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QoS Optimisation in Vehicular Networks Based on Predictive AI

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Abstract

Vehicle networking refers to using communication systems, computing facilities, and storage in a vehicular context to enable Intelligent Transport Systems (ITS). Its main objective is to reduce accidents and ensure road safety.

Vehicular networking has been studied for many years and several solutions and standards have been proposed in the literature. Nevertheless, it is a field that remains in tune with the constant evolution of the automobile, thanks to the development of wireless communication technologies, the integration of IoT and ITS, by adopting different types of communication between vehicles, between vehicles and their infrastructure or with passers-by.

These communications enable various services such as safety, management, or comfort.

With the advent of 5G and the move towards 6G, new use cases such as IoV as part of ISAC, integrating and using multiple radio access techniques to move towards ORAN and the trend towards green solutions and practices or the GREEN concept are becoming essential. This brings new challenges such as coverage, mobility, and handover support, resource allocation, security, routing, location systems, etc. Energy is also an important aspect, although it is not the primary concern of vehicular networks. Therefore, to control the performance of vehicular networks and guarantee a minimum level of QoS, it is now crucial to consider (and find solutions for) mitigating these challenges.

In this sense, this work aims to study mechanisms to mitigate some of these challenges to optimize QoS in vehicular networks. First, we propose the use of LoRaWAN, an LPWAN technology, in the context of IoV. LoRaWAN is characterized by its long range, good coverage, and energy efficiency. We then study the optimal deployment of IRS, an energy-efficient relay system that can be used to reflect the signal to improve coverage. Different deployment mechanisms will be tested in one-hop and two-hop configurations.

Keywords: VCN ; QoS ; RIS ; LoRaWAN ; Optimization ; AI ; Heuristic

Résumé

La mise en réseau de véhicules fait référence à l'utilisation de systèmes de communication, d'installations informatiques et de stockage dans un contexte véhiculaire afin de permettre l'utilisation des systèmes de transport intelligents (ITS pour Intelligent Transport Systems). Son objectif principal est de réduire les accidents et d'assurer la sécurité routière. Étudiée depuis de nombreuses années, la mise en réseau des véhicules a donné lieu à plusieurs solutions et normes proposées dans la littérature spécialisée. Néanmoins, ce domaine évolue en parallèle avec l'industrie automobile, grâce au développement des technologies de communication sans fil, à l'intégration de l'Internet des objets et aux systèmes de transport intelligents (STI), en adoptant différents types de communication entre les véhicules, entre les véhicules et leur infrastructure ou avec les usagers de la route. Ces communications permettent de fournir divers services, comme la sécurité, la gestion ou le confort.

Avec l'avènement de la 5G et le passage à la 6G, de nouveaux cas d'utilisation tels que l'IoV dans le cadre de l'ISAC, l'intégration et l'utilisation de techniques d'accès radio multiples pour évoluer vers l'ORAN, ainsi que la tendance vers des solutions et des pratiques écologiques, ou encore le concept VERT deviennent essentiels. Cela entraîne de nouveaux défis tels que la couverture, la mobilité et la prise en charge du transfert, l'allocation des ressources, la sécurité, le routage, les systèmes de localisation, etc. L'énergie est également un aspect important, même s'il ne s'agit pas de la préoccupation première des réseaux de véhicules.

Par conséquent, pour contrôler les performances des réseaux véhiculaires et garantir un niveau minimum de qualité de service, il est désormais crucial d'envisager des solutions pour atténuer ces défis. En ce sens, ce travail vise à étudier les mécanismes permettant d'atténuer certains de ces défis afin d'optimiser la qualité de service dans les réseaux de véhicules.

Tout d'abord, nous proposons d'utiliser LoRaWAN, une technologie LPWAN, dans le contexte de l'IoV. LoRaWAN se caractérise par sa longue portée, sa bonne couverture et son efficacité énergétique.

Nous étudions ensuite le déploiement optimal de l'IRS (système de relais économe en énergie permettant de réfléchir le signal afin d'améliorer la couverture). Différents mécanismes de déploiement seront testés dans des configurations à un et deux sauts.

Mots clefs: VCN ; QoS ; RIS ; LoRaWAN ; Optimisation ; IA ; Heuristiques

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List of Abreviations

2G	Second Generation.
3G	Third Generation.
4G	Fourth Generation.
5G	Fifth Generation.
6G	Sixth Generation.
ADR	Adaptive Data Rate.
AI	Artificial Intelligence.
ARIB	Association of Radio Industries and Businesses.
ASTM	American Standards of Technical Material.
BADR	Blind Adaptive Data Rate.
BBR	Bluetooth Base-band Radio.
BBU	Base-Band Unit.
BLE	Bluetooth Low Energy.
BS	Base Station.
CEN	European Committee for Standardization.
CPLEX	Complex Linear Programming Expert.
CRAN	Centralized Radio Access Network.
DC	Data Center.
DSRC	Dedicated Short Range Communication.
EMF	Electric and magnetic fields.
ETSI	European Telecommunications Standards Institute.
GPRS	General Packet Radio Service.
GW	Gateway.
IBM	International Business Machines Corporation.
ICT	Information and Communication Technologies.
IEEE	Institute of Electrical and Electronics Engineers.
IoT	Internet of Things.
ISAC	Integrated Sensing And Communication.
ISO	International Organization for Standardization.
IT	Information Technologies.
ITS	Intelligent Transport Systems.
ITU-T	International Telecommunication Union - Telecommunication Sector.
LED	light-emitting diode.
LoRa	Long Range.
LoRaWAN	Long Range Wide Area Network.

LPWAN	Low Power Wide Area Network.
LTE	Long Term Evolution.
LTE-M	Long Term Evolution-for Machines.
MANET	Mobile Ad hoc Network.
MIMO	Multiple Input Multiple Output.
ML	Machine Learning.
mmWave	millimeter Wave.
MU-MIMO	Multi User - Multiple Input Multiple Output.
NB-IoT	Narrow Band - IoT.
NFC	Near Field Communication.
OFDM	Orthogonal Frequency Division Multiplex.
ORAN	Open Radio Access Network.
QoS	Quality of Service.
RAN	Radio Access Network.
RIS	Reconfigurable Intelligent Surface.
RSU	Road Side Unit.
SF	Spreading Factor.
SNR	Signal-to-Noise Ration.
V2I	Vehicle to Infrastructure.
V2V	Vehicle to Vehicle.
V2X	Vehicle to everything.
VANET	Vehicular Ad hoc Network.
	.
VCN	Vehicular Communication Networks.
VLC	Visible Light Communication.

Introduction

Vehicular Communication Networks (VCN) refers to using communication systems, computing facilities, and storage in a vehicular context to enable Intelligent Transport Systems (ITS). Its main objective is to reduce accidents and ensure road safety.

In 2021, road accidents were estimated at 1.19 million, translating to 15 accidents per 100,000 people. Africa accounted for 19% of these incidents, while Senegal reported 24 per 100,000, despite a 5% decrease since 2010 [1]. Besides the impacts of air and noise pollution, road congestion also has economic consequences, causing delays that may lead to tardiness at work, meetings, and classes, ultimately resulting in commercial losses. As a result, international [2], national, and local policies have been initiated to decrease road accidents. This includes the introduction of legislation, increasing awareness, improving road infrastructure, and incorporating Information and Communication Technologies (ICT) into transport through ITS [3], among other measures.

ITS have been highlighted as a potential solution to many difficulties facing the transportation industry today. These difficulties include increased urban congestion, which causes longer travel times for individuals and places a considerable demand on the infrastructure [3]. These issues have a significant financial impact, with billions of dollars spent yearly on maintenance, traffic accidents, and fatalities. ITS have been identified as a potential solution to these challenges, promising improved transit efficiency, increased safety, optimized system and process efficiency, cost and fuel savings, and reduced environmental impact of transportation.

The field of ITS has already begun to exert a considerable influence on the transportation industry, as evidenced by the emergence of applications such as electronic toll collection, ramp meters, traffic light cameras, traffic signal coordination, transit signal priority, and traveler-information systems. Implementing these systems offers a variety of benefits for the general public and commercial users, including a reduction in environmental impact and economic gain.

These goals entail gathering, sharing, and communicating data among the different participants that comprise a VCN. Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), vehicle-sensor, vehicle-passenger, vehicle-pass-by, and Vehicle to everything (V2X) [4] are examples of these communications. Wireless technologies including Dedicated Short Range Communication (DSRC), WiFi, Bluetooth, cellular technologies (Long Term Evolution (LTE), Fourth Generation (4G), Fifth Generation (5G)), luminous technologies (LiFi), millimeter Wave (mmWave), etc. [5], constitute the foundation of these communications.

With the advent of 5G and the trend towards Sixth Generation (6G), new use cases are emerging, such as Integrated Sensing And Communication (ISAC) with the massive integration of Internet of Things (IoT) for location and trajectory prediction, the integration and deployment of multiple radio access techniques to move toward an Open Radio Access Network (ORAN) [6], and trends toward eco-friendly solutions and practices or GREEN approaches. This brings new challenges such as coverage due to ever-increasing demand, support for mobility and handover in a multi-operator context, resource allocation, security, routing, location-based systems, etc. Energy is also an important aspect, although it is not the primary concern of vehicular networks.

Research Issues

VCNs are highly dynamic systems characterized by user diversity, fluctuating node density, quasi-random user speeds, and increasing demand. VCNs consist of a set of communicating actors designed to improve traffic safety, maintenance, and user experience. This partially means improving the functionality of the vehicle to make it more aware of its environment. Sensors and communication technologies, especially wireless, are used to achieve this.

Different wireless communication technologies are used for communication, often over short distances: Bluetooth, Wifi, DSRC, or expensive and not uniform: cellular. Providing connectivity in a vehicular network with fluctuating node density, random vehicle speed, and fast topological changes presents many difficulties. The first solution is the use of Road Side Unit (RSU) antennas [7] to bring users closer to antennas and improve coverage. However, the massive deployment of antennas can lead to interference. In addition, deployment and maintenance costs are likely to be high. These costs can be improved while increasing coverage by using relays, as in a traditional communications network. However, their placement remains a major concern regarding boosting performance while minimizing expenses.

Another solution would be to promote heterogeneity in VCNs by integrating different wireless network cards in vehicles to increase the chances of accessing a network, using multiple communication protocols in combination, and implementing secure handover mechanisms [7]. The latter is even more essential with the introduction of IoT in vehicles and their environment, which makes intelligent traffic management, dynamic information services, and vehicle control possible.

Furthermore, today's solutions tend to use greener, more ecologically friendly resources, in the context of green Information Technologies (IT) and digital sobriety, which are approaches to continual improvement that try to lessen the negative effects of digital technology on the environment, society, and economy. With a share of between 6% and 32% of the overall energy consumption forecast for 2025 [8], in systems such as networks, this mainly means lowering energy bills. Networks consume a lot of energy, from turning on equipment, watching streaming, performing calculations, to communicating with other devices. Identifying solutions to reduce energy consumption while maintaining a minimum of Quality of Service (QoS) is crucial.

Some methods for lowering energy consumption include integrating energy-efficient communication protocols and eliminating overheads in communication protocols. Network overhead is the additional data and resources required to manage and control the network connection. It consists of different components, such as: - Protocol headers: which add additional information to data packets to ensure reliable and orderly delivery. This comprises header data, error codes, and sequence numbers;- Error-correcting mechanisms: add redundancy to detect and rectify transmission problems, resulting in larger data sizes; - Routing protocols generate control packets to exchange routing information, optimize data transmission pathways, and manage congestion; and - Congestion control systems necessitate additional signaling and processing to govern data flow and prevent network congestion. This reduction in overheads is at the root of most energy-efficient communication protocols. The use of low-energy technology improves energy consumption but with certain limitations: low coverage, low throughput, long latency, etc. This is the case for Bluetooth Low Energy (BLE), Zigbee, or Low Power Wide Area Network (LPWAN) technologies, which combine long-range and low power consumption [9].

Objective

This work involves the use of predictive Artificial Intelligence (AI) to optimize QoS in VCNs based on energy-efficient technologies. We use energy-efficient technologies to try to solve specific connectivity problems in VCNs.

Our first goal is motivated by the ever-increasing number of connected objects. These objects may be far from the RSU or Gateway (GW), and to reduce the number of intermediaries as much as possible for overhead and energy reasons, we propose using a long-range technology. Long Range Wide Area Network (LoRaWAN) was chosen for its coverage and energy efficiency. The aim is to propose a LoRaWAN-based solution that solves the connectivity problem in vehicular IoT while mitigating the limitations of LoRaWAN.

Coverage can be enhanced by filling gray regions, which are gaps in the coverage. These can be places that are restricted by natural or architectural characteristics, in which case they are fixed and clearly defined. These blind zones may also be ephemeral and mobile. For example, consider a user, a car whose signal is obstructed by another vehicle, and so on. Since increasing the number of RSUs or antennas can lead to interference and expensive costs, we propose using Reconfigurable Intelligent Surface (RIS), a type of reflector-based relay that redirects the signal with a lower energy footprint. The first step is to find a mechanism to optimize the deployment, and the second is to extend the range.

Contributions

Investigating energy-efficient methods to enhance QoS in VCNs from two primary angles is the goal of this research.

First, we utilize LoRaWAN in the context of IoT in VCN. Range, coverage, low energy consumption, handover assistance, and inexpensive implementation costs are the characteristics that define this LPWAN technology. In light of LoRaWAN's shortcomings, particularly concerning latency, we suggest a resource reservation system in a multi-operator setting using prefetching techniques. Furthermore, the model has a mechanism for service differentiation to account for QoS.

Second, in a general setting, mobile RIS is being used to increase coverage, particularly in gray areas.

The issue of optimizing mobile RIS deployment is examined to maximize connection under various limitations. The International Business Machines Corporation (IBM) Complex Linear Programming Expert (CPLEX) optimizer is used to model and run the problem. Coverage, connectivity, connection time, and RIS change are all taken into account when comparing fixed versus mobile deployment.

As a second step, we suggest a system with many hops. Four heuristic-based RIS selection techniques are presented and contrasted. The coverage, connection, and RIS changes between one hop and multiple hops are used to compare the performance of these various approaches.

This work is based on knowledge of the future positions of vehicles and therefore relies on a trajectory predictor and information from transport systems about bus times.

Structure of the thesis

Apart from the chapters on the general introduction and conclusion, this thesis is structured as follows.

Chapter 1 presents the state of the art on the main concepts used: VCN, AI, LoRaWAN, and RIS. Section 1.1 addresses VCNs. It describes the objectives of VCNs in ITS, the types and technologies of communications generally used, QoS and some key characteristics to be taken into account in VCNs. In Section 1.2, a general presentation of AI and the most commonly used models is given before discussing machine learning based on predictive AI and the general integration of AI in vehicular networks. LoRaWAN is studied in Section 1.3. This section presents the Long Range (LoRa) modulation, the LoRaWAN architecture, and the different object classes. Notions such as activation, duty cycle, and Adaptive Data Rate (ADR) are explained in the following sections before ending with LoRaWAN solutions integrating mobility. The last part of this chapter deals with RIS, its architecture, use cases, and challenges in Section 1.4.

Chapter 2 describes our work on integrating LoRaWAN into VCNs. It briefly introduces LoRaWAN and its mobility and handover technologies. Section 2.2 explains the used ap-

proach, then Section 2.3, Section 2.4, and Section 2.5 explain the results obtained and their limitations, ending with the conclusion.

Chapter 3 presents our work on the use of RIS. After a brief introduction to the IRS and its applications, the used optimizer is described in Section 3.2. Next, a description of the problem and its modeling is provided in Section 3.3. The implementation setting and various results are detailed in Section 3.4 and Section 3.5. Section 3.6 wraps up this section with a summary of the different parts and the results obtained.

In Chapter 4, we propose to tackle another issue, specifically improving coverage through multi-reflection with IRS. The heuristic-based approach is outlined in Section 4.2, which includes the settings and strategies after Section 4.1. Section 4.3 and Section 4.4 showcase the results and the various parameters influencing them, concluding with the summary in Section 4.5.

Chapter 1

State of art

As a prelude to this study, and as announced in the introduction, this chapter presents the state of the art of the various technologies used, particularly in VCNs, AI, LoRaWAN, and IRS.

1.1 Vehicular Communication Networks (VCN)

The goal of VCN is to improve the vehicle's functionality and make it more aware of its surroundings. Initially, communications were limited to vehicles, but with the advancement of ITS and the widespread integration of the Internet of Things, communications have expanded to include roadside infrastructure equipment, cloud servers, passengers, and pedestrians. This openness has resulted in adopting new names such as Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), and Vehicle to everything (V2X) (Figure 1.1) to identify the many modes of communication in ITS. V2V connections are solely between vehicles. Its primary goal is to prevent accidents. Under an ad-hoc mesh topology, vehicles can communicate directly in the case of an entire mesh or via multiple hops to transmit information such as their position, speed, etc.

V2I refers to communications between automobiles and road infrastructure (RSU, Base Station (BS), traffic lights, cameras, etc.). The information exchanged might be about potential traffic jams, road conditions, accidents, etc. V2X encompasses all communications between a vehicle and anything on the other side, including other vehicles, road infrastructure, passengers, pedestrians, IoT, etc.

1.1.1 Intelligent Transport Systems (ITS)

ITS adds information and communications technology to transport infrastructures and vehicles to improve their safety, reliability, efficiency, and quality [3] (Figure 1.2). ITS provides a more intelligent approach to conventional transportation networks, characterized by enhanced efficiency, safety, and security. Moreover, it addresses prevalent transit concerns,

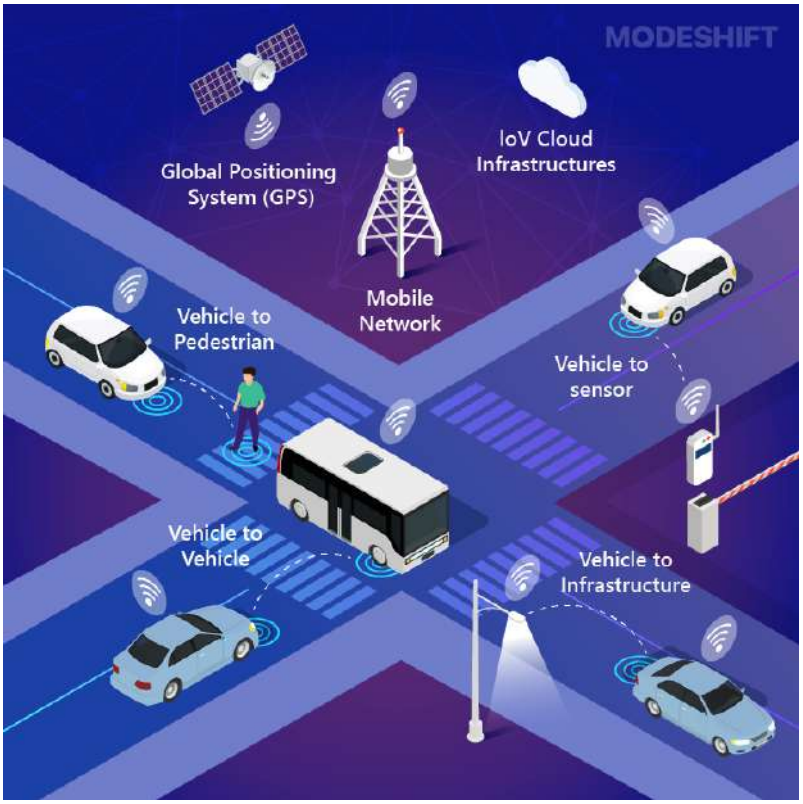


Figure **(1.1)** – *Vehicular communications. [10]*

such as congestion. ITS enables a range of applications such as electronic toll collection, ramp meters, traffic light cameras, traffic signal coordination, transit signal priority, and traveler-information systems. Implementing these systems offers a range of benefits for the general public and commercial users, including a reduction in environmental impact and economic gain.

1.1.2 Vehicular Ad hoc Network (VANET)

Vehicular Ad hoc Network s (VANETs) are a type of vehicular network in which vehicles connect directly with each other, thus obviating the need for centralized infrastructure such as base stations. Each vehicle in a VANET can act as both a communication node and a relay for other vehicles. As illustrated in Figure 1.3, the architecture of a VANET comprises three parts [11]:

- the in-vehicle domain: consists of an On Bard Unit (OBU) and one or more Application Units (AUs). An OBU is an electronic device installed in a vehicle that records traffic and driving data and can connect to roadside and satellite navigation systems. An AU is a device installed in the car that makes use of the OBU's communication capabilities to run programs supplied by the provider. The difference between the AU and the OBU is logical; the AU can be a specialized device for safety applications or a typical device like a personal digital assistant (PDA) to run the Internet. The AU can



Figure **(1.2)** – *ITS architecture. [3]*

be connected to the OBU via a wired or wireless connection (Bluetooth, for example), and it may reside with the OBU in a single physical unit.

- the ad hoc domain: It is made up of vehicles equipped with OBUs and stationary units along the road known as RSUs. An OBU is at least outfitted with a (short-range) wireless communication device dedicated to road safety, and maybe with other communication devices. OBUs constitute a Mobile Ad hoc Network (MANET), which enables fully distributed communication between nodes without the requirement for a centralized coordination instance. If there is wireless connectivity between OBUs, they will communicate directly. In the absence of direct connectivity, dedicated routing protocols enable multi-hop communications, in which data is routed from one OBU to another until it reaches its target. An RSU's major function is to improve road safety by executing particular applications and sending, receiving, or forwarding data in the ad hoc domain to extend the network's coverage. OBUs and RSUs are ad hoc network nodes, with the former being movable and the latter being static. An RSU can be linked to an infrastructure network, which can then be connected to the Internet. As a result, RSUs may grant OBUs access to the infrastructure. This allows AUs registered with an OBU to communicate with any host on the Internet as long as at least one infrastructure-connected RSU is accessible. The OBU can also interface with Internet nodes or servers through wireless technologies (Hot Spot (HS) Wifi, 4G/5G).

- the infrastructure domain: constitutes the network beyond the RSUs. It includes

RSUs, HSs, GWs, BSs, etc.

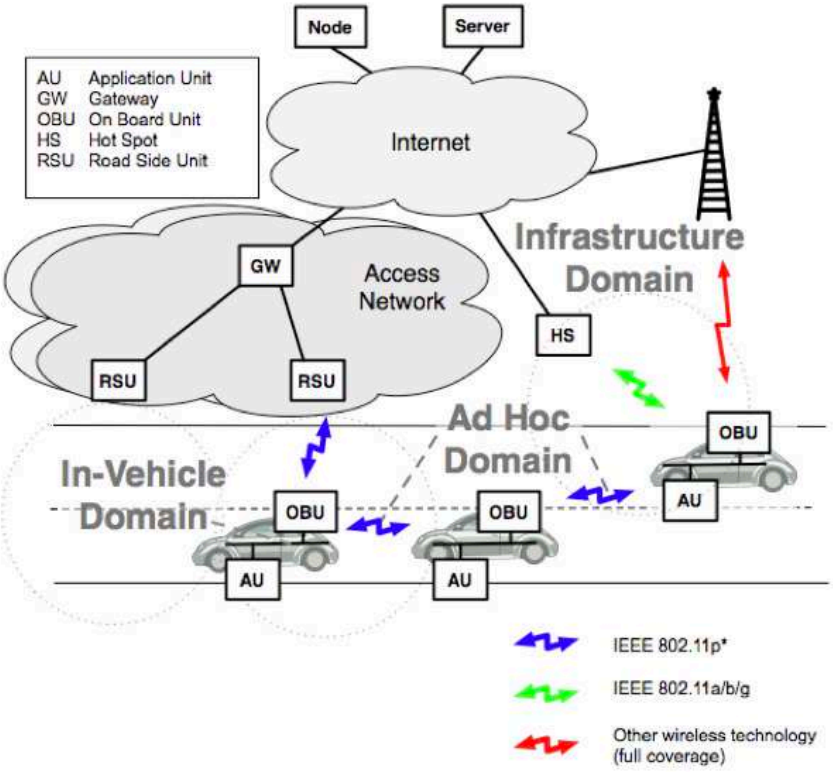


Figure **(1.3)** – *VANET architecture. [11]*

1.1.3 Services

These communications provide a variety of services, with a focus on security, administration, and comfort [12].

- **Safety**: Accidents are often caused by poor driving habits, bad weather, or technical faults. An important alternative is to employ VCN to prevent accidents using collusion detection methods [12], vehicle anomaly detection, planned maintenance, and other features that improve visibility and share safety information.
- **Traffic management**: Traffic management and monitoring improve vehicle mobility and reduce traffic delays caused by bottlenecks or collisions. In the case of road traffic, this reduction depends not only on physical infrastructure but also on fast information about traffic conditions over many kilometers, the detection of alternate routes, and geolocation; resulting in less travel time and less pollution.
- **Comfort**: Vehicles are often used for extended periods, therefore, ensuring adequate comfort can improve the user experience. Examples include weather, information, gaming, telephony, etc.

1.1.4 Communication technologies

Vehicular networks, like other networks, are built on communication technologies, specifically wireless technology, as determined by the network's mobility. The wireless communication protocol used is determined by the demands and kind of communication. Some technologies are used only for intra-VCN, such as Near Field Communication (NFC). NFC is a set of short-range wireless technologies, typically requiring a distance of 4 cm or less to initiate a connection.

Alongside, there are other technologies suitable for both intra/inter - vehicular, and V2X applications. Among these radio access technologies:

Dedicated Short Range Communication (DSRC)

The primary radio access technique for vehicle communications. It is a short- to medium-distance communication technology. It is used for V2V and V2I communications [13]. Its primary goal is to improve road safety and traffic efficiency [7]. Depending on the zone, there are three specifications, particularly for the frequency bands used, supported by Institute of Electrical and Electronics Engineers (IEEE):

- the American Standards of Technical Material (ASTM) in the United States,
- the European Telecommunications Standards Institute (ETSI) and European Committee for Standardization (CEN) in Europe,
- and the Association of Radio Industries and Businesses (ARIB) in Japan.

Bluetooth

Bluetooth is a short-range wireless communication method. It operates at 2.4GHz. Bluetooth wireless technology's primary features include resilience, low power consumption, and low cost. Bluetooth wireless technology systems are classified into two types: Bluetooth Base-band Radio (BBR) and Bluetooth Low Energy (BLE). BLE is particularly used in IoT. [14]

Wi-fi

It is one of the most popular wireless networks, with millions of hot spots available. The term "hotspot" refers to a location where users can access the Internet, usually using a wireless local area network (WLAN). It operates in the 2.4 and 5 GHz frequency bands. It is the IEEE 802.11 standard, with a range of only a few tens of meters. [15]

millimeter Wave (mmWave)

mmWave is an electromagnetic wave radar technology that falls midway between microwaves and light waves. It is distinguished by its wide range of 30 to 300 GHz [16].

Visible Light Communication (VLC)

Visible Light Communication (VLC), by Li-Fi, is a communication method that uses visible light. VLC technology employs light-emitting diode (LED) that can be manipulated at high rates. This technology has two applications: illumination and communication [17].

LTE-A, 4G, 5G and beyond

Cellular connections have been utilized in vehicles for many years, beginning with General Packet Radio Service (GPRS), a mobile telephone standard introduced with Second Generation (2G). Its development was hampered by the slow speeds of 2G and Third Generation (3G). Since the launch of LTE/4G, more and more applications have relied on cellular, which provides faster throughput and lower latency, particularly with 5G and beyond technologies.

Satellite

Satellite communication involves three primary components: sender stations, satellite systems, and reception devices. Data is delivered from the sender station to the satellite, which then forwards it to the receiving devices. Satellite communications have extremely broad coverage and excellent broadcast capabilities. This technology is ideal for providing connectivity in isolated areas, including mountains and islands. Sender stations and reception devices are typically fixed, but can also be mobile.

The majority of these technologies have a high enough data throughput, while some are sensitive to obstructions and interference or have significant operating costs. That is why there has been a recent surge of interest in integrating LPWAN, a family of long-range, low-power communication protocols, into the vehicular environment. LPWANs have sparked interest in the research community because of their timely integration with the IoT.

Low Power Wide Area Network (LPWAN)

LPWANs, known for their low energy consumption, allow small amounts of data to be transmitted over large distances. This makes them an indispensable ally for low-power, long-range IoT systems, in which the majority of objects are battery-powered and can be placed in inaccessible regions. LPWANs use a variety of protocols, including cellular-based Long Term Evolution-for Machines (LTE-M) and Narrow Band - IoT (NB-IoT), as well as non-cellular protocols like SigFox and LoRaWAN. LoRaWAN is the most notable of

them due to its affordability, ease of deployment, coverage, range, and roaming capabilities. These functions make it appropriate for metropolitan settings with several operators.

The table 1.2 summerises most used communication technologies in vehicular context with their advantages and drawbacks.

Technology	Range	Data Rate	Latency	Energy	Usage	Avantages	Drawbacks
NFC	Few cm	Low (kbps)	Low	+		Security, Simplicity, Energy efficient	Short range, Compatibility, Low transmission rate
VLC (Li-fi)	10m	Moderate to high	Low	+	Vehicle signaling using visible light	High speed, security, free EM interference, free spectrum, Low latency	Short range, Interference with other lights, Specific installations
Bluetooth	10-400m (v5)	Low	Low	+	Sensor connexion	Low consumption	Low data rate, Short range
Wi-fi	150m	Moderate to high	Medium	+++	Urban communication, V2V	High rate, well deployed	Energy consumption, Limited range, Interference
mmWave	> 100m	High	Very low	+++	V2V, autonomous vehicle	High speed, Low latency, Real time support	Short range, Sensitive to obstacles, Cost
DSRC	> 300m to 1km	Moderate	Low	++	V2V, Crital data sharing (traffic condition, crash information, etc.)	High rate, Low latency, Standardised	Limited frequency band, Cost
Cellular	1-10km	High	Low	+++	V2X	High speed, low latency, coverage, mobility handeling	Cost, licence plan, interference, uneven coverage
LPWAN	10-50km	Low	Moderate	+	Tracking, Fleet monitoring, environnement monitoring	Low power, long range, low interference, generally free licencing	low rate
Satellite	> 1000km	Moderate	High	+++	Long range communication	Coverage, long range	Cost, High latency, High energy consumption , meteorologic sensibility

Table **(1.2)** – *Communication technologies in VCN.*

1.1.5 Quality of Service (QoS)

QoS can be defined in many ways, depending on the target system. International Organization for Standardization (ISO), a standardization organization, defines QoS as 'the totality of characteristics of an entity that bear on its ability to satisfy stated and implied needs' (ISO 9001) [18]. The International Telecommunication Union - Telecommunication Sector (ITU-T), another telecommunications standardization organization, defines QoS as the 'Totality of characteristics of a telecommunications service that bear on its ability to satisfy stated and implied needs of the user of the service' [19][20]. ETSI defines it in terms of service differentiation as 'the ability to segment traffic or differentiate between traffic types in order for the network to treat certain traffic differently from others' [21][22]. QoS is a process and management concept that employs procedures to control network traffic, optimize network resources, and ensure that each application performs optimally under its requirements. It is dependent on network performance and is monitored at the user level. QoS requirements in vehicular networks are similar to those of wireless networks and MANET, with certain particularities. In the literature, certain criteria are used in networks to improve QoS:

- Speed: refers to how rapidly a service or resource may be accessible; this can include access methods, routing, etc.
- Availability: access to the service/resource at the required time and location; can include coverage, mobility support, handovers/roaming, routing, etc.
- Reliability: can measure the state of communication or the signal, the number of deletions.
- Security: the existence of security measures such as authentication and encryption, etc.

1.1.6 Coverage

Wireless communication technologies facilitate communications and offer greater freedom in terms of mobility, network setup, etc. The evolution of communication needs has led to the use of broadband frequencies, which combine high throughput with reduced latency for a better quality of experience and the integration of mission-critical applications. However, the higher the frequency, the greater the attenuation and the more sensitive the signal is to obstacles. In particular, in urban environments, where coverage is uneven and with areas with little or no coverage, covering this dense network while guaranteeing a semblance of QoS is an ongoing problem. To extend the signal, several solutions have been proposed, including densification and the use of relays.

Network densification:

Network densification is a mechanism used in networks to improve coverage and extend the signal. It includes **spatial densification**, which aims to add BS equipment, antennas,

links, etc., and **frequency densification**, which consists of using larger portions of the radio spectrum in various fields of activity [23].

Frequency densification is achieved by **Spectral aggregation:** which is the combination of contiguous or non-contiguous spectrum fragments to create a virtual broadband channel [24].

Spatial densification can be achieved in some ways:

- **Cell size reduction (small cells, pico cells):** involves increasing the number of cells in a given area. As each cell delimits the range of the base station BS, this means increasing the number of BSs serving an area, resulting in smaller cells. This reduction in the distance between the BS and the user reduces the path loss and possible interference [23].
- **Backhaul densification**: this consists in adding and improving backhaul links using different technologies, notably **Cloud Radio Access Network** or Centralized Radio Access Network (CRAN). CRAN is a centralized cloud-based architecture for RAN. It features different wireless communications standards and enables the use of the latest common public radio interface and hardware acceleration standards, offering operators agility and performance. The principle is the virtualization of Radio Access Network (RAN) functions, with virtual separation of the software and physical parts: Base-Band processing and Base-Band Unit Base-Band Unit (BBU). It tends towards an Open RAN, with the use of an open shared infrastructure that enables network resources to be used more efficiently and cost-effectively [25].
- **Multi-User Multiple Input Multiple Output (MIMO) and massive MIMO** «Multiple Input Multiple Output communications, refers to a collection of signal processing techniques that have been developed to improve the performance of wireless communication systems using multiple antennas at the transmitter, receiver, or both.» [26]. MIMO technology makes it possible to achieve high speeds and data volumes. There are several types of MIMO, depending on the number of antennas and users. In Multi-User MIMO, several simultaneous connections are created between different users to increase network capacity, unlike Single User MIMO, where only one user is served at a time. Multi User - Multiple Input Multiple Output (MU-MIMO) allows several users to access the BS at the same time and requires as many antennas at the BS as there are users. A certain evolution of MU-MIMO is Massive MIMO, where the BS is composed of many more antennas than there are users, to increase the capacity and range of the BS while minimizing inter-cell interference.

With these different methods, densification has the following advantages:

- Improved coverage: On the one hand, the reduction in cell size brings nodes closer together; on the other, the addition of new cells enables access to areas with little or no coverage.
- Increase network capacity: Increasing the number of BS leads to an increase in the amount of traffic the network can handle, which in turn reduces congestion and improves the overall network quality of service.

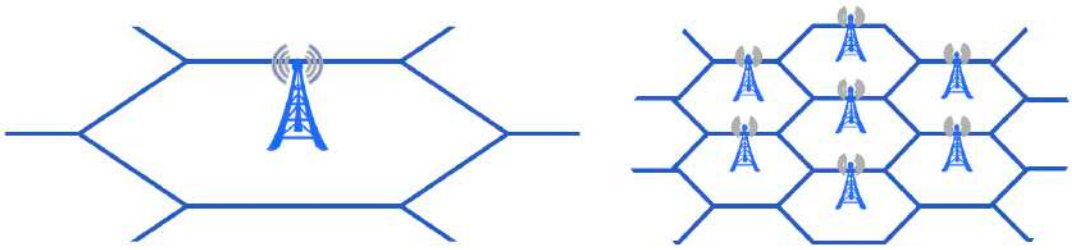


Figure **(1.4)** – *Network densification: cell size reduction.*

- Reduce interference: In the sense that it increases the Signal-to-Noise Ration (SNR) as users are closer to the BSs, which means a stronger signal that can be easily differentiated from noise.
- The data rate increases with the proximity of the BS node.

This improves the user experience and therefore the network's quality of service. However, it comes at a cost:

- Increased costs: due to the deployment of new BS, associated infrastructure, and operating costs.
- Increased energy consumption: adding new BS will increase the size of the network and its total energy consumption. This is an obstacle in areas where power is limited.
- Increased interference: this is the opposing perspective. Decreasing cell size brings BSs closer together, which can lead to interference, especially at cell boundaries. This phenomenon may potentially generate a series of subsequent consequences: lower data rates, more collisions, etc., leading to a degradation in overall performance. Consequently, achieving optimal deployment is imperative. However, this process can introduce another challenge: the management and coordination of relays to ensure optimal deployment and distribution.

- Increased Electric and magnetic fields (EMF) exposure: due to proximity and an increased number ofBS.

To alleviate these costs, relaying systems have been initiated.

Relay antennas:

The role of relays is to extend the signal, i.e. they retransmit the signal from the BS to the user and can amplify or generate this signal. The two most common types of relays are Amplify and Forward (AF) relays and Decode and Forward (DF) relays. AF relays simply amplify the received signal before retransmitting it, whereas DF relays first decode and re-modulate the signal before retransmitting it. As a result, DF relays are more complex and require a Medium Access Control (MAC), making them almost BS-like. In fact, in some LTE cell architectures, relays can occupy two positions: managing a cell as a BS and thus extending coverage, or being transparent in a cell already served by a BS and serving to increase cell capacity [27] [28].

On the deployment side, relays generally do not require a wired backbone, making them easier to deploy and more energy-efficient. Relays can be mobile and, in most cases, they are mounted on Unmanned Aerial Vehicle (UAV), commonly known as drones [29], to cover areas that are difficult to access geographically or in the event of disasters, peak demand, etc.

Relays are a good way of extending coverage, although their power consumption is lower than that of a BS. Nevertheless, this consumption remains relatively elevated. The half-duplex function of most relays can also be an obstacle to their integration in highly dynamic systems, hence the need for technology with optimum energy consumption.

Recently, in the field of beyond 5G and 6G enabling technologies, the use of reflectors has seen a period of significant growth, in particular RIS, which generally enable the signal to be passively extended without amplification, unlike relays [30].

1.1.7 Resource allocation

As the number of vehicles and users increases, along with improvements in V2X applications, data volumes, and resource allocation challenges will also rise. Mechanisms such as edge and fog computing alleviate the burden of accessing data and services, bringing them closer to end users at the RSU or antenna level. This reduces the amount of data transmitted to the cloud, resulting in lower latency and faster response times. This enhances both QoS and Quality of Experience (QoE). The work in [31] introduces a new scheme for allocating power and resource blocks in V2V communication while adhering to queue latency and reliability constraints. They propose a two-timescale resource allocation technique. A matching algorithm assigns resource blocks to each vehicle user's equipment based on their preference list for each time slot, while RSUs group vehicle user equipment into virtual zones according to their spatial and temporal attributes over a longer timescale. Each

vehicle within a designated zone maximizes its transmit power based on optimization. The spectrum sharing issue in high mobility vehicular networks, where several V2V links try to share the frequency spectrum occupied by V2I links, is examined in [32]. The problem is first modeled as a multi-agent reinforcement learning problem in which the frequency spectrum occupied by vehicle-to-infrastructure (V2I) links is reused by several vehicle-to-vehicle (V2V) links. Then, they used a deep Q-network approach based on fingerprints to solve it.

1.2 Artificial Intelligence (AI) in VCN

According to the Larousse dictionary, artificial intelligence (AI) is 'the science and engineering of making intelligent machines'. For John MacCarthy, one of the creators of this concept, AI is 'any intellectual activity that can be described with sufficient precision to be simulated by a machine' [33]. Its history goes back to the construction of automata, causal reflections on logic, and so on. The concept of AI began in 1950 with the "Imitation Game" by the mathematician and computer precursor Alan M. Turin [34]. AI relies on mathematical formulas and algorithms that use probability and statistics to mimic cognitive functions such as learning and decision-making. AI is a broad field with many sub-fields and branches. Branches define how different methods are used to enable machines to imitate the intelligence of human beings.

1.2.1 Types of AI

We can already count three types of AI, depending on capability:

- **General or deep AI:** AI capable of performing any cognitive task as a human or animal would. GPT-4 can possibily be considered as the first form of general AI.
- **Strong AI or super-intelligence:** philosophical knowledge and signs of proper consciousness are demonstrated by the model. Considered unfeasible at present, since the notion of consciousness and feelings cannot emerge in mathematical systems that manipulate and respond with symbols and calculations.
- **Weak or narrow AI:** capable of performing a single task (almost) perfectly.

In his book [33], McCarthy cited several branches of AI among which are Ontology, Search, Pattern Recognition, Heuristics, and Learning from experience (Figure 1.5).

However, the 7 most widely used branches are (Figure 1.5):

- **Computer Vision:** analyzing, understanding, and deriving information from an image or video, or any other visual data in general.
- **Fuzzy Logic:** an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0).

- **Expert System:** used to solve problems or make decisions in specific fields that normally require an expert.
- **Machine Learning:** uses algorithms or statistical models to perform tasks without explicit instructions and evolve through experience.
- **Evolutionary Computation:** imitates natural evolution to find optimal solutions to complex problems.
- **Swarm Intelligence:** collective learning and decision making based on decentralized self-organizing systems.
- **Cognitive Computing:** computerized models to simulate human thought processes in complex situations where responses may be ambiguous and uncertain.

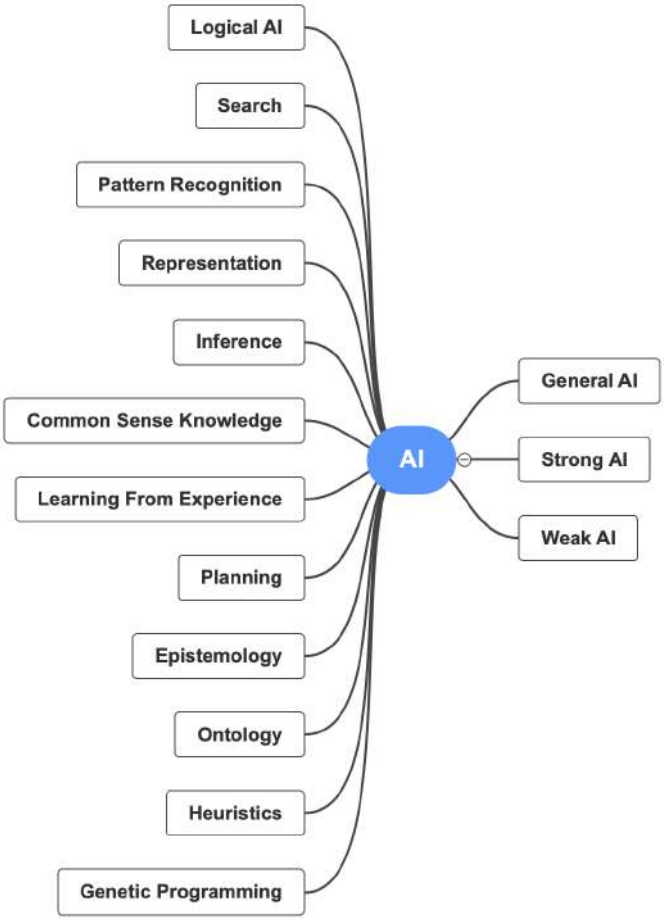


Figure **(1.5)** – *AI types and branches.*

Use Case

AI is used in various fields.

- Stock or resource management: can help determine peak demand periods for a brand, store, or resource in general.
- User experience and recommendation systems: can help providers anticipate user requests, enhance customer experiences, and predict behavior based on customer data and past activity. It can lead to recommendation systems where a predictive model is applied to suggest personalized content that matches user's behavior.
- Predictive maintenance: by monitoring vibration, temperature, and other machine sensor data, predictive AI pinpoints equipment at risk of failure so it can be proactively serviced and avoid downtime.
- Weather forecasting: predictive AI can help forecast weather and anticipate disasters.

1.2.2 Machine Learning

Machine Learning (ML) is one of the most used AI techniques. ML look for patterns in a dataset. Over time, they improve their ability to perform tasks on their own and make predictions based on data. The goal of the algorithm is to use fresh data to identify trends. The foundation of an ML model involves four steps:

- Data preparation: This is a crucial step; it consists of selecting and preparing the data set to be used for training.
- Choice of algorithm: determine which algorithm to use on the dataset. This depends on three factors: the type and volume of data, and the nature of the problem to be solved.
- Training phase: This process is iterative. Variables are subjected to the algorithm, and the results are then compared with the expected outputs. Thereafter, the 'weights' and bias can be adjusted to enhance the accuracy of the results. Subsequently, the variables are re-run until the algorithm consistently produces the correct result. Through this training process, the algorithm is developed into a machine-learning model.
- Model use and improvement: The fourth and final phase is to apply and refine the model.

ML techniques

There are different types of ML techniques: supervised learning, unsupervised learning, and reinforcement learning.

- **Supervised learning**: The process of labeling data is instrumental in facilitating the machine's comprehension of the specific patterns it is designed to identify. The training step uses labeled data and requires less data than other methodologies. The ability to compare the model's results with prelabeled data simplifies the training

process. Data labeling might be expensive or result in a biased model based on the training data.

- **Unsupervised learning**: This process does not involve the use of labels. The model examines the data to identify patterns. It will attempt to automatically group the data based on their intrinsic properties to label, sort, and categorize them in real-time.

- **Semi-supervised learning**: represents an intermediate approach between supervised learning and unsupervised learning. It is distinguished by the use of a small collection of labeled training data to direct classification and feature extraction from a larger range of unlabeled data.

- **Reinforcement learning**: is a strategy in which the model learns from its mistakes to achieve a goal. It attempts a variety of techniques to achieve its goal and is rewarded or penalized to encourage it to continue or change direction.

1.2.3 Predictive Artificial Intelligence (AI)

Predictive AI is the ability of a computer program to identify patterns, anticipate behavior, and forecast future events, based on statistical analysis and ML. Predictive AI uses machine learning (ML) algorithms and the vast amounts of data, to speed up and improve the accuracy of statistical analysis, which has long been used to make future predictions. These forecasts assist businesses in anticipating future trends, forecasting the climate, and personalizing the user experience (recommendation systems, etc.).

Predictive AI is commonly mistaken for descriptive or prescriptive analytics. While predictive analytics helps organizations predict what is likely to happen, descriptive analytics helps them understand why something happened in the past. Prescriptive analytics suggests steps a company may take to ensure certain results occur. Predictive AI performances depend on the quantity and quality of the data used.

Predictive AI techniques

Several statistical and ML techniques can be used to perform predictive AI.

- Clustering: classifies underlying data patterns or clusters of various observations or data points according to their commonalities. In contrast to supervised learning, which has a target variable, this approach falls under the category of unsupervised learning, which seeks to learn from unlabeled data points. Metrics such as the Manhattan distance, the Cosine similarity, and the Euclidean distance are used to assess similarity [35].

- Decision Tree: is a non-parametric supervised learning algorithm, which combines tasks from both classification and regression. It has a hierarchical tree structure with

nodes representing decisions or tests on attributes, branches representing the outcome of these decisions, and leaf nodes representing outcomes or predictions. Decision Tree has a recursive operation in a three-stage process: the selection of the best attribute to split the data, the splitting of the dataset into subsets based on a selected attribute, and repeating recursively for each subset the process of creating a new node (internal or leaf) until the stopping criterion. The stopping criterion can be either a predefined depth is reached or all instances in a node belong to the same class [36].

- Regression Models: Determine the correlation between variables: a dependent variable or target variable, and independent or predictor variables. The objective is to determine the most suitable function that characterizes the connection between these variables. The objective is to find the best-fitting model that can be utilized to make predictions or draw conclusions. Some regression algorithms are linear regression, polynomial regression, Support Vector Regression, Decision Tree, Random Forest, etc [37].
- Time-series: Based on historical data to predict future values. The dataset consists of observations collected at regular time intervals with a trend, seasonality, irregularity, and cyclicity. Multi-layer perceptron (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Decision Tree Models such as Random Forest, Gradient Boosting, and Transformer Neural Networks are methods used for Time Series Forecasting [38].

Generative AI vs Predictive AI

Frequently contrasted with generative AI since certain generative AI tools appear to incorporate predictive AI techniques as well. Copilot, for instance, can recommend the subsequent lines of code. New data is produced by generative AI. It creates unique content - such as writing, audio, photos, software code, or video - in response to user requests, whereas predictive AI makes predictions based on existing data. Large amounts of unprocessed data are used to train Gen AI algorithms. To comprehend user requests and produce pertinent new material that is comparable to yet distinct from the original data, these models subsequently utilize the encoded patterns and relationships in their training data. Large Language model (LLM)s are a common base model for text generation.

1.2.4 AI in vehicular

AI is use in various sector such as IoT [39], MANET [40] to improve performance and accuracy of combinatorial optimization [41].

In the mobile and particularly vehicular sector, there are several AI-based solutions. This is often due to the complexity of optimization problems: resource allocation, positioning, routing, security, etc.

For mobile based solution, [42] studies a resource management scheme based on deep Q learning [43] that infers the optimal resource management strategy as a function of net-

work state, drone actions and a corresponding Q value. This optimal Q value is learned by training the deep-Q network on the UAV, where node selection and the associated modulation scheme are based on Q values. [44] tries to maximise spectrum efficiency by optimizing UAV speeds and channel allocation for all users.

In [45], the authors propose an improvement in location data privacy and security in vehicular ad hoc network (VANET) location protocols using artificial intelligence. The method relies on GPS data to calculate distance and adjust RF transmission as required. The adjustment is made using a neural network to estimate the RF power required according to need. The graphs show a non-linear relationship between distance and RF transmission power, influenced by various factors such as signal loss and environmental conditions. The results show that the algorithm and neural network are effective in estimating the RF power required.

Still in the field of security, [46] propose a recurrent gate unit (GRU)-based anomaly detection model for VANETs, to overcome the challenges of detecting unknown attacks and Denial of Service (DoS) flooding. First, the data is converted into binary features and fed to the GRU. The proposed model, called SEMI-GRU, improves anomaly detection accuracy using a semi-supervised technique. It combines GRU with a symmetric reduction feed-forward neural network (SR-FNN) and a data oversampling method (SMOTE). Experimentation on the NSL-KDD dataset shows that the SEMI-GRU model outperforms existing methods with reduced false positive rates and improved accuracy.

[47] proposes a Markov Decision Process (MDP) modeling of three RSU problems: service scheduling, cach replacement and message collision control.

The study in [48] reviews the literature on intelligent routing protocols in VANETs, focusing on the techniques used and how solutions are evaluated. A systematic review was carried out using the "snowballing" method. Research questions include recent activity in the field, classification of AI/ML-based routing protocols, techniques used to improve the performance of routing protocols, and methods for evaluating these protocols. The results show an increase in research activity since 2013, with a peak in 2019. The AI/ML techniques used are grouped into four categories: heuristics and swarm intelligence, ML algorithms, fuzzy logic systems, and game-theoretic approaches. Nature-inspired heuristics and techniques, such as ant colony optimization (ACO) and particle swarm optimization (PSO), are widely used. Reinforcement learning (RL) approaches and fuzzy logic systems are also important, with successful applications in route discovery and cluster management.

Paper [49] explores the integration of VANETs and deep learning to improve road safety and real-time mapping in a dynamic urban environment. The system features a 3D point cloud object detection module based on a deep learning system. The study examines how data loss due to packet loss affects the accuracy of object detection by deep learning. It also identified parameters such as packet loss, and traffic conditions that can reduce detection accuracy and the detection accuracy of the algorithm. This article highlights the challenges of integrating VANET technologies and deep learning while proposing solutions to overcome limitations linked to data loss in dynamic urban environments.

[50] presents a method for predicting flight paths based on a Long Short Term Memory (LSTM) neural network. The aim is to improve safety in air traffic management (ATM) by

providing accurate predictions of flight paths, a more complex domain than terrestrial path prediction due to the scarcity of waypoints and the many external factors affecting flights. LSTMs are chosen for their ability to handle long-term dependencies in time series, crucial for predicting complex trajectories. The LSTM model uses sliding windows to maintain sequence continuity and preserve dynamic dependencies between adjacent states. In addition, the model predicts trajectories in 3D (time, latitude, longitude) and 4D (addition of altitude) to assess its effectiveness. The data used come from ADS-B stations, which offer high positioning accuracy. Results are compared with the classical and weighted Markov models, with performance measured using Mean Absolute Error (MAE), Mean Relative Error (MRE), Root Mean Square Error (RMSE), and Dynamic Warping Time (DWT). The results show that the LSTM model outperforms these approaches in terms of prediction accuracy.

1.3 Use of LoRawan in VCN

LoRa and LoRaWAN are part of the family of protocols that enable LPWAN, featuring high coverage capacity coupled with low energy consumption. LPWANs have gained momentum with IoT development.

This section will briefly contextualize the use of LoRa - LoRaWAN technologies with the advent of the IoT. We will then talk about LoRa's key features, before exploring the LoRaWAN architecture with its various components and device types. Finally, we will look at the different activation modes and how LoRaWAN manages devices, before discussing its uses in mobile and vehicular networks in particular.

1.3.1 Internet of Things (IoT)

GlsIoT is a network of connected objects, often equipped with sensors, actuators, etc., A sensor is a device used to collect and transmit data. An actuator is used to perform simple operations. GlsIoT is often used to monitor a state using sensors and in some cases to generate an alert or action, making the systems intelligent, leading to the use of 'smart' concepts (smart home, smart city, etc.). Sensors are systems capable of gathering information from their environment. They can collect information on room temperature, room humidity, soil humidity, soil ph, speed, presence of obstacles, etc. Actuators are devices that act in response to data collected by sensors or according to commands received from a control system. They are used to perform physical actions in the real world in response to specific events or conditions [51]. For example, in home automation, it is possible to regulate the temperature of a room thanks to actuators that act on the system to increase/decrease the temperature when a threshold is reached. The system is based on information sent by temperature sensors.

This ability to collect information is being introduced in many fields, including agriculture, home automation, transport, health, environmental monitoring, and more. In some use cases, such as environmental monitoring or ship tracking for exemple, objects may be remote or accessibility may be restrictive. The sensors can be located in mountains, by

the sea or underwater, making power recharging and connectivity hard. Hence, one major requiremment is low power consumption. This has led to the use of connected objects with lower energy consumption, but also of low-power communications protocols. Some of them are long range and allow to minimize the frequencie of battery changes and cover long distances. Therefore, LPWANs have gained momentum as they offer an efficient solution for connecting remote objects.

1.3.2 Long Range (LoRa)

LoRa is a low-power long-range modulation technology created in 2009 by the startup Cycléo, which was subsequently acquired by the American company SEMTECH in 2012. LoRa enable long range coverage with distances that can reach five (5) kilometers in urban areas and up to fifteen (15) kilometers or more (in case of line-of-sight) in rural areas [52].

This technology is used to transfer data between devices using radio waves. It is based on a broadband modulation technique, creating linear frequency-modulated signals called "chirps" based on the Chirp Spread Spectrum (CSS). CSS [53] is a method used in radar communications and by bats.

Forward Error Correction (FEC)

Another feature of LoRa is Forward Error Correction (FEC), which consists of sending redundant bits, which are used on reception to correct corrupted bits, after each series of bits. The number of useful bits or bits containing real data out of the total number of bits sent is called the Coding Rate (CR). For example, a CR of 4/6 means that for every 4 bits of useful information, the system generates a total of 6 bits of data, 2 of which are redundant. As a result, LoRa is a variant of CSS that includes FEC.

Chirp Spread Spectrum (CSS)

Chirps operate in the 2.45 GHz Industrial Scientific and Medical (ISM) bands (Table 1.3). They enable radio signals to be distributed over a wider range of frequencies, generate signals with wider bandwidths, and retain the original signal power.

The objective is to transmit a signal whose frequency increases (or decreases) over a specific period. The signal during this period is called a chirp. The structure of this signal has some good attributes:

- multipath resistance occurs when the signal encounters obstacles and reaches the recipient in several time-shifted copies;
- adequate resistance to the Doppler effect, which alters the frequency as the transmitter moves.

ISM Band Frequencies
6.765 - 6.795 MHz
13.553 - 13.567 MHZ
26.957 - 27.283 MHz
40.66 - 40.70 MHz
83.996 - 84.004 MHZ
167.992 - 168.008 MHZ
433.05 - 434.79 MHZ
886 - 906 MHz
2.400 - 2.500 MHz
5.725 - 5.875 MHz
24.0 - 24.25 GHz
61.0 - 61.5 GHZ
122 - 123 GHZ
244 - 246 GHZ

Table **(1.3)** – *ISM Band Frequencies.*

Chirp pulses (Figure 1.6) are divided into upward and downward pulses. They are sent from a transceiver to a receiver. They can also be exchanged between transceivers capable of transmitting and receiving communications with one or more devices simultaneously. The receiving devices analyze the received pulses and transform them into data.

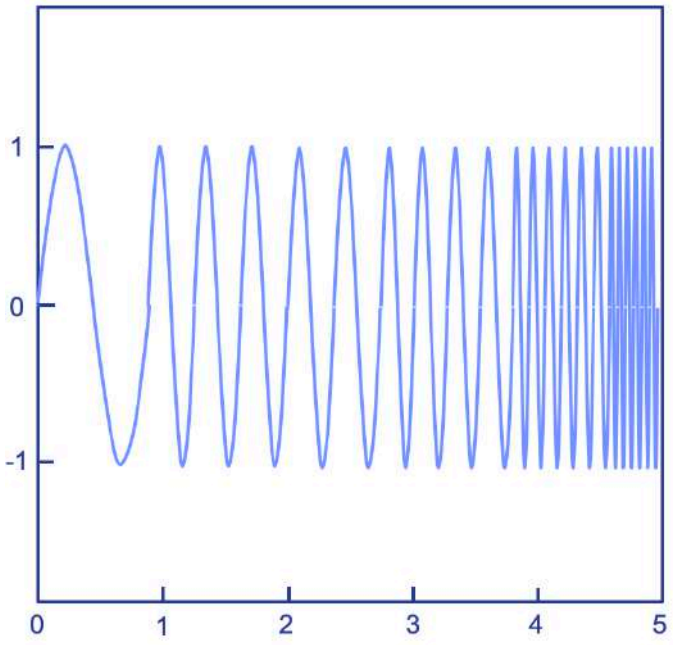


Figure **(1.6)** – *CSS chirp.*

The advantages of using CSS are the wide coverage and robustness against interference.

Data Rate (Spreading Factor)	Sensitivity	Time On Air
SF7	-123.0 dBm	41 ms
SF8	-126.0 dBm	72 ms
SF9	-129.0 dBm	144 ms
SF10	-132.0 dBm	288 ms
SF11	-134.5 dBm	577 ms
SF12	-137.0 dBm	991 ms

Table **(1.4)** – *SF in LoRa.*

The receiver can discern a signal with a lower SNR because LoRa has a higher signal link budget introduced by multiplying the signal by a spreading code. This amount of spreading code applied to the original data signal is called the Spreading Factor (SF).

The SF, like the Transmission Power (TP), Carrier Frequency (CF), Bandwidth (BW), and CR, is part of the transmission parameters [54]. A transmission parameter is a changeable setting that can be changed to improve network performance in a variety of scenarios.

Carrier Frequency (CF)

CF is the center transmission frequency in a band. LoRa uses ISM bands, with specific bands allocated for each region: EU868 (863–870/873 MHz) in Europe and some African contries; US915 (902–928 MHz) in North America; AU915/AS923-1 (915–928 MHz) in South America; etc. [55]. The EU863-870 MHz spectrum can accommodate a minimum of 24 channels and a maximum of 80 channels [56].

Spreading Factor (SF)

LoRa has 6 SFs from SF7 to SF12. The higher the number, the greater the coverage and sensitivity and the lower the power. This means that the same message at the same frequency will take longer to be sent with an SF7 than with an SF8. Table 1.4 shows the different SFs and their equivalent sensitivity and transmission time for a 125 kHz bandwidth with the same packet size [52].

Bandwidth (BW)

BW refers to the range of frequencies available for transmission. A bigger BW enables transmission at faster data rates, but at a shorter Time-On-Air (TOA) and with lesser sensitivity. In contrast, a lower BW allows for increased sensitivity but a lower data bit rate. The typical BW values in the high frequency ISM 868 and 915 MHz bands are 125, 250, and 500 kHz, whereas in the low frequency 160 and 480 MHz bands they are 7.8, 10.4, 15.6, 20.8, 31.2, 41.7, and 62.5 kHz [57].

Coding Rate (CR)

FEC protects against interference and can be adjusted to 4/5, 4/6, 5/7, or 4/8. In LoRa, more effective interference prevention necessitates a larger CR, which raises the TOA. Increased coding rates are an effective defense against decoding errors and interference bursts. However, these rates come at the expense of longer packets and increased power consumption [58].

Transmission Power (TP)

TP denotes the power needed to send a certain data packet. TP on a LoRa radio can be set to 14 dBm for uplinks and 27 dBm for downlinks on ISM band frequencies (863 MHz - 870 MHz). All European countries, as well as several non-European countries, use the EU863-870 band [59].

LoRa is positioned at the Physical (PHY) of the Open System Interconnection (OSI) model. Above LoRa, there are several protocols, notably LoRaWAN (Figure 1.7).



Figure **(1.7)** – *LoRa Stack.*

1.3.3 LoRaWAN

LoRaWAN is a standardized and maintained communication protocol by the LoRa Alliance. The first LoRaWAN specification was released in 2015 [52]. To date, there are two main series of LoRaWAN versions: 1.0 and 1.1.

LoRaWAN Architecture

The architecture of a LoRaWAN network is composed of four (4) main parts as shown in Figure 1.8.

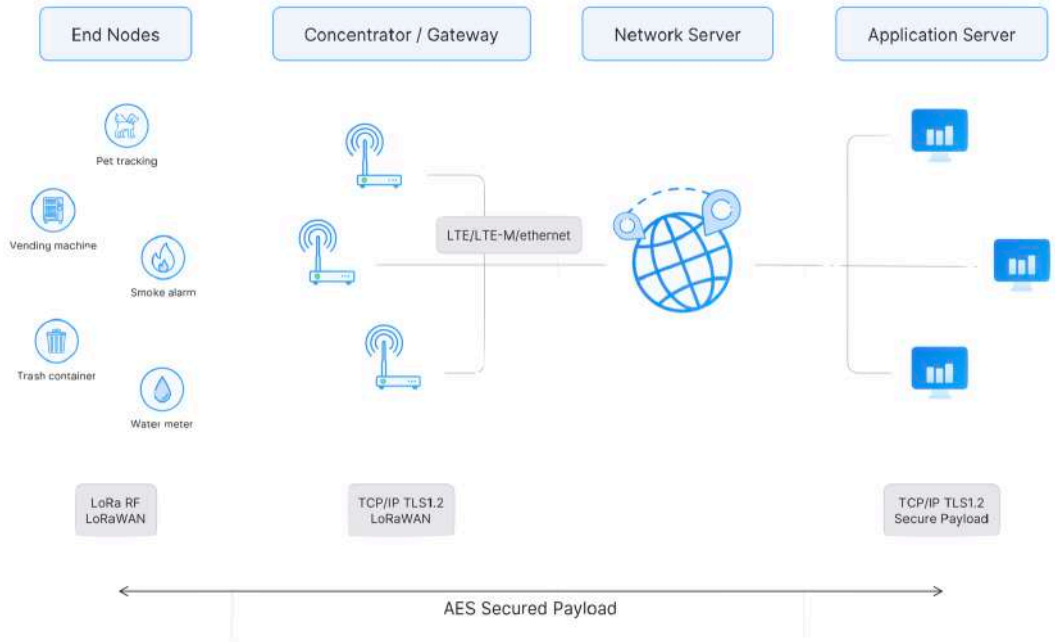


Figure **(1.8)** – *LoRaWAN Architecture. [60]*

- **End-devices (ED)** can be sensors, which collect physical measurements, or actuators, which perform operations, and send or receive information from GW using LoRa modulations. Examples of sensors include temperature, light,humidity, noise, velocity, etc. Examples of actuator are wireless lock, lamp ignition system, often used in home automation (Figure 1.9)
- **GW** is the gateway between the End Device (ED)s and the network server. The GW retransmits the correct messages to the Network Server (NS). It can be linked to the NS via a wired IP connection (Ethernet for example), or wirelessly via Wi-Fi or cellular.



Figure **(1.9)** – *End devices.*

The GWs have a purely physical role, which is to check whether the messages received are correct based on the CRC. In such a scenario, the message is decoded and translated into an IP packet, before being retransmitted to the NS with additional information such as the RSSI (Received Signal Strength Indicator), which measures the quality of the received signal [61]. Otherwise, the message is discarded.

In the LoRaWAN architecture, a message sent by an ED is received by all the GWs in its vicinity, and each of the GWs retransmits the message to the NS. The NS then, based on the RSSI, chooses which GW to use for the downlink and deletes the copies of the message received. This mechanism reduces loss rates in general and is particularly useful for mobile sensors and geolocation.

- **Network Server (NS)** is the brain of the network, with a global view of the network. It manages the entire network by:
  - controlling transmission parameters
  - authenticating the various EDs
  - encrypting its exchanges with EDs, and with end-user's application servers.
- **Application servers:** are responsible for processing, managing, and interpreting sensor application data. They also generate all downlink payloads from the application layer to the connected end devices.

Another important server in the LoRaWAN architecture is the **Join Server (JS)**. The Join Server (JS) is responsible for managing the processes related to activating and adding new EDs. The JS performs the derivation of application and network session encryption keys for the NS and signals to it which application servers to connect to each ED.

Devices Class

There are three (3) LoRa ED classes:

- **class A:** basic class, most energy-efficient class, in which the ED is mainly in an inactive state. It wakes up as soon as there is a change in the monitored environment and goes into a transmitting state (Tx), then observes a waiting time of about one (1) second for reception (Rx1). If no message is received within one second, it briefly switches back to wake-up mode to listen for reception (Rx2). If there is still no reception, it returns to standby until the next transmission.

- **class B:** In addition to the properties of class A, it provides regularly programmed reception windows. This programming requires a beaconing system that allows the ED to synchronize itself with the NS and thus enter the reception state at the right time.

- **class C:** EDs in this class are always up, waiting for a downlink message. The second reception window is not closed until a new message is sent.

Activation

To be able to send or receive messages, LoRaWAN devices must be registered on the network. This is known as activation or joining. There are two activation methods [62]:

- Over-The-Air-Activation (OTAA): For end devices, OTAA is the safest and most advised activation technique. Devices and the network undergo a collaborative process during which security keys are negotiated and a dynamic device address is assigned (Figure 1.10).

- Activation By Personalization (ABP): The device address and security keys must be hardcoded to use ABP (Figure 1.11). ABP has the disadvantage of not allowing devices to swap network providers without manually changing the device's keys, making it less secure than OTAA.

The activation process differs according to the LoRa version used. In particular, version 1.1 introduces a separate join server from the network server.

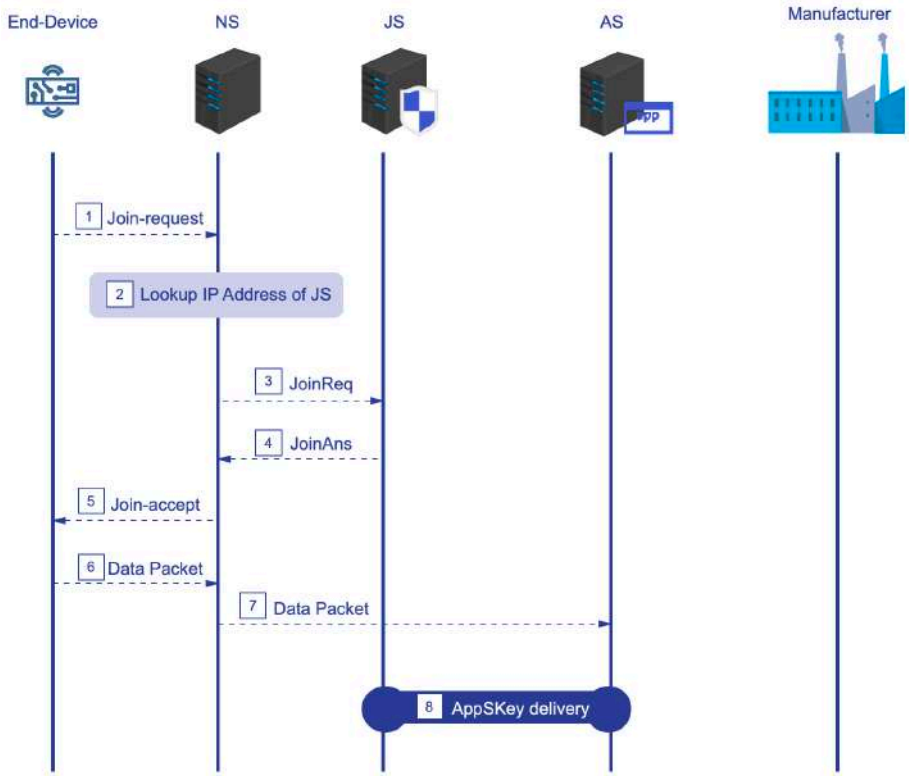


Figure **(1.10)** – *OTAA process. [62]*

Duty cycle

The duty cycle is a limitation on the operating time of a device on a given frequency band. The aim is to ensure that devices operating in the ISM band do not cause harmful interference to other devices operating in the same band. For the 863-870 bands used in parts of Africa, Europe, and India, the duty cycle is generally equal to 0.1% or 1% ([63]- [64]).

Adaptive Data Rate

To manage network performance, LoRaWAN uses **ADR** to manage objects. This mechanism optimizes data rates, airtime, coverage, and energy consumption in the network [65]. The ADR algorithm consists of two parts. The first is decentralized and aims to increase the probability of reaching a network BS. To achieve this, SF or TP are increased if several consecutive uplink transmissions do not receive an acknowledgment. The second part of this mechanism is centralized, with the network server aiming to enhance communication efficiency. Therefore, it records the SNR of 20 uplink packets, then calculates a margin to determine how TP and SF can be modified to reduce transmission power consumption [66]. Figure 1.12 shows the workflow of the ADR algorithm.

The use of ADR in LoRaWAN results in greater scalability with the addition of more gateways and higher network capacity [65]. The ADR is supposed to be an efficient and

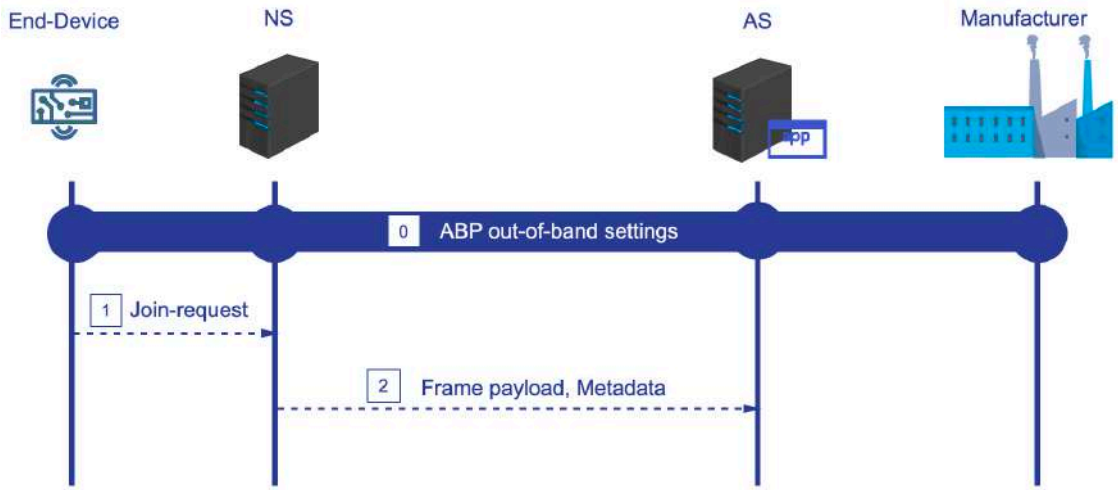


Figure **(1.11)** – *ABP process. [62]*

reliable network management mechanism in theory, but various studies have shown that in practice, it suffers from performance issues such as unfairness, slow convergence, and increased collision rate, all of which reduce LoRaWAN reliability and scalability [67]. Several papers propose optimizations in LoRa resource allocation. These solutions often involve setting options such as SF and TP [68] [69] [70] to ensure good performance. [71] proposes a semi-decentralized approach to the allocation of transmission parameters such as SF and TP, taking into account the different application requirements to mitigate network performance degradation. With the arrival of $5G$, which promotes the association of several networks, and new technologies such as Software Defined Network (SDN) [72], approaches taking into account the Quality of Services(QoS) are increasingly seen. They try slicing the network into virtual sub-networks, each grouping EDs with similar QoS needs [73] [74]. These models are often based on mathematical models [74] or machine learning to do clustering [75] [76] to place devices in the right slices and are accompanied by methods of resource reservation by the slice. Still in the QoS category,[77] proposes a multi-hop routing protocol grounded in Deep Reinforcement Learning that considers QoS requirements. The authors in [78] use a Mixed Interger Linear Programming (MILP) model to optimize the allocation of the SF and frequency. Their goal is to enhance QoS using metrics such as Data Extraction Rate, collision frequency, and Network Energy Consumption (NEC). Lima et al. propose APRA an optimization of LoRaWAN resource allocation by juggling the different communication parameters (SF, TP, and BW) [79]. This approach is based on the classification of the EDs, according to the applications used, into three priority classes: high, medium, and low. The high-priority EDs are chosen first and are assigned the

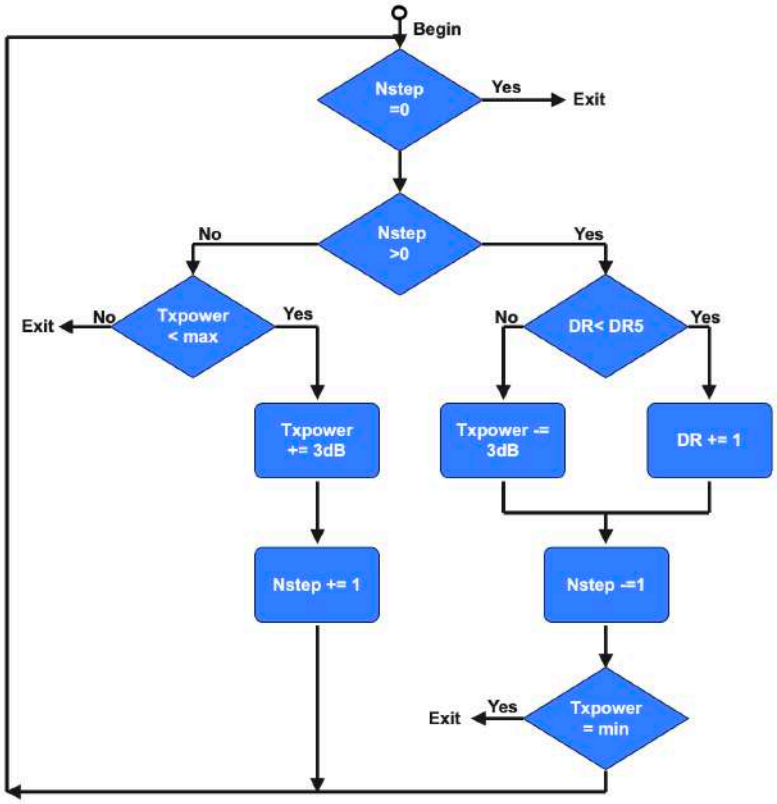


Figure **(1.12)** – *ADR Algorithm. [66]*

smallest SF and largest BW meaning the best DR so that the message is well received and decoded within the limit of the number of EDs per SF. Then the TP is adjusted to optimize the energy consumption. The model is compared to other solutions and shows convincing performance. However, the simulation's scope is limited to a single GW, and it does not consider the support of new nodes or mobility. A Packet Delivery Ratio (PDR)-based QoS differentiation is proposed in [80] in a dense IoT environment. Devices are assigned to each cluster based on their PDR requirements and then frequency, SF, and TP are assigned based on the clusters.

Three solutions are presented in [81] for SF assignment in a multi-operator environment. According to different levels of cooperation: partial, minimal, or absent, the respective solutions based on gradient ascent, game theory, and LSTM are proposed and compared with other existing solutions. Another ADR improvement is proposed in [82]. The authors attempt to minimize both energy consumption and packet loss of end devices. They rely on multi-armed bandit (MABA) algorithms to address these conflicting goals. MABAs help navigate the fundamental exploitation-exploration dilemmas that arise in decision problems with partial information, where decisions must be made over time and impact rewards and information obtained [83]. A player has a set of K weapons, and at each stage, he must choose one and receive the corresponding reward, ignoring any reward he might have. The approach aims to allow objects to select SF and TP rather than NS as in conventional ADR. Simulations are conducted with various MABAs and classical ADR. [84] also proposes using the MAB, specifically Exp3 [85], to autonomously guide the decisions of each LoRa end-

device towards the least requested SF while ensuring responsiveness to possible changes in shared resource utilization. [86] suggests optimizing the ADR by adapting the CR to balance the trade-off between CR value and energy consumption. [87] further reduces energy consumption by considering network behavior and allowing nodes to dynamically select the optimal TP value for each node. Another study based on Random Forest introduces a new method to address the slow configuration of network parameters. [88] proposes a congestion classifier based on logistic regression. A classifier is used in [89] to predict future transmissions for a node and thus assign it a SF while considering the probability of collision. The subject of effective bandwidth management is studied in [90]. The authors use RL to find the best transmission parameters and thus optimize the duty cycle.

In [91], a new SF allocation model in LoRaWAN is based on load-balancing where each ED is initialized with an SF according to the Received Signal Strength Indicator (RSSI) and the SNR. Then, to avoid overloading the smaller SFs due to the distribution of the EDs, a distribution of the EDs on the higher SFs ($8 - 10$) is performed each time a class is full. Moreover, the authors show that the 3GPP Urban Macro Model is closer to reality after comparing the SNR with real measurements and log distance. Due to ADR restrictions, most of these solutions are not designed for mobile devices.

LoRaWAN and Mobility

LoRaWAN is a widely used IoT technology, thanks to its coverage capacity, low network power consumption, and low set-up costs. It has been integrated into many fields, such as agriculture [92], cattle tracking [93], environment monitoring [94], etc.

However, its effectiveness is hindered when objects are in motion. Indeed, when ADR is activated on a mobile device, by the time the change command reaches the device, the propagation environment may have changed due to mobility. This means that the data rates to be programmed, contained in the message received, are no longer adapted to the situation [95]. This is why Semtech recommends **BADR** or **Blind ADR** for mobile use [95].

Blind Adaptive Data Rate (BADR) uses a set of SFs (SF12, SF10, and SF7) at different intervals. The system is therefore not limited to a single DR as in ADR. SF12 is used once an hour, SF10 twice an hour, and SF7 three times an hour (Figure 1.13). BADR provides superior coverage, extended battery life, and enhanced overall performance compared to ADR for pet tracking applications. However, BADR will periodically change the SF without taking mobility into account. It does not reflect the real mobility of objects. This is why several research projects have looked at mobility optimization mechanisms in LoRaWAN ([96] [97] [70] [98]).

In [96], the authors provide an ADR enhancement for mobile devices following predefined mobility patterns (e.g. household robot, store camera, production line robot). They also rely on RSSI measurements to determine the optimal transmission parameters. Thus this approach has limitations for devices with unknown or undefined trajectories. Hence, its optimized version [98] is based on a Variable Order Hidden Markow Model (VHMM) to predict the node trajectory. Robbe et al. propose a mobility handling mechanism [97] that supports QoS. It relies on SNR measurements to identify different cases: exit, entry into a

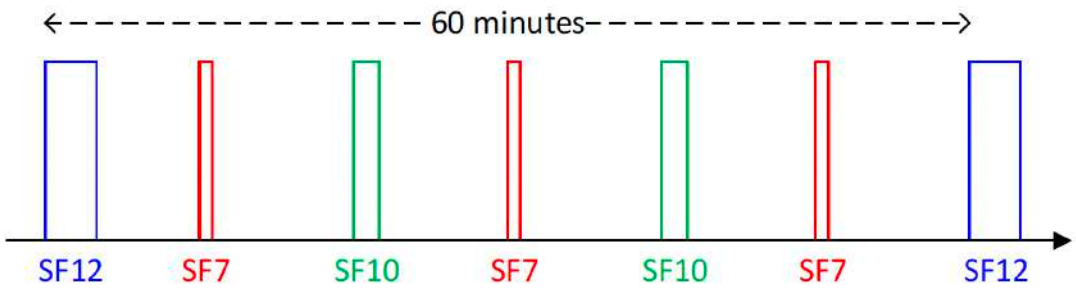


Figure **(1.13)** – *BADR. [95]*

cell, on the Packet Error Rate (PER) desired by the ED, and adjusts accordingly the SF and transmission power. The model tries to obtain a reliable application while reducing energy consumption. This solution requires a modification at the ED level to introduce the desired PER. The signal reception power is measured in [70] to choose the initial SF taking into account the traffic differences (packet length) in the first step before choosing the right SF. This choice is based on a calculation of the distance between the positions at the initial and current time. This distance is then compared to a constant α fixed at 10m. They justify this choice by the constancy of RSSI up to 40m. If the distance is less than alpha, the SF is not modified, but if it is greater than or equal to alpha, the application assigns a new SF according to the new value of the received signal strength. However, the solution requires calculations at the ED and GW levels. Moreover, it is only suitable for devices with low mobility. [99] investigates and evaluates LoRaWAN for end-user mobility. It compares two mobility models: random waypoint [100] [101] and Gauss-Markov model [102] with the stationary model. Simulations are performed with two velocities, 5m/s and 25m/s, and two types of zones, large and small. The results show the best /glsPDR for the Radom waypoint at a speed of 5m/s on the large zone, and the worst for the small zone. When the speed is increased to 25m/s, almost the same performance is observed for all three models, with more collisions for the random waypoint and the small zone. RM-ADR, a device for managing SF and TP implemented at ED and NS level, is proposed in [103] to take mobility into account.

Most of these solutions are ADR optimizations based on knowledge of the device's po-

sition from the GW. Knowledge of the distance between the served device and the GW is important in LoRaWAN networks, as it allows the right SF to be assigned or chosen. This opens up two types of approach: solutions based on calculating the distance at each point between the object and the GW [97, 70] and solutions based on trajectory prediction [96, 98]. An evaluation of the impact of mobility with the use of LoRaWAN is proposed in [104]. The study compares two mobility models Random ways-point and the Gauss-Markov model with the stationary model through simulations on FloRa simulator with different scenarios. The PDR, the number of collisions, and the energy consumption are compared in the different cases. HADR(Hybrid ADR) is proposed in [105] to meet the needs of applications alternating mobile and stationary conditions in response to ADR and BADR. It proposes a two-step mechanism starting with the computation of the distance between the current and previous positions of the device to evaluate its mobility. In the case of mobility, an optimized version of BADR is executed at the ED level using all the SFs. And in the opposite case, a modified version of ADR is executed on the NS side. The performances are compared to ADR and BADR. [106] proposes a model based on Support Vector Machine (SVM) to determine the level of mobility of a node. This feature enables the selection of the adapted ADR algorithm without requiring knowledge of the node trajectory. They rely on the data present at the NS level, especially the RSSI and the SNR, as training data for the classification of EDs in the three classes: fixed, mobile or deep indoor.

In the vehicle domain, the adoption of LoRa/LoRaWAN, and LPWAN is a recent development, primarily due to their low transmission rates. However, the massive integration of IoT has resulted in novel use cases enabled by the properties of LPWAN. Due to their low transmission rates, LPWAN technologies possess certain characteristics that make them well-suited for use in vehicular networks.

- Great range: ranging from a few hundred meters for LTE-M to roughly ten (10) kilometers for SigFox, allowing access to numerous nodes without the need for intermediate equipment between the transmitter and the receiver. This will:
  - lighten routing by lowering the number of hops compared to when a short-range technology is employed;
  - minimize overheads caused by intermediary nodes;
  - reduce the network's total energy consumption, and
  - prevent exceeding the duty cycle of these intermediate nodes, in constraint networks.
- Low energy consumption: LPWAN technologies are known for their low energy consumption, especially LoRaWAN and SigFox.
- Less susceptible to interference and path fading

Finally, LoRaWAN and Sigfox have lower deployment costs than cellular LTE-M and NB-IoT, making them promising options for experimentation. The primary benefit of LoRaWAN over SigFox is its status as an open standard, enabling anyone to deploy a private network. Additionally, the deployment cost of LoRaWAN is typically lower compared to

SigFox. It can be integrated into use cases involving non-latency-sensitive applications, such as ISAC([107]), tracking [108], monitoring [109], in the context on Internet of Vehicles (IoV) [110], [111]. In IoV, the vehicle is considered not just as a mobile network node but as an intelligent vehicle that interacts with other users and RSUs and has components and services received via the Internet [112].

[113] introduces a vehicular Monitoring System (VMS), designed for mobile environmental monitoring. This system is installed in vehicles and can track various environmental parameters, such as ambient temperature, humidity, and air quality, along with vehicle information like GPS location and speed. It consists of three components: a front-end sensor node, a gateway, and a backend smart platform. Communication between the sensor node and gateway occurs via LoRa. [114] presents an agreement-less roaming system that utilizes a distributed server across multiple companies to enhance ship tracking. Additionally, [115] assesses the use of LoRa technology in vehicle tracking. Asiain et al. [116] present a wireless traffic flow detection system that primarily addresses scenarios when traffic flow is slow or halted, thus elevating the risk of highway accidents. They investigate the relationship between vehicle speed, gate distances, and RSSI attenuation. [104] explores how mobility affects the performance of mobile IoT devices. Alongside the stationary model, this study examines two well-known mobility models: the random waypoint and Gauss–Markov models. The experiments were conducted with various network sizes, numbers of end devices, mobility speeds, and payloads. The results demonstrate that LoRaWAN performs effectively with both mobility models in high-density networks. Furthermore, it shows good performance even under high speeds and larger payloads.

[117] propose an experimentation of LoRa in a suburban environment to evaluate RSSI and coverage for two scenarios V2I and V2V and two values of SF (7 and 12). Haque and al. propose in [118], a LoRa architecture for reliable, low-power V2X communications. The RSSI values received during acknowledgment messages are used to select the optimal RSU for communication. Additionally, the Kaulman filter is employed to ensure the accuracy of the measurements and identify any outliers. Performance tests are conducted in a real environment to evaluate reliability at various speeds. [119] proposes a communication framework combining BLE and LoRaWAN. The authors use BLE for the communication between vehicles (V2V) and LoRaWAN between vehicles and road infrastructures. They analyze the performance of each type of communication by different types of practical scenarios. Li et al propose simulations of LoRa with different configuration parameters on different typical V2X communication scenarios with LoRa [120] and LPWANs in general in [121] [122] define the main challenges of V2X communication such as application latency intolerance and security. In the same context, a study of LoRaWAN in the vehicular environment is proposed in [123] with a comparison of a simulation on Network Simulator 3 (NS3) and real experimentation. The impact of mobility with different speeds is evaluated with metrics such as RSSI, PDR, and Packet Inter-Reception (PIR) time. The results show consistent values between the simulation and the real tests. Similarly, Torres et al. consider a simulation and an experimental study of V2V and V2I communications in LoRa to evaluate the reception power, the received signal rate, and the Doppler effect in the suburban context [124].

Observations indicate that the majority of LoRaWAN optimizations in mobile do not

consider highly dynamic environments, such as VANETS. Furthermore, research on LoRaWAN for vehicular primarily focuses on application or experimental studies to assess the compatibility of LoRa with VANETs. Thus the optimization of LoRaWAN in VANETs remains a rather unexplored topic.

1.4 Intelligent Reflecting Surface/Reconfigurable Intelligent Surface technologies integration in VCN

Intelligent Reflecting Surface (IRS)

An IRS, or Intelligent Reflecting Surface, is a passive reflecting surface that may modify signals in a controlled manner. It is frequently used interchangeably with Reconfigurable Intelligent Surface (RIS). A RIS is a reflective surface made up of numerous reconfigurable or programmable elements. These elements can adjust the way they interact with radio signals to optimize coverage and signal quality [125]. A RIS can be implemented using **meta-surfaces** or **reflectarray antennas** [126].

A meta-surface is a surface whose layers are composed of meta-material, which is a synthetic material with physical properties (optical, electromagnetic, etc.) not found in its natural state. Meta-materials are composed of meta-atoms or unit cells whose electrical thickness is of the order of the sub-wavelength of the operating frequency under consideration, arranged on a generally flat surface. Meta-surfaces can offer electromagnetic wave control properties depending on the properties and shape of the unit cells [127], [128].

The reflectarray antenna combines the characteristics of phased-array and parabolic antennas. It uses a flat or slightly curved surface composed of numerous radiating elements, similar to those of phased-array antennas, but arranged to reflect radio waves. The elements of the reflectarray antenna are designed to react to electromagnetic waves in such a way as to produce a beam of radiation directed in a specific direction, just like a parabolic antenna. However, unlike a traditional parabolic antenna, the surface of the reflectarray antenna is flat or slightly curved, which simplifies its manufacture and adjustment [129]. A reflectarray can behave like a metasurface when the size of its elements and their spacing are reduced [126].

RIS offers some advantages, including the ability to adapt the beam direction by adjusting the surface elements, thus providing multiple functions. It can also be manufactured more cheaply and easily than traditional parabolic antennas.

These surfaces are used as an alternative or in support of traditional relay or UAV communications. The table 1.5 describes the differences between IRS, UAV and traditionnal relays.

Technology	Type	Duplex	Energy consumption	Cost	Mobile	Maturity
Traditionnal relay	Actif	Half duplex in most cases	++++	++	No	++++
UAV	Actif	Half duplex generally	+++	++++	Yes	++
IRS	Passif	Full duplex	+	+	Yes	+

Table **(1.5)** – *Comparison between Traditionnal Relay, UAV and IRS.*

1.4.1 RIS hardware architecture

The hardware architecture of a RIS consists of two parts: a sensing part and a control part (Figure 1.14).

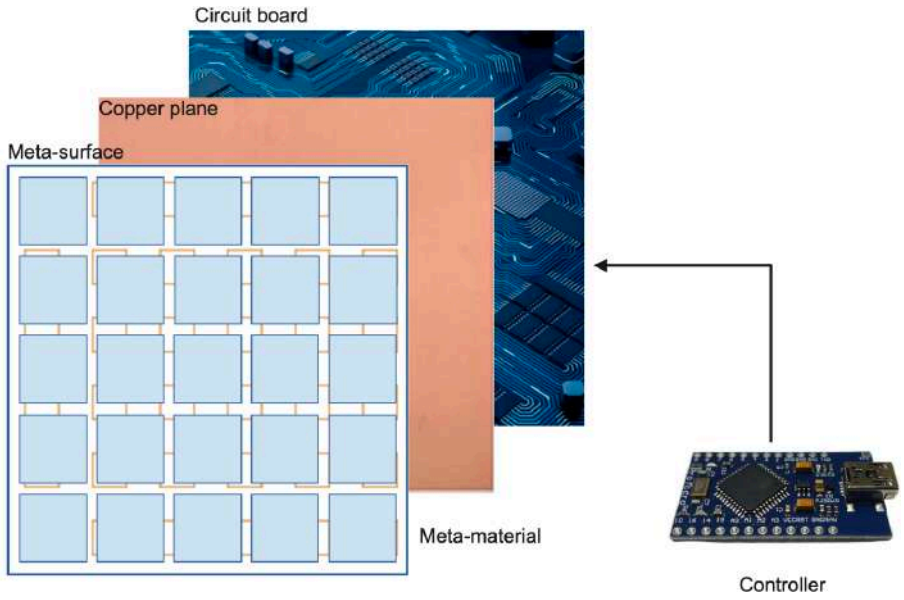


Figure **(1.14)** – *RIS hardware architecture.*

The sensing component is composed of two layers: the outer layer contains a large number of metal plates (elements) printed on a dielectric substrate to interact directly with the incident signals; and the intermediate layer which plays an essential role in preventing leakage of signal energy. It is composed of a copper plate. In the metamaterial version, the outer layer can be composed of different elements such as pin diode: digital, varactor: mechanical, microelectromechanical system (MEMS): electrical and mechanical, field-effect transistors (FETs), liquid crystal or graphene resulting in different optical properties and level of programmability.

The control part is composed of the inner layer, which is a control circuit layer responsible for adjusting the reflection amplitude/phase shift of each element. The adjustment is triggered by an intelligent controller attached to the RIS capable of communicating with users or BSs. It will adjust the amplitude and phase shift of each RIS element via the circuit layer [130]. Programmable platforms such as Field Programmable Gate Array (FPGA) are often used to implement an RIS controller. It relies on control information received from the BS to generate control signals and the necessary voltage, which are sent to the circuit layer.

Reconfiguration can be triggered by electrical, mechanical, or thermal stimuli [131], [132]. There are different types of RIS, depending on the degree of programmability: active or passive, static or dynamic.

Passive RISs reflect the signal directly, without amplification, resulting in optimum energy consumption. However, they face the problem of signal fading or multiplicative fading [133] or path loss.

Active RIS are proposed to solve this problem, amplifying the signal before reflection by integrating amplifiers into its elements. This also leads to higher power consumption [133].

RIS can also be static or dynamic if the phase shift can be modified. A static RIS retains the same beam and orientation. The semi-static version can be changed at fairly long intervals, unlike dynamic RIS, which can change the beam in real-time. The static and semi-static versions are ideal for rapid deployment, fixed-area requirements, and less dynamic, more energy-efficient networks. Dynamic RIS, on the other hand, requires bridge control and is used to track users, making it suitable for highly dynamic environments such as mobile and vehicular networks [134].

RIS meta-atom: The unit cell is equivalent to a circuit of isolated elements with load impedance. Figure 1.15 shows a RIS unit cell with pin diode activation.

1.4.2 RIS functions:

The composition and architecture of RIS entail a certain degree of reconfiguration resulting in certain functions (Figure 1.16) such as:

- **Reflection:** This is the primary function and consists of reflecting an incident signal in a specific direction.
- **Refraction:** also called transmission, consists of refracting the incident signal toward the desired direction.
- **Focus:** concentrates the incident signal in one direction, resulting in a beam, hence the other name of beamforming.
- **Absorption:** This function cancels the reflection or refraction of an incident signal.

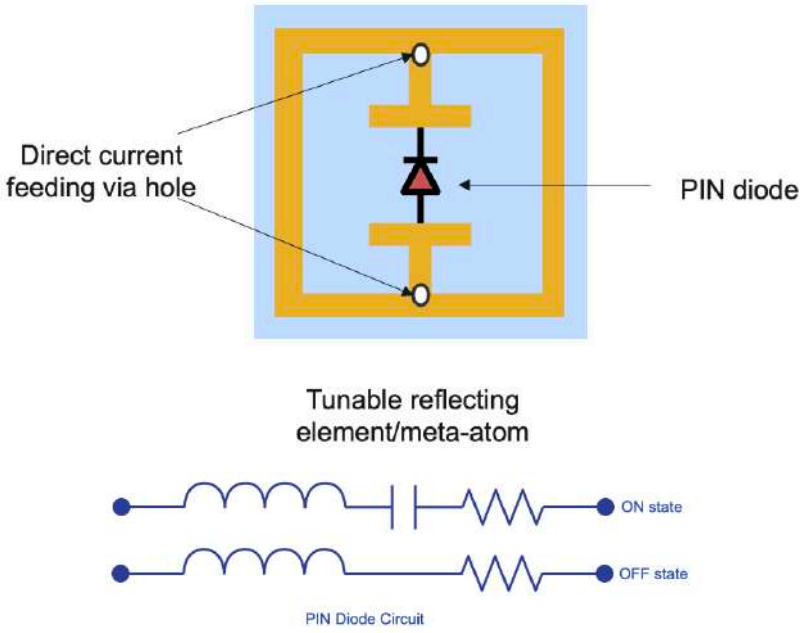


Figure **(1.15)** – *RIS element.*

- **Polarization:** involves changing the polarization of the incident signal: for example from electrical to mechanical, etc.
- **Splitting** subdivides the incident signal into several directions.
- **Analog processing:** introduces a mathematical calculation (derivative, integral, etc.) directly to the incident signal before refraction.
- **Collimation:** inverse of focus.

1.4.3 STAR-RIS, LIMS/RMS, SCS

There are many technologies based on reflectors and used in similar contexts.

Simultaneously Transmitting And Reflecting-RIS (STAR-RIS)

Also called IoS, it is an expansion of RIS that, in addition to reflection, allows for simultaneous signal transmission [136]. This provides for additional degrees of freedom because coverage may be bi-directional in both planes, as opposed to basic surfaces that only cover one [137]. It is intended to be transparent at particular frequencies, allowing signals to be delivered without disrupting their path. This transparency is achieved through the use of sophisticated materials and surface modulation techniques that regulate both wave reflection and transmission.

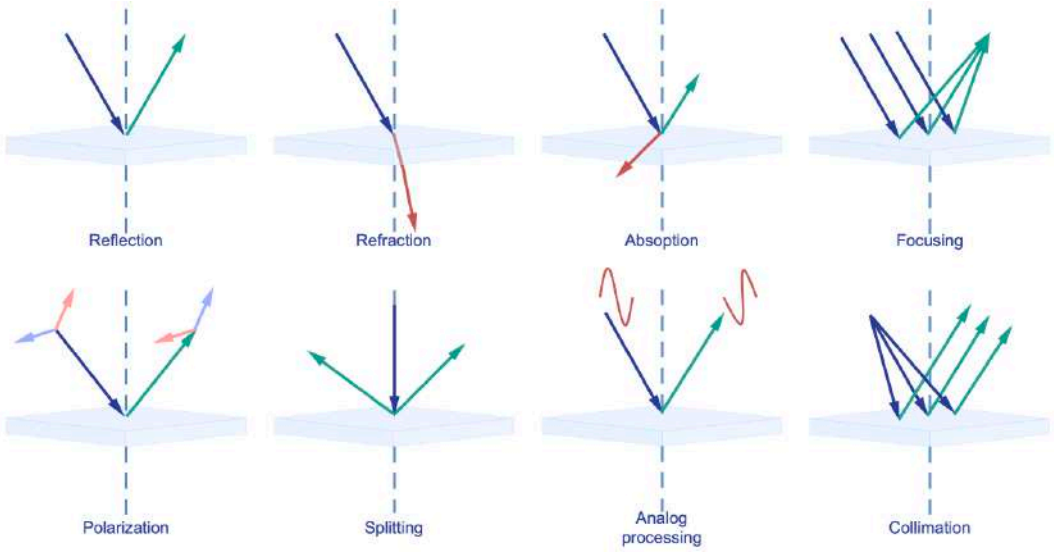


Figure **(1.16)** – *RIS functions. [135]*

Software Controlled Surfaces (SCS)

When surfaces are managed by SDN (Software Defined Network), we refer to them as Software Controlled Surfaces (SCS) or Software Defined Surfaces [138]. The surface's unit components are outfitted with low-power sensors and a nano-communication network that allows the unit cells to communicate with one another [139]. The combination of sensing and communication capabilities allows the smart surface to undertake simple local tasks, increasing its autonomy. However, this can affect the overall complexity and energy consumption of the smart surface.

Large Intelligent Meta-surfaces (LIMS)/Reconfigurable Meta-surfaces (RMS)

Large intelligent metasurfaces, also known as reconfigurable (or programmable) metasurfaces, are metamaterial-based surfaces. These metamaterials are a collection of elements that have features that do not occur naturally in meta-atoms, thus the prefix meta. Compared to RIS and IRS, it takes a more technical approach based on material physics.

1.4.4 Channel State Information (CSI)

RIS is used to increase wireless network coverage, capacity, and signal quality by intelligently diverting radio signals to the receiver or decreasing interference through wave propagation adjustments. RIS, unlike traditional antennas, do not require an elaborate power supply or costly signal processing; instead, they are controlled by characteristics such as the orientation and qualities of the reactive components that comprise the surface. They achieve this by using information on the status of the communication channel, often known as CSI. In wireless networks, CSI refers to the information that characterizes the status of a communication channel between two sites, often a transmitter and receiver . This information is crucial for optimizing transmissions in a wireless network, as it provides information on channel conditions in terms of propagation gains, losses, noise, and interference [140] as for RSSI [141]. Based on this information, the system can adjust several parameters such as transmit power, modulation, coding, and antenna management to improve transmission quality. CSI can be obtained by several techniques, such as channel estimation, which involves pilot signals sent by the transmitter, or feedback techniques, where the receiver sends a channel estimate back to the transmitter [142]. It can be global, meaning the information relates to the complete state of the channel between a transmitter and a receiver. or local, in which case only information about a specific subset of the channel (for example, a certain subcarrier in an Orthogonal Frequency Division Multiplex (OFDM) system) is available.

In RIS architecture, knowledge of the CSI enables RIS performance to be maximized by optimizing the phase and orientation of RIS elements. An RIS can adjust the phase of each element on its surface to improve signal quality or reduce interference. To do this, it is necessary to know the state of the channel, i.e. the CSI, to determine how each reflection modifies the signal. In this way, the RIS controller uses the CSI to calculate the optimal surface configuration parameters. Integrating RIS into an architecture dynamically modifies the channel. Hence the need to regularly re-estimate the CSI.

1.4.5 Use cases:

RIS are generally used to improve the quality of service, with several different uses in particular [126]:

- **Coverage enhancement**: like relays, RISs are used to improve coverage in wireless networks [143] where coverage is uneven, with the presence of areas with little or no coverage. In these cases, RIS can increase the total signal received in the poorly covered area. When the line-of-sight (LoS) between the recipient and the BS is obstructed, RIS can establish a LoS path between a recipient in a blind zone. A multi-RIS system can increase the communication range [144] [145]. [146], [147], [148].
- **Spectrum enhancement**: increase in the received signal, suppression of interference (intra-channel and inter-cell). RIS can be configured to suppress interference in certain areas between two cells or in the presence of noise that may interfere with legitimate communications. The number of available channels for simultaneous data

transmission in wireless communication networks is limited by the strong correlations that can exist between the transmitter and receiver antennas. This problem can be solved by implementing RIS. Communication networks can achieve higher spectral efficiency [130] and spatial multiplexing benefits with a larger number of available channels. Specifically, a higher received signal power that improves coverage also translates into greater spectral efficiency. However, there are additional ways in which an RIS can improve spectral efficiency. In some situations, the channel is often dominated by one or two channels, for example, at high frequencies. Installing an RIS increases the level of spatial multiplexing and offers more degrees of freedom in the channel.[149], [150], [151].

- **Beam management**: thanks to their "reconfigurability", RIS can adjust their beamforming and serve different receivers with less energy than MIMO. They can therefore be used in beam management, which is a set of level 1 (PHY) and 2 (MAC) procedures designed to establish and maintain an optimum beam pair between the transmitter and the receiver to optimize connectivity. In wireless communication systems, beam management is a frequently used approach to lower signal propagation losses during wireless transmission. Establishing and maintaining a network of beam pair links between the transmitter and the receiver is the aim of beam management. This can improve the system's spectral efficiency and provide a reliable, cost-effective solution, especially in high-frequency bands.[152], [153], [154], [155], [156].

Other applications for RIS include :

- **Security**: wireless networks often fall victim to eavesdropping attacks, where a third party eavesdrops on communications between two entities. IRS is used to mitigate this type of attack in two ways. Either by reconfiguring the beam entirely towards the legitimate destination. This will reduce signal scattering to dubious areas and improve the signal received by the legitimate destination; or reflect a signal that will cancel the signal received by the eavesdropper and generate interference [157], [158], [159], [160], [161].

- **Sensing**: One of the criteria for 6G is ISAC, or Integrated Sensing and Communication ([107]). The term ISAC describes the process of using radio signals to "sense," or detect and identify, different surfaces and objects in a surrounding environment. Sensing is the process of identifying and measuring the characteristics of target objects in the surrounding environment using radio signals. By incorporating sensing technology into the communications network, it transforms into a "radar" sensor. It senses and comprehends the physical environment in which it operates by using its radio waves. This facilitates the collection of data on the materials, dimensions, shape, image, orientation, velocity, position, and range of various objects and gadgets by the network [162], [163],[164], [165].

- **Localization**: in wireless networks, localization can be obtained in various ways, including triangularization, which requires three (3) BS to obtain an approximation of position. The use of RIS can improve this approximation without the use of BS [166]. It is often paired with sensing [164], [165].

- **Energy**: on the energy side, using RIS instead of conventional relays or micro BS reduces total network energy consumption by optimizing functions, even with an active RIS. At the same time, it also reduces EMF exposure due to the installation of many BS or relays. RIS is also used for energy transfer and energy harvesting [167] in sensor networks and backscatters [168], [151],[169], [170].

- **Link Management**: Cabling in data centers is often a tedious task, not only in terms of installation and maintenance but also in terms of cost and scalability. Studies have proposed the use of wireless networks in data centers as a solution to this problem. Specifically, the use of a wireless communication protocol in the 60 GHz band will replace the use of cables to link a server to a router or switch [171]. The main limitations of wired networks (mobility, dynamism, and maintenance) that led to the adoption of wireless networks are now also driving the use of wireless networks in Data Center (DC)s, despite the uncertainty surrounding the implementation. One use case for wireless networks would be to set up several RISs to increase coverage and avoid as far as possible inaccessible areas, i.e. NLoS, which can be very numerous in DCs.

1.4.6 Challenges in RIS

Despite their performance, RIS face some issues [126]:

- **Path loss and channel modeling** [135] Path loss is defined as the decrease in signal strength that occurs during signal propagation. Channel modeling is a comprehensive approach that considers this loss as well as other phenomena that describe how a signal is affected in a particular environment; fading, which is a fluctuation in the signal due to phase variations between multiple paths; noise, which is anything that can disrupt the signal, such as electronic equipment, interference with other signals, or even propagation conditions; and multipath, which is the case where the signal takes several different paths before reaching the receiver (e.g. reflection, refraction, etc.). These are important principles in wireless communications, particularly in RIS, which is based on fundamental optical operations. Therefore, a good modeling of the latter could help assess the performance limits of RIS in wireless networks.

- **Deployment**: A RIS is a device used in wireless networks to extend coverage. It can be placed at the BS level or between the BS and the users. It prevents NLoS and reduces path loss. Good RIS positioning is therefore crucial to optimizing network performance [131].

- **Channel acquisition and estimation** One of the most important problems to solve in networks that use nearly passive RISs is channel estimation. Compared to other communication systems, like relays, which have powerful enough signal processing capabilities, nearly-passive RISs have few on-board signal processing units that are not meant to be employed during regular operation. As a result, new protocols and algorithms are required to perform channel estimates while minimizing the complexity of RISs and minimizing the need for on-board signal processing activities.

- **Optimization and resources allocation** One of the most studied subjects in the context of RIS-based systems is system radio resource optimization. A sizable portion of research articles have addressed the issue of passive and active beamforming in Multiple Input Single Output (MISO) systems, specifically the optimization of the transmit (active) beamforming and the (passive) RIS phase shifts. To address the non-convexity of the optimization problem, the widely used technique of alternating maximization has been employed.

- **Control and dynamic RIS configuration**: For a controller to provide the necessary phase shift, RIS components must be properly controlled. To ensure reliable and consistent link performance, it is essential to explore innovative approaches for managing signaling and processing overheads. Depending on the ML controller, the IRS phase shift may be modified. However, this may result in additional limitations on power and memory usage.

- **Performance evaluation**: Performance analysis in RIS-enhanced networks faces several significant obstacles. Evaluating the precise distributions of the cascade channels between the BS and users via RISs is one of the primary issues. Assessing the effective channel gain following passive beamforming at the RIS is another difficulty.

1.4.7 Use of RIS

The introduction of RISs into networks is somewhat recent but offers some advantages, which is why there are many studies on the subject. The use of a fixed-site single IRS in wireless communications, as in [172] and [173], has been proposed in several papers. [174] provides an evaluation of RIS usage with NOMA. The article shows the benefits of rate-splitting multiple access for uplink IoT traffic.

[175] includes a survey of the general use of IRS in 6G networks. [176] reviews the state of the art of RIS before presenting challenges such as channel acquisition, implementation, testing, deployment, and design. Another survey on IRS is done in [177] where the authors divide the literature approches into two categories: airborne and ground-based vehicular communications, along with their applications. The authors' analysis identifies three challenges: the need to combine control systems tailored to the dynamics of vehicle networks, channel estimation, and deployment.

[178] proposes target detection at the level of the IRS itself, using sensors and a controller, which is an omnidirectional antenna. [179] attempts to secure communication against eavesdropping, taking into account QoS requirements. The solution is based on DRL. The QoS criteria considered are the security rate and the minimum data rate. Xu et al. proposed an architecture composed of a BS, UEs (User Equipments), IRSs, and a PB (Power Beacon). TThe IRSs, in this study, do more than reflect; they retransmit the signal thanks to the energy collected from the PB radiations to retransmit the UEs' message to the BS. The PB acts as a scheduler, providing modulation information to each IRS to identify the user who will communicate with its dedicated IRS. It also acts as an energy supply, as the IRS uses the radiation transmitted by the PB to charge itself, as in back-scatter networks [180].

[181] proposes a distributed IRS architecture where multiple nodes use multiple IRS to maximize the achievable sum rate. It relies on a centralized controller to optimize the phase shift and the transmitted power. The algorithm presented is based on Lagrangian dual reform, which attempts to solve the different objectives iteratively and alternatively. A numerical simulation compares the proposed optimization method with three others: communication via antennas, with IRS back-scatter but without PB, and discrete as the proposed version with the difference that the passive beamforming at each IRS is discrete [168]. In [182], the authors propose propose IRS coordination with a centralized controller to maximize the sum rate. Faced with the problem's non-convexity, they attempt to tackle the power and phase shift optimization objectives alternatively using an iterative technique.

To optimize the throughput, [183] proposes to study the IRS placement. The proposed architecture is a disc layout with an AP at the center. The location of the IRS - near or far from the AP - is evaluated to determine the correct placement. The authors then vary the number of IRS and disks to see the effect on throughput. [184] proposes to study the placement of multiple IRS indoors by jointly optimising the number, locations and phase-shift coefficients of the IRS, with the aim of minimising the number of IRS as a function of the average achievable data rate based on the Differential Evolution (DE) algorithm, which is a population-based heuristic algorithm. In [185], one or more IRSs are placed on the source, destination, or relay side, and their use is investigated. In addition, [186] tries looking into how IRS is used in smart industries. It examines two deployment models—collocated and dispersed—while keeping QoS in mind. And [144] studies the limits of coverage performance in multi-IRS with mm-Wave using stochastic geometry for IRS positioned between 30 and 150m.

In the field of IoS and STAR-RIS, [187] propose an hybrid beamforming mechanism, with a digital first beamforming on the BS, while the one on the IoS is analog. [188] proposes a channel estimation method based on Multi-task learning in a STAR-RIS system. In [189], to minimize network consumption, a caching system based on Deep Q Network (DQN) is proposed with STAR-RIS equipped with a controller and a cache.

[190] suggests employing multiple-IRS deployment to enable wireless communication between BS and mobile users. First, the authors proposed picking the IRS group based on the maximum signal strength received by the cell phone user. Second, a derivation is shown to determine the trade-off between the ideal path of the base station and the mobile user and the beam-forming gain to reduce path loss. In addition, this trade-off is optimized using graph theory. Then, the authors studie the problem of multi-beam multi-hop routing for downlink communication in a massive MIMO system in [191]. The use of drones to send radio signals to a ground station or to another drone to create a multi-hop transmission is suggested in the work of [192]. The study also looked at the effects of utilizing an IRS to enhance the quality of service (QoS) between the drone and the base station. This is accomplished by proposing a heuristic graph-based power consumption model to lower drone power usage. An overview of the deployment of single, double, and triple IRSs is provided in the publication [193]. Additionally, the goal is to enhance channel use and IRS passive reflection. [194] investigate the use of RIS with a full duplex relay. They compared a system consisting solely of RIS to a system with several RIS and an full duplex relay in the environment. The results show an improvement in the selected metrics, which are average Bit Error

Rate (BER), average spectral efficiency and outage power depending on the number of RIS elements. When compared to a system with RIS alone, the cascade version demonstrates the interest of an intermediate full duplex on performance. In their study, [195] proposed a new design for phase shifting and precoding in a MIMO network using two IRSs. The weighted sum rate, whose model is non-convex, is maximized. Majorization-minimization and block coordinate descent are the two approaches used to tackle the optimization problem because non-convex models cannot be handled using conventional tools. In [196], the authors suggest integrating the IRS into the base station (BS) to facilitate its reconfiguration. The antenna is framed by four (4) IRS that reflect and strengthen the signal. Multi-hop is used to reach remote users. A variety of metrics are evaluated and compared, and the results indicate that the proposed algorithm offers a superior sum rate. Additionally, an optimization model for multiple-IRSs deployment is proposed in the work of [197]. For a variety of IRSs and graph network topologies, the objective function aims to optimize two parameters that maximize the transmission rate and achieve non-interference transmission.

In the mobile context, several studies have looked at the use of IRS to facilitate Unmanned Aerial Vehicle (UAV) communications. This is the case in [198], in which the power gain received when using an IRS in downlink communications between a base station and a UAV is evaluated. Various parameters are addressed, such as the number of IRS elements, the UAV altitude, and the distance and height of the IRS from the base station. In [199], the authors consider a scenario in which UAVs have to communicate with their base stations. The IRSs are fixed and placed close to the BS and are used to reduce or mitigate interference. Whereas in [200], communications between UAVs and mobile UEs are emphasized, to jointly optimize UAV trajectory and IRS phase shifts. They are based on UE trajectory knowledge and use Deep Q Network (DQN) for discrete trajectories. In the case of continuous trajectories Deep Deterministic Policy Gradient is applied to determine the best trajectory and to select the IRS to use. In [201], the authors propose the use of a mobile IRS to support UAV communication and NOMA, a non-orthogonal multiple access technique. They aim to jointly optimise the UAV trajectory, the mobile IRS path, and the power allocation to the users to maximise the average data rate for the users. The approach is based on the Genetic Algorithm (see), and the results show better performance for the proposed system than with a fixed IRS or without an IRS. [202] presents a model for optimising IRS placement and resource allocation in a mobile edge computing environment. IRS are placed at the UAV level. The paper attempts to maximise the energy efficiency of low-power IoT devices during computation by jointly optimising computational and communication resources. [203] proposes a delay reduction in an IRS-assisted mobile edge computing system. Another work also addresses IRS placement in millimeter wave networks with mobile users [204]. The aim is to optimize the rate and coverage. Still on the subject of IRS placement, Mu et al. [205] propose to study the optimal deployment of IRS for three multiple access mechanisms: NOMA (Non-Orthogonal Multiple Access), FDMA (Frequency Division Multiple Access), and TDMA (Time Division Multiple Access). The results show the gain of optimal IRS placement and the ideal type of placement for these types of modulation. Furthermore, [206] proposes an optimization of both the beam-forming transmission and the positioning of an Aerial IRS (AIRS). The goal is to maximize the SNR peak value.

1.5 Discussion

VCNs are highly dynamic systems characterized by user diversity, fluctuating node density, quasi-random user speeds, and increasing demand. Because they rely on wireless communication technologies, VCNs often approach the limits of these systems. For example, technologies like Wi-Fi and Bluetooth have short ranges, cellular networks can be costly and unreliable, and millimeter wave (mmWave) technologies are sensitive to obstacles. The topology amplifies obstacles and interference, especially in urban areas. This creates a need for solutions that are less affected by obstacles or that enhance coverage while controlling costs, rather than traditional densification of cellular networks. As the IoT becomes integrated into the vehicular domain, incorporating IoT-specific technologies becomes more evident. These include BLE, LPWAN, and LoRaWAN.

LoRaWAN is a long-range wireless communication technology widely used in IoT. While it is resistant to interference, it has relatively high latency. Therefore, it is mainly used for non-critical applications. It provides various mobility support features and two roaming options: passive roaming, which is seamless to the user, and handover roaming. In vehicular settings, LoRaWAN integration primarily targets smart parking, waste management, and disaster recovery. Recent studies have shown its effectiveness in vehicular communication. However, implementing a suitable resource allocation method could reduce latency and allow for more adaptive integration.

Another technology to enhance coverage is IRS. IRS enhances network coverage by establishing a Line of Sight (LoS) link between sender and receiver. It can also amplify the signal to the user. IRS can be employed for interference reduction, security, and other purposes. It can also facilitate multi-reflection to extend signal reach and coverage. Most studies on IRS assume fixed positioning to address static issues. Mobile IRSs are mainly used for UAV communications, where they are positioned at the UAV's level. This improves coverage and grants access to areas unreachable by fixed IRS or ground-based mobile IRS. However, incorporating IRS on UAVs can pose several challenges, many related to UAV use. First, UAVs tend to consume more energy due to movement, a problem worsened by the weight of the IRS. Second, optimal deployment is crucial to minimizing energy use. Lastly, UAVs are vulnerable to weather conditions, which can cause instability during flight. Additional weight from the IRS can exacerbate this and may also disrupt communication between the IRS and users. One study suggests using a ground-based IRS paired with a single IRS mounted on a dedicated vehicle. This setup offers better coverage than a fixed IRS alone. However, a single IRS cannot solve problems in distant areas simultaneously. Therefore, multiple IRSs would be required to improve coverage and penetration. As with UAVs, careful deployment is essential for optimal performance.

1.6 Conclusion

VCN is a mobile network known for its dynamism. It is based on wireless communication technology. Studies on VCN have been ongoing for many years, with several solutions and

standards proposed in the literature. Nevertheless, thanks to the integration of IoT, the adoption of different types of communication, and the enabling of new use cases, the field remains in tune with the constant evolution of the automobile. Today's solutions tend to take greener, more ecologically friendly methods of resource use. In systems like networks, this mostly means lowering energy bills. Networks consume much energy, from turning on equipment to communicating with other devices. It is consequently crucial to identify solutions to reduce energy consumption while maintaining a minimum of QoS. Some methods for lowering energy consumption can be: including integrating energy-efficient communication protocols, eliminating overheads in communication protocols, and employing low-energy technology. Bluetooth LE, Zigbee, and LPWAN are some energy-efficient communication protocols. While the two first technologies are short-range communications, LPWAN offers long-range and better coverage. In LPWAN, LoRaWAN, a low-power, long-range technology that is simple to implement, seems to be a good candidate. It is based on ADR, a node management approach that provides excellent performance when the devices are fixed. However, this mechanism encounters problems when the application integrates mobile objects. Several strategies are proposed in the literature for mobility management, but the dynamic nature of vehicle networks is rarely considered. This question relates to performance management in the event of mobility. Thus, the question of optimizing LoRaWAN in VANET and simply in case of mobility arises. This can be accomplished using a variety of approaches, such as resource allocation management and latency reduction. On the other hand, some strategies are proposed, in the literature, for QoS enhancing, including prefetching and slicing. Prefetching is the process of searching for a resource in advance to minimize request times. Slicing is a strategy for separating applications based on their demands. Applying these methods to LoRaWAN in a mobile context is the first stage in this research.

To alleviate coverage concerns, RIS, which reduces equipment consumption, can be used instead of regular relays. In some circumstances, RIS solutions can replace traditional relays. They serve a variety of purposes, including enhancing coverage and signal quality, as well as decreasing or canceling interference. However, to ensure optimal performance, proper deployment is essential.

To make the best of these solutions, we apply predictive AI to tackle two main problems, resource allocation and coverage enhancement with optimizing deployment, in the dynamic and dense vehicular network.

Chapter 2

Resource reservation method for LoRaWAN

VCN is the use of storage, computing power, and communication technologies in a vehicle context to facilitate ITS implementation. The previous chapter highlighted several VCN issues, including resource allocation, coverage, QoS, security, and more. With the advent of IoT and its massive adoption in almost all areas, including ITS with IoV, there is a growing trend to integrate the communication means used in IoT into vehicular communications. This is the case with LoRa/LoRaWAN. However, this integration can lead to problems in vehicular communications that are inherent to the characteristics of LPWANs. In this chapter, we study LoRaWAN resource allocation in VCNs, taking into account QoS [1].

2.1 Introduction

VCNs are based on different wireless communication technologies in the three areas of their architecture: in-vehicle, ad-hoc, and infrastructure domains. In the in-vehicle domain, Wireless Personal Area Network (WPAN) technologies are used for communication. A WPAN is a wireless connection between personal devices, peripherals (headphones, keyboard, mouse), mobile phones, tablets, and biometric sensors (pacemaker, insulin pump, etc.) [208]. It uses low-power wireless technologies: Bluetooth, NFC, Radio Frequency Identification (RFID), Ultra Wideband (UWB), Wireless USB (WUSB), etc. In the ad-hoc area, wireless technologies with a longer range are used. These include DSRC, Wi-Fi, cellular networks (4G, 5G), etc. Wi-Fi has a range of a few tens of meters, DSRC a few hundred of meters while cellular offers greater coverage but at a higher price. Additionally, these technologies are generally high rate which make them more sensitive to obstables.

Faced with the short range of DSRC and the cost of 5G technologies, the integration of Low Power Wide Area (LPWA) technologies, LoRain particular, seems to be a way to combine long-range and low cost [117]. LoRa is a low-power long-distance communication

[1] This chapter has been the subject of a publication [207]

technology. LoRaWAN defines the communication protocol and system architecture for the network while the LoRa physical layer enables the long-range communication link [52].

LoRaWAN uses ADR to manage the devices by proposing sets of values for the transmission parameters. These parameters (SF, TP, BW, and CR) which depend on the number and position of the device relative to the gateway are proposed taking into account the current situation of the network to avoid collision [65]. This technique, however, has issues when the application incorporates mobile objects [65]. When ADR is enabled on a mobile device, the propagation environment may have changed due to mobility by the time the command to change the propagation parameters arrives. This means that the data rates intended for programming, as included in the received message, are no longer appropriate for the current situation. This can lead to an increase of network congestion. Semtech proposes BADR [95], a version of ADR that alternates between SF 7, 10, and 12 for limited mobility, such as pet monitoring. In [96, 97, 70, 98], alternatives to ADR for instances when the device is mobile are proposed based on the knowledge of the device's position. As a result, positional awareness is a critical component of these solutions.

However, the speed and the rapid change of positions in addition to the density are factors that have a very large influence on the quality of the received signal. As a result, the subject of LoRaWAN optimization in VANET arises. Its application in the vehicular environment is quite new, en questions like coverage, resource allocation arise.

In general, prefetching and slicing are used for resource allocation and QoS issues. Prefetching, which is frequently used with web sites, entails searching for specific documents or sub-resources in the background for pages to which the user may navigate in the near future. This can significantly reduce the time it takes to load the prefixed page if the user chooses to visit it. When it comes to network slicing, it is a technology that allows for the creation of multiple virtual networks on top of a shared physical network in order to provide greater flexibility in network utilization and allocation. With the prefetching mechanism in mind, we use vehicular prediction to book in advance LoRaWAN resources. We opted to apply it to resource allocation in a vehicular LoRaWAN network. This means that resources that are likely to be used are kept on the GW/NS waiting for the next movement. To determine which GWs will be subject to prefetching, we depend on trajectory prediction data.

The majority of existing LoRaWAN research involve scenarios in which the EDs are mobile but still belong to the same NS. However, in practice, many NS and operators can be requested. A logistics organization may utilize LoRaWAN to monitor the conditions of item preservation in its fleet, for exemple. LoRaWAN supports handover/roaming and proposes two handover methods to support a mobile device: passive roaming et handover roaming [209].

Passive Roaming lets an ED use the LoRaWAN service of a different NS while connected to its glsplGW, subject to overlapping Radio Frequency (RF) capabilities (i.e., channels). The home NS (hNS) retains the LoRa session and MAC-layer control, while the visiting NS (vNS) manages frame forwarding to/from the air interface. There can be multiple vNSs for a session, but only one hNS.

Handover Roaming allows MAC-layer control transfer between NSs. Even during Han-

dover Roaming, the hNS maintains control-plane and data-plane management with the JS and AS until the ED performs a Join Procedure. The hNS's ability to adjust End-Device RF parameters, unlike the vNS, supports more flexible roaming options.

Figures 2.1 and 2.2 describe the passive roaming and handover roaming steps respectively.

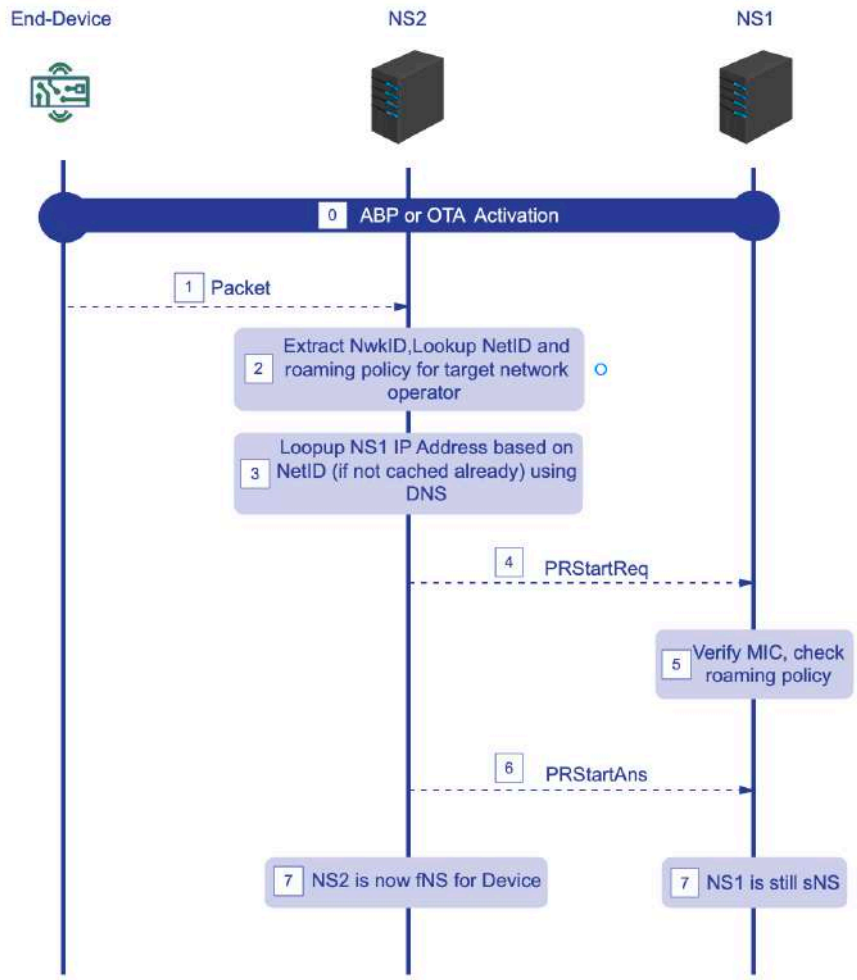


Figure **(2.1)** – *Message flow for Passive Roaming. [209]*

A roaming procedure requires an existing roaming agreement between the two NSs. It should also be noted that there are only two outputs for the roaming procedure. The roaming is either accepted or rejected.

The idea behind this appraoch is to accept newly arrived devices at an NS only when there is sufficient resource to serve the devices with a sufficient QoS, assuming there is a

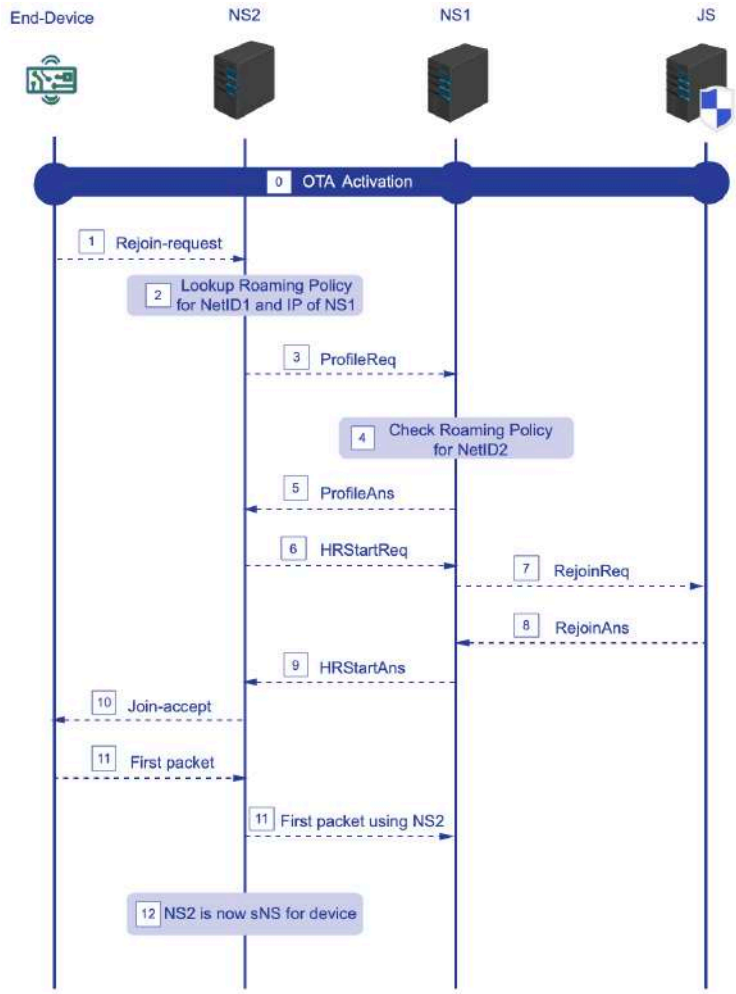


Figure **(2.2)** – *Message flow for Handover Roaming. [209]*

roaming agreement between different operators. This approach is motivated by the potential for congestion arising from the concurrent transmission of multiple devices, despite the low probability of such occurrences. Then we consider two different classes of service: a priority one and a non-priority one. For example, the priority ones could originate from the operator's customers, while the non-priority ones generated from incoming other operator's customers.

The study considers a scenario where a neural network-based vehicular mobility prediction is used to reserve the resource in advance. The remainder is organized as follows: Section 2.2 describes our approach. Sections 2.3 and 2.4 present the results obtained and the limitations. Finally Section 2.5 concludes this chapter with the conclusion and some perspectives.

2.2 LoRaWAN Reservation Mecanism

2.2.1 Dataset and setting

The proposed solution is based on the Rome taxi dataset and an LSTM-based trajectory predictor. The equivalent of one day's data between 10 a.m. and 11 p.m. is used to account for both high- and low-traffic times. Each trajectory has ten positions separated by one minute. Each trajectory is denoted by a trajectory number (numTraj) and each position by an identifier ranging from 0 to 9, idenfying the numero of the position in the trajectory. This data provided to the trajectory predictor [210] yields four predicted positions for each position at time t: t+1,t+2,t+3, and t+4 minutes. From the current position and the forecasted positions, the antenna or GW closest to each of these positions is added to the dataset. The positioning of antennas is added virtually on the map. 530 antennas are placed around 7 km apart in a grid manner (cf Figure 2.3). The complete dataset thus includes the trajectory number, the trajectory identifier, the date, the current antenna that supports the taxi, and the four future antennas that are expected to support the taxi based on the predictions.

The goal is to maximize resource allocation in a multi-operator mobile scenario employing LoRaWAN. We suppose that the antennas are shared between 5 operators to mirror reality. To emphasize the phenomenon of roaming, each antenna houses an NS. Operators are assigned antennas at random using python random module.

The proposed strategy relies on two mechanisms: traffic differentiation and reservation.

2.2.2 Traffic differentiation

To implement service differentiation, we divide the traffic into two types: priority and non-priority. A traffic has priority if the operator, where the device is subscribed called home Operator (hO), is the same as the operator owning the antenna. It is a non-priority traffic in case the hO of the device is different from the operator owning the antenna. This means that the current operator, owning the antenna, is a visiting Operator (vO) for the device.

The objectif of this differentiation is to make the resource reservation exclusive to the device in priority traffic. This should favor current operator customers at the expense of other roaming customers. In principle, if a mobile device has A as its hO, then it has the right to make a reservation on all of the antennas that belong to A.

We assumed that each device starts from its hNS and hO. From the first position, for each device, the hO is deduced. Then, for the next positions, the operator owning the current antenna is retrieved and compared to the hO of the mobile device to know the type of traffic (priority, non-priority) to decide whether to make a reservation or not.

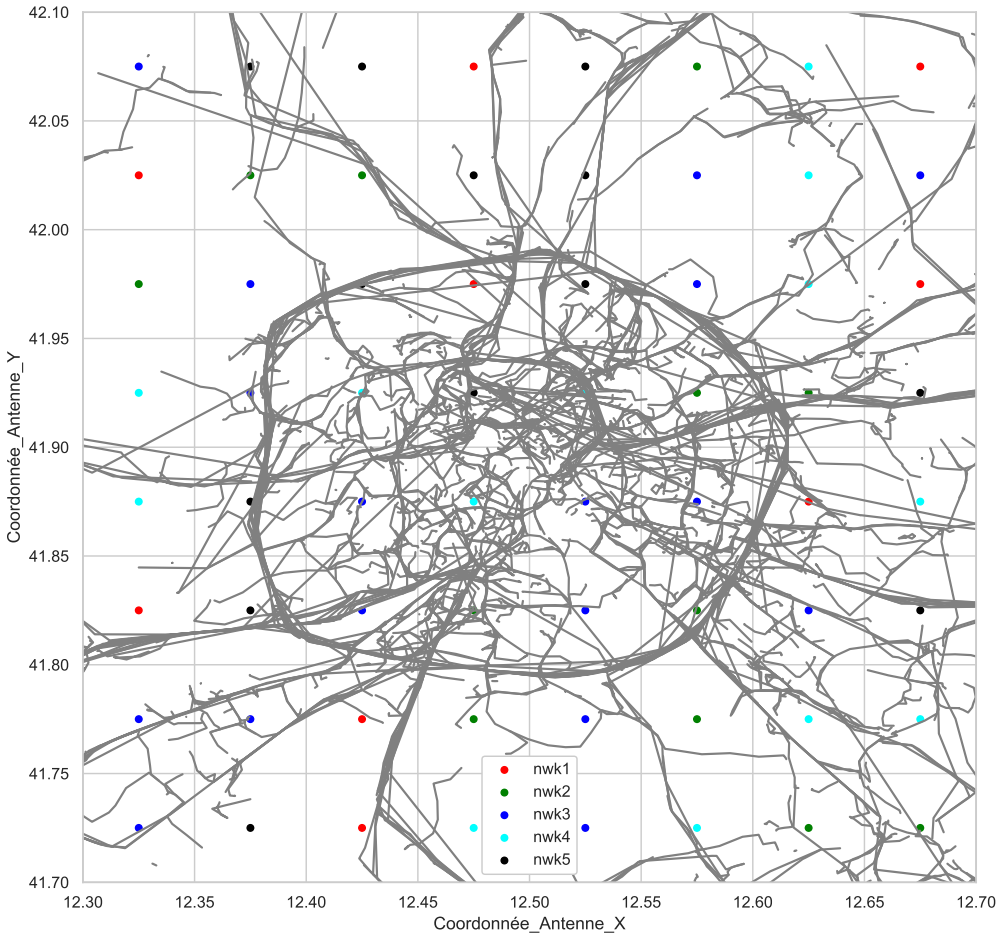


Figure **(2.3)** – *Antennas distribution per operator within Roma.*

2.2.3 Reservation mechanism

Resource reservation is only possible for priority traffic. Depending on the capacity of the GW/NS, the resource will be conserved for possible priority traffic. This also means that a non-priority device can only access a resource if there is capacity remaining outside the reservation. Therefore:

- The normal join procedure is performed: the connection is allocated as best as possible, regardless of its class and according to the available capacity;
- Then the resources for the car are provisioned on the base stations next to the one where the join is done, in view of a move and thus a next join. Using the results of the mobility prediction algorithm, reservations are made, if possible, on these candidate

antennas. For each position, an attempt is made to make a reservation on the four predicted future antennas.

We have studied two reservation mechanisms: Nominative and Non-Nominative reservations.

Nominative reservation

This is the basic case where each reservation is recorded with the identifier of the reserving party and the expiration date. The identifier is the trajectory identifier, the numTraj which is unique. The expiration date depends on the reservation duration which represent how long a reservation is valid. When a device arrives at an antenna, the system first checks whether it has priority. If so, the system verifies if the device is on the reservation list. If the result is positive, the resource is allocated. If not, it checks whether the resource is available and the device is treated as simple traffic. Figure 2.4 shows the flow diagram of the Nominative reservation process.

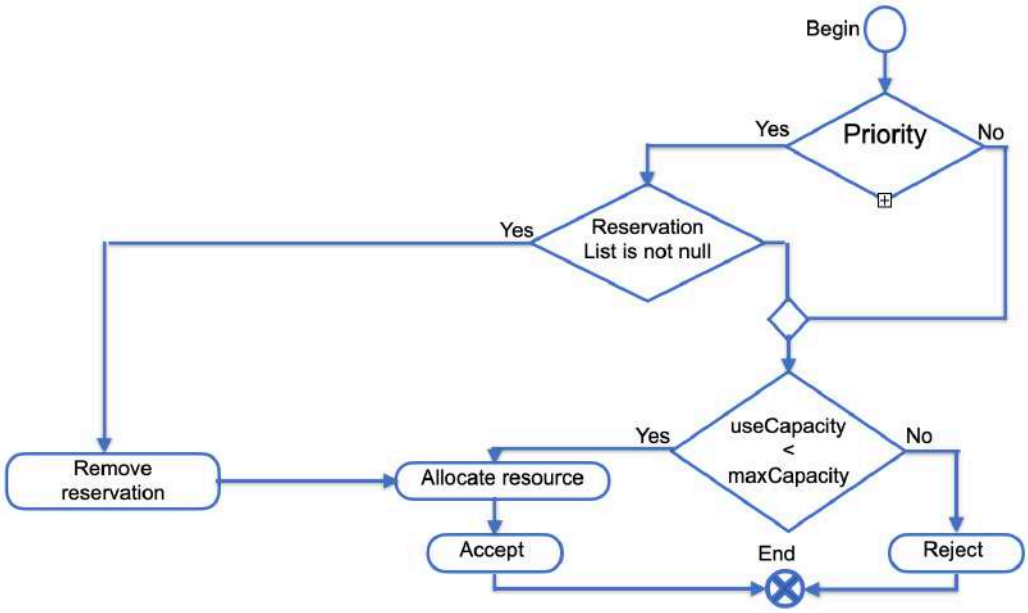


Figure **(2.4)** – *Nominative Reservation process.*

Non-Nominative reservation

In this case, reservations are only registered with their expiration date. Consequently, any device in a priority traffic condition is eligible to use a reservation even if no reservation

has been made. Upon the arrival of a device, the system first verifies whether a reservation has been made. In the event of a confirmed reservation, the system allocates the necessary resources. Otherwise, it will check to see if there are available resources (non-priority treatment). Figure 2.5 shows the flow diagram of the Non-Nominative reservation process.

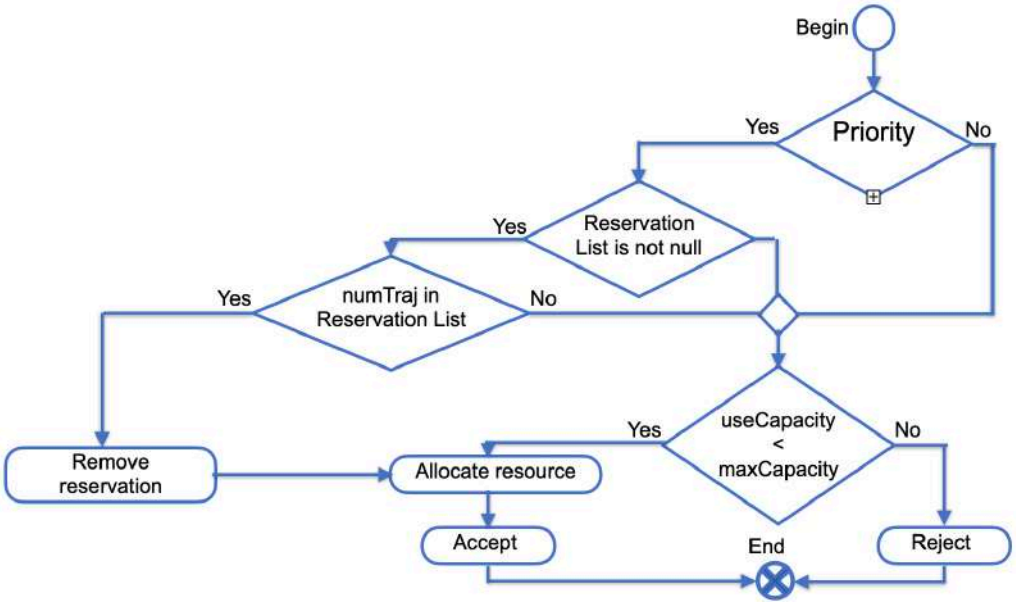


Figure **(2.5)** – *Non-Nominative Reservation process.*

A priority device with no reservation on the antenna is treated the same as non-priority traffic.

The reservation duration is initially set at 4 minutes. This corresponds to the average time a vehicle takes to travel from one antenna to another, assuming a distance of approximately seven (7) kilometers between the two antennas. The gateway capacity is at 400 nodes. Represents the amounts of the resource available. The duration of a join at 17 minutes. This is the minimum time required to keep a join active [209]. We tested different reservation thresholds. These thresholds correspond to the maximum reservation percentages for a given capacity. To assess the impact of a specific parameter, we methodically vary its possible values while fixing all other parameters.

We are interested in the number of rejected joins called rejections because the notion of reservation, as defined here, intervenes during the process of rejoining a new NS and the latter involves only two states: acceptance or rejection. Thus, evaluating the number of rejections seems to be the most appropriate criterion to measure QoS. Other parameters such as SNR, and RSSI can evaluated the QoS but they are managed at another level with other mechanisms such as ADR for example. In this regard, , the total number of rejections and per traffic type are collected for each reservation mechanism.

2.3 Results

For each case, the total number of rejections per priority type is collected. The antenna closest to the vehicle is chosen for prototype purposes.

Figure 2.6, describes the total, priority, and non-priority rejection ratios for the Nominative and Non-Nominative reservation mechanisms, with a GW capacity of 400, a join time of 17 minutes, and a reservation time of 4 minutes. The threshold 0.0 means a reservation of 0% of the total capacity. It represents the reference scenario.

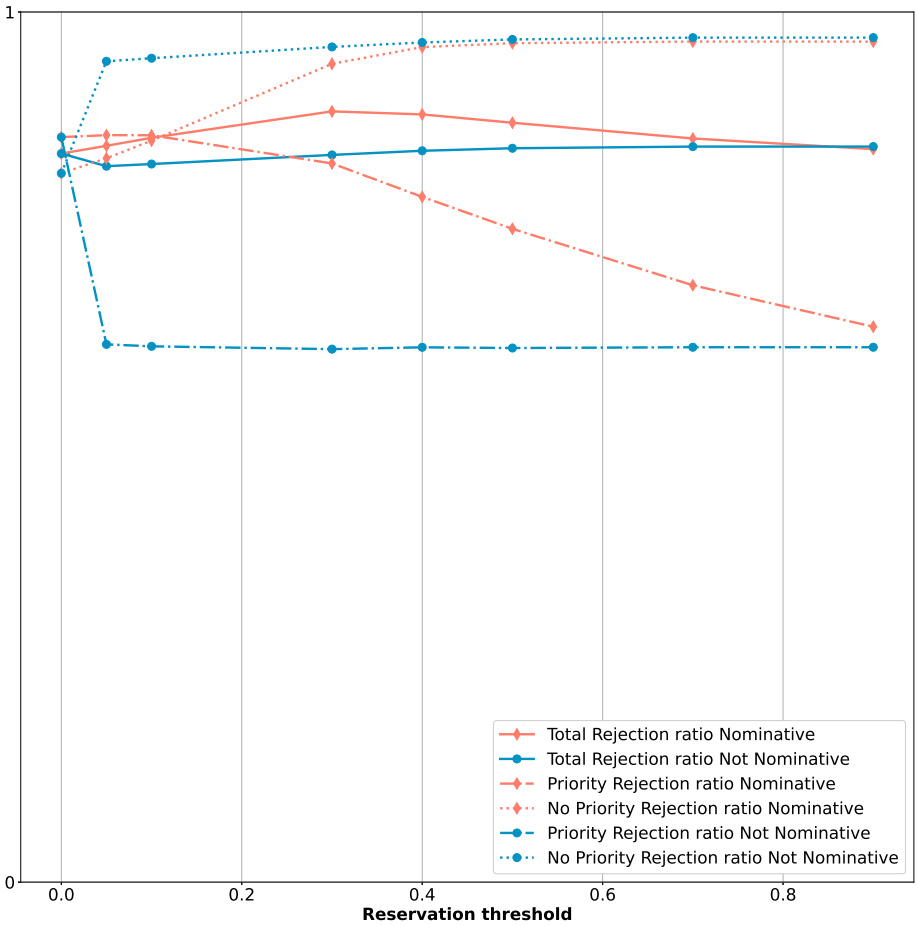


Figure **(2.6)** – *Total, Priority and Non-Priority rejection ratios for the Nominative and Non-Nominative reservation mechanisms per thresholds, capacity=*400*, interval join=*$17 minutes$*, reservation duration=*$4 minutes$*.*

At the beginning of the curves,there are more rejections in priority traffic than in non-priority traffic until 10% where we note fewer rejections for priority traffic and in contrast

more for non-priority traffic. This can be explained by the fact that less than 10% of the traffic is booked and therefore treated as priority, so more than 90% of the traffic is treated as non-priority. The rejections are shared but with even more rejections due to unused reservations. As the reservation is nominative, only the device that made the reservation can use it. This leads to total rejection rates often higher than the reference, especially when the reservation threshold increases.

The Non-Nominative version allows for the minimization of these unused reservations, thereby reducing prediction errors. It should be noted that a device with a higher priority may benefit from a reservation even if no reservation has been made. As early as the 5%, a clear distinction between priority and non-priority traffic emerges. This discrepancy grows as the threshold rises. However, for very high thresholds, this type of reservation will generate more losses and will converge in the same way as the Nominative version.

The point at which these two mechanisms converge or begin to generate more rejections is dependent on several factors, including the number of requests, the capacity of the gateways, the duration of the reservations, and the duration of the join. This prompts us to examine the variation of these parameters.

According to [211] a gateway can support up to 1000 nodes. [212] exposed a PDR of 10% for 1000 nodes. So we tested with a few antenna capacities: $200, 400, 600, 800$, and 1000 to evaluate the impact of the different parameters: capacity, join interval, and reservation duration. We set the threshold at 40% and vary each time one of these three parameters.

2.3.1 Capacity variation

In the first step, the join and reservation times are set to 17 and 4 minutes, respectively. The capacity varies between 200 and 1000 devices per GW. Figure 2.7, depicts the total, priority, and non-priority rejection ratios for the Nominative and Non-Nominative mechanisms as a function of capacity. For the same amount of traffic, the increase in the gateway capacity reduces the number of rejections. This is especially true for Non-Nominative reservations, for which there is a large downward trend in the priority rejection curve. The more capacity the gateway has, the fewer unused reservations there are. Therefore there are more resources for non-priority traffic, especially in the Non-Nominative case and for both traffic types in the Nominative case.

2.3.2 Join variation

Then in addition to the 40% threshold, we set the capacity at 400 and the reservation time at 4 minutes. We then varied the duration of the joins. Figure 2.8 represents the total, priority, and non-priority rejections for both Nominative and Non-Nominative mechanisms as a function of the joint duration. The join interval defines how long the resource is used before it is released. The bigger this interval, the fewer resources there are for new arrivals and therefore the more the losses. Additionally, each device has ten positions in the used data set. As a result, we lack information regarding the subsequent actions of the device. A

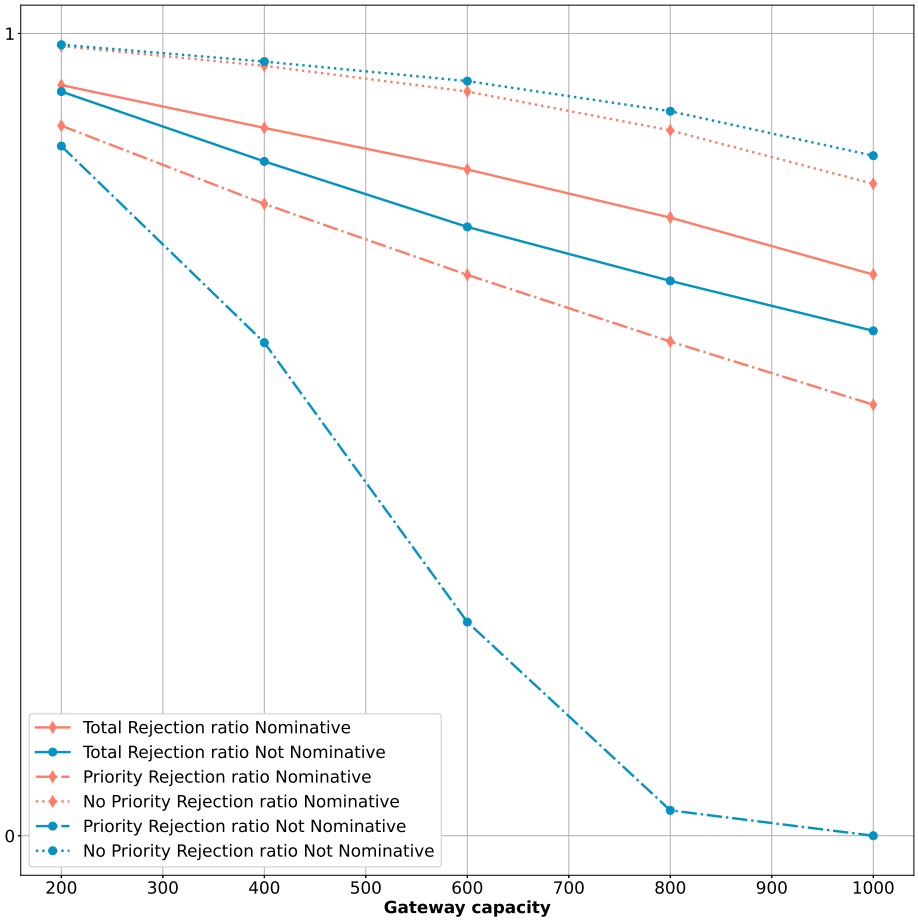


Figure **(2.7)** – *Total, Priority and Non-Priority rejection ratios for the Nominative and Non-Nominative reservation mechanisms as a function of capacity,threshold=*40%*, interval join=*$17 minutes$*, reservation duration=*$4 minutes$.

smaller join interval allows resources at the last positions to be freed up quickly.

2.3.3 Reservation variation

Finally, the join interval is set to 17 minutes, the reservation threshold at 40%. We vary the duration of the reservations. Figure 2.9 represents the total, priority, and non-priority rejections for both Nominative and Non-Nominative mechanisms by the duration of the reservation. The Nominative reservation curves show an inversion of the trends from a certain threshold. The duration of reservations has little impact on the Non-Nominative mechanism. The underlying raison pertains to the potential use of reservations, in in-

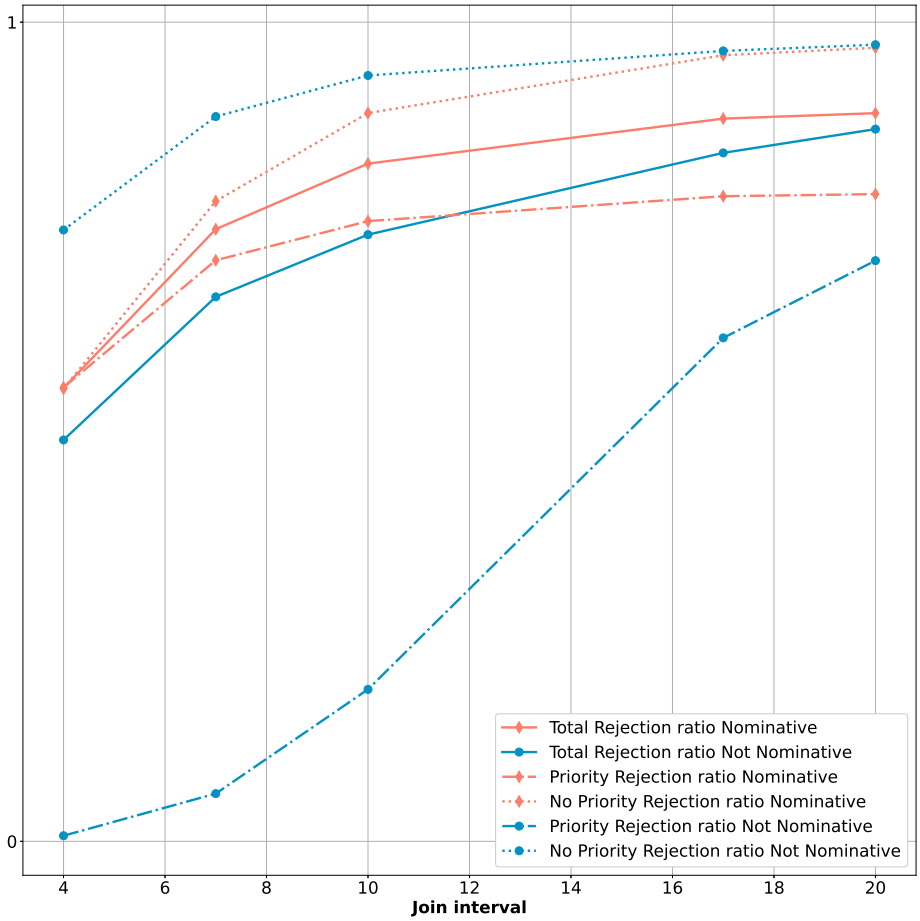


Figure **(2.8)** – *Total, Priority and Non Priority rejection ratios for the Nominative and Non-Nominative reservation mechanisms as a function of the join duration, threshold*=40%, *capacity*=400, *reservation duration*=4*minutes*.

stances where they have not been previously employed by the designated device. These reservations can subsequently be allocated to another device in a priority traffic situation. However, it presents a small difference for the nominative type. That's because, each time, a device can make up to 4 reservations that can only be used by device itself. A shorter reservation time consequently reduces the number of resources lost in reservations. This increases the chance of having more devices covered.

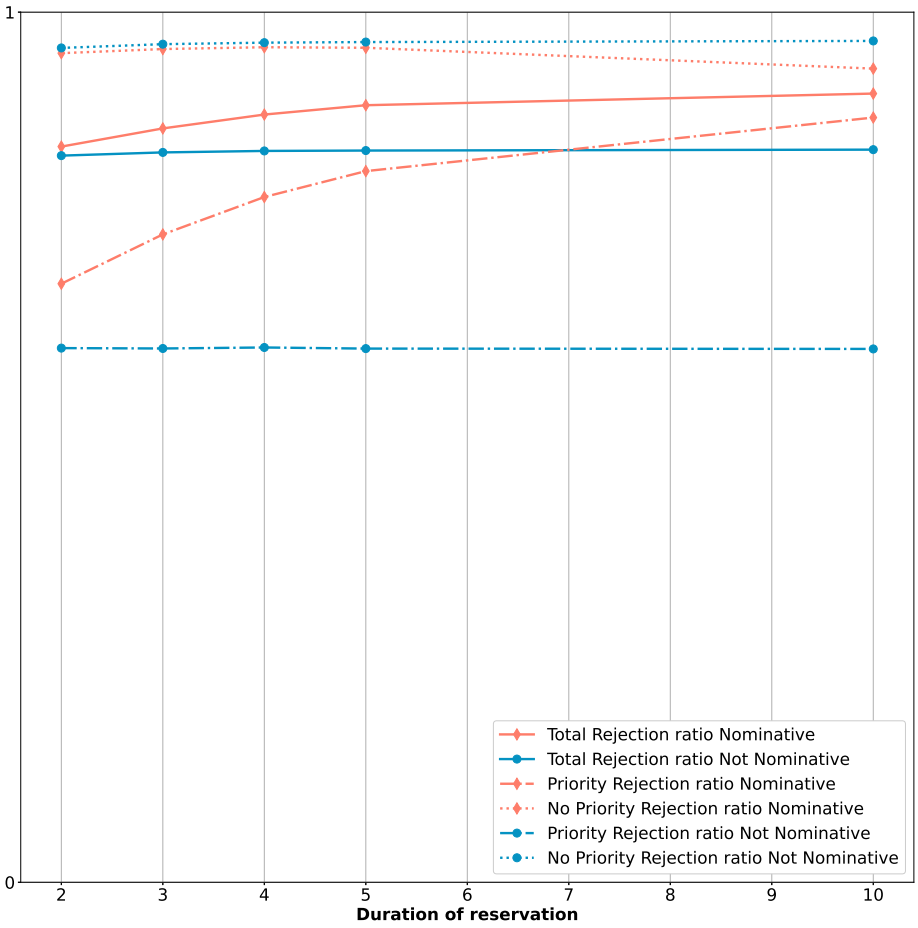


Figure **(2.9)** – *Total, Priority and Non-Priority rejection ratios for the Nominative and Non-Nominative reservation mechanisms per reservation duration, capacity*=400, *interval join*=17$minutes$, *threshold=40%.*

2.4 Discussion

In this chapter a ressource reservation mecanism is proposed within the context of vehicular IoT. The use of LoRaWAN is motivated by its numerous benefits, including, but not limited to, wide coverage, energy efficiency, and easy deployment. Additionally, as part of the LP-WAN (Low Power Wide Area Network) family, LoRa (Low Range) waves are less affected by obstacles and thus offer greater resistance to fading and interference compared to other commonly used vehicular network technologies. Despite these advantages, the system does have certain performance issues related to latency and movement of devices. Therefore, we suggest a prefetching method to lower delays by reserving upstream resources, combined

with traffic prioritization based on predictive data. Two reservation mechanisms are proposed: the first is Nominative, wherein reservations are tied to the user's ID, and the second is Non-Nominative, wherein reservations are made without associating them with a user ID.

In Nominative reservation, the reserved resource can only be used by the device that made the reservation. As we can reserve on up to 4 antennas, this means less resources for non-priority traffic and other priority traffic, too. This imposes the need for a very accurate predictor to prevent unused reservations, which could increase rejection rates during high demand. Allowing up to four reservations per user location has been shown to improve the chance of the resource being available on the next move (up to ten reservations available). However, if a reservation is not used or all four predictions fail, these resources remain unavailable for the duration of the reservation. In this case, it would be wise to consider shortening the reservation period.

The second mechanism avoids this problem because the reservation can be used by any device in a priority traffic situation. However, given that the reservation is not nominative, a device with priority that has not made a reservation on an antenna can benefit from the reservation made by another device if it arrives before the latter. In addition, the reserved resource is deducted from the maximum capacity and cannot be used by non-priority traffic, even if the latter arrives first.

In addition, we assume that the device communicates with only one antenna at any given time and that each antenna hosts an NS, whereas in reality a message can be received by several antennas at the same time. The case exploited here can be considered as one of the worst-case scenarios.

2.5 Conclusion

LoRa/LoRaWAN is a long-range, energy-efficient technology in the LPWAN family. It is widely used in IoT due to its easy, low-cost, and license-free implementation, as well as its multiple deployment options [213]. A multitude of solutions have been proposed in this direction due to its performance problems in mobility integration, in addition to studies conducted in the automotive field. It has also been proven suitable for non-critical applications, i.e., non-delay-sensitive applications.

To mitigate this latency problem, this section presents a resource reservation mechanism in a vehicular environment for LoRaWAN-based IoT devices. The solution, built on a prefetching mechanism, allows for the prior reservation of available resources. This mechanism is widely used in caching systems such as Domain Name System (DNS), web services, etc.

We have implemented a service differentiation system that enables reservations for the operator's customers. Traffic differentiation is a method commonly employed in QoS management. In this context, it is used to prioritize primary subscribers in roaming states. This serves as a textbook case applicable to various scenarios, such as differentiating between

different application needs. It can also be adapted to other aspects, such as addressing QoS differentiation needs between various application flows.

The metric employed in this study is the number of rejections, as the concept of reservation, as defined herein, becomes relevant during the process of rejoining a new NS, which involves only two states: acceptance or rejection.

Each of the two reservation methods presented here has its own strengths and weaknesses. The Non-Nominative mechanism is the most optimal, yielding fewer rejections while offering service differentiation between subscribers and others. It is also the most computationally efficient method. The Nominative mode is more stable and provides more limited service differentiation than the Non-Nominative method, but it encounters more rejections during periods of congestion.

This study explored several experiments, varying parameters such as reservation duration, gateway capacity, join interval, and reservation threshold to observe their impact on the results.

Chapter 3

Placement optimization

The previous chapter presented a resource reservation mechanism based on LoRaWAN in a vehicular IoT environment. Two reservation methods were proposed, and their impact on the rejection rate and a QoS management mechanism were also discussed. In this chapter, we will address another VCN problem: uniform coverage based on IRS [1].

3.1 Introduction

Wireless communications technologies are constantly evolving. If we were talking about 3G, and 4G a few years ago, today we hear more about beyond 5G and 6G. However, the primary objectives remain the same: connection speed and coverage.

Connection speeds have improved dramatically from the hundreds of megabits of 4G to the gigabits of 5G, as has coverage. As ever, however, coverage always comes up against the problem of Non Line Of Sight (NLoS), especially in urban environments, where many obstacles block the path between the Base Station (BS) and the user.

To solve this problem, relays are used to extend the signal. Initially fixed, they can be mobile, with the use of drones for example. They can be used to extend the signal: for temporary needs [216], in hard-to-reach areas, or, in the event of a disaster [217]. Their main problem remains task coordination and energy consumption [218].

With new types of communication, Intelligent Reflecting Surfaces, or IRS for short or RIS, provide a solution to this coverage problem, while consuming very little energy. In general, these reflective surfaces, as their names suggest, reflect the signal toward the user, without amplification or regeneration, hence the term "passive relay" as opposed to the traditional "active relay". Intelligent Reflecting Surfaces (IRSs) are designed with multiple small components that enable independent signal reflection with adjustable phase shift, to achieve passive beamforming without the need for Radio Frequency (RF) transmission chains [130]. However, simple IRS only allows the signal to be reflected on the same plane.

[1] Results of from this chapter has been submitted for publication [214] and [215]

To overcome this problem, Simultaneously Transmitting And Reflecting-RIS (STAR-RIS) or Input Output Surface (IOS) are introduced [136]. They allow the signal to be reflected on the same plane and transmitted on the other plane, thus increasing coverage.

Mostly fixed, IRS can be placed on signs, building facades, etc. Several studies have examined the benefits of fixed IRSs and their placement. Fixed placement offers certain advantages, such as solving a fixed need in a well-defined, limited area. Nevertheless, it requires the rental of panels or building facades, which is not always easy, as most surfaces are opaque and most facades in certain cities are glazed or historic. To overcome this problem, and reach more remote areas, some studies propose mobile IRS The advantage of mobile IRS is its ease of deployment and the flexibility to monitor traffic and support base stations in the event of NLoS, loss of signal, or peak demand in the context of an event, for example.

Mobile IRSs are essentially used in an aerial setting. Therefore, several studies have looked at the use of IRS to facilitate UAV communications. This the case for [202] [219], [220], [221], [222], [223]. Some works try to enhance security with UAV-IRS, like in [224] and [225]. Very little scholarly attention has been paid to the use of ground mobile IRS, except in [201]. The authors propose the use of a mobile ground IRS to support UAV communication and NOMA, a non-orthogonal multiple access technique. They aim to jointly optimize the UAV trajectory, the mobile IRS path, and the power allocation to the users to maximize the average data rate for the users. The approach is based on the Genetic Algorithm, and the results show better performance for the proposed system than with a fixed IRS or without an IRS. As can be seen, most studies consider a fixed IRS positioning and when IRS are mobile, they are mainly aerial. As a result, we suggest looking at a mobile deployment of several ground IRS.

The table 3.2 compares this work with related work.

Work	Objective	Placement	Ground	Multi-IRS	Based ML
[202]	Enhance the computational energy efficiency of the system through optimized resource allocation in a mobile edge computing environment	Mobile	No	No	No
[219]	Maximize the spectrum efficiency and the energy efficiency of the system by jointly optimizing the active beamforming, passive beamforming and UAV trajectory	Mobile	No	No	No
[220]	Maximize the average rate of the proposed IRS-UAV assisted covert communication system as an optimization problem with respect to the UAVs trajectory and the IRSs phase shift	Mobile	No	No	No
[221]	Examine the security of simultaneous wireless information and power transfer (SWIPT) systems assisted by intelligent reflecting surfaces (IRS) and UAVs while considering the flight energy of rotary-wing UAVs	Mobile	No	No	No
[222]	Study the multi-aerial IRS (AIRS) assisted secure simultaneous wireless information and power transfer (SWIPT) system with UAV jitter taken into account	Mobile	No	Yes	No
[223]	Develop the joint UAV trajectory, RIS passive beamforming and MEC resource allocation design to maximize the energy efficiency of the system	Mobile	No	No	No
[224]	Study the average secrecy rate maximization problem to jointly optimize the 3D trajectory of the UAV and the phase-shift matrix of the aerial IRS	Mobile	No	No	No
[225]	Address the intricate challenges of data freshness, and security, especially in the context of eavesdrop-ping and jamming in modern UAV networks	Mobile	No	No	Yes
[201]	Find an efficient trajectory for the UAV, an efficient path for the M-IRS, and users' power allocation coefficients that maximize the average data rate for mobile ground users	Mobile	Yes	No	No
Our work	Comparison between optimal fixed and mobile placement	Mobile	Yes	Yes	Yes

Table **(3.2)** – *A comparison between the related work and the proposed work.*

For the sake of feasibility and to reduce energy consumption, we propose a scenario where not all buses can become IRS at the same time. In other words, we set a certain number of IRS to be used. The resulting problem is the choice of these IRS to guarantee a certain stability of the network. This leads to an optimization problem that we try to solve using an optimizer.

An optimization problem aims to discover the best possible solution from all potential options available. This involves identifying a solution in the feasible region with the objective function's minimum or maximum value. The complexity of an optimization problem and the techniques or algorithms applied to uncover the optimal solution are influenced by the types of mathematical relationships that exist among the objective, constraints, and decision variables [226].

The problem is modelled using IBM ILOG CPLEX Optimization [227]. And to assess the benefits of mobile IRS, we'll compare it with fixed IRS in terms of connectivity and network stability. Connectivity is the number of times a device is connected during its trajectory. Stability is the number of IRS changes.

In the remainder of the chapter, we will present the problem and its formulation in Section 3.3 after a brief presentation of IBM ILOG CPLEX Optimization software in Section 3.2. Then, in Sections 3.4 and 3.5, we present the results obtained and their significance, before concluding with an outlook in Section 3.6.

3.2 IBM ILOG CPLEX Optimisation Studio

When it comes to scheduling, allocating, and planning limited resources, optimization solvers aid in better decision-making. They include strong algorithms capable of resolving constraint programs, constraint planning models, and mathematical programming models. Mathematical programming is a modeling technique that serves as an effective decision-making tool [228]. And constraint programming incorporates a variety of methods from graph theory, operations research, artificial intelligence, and other fields. It is a strong paradigm for resolving combinatorial search issues. The fundamental concept of constraint programming is that constraints are specified by the user and then solved by a general-purpose constraint solver [229].

IBM® ILOG® CPLEX® Optimisation Studio is a prescriptive analytics system that enables the quick development and deployment of decision optimisation models based on mathematics and constraint programming [227]. This framework assistes to create and deploy optimization models.

It uses the Optimization Programming Language (OPL) modeling language. The purpose of modeling languages is to make mathematical programming issues easier to solve [230]. The realization that many mathematical programming issues can be described in a computer language with syntax similar to how these problems are typically presented in textbooks and scientific publications is the fundamental realization that underlies traditional modeling languages [231].

IBM ILOG CPLEX can be used with the Python language by installing the module docplex [232].

3.3 Model and problem formulation

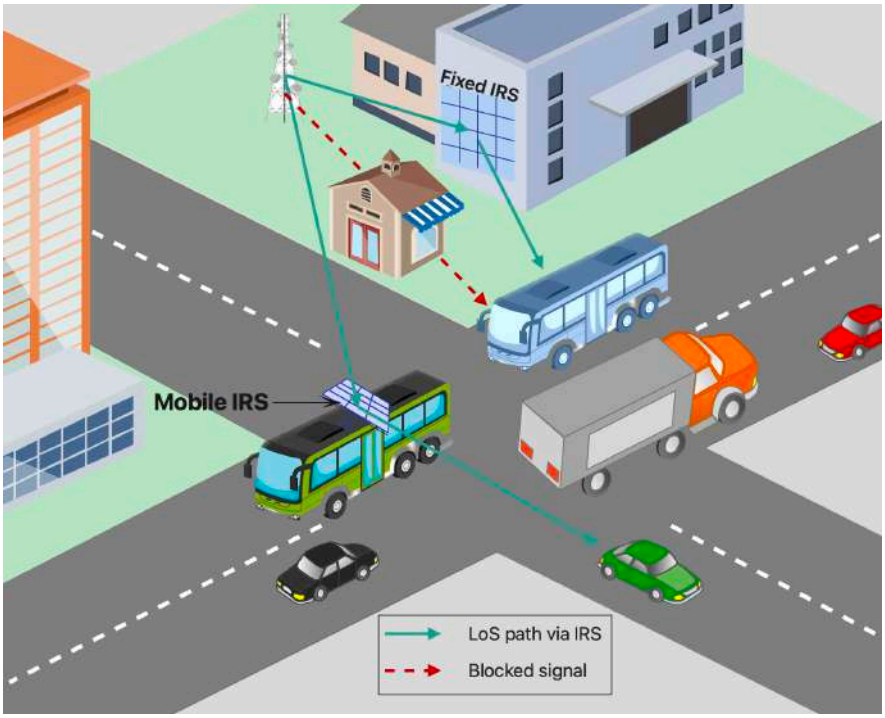


Figure **(3.1)** – *Mobile IRS use case.*

We consider a mobile and vehicular architecture where some vehicles we'll call users are in NLoS and need an IRS to communicate. The aim is to compare the IRS's optimal fixed and mobile placements. In the fixed case, positions are randomly selected in the study area, and in the mobile case, IRSs are installed on buses to track traffic as presented in Figure 3.1. To optimize the number of IRSs and energy consumption, we choose several IRSs to be activated to serve users. We therefore try to maximize link stability or minimize the number of IRS changes. To be able to compare fixed and mobile, we will choose IRS for a period p. At the start of each period, a set of IRS is calculated or chosen according to the scenario. The objective is to minimize the IRS change in each period as much as possible. To see the interest of trajectory prediction knowledge in performance optimization, we consider two cases: with prediction i.e. with knowledge of the future positions of mobile IRS (buses) and users (taxis), and without prediction.

The application of prediction models has consistently shown improvements in performance across various fields. Prediction enables the anticipation of behavior, helping rapid

Strategy	Principle	Based prediction
Q	Choose the bus with the highest stability value at t0 begenning of the period	No
Q'A	Choose the bus with the highest stability rate during the period	Yes
Q'B	Choose the previous IRS if available else the bus with the highest stability rate during the period is chosen	Yes

Table **(3.3)** – *Strategies presentation.*

adaptation, especially in highly dynamic environments such as vehicular networks. The use of prediction data, such as trajectory prediction, helps in selecting the optimal IRS to meet the user's needs during a specific period. This is because a bus might be present at the start of the period when calculations are made, but not for the rest of the time. Therefore, activating the IRS on this bus may lead to a decline in performance over time. In another case, the bus might not be there at the beginning, but is guaranteed to appear later, ensuring better performance. As a result, prediction helps consider these different scenarios. This goal guided our study of three IRS selection strategies, two of which rely on prediction.

The version without prediction is called the Q strategy, which aims to optimize stability during the period based only on information available at t0, the start of the period. This allows for a meaningful comparison with current practices.

In the prediction-based versions, there are two strategies, Q'A and Q'B. Both aim to maximize connectivity and stability over the period, based on prediction and scheduling information throughout the entire period. The difference between Q'A and Q'B is how they select the bus with the highest value during the period. In Q'A, the bus with the highest value is chosen, leading to IRS activation on that bus. In the initial phase, Q'B evaluates the previous IRS as a potential candidate, and, in the absence of such a candidate, Q'B's behavior is consistent with that of Q'A. This helps reduce disconnections from one period to the next. The following table 3.3 summarizes the main principles of each strategy.

In the prediction scenario, the future position of buses is supposed to be known as it is scheduled. For taxis, it is assumed to be known by a prediction algorithm [210].

Based on this knowledge, at each period, we calculate the set of IRS that maximizes link stability for the period. The objective function is thus defined as follows:

Objective:

$$maximize[Link = \sum_{c \in E_C} \sum_{p \in E_P} \sum_{b \in E_B} \sum_{b' \in E_B} \lambda_{c,b,b',p} \cdot q_{c,b',p}] \tag{3.1}$$

$$maximize[Link = \sum_{c \in E_C} \sum_{p \in E_P} \sum_{b \in E_B} \sum_{b' \in E_B} \lambda_{c,b,b',p} \cdot q'_{c,b',p}] \tag{3.2}$$

$$\begin{aligned} maximize[Link = & \sum_{c \in E_C} \sum_{p \in E_P} \sum_{b \in E_B} I_{q'_{c,b,p}} \cdot \lambda_{c,b,b,p} \\ & + (1 - I_{q'_{c,b,p}}) \sum_{b' \in E_B, b' \neq b} \lambda_{c,b,b',p} \cdot q'_{c,b',p}] \end{aligned} \tag{3.3}$$

subject to:

$$\forall b, p, 0 <= irs_vars_{b,p} <= 1 \tag{3.4}$$

$$\forall b, \forall b', \forall p > 0, irs_vars_{b',p} >= \lambda_{c,b,b',p} \tag{3.5}$$

$$\forall p, nb_irs = \sum_{b in E_B} irs_vars_{b,p} \tag{3.6}$$

$$\forall b, \forall b', \forall p, \forall c, 0 <= \lambda_{c,b,b',p} <= 1 \tag{3.7}$$

$$\forall c, \forall p, \forall b1, \forall b2, \forall b3 \neq b2, \forall b4, \lambda_{c,b1,b2,p} + \lambda_{c,b3,b4,p+1} <= 1 \tag{3.8}$$

with:

τ: duration of a period;

$d_{c,b,t}$: distance between c et b at time;

$I_{q'_{c,b,p}} = \mathbf{1}_{q'_{c,b,p}}$ number of links between b and c at period k, can take the value 0 or 1;

$q'_{i,j,n}$: an expected measure of the quality of the connection between vehicle *i* and bus *j* from slot *n* (i.e. including a future time horizon of length τ, not only slot n);

$irs_var_{b,p}$: indicates whether the b bus is an IRS for the period p, takes the values 0 or 1;

R: coverage (a kind of threshold) radius of buses or vehicles (either in km or in terms of SNR);

$\lambda_{c,b,b',p}$: bus b is the IRS for vehicle c at period p, and bus b' is the IRS for c at period p. These $\lambda_{c,b,b',p}$ are the decision variables;

nb_irs: maximum number of IRS for each period

E_C: set of clients

E_B: a set of IRS in c i.e coverage such that distance <= coverage threshold for a period; can be all the bus or all the fixed positions for the fixed mode

E_P: list of periods

$$q(i,j,n) = \begin{cases} 0 & \text{if } d(i,j,n) > R \\ 1 & \text{otherwise.} \end{cases} \tag{3.9}$$

$$q'(i,j,n) = \frac{1}{\tau} \sum_{k=0}^{\tau} \mathbf{1}_{\{d(i,j,n+k)<R\}} \tag{3.10}$$

Constraint (3.4) indicates that $irs_var_{b',p}$ has a value between 0 and 1. It equals 1 if b' is IRS-enabled for period p and 0 otherwise. Constraint (3.7) similarly indicates that $\lambda_{c,b,b',p}$ value falls between 0 and 1. It equals 1 when b' is an activated IRS serving c at p, and b is an activated IRS serving c at p-1. It equals 0 when b or b' do not serve c, or when one of them is not activated within the specified period.

Constraint (3.5) states that the variable indicating whether b is selected as IRS during period p must be larger than or equal to the variable indicating whether the b' covers taxi c during period p **and** b1 covering c for the prior period. Specifically, if b is chosen as the IRS for p, then $irs_var_{b',p}$ is positioned at 1. $\lambda_{c,b,b',p}$ will have a value of 1 if b was the IRS for c during period p-1 **and** b' was the IRS for c during period p. It will equal zero otherwise. However, if b is not chosen as IRS for p, b cannot serve c for p, which means that $\lambda_{c,b,b',p}$ can only be equal to 0.

The constraint (3.6) limits the number of active IRS.

The final constraint (3.8) states that if $\lambda_{c,b1,b2,p}$ = 1, then b3 must equal to b2.

Eq. (3.9) serves to maximize the expected connection duration at the slot.

Eq. (3.10) tries to maximize the expected connection future duration from slot n.

In the case without prediction, the calculation is made only with present knowledge, i.e. at the beginning of the period, for a single t.

Eq. 3.1 represents the objective function for non-prediction, called strategy Q.

Eq. 3.2 and 3.3 represent the objective function for prediction for strategies Q'A and Q'B, respectively.

The same constraints are used with prediction and without prediction.

In the absence of prediction, the calculation is based solely on current knowledge, i.e., at the beginning of the period, for a single t. 3.1 and 3.2 represent the objective function for prediction et non-prediction respectively.

3.4 Results

We use taxi traces from [233] and bus programming traces in the city of Rome ([234]).

The user dataset is the similar to the one used in the previous chapter. It comprises different taxi trajectories in Rome with their ID, coordinates. The second dataset represents

the bus programming traces in the city of Rome [234] including bus_ID, position, and stops.

For mobile placement, IRSs are placed on the buses. According to bus data, there are around 425 buses per minute. Therefore, we took 425 fixed positions, randomly selected on the study surface for the fixed case. To avoid using every bus as an IRS, a maximum number of IRS is chosen for each period. This can reduce the overall network energy consumption. We tested different numbers of activated IRS: 5, 10, 30, and 50 IRS. The following metrics are evaluated in this work:

- ***connectivity***: represents the number of times a user is covered during its trajectory.
- ***number of handovers***: defines how often a customer changes IRS during its trajectory and
- ***connection duration***: represents the longest time a customer stays with the same IRS.

3.4.1 With prediction vs Without prediction

This section examines the effect of prediction on the results.

In the non-prediction part, the IRS set is calculated at the start of each study time window, which is a period over which the same set of IRS is maintained, taking into account only the present state for the simple MILP (Mixed-Integer Linear Programming) [235] version. This represents the Q strategy.

For prediction, all buses that will be in the vicinity of each customer taxi during the period are collected. Then we determine the best IRS set that maximizes the link stability for each user taxi along its trajectory. In this way, the calculation is made using all the buses present at the start of the period and those that will appear later in the period. Because a bus may be present at the start of a period, with good performance at t0 (start of period), and no longer appears within the period, resulting in poorer overall performance for the period and the entire trajectory of taxi users. The prediction part is presented by the strategies Q'A and Q'B.

Connectivity - Figure 3.2 shows the evolution of the connectivity rate per trajectory as a function of the maximum coverage radius for different maximum IRS numbers for Q, Q'A, and Q'B strategies. We observe a logical progression in connectivity as a function of coverage radius, reaching 35% with 50 IRS and 150 meters for the Q'B strategy. Enhancing visibility and coverage increases the population that can be served, leading to its evolution. Also, as shown in the image, when the number of activated IRS increases, the odds of coverage improve, resulting in better performance. Fixed IRSs provide better results than mobile ones. But with for 5 or 10 IRS, and particularly when coverage is below 30m this difference is reduced. This indicates that the mobile device may outperform the fixed device when there is a small number of IRS compared to the population needing a small coverage. The fixed device takes precedence when this number rises in proportion to an increase

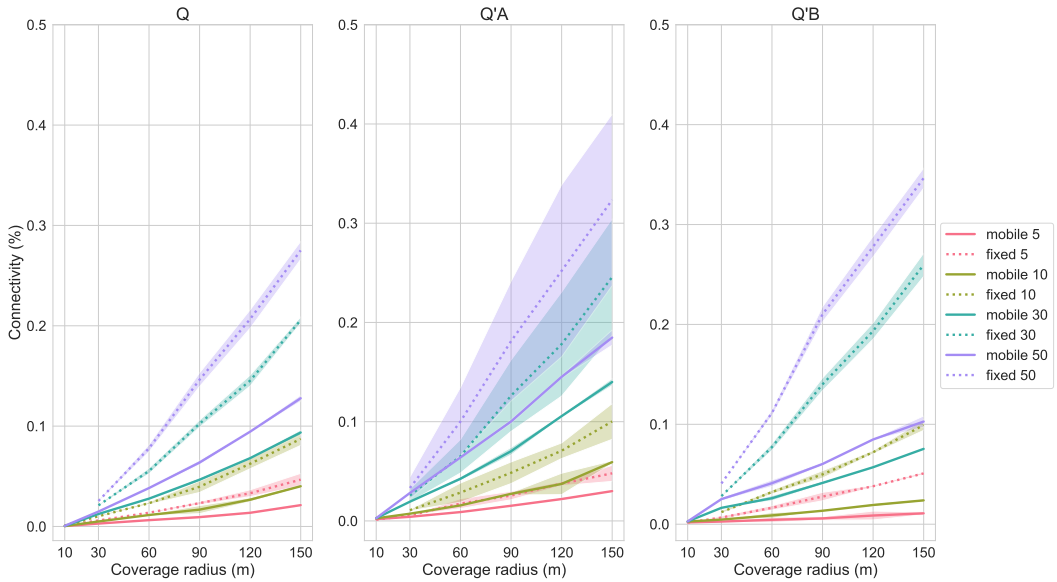


Figure **(3.2)** – *Evolution of connectivity rate per trajectory as a function of maximum coverage radius for Q, Q'A, and Q'B strategies for different numbers of IRS.*

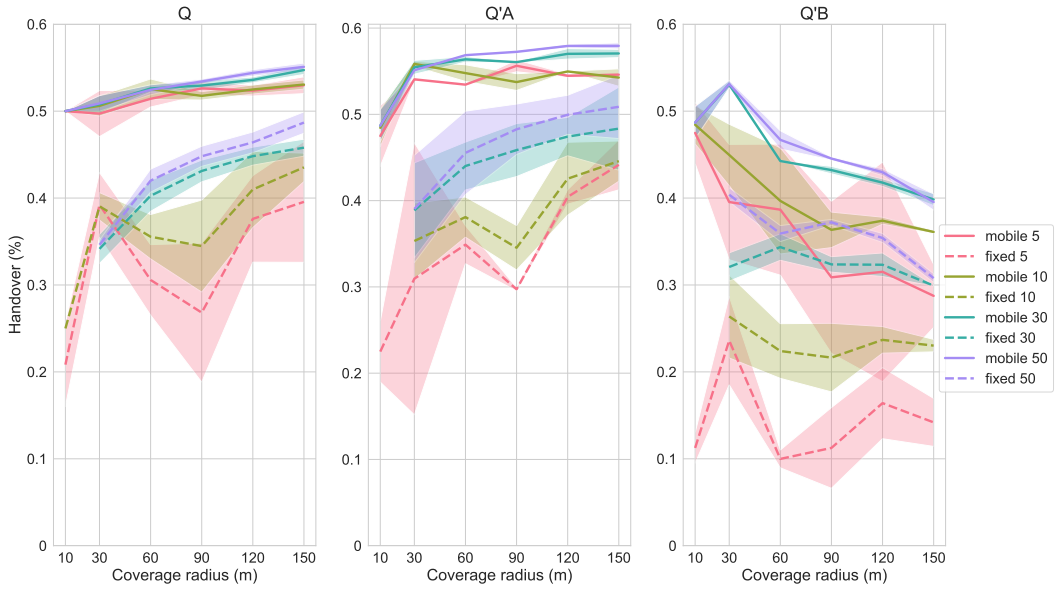


Figure **(3.3)** – *Evolution of the handover rate per trajectory as a function of the maximum coverage radius for Q, Q'A, and Q'B strategies.*

in coverage, suggesting an improved placement of fixed IRS compared to mobile IRS. We can note better performance for Q'B followed by Q'A and Q. With prediction, the future positions of the IRS candidates are known, so that at the output of the optimizer, the set chosen is the most optimal for the whole period, resulting in good connectivity.

Handovers - Figure 3.3 shows the evolution of the average number of handovers per trajectory as a function of the coverage radius for different numbers of IRS for Q, Q'A, and

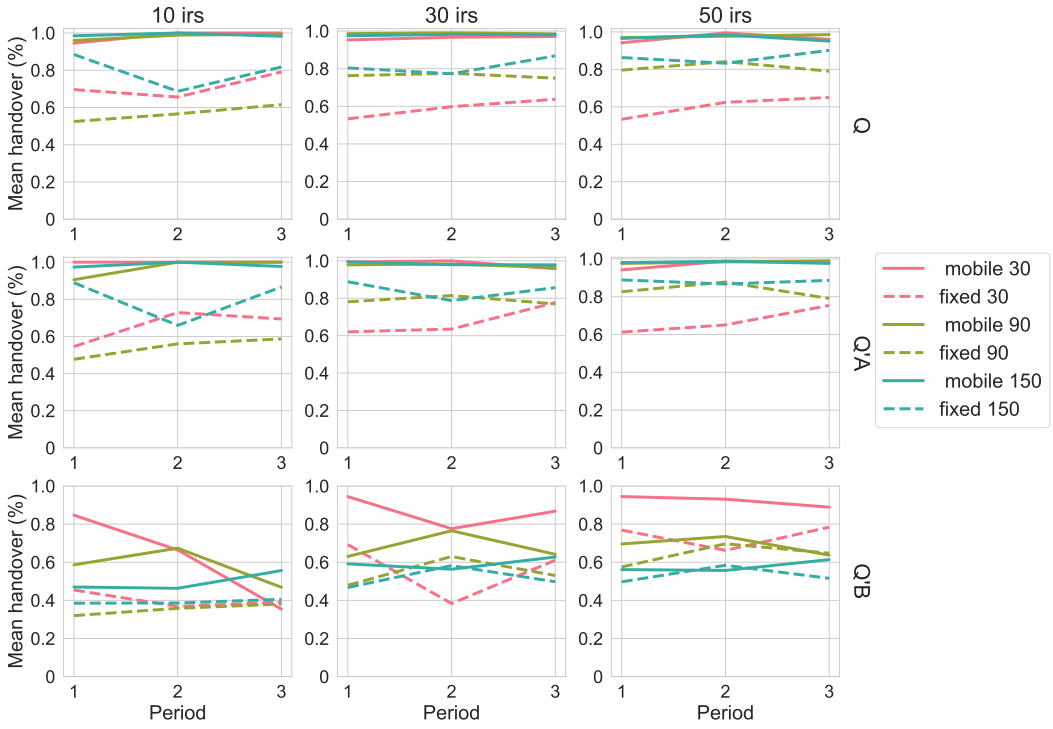


Figure **(3.4)** – *Evolution of handover, based on periods, for 30, 90, and 150m coverage for Q, Q'A, and Q'B strategies.*

Q'B strategies. In general, the number of handovers increases with the coverage radius and the number of IRS for strategies Q and Q'A. Increasing the number of IRS or extending the coverage radius increases the possibility of IRS candidates at each point of the trajectory, with new possibilities that can lead to better performance in terms of connectivity.

We can also observe that the mobile scenario tends to have more changes than the fixed one. This may be due to better coverage (better location) of fixed IRS compared with mobile. But it can also mean that the trajectories of mobile IRS candidates do not necessarily overlap with those of taxis, resulting in areas without coverage.

Figure 3.4 shows the evolution of the handover, based on periods, for the coverage radius of 30, 90, and 150m, for the various strategies and also illustrates this trend. This trend is somewhat similar for the Q and Q'A strategies, with less handover for the fixed compared to the mobile and its augmentation based on the coverage radius. In contrast, Q'B sometimes has fewer handovers for mobile than for fixed coverage with a large radius.

Connection Duration - Figure 3.5 shows the evolution of the average connection time per trajectory as a function of the coverage radius for different maximum IRS numbers for Q, Q'A, and Q'B strategies. In contrast to the number of handovers, the fixed line has an average connection time that is generally better than that of the mobile line. We can see the difference between fixed and mobile, with better performance for fixed than mobile with and without prediction, and better values for Q'B strategy than the others. But also a slight evolution of the average connection time as a function of the coverage radius. With an

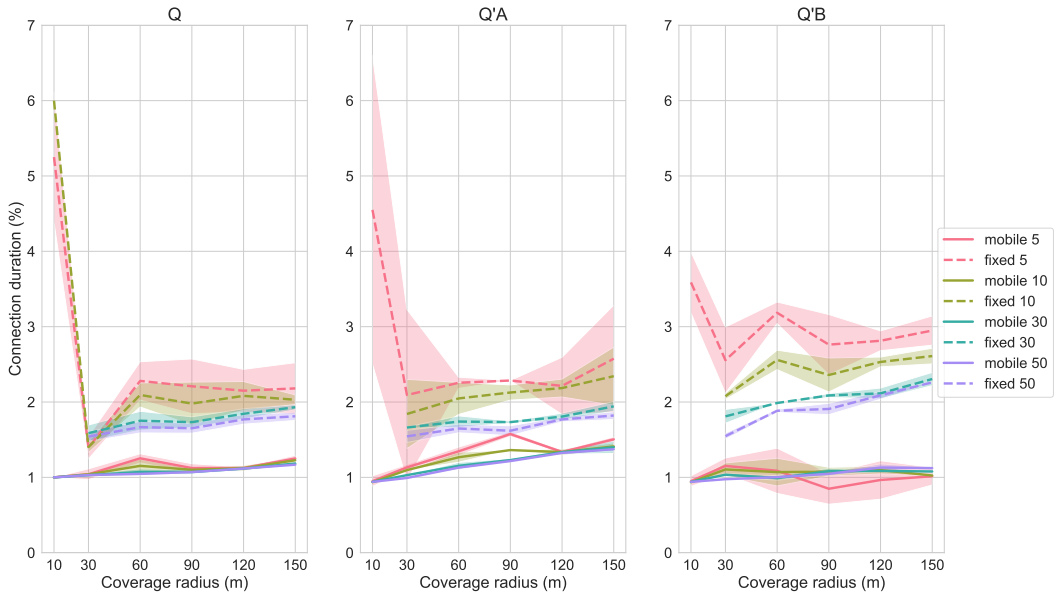


Figure **(3.5)** – *Evolution of connection duration per trajectory as a function of coverage radius for Q, Q'A, Q'B strategies.*

increased coverage radius, the number of potential IRSs increases, as does the likelihood of remaining with the same IRS. That is the probability of having the same IRS to which the taxi was previously connected at t in the list of candidate IRS at t+1 due to a larger coverage radius.

Since the initial results showed better performance for the fixed than the mobile IRS, we assumed that a better placement of the fixed IRS could be the reason. Therefore, randomly selecting a set of IRS at the beginning of each period could provide some fairness.

3.4.2 Random choice of IRS candidates

In this part, we evaluate impact of a random choice of IRS at the begenning of the a period. There are also two cases: without a starting set and with a random set. In the case without a starting set, all buses present are considered candidates in the calculation of the IRS set for the period. In the random case, however, an IRS set is chosen pseudo-randomly, to maximize link stability within this set. In addition to faster calculation times, the advantage of the random method lies in the need for fairness between the fixed, where the IRSs are well dispersed throughout the study area, and the mobile, which uses buses that for the most part leave from the same location.

This approach introduces a degree of fairness, as fixed IRS is more evenly distributed across the study area compared to mobile IRS. By selecting the IRS randomly at the beginning, fixed and mobile placements tend to have the same setting for a fair comparison. With equal chance, mobile may perform better than fixed.

Connectivity - The same trend holds with and without an initial set, as shown in Figure 3.6 that presents the evolution of the mean connectivity rate per trajectory as a function of maximum coverage radius with and without a starting set for Q strategy. Its increase is noted as the coverage radius increases, with better performance observed for the fixed compared to the mobile, as the number of IRS increases, but with much lower connectivity for the random set.

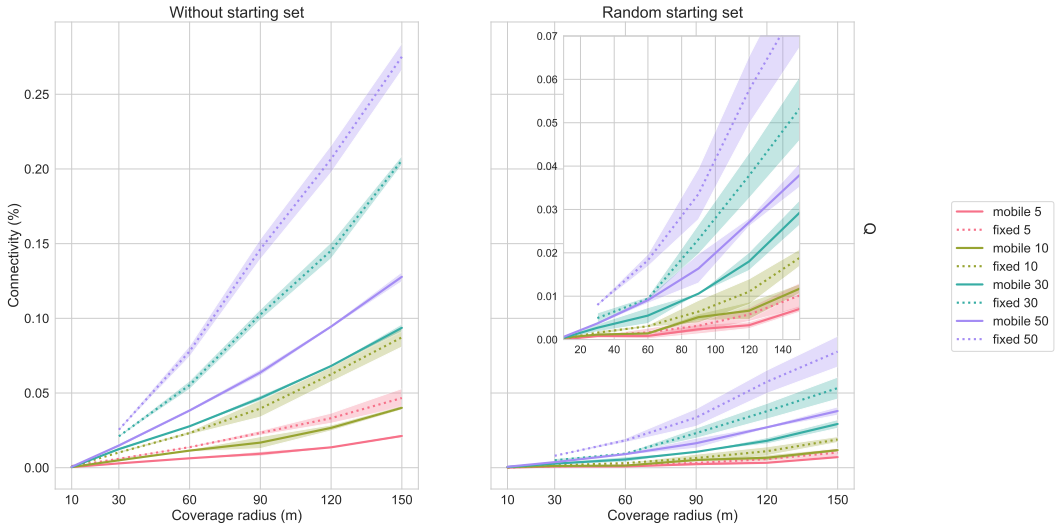


Figure **(3.6)** – *Evolution of connectivity rate per trajectory as a function of maximum coverage radius with and without starting set for Q strategy.*

The explanation for this is inadequate connectivity caused by suboptimal IRS selection, as evidenced by the connectivity curves. This is also evident in the introduