataset are broadcasting the "NOS_WIFI_Fon" and "MEO-WiFi" networks. These networks belong to the NOS and MEO ISPs (Internet Service Providers), respectively, which at the

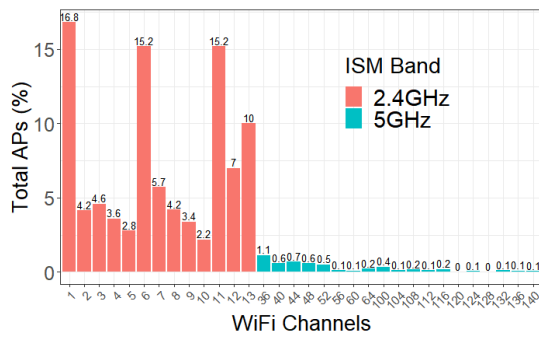


Figure 3.13: WiFi spectrum usage.

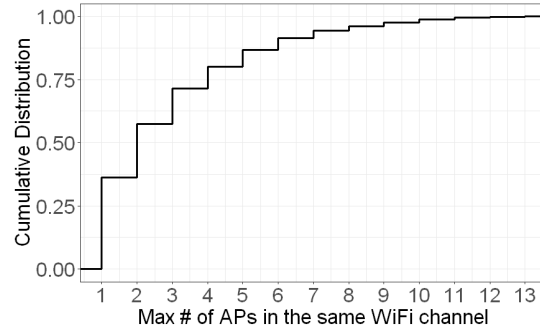


Figure 3.14: Number of APs in the same WiFi channel in the same location.

time of data collection were two of the main **ISPs** and **MNOs** in Portugal. The **APs** broadcasting the "FON_ZON_FREE_INTERNET" network belong to the "NOS" operator and is the result of a partnership between *NOS* and *FON*⁴. *FON*'s primary mission is to create a global network of shared WiFi hotspots, allowing users to share a portion of their home or business WiFi bandwidth in exchange for accessing WiFi hotspots provided by other *FON* members. This business model is now adopted by the major **ISPs** in Portugal, such as *NOS* and *MEO*, where a subscriber can access any of the open **APs** of its operator facilitating Internet connectivity through WiFi when users are not at home.

When inspecting the geographical distribution of the WiFi infrastructure in terms of its ownership, Figure 3.16 shows that both *NOS* and *MEO* operators are in the majority of locations with WiFi coverage (blue locations). The only exception is the downtown area where the *NOS* operator is less present.

3.3 Access Points Characterization

In dense WiFi deployments, several **APs** are usually available to be used to offload data or computation, however, not all of them would be suitable for these tasks. Therefore, it is crucial to have a better understanding of what attributes can characterize **APs** as possible offloading surrogates. In this section, the different attributes that can characterize the quality and availability of an **AP** for offloading based on passive WiFi data are defined. Then, unsupervised learning is used to identify

⁴<https://fon.com/>

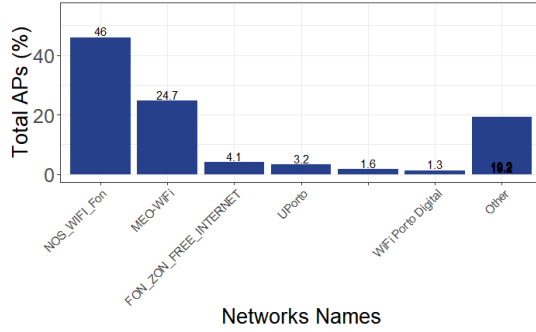


Figure 3.15: Number of APs per network.

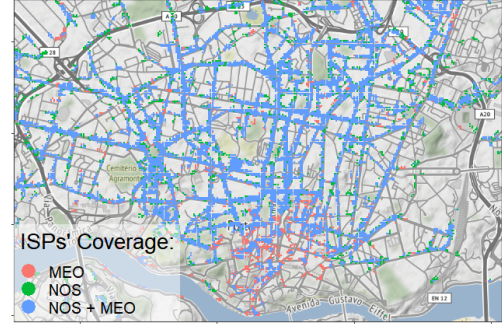


Figure 3.16: Spatial coverage map of the main ISPs.

and analyze the relevant attributes of APs that can provide a better understanding of the offloading network infrastructure.

3.3.1 Surrogates Characterization Attributes

Two domains related to the characterization of an offloading surrogate are identified: one related to the observed quality of WiFi, and the other related to the existing opportunities of contacting an AP.

3.3.1.1 Contact Quality Attributes

Contact quality is defined as the expected data volume that can be exchanged between a user and an AP. In order to characterize the contact quality, both throughput and transmission duration need to be characterized, as these variables determine the transferable data volume. Since it is impossible to assess the load in the APs based on passive client-side measurements of WiFi coverage, signal quality attributes are used to characterize throughput, namely:

- Signal Power Received: represented by the RSSI collected in the probes;
- CCI (Co-Channel Interference): corresponds to the number of APs operating in the same channel. In WiFi, as CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance) is used to manage access to the transmission medium, a large number of APs operating in the same channel will decrease the probability of having opportunities for transmission, leading to lower throughput;

- **ACI (Adjacent-Channel Interference):** APs transmitting in adjacent channels increase the noise levels, increasing the number of frame errors, consequent retransmissions, and preclude achieving high data rates. The ACI affecting an AP is computed as a function of a modified version of the Signal-to-Interference ratio, $\widehat{SIR}$, with the following variables:
 - P_c , Power received from the AP under evaluation
 - f_c , Central frequency of the AP under evaluation
 - N , Neighboring AP operating in an adjacent channel
 - n , Set of interfering APs
 - P_N , Power received from the interfering AP
 - f_N , Central frequency of the interfering AP
 - W_{cN} , Interference-level factor between the AP under evaluation and the interfering AP

Therefore, $\widehat{SIR}$ is computed as follows:

$$\widehat{SIR} = \begin{cases} \frac{P_c}{I} & , I \neq 0 \\ 20 & , I = 0 \end{cases} , \quad I = \sum_{i=1}^n (P_{Ni} \cdot W_{cNi}) \quad (3.1)$$

where I is calculated considering the power from the interfering AP and an interference-level factor W_{cNi} that takes into account the number of non-overlapping frequencies as a function of the channel width [51]:

$$W_{cN} = \max(0, 1 - \frac{|f_c - f_N|}{20}) \quad (3.2)$$

It is assumed a WiFi channel of 20 MHz, typically used in IEEE 802.11g/n. In opposition to the 40 MHz channel also used in IEEE 802.11n, the 20 MHz version improves the number of orthogonal channels, having a higher probability of being used in dense WiFi network deployments. A $\widehat{SIR}$ equal to 20 is assigned when an AP does not suffer ACI. This value is slightly above the maximum $\widehat{SIR}$ found in our dataset. It is important to note that $\widehat{SIR}$ does not represent the exact value of ACI, but instead serves as a reference value to compare APs with respect to the level of interference they are suffering.

The contact window is defined as an abstraction of the duration of transmission, assuming that a user will always be able to transmit data whenever he/she is within the coverage of an AP.

Therefore, the contact window can be characterized by two dimensions: one related to the time spent inside the coverage area of an AP, and the other related to the AP coverage area itself. While the first reflects the user's behavior (e.g. mobility), the second reflects the signal propagation characteristics of the deployment site of an AP. Three main attributes are used to characterize the contact window of an AP:

- **Contact Duration:** represented as the duration in seconds of a contact. A contact is the period where a probe (smartphone) can listen to consecutive advertisement beacon frames from an AP;
- **Distance traveled during contact:** represented as the euclidean distance between the initial and the final location of a probe during contact;
- **Number of Cells crossed during contact:** represented as the number of different cells (11x11m grid squares) crossed by a probe during contact. This attribute tries to capture the non-straight movements of the probe during contact that cannot be obtained through the previous attribute;

3.3.1.2 Contact Opportunities Attributes

In a dense WiFi deployment scenario, the availability of the network infrastructure is characterized as the opportunities to contact an AP. Therefore, three attributes are identified with respect to the contact opportunities, namely:

- **Contact Rate:** represented as the average number of contacts per day between a probe and an AP;
- **Importance:** represented as the percentage of days with contacts between a probe and an AP, considering all the days with data from a probe;
- **Popularity:** represented as the percentage of different probes that had contact with an AP, considering the total number of probes present in the dataset;

3.3.2 Characterization Methodology

The methodology adopted was first to identify APs that were similar in their offloading capabilities based on clustering, and then analyze the offloading attributes for each group.

Before characterizing the **APs**' attributes, data cleaning was carried out. Most **APs** did not possess more than two samples for the same probe with a small georeferencing error. This did not allow the computation of the **APs**' coverage attributes, and therefore, those **APs** were filtered out. In addition, only **APs** with information from at least two different probes were considered, causing a reduction in the number of **APs** to be considered in the analysis to 11k.

The attributes resulting from each probe for each **AP** in different contacts were aggregated, and the median value of each attribute characterized was used. Therefore, each **AP**'s attribute is expressed as a distribution of the median values of all probes that had contact with the **AP**. The exception is the popularity attribute, which is represented by a unique value for each **AP**.

Statistical tendency measures such as minimum, maximum, mean, median, mode, standard deviation, first, and third quartiles were used to describe the attributes distribution of each **AP**. In the end, each **AP** is represented by a total of 65 features.

Some features presented outliers. However, most of these outliers corresponded to valid observations, e.g. very good **RSSI** for only a few **APs**. So, the option was not to remove them, being instead reassigned to a minimum or maximum non-outliers value depending on which side of the median they were located.

In order to find **APs** that were similar in terms of their offloading attributes, the *k-means* clustering algorithm was used. The number of clusters (k) was determined using the elbow method along with the total **WSS (Within Sum of Squares)** that measures the compactness of the clusters [71]. Thus, k was chosen as the number of clusters where the **WSS** curve stabilizes, and therefore, increasing k would not cause a significant reduction on the total **WSS**. Other clustering algorithms, namely, k-medoids, were also tested, presenting similar results to k-means.

3.3.3 Characterization Results

The **APs**' characterization results are analyzed in two phases. First, the clusters for the different attributes are presented in Section 3.3.3.1 and Section 3.3.3.2. Then, the implications of these results in an offloading scenario are discussed in Section 3.3.3.3.

3.3.3.1 Contact Quality Characterization

To characterize **APs** with respect to their contact quality, all attributes related to signal quality and contact window were used.

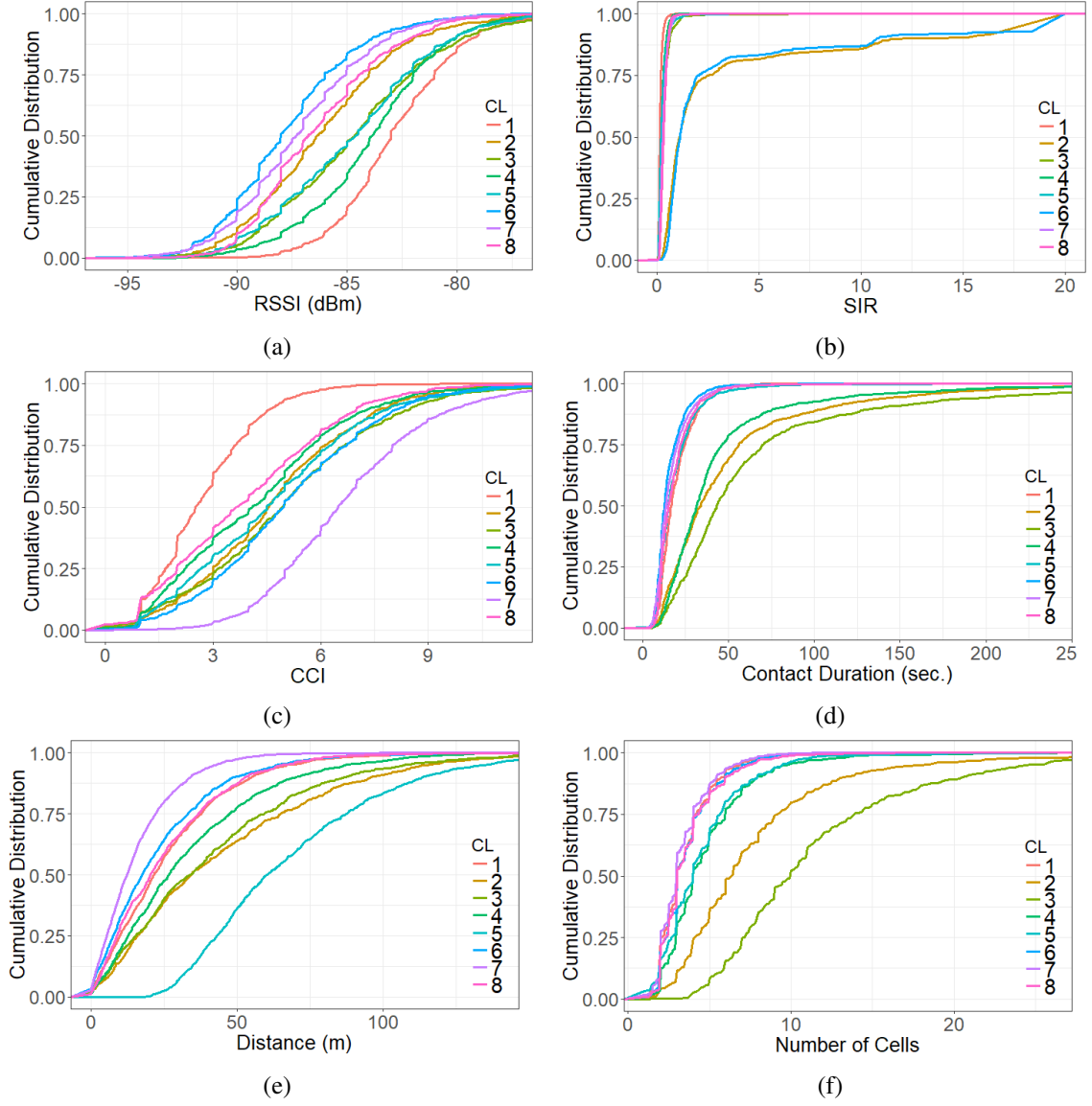


Figure 3.17: Contact Quality attributes per cluster.

Signal Quality: Figure 3.17a shows that the RSSI is not the best attribute for characterizing APs from different clusters. In fact, the difference of the median RSSI between the best APs (CL 1) and the worst (CL 6) is only 5 dBm.

Figure 3.17b shows the ACI affecting the APs in each cluster and shows that APs can be aggregated into two groups. The group consisting of APs from clusters 2 and 6 is the one with lower ACI. In fact, only 4.9% of all APs presented in the dataset do not suffer any ACI, being mainly divided between the two clusters in this group. The other group encompasses all the remaining clusters.

Figure 3.17c shows the CCI and allows to identify three groups of APs with different CCI values. The APs belonging to cluster 1 exhibit the lowest values of CCI; 75% of them suffer interference from less than 3.6 APs. The APs of cluster 7 show the highest values of CCI; 75% of them suffer interference from more than 5 APs. At the same time, these APs also belong to the group of clusters that are suffering more ACI. As a consequence, it is reasonable to assume that APs from cluster 7 will provide the worst signal quality, as they suffer more interference, both CCI and ACI.

Contact Window: Figure 3.17d shows the contact duration for the APs in each cluster, and it shows that APs can be divided into two groups. The group consisting of clusters 3, 2 and 4 presents the highest values for the contact duration, where 50% of the APs from the worst cluster in this group (CL 4) have contact durations higher than 31 seconds. The other group, including the remaining clusters, presents a contact duration below 25 seconds for 75% of the APs in the cluster 1 (the best cluster from this group).

The other dimension of the contact window is the coverage area provided by the APs. Figures 3.17e and 3.17f show the distance traveled and the number of cells crossed during contact. When analyzing the distribution of these attributes per cluster, it is observed that, with the exception of cluster 5, the cluster distributions exhibit a similar behavior the duration of contact in terms of clusters ranking; clusters 3, 2 and 4 present the highest values both in the number of cells cross and the distance traveled during contact. The APs from cluster 5 are differentiated by the long distances traveled by the probes during contact; 75% of APs have a distance greater than 43 m. However, cluster 5 has small contact durations (median of 15 seconds). This small contact duration can be explained by the probes' speed during contact where, after inspection, it was observed that 50% of the APs in cluster 5 presented a median probes' speed during contact higher than 4.6 m/s. This speed was considerably higher than the 1.5 m/s observed for APs in the cluster with the highest contact duration (CL 3).

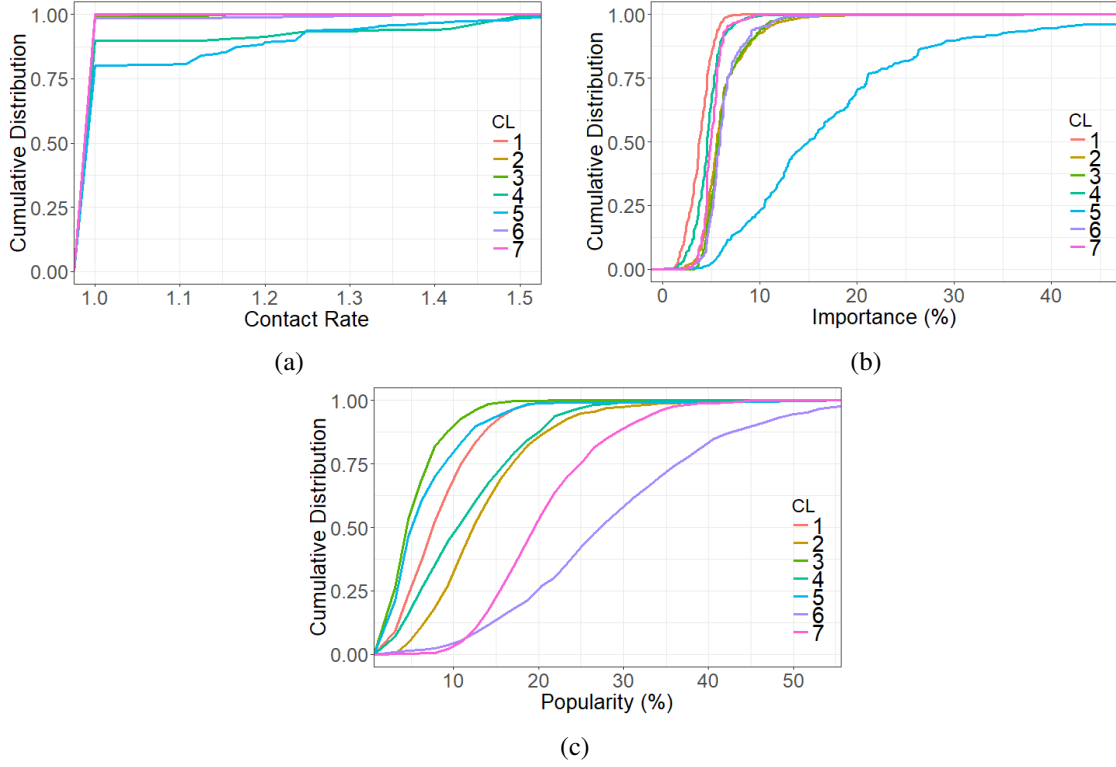


Figure 3.18: Contact Opportunities attributes per cluster.

3.3.3.2 Contact Opportunities Characterization

For the characterization of contact opportunities, the same clustering process was applied. However, only attributes related to contact opportunities were considered. These attributes are totally dependent on the probes' mobility, and, therefore, to ensure that this mobility is truly represented by our dataset, only the probes having at least 15 days of data collected are considered. This implied a reduction in the total number of probes from 208 to 61.

As shown in Figure 3.18a, the contact rate does not offer a distinction between clusters, where 80% of APs have a contact rate equal to one contact per day.

The importance of APs per cluster is illustrated in Figure 3.18b, and shows that APs can be divided into three groups. The group comprising clusters 1, 4, and 7 presents the lowest importance values. Clusters 2, 3 and 6 present similar distributions with 75% of APs having an importance between 1.6% and 6.7%. The APs with the highest importance belong to cluster 5, where 75% have an importance greater than 10.5%.

The distribution of the popularity attribute is presented in Figure 3.18c. As shown, popularity offers a very good separation among clusters, with APs from cluster 6 being the most popular. However, note that APs having high values of importance (CL 5) may not be so popular.

3.3.3.3 Discussion

Regarding signal quality, the results show that RSSI is not a good attribute to characterize APs. Consequently, special attention should be given to interference factors, such as ACI and CCI. Due to the limited number of WiFi channels and the large number of APs deployed in dense WiFi networks, interference levels tend to increase.

Concerning the attributes of the contact window, the results show that it is possible to identify APs that can provide a longer duration of contact based uniquely on the number of cells crossed during contact. Although the contact duration attribute is probe dependent, as it reflects the time spent by a probe inside an AP's coverage, the number of cells crossed during contact reflects the AP coverage area. Therefore, it can be argued that probe heterogeneity is not a key factor in characterizing the contact window. This knowledge allows to decrease both the time and effort during the data gathering process for the characterization.

Concerning contact opportunities, several strategies that rely on multiple contacts between a user and an AP (e.g., IP caching to reduce connection setup time [133]) have been proposed to improve data offloading. However, our results with respect to the contact rate attribute show that most probes usually have one contact per day with the same AP (Figure 3.18a), suggesting that these sort of strategies would only be effective when applied to a subset of APs.

Figure 3.19 shows the location of the most important (CL 5) and popular (CL 6) APs. Popularity reflects the possibility for an AP to have contact with different users, and therefore the location of popular APs is correlated with regions with high affluence of people, e.g., near main roads, commercial or cultural reference points in the city. Popularity can be used by offloading strategies to guide decision making when the objective is to identify APs that can be contacted by many users. However, further analysis is required regarding this attribute as it may also help characterize the APs' load. In fact, popular APs may have a higher probability of supporting more users at the same time.

Unlike popular APs, it is interesting to note that important APs are mainly aggregated in specific regions throughout the city. As importance describes the possibility for an AP to have contact with the same user, these regions represent places regularly visited by participants involved in the

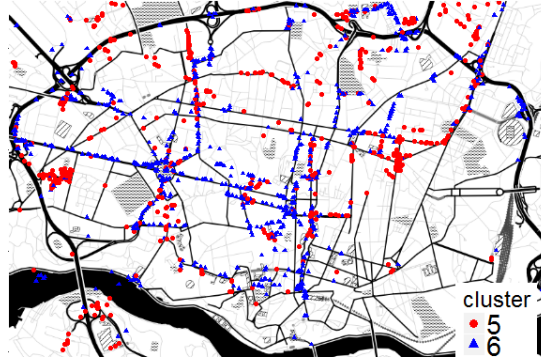


Figure 3.19: Location of the most important (CL 5) and popular (CL 6) APs.

crowdsensing campaigns. Similarly to the popularity attribute, the importance can be used by offloading strategies to characterize APs that can be reached by the same users regularly.

3.4 Concluding Remarks

In this chapter, the datasets on user mobility and WiFi coverage information used in this work were presented and analyzed. The crowdsensing data collection process as well as the data sources used to build the datasets were described in Section 3.1. This process allowed to collect GPS traces providing three unique features to the mobility dataset: (i) high temporal resolution of positioning data of 1Hz; (ii) mobility traces that correspond to trips where the beginning and the ending of a trip are annotated; and (iii) identification of the transportation mode used for the trip.

In Section 3.2, the imprecision in crowdsensing WiFi data was addressed, both in terms of geo-referencing and reliability of WiFi signal indicators. The variability of RSSI was found to be more affected by the position of the smartphone itself than by the fact that the smartphones differ. In the first case, the increase in variability RSSI may be due to the smartphone being in a pocket, bag, in the hand, etc., while in the second case it is due to different hardware. The resulting WiFi coverage dataset that contains information from $\approx 14k$ open APs, together with the mobility traces dataset presented in Section 3.1.1 will be made available to the scientific community.

Finally, in Section 3.3, the WiFi coverage dataset was further analyzed by inspecting what attributes can characterize APs as possible offloading surrogates. Different attributes capable of characterizing the quality and availability of an AP for offloading were defined. Then, unsupervised learning was used to identify and analyze the relevant APs' attributes that can lead to a better

understanding of the offloading network infrastructure. The results show that **RSSI** is not a good attribute to characterize **APs**. Consequently, special attention should be given to interference factors, such as **ACI** and **CCI**. Concerning contact window attributes, the results show that probe heterogeneity is not a key factor in characterizing the contact window, since **APs** that can provide longer contact duration can be identified based uniquely on their spatial coverage, which can be determined based on the number of cells crossed during contact. This knowledge allows to decrease both the time and effort during the data gathering process for the characterization as this metric is not probe-dependent.

Concerning contact opportunities, the results on the contact rate attribute show that strategies relying on multiple contacts between a user and an **AP** would only be effective when applied to a subset of **APs**, as most users usually have one contact per day with the same **AP**. In addition, the popularity attribute can be used by offloading strategies to guide decision making when the objective is to identify **APs** that can be reached by many users, while the importance attribute can be used to identify **APs** that can be reached by the same users regularly.

Chapter 4

Human Mobility Support for Personalized Data Offloading

Deferring data transmissions while the user is traveling and offloading only to the destination of the trip was shown to be a feasible solution [83]. However, most applications cannot sustain long delays without impacting the user's QoE. Therefore, it is crucial to develop mobile offloading systems that can leverage users' mobility to proactively make decisions on WiFi places and connectivity windows to offload data or tasks while the users are in transit.

In this chapter, the second research question presented in the introduction of this thesis is addressed, namely: How can individual offloading mobility profiles be established and leveraged to improve mobile data offloading?

To properly answer this question, human mobility from the offloading perspective is extensively studied and the methodology pipeline represented in Figure 4.1 proposed. The methodology encompasses a method to establish individual offloading mobility profiles that can be part of the offloading strategies — *system components*; and the steps that provide quantitative answers on the feasibility of such a system — *system evaluation*. This methodology is used to answer the main research questions addressed in this chapter, namely: How can individual commuter offloading mobility profiles be established?; Does human mobility in urban areas allow for offloading to limited coverage technologies?; What are the limits of the predictability of per user offloading connectivity and which factors impact on that predictability? and, Which trade-offs should be considered in the offloading system design?

The remainder of the chapter is organized as follows. The related work on human mobility is discussed in Section 4.1 and the datasets used to study human mobility from the offloading

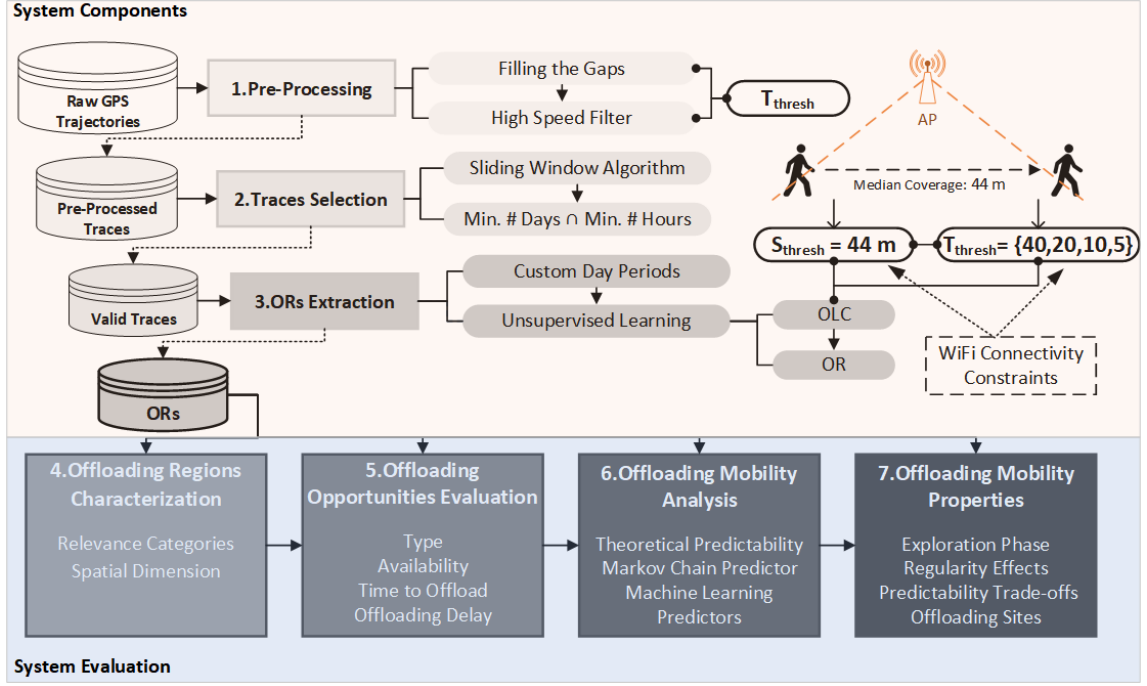


Figure 4.1: Methodology for offloading mobility analysis.

perspective are described in Section 4.2. The methodology for extracting ORs from the trajectory traces is introduced in Section 4.3, and the characteristics of ORs are detailed in Section 4.4. The analysis of the offloading opportunities offered to users in transit is detailed in Section 4.5 and the predictability of mobility in an offloading scenario is studied in Section 4.6. The mobility proprieties for offloading and their impact on the design of offloading systems are discussed in Section 4.7. Finally, the main results and conclusions obtained in this chapter are summarized in Section 4.8.

4.1 Human Mobility for Offloading

The study of human mobility has been focused mostly on two main domains: the identification and characterization of locations as users' personal PoIs and the study of mobility patterns between these locations using a multitude of data sources. In [67, 117], users' PoIs are extracted from CDR (Call Detail Record) data that provide the user identifier and cell tower location every time a network event is initiated (e.g., a voice call, SMS (Short Message Service), etc.). However, due

Table 4.1: Main characteristics of the datasets.

	Porto	Beijing
Period	2016-2018	2007-2012
Users	408	133
Area km^2	24	723
Locations Samples	9.7M	10M
Temporal resolution	1s-2s	1s-5s

to the nature of this data source, this makes the mobility data collected often sparse in space and time, and therefore not suitable for studying an offloading scenario. On the other hand, the low cost of [GPS](#) devices increases the possibility of collecting mobility data with high space and time granularity.

Several other works have been proposed to infer [PoIs](#) from [GPS](#) mobility traces [174, 172, 173, 22]. Usually, [PoIs](#) are associated with a stay time that confers their degree of importance, usually in the order of several minutes. This time is suitable for detecting important locations but not for inferring offloading occasions, where short contacts with WiFi [APs](#) can be leveraged for mobile data offloading.

Human mobility between [PoIs](#) was shown to be very predictable. In [140], a theoretical framework is proposed that shows that the upper limit for predictive performance in predicting the next [PoI](#) visited by a user is surprisingly high (93%), staying constant throughout heterogeneous sets of users (e.g., for different gender, age, geographical attachment). When spatial reachability constraints are considered, a tighter upper bound of 81-85% can be obtained [138]. A large diversity of mobility predictors using Recurrent Neural Networks [95], Bayes models [38], [RF](#) [160], and [MCs](#) [98, 76] has been proposed, approaching theoretical predictability. However, most of these studies focus on mobility between personal [PoIs](#) and not on scenarios of offloading opportunities while users travel between these locations. To the best of our knowledge, the work in this chapter is the first to study and characterize human mobility for the purpose of data offloading when users are in transit.

4.2 Mobility Datasets

Several data sources have been used to study human mobility, but high-sampled [GPS](#) trajectories remain the most reliable way to track outdoor movements.

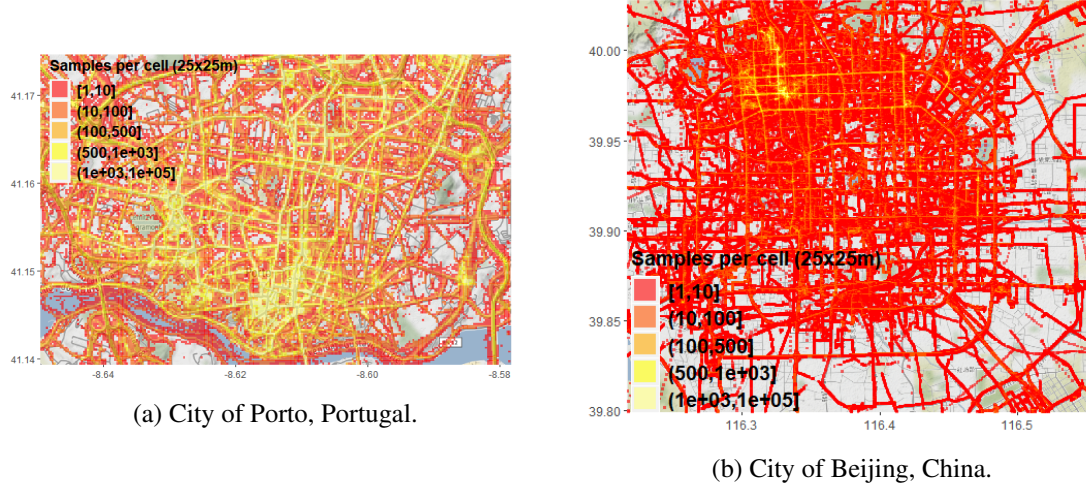


Figure 4.2: Heatmap of collected location samples per 25x25m cells.

The mobility dataset presented in the previous chapter is used to study mobility from a mobile data offloading perspective. However, in order to ensure that the results presented in this work are not biased by the use of a single dataset, a second dataset is used, namely Geolife [171]. This dataset provides time-stamped GPS locations of 182 individuals collected from 2007 to 2012; its choice was due to two main factors: (i) it is widely used in human mobility studies, as it is one of the first publicly released datasets containing mobility; and (ii) the trajectories are logged in a dense representation – 91.5% of the trajectories are logged every 1-5 seconds or every 5-10 meters per point. As most of the Geolife data was collected in Beijing, only the mobility traces collected in the metropolitan area of this city (area in Figure 4.2b) are considered in this work, comprising data from a total of 133 users, see Table 4.1.

Both Porto and Beijing datasets include a similar amount of location samples ($\approx 10M$), however, as shown in Figure 4.2, due to the different cities' area, the Porto dataset presents a higher density of location samples per cell (25x25m).

Although there are far more users in the Porto dataset when inspecting the number of weekdays with data per user, Figure 4.3 shows that Beijing users have almost six times more days with data. Although the median number of weekdays for Porto users is 5 weekdays, in Beijing it is 28 weekdays. However, when focusing on weekends, both datasets present a median number of 2.5 days per user. The large difference between the number of weekdays and weekends in the Beijing dataset is mainly due to the fact that most of the users lived outside the Beijing metropolitan area (Figure 4.2b), therefore, they did not travel to the city center on weekends.

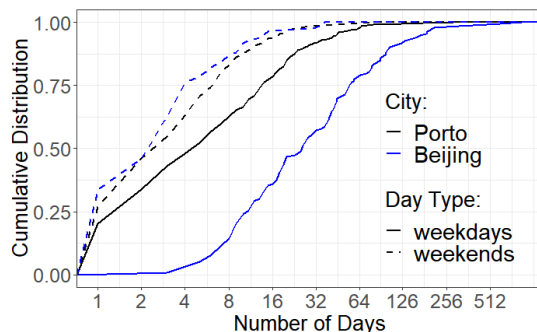


Figure 4.3: Number of days with data per user.

4.3 Extracting Offloading Regions

ORs are defined as geographical areas where a user exhibits a mobility suitable for offloading. In this section, the key concepts and the methodology to define and extract **ORs** from trajectory traces (corresponding to the stages 1-3 of the pipeline presented in Figure 4.1) are introduced, and the first question presented at the beginning of this chapter: How can individual commuter offloading mobility profiles be established? is addressed.

4.3.1 Mobility Constraints for Offloading

Due to the limited coverage of WiFi **APs**, the mobility of the users dictates the time window available for offloading. Locations where a user is stopped or moving at low speeds are preferred for offloading, as the time window is maximized. **ORs** are identified by applying space and time constraints to the mobility of the users. Space and time are interrelated as a user stays in a geographical area for a certain amount of time. Therefore, the space and time thresholds - S_{thresh} and T_{thresh} - are defined to identify **ORs**. The spatial threshold S_{thresh} is defined as the maximum distance between two points that can be considered to be in the same offloading opportunity. This threshold should reflect the coverage of the technologies used. The time threshold T_{thresh} is defined as the minimum time that a user must spend in a geographical area, defined by S_{thresh} , to be able to take advantage of offloading. Therefore, in order to define an **OR**, the concept of **OLC (Offloading Location Candidate)** is introduced. An **OLC** is a geographical area defined by S_{thresh} , where a user stays during T_{thresh} . Then, an **OR** is defined as the aggregation of contiguous **OLCs**, reflecting aggregated areas where the user has a suitable mobility for offloading, for example, the path of walking from home

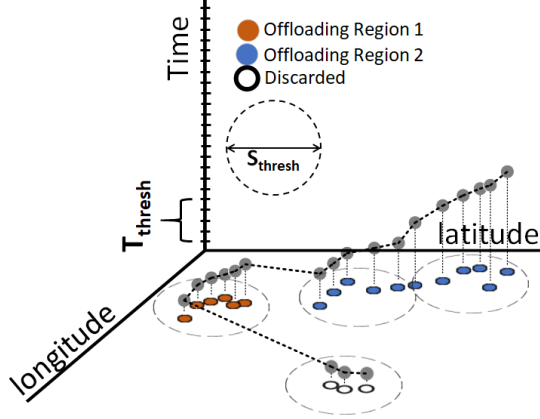


Figure 4.4: Illustration of ORs extraction from a mobility trace.

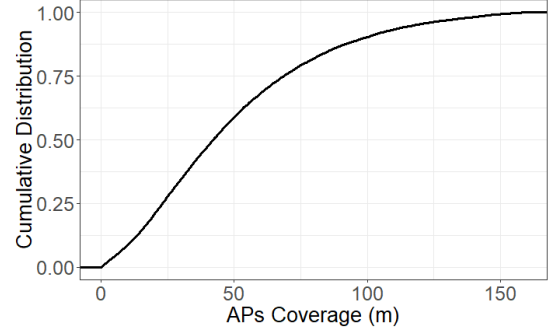


Figure 4.5: APs coverage from over 40k APs in the crowdsensed dataset.

to the bus station (see Figure 4.4). When aggregation cannot be performed, an OR corresponds to an OLC. Section 4.3.4 gives more details on the ORs' extraction methodology.

Considering an offloading scenario based on WiFi networks, the coverage of WiFi APs within an urban environment is used as a space threshold. The ground truth of more than 40k APs shows that the median coverage of an AP in an urban scenario is 44m (see Figure 4.5). Thus, this value is used for S_{thresh} . The time threshold should reflect that different applications may require different minimum time windows for offloading, and that some offloading orchestration time is necessary. In order to discover opportunities that could use short time windows to offload as well as less mobility friendly configurations, this study considers $T_{thresh} = \{40, 20, 10, 5\}$ seconds.

4.3.2 Trajectories Pre-Processing

As shown in Figure 4.1, the first stage for ORs' extraction is the pre-processing stage. The users' trajectories may present gaps corresponding to periods in which no GPS data was collected. This is mainly due to the lack of GPS signal in indoor environments or because mobile devices (or the sensing application) were turned off. In order to avoid underestimation of ORs and capture the locations where users stopped or were inside buildings, but there are no GPS data to prove it, the gaps G corresponding to these cases are first identified using a $G_{dist} = 100m$ (see Definition 1). Then, for the duration of G (in seconds), linear interpolation is used to fill these gaps and add pseudo-locations to it.

Definition 1 Let a user's trajectory for the user u be a set of locations $L_i^u = (\text{latitude}, \text{longitude})$ collected at the i^{th} timestamp represented as $\text{Traj}^u = L_i^u, L_{i+1}^u, \dots, L_{i+n}^u$. Then, we define G as the spatio-temporal break satisfying the logical condition $(\text{distance}(L_i^u, L_{i+1}^u) < G_{\text{dist}}) \wedge (\text{time}(L_i^u, L_{i+1}^u) > T)$, for $T = \frac{G_{\text{dist}}}{\text{max_speed}}$, where max_speed is given by Eq. 4.1.

Since ORs are defined by T_{thresh} and S_{thresh} , the user's speed is limited by the relation of these constraints, such as:

$$\text{max_speed} = \frac{S_{\text{thresh}}}{T_{\text{thresh}}} \quad (4.1)$$

Thus, a high-speed filter is used to remove samples that do not satisfy Eq. 4.1 from the data traces.

4.3.3 Mobility Traces Selection

In the second stage illustrated in Figure 4.1, a filter is also applied to the mobility traces to select users that provide enough historical data to study their mobility patterns. As there is a reduced number of weekends in both datasets (see Figure 4.3), only the mobility traces collected on weekdays are considered.

Due to the extensive data collection period in both datasets, some users exhibit mobility traces that were collected several months or even years apart. Traces with such a large time offset may lead to wrong assumptions regarding the user's mobility behaviors. Therefore, a time sliding window of 4 months is defined and applied to each user in order to select consecutive months where the user presents the highest number of days with data in the dataset. The users are then selected on the basis of two filters: (i) minimum number of days, and (ii) minimum number of hours with at least one GPS sample. Figure 4.6, representing the number of users after intersecting these two filters, shows that both datasets present a similar number of users with a large number of hours per day with GPS (top left corner of the heatmaps). However, as the minimum number of days threshold increases, the Beijing dataset provides more users with a high number of GPS hours per day (top right corner of the heatmaps). This reveals a higher degree of engagement of users in Geolife towards the data collection process compared to users in Porto.

To avoid favoring a single dataset, we only consider traces from users having at least 5 weekdays with 8h of GPS data, resulting in mobility traces from a total of 55 and 57 users in the Porto and Beijing datasets, respectively.

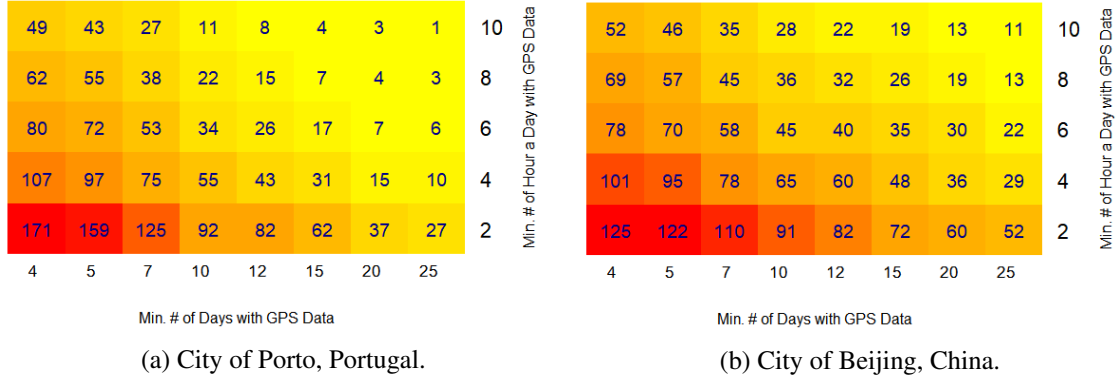


Figure 4.6: Number of users as the intersection of number of days and hours filters.

4.3.4 Offloading Regions Extraction

Finally, in order to extract **ORs** from the users' trajectory traces, the DBSCAN [41] clustering algorithm is used for the identification and aggregation of **OLCs**. The use of a density-based clustering algorithm to extract **ORs** allows to obtain clusters with arbitrary shapes, focusing only on locations/areas with a high concentration of points. There are two parameters that must be set in DBSCAN before the clustering process: $MinPts$ and ϵ . A data point is a core point if it has at least $MinPts$ in its neighborhood ϵ . This notion of core point is adopted to define an **OLC**. As in the mobility dataset the location samples are produced at a fixed rate of 1Hz, $MinPts$ is defined as T_{thresh} and ϵ as S_{thresh} , once more reflecting the WiFi connectivity into spatial constraints. Then, **ORs** are the clusters comprising **OLCs** that are density connected. Clusters that do not meet the **OLC** criterion are discarded, while adjacent **OLCs** are aggregated in the same cluster, forming **ORs**.

The analysis is focused on weekdays considering periods that usually represent daily routines in people's lives, as shown in Table 4.2. Therefore, for each user, the clustering process described above is applied to the trajectories in each period. In the downstream analysis, it is assumed that inside an **OR**, there is adequate contiguous and continuous connectivity for offloading data or computation.

4.4 Characterizing Offloading Regions

ORs represent locations where offloading tasks can be performed. In this section, these locations are characterized in detail as the first stage to characterize offloading mobility, and continue to answer the first question presented in this chapter.

Table 4.2: Typical human activity periods in a day.

Definition	Day Period	Usual Activities
DP1	01:00h to 06:59h	Sleeping
DP2	07:00h to 09:59h	Commuting
DP3	10:00h to 11:59h	Working
DP4	12:00h to 13:59h	Lunch
DP5	14:00h to 16:59h	Working
DP6	17:00h to 19:59h	Commuting
DP7	20:00h to 00:59h	Social

4.4.1 Categories of Relevance

In order to better characterize **ORs**, a classification process based on relevance categories is applied. Therefore, the relevance $R_{OR_x}^u$, of an **OR** is defined based on the frequency the user u visits OR_x , and is given by the equation:

$$R_{OR_x}^u = \frac{D_{OR_x}^u}{D_{DP}^u} \quad (4.2)$$

where $D_{OR_x}^u$ is the total number of days that OR_x was visited by the user u and D_{DP}^u is the total number of days in the dataset for the user u for the day period DP (Table 4.2).

The number of relevant categories that best suits all users is estimated using unsupervised learning. In this way, the k-means algorithm is applied to each user's relevance values for a different number of clusters (k), where k represents the relevant categories used. The optimal k is then determined using the elbow method along with the total **WSS** [71]. For the vast majority of users, $k=3$ gives the best number of clusters, which determines three categories of relevance: *low*, *medium* and *high*.

The mapping of **ORs** into these categories implies the definition of relevance values to be used as bounds for each category. As these bounds are dependent of the users' mobility patterns, they cannot be predefined as each user has its own notion of relevance. Figure 4.7 shows an example of this challenge using two users, Bob and Alice, for demonstration purposes. As can be seen, Bob, which presents a more regular mobility pattern compared to Alice, will have his less visited **ORs** classified as having medium relevance if a general threshold approach is used. To solve this problem, user-base thresholds are needed, and therefore the **ORs** relevance values of each user are clustered using k-means with $k=3$, and then, each cluster is classified as *low*, *medium* or *high* category according to the distribution of relevance values.

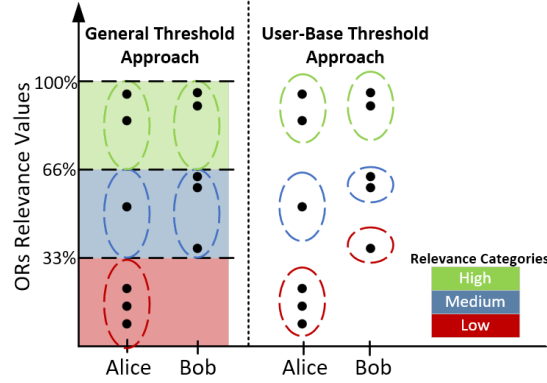


Figure 4.7: Approaches for categorizing ORs' relevance.

Figure 4.8 shows the probability density function of the relevance of ORs from all users obtained using the kernel density estimation for both cities. The good separation between the categories' distributions validates the choice of the number of categories of relevance ($k=3$). In addition, the small overlap area between the distributions reveals that most users have similar bounds for each relevance category. However, the fact that there is an overlap shows the importance of a user-base threshold approach for the ORs' relevance classification, as an OR with 25% relevance may be low-relevant to a user, while other OR with the same relevance value may be medium-relevant to other user. In addition, users from Porto and Beijing are shown to have a similar relevance distribution with respect to relevance categories. *This reveals that ORs' visiting behaviors appear not to depend on the country or city but instead on the mobility pattern features in the offloading scenario.* ORs within the high-relevance category are visited by users almost daily with the distribution peaking at 100%. The high-relevance category includes locations such as home, work, and commuting paths. The ORs within the medium-relevance category may be occasionally visited by users (favorite restaurant, gym, etc.) with the distribution peaking at $\approx 33\%$. Finally, ORs within the low-relevance category are visited sporadically (distribution peaking approximately at 7%, 14%, and 20%).

4.4.2 Spatial Characteristics

As ORs can be used as offloading sites, their spatial characteristics represent the areas where offloading can be performed. Figure 4.9 shows the distribution of the number of cells (11x11m grid squares) in ORs for each category of relevance. As illustrated, the size of ORs increases with the relevance category for both datasets. The median number of cells when considering a

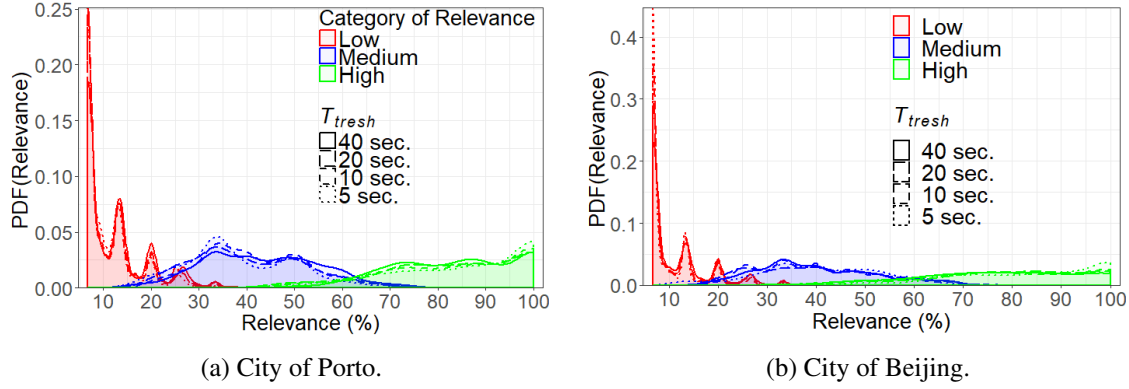


Figure 4.8: ORs' relevance values per category.

$T_{thresh} = \{40, 20, 10, 5\}$ seconds is 8, 6, 6 and 10 for the low-relevance category; 12, 11, 14 and 26 for the medium-relevance category; and 39, 64, 89 and 168 for the high-relevance category, respectively. Interestingly, similar ORs' dimensions are observed when considering a different city, with the ORs from Beijing's dataset presenting a median number of cells per OR of 7 for the low-relevance category; 13, 15, 19 and 47 for the medium-relevance category; and 29, 59, 81 and 238 for the high-relevance category, when considering a $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively.

Note that the ORs extracted for $T_{thresh} = 5$ seconds are the largest in both datasets. Defining small time windows for the OR extraction increases the number of OLCs that can be aggregated, forming larger ORs in the clustering step. Furthermore, since high-relevance ORs are often personal PoIs and indoor, their larger size is due to large indoor GPS errors.

These results show that *although collected in different cities and time periods, the offloading sites present similar characteristics evidencing that the laws driving users' mobility of both datasets are similar.*

4.5 Identifying Offloading Opportunities

In this section, offloading opportunities are inspected, addressing the second question presented at the beginning of this chapter: Does human mobility in urban areas allow for offloading to limited coverage technologies? Contrarily to Geolife data, the dataset from Porto provides precise information regarding the start and the end of each user's trip, and therefore it is preferred for this analysis. Thus, ORs are first characterized by type, and then the offloading opportunities provided by the transition ORs are evaluated.

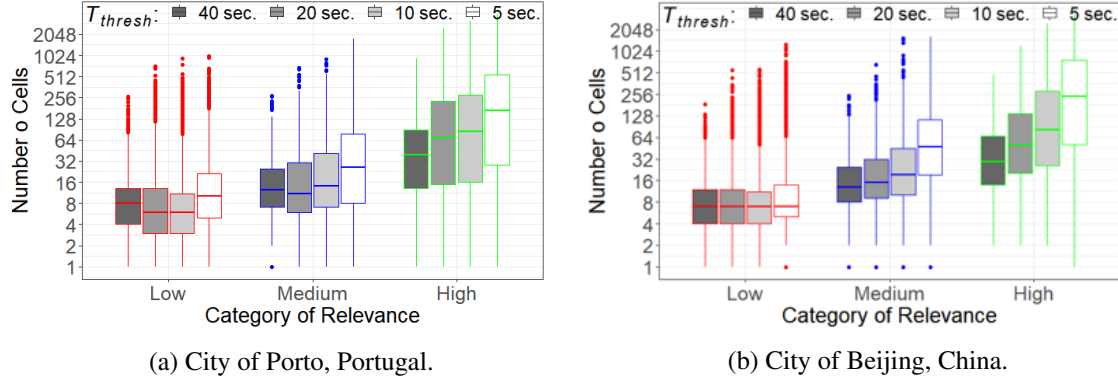


Figure 4.9: ORs' number of cells (11x11m).

4.5.1 Type of OR

To understand how ORs are encountered during a trip, ORs are classified into three types: departure, arrival, or transition OR. If the departure location of a user's trip belongs to an OR, that OR is classified as a departure OR. In the same way, if the destination location of the trip belongs to an OR, that OR is identified as the arrival OR. All remaining ORs visited while the user is traveling are identified as transition ORs.

When inspecting the relevance of ORs according to their type, Figure 4.10 shows that the majority of departure and arrival ORs exhibit medium or high relevance, while the majority of transition ORs have low relevance. The reason for having slightly more high-relevance arrival ORs than departure ORs is due to a small delay of the crowdsensing application on starting data collection at the beginning of a trip (Section 3.1.1.1). Hence, for some of the trips, the departure location ended up being associated with a transition OR. The transition ORs correspond to stops during the trip caused by factors such as waiting for public transportation, traffic congestion, traffic lights, etc.. These stops have a higher degree of randomness than the stops corresponding to the start and end of the trips, contributing to a decrease in the probability that these ORs are visited frequently. This will be further analyzed in Section 4.6.

4.5.2 Availability of ORs

To evaluate the offloading opportunities offered to users while traveling, the number of transition ORs visited per trip is evaluated (Figure 4.11). For 50% of the trips, users visit 1-5 ORs while in transit, revealing that there are several offloading opportunities to explore in addition to the

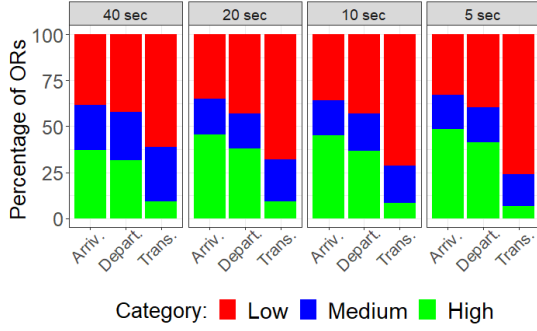


Figure 4.10: Relevance of the types of ORs.

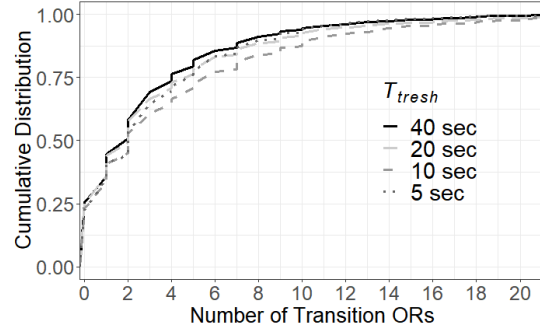


Figure 4.11: Number of transition ORs visited per trip.

destination of the trip. When inspecting the impact of considering distinct T_{thresh} , it is shown that a $T_{thresh} = 40$ seconds provides slightly less transition ORs per trip compared to smaller T_{thresh} . This is because smaller T_{thresh} allow to extract ORs when users are moving at higher speeds because they need to stay less time in a location for it to be considered an OR. In Figure 4.11, it is also observed that for 25% of the trips users cannot offload while in transit as these trips do not provide any transition OR. In these cases, the user can only offload at the trip destination, and the maximum offloading delay will depend on the trip duration.

When analyzing whether users revisit the same transition OR during the trip, it was verified that this scenario is rare (less than 5% of ORs are revisited in the same trip). *This suggests that offloading strategies that rely on multiple contacts between a user and APs, e.g. IP caching to reduce connection setup time [120], would not be effective when the goal is to offload during the trip.* These results are therefore aligned with the previous finding when exploring the interactions between users and APs in urban scenarios, presented in Section 3.3.3.3.

4.5.3 Time Window for Offloading

The time available for offloading represents the time window that mobile devices can use to offload, therefore, it can be estimated based on the time period a user stays inside a transition OR during a trip. Figure 4.12 shows the users' average sojourn time in transition ORs per trip. As shown, 50% of the users spent more than 66, 56, 56 and 48 seconds on average inside transition ORs for $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively.

The possibility of offloading depends not only on the time window to offload in each OR, but also on the overall coverage provided by ORs during the trip in the time domain. For example,

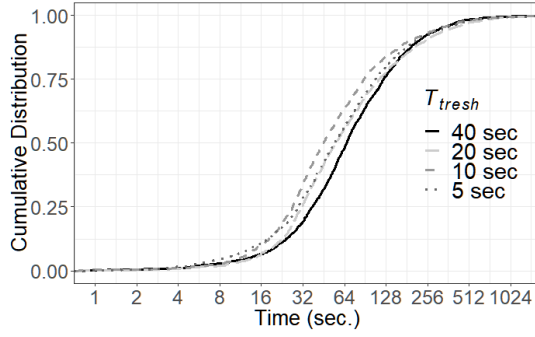


Figure 4.12: Users' average sojourn time in transition ORs per trip.

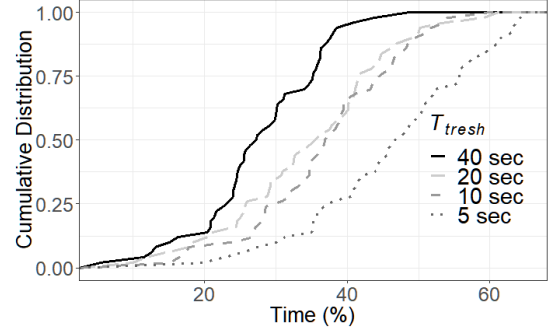


Figure 4.13: Users' average percentage of time inside ORs per trip given the trips' duration.

offloading performance is maximized when users spend most of the duration of the trip inside ORs. Computing this time parameter, Figure 4.13 shows that 75% of the users stay, on average, more than 22, 25, 30 and 37% of the duration of the trips within ORs for $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively. Smaller T_{thresh} leads to larger ORs (Section 4.4.2), which increases the spatial coverage of ORs and the overall time users are within ORs, and consequently, the ability to offload. These results show that *the users' mobility clearly provides offloading opportunities while users are in transit.*

4.5.4 Offloading Delay

Depending on the traffic's requirements, applications can defer data transmission until a WiFi connection is available. This deferred transmission time, here called offloading delay, can be estimated based on the time it takes users to move between transition ORs. In this case, the observed travel time between the transition ORs can serve as a lower bound for the minimum offloading delay regarding the offloading process. Figure 4.14 shows the average travel time of users between the transition ORs. As shown, 50% of the users spend, on average, less than 96, 62, 48 and 28 seconds traveling between ORs for $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively, evidencing that ORs extracted with lower T_{thresh} values provide lower offloading delays to the users. Smaller T_{thresh} allow for greater mobility for users (Eq. 4.1) creating larger ORs (Figure 4.9a), which leads to a decrease in the overall offloading delay at the expense of shorter time windows for offloading.

To conclude, *the results show that small offloading delays along with high-temporal coverage of ORs confirm a clear opportunity to offload data while users move in the city.*

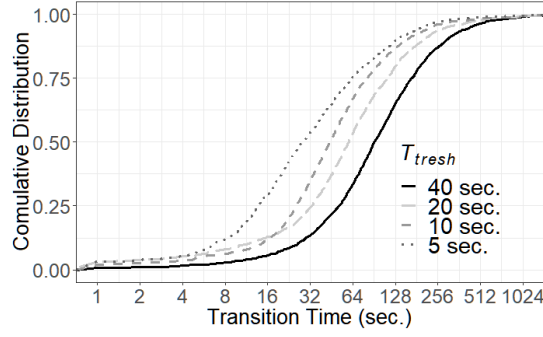


Figure 4.14: Users' average travel time between ORs.

4.6 Next Offloading Region Prediction

To take advantage of the offloading opportunities provided to users, it is relevant to predict the next OR to be visited by a user. This allows offloading systems to take preemptive actions to manage the offloading process, e.g., use strategies to improve the link setup time with APs in ORs [120] or, ultimately, to support the offload decision. Thus, the following study will focus on the spatial OR prediction task, bringing the answer to the third question presented in the introduction of this chapter: What are the limits of the predictability of per user offloading connectivity and which factors impact on that predictability? Initially, the theoretical predictability of the mobility patterns is explored. Next, MC and ML predictors are used as attempts to achieve this predictability.

4.6.1 Theoretical Predictability

The theoretical predictability of a sequence is correlated with uncertainty, which is usually measured by the entropy rate in information theory. This measurement has been adopted in human mobility studies to establish predictability limits under certain assumptions [140, 138, 145]. Here, the three most common entropy measures are assigned to each user mobility pattern represented by the sequence of transitions between its ORs, namely:

- random entropy S_u^{rand} , defined as $S_u^{rand} = \log_2(N_u)$, where N_u is the number of distinct ORs visited by the user u , assuming that each OR is visited with the same probability, ignoring both the frequency of visits and the temporal order of the visits to the ORs;
- temporal-uncorrelated entropy S_u^{unc} , defined as $S_u^{unc} = -\sum_{i=1}^{N_u} p_u(i) \log_2 p_u(i)$, obtained by ignoring just the temporal order information of visits to the ORs and applying the entropy

formula to the frequency of visits, where $p_u(i)$ is the historical probability that OR i was visited by the user u ;

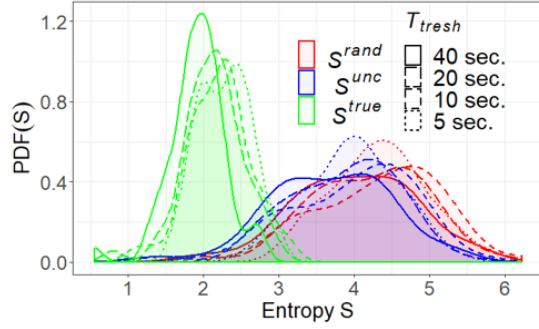
- the true entropy S_u^{true} , defined as $S_u^{true} = (\frac{1}{n} \sum_i L_i)^{-1} \ln(n)$, that considers both the frequency and the temporal order information of the visits to the ORs; an estimator based on Lempel-Ziv data compression [74] is adopted, as it allows rapid convergence to the real entropy of a time series. Here, L_i is the length of the shortest sub-string starting at position i , which does not previously appear from position 1 to $i-1$ and n is the sequence of ORs' length.

Figure 4.15 shows the entropy distributions between the users of the Beijing and Porto datasets and, naturally, $S^{true} \leq S^{unc} \leq S^{rand}$. Moreover, for both datasets, the results show that considering a small T_{thresh} increases the entropy of the time series. As shown in Figure 4.15a, for users from the city of Porto, S^{rand} peaks approximately at ≈ 4.4 and ≈ 4.7 for a $T_{thresh} = 40$ and 5 seconds respectively, indicating that a user who randomly chooses his/her next OR could be found, on average, in any of $2^{4.4} \approx 21$ or $2^{4.7} \approx 26$ ORs. However, it is important to note that for $T_{thresh} = 40$ and 5 seconds, S^{true} peaks at ≈ 2 and ≈ 2.5 , indicating that the real uncertainty in the users' next OR is now $2^2 \approx 4$ and $2^{2.5} \approx 5.6$ ORs. Interestingly, the same entropy behavior and values can be identified in the Beijing users, suggesting that the uncertainty on the mobility for offloading is independent of the users' geographical location at a country scale or even at a city scale.

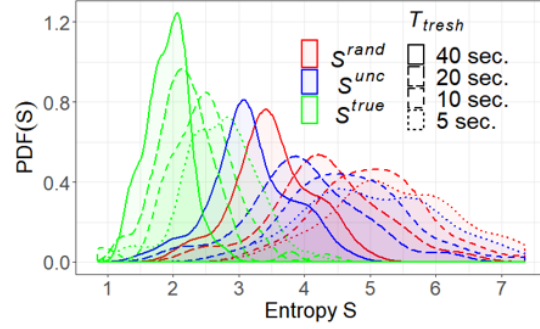
Given the entropy $S^\bullet$ of an individual moving between N ORs, the upper bound of mobility predictability is given by the probability $\Pi^\bullet$, which represents the maximum accuracy that can be achieved by a prediction algorithm. This probability $\Pi^\bullet$ is expressed by $S^\bullet = H(\Pi^\bullet) + (1 - \Pi^\bullet) \log_2(N - 1)$ with the binary entropy function $H(\Pi^\bullet) = -\Pi^\bullet \log_2(\Pi^\bullet) - (1 - \Pi^\bullet) \log_2(1 - \Pi^\bullet)$. This quantity is subject to Fano's inequality (see [140, 40] for more details). After determining $\Pi^\bullet$, and as Figure 4.16 illustrates, for both cities, Π^{true} peaks between $\approx 62\%$ and $\approx 70\%$ for all T_{thresh} , a value considerably lower compared to related work. For example, a Π^{true} of 93% is obtained when considering human mobility between personal PoIs [140]. *This result clearly shows that the prediction task for offloading is more challenging, though possible, motivating the need for further investigation of the mobility properties under offloading conditions.*

4.6.2 Markov Chain Predictor

MC is the most commonly used predictor for users mobility [98, 76]. To evaluate the user's mobility between ORs, the mobility behavior is modeled as a discrete stochastic process using a MC consisting of a set of states $S = \{S_1, \dots, S_i, \dots, S_n\}$, where S_i corresponds to OR i visited by the user,

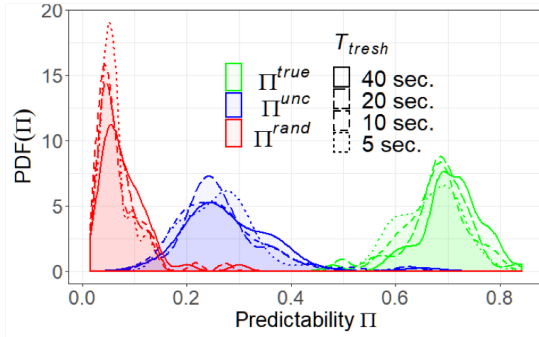


(a) City of Porto, Portugal.

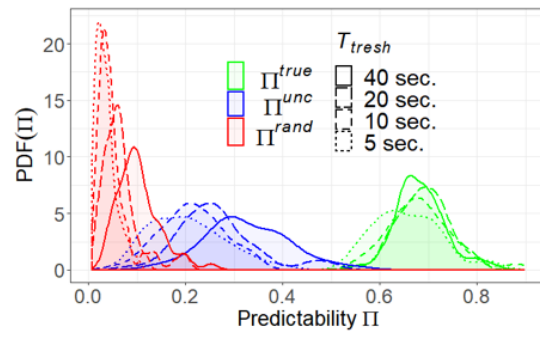


(b) City of Beijing, China.

Figure 4.15: Entropy values for the sequence of ORs.



(a) City of Porto, Portugal.



(b) City of Beijing, China.

Figure 4.16: Predictability values for the sequence of ORs.

and a transition probability matrix P , where each element p_{S_i, S_j} represents the user probability of moving from S_i to S_j , with $(i, j) = \{x \in \mathbb{N} | 1 \leq x \leq n\}$ and $i \neq j$.

For each user and day period, the sequence of **ORs** visited is extracted in chronological order. The first 75% of the sequence is used as a training set to build the transition probability matrix P and the remaining 25% as a testing set to validate the predictions. Only users with a sequence of visited **ORs** greater than 10 were considered. For each prediction, the current state S_i is defined as the last **OR** of the training sequence and the prediction of the next **OR** to be visited S_j is performed selecting the **OR** with a higher transition probability p_{S_i, S_j} . In the case of two **ORs** with the same transition probability, one is chosen at random. If there is no information on the current **OR** in P (e.g., the first time the user visits this **OR**), it is assumed that the predictor fails, as it cannot predict the next **OR**. The predictor evaluates in runtime – after each prediction, the training sequence is updated with the right prediction, and a new P is computed.

The accuracy of the predictor is evaluated as the number of correct predictions over the total number of predictions. As shown in Figure 4.17, the **MC** predictor presents similar results for both cities. An accuracy below 23% and 13% is achieved for 75% of the Porto city users (refer to Figure 4.17a), when considering only the current location ($k=1$) and respectively, a $T_{thresh} = 40$ seconds and $T_{thresh} = \{20, 10, 5\}$ seconds. Although an increase of $\approx 10\%$ is observed in the **MC** predictor in Beijing users for $T_{thresh} = 40$ seconds (refer to Figure 4.17a), these values are considerably lower than the upper bound presented in Figure 4.16. This accuracy is even worse when the past history is considered, that is, the current and the previous **OR** ($k=2$). The reason is that Markovian predictors have a large probability space that increases quickly following a power law of order k . Therefore, when $k > 1$, these predictors may suffer from insufficient samples.

Taking into account the poor performance of the **MC** predictor compared to the theoretical upper bound, possible causes leading to this performance are first investigated, and then approaches to improve its performance are proposed and explored.

4.6.2.1 Inspecting MC Predictor

A matrix P built using a short history (length of the sequence of transitions between **ORs**) may not capture the diversity of user routines (movement between **ORs**). To test this hypothesis, Pearson's correlation coefficient (ρ) between the accuracy of the predictions and the length of the sequences was calculated and no statistically significant correlation was found. This suggests that small sequences may not be responsible for the predictor's poor performance. Instead, a negative correlation was found between the predictor accuracy and the number of unique **ORs**

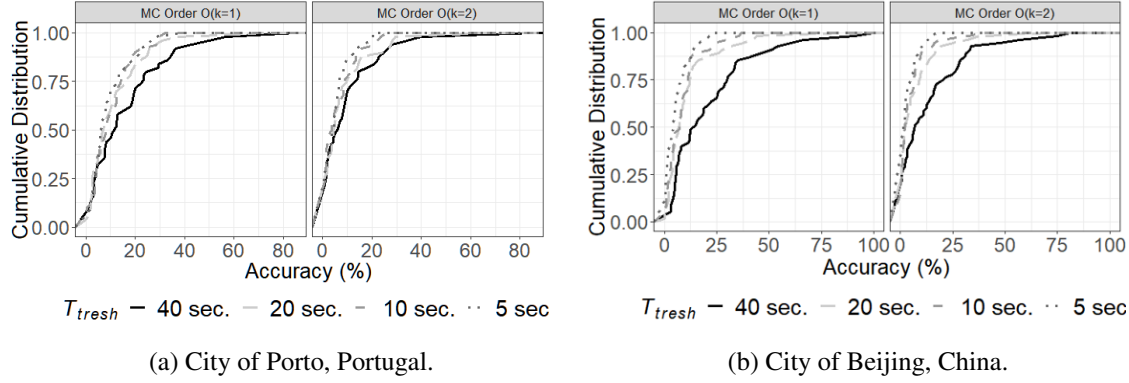


Figure 4.17: Accuracy of the MC predictor for all users.

of the sequence, $\rho = \{-0.38, -0.29, -0.30, -0.29\}$ for $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively. Similar ρ values were found for the Beijing dataset, $\rho = \{-0.46, -0.33, -0.31, -0.27\}$ for $T_{thresh} = \{40, 20, 10, 5\}$ seconds, respectively. This shows a novelty, which consists in finding new ORs, which may have more impact on the performance of the predictors than the sequence length.

The appearance of new ORs in a sequence will make the predictors fail the prediction in two scenarios, namely, when: i) the current state is a new OR, as there is no information in matrix P and, therefore, the prediction fails; and ii) the next state is a new OR, as the predictor can only predict the transitions reflected in P (what has occurred before). To further study the first scenario, three types of prediction are defined based on P information during the decision phase, namely:

- *Unknown-based prediction*: occurs when there is no information in P regarding the current state (new OR);
- *Draw-based prediction*: occurs when two or more ORs in P have the same transition probability;
- *Regular-based prediction*: occurs when only one OR exhibits the highest transition probability.

Figure 4.18 shows the distribution of the predictions for each prediction type. It is clear that in both datasets the number of predictions is evenly distributed among the prediction types, showing that the majority of predictions are not regular-based. In addition, unknown-based predictions, which are nearly one-third of predictions, are bound to fail.

To further inspect the second scenario mentioned above, the probability of the next OR being a new OR for each sequence is computed. For that, an OR is considered a “new OR” if it appears

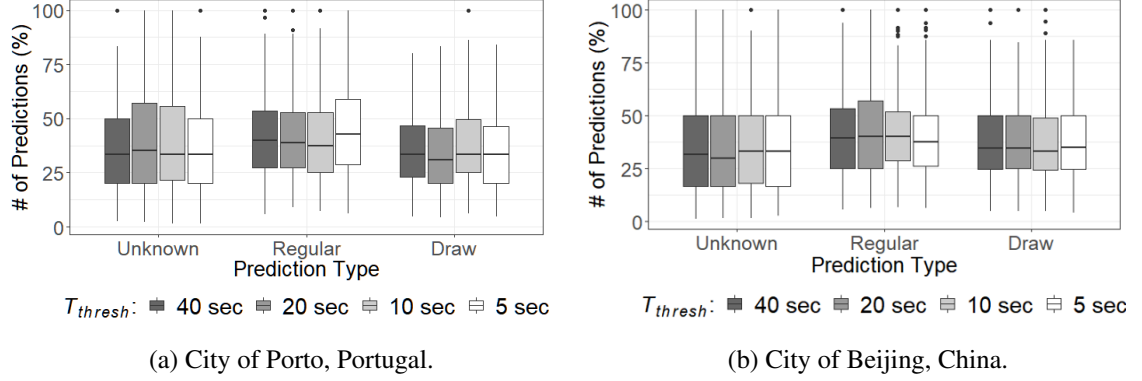


Figure 4.18: Distribution of the type of predictions.

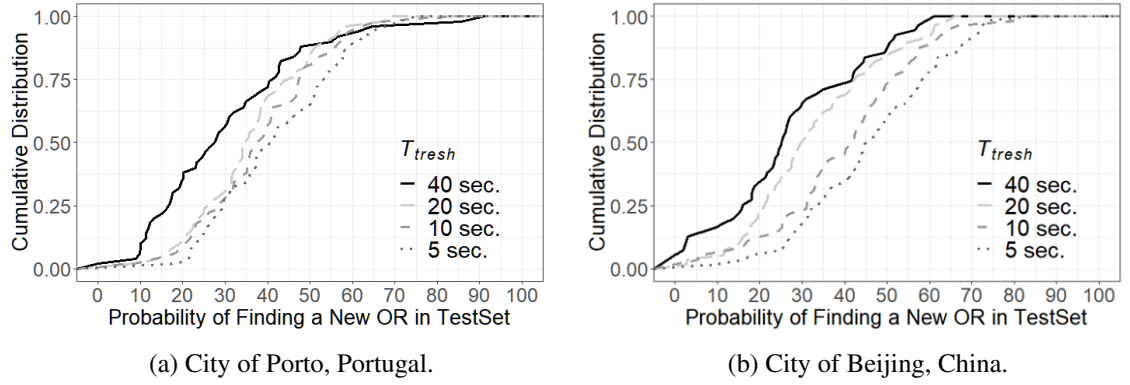


Figure 4.19: Users' probability of finding a new OR.

in the sequence for the first time or a "repeated OR" otherwise. Note that the predictor is an online predictor; consequently, even after training, P is updated after each prediction. To capture this behavior, the probability of finding a new ORs is given by the fraction of "new ORs" in the test sequence over the length of the test sequence, see results in Figure 4.19. For the sequences from Porto's dataset in Figure 4.19a, the median probability of the next ORs being a "new OR" is 27% for $T_{thresh} = 40$ seconds. This means that an online MC predictor will fail, on average, 27% of its regular-based predictions. This value increases to $\approx 40\%$ for $T_{thresh} = 5$ seconds. Similar results can be observed in the Beijing dataset in Figure 4.19b. Smaller T_{thresh} values increase the probability of finding new ORs as the spatial-temporal constraint (see Section 4.3.1) for a location to be considered as an OR is relaxed, increasing the number of unique ORs extracted from a mobility trace.

Table 4.3: Strategies to improve MC predictor.

Strategies	Prediction Type	
	Draw	Unknown
Baseline	Random	None
Method 1	Closest OR from P	None
Method 2	Closest OR from P	Closest OR
Method 3	Closest OR from P	Most Visited OR

4.6.2.2 Improving MC Predictor

As most of the prediction types are draw-based and unknown-based, different strategies are combined to improve the MC predictor's performance in these cases, also evaluating their impact. When the MC predictor faces a draw-based prediction, the following strategies are applied to the set of ORs with the same transition probability in P : i) randomly select one of the ORs as next OR; or ii) select the closest OR to the current OR. Additionally, when the MC predictor faces an unknown-based prediction, the following strategies are applied to select the next OR considering all ORs present in P : i) no OR is selected and the prediction fails; ii) select the closest OR to the current OR; or iii) select the most visited OR in P . While distance-based strategies try to capture the human mobility tendency to favor shorter paths, history-based strategies such as, *Most Visited OR*, try to capture the regularity behavior of human mobility. Table 4.3 shows the different combinations of these strategies when evaluating the performance of the MC predictor.

Figure 4.20 shows the accuracy of the MC predictor for both datasets for $k = 1$, when applying the strategies described above. Solving the ties by selecting the closest OR (Method 1) has a minor impact on the predictor's performance in both datasets. However, solving the unknown-based predictions improves the accuracy around two times in both datasets. Similar results were obtained for methods 2 and 3, revealing no difference between distance-based and historic-based strategies in unknown-based predictions.

Even with improvements in the predictor's performance, its median accuracy is less than 24% for the Porto and Beijing datasets. *Although Markovian predictors have been proposed as feasible solutions to predict mobility between users' PoIs [98, 76], the results show that their performance is significantly reduced in offloading scenarios.*

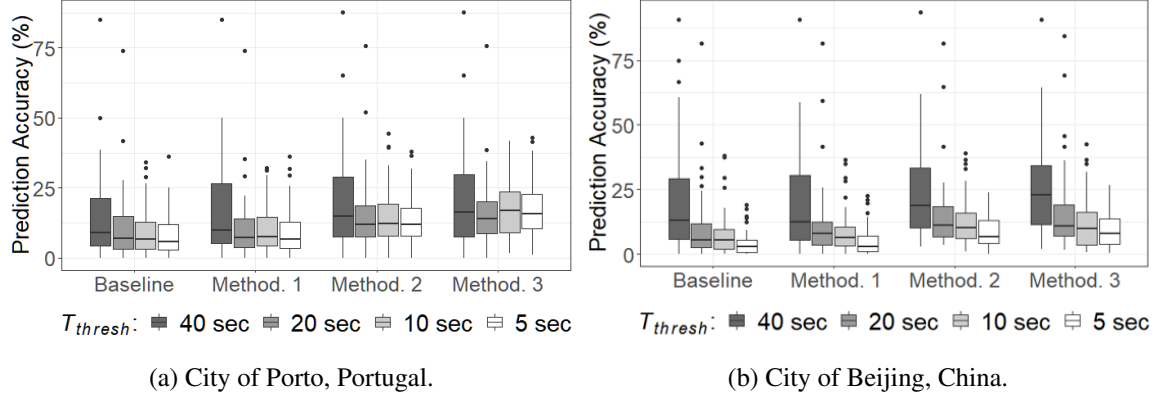


Figure 4.20: Accuracy of the improved MC predictor.

4.6.3 Machine Learning Predictors

From the previous analysis, it was clear that the MC predictor is not capable of predicting the next OR conveniently. Other types of predictors are ML predictors. In our mobility prediction task, the input consists of a series of contextual features associated with the current OR, while the output is the next OR to be visited by the user. The context features of the current OR were divided into three feature domains: location, time, and relevance. Table 4.4 details the features extracted from the user mobility traces. The nominal variables were converted to binary features using one-hot encoding. Then, different types of ML predictors were used, namely DT (Decision Trees), NN (Neural Networks) with a single hidden layer, Bayesian (Bayes) and RF, using the CARET package in R with the algorithms C5.0, avgNN, bayesglm, and ranger, respectively, and the default parameter settings.

Table 4.4: Mobility features for predicting the next OR.

Features Domain	Feature	Type	Description
Location	Current OR (COR)	Nominal	OR where the user is
	Previous OR (POR)	Nominal	OR from where the user comes from
	Cell in COR	Numeric	Coordinates of the grid cell (11x11m square) where the user is inside the OR
Time	Duration in COR	Nominal	Time spent in the current OR
	Day	Nominal	Weekday name
	Hour	Numeric	Hour of the day
Relevance	Category	Nominal	Relevance Category of the COR

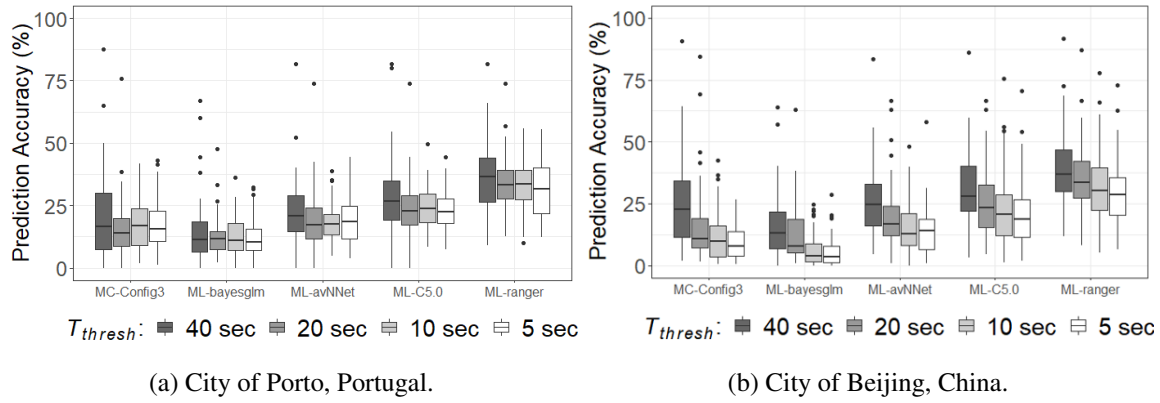


Figure 4.21: Accuracy of the ML predictors.

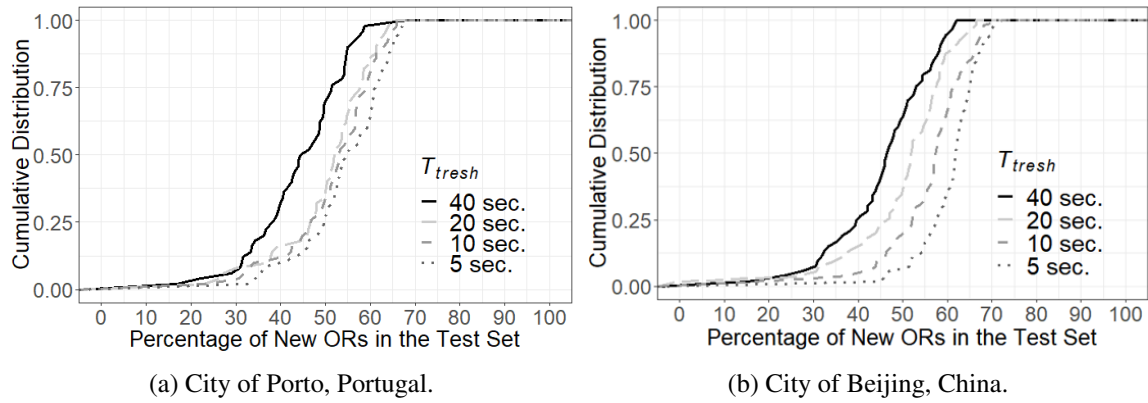


Figure 4.22: New ORs in the test set when compared to the training set.

Figure 4.21 shows the accuracy of ML predictors using a cross-validation of $k = 3$. With the exception of the Bayesian predictor, the ML predictors perform better than the MC predictor, with RF presenting the best results for both datasets with median accuracy between $\approx 30\%$ and $\approx 37\%$ for all T_{thresh} values. However, it is important to note that considering a higher T_{thresh} improves prediction accuracy, this being more evident in the Beijing dataset, see Figure 4.21b. Note that the models considered could be further fine-tuned or even replaced by others, which could lead to better results. However, our goal is not to produce a state-of-the-art prediction model, but rather to inspect the limitations and sources of predictability in an offloading scenario.

In contrast to the MC predictor, the online version of the ML predictors is not considered, as the training phase may have a high processing cost and is likely unfeasible when the offloading process is handled on mobile devices. Therefore, the new ORs can have more impact on the performance of ML predictors, as the predictors can only predict ORs that are present in the initial training sequence (75% of the sequence). Figure 4.22 shows the percentage of new ORs in the testing sequence compared to the training sequence. Once more, similar results can be observed for both datasets, where the lower number of new ORs in the test set is obtained for a $T_{thresh} = 40$ seconds. Here, the median percentage of new ORs in the test set per user is $\approx 45\%$ for $T_{thresh} = 40$ seconds, showing that, for half of the users, the maximum accuracy that ML predictors would be able to achieve is $\approx 55\%$. Note that while Porto users present a similar number of new ORs in the test set for the other values of T_{thresh} , in Beijing, the number of ORs increases as smaller values of T_{thresh} are considered. This causes the reduction in the ML predictors performance observed in Figure 4.21b as higher percentages of new ORs in the test set lead to a decrease in the performance of the predictors.

Even though the new ORs phenomenon is more challenging for ML predictors without an online nature (as the MC predictor used before), the performance of predicting the next OR is higher. *In an offloading scenario, the smaller spatial-temporal constraint determined by T_{thresh} causes the users to discover new ORs constantly, which may count with just a few visits. Even compared to an online MC predictor, our results show that ML present better performance in predicting offloading opportunities, revealing the importance of contextual information (Table 4.4) in offloading scenarios.*

4.7 Mobility Properties for Offloading

The previous section shows that looking at mobility from an offloading perspective imposes different challenges when compared to human mobility, as studied in related work. Thus, previous

conclusions on human mobility do not apply, e.g., high performance of MC predictors [98, 76]. The work in this section aims to shorten this gap by inspecting the properties of human mobility in an offloading scenario and their impact on designing offloading systems, answering the fourth and last question presented in this chapter’s introduction: Which trade-offs should be considered in the offloading system design?

4.7.1 Exploration Phase Characteristics

The *exploration phase* of a user is defined as the time to visit each OR for the first time. As discussed in Section 4.6, the high probability that a user finds a new ORs is the main challenge to user mobility predictability. One may argue that this occurs due to the lack of historical information and that the new OR phenomenon will have less impact if longer mobility traces are considered. To evaluate this hypothesis, the user discovery factor DF is computed and analyzed. The discovery factor DF_i^u of a user u on the i^{th} day of its mobility trace is defined as the percentage of ORs visited by that user u at the i^{th} day, with respect to the total number of different ORs visited by the same user during D days. DF is computed during the commuting periods for users with 15 days of historical data.

Figure 4.23 shows the users’ discovery factor for the morning commute period (DP2); similar results were found for DP4. *The similarity of the results from both datasets shows a clearly indication that the user’s exploration phase on an offloading scenario is common even across datasets collected from different countries at different times.* When considering only medium and high-relevance ORs, it can be observed that the user exploration phase is very short – 50% of users visit all their medium and high-relevance ORs after just 3 days (median $DF_3^u = 100\%$). However, when also considering the low-relevance ORs (then considering all ORs), it is shown that users are constantly discovering new low-relevance ORs every day. This is illustrated by the trend line of the discovery factor indicator, which increases almost linearly with the number of days. As shown in Figure 4.8, most low-relevance ORs are rarely visited by users (max. distribution peaking approximately at 7%), which makes them very likely to correspond to random stops taken by the users while moving, and therefore very probable to continue to appear even if a larger periods of historical data are considered. *This shows that the new OR phenomenon is due to the mobility characteristics in an offloading scenario and not due to the lack of historical data: In [7, 144], the authors discuss the hardness in prediction given by the novelty component in mobility. Therefore, considering longer learning periods for offloading systems is unlike improving their ability to predict mobility.*

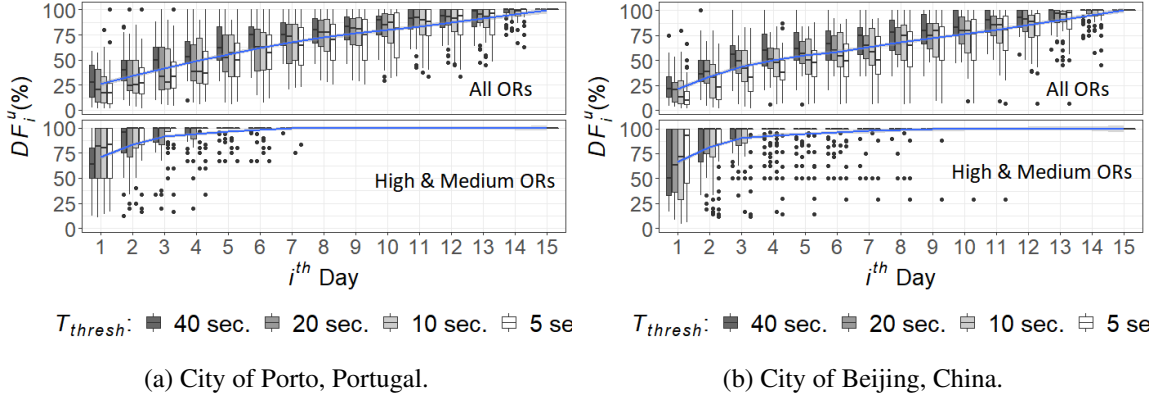


Figure 4.23: User's discovery factor for the DP2 day period.

4.7.2 Mobility Regularity Effects

The regularity of users' mobility is characterized by the **ORs**' visiting patterns, which might be used to improve mobility predictability. The regularity impact is further evaluated by answering the question: Can specific characteristics of regularity be used to improve the predictability of mobility between **ORs**?

4.7.2.1 Relevance Filter

Offloading systems may try to improve the user's mobility regularity using relevance as a filter, e.g., considering only **ORs** that have a specific level of relevance to the users.

ORs with a relevance lower than 7%, 10% and 15% were filtered from the sequence of visited **ORs** and the predictors re-trained. Figure 4.24 shows the accuracy of the **RF** predictor (the best from Figure 4.21) for the different relevance filters, for both datasets. The results show that the predictor's accuracy improves when **ORs** with low relevance are removed. In fact, the prediction accuracy improves approximately 20% in both datasets when a 15% relevance filter is used, reaching a median accuracy of $\approx 55\%$ for $T_{thresh} = \{40, 20, 10\}$ seconds and $\approx 60\%$ for $T_{thresh} = 5$ seconds. Higher values for the relevance filter could be used to improve the mobility predictability in an offloading scenario, however, this affects the offloading opportunities. This trade-off will be further studied in Section 4.7.3.

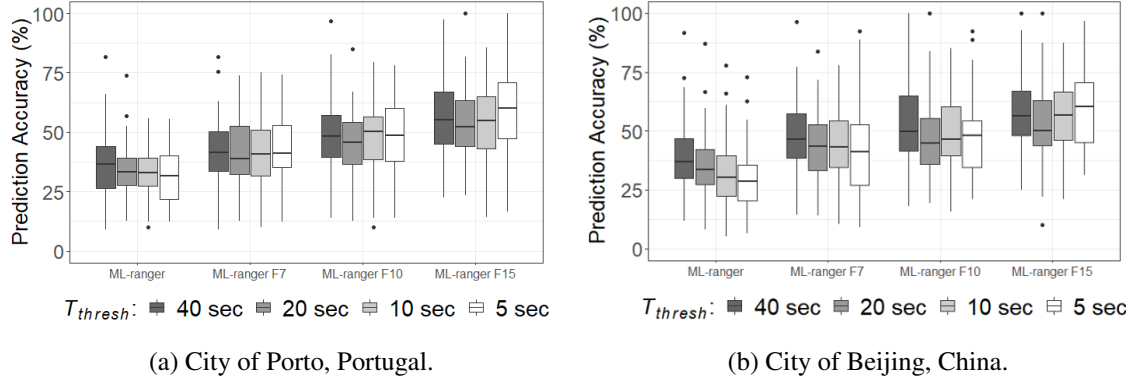


Figure 4.24: Accuracy of the *ML-ranger* predictor for different relevance filters values.

4.7.2.2 Multiple OR Prediction

Depending on how the offloading process is managed, offloading systems can consider more than one **OR** in advance to prepare the offloading process, e.g., launch mechanisms to provide seamless network access to mobile devices. In this case, all the setup actions anticipating the users' arrival can be performed in two or more **ORs**, and the final **OR** choice can be made online using contextual information such as the current user's path. This scenario is only convenient for offloading systems if the uncertainty associated with the prediction of the next **OR** is concentrated in a small subset of **ORs**, for each prediction. Thus, the problem formulation for the prediction task can be loosened: what will be the **ML** predictor accuracy if the N most probable **ORs** are considered as being the next **OR**? For this, in each prediction, the top N **ORs** with the highest probability of being the next **OR** visited by the user are selected. Then, a prediction is assumed to be correct if one of the top N selected **ORs** is, in fact, the next **OR** visited by the user. For this, the **RF** predictor is used and only **ORs** with relevance greater than 15% are considered.

Figure 4.25 shows the predictor's accuracy when considering that the next **OR** will be one of the top N **ORs** selected by the predictor, where $N = \{x \in \mathbb{N} | 1 \leq x \leq 6\}$. As shown, for both datasets, the predictor accuracy increases significantly when considering multiple options as the next **OR**; in these case, from $\approx 15\%$ for $N = 2$ to $\approx 27\%$ for $N = 4$. *This reveals that the uncertainty of predicting the next visited **OR** is concentrated in a small subset of **ORs** which can be leveraged by offloading systems. However, considering more than four possible next **ORs** does not bring a significant added value since for $N > 4$ only marginal improvements are obtained.*

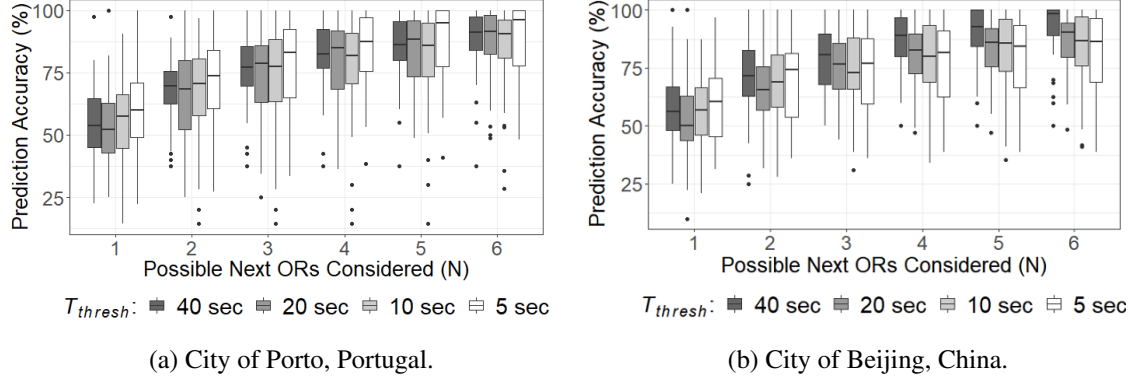


Figure 4.25: Accuracy of the *ML-ranger* predictor for N possible next ORs.

4.7.3 Mobility Predictability Trade-offs

The deterministic or opportunistic nature of the offloading strategies used by offloading systems depend on the users' mobility predictability. Ideally, high predictability is preferable as it allows using more sophisticated and deterministic strategies anticipating the arrival of users to a OR to maximize offloading performance. In addition, opportunistic strategies should be preferred when the predictability is lower. In this case, the offloading process can start opportunistically every time a user enters an OR without the need to take any anticipatory action.

As demonstrated in the previous sections, although mobility predictability is a challenge in an offloading scenario, it can be improved if: (i) more than one OR is considered as the next OR; and (ii) low-relevant ORs are not considered during the prediction process. However, most of the transition ORs are low-relevance ORs and removing them may affect the offloading opportunities provided to users in transit. Figure 4.26 and Figure 4.27 show the impact of removing low-relevance ORs on the number of transition ORs and the percentage of time inside ORs per trip (Porto dataset), respectively. For clarity purposes, only results for $T_{thresh} = 10$ seconds are shown as similar results were found for other T_{thresh} . Removing low-relevance ORs reduces offloading opportunities while the user is traveling. In fact, when only ORs with relevance greater than 15% are considered, the number of trips where users cannot offload while traveling increases from 25% to 38% (Figure 4.26). Furthermore, when offloading while traveling is possible, the median percentage of time spent by users inside ORs decreases from 37% to 28% (Figure 4.26). *These results clearly show a trade-off between the mobility predictability and the offloading opportunities. Therefore, to maximize the offloading opportunities for users in transit, an efficient offloading strategy should combine opportunistic and predictive strategies.*

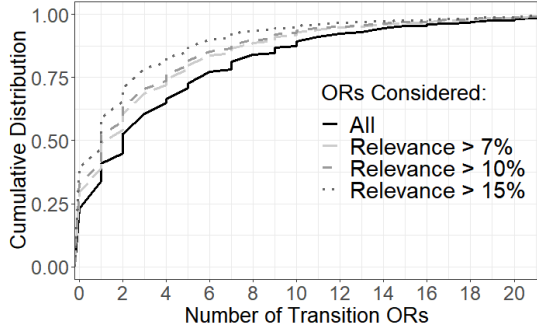


Figure 4.26: Number of transition **ORs** per trip ($T_{thresh} = 10$ seconds).

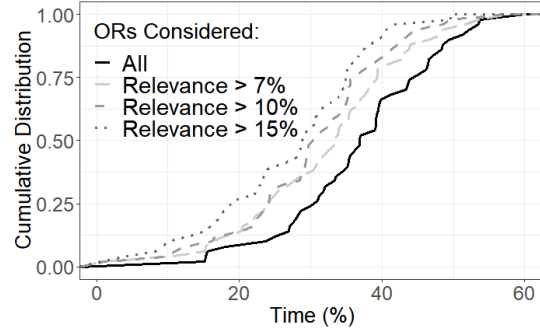


Figure 4.27: Users' average time inside **ORs** per trip ($T_{thresh} = 10$ seconds).

4.7.4 Offloading Sites Considerations

In a mobile data offloading scenario, WiFi **APs** should provide Internet connectivity in the offloading sites. Larger **ORs** may require more **APs** and, consequently, more handovers to provide full WiFi connectivity during the offloading process. Figure 4.28 shows the maximum coverage of the offloading sites computed as the maximum euclidean distance between two geographical coordinates belonging to the same **OR**. Similarly to the number of cells (see Section 4.4.2), the maximum coverage of **ORs** is very similar in both datasets. The horizontal lines in Figure 4.28 represent the typical coverage of an **AP** (44m, see Figure 4.5) obtained through WiFi measurements in an urban scenario. *As the vast majority of transition **ORs** belong to the low-relevance category, this indicates that mobile devices will not need to perform multiple handovers during the offloading process as few **APs**, e.g. two **APs**, can provide full WiFi coverage for the transition **ORs**.*

Attending that most **APs** in our WiFi coverage dataset described in Section 3.2.2 were inside buildings and homes, *this indicates that already deployed WiFi infrastructure can be leveraged by offloading systems to offload since they provide a feasible coverage.* Therefore, large studies such as [169, 23, 91] characterizing WiFi **APs** deployments on the city scale can be used to design offloading decision models that can take advantage of the already deployed WiFi infrastructure. This topic will be further investigated in the next chapter of this thesis.

4.8 Concluding Remarks

This chapter proposes the use of granular human mobility profiles to inform offloading strategies during commuter trips. **ORs** can be extracted from individual trajectories using unsupervised learn-

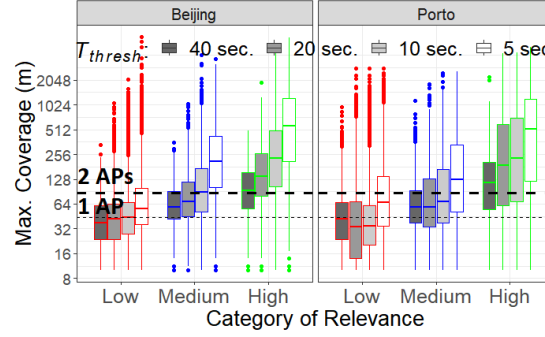


Figure 4.28: Maximum coverage of the ORs.

ing methods that were validated on data collected from two different cities at different times. Offloading opportunities were investigated and the results show that users can offload while in transit considering the availability of ORs along with reasonable sojourn times and small offloading delays between ORs.

The mobility predictability for offloading on commuter trips was revealed to be much more challenging compared to the mobility predictability between PoIs. Here, ML predictors outperform MC predictors ($\approx 37\%$ vs. $\approx 12\%$ acc.), revealing the importance of a contextual feature when predicting the next OR to be visited by a user. The results indicate that the high probability for users to find new ORs is the main cause of the poor performance of the predictors. However, inspecting the user exploration phase showed that this behavior is due to mobility characteristics in offloading scenarios, and considering longer learning periods will not improve mobility predictability. Nevertheless, the results also show that a significant improvement in mobility predictability can be obtained if mobility regularity properties are used. Here, offloading systems can consider up to four possible ORs as the next OR and use a relevance filter to improve prediction performance. This implies the implementation of both opportunistic and deterministic strategies to maximize offloading performance. The results also show that mobile devices will not need to perform multiple handovers within an OR during the offloading process, as ORs can be covered by a small number of APs.

Finally, the findings can be considered general since they are based on two datasets collected independently on two sides of the world. A high degree of similarity was found between the results from both the Porto and Beijing datasets, indicating that offloading mobility is highly dependent on how regular people move in cities. Therefore, the findings and conclusions of this work are likely to be generalized to other urban scenarios.

Chapter 5

Enhancing Urban WiFi Offloading for Commuters: Performance and Influencing Factors

Designing a system for offloading that can use WiFi [APs](#) effectively is a complex task, since it involves coordinating activities between different layers of the network stack and various network elements. Therefore, offloading systems should have specialized support, specifically during periods when users are in transit, such as during their commutes, as these are the moments when the cellular network is the default mode for Internet access.

In this chapter, the effectiveness of mobile data offloading when users are on the move is investigated, bringing answers to the third, and final, research question presented in the introduction of this thesis: What are the expected performance outcomes for users in transit when using urban WiFi [APs](#) for offloading, and what are the key factors influencing the offloading process?

To answer this question, the offloading process is investigated under different network conditions, traffic requirements, offloading strategies, and mobility modes using the evaluation process represented in Figure [5.1](#). Real-world data on users' mobility and WiFi coverage is used to study mobile data offloading when users are commuting seeking answers for questions such as: How much can users offload while commuting? Which fundamental aspects do affect the amount of offloaded data? and How can the offloading process be improved?

The remainder of the chapter is organized as follows. Section [5.1](#) discusses related research on mobile data offloading performance. Section [5.2](#) describes the mobility traces datasets utilized

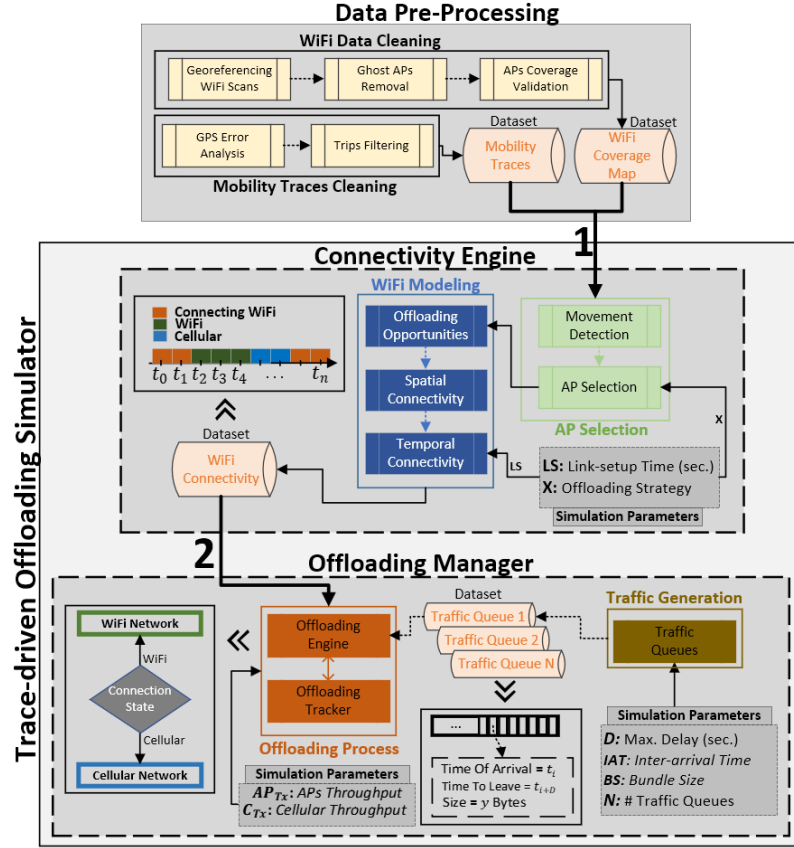


Figure 5.1: Overview of the mobile data offloading evaluation process.

in this work. Section 5.3 proposes a framework for modeling WiFi connectivity and Section 5.4 elaborates on the offloading evaluation methodology used and the trace-driven simulator developed in this study. The performance of mobile data offloading is analyzed in Section 5.5 and the effects of context information in the offloading decision process are discussed in Section 5.6. Finally, Section 5.7 explores how mobile data offloading capabilities can be enhanced and Section 5.8 summarizes the main conclusions of this chapter.

5.1 Mobile Data Offloading Performance With WiFi Networks

Several works have been proposed that study the feasibility of WiFi networks to offload mobile data traffic for the on-the-spot and delayed offloading. On-the-spot offloading requires immediate data

transmission without delays, while in delayed offloading, data can be buffered within a specified time frame (offloading deadline) until a WiFi connection is possible [134].

In [10], a system called *Wiffler* is introduced as the first to jointly characterize the 3G and WiFi offloading performance using trace-driven simulations based on a vehicular testbed. It anticipates future WiFi throughput and waits for opportune moments to offload data. The authors claim to be able to achieve a 45% reduction in 3G usage when using a 60 second delay tolerance. However, these results do not account for normal users in their daily lives, as they are meaningful only when mobile data is generated on a city transit bus or in war-driving scenarios. In [84], a more generic dataset is used using an application installed on smartphones of 97 participants. The application was tracking the users' mobility and WiFi connections on a daily basis. The authors demonstrated that on-the-spot offloading could effectively offload 65% of total data traffic to WiFi networks but that delayed offloading would only bring substantial gains if the deadline is fairly longer than tens of minutes. The work in [104] considers the network conditions, the availability of APs, and their distance to mobile devices to present a model based on queuing theory to analyze the performance of on-the-spot offloading. The same authors propose in [105, 106] a queueing analytic model for delayed offloading and derive the mean delay, offloading efficiency, and other metrics, as a function of the user's "patience" and key network parameters. In [65], an offloading system called *AMUSE* is proposed and it is shown that it can outperform the results obtained in [104] by using utility functions to make decisions about when to offload data.

Despite the detailed investigation regarding both on-the-spot and delayed offloading performance, most works focus on prior individual user interactions with the WiFi infrastructure to characterize offloading opportunities. Therefore, offloading is limited to a subset of APs known by users, which may not fully explore the potential of mobile data offloading if the entities managing the offloading process could leverage existing urban WiFi APs to offload. Furthermore, most studies consider indoor periods during the analysis. Even without dedicated offloading systems, indoor periods are naturally used for offloading, as users tend to be connected to WiFi networks in places where they spend a significant amount of time [63]. Consequently, it is crucial to assess offloading performance in situations where users are in transit, moving from one location to another, and relying on cellular networks as the default behavior.

Other works were proposed that study offloading while users are in transit [158, 31, 150]. However, they primarily focus on scenarios V2I, which often rely on dedicated infrastructures, such as RSUs (Road Side Units), to build vehicle connectivity and do not address the opportunistic use of commercial and residential connectivity provided by urban APs. Nevertheless, V2I works are predominantly concerned with vehicular mobility, leaving out scenarios where users are not in

vehicles, such as when walking.

To address these limitations, the work in this chapter aims to study the offloading of mobile data to WiFi networks when users are on the move in urban environments. To our knowledge, this is the first work to consider the impacts of different travel modes on offloading and to investigate the factors influencing the offloading process to provide insights for optimizing offloading capabilities.

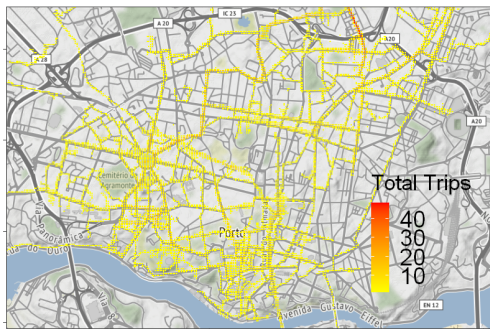
5.2 Mobility Trip Traces

As shown in Figure 5.1, two different data cleaning processes were applied to the raw mobility traces dataset presented in Section 3.1.1 during the pre-processing stage. First, the GPS error associated with the data samples was analyzed, and then a filter based on the GPS error and trip duration was applied to capture mobility traces with accurate location information. Therefore, only trips with a duration longer than 5 minutes and where at least 90% of the data samples have a GPS error smaller than 15m were considered. Due to the small number of bike and metro trips in the dataset (see Table 3.1), this filtering process was only applied to trips where the user was commuting by foot, bus, or car. The resulting dataset, presented in Figure 5.2, includes a total of 1049 trips from 45 different users where 379 are foot trips, 63 are bus trips and 607 are car trips.

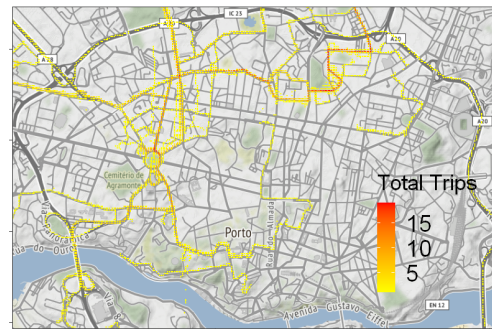
The distribution of the trips' duration, represented in Figure 5.3, shows that the trips' median duration is very similar between the different modes of travel – 14 minutes for the foot and car trips and 15 minutes for the bus trips. Figure 5.4 shows the radius of gyration of the trips, rg , given as:

$$rg = \sqrt{\frac{1}{n} \sum_{i=1}^n (l_i - l_{cm})^2} \quad (5.1)$$

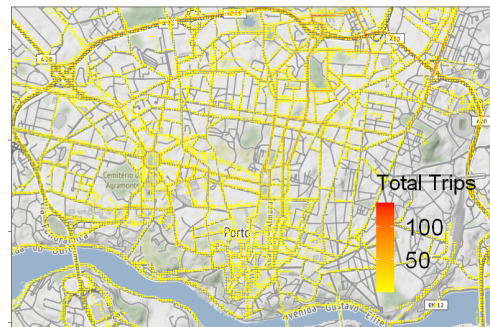
where l_i is the user's i -th location during the trip and l_{cm} is the trip center of mass given as $l_{cm} = \frac{1}{n} \sum_{i=1}^n l_i$. The parameter rg represents the typical range of the trips trajectories and, as shown, although trips from different travel modes share a similar duration, they present significant differences regarding rg . As expected, the foot trips present the lower rg values, with a median rg of 0.2 km. For the vehicle trips, car trips present almost the double of the median rg when compared to the bus trips – 0.9 km when compared to 0.51 km – as cars are usually preferred for traveling longer distances e.g. commuting from locations outside the city while buses are preferred for commuting inside the city.



(a) 379 foot trips.



(b) 63 bus trips.



(c) 607 car trips.

Figure 5.2: Heatmap of the resulting trips traces after the pre-processing stage.

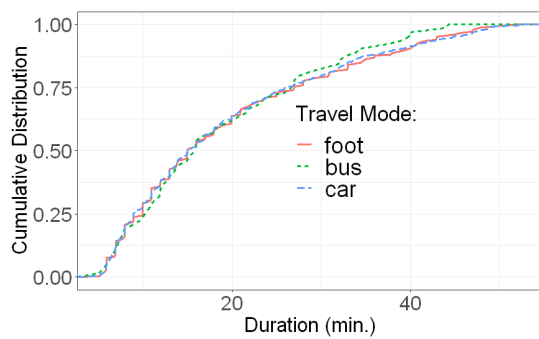


Figure 5.3: Duration of the trips.

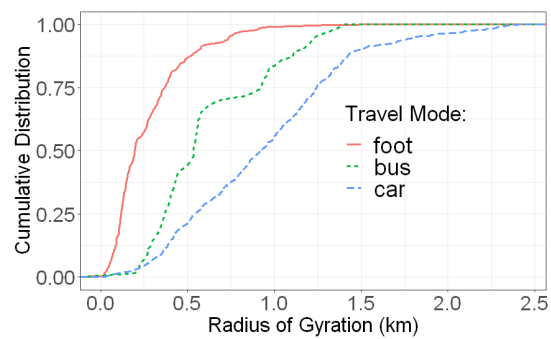


Figure 5.4: Radius of gyration of the trips.

5.3 Modeling WiFi Connectivity

To study the performance of offloading while users are on the move and using a urban WiFi infrastructure to offload, it is essential to model the WiFi connectivity experienced by users during their trips. In this section, a WiFi connectivity model is proposed that can model offloading opportunities as WiFi connections using the notion of spatial and time connectivity.

5.3.1 Offloading Opportunities

The WiFi connectivity of users while commuting is modeled by identifying possible offloading opportunities during a trip, which are then mapped to WiFi connections. The opportunities to offload O can be characterized by the set of APs to connect in each location during a trip.

Therefore, let c be a cell corresponding to a geographical area with 20x20m and $cells^{(u,T)}$ be the set of cells crossed by the user u during the trip T given by $cells^{(u,T)} = \{c_i, c_{i+1}, \dots, c_{i+n}\}$ where c_i is the identification of the i -th cell crossed during the trip. Then, let c_i^{wf} be the WiFi coverage information at the cell c_i defined as $c_i^{wf} = \{AP_1, AP_2, \dots, AP_n\}$, where AP_n is a tuple containing the APs identification, RSSI and the throughput at c_i .

Finally, let $f(c_i^{wf} | X)$ be a function that selects an AP to be connected at c_i given the information in c_i^{wf} and an AP selection criterion X , where:

$$f(c_i^{wf} | X) = \begin{cases} AP, & \text{if } c_i^{wf} \neq \emptyset \\ 0, & \text{otherwise} \end{cases} \quad (5.2)$$

Since the WiFi coverage dataset presented in Section 3.2 does not contain link-state information, just WiFi coverage data, the following assumptions are considered to define O , namely:

1. the information in c_i^{wf} is extracted from the WiFi coverage map dataset detailed in Section 3.2 and all APs can be used for offloading;
2. WiFi connection conditions, namely, RSSI and throughput, are the same in any geographical point inside a cell c ;
3. the throughput value of an AP is equal in all cells covered by that AP and constant throughout a connection's duration;
4. WiFi connections are uninterrupted while the user is inside the same cell, c_i , and the AP selection process is only triggered when a user moves to a new cell, c_{i+1} , with WiFi coverage.

With these assumptions, the opportunities to offload during a trip T for a user u can finally be defined as $O^{(u,T)} = \{f(c_i^{wf} | X)\}, \forall c_i \in \text{cells}^{(u,T)}$.

5.3.2 Spatial and Time Connectivity

To map the opportunities to offload to WiFi connections, the notion of spatial and time connections, $scon$ and $tcon$, respectively, is applied.

Figure 5.5 depicts the model more clearly. A spatial connection $scon$ is represented by a cell or a set of adjacent cells crossed by a user during a trip where the selected AP was the same. Thus, $scon$ can be defined as $scon = \{c_i, c_{i+1}, \dots, c_{i+n}\} \forall c_i \in \text{cells}^{(u,T)}$, where $f(c_i^{wf} | X) = f(c_{i+1}^{wf} | X)$ and $f(c_i | X) \neq 0$. The set of spatial connections for a trip T from a user u can then be defined as $S^{(u,T)} = \{scon_i, scon_{i+1}, scon_{i+n}\}$.

The time connection $tcon$ can be obtained by converting the spatial connection to the time domain. Here, each spatial connection $scon$ from $S^{(u,T)}$ is converted to its counterpart in the time domain using the user mobility information. Therefore, the set of connections in the time domain of a user u for a trip T can be defined as $T^{(u,T)} = \{tcon_i, tcon_{i+1}, tcon_{i+n}\}$, where $tcon_i$ is the total time in seconds that the user remained in the cells of $scon_i$ given by the difference between the timestamps when the user entered the first cell of $scon_i$ and left the last cell of $scon_i$.

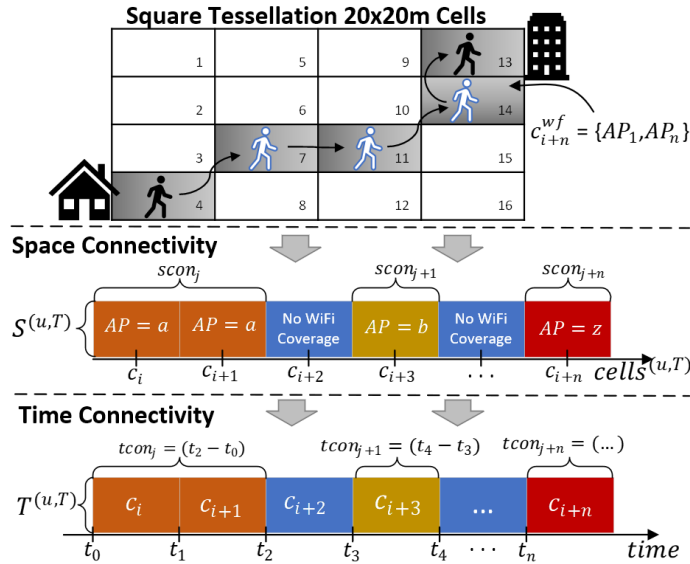


Figure 5.5: Overview of the connectivity modeling framework.

5.3.3 Connectivity Model

To model the users' connectivity during a trip, the connection and disconnection periods, as well as the offloading capacity of each connection, are computed.

The duration of a connection can be obtained from $tcon_i$ as $dur(tcon_i) = tcon_i - ls$, where ls is the link-setup time that refers to the time period required for a device to establish a connection with a new AP. During this period, processes such as network discovery, authentication, and association are performed and, as a consequence, data offloading via the WiFi network is not possible. A connection is only considered successful if $dur(tcon_i) > 0$.

Disconnection periods are time periods during which the mobile device was unable to connect to the WiFi infrastructure to offload. They can be computed as the time period between successful connections and can occur when the user is in a location without WiFi coverage, or the connection duration was not long enough to surpass the link-setup phase.

Finally, the offloading capacity of a connection represents the amount of data that can be offloaded through an AP. This value depends on the duration of the connection and the throughput of the AP and can be computed as $oc(tcon_i) = dur(tcon_i) * AP^{tx}$, where AP^{tx} is the throughput of the AP during the connection $tcon_i$.

5.4 Evaluating Offloading Performance

This section introduces the methodology adopted for examining mobile data offloading during users' commutes, where the objectives and approach guiding the analysis throughout this chapter are outlined. The offloading strategies under exploration are presented along with an overview of the trace-driven simulator developed to analyze these strategies.

5.4.1 Objectives and Approach

This work aims to inspect the offloading process under different WiFi conditions, traffic requirements, and offloading strategies. However, the extensive set of parameters within each of these settings and the inter-dependencies between them make evaluating offloading performance a non-trivial task. Therefore, the details regarding the objectives and approaches adopted to evaluate mobile data offloading in each management are presented next.

5.4.1.1 WiFi Conditions

The offloading opportunities during commuting are affected by the availability of APs belonging to the WiFi offloading infrastructure and their instant offloading capacity (throughput). The APs from the WiFi coverage dataset presented in Section 3.2 are considered as the WiFi offloading infrastructure, as they represent a real-world WiFi deployment in a urban area.

Regarding instant throughput of APs, it depends on several factors ranging from radio signal conditions to current load of AP, which contribute to variations in throughput from one AP to another. To evaluate how the throughput variability between APs can affect the offloading process, three scenarios of WiFi infrastructure are considered, namely: *low-variance* (LV), *medium-variance* (MV) and *high-variance* (HV). Each scenario is used to define the typical standard deviation found in the average throughput of APs from the WiFi offloading infrastructure. Therefore, random throughput values are extracted from a normal distribution with mean of 2 Mb/s, and standard deviation values of 0.2 Mb/s, 0.8 Mb/s and 1.5 Mb/s are used for the LV, MV and HV scenarios, respectively. While for an LV scenario the disparity in throughput between APs is minimal, in an HV scenario it reaches its maximum. By considering different throughput values for individual APs, it is possible to assess the impact of using throughput as an AP selection criterion and evaluate the offloading process under different networking conditions.

5.4.1.2 Mobile Data Traffic Profiles

The demands for mobile data traffic can vary considerably from one user to another, depending on the mobile applications they use and their usage habits. The goal of this work is not to evaluate the offloading performance for a specific set of applications. Instead, it focuses on investigating how the offloading process is influenced by mobile data traffic demands, especially in terms of their volume and delivery deadlines.

Regarding the volume of mobile data traffic, in this work, the traffic intensity is defined as a measure that quantifies the relationship between the amount of traffic generated by a mobile device and the offloading capacity of the WiFi infrastructure. Three different traffic intensity profiles are considered, namely: *low-intensity* (LI), *medium-intensity* (MI) and *high-intensity* (HI). In the LI profile, the volume of data generated by the mobile device is lower than the average throughput of APs, and, therefore, offloading is less challenging. On the other hand, with the HI profile, a mobile device generates more traffic that can be offloaded to an AP, making offloading more challenging. The traffic sources are modeled as a Poisson process with a mean inter-arrival time of 1 second, and the size of the data bundles is used to regulate the traffic intensity for the specific profile. Given

the **APs**' average offloading capacity of 2 Mb/s, traffic intensity is mapped to the different traffic throughput values of 1, 2 and 3MB/s that are used for the LI, MI and HI profiles, respectively.

Different applications may sustain different offloading deadlines that can be leveraged by offloading strategies during the offloading process, e.g., delaying data transmissions until a WiFi connection is available. This work aims to investigate the offloading process for on-the-spot and delayed offloading. Therefore, different offloading deadline values are considered during the analysis, ranging from 0 to 120 seconds.

5.4.1.3 Context Data

This work seeks to investigate the influence of using different context data during the offloading decision process. Different offloading strategies may use different sources of information to determine the most suitable **AP** for offloading. Therefore, context data is categorized into two sources: client-side and network-side, and crucial metrics that can be used during the **AP** selection process are identified.

The client-side information is user-specific reflecting user behaviors or data that can only be collected from the client's perspective. Therefore, **RSSI** and the duration of the connection are considered as client-side contextual data that can be used by the offloading strategies to choose the **AP** for offloading. **RSSI** is exclusively collectible from the client side and is the current default method for mobile devices to select the **AP** for connection. On the other hand, the typical time window for offloading provided to a user can be collected from the network-side, by inspecting the connection duration between the user and the **APs**. However, due to the limited coverage of WiFi **APs**, in a commuting scenario, the duration of a connection is mainly dependent on the mobility of the user. For this reason, the typical time window for offloading is considered as contextual data from the client-side. In this sense, the mobility patterns of a user can be used by decision models to predict the duration of future WiFi connections and make informed choices about the ideal **APs** for offloading.

While client-side information is related to the user, network-side information is related to WiFi offloading infrastructure. The estimated throughput of **APs** is considered the contextual data that offloading strategies can leverage when choosing **APs** to offload. The throughput value of an **AP** is considered to be accurately estimated and passed to decision models at the decision time, as these data can be easily provided by the WiFi infrastructure owner, taking into account the current load of **APs**.

Table 5.1: Offloading strategies summary.

Strategy Name	Design	Information Source	Context Data
rss-aware	Opportunistic	Client	RSSI
network-aware	Opportunistic	Network	Throughput
mobility-aware	Deterministic	Client	Connection Duration
oracle	Deterministic	Client+Network	Connect. Dur.+Throughput
OR-aware	Opportu.+Determi.	Client+Network	ORs+Throughput

5.4.2 Offloading Strategies

Different offloading strategies that use contextual data were developed to choose the most suitable APs for offloading during the trip of a user. These strategies, summarized in Table 5.1, may adopt an opportunistic or deterministic design in their decision-making processes.

5.4.2.1 Opportunistic Design

In the opportunistic design, the decision-making operates in a short-term greedy fashion, prioritizing immediate gains. The choice of AP to offload is made in real-time as the user travels, based on a specific AP selection criterion.

Two opportunistic offloading strategies were implemented, namely, the *rss-aware* and the *network-aware*. Algorithm 23 details the functioning of both strategies. While the *rss-aware* strategy considers the RSSI data from the client-side, the *network-aware* strategy takes into account the APs' throughput information coming from the network-side when choosing the AP for offloading.

The *rss-aware* strategy was designed to emulate the typical behavior of current mobile devices when choosing an AP to connect. As a result, the AP selection process is initiated each time a user moves to a new cell with WiFi coverage during a trip. If the user was not connected to an AP in the previous cell, the AP with the highest RSSI is selected to offload, otherwise, an hysteresis value of 5 dB is used to decide when handovers between APs should occur. Given its design, the offloading performance achieved using this strategy serves as the baseline to evaluate the performance of mobile data offloading systems.

Although there is a correlation between RSSI and throughput, relying solely on RSSI as an indicator of throughput is not sufficient. Factors such as instant load significantly impact the APs' throughput and are not captured by this client-side indicator. By employing the *network-aware* strategy, it is possible to study mobile data offloading when accurate network-side information,

namely, throughput, can be provided to decision models during the **AP** selection process. The functioning of the *network-aware* strategy is very similar to the *rssi-aware* strategy – the **AP** selection process is initiated each time a user moves to a new cell with WiFi coverage during a trip and the **AP** with the highest throughput is chosen for offloading. However, in contrast to the *rssi-aware* strategy, in the *network-aware* strategy there is no hysteresis value used to manage the handover process when the user changes cells – if **APs** with higher throughput are available, they will always be selected.

```

Input: The finite set  $cells^{(u,T)} = \{c_i, c_{i+1}, \dots, c_{i+n}\}$ 
Input: An hysteresis value  $H$ 
Input: An offloading strategy  $X$ : rssi-aware  $\vee$  network-aware
Output: The opportunities to offload  $O$  given as the set of APs to connect in each cell:
 $O^{(u,T)} = \{AP_{c_i}\}, \forall c_i \in cells^{(u,T)}$ 

/* Auxiliary Functions */
1 getRSSI( $c_i^{wf}, AP$ ) /* get the RSSI of AP in cell  $c_i^{wf}$  */
2 getAP( $c_i^{wf}, criterion$ ) /* get the AP from cell  $c_i^{wf}$  with the highest value for the
   criterion */
3 begin
4    $O = \{\}$ ;
5   for  $c_i$  in  $cells^{(u,T)}$  do
6     if  $c_i^{wf}$  is empty then
7       /* Cell has no WiFi coverage */
8        $AP_{c_i} \leftarrow 0$ ;
9     else
10      if  $X$  is rssi-aware then
11         $AP_{c_i} \leftarrow \text{getAP}(c_i^{wf}, rssi)$ ;
12        if  $AP_{c_{i-1}} \neq 0$  then
13          /* Previous cell had WiFi coverage */
14          if  $AP_{c_{i-1}}$  in  $c_i^{wf}$  then
15            /* AP selected in previous cell is present in this cell */
16            if  $\text{getRSSI}(c_i^{wf}, AP_{c_{i-1}}) + H \geq \text{getRSSI}(c_i^{wf}, AP_{c_i})$  then
17              /* Handover is not required */
18               $AP_{c_i} \leftarrow AP_{c_{i-1}}$ ;
19            end
20          end
21        else if  $X$  is network-aware then
22           $AP_{c_i} \leftarrow \text{getAP}(c_i^{wf}, throughput)$ ;
23        end
24       $O \leftarrow O \cup \{AP_{c_i}\}$ 
25    end
26  end
27 end

```

Algorithm 1: Opportunistic strategies algorithm

5.4.2.2 Deterministic Design

In contrast to opportunistic approaches, strategies that use a deterministic design do not rely on local, short-term decision-making, but instead strive for a globally optimal solution. They can leverage historical data to anticipate network and user behaviors and make choices that maximize a certain criterion. In this context, it is considered that deterministic strategies can precisely anticipate both the duration of connections and the throughput between the user and APs encountered during a trip. As a result, they perform the AP selection process offline, before the beginning of a trip, by choosing the optimal combination of APs that maximizes the amount of data offloaded.

In order to implement offloading strategies that adopt a deterministic design, the AP selection process is mapped to a graph, the edge weights are defined, and an algorithm for identifying the shortest path is then applied. Therefore, for each user u and trip T , the set of adjacent cells crossed by the user that provide contiguous WiFi coverage is selected as $wf^{(u,T)} = \{AdjCells_i^{wf}, AdjCells_{i+1}^{wf}, \dots, AdjCells_{i+n}^{wf}\}$, where $AdjCells_i = \{c_i^{wf}, c_{i+1}^{wf}, \dots, c_{i+n}^{wf}\}$. Then, for each $AdjCells$, a graph is constructed where the vertices correspond to APs within each cell c_i^{wf} . The edges of the graph represent the possible choices of APs to connect when the user moves to a new cell, as illustrated in Figure 5.6. The edge weight w_{uv} between two vertices, denoted u and v , is determined as the offloading capacity offered by the AP at vertex v and is calculated as follows:

$$w_{uv} = \begin{cases} 0, & \text{if } v \text{ is an end vertex} \\ (\Delta t(v) - l_{s_{uv}}) \cdot AP_v^{tx}, & \text{otherwise} \end{cases} \quad (5.3)$$

where $\Delta t(v)$ is the time spent by the user in the cell c_i for the vertex v , $l_{s_{uv}}$ is the link-setup cost associated with the handover, and AP_v^{tx} is the throughput for the AP at v . The link-setup cost is measured in seconds and will be zero if the AP at vertex u is the same as the AP at vertex v , as no handover is required, i.e., when the user enters a new cell with the same AP. Additionally, as detailed in Section 5.3.1, it is assumed that the throughput of an AP remains constant across all cells where that AP provides coverage.

Finally, in order to determine the combination of APs that maximizes the overall offload performance, the weights are converted to negative values and the Bellman-Ford [2] algorithm is used to find the shortest path.

Two different deterministic offloading strategies were implemented, namely the *mobility-aware* and the *oracle*. The *mobility-aware* strategy relies solely on connection duration data during the AP selection process. It does so by considering a fixed value of $AP_v^{tx} = 1$ in Equation 5.3, when calculating the edges' weights. Therefore, for each user's trip, the *mobility-aware* strategy selects

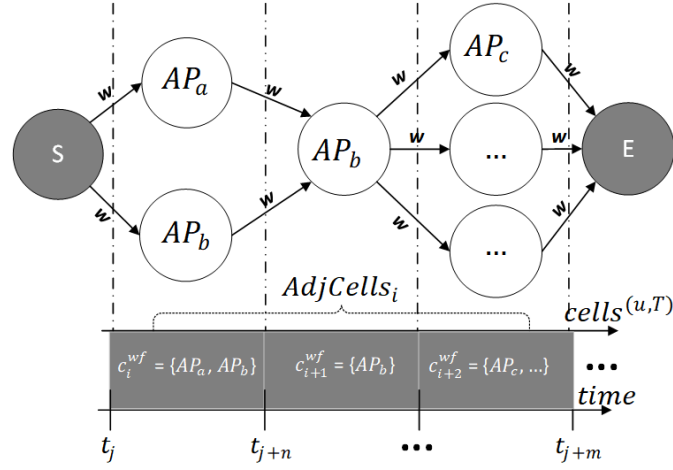


Figure 5.6: Graph mapping of the deterministic offloading strategies.

the set of **APs** that maximizes the total connectivity time, which is the cumulative time spent connected to the WiFi infrastructure.

In contrast, the *oracle* strategy takes into account both the connection duration and the throughput data in the **AP** selection process. For each user's trip, the *oracle* strategy selects the set of **APs** that maximizes the amount of data offloaded. Thus, the offloading performance achieved by the *oracle* strategy can be considered the upper-bound limit for the offloading performance of a given scenario.

5.4.3 Trace-driven Offloading Simulator

In order to study the different aspects of the offloading performance, a trace-driven offloading simulator was developed. This simulator is capable of evaluating the user mobility and emulating the offloading process given a set of simulation parameters. Figure 5.1 shows the architecture of the developed simulator that contains two main components, namely, the connectivity engine and the offloading manager.

5.4.3.1 Connectivity Engine

The *connectivity engine* component utilizes the WiFi modeling framework presented in Section 5.3 to determine the connectivity status for each second of a user's trip. It takes as input the user's mobility traces and the WiFi coverage map of the city, along with simulation parameters such as

link-setup time and the offloading strategy. The connectivity engine executes two main procedures during the simulation, namely, the selection of AP and the modeling of WiFi connectivity. During the AP selection process, a movement detection process is used to track the cells the user crosses during a trip and initiate the AP selection routine whenever the user moves to a new cell. Then, an AP is chosen from the available APs within the cell (c^{wf}) based on the selected offloading strategy, passed as a simulation parameter. The WiFi modeling framework presented in Section 5.3 is then applied to convert the offloading opportunities into WiFi connections, and the connectivity status is determined for each second of the user trip, which includes the following information:

- *Connecting WiFi*: the mobile device is in the link-setup stage trying to connect to an AP. During this process offloading is not possible;
- *WiFi*: the mobile device is connected to an AP and offloading is possible;
- *Cellular*: the mobile device is connected to the cellular network.

5.4.3.2 Offloading Engine

The *offloading engine* component is responsible for managing the offloading process and tracking the amount of data sent through the WiFi and cellular networks. It includes two major procedures, namely, the traffic generation and the offloading process.

The traffic generation procedure simulates traffic coming from mobile data applications to be offloaded during user commutes. Two main traffic parameters are used to control how traffic is being generated, namely: flow inter-arrival time and bundle size. The first parameter specifies the time interval between consecutive arriving bundles of data, while the second is used to control the bundles' size in bytes. By adjusting these two parameters, it is possible to create different traffic profiles in terms of volume and burstiness. A maximum deadline value is also defined for each bundle, representing the maximum amount of time that a bundle of data can be buffered before being transmitted. This deadline allows to assign a maximum time-to-leave that is evaluated during the offloading process.

During the offloading process, for each second of a user's trip, the offloading manager checks the user's connectivity status. If there is traffic to be sent, the data is sent to the respective network at the correspondent transmission rate, which is a simulation parameter. Furthermore, for each second, the offloading manager monitors the time-to-leave for data bundles. If the time-to-leave has elapsed, indicating that the data can no longer be delayed for transmission, data is sent via the cellular network.

5.5 Offloading Performance Evaluation

This section gives answers to the first question presented in the introduction of this chapter: How much can users offload while commuting? To answer this question, the *rssi-aware* offloading strategy is used to evaluate the on-the-spot and delayed offloading performance while users commute and use urban WiFi APs to offload. The *rssi-aware* strategy emulates the default offloading strategy employed by current mobile devices and therefore serves as the reference point of offloading performance.

5.5.1 Experimental Setup

The trace-driven simulator is used to evaluate the offloading performance of the *rssi-aware* strategy in different network conditions, namely LV, MV and HV. A link-setup time of 3 seconds is used as it is considered the time required to establish a WiFi connection [43]. Regarding the mobile data traffic, an MI traffic profile is used, ensuring that the traffic generated by mobile devices is similar to the average APs' throughput. This allows to focus the analysis on the impact of different network conditions and mobility profiles in the offloading process.

Finally, the performance of offloading is analyzed for one-the-spot and delayed offloading using offloading deadlines ranging from 0 to 120 seconds.

5.5.2 Offloading Efficiency

In this analysis, the offloading efficiency is used as the main metric to evaluate offloading performance as it is considered the fundamental parameter to evaluate any offloading strategy [125]. The offloading efficiency is computed on a trip basis as the ratio of data offloaded through the APs considering all the data traffic produced during the trip. Higher offload efficiency is desired as it represents less usage of the cellular network where more data is offloaded through the WiFi infrastructure.

5.5.2.1 On-the-spot Offloading

For the on-the-spot offloading, data traffic cannot sustain any delay (offloading deadline = 0 seconds) and must be transmitted immediately. This is the typical approach to the offloading of mobile data used in current mobile devices.

Figure 5.7 shows the offloading efficiency of trips for different travel modes. The results show that traveling on foot provides the best mobility profile for offloading. For on-the-spot offloading,

when commuting by foot, a median offloading efficiency of 50%, 46%, and 43% can be achieved for the scenarios LV, MV and HV, respectively.

When users commute in vehicles, the results show that buses provide better offloading opportunities than cars. When traveling by bus, users can offload a median of 42%, 39% and 36% of their data traffic for the LV, MV and HV scenarios, respectively. The high mobility associated with traveling by car makes offloading to WiFi [APs](#) more challenging. In 25% of the car trips, the efficiency of the offloading is below 21%, 19%, and 17% for the LV, MV and HV scenario, respectively. However, the results indicate that a significant portion of car trips can still achieve substantial offloading efficiency. For 40% of the car trips, the offloading efficiency varies between 35% to 46%, 32% to 42% and 30% to 40% for scenarios LV, MV and HV, respectively.

When analyzing the mobility of users in vehicles, Figure 5.8 shows that users spend a significant portion of the duration of trips moving at speeds below the typical walking speed (1.42m/s). In fact, users spend more than 51% and 40% of the duration of the trip moving at speeds lower than the walking speed for half of bus and car trips. This observation supports the offloading efficiency results obtained for car trips and suggests that there are chances of data offload even when users commute by car. Traffic-related events that force vehicles to slowdown, such as traffic jams, traffic lights, or crosswalks, can provide real opportunities for offloading if there is WiFi coverage in those areas.

When we compare our findings with the existing literature, some notable differences emerge. The study in [84] states that WiFi can offload 65% of the data traffic for the on-the-spot offloading. However, the analysis considers indoor periods where users spent a significant amount of time connected to the WiFi network. When considering only offloading while commuting, our results show that these values for offloading efficiency can only be approximated when users commute on foot in the LV scenario. As the throughput variability between [APs](#) increases from the LV to the HV scenario, there is a noticeable decrease of 7 percentage points in the median offloading efficiency. In the HV scenario, users have a higher probability of finding [APs](#) that are unable to offload all their traffic immediately, which in turn reduces the efficiency of offloading since in the on-the-spot offloading traffic transmissions cannot sustain delays.

When commuting by bus, [10] reported a 10% average offloading efficiency for the on-the-spot offloading. In our results, the average offloading efficiency when commuting by bus varies between 35–40% depending on the WiFi infrastructure scenario considered. The main reason for the higher offloading efficiency results in our scenario is due to the increased availability of [APs](#) in our dataset. However, it is widely recognized that WiFi coverage and [APs](#)' density in urban scenarios tend to increase [97], and therefore our results present a more up-to-date perspective of

the obtained offloading gains when users commute via public transports, such as buses.

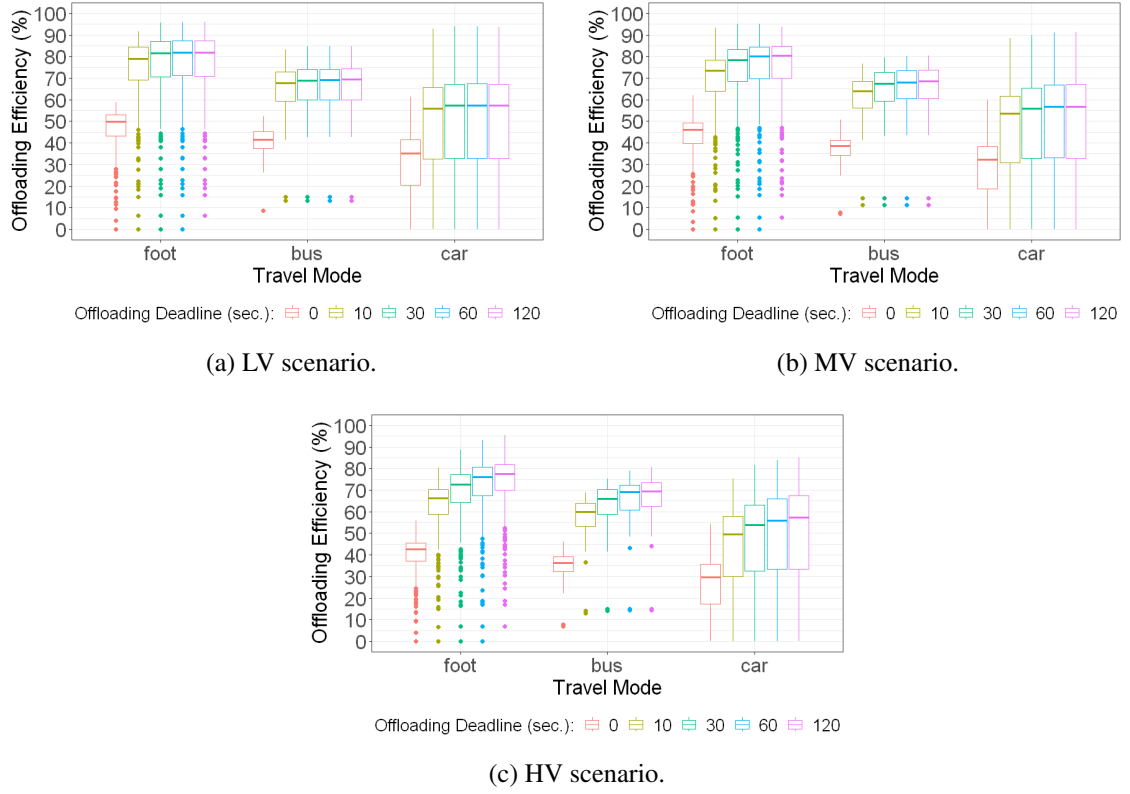


Figure 5.7: Trips' offloading efficiency for the *rssi-aware* offloading strategy.

5.5.2.2 Delayed Offloading

Delayed offloading is known to improve offloading performance as applications can defer data transmissions for a certain period of time while WiFi connectivity is not available [84].

Figure 5.7a shows that delaying data transmissions for just 10 seconds can increase the median offloading efficiency for the LV scenario by 29, 26, and 21 percentage points for foot, bus and car trips, respectively. These gains decrease by 2 to 6 percentage points for the scenarios MV (Figure 5.7b) and HV (Figure 5.7c), depending on the travel mode used. Furthermore, the results indicate that extended offloading deadlines beyond 10 seconds will only lead to substantial improvements in offloading efficiency when there is substantial throughput variability between APs, as depicted in Figure 5.7c. In these cases, improvements of 10, 9 and 7 percentage points

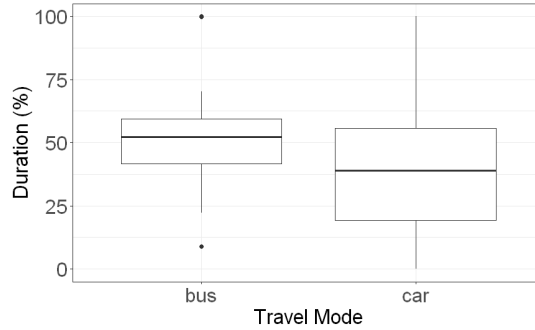


Figure 5.8: Proportion of the vehicular trips travelling under walking speed (1.42m/s).

can be seen in the median offloading efficiency for foot, bus, and car trips, respectively, when the offloading deadline increases from 10 to 60 seconds. However, beyond this point, no significant improvements in the efficiency of the offloading are observed.

To inspect the impact of the delay in offloading when using different traffic profiles, Figure 5.9 shows the efficiency of offloading for the LI, MI and HI traffic profiles. The MV scenario was considered with respect to the WiFi infrastructure as the main conclusions can be applied to the LV and HV scenarios. As the results in Figure 5.9 indicate, increasing the offloading deadline beyond 10 seconds will only bring considerable improvements to the offloading efficiency for the LI traffic profile. With the LI traffic profile, the volume of data generated by the mobile device is lower than the average AP throughput, and therefore, offloading is less challenging. Consequently, if the offloading process can be postponed until a WiFi connection is available, there is a high likelihood that users will be able to offload all buffered data. However, with increasing mobile data traffic intensity, MI and HI traffic profiles, the likelihood of this scenario to occur decreases, and therefore, for the MI and HI traffic profiles, offloading delays exceeding 10 seconds may result in diminished rewards.

When comparing our findings with the literature, the work in [84] reports significant gains from delayed offloading only if several minutes or even hours are considered for the offloading deadline. However, the work limits the offloading opportunities to the user's previous connected APs. This basically implies that users will only be able to offload in their PoIs which are locations where they spend a significant amount of time and have WiFi access. This is not the offloading scenario considered in the present work as users can use any AP from the urban WiFi infrastructure to offload while commuting. The results suggest that when offloading during commuting is implemented,

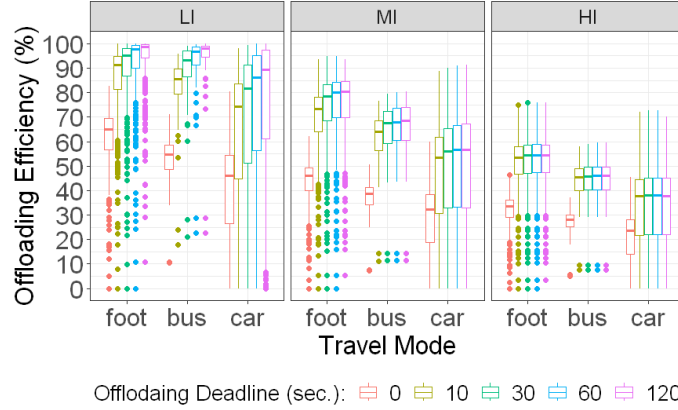


Figure 5.9: Offloading efficiency for the MV scenario using different traffic profiles.

data traffic no longer needs to support delayed offloading on the scale of several minutes, as even just 10 seconds can bring significant gains in offloading efficiency. However, attending to the trips' duration in the mobility trips dataset (Figure 5.3), if offloading during commutes was not possible and users were limited to offload at their destination, delays on the order of several minutes would also be required.

5.5.3 Offloading Connections

The offloading connectivity during commutes is analyzed by inspecting the connections and inter-connections periods. Since the *rssi-aware* strategy selects APs for offloading based on RSSI, it will always select the same APs independently of the WiFi scenarios used (LV, MV, or HV). Therefore, in this section, only the MV scenario is considered, as the results will be the same for the LV and HV scenarios.

The analysis starts by inspecting the duration of the successful WiFi connections. A successful connection has a duration longer than the link-setup time (3 seconds) and represents the time window available for offloading. Figure 5.10 shows the distribution of the duration of successful connections. As expected, different travel modes provide different time windows to offload. For foot trips, only 25% of the successful connections have a duration shorter than 8 seconds and 50% of the connections have a duration of 16–32 seconds, which provides a considerable time window for offloading. However, when traveling in vehicles, 25% of the duration of the connections is less than 2 seconds and 50% of the connections have a duration of 2–12 seconds for bus trips and 2–8

seconds for car trips. This reduced time window for offloading makes offloading while commuting in vehicles more challenging.

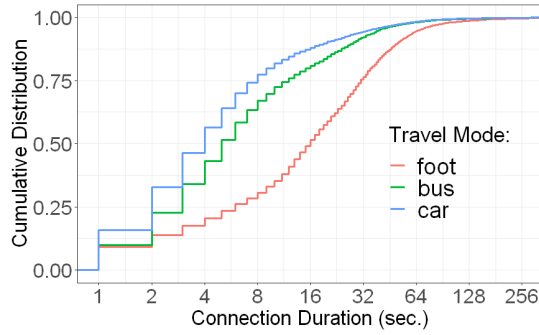


Figure 5.10: Trip's connection durations.

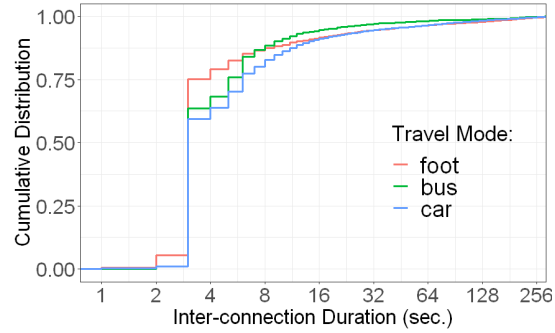


Figure 5.11: Trip's inter-connection durations.

The inter-connection duration is defined as the time period between two consecutive successful connections. During inter-connection periods, offloading through WiFi is not possible since a user is not connected to a WiFi AP. Figure 5.11 shows the duration of inter-connections for all trips showing that the majority of these periods are short – only 25% of the inter-connections have a duration higher than 4, 6 and 8 seconds for the foot, bus and car trips, respectively. These short inter-connection periods indicate that devices will not spend long periods without being able to offload. These results highlight the evidence shown in Section 5.5.2.2 where a 10 seconds delay tolerance can have a significant impact on offloading efficiency, as this duration is generally sufficient for most users to discover an alternative WiFi connection and initiate data offloading.

To understand the overall connectivity provided by successful connections, the connectivity time of a trip is computed as the percentage of time that a user is connected to the WiFi infrastructure during a trip. Figure 5.12 shows that while commuting, users can be connected to the WiFi infrastructure for a considerable portion of the duration of the trips, even when traveling in vehicles: a median connectivity time of 64%, 56% and 45% can be observed for foot, bus, and car trips, respectively.

5.6 The Influence of AP Selection Context on Offloading

In the previous section, offloading performance was analyzed considering the AP selection method of current mobile devices using the *rssi-aware* strategy. However, more sophisticated decision

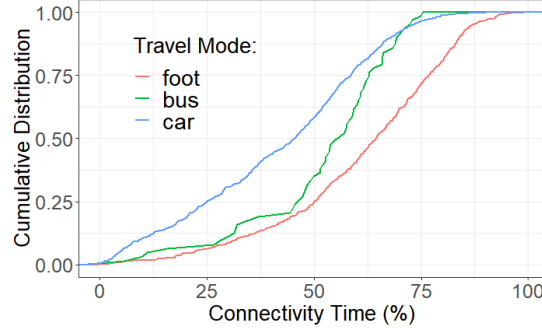


Figure 5.12: Trips' connectivity time.

models can use different context data during the decision process to improve offloading performance. This section seeks to provide answers to the second question presented in the Introduction to this chapter: Which fundamental aspect connects the amount of offloaded data? For this, the offloading process is analyzed when different context data from the client-side or the network connection throughput, AP selection.

5.6.1 Client-side Context

In the context of commuting scenarios, offloading connections tend to be short as shown in Section 5.5.3. By leveraging user's mobility, decision models can predict the duration of future connections between a user and the WiFi infrastructure and select the set of APs that maximize the time window for offloading. To assess the impact of using this client-side information on the offloading process, the *mobility-aware* strategy (Section 5.4.2.2) is evaluated for on-the-spot offloading. An experimental setup with a link-setup time of 3 seconds, an MI traffic profile and equal throughput for all AP is considered. In this scenario, data offloaded to the WiFi infrastructure is based solely on the duration of the offloading connections. Maximizing offloading performance is to maximize the connectivity time during a trip, which is the goal of the *mobility-aware* strategy. The *rssi-aware* strategy is used for the baseline comparison, since it does not consider the mobility of users during the offloading process, only RSSI of APs.

5.6.1.1 Inspecting Offloading Efficiency Impacts

Figure 5.13 depicts the offloading efficiency results for the *mobility-aware* and *rssi-aware* strategies and shows that the mobility of the user can be used to improve the efficiency of offloading, especially when users travel in vehicles. Compared to the *rssi-aware* strategy, the *mobility-aware*

strategy improves the median offloading efficiency per trip by 4, 6 and 8 percentage points for foot, bus and car trips, respectively. Given the equal throughput for all APs, the *mobility-aware* strategy improves offloading efficiency by extending the user's time window for offloading, enabling users to offload more data during a connection. This is observed in Figure 5.14 that shows the average connection duration of the trips for both strategies. As shown, the *mobility-aware* strategy can roughly double the average connection duration in a trip, compared to the *rsssi-aware* strategy. The median value for the trips' average connection duration for the *rsssi-aware* strategy is 20, 8 and 5 seconds for the foot, bus and car trips, respectively, while for the *mobility-aware* strategy is 43, 17 and 12 seconds. Longer time windows for offloading lead to a longer connectivity time provided to users while commuting. Figure 5.15a shows that the *mobility-aware* strategy increases the median connectivity time per trip by 8, 12 and 11 percentage points for foot, bus and car trips, respectively, compared to the *rsssi-aware* strategy.

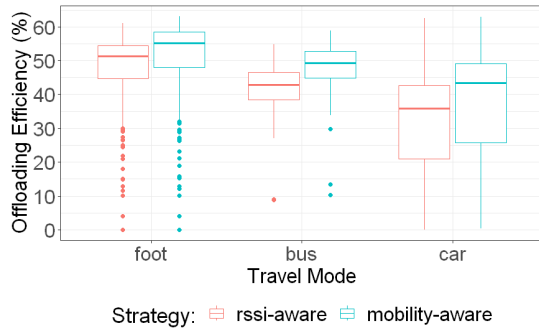


Figure 5.13: Trips' offloading efficiency for the *rsssi-aware* and *mobility-aware* strategies.

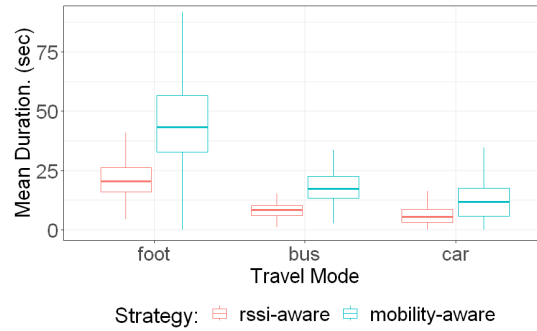


Figure 5.14: Trips' connection durations for the *rsssi-aware* and *mobility-aware* strategies.

5.6.1.2 Inspecting Connectivity Impacts

When inspecting how offloading connections are established and maintained during a trip, the results show that leveraging users' mobility during the AP selection process has two major impacts: i) it increases the probability of establishing a successful connection; and ii) it decreases the number of connection attempts during a trip.

Regarding the first impact, Figure 5.15b shows the connection success rate of the trips calculated as the percentage of connections that passed the link-setup stage (duration greater than 3 seconds). The *mobility-aware* strategy greatly improves the chance of establishing a successful WiFi

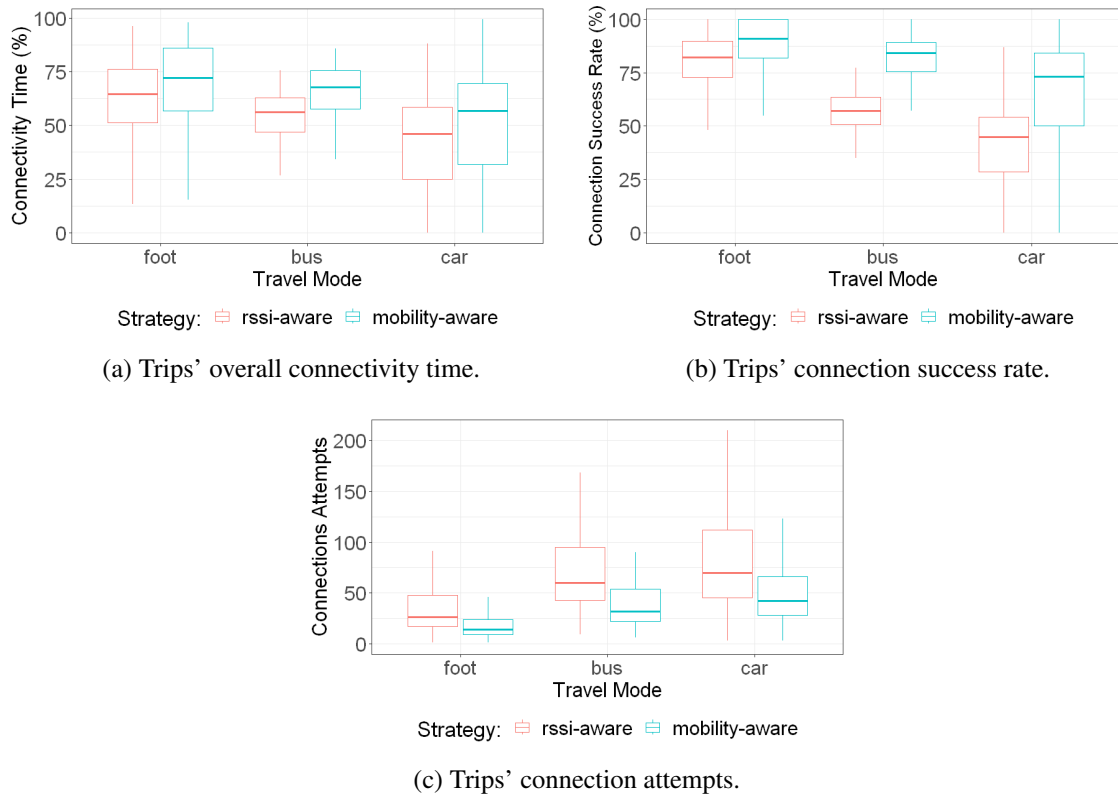


Figure 5.15: Connectivity performance for the *rssi-aware* and *mobility-aware* strategies.

connection compared to the *rss-aware* strategy, specially when the users are traveling in vehicles. Here, a median connection success rate of 84% and 73% can be achieved with the *mobility-aware* strategy for the bus and car trips, respectively. This corresponds to an increase of 27 and 28 percentage points in the median connection success rate compared to the *rss-aware* strategy. When traveling in vehicles, offloading connections are typically very short (see Figure 5.10) which leads to more connection failures compared to foot trips. However, by leveraging mobility information, mobile devices are much more likely to establish a successful offloading connection.

Regarding the second impact, Figure 5.15c shows that the *mobility-aware* strategy greatly reduces the number of connection attempts during a trip, as the devices remain longer periods connected to the same AP. The median number of connection attempts per trip for the *rss-aware* strategy is 26, 60 and 70 for foot, bus and car trips, respectively. However, for the *mobility-aware* strategy, these values decrease to 12, 32 and 42 for the foot, bus, and car trips, respectively – this represents a reduction of 46%, 46% and 40%, respectively. Switching from one AP to another will cause a disruption in the offloading process and time will be spent on the link-setup stage, during which offloading is not possible. Therefore, reducing connection attempts and consequent link-setup stages can increase the connectivity time and improve the overall offloading performance.

5.6.2 Network-side Context

The instant APs' throughput can be used by the offloading decision model to choose the best AP to offload. To inspect the impact of using this network-side information on the offloading process, the on-the-spot offloading process is analyzed using *network-aware* strategy for different WiFi scenarios using a link-setup time of 3 seconds and an MI traffic profile. The results of the *rss-aware* and the *oracle* strategies are considered for comparison. Both the *network-aware* and *rss-aware* strategies are opportunistic and choose the APs to offload in a short-term greedy fashion by making online decisions based on the AP selection criterion presented in Table 5.1. In contrast, the *oracle* strategy is deterministic and considers both the user's mobility and the APs' throughput during the AP selection process. As explained in Section 5.4.2.2, the results of the offload obtained using the *oracle* strategy represent the upper limit of the performance of the offload in a given scenario.

5.6.2.1 Inspecting Offloading Efficiency Impacts

Figure 5.16 shows the results of the efficiency of offloading for the different strategies. As shown, the *network-aware* strategy can considerably outperform the *rss-aware* strategy, specially when

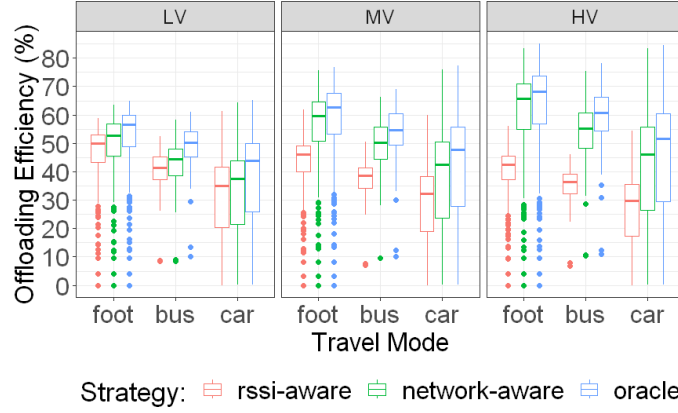


Figure 5.16: Trips' offloading efficiency for the *rssi-aware*, *network-aware* and *oracle* strategies.

the throughput variability among the APs is high (HV scenario). In the HV scenario, the use of network data during the AP selection process can improve the median performance of the offload efficiency by 23, 19 and 16 percentage points for foot, bus and car trips, respectively, compared to the *rssi-aware*. The *rssi-aware* strategy chooses the APs with the highest RSSI in a cell, even if it results in lower throughput, for example APs experiencing heavy loads could face challenges in delivering higher throughputs. In contrast, the *network-aware* strategy adjusts its decision-making to the current WiFi infrastructure offloading capacity by selecting the APs with higher throughput as the user moves to a new cell. This adaptability leads to higher offloading efficiency, especially in the HV scenario, where the throughput difference between APs is higher.

The results also show that the *network aware* strategy can really approximate the upper limit for the efficiency of offloading, especially for foot trips: the median efficiency of offloading for the *network aware* strategy is just approximately 2, 5 and 5 percentage points lower than what is achieved with the *oracle* strategy for foot, bus, and car trips, respectively. When traveling at lower speeds, such as by foot, offloading connections are typically longer, as shown in Figure 5.13. In these situations, using mobility data to extend the time window to offload has less noticeable performance improvements compared to vehicle trips. As a result, the performance gap between the *network-aware* and *oracle* strategies is minimal on foot trips.

5.6.2.2 Inspecting Connectivity Impacts

Contrarily to the *mobility-aware* strategy, the *network-aware* strategy does not increase offloading efficiency by increasing overall connectivity time. Figure 5.17a shows that the *network-aware* strategy slightly decreases the median connectivity time by approximately 2 and 10 percentage points compared to the *rssi-aware* and *oracle* strategies, respectively, for all travel modes and WiFi scenarios.

By analyzing the variance in the median number of connections attempts per trip in Figure 5.17b, it can be seen that, the *network-aware* strategy can, approximately, cause up to 23 and 73 more connections attempts during a trip compared to the *rssi-aware* and *oracle* strategies, depending on the travel mode and WiFi scenario considered. The higher frequency of connection attempts ultimately results in slightly shorter time windows to offload, as can be observed in Figure 5.17c. Furthermore, Figure 5.17c also shows that this impact is higher when users travel by foot, where the median value of the average duration of the connection can decrease by 3 seconds compared to the *rssi-aware* strategy and 10–17 seconds compared to the *oracle* strategy, depending on the WiFi scenario used.

When using the *rssi-aware* strategy, mobile devices establish a new connection only under two conditions: i) the user experiences a loss of WiFi coverage; or ii) there is another AP in the range with a significantly higher RSSI (see Algorithm 23). This approach favors the preservation of existing WiFi connections, minimizing the occurrence of new connection attempts, and consequently, reducing the number of link-setup stages. The same behavior is adopted by the *oracle* strategy, where an handover between APs is performed only if it means an increase in the data offloaded with the new connection. In contrast, the *network-aware* strategy always attempts to connect to AP offering the best throughput, independently of the previously connected AP. This aggressive pursuit for APs with superior offloading capacity leads to a decrease in overall connectivity time due to an increased number of connection attempts, causing shorter time windows for offloading.

Figure 5.18 shows the average connection throughput for trips in the different WiFi scenarios. As the variability in connection throughput between APs increases (from LV to HV), so does the disparity in connection speed between the *network-aware* and *rssi-aware* strategies – *network-aware* can provide an average connection throughput that is approximately twice what *rssi-aware* can achieve in the HV scenario. Compared to the *oracle* strategy, the connections' throughput for the *network-aware* strategy are still superior presenting more 250–750 kB/s on the median value of the average connections' throughput, depending on the travel mode and WiFi scenario considered.

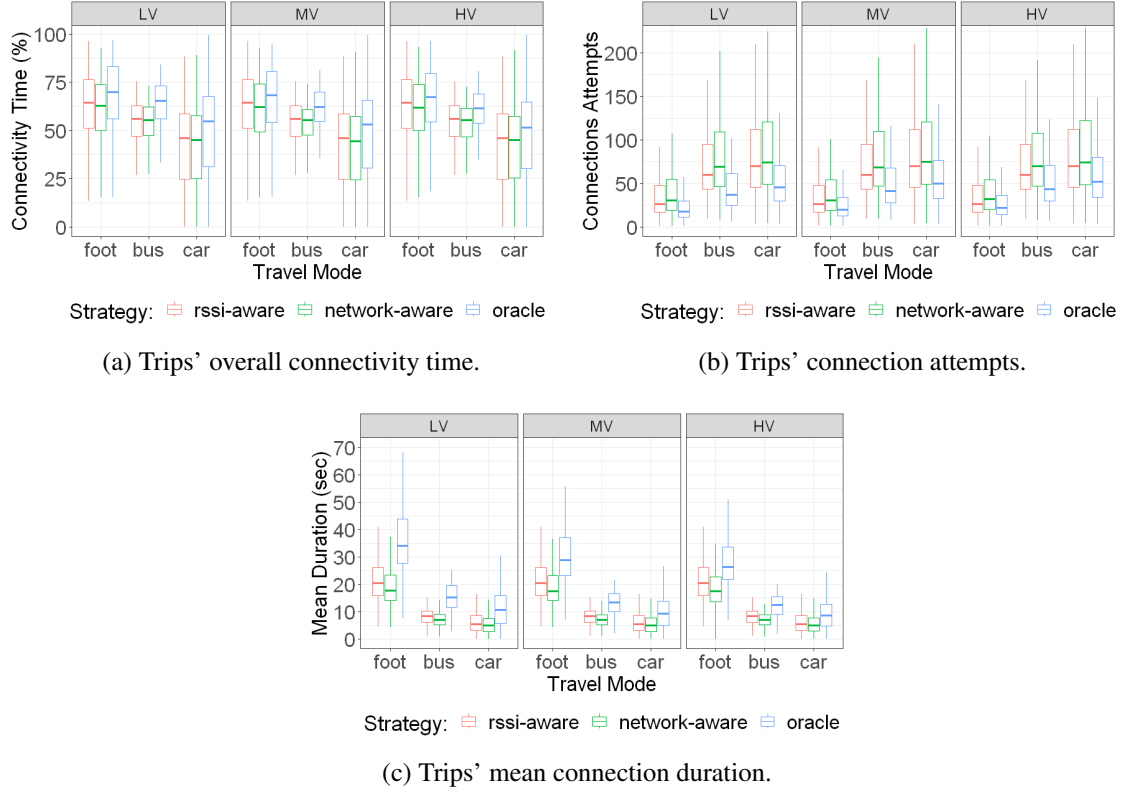


Figure 5.17: Connectivity performance for the *rssi-aware*, *network-aware* and *oracle* strategies.

5.6.3 Offloading Implications from AP Selection Context

Although mobility information can in fact improve offloading efficiency through increased connectivity time, it is important to note that the results provided by the implemented *mobility-aware* strategy represent the upper-bound for offloading performance in the tested scenario. The *mobility-aware* strategy considers that user mobility can be accurately predicted at any given time during a trip and selects the APs to be used for offloading based on this assumption. However, as shown in Chapter 4, predicting mobility in an offloading scenario is a challenging task. Therefore, offloading strategies that aim to increase the efficiency gains of offloading by selecting APs that provide longer time windows to offload, will need to rely on accurate mobility prediction models, otherwise, offloading efficiency gains will be marginal.

From a connectivity point of view, using mobility information during AP selection has a major impact on the offloading process. Choosing APs that maximize the time window to offload

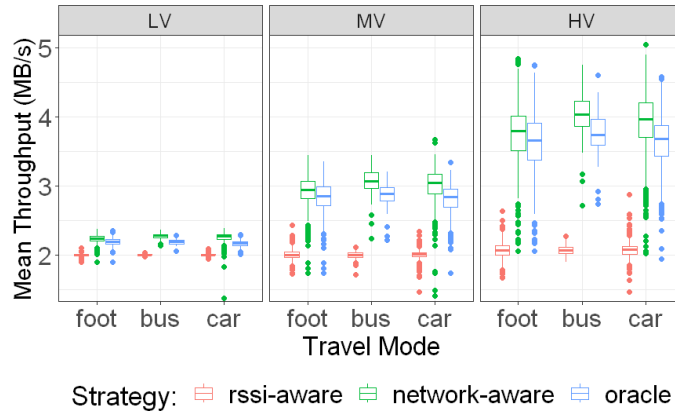


Figure 5.18: Trips' connections speed for the *rssi-aware* and *network-aware* strategies.

allows a reduction in the frequency of connection attempts and significantly increases the duration of offloading connections. Longer connections can benefit strategies that require bidirectional communication to manage the offloading process, since they have more time to exchange metadata.

When accurate network data is used during the *AP* selection process, the results show that being able to estimate the *APs*' throughput is more important than estimating the duration of their connectivity periods. By selecting *APs* that have higher throughput, the results show that the offloading systems can approximate the upper-bound for offloading, especially when users commute by foot.

Having highly accurate estimations regarding the *APs*' throughput using prediction-based methods [112, 18] is a challenging task. However, if the offloading process is managed by a third-party that has access to the WiFi infrastructure, such as an *ISP*, this data can be easily obtained. In this case, the entity managing the offloading process can have accurate estimations of the *APs* instant load and provide this information in real-time to the offloading decision models during the *AP* selection process. In this scenario, the challenge becomes: How to manage a large WiFi infrastructure at a city scale in order to have accurate network data in real-time? In Section 5.7.2, it is explored how mobility data can be used to facilitate this task.

Contrary to what happens with the *mobility-aware* strategy, the *network-aware* strategy tends to cause shorter time windows to offload as switching to a fast connection is always preferred. This may pose challenges to applications that struggle with short connection periods. For instance, applications that use *TCP* and have to cope with the *TCP* slow-start mechanism may not reach their

maximum offload transmission rates. Additionally, applications that undergo a long handshaking phase that must be performed before offloading starts may not be able to offload at all. Therefore, it is crucial to consider the requirements of the offloading solution when designing a strategy that can incorporate both mobility and network data during the AP selection process to ensure maximum offloading gains.

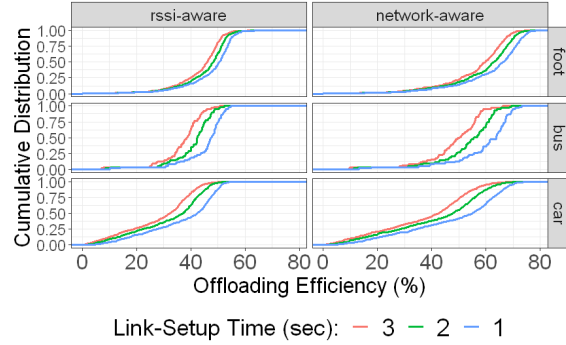
5.7 Exploring Augmentation of Offloading Capabilities

This section provides answers to the third and last research question tackled in this chapter: How can offloading be improved? Different approaches to the offloading process are explored in order to provide insight into designing a mobile data offloading system capable of maximizing offloading performance while users are in transit.

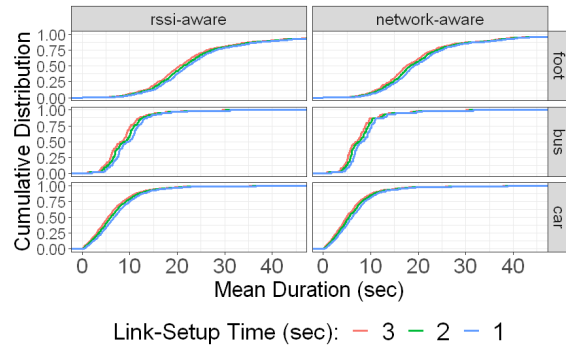
5.7.1 Connect More Quickly

Throughout the analysis presented in this chapter, a fixed link-setup time of 3 seconds was considered, as this value has been identified as the typical time required to establish a WiFi connection [43]. However, the question remains: What would be the impact on the offloading performance if the link-setup time could be reduced? To answer this question, the offloading performance is evaluated for the *rss-aware* and the *network-aware* strategies using different values for the link-setup time, ranging from 3 to 1 second. An MI traffic profile and an MV WiFi scenario are considered for the experimental setup.

Figure 5.19a presents the efficiency of the offloading of trips for both strategies, and the results show that decreasing the link-setup time will offer increased benefits, especially when users travel in vehicles. In these cases, reducing the link-setup time from 3 to 1 second can improve the median efficiency of offloading by 9 and 13 percentage points for bus trips and 10 and 12 percentage points for car trips for the *rss-aware* and the *network-aware* strategies, respectively. For foot trips, reducing the link-setup time will cause marginal improvements in the offloading efficiency – 4 and 6 percentage points for the *rss-aware* and *network-aware* strategies, respectively. As discussed in Section 5.5.3, when users travel in vehicles, the offloading connections are typically shorter, and therefore, reducing the link-setup time will have more impact on the time window for offloading when compared to foot trips, where the connections' duration are typically longer. In addition, the results show that the *network-aware* strategy tends to benefit more from reducing the link-setup time. As discussed in Section 5.6.2.2, the *network-aware* strategy tends to increase the number of



(a) Trips' offloading efficiency.



(b) Trips' mean connection duration.

Figure 5.19: Link-setup impact on the offloading performance for the *rssi-aware* and *network-aware* strategies.

connection attempts during a trip compared to the *rssi-aware* strategy. An increase in connection attempts leads to a longer duration spent on the link-setup process. Consequently, strategies that result in more connection attempts are expected to be more significantly impacted by reducing the link-setup time.

The mean duration of connection of the trips, represented in Figure 5.19b, shows that reducing the link-setup time has a proportional impact on the duration of the connection. This is visible by the similar spacing between the three distributions regardless of the offloading strategy and the travel mode used. Therefore, unless it becomes possible to completely eliminate the link-setup, the time window for offloading will continue to be proportionally affected by the reduction of the link-setup time. In this case, if the link-setup time is reduced by one second, for instance from 3 to 2 seconds, a corresponding increase in the average connection time of approximately 1 second can be anticipated.

5.7.2 Capitalize on Human Mobility

One of the biggest challenges of an offloading system is managing the offloading process. As shown in Section 5.6.2, accurate network information used during the AP selection process can significantly improve offloading efficiency. However, considering that the WiFi infrastructure on a city scale can have thousands of APs, providing this information to mobile devices in real-time is a non-trivial task.

Therefore, it is proposed that the offloading systems should rely on a divide-and-conquer approach, where the offloading process targets a subset of APs at specific locations visited by a user during a trip. This not only makes the offloading process easier to manage, but also allows more evolved offloading strategies to be used to maximize offloading gains. The next sections describe how users' mobility can be leveraged towards this purpose.

5.7.2.1 Managing Offloading Sites

It is proposed that users' mobility data can be leveraged to identify offloading sites in advance where preparatory measures can be deployed anticipating the user's arrival to these locations, with the goal of reducing link-setup time.

In Chapter 4, a methodology is proposed and evaluated that is able to identify ORs from individual mobility traces as areas where the user presents a mobility suitable for offloading. OLCs are identified by applying space and time constraints to the mobility of users using space and time thresholds, S_{thresh} and T_{thresh} respectively. The S_{thresh} represents the maximum distance between two locations that can be considered to be in the same offloading opportunity and should reflect the coverage of the technologies used. On the other hand, T_{thresh} defines the minimum time that a user must spend in a geographical area defined by S_{thresh} to be able to take advantage of offloading. An unsupervised learning technique is then used to aggregate OLCs to form ORs that the offloading systems can use during the offloading process.

Therefore, ORs are extracted from the users' mobility traces dataset (Section 5.2) using a $S_{thresh} = 44m$ and a $T_{thresh} = 5sec$. As an illustrative example, Figure 5.20 shows the ORs extracted from a user.

5.7.2.2 OR-aware Strategy

The goal is to explore the scenario where ORs can be managed by the entity coordinating the offloading process, e.g. ISP, and preparatory measures can be deployed anticipating the users

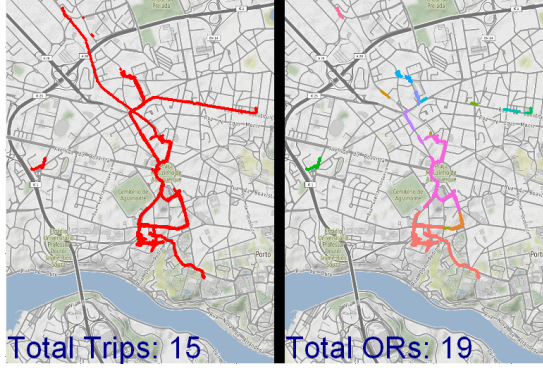


Figure 5.20: **ORs** extracted from the mobility traces of a user.

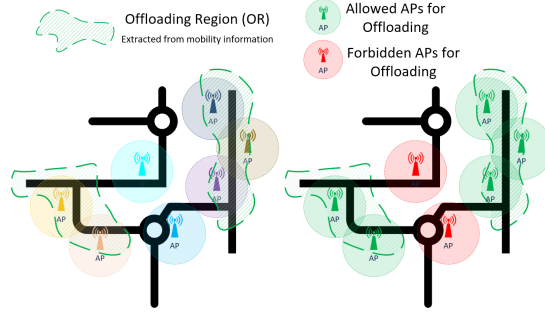


Figure 5.21: Illustration of the *OR-aware* strategy.

arrival. These measures can allow to: i) assist the **AP** selection process by providing real-time and accurate information regarding the **APs**' throughput inside an **OR**; and ii) eliminate the handover cost between **APs** in the same **OR**. Several works have been proposed that try to improve or even eliminate the handover costs in WiFi networks [37, 119, 161] that can be used in **OR** to provide seamless connectivity between **APs**.

Taking into account the scenario introduced above, a strategy named *OR-aware* was developed. This strategy explores both opportunistic and deterministic methods during the **AP** selection process (see Table 5.1). Therefore, as illustrated in Figure 5.21, the **ORs** extracted from the user mobility traces are used to identify the **APs** eligible for offloading during the user's commutes. **APs** located outside of these **ORs** are not considered for offloading. Then, when inside an **ORs**, the **AP** selection process is performed opportunistically, by selecting the **AP** that presents the highest throughput inside a cell, similar to what happens with the *network-aware* strategy.

Lastly, it is considered that handovers between the **APs** within the same **OR** are soft-handovers. In this case, only the connection to the first **AP** within a **OR** incurs a link-setup time of 3 seconds. After that, no additional cost is associated with the handover process between **APs** within the same **OR**, where the link-setup time is reduced to 0 seconds.

5.7.3 Exploring Offloading Performance Capabilities

The *OR-aware* strategy was evaluated for the LV, MV, and HV scenarios using the MI traffic profile. The *network-aware* and *oracle* strategies are used for comparison. It is important to note that, when using the *network-aware* or the *oracle* strategies, offloading is allowed for any encountered

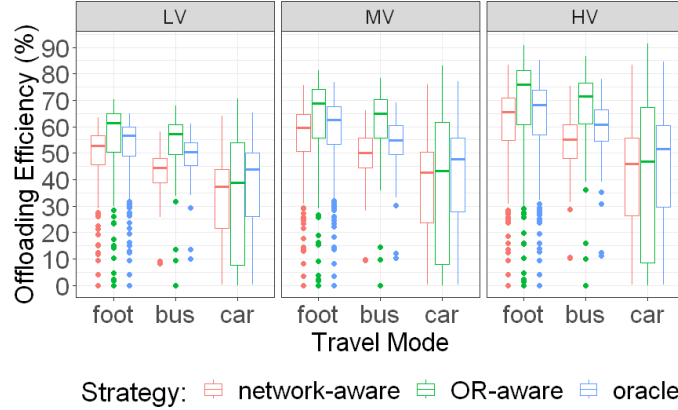


Figure 5.22: Offloading efficiency when using the ORs.

AP during a user's commute, with a link-setup cost of 3 seconds for new connections. On the other hand, for the *OR-aware* strategy, offloading is only allowed in APs that are within the user's OR but soft-handovers are considered between APs that belong to the same OR, resulting in a link-setup cost of 0 seconds between these APs.

5.7.3.1 Augmenting Offloading Efficiency

Figure 5.22 presents the offloading efficiency results for the different strategies and shows that the *OR-aware* strategy has the potential to greatly improve the efficiency of loading, especially for trips by foot and bus. Moreover, these gains are similar across multiple WiFi infrastructure scenarios, LV, MV and HV. When compared to the oracle strategy, the *OR-aware* strategy can increase the efficiency of offloading by 4 and 7 percentage points for foot and bus trips, respectively, in the LV scenario – these values increase by 3 percentage points in the HV scenario. These results indicate that even when the offloading is restricted to a subset of APs, eliminating the handover cost for these APs not only improves the efficiency of offloading during foot and bus trips, but can also exceed the efficiency of the offloading achieved by the *oracle* strategy (that considers all APs during the offloading, but with a link-setup cost of 3 seconds).

When inspecting car trips, it is shown that using the *OR-aware* strategy leads to a large variability in the offloading efficiency results. An average difference of approximately 57% percentage points can be observed between the first and third quartiles of the distribution for all scenarios of the WiFi infrastructure, which is significantly higher than the approximately 30% obtained in the other strategies. This suggests that the outcome of using the ORs will differ depending on the

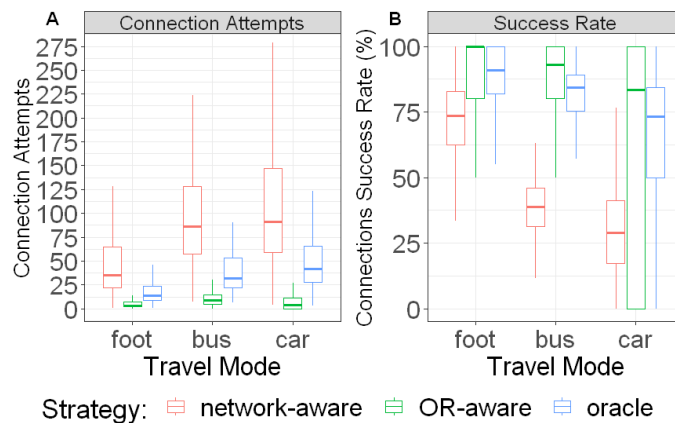


Figure 5.23: Trips' connection attempts (A) vs connections' success rate (B).

particularities of each trip. However, for a non-negligible portion of trips, approximately 27%, the *OR-aware* strategy outperformed the *oracle* strategy indicating that further analysis of the user mobility patterns is required to identify the type of trips that can benefit from the usage of ORs when users commute by car.

5.7.3.2 Optimizing Offloading Operations

In a standard offloading connection, mobile devices must scan their surroundings, choose an AP, and follow the authentication and association procedures to establish a connection to offload data. Each of these actions has a non-negligible energy cost in the mobile device which can potentially impact the feasibility and adoption of an offloading strategy. Therefore, offloading systems should not only try to minimize the number of connection attempts but also maximize the connections' success rate in order to reduce the energy burden caused by the offloading process.

Figure 5.23 shows the connection attempts of the trips and the connection success rate for the different strategies. When all APs encountered during a trip can be used for offloading, the *network-aware* strategy presents a median of 35, 86 and 91 connection attempts per trip for foot, bus, and car trips with a respective median success rate of 73%, 39% and 29%. With the *oracle* strategy, that combines mobility and network information to select the best AP to offload, the number of connection attempts could ultimately be reduced to a median of 14, 32 and 42 for foot, bus and car trips, and the respective median success rate of connections increased to 90%, 84% and 73%. However, with the *OR-aware* strategy, the results show that the median number of connections

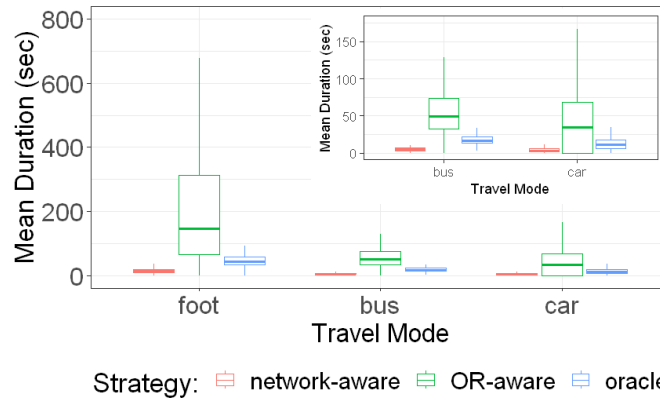


Figure 5.24: Trips' connections duration for the when using the ORs.

attempts can be reduced to 3, 10 and 6 for foot, bus and car trips, and the respective median connections' success rate increased to 100%, 92% and 82%. This corresponds to a reduction of approximately 5, 3 and 7 times in the number of connection attempts for foot, bus, and car trips, respectively, compared to the *oracle* strategy.

Therefore, as the results suggest, besides improving the offloading efficiency, the *OR-aware* strategy is also capable of significantly reducing the cost of the offload operations. These findings clearly demonstrate that restricting offloading to areas where the user exhibits suitable mobility for offloading, and taking preemptive measures to eliminate handover costs can significantly enhance the efficiency of the offloading process, making it more appealing for user adoption.

5.7.3.3 Maximizing Offloading Time Window

Once a successful offloading connection is established, mobile devices can start to offload data. Some applications may struggle with short-time windows to offload depending on how the offloading protocols are implemented. Therefore, maximizing the time window for offloading is crucial to ensure that applications can reach their maximum offloading capability.

Figure 5.24 shows the average connection duration of the trips for the different offloading strategies. It shows that the *OR-aware* strategy can provide an average connection duration of 197, 55 and 36 seconds for more than 50% of foot, bus, and car trips, respectively. This corresponds to a time window that is 4 times longer for foot trips and 3 times longer for bus and car trips, compared to what can be achieved with the *oracle* strategy. By allowing seamless handovers between APs

within the same [OR](#), an offloading connection can be maintained while the user is moving and has WiFi coverage. This results in great improvements in the time windows for offloading that can be used by mobile applications during the offloading process.

5.8 Concluding Remarks

In this chapter, the effectiveness of redirecting mobile data traffic through urban WiFi [APs](#) while users commute was extensively analyzed. A framework for modeling WiFi connectivity was proposed, coupled with a trace-driven simulator and various offload strategies, to evaluate the mobile data offloading process in different scenarios.

The expected offloading performance achieved by users while commuting was explored, examining both on-the-spot and delayed offloading process. The results indicate that foot commutes offer the best offloading opportunities with a median offloading efficiency of 50% and even when commuting by car, a median offloading efficiency of 35% can still be achieved. Delaying transmissions by just 10 seconds increases offloading efficiency by 21–28 percentage points, but waiting over 60 seconds does not yield significant gains. The results also show that users typically spent less than 3 seconds waiting for an opportunity to offload, but, unless commuting by foot, the time window for offloading is typically short, 4 to 7 seconds.

The offloading process was investigated when different context information is used during the [AP](#) selection process. The mobility of users and [APs](#)' throughput were considered as client-side and network-side data, respectively, that can be leveraged by decision models to choose the best [AP](#) to offload. Mobility information was used to estimate the duration of each possible offloading connection during a user's trip. The results show that choosing [APs](#) that maximize the time window to offload will only improve the offloading efficiency if decision-making can rely on accurate mobility prediction models, otherwise, the offloading efficiency gains will be marginal. However, from the perspective of connectivity, the results show that using mobility information during decision making can double the time window to offload and decrease connection attempts in 40–46%.

When using network-side data during the [AP](#) selection process, the results suggest that choosing the [APs](#) with higher throughput allows the offloading efficiency to approximate the upper-bound performance, especially when users commute on foot. An overall increase of 16–23 percentage points can be obtained compared to the current [AP](#) selection process in mobile devices (based on [RSSI](#)) depending on the travel mode considered, although users can experience shorter time windows to offload.

Diverse approaches to the mobile data offloading process were investigated to provide insights on designing an offloading system that targets scenarios where users are on the move. The impact of reducing handover cost was analyzed and revealed that unless it becomes possible to completely eliminate the handover cost, the time window for offloading will consistently be proportionally influenced by the reduction in link-setup time.

Finally, a solution was proposed and evaluated that uses [ORs](#) with soft-handovers between [APs](#). The findings suggest that these sort of strategies have the potential to greatly improve the overall offloading performance as results show that they can surpass the upper-bound for the median offloading efficiency in 5–7, 7–10 and 7–9 percentage points while reducing the number of connection attempts in 5, 3 and 7 times for foot, bus, and car commutes, respectively.

Chapter 6

Conclusion and Outlook

This concluding chapter provides an overview of the research conducted in this thesis. It summarizes the main conclusions and findings of this work, discusses its limitations, and highlights key areas for future research. Finally, it offers concluding remarks by addressing the overall contributions of this thesis.

6.1 Thesis Summary

In this thesis, a thorough examination is conducted on the subject of offloading mobile data using urban WiFi [APs](#). Crowdsensed data, collected from more than 400 participants using smartphones as probes, was used to study mobile data offloading opportunities provided to users in transit. Smartphones collected [GPS](#) and passive WiFi information while users were traveling in the city of Porto, Portugal. The information collected was used to build two main datasets explored in this work, namely, a mobility traces dataset and a WiFi coverage dataset. The mobility traces dataset has three unique features: i) high temporal resolution of positioning data of 1Hz; ii) mobility traces corresponding to trips where the beginning and the ending of a trip are annotated; and iii) identification of the transportation mode used during a trip. Regarding the WiFi coverage dataset, the imprecision in crowdsensed WiFi data was addressed, both in terms of geo-referencing and reliability of WiFi signal indicators. The result was a dataset containing high-quality data on WiFi coverage information from more than 14k open [APs](#). Both datasets will be made public to the research community as a contribution of this thesis.

In this work, the various facets of mobile data offloading were investigated through a comprehensive analysis of the offloading infrastructure, offloading mobility, and offloading decision.

Urban WiFi Infrastructure Characterization for Offloading

A detailed characterization of an urban WiFi offloading infrastructure was performed by inspecting the attributes that can characterize APs as possible offloading surrogates. Different attributes capable of characterizing the quality and availability of an AP for offloading were defined. Then, unsupervised learning was used to identify and analyze the relevant APs' attributes that can lead to a better understanding of the offloading network infrastructure. The results show that RSSI is not a good attribute to characterize APs. Consequently, special attention should be given to interference factors, such as ACI and CCI. Concerning contact window attributes, the results show that probe heterogeneity is not a key factor in characterizing the contact window, as APs that can provide longer contact duration can be identified based uniquely on their spatial coverage, which can be determined based on the number of cells crossed during contact. This knowledge allows to decrease both the time and effort during the data gathering process for the characterization, as this metric is not probe-dependent.

Concerning contact opportunities, the results on the contact rate attribute show that strategies relying on multiple contacts between a user and an AP would only be effective when applied to a subset of APs, as most users usually have one contact per day with the same AP. In addition, the popularity attribute can be used by offloading systems to guide decision-making when the objective is to identify APs that can be contacted by many users, while the importance attribute can be used to identify APs that can be reached by the same users regularly.

Human Mobility in Offloading Scenarios

Human mobility from the offloading perspective was extensively analyzed in order to understand how users move in an offloading scenario and how mobility can dictate connectivity windows to offload. Due to the limited coverage of WiFi APs, users' mobility dictates the time window available for offloading. Locations where a user is stopped or moving at low speeds are preferred for offloading, as the time window is maximized.

A novel methodology leveraging unsupervised learning was proposed and evaluated to identify and extract individual ORs from trajectories traces on data collected from two different cities, Porto and Beijing. Different time windows to offload were explored when investigating the offloading opportunities presented to users while on commuting. The results show that ORs can be used for offloading while users are in transit according to their availability and the users' typical sojourn

times in these locations. Moreover, the short travel time between **ORs** indicate that short offloading delays would be required to ensure that the user reaches the next **OR**.

The predictability of user mobility in an offloading scenario was analyzed by evaluating multiple predictors theoretically and algorithmically. This analysis revealed that the predictability of mobility for offloading purposes poses a significantly greater challenge compared to mobility between **PoI**. The results show that **ML** predictors outperform **MC** predictors used in the literature ($\approx 37\%$ vs. $\approx 12\%$ acc.), revealing the importance of contextual features when predicting the next **OR** to be visited by a user.

A detailed analysis of the mobility predictability challenges faced in an offloading scenario revealed that the high probability that users find new **ORs** is the main cause of the poor performance of predictors. Moreover, the analysis of the users' exploration phase indicates that this behavior is due to how users move in offloading scenarios, and considering longer learning periods will not improve mobility predictability. However, the results also show that a significant improvement in mobility predictability can be obtained if mobility regularity properties are used. In this case, the offloading systems can consider up to four possible **ORs** as the next **OR** and use a relevance filter to improve the prediction performance.

Throughout the human mobility analysis in an offloading scenario, a high degree of similarity was found between the results of the Porto and Beijing datasets. This indicates that the mobility patterns associated with offloading are more influenced by the regular movements of individuals within urban environments than by the distinct characteristics of the cities. Therefore, the findings and conclusions of this work are likely to be generalized to other urban scenarios.

Offloading Performance and Decision-making Process

The effectiveness of redirecting mobile data traffic through urban WiFi **APs** while users commute was thoroughly examined. A WiFi connectivity framework was proposed to model offloading opportunities as WiFi connections and was integrated into a trace-driven simulator used to study different aspects of the offloading process. The simulator uses real-world mobility traces from user's commutes to assess the offloading performance using specified simulation parameters, including different WiFi conditions, traffic requirements, and offloading strategies.

Various offloading strategies were explored, employing opportunistic or deterministic decision-making methods. Opportunistic methods involve greedy, short-term decision-making, and prioritize immediate gains. Deterministic methods avoid prioritize immediate gains, but instead aim for a globally optimal solution by leveraging historical data to anticipate network and users' behaviors, making choices that maximize a specific criterion.

The expected offloading performance achieved by users while commuting was quantified, examining both the on-the-spot and delayed offloading process. The results indicate that walking commutes are preferable for offloading, achieving a median offloading efficiency of 50%. Interestingly, even during car rides, which represents a challenging scenario for mobile data offloading, a median offloading efficiency of 35% can still be obtained. When data transmission can be delayed, delaying it by just 10 seconds increases the efficiency of offloading by 21–28 percentage points. However, waiting for more than 60 seconds does not yield significant gains. The findings also indicate that users typically spent less than 3 seconds waiting for an opportunity to offload. However, unless users are walking, the time window for offloading is typically short, typically lasting 4–7 seconds.

The influence of using different context information during the AP selection process was also investigated. The mobility of users and APs' throughput were considered as client-side and network-side data that can be leveraged by decision models to choose the best AP to offload. From a connectivity perspective, the results indicate that the use of mobility information during decision-making has a major impact on the offloading process. Choosing APs that maximizes the time window to offload allows a significant reduction in the frequency of connection attempts and greatly increases the duration of offloading connections. However, in order to use mobility information to improve offloading efficiency, offloading strategies will need to rely on very accurate mobility prediction models; otherwise, offloading efficiency gains will be marginal. However, as shown in Chapter 4 of this thesis, mobility predictability in an offloading scenario is a challenging task.

On the other hand, when using network-side data during the AP selection process, the results suggest that choosing APs for offloading based on throughput allows offloading systems to approximate the upper-bound for offloading efficiency performance during a commute, especially when users commute by foot. However, the findings also indicate that consistently opting for a fast connection tends to reduce the time windows available for offloading, posing challenges for applications that may struggle with short connection periods. Hence, it is crucial to consider the requirements of the offloading solution when designing a strategy that incorporates both mobility and network data during decision-making to ensure maximum offloading gains.

Finally, to offer guidance on designing a mobile data offloading system targeting scenarios where users are on the move, various approaches to the offloading process were explored. The impact of reducing link-setup time was examined and revealed that unless it becomes feasible to completely eliminate link-setup time, the time window for offloading will consistently be proportionally affected by the reduction in link-setup time. Therefore, to simplify the management of the

offloading process and allow the use of more advanced offloading strategies to maximize gains, a solution incorporating **ORs** to oversee the offloading process was proposed. This solution utilizes both opportunistic and deterministic methods to choose specific locations and their respective **APs** for offloading. The results indicate that by eliminating the handover cost for **APs** within **ORs**, the upper-bound for the median offloading efficiency can be surpassed by 5—7, 7—10, and 7—9 percentage points, while reducing the number of connection attempts by 5, 3, and 7 times for foot, bus, and car commutes, respectively. In addition, the time window for offloading can be increased by 4 times for foot trips and 3 times for bus and car trips, respectively. These findings highlight that restricting the offloading to areas with suitable user mobility and minimizing handover costs can significantly increase the efficiency of the offloading process, making it more appealing to users and **MNOs**.

6.2 Limitations and Future Directions

In this section, some of the implications that may constrain the analytical insights and technical contributions outlined in this thesis are discussed. In addition, further research directions are also introduced that aim to enhance and expand the work on this thesis.

Offloading Infrastructure: While the offloading infrastructure examined in this thesis encompasses data from over 14k open **APs**, it is important to mention that these **APs** were not deployed with the goal of maximizing the offloading process. Further analysis could be performed to understand the benefits of offloading provided by a dedicated offloading infrastructure where the WiFi **APs** deployment process is guided toward a mobile data offloading scenario. Additionally, it is worth mentioning that the WiFi data used in this work is solely related to the **APs**' coverage, inferred from the collection of WiFi beacon frames in specific geographical locations. Using these data alone does not allow us to consider the typical transmission rates experienced by the users during the offloading process. Therefore, using real-world measurements of **APs** throughput can provide a more accurate assessment of the offloading potential.

Offloading Connections: The analysis in this work entails certain simplifications regarding the network processes and WiFi connections between a mobile device and a WiFi **AP**. The abstraction of the typical processes involved in the establishment of a WiFi connection is performed through the utilization of a link-setup time for the sake of simplification. Moreover, assumptions such as constant throughput and uninterrupted connectivity inside a cell, are used to allow the analysis of the offloading process, but may overlook important details that can affect offloading performance.

Therefore, considering more realistic network conditions that take into account throughput fluctuations during connection, or even unexpected connectivity losses during the offloading process, can help to deliver a more precise analysis of the offloading capabilities.

Offloading Mobility Predictability: The study of offloading mobility predictability presented in this work was not focused on finding the best mobility predictor, but instead, to inspect the limitations and sources of unpredictability in an offloading scenario. However, expanding the study of human mobility predictability during offloading presents a promising avenue for future research. By exploring a wider array of machine learning algorithms and incorporating additional relevant features, it is possible to enhance the accuracy of mobility predictions. During the analysis presented in Chapter 4, the transportation mode associated with each user trip was not available at the desired level of correctness. As a consequence, it was not considered during the feature selection process. As next steps, the assessment of different types of offloading mobility profiles, e.g. considering the transportation mode, and the evaluation of different mobility predictors can contribute to a better understanding of human mobility patterns in offloading scenarios.

6.3 Concluding Remarks

This thesis represents a comprehensive exploration of mobile data offloading, with a specific focus on leveraging urban WiFi networks while users are in transit. Through the analysis of real-world data, this work makes significant contributions to the understanding and enhancement of mobile data offloading systems, offering a multifaceted set of contributions to the field.

The focus on real-world datasets in this thesis transcends the mere presentation, encompassing analyzes that go further by addressing the imprecision of crowdsensed WiFi data, evaluating WiFi coverage, and identifying attributes to define **APs** suitable for offloading. The resulting dataset, comprising WiFi and **GPS** data, serves as a valuable resource for the scientific community.

The exploration of human mobility in the context of offloading presented in this work produces notable contributions, particularly significant given that most of the existing work focuses on mobility between **PoIs**. These include the development of an unsupervised learning methodology to identify **ORs** that reflect individual user habits. The work carried out categorizes **ORs**, evaluates offloading opportunities, and provides a detailed analysis of the intricacies of mobility predictability in an offloading scenario. Potential factors that affect **ORs** extraction and predictability were also considered, providing information on the design implications of offloading systems.

A comprehensive examination of the performance of the offloading is another major contribution of this thesis, which includes the development of a trace-driven simulator, the evaluation

of multiple offloading strategies, and the analysis of the impact of using context data on the AP selection process. Techniques to enhance offloading performance in large-scale deployments were also explored, demonstrating the practical implications of the research. Collectively, these contributions significantly improve the understanding of how mobile data offloading can be optimized for real-world deployments.

In conclusion, this thesis significantly advances the comprehension of different aspects involved in mobile data offloading by addressing critical challenges and providing innovative solutions. The key findings and conclusions presented in this research validate the initial thesis statement: "Offloading mobile data through urban WiFi APs while users are in transit can significantly reduce the cellular network overload, especially if mobility information is leveraged to identify locations where strategies to improve the offloading conditions can be deployed."

The comprehensive exploration of the diverse facets of mobile data offloading in this thesis, coupled with their respective contributions, collectively establishes a robust foundation for the development of effective solutions in mobile data offloading, laying the groundwork for future advancements in this dynamic and evolving field.

Appendix A

802.11 Frame Types and Sub-Types

Table A.1: 802.11 Frame Types and Sub-Types [130]

Type	Type Description	Sub-Type Value	Sub-Type Description
00	Management	0000	Association request
00	Management	0001	Association response
00	Management	0010	Reassociation request
00	Management	0011	Reassociation response
00	Management	0100	Probe request
00	Management	0101	Probe response
00	Management	0110-0111	Reserved
00	Management	1000	Beacon
00	Management	1001	Announcement traffic indication frame (ATIM)
00	Management	1010	Disassociation
00	Management	1011	Authentication
00	Management	1100	Deauthentication
00	Management	1101-1111	Reserved
01	Control	0000-1001	Reserved
01	Control	1010	PS-Poll
01	Control	1011	RTS
01	Control	1100	CTS
01	Control	1101	Acknowledgment (ACK)
01	Control	1110	CF-End
01	Control	1111	CF-End+CF-Ack
10	Data	0000	Data
10	Data	0001	Data+CF-Ack
10	Data	0010	Data+CF-Poll
10	Data	0011	Data+CF-Ack+CF-Pol
10	Data	0100	Null function (no data)
10	Data	0101	CF-Ack (no data)
10	Data	0110	CF-Poll (no data)
10	Data	0111	CF-Ack-CF-Poll (no data)
10	Data	1000-1111	Reserved
11	Reserved	0000-1111	Reserved

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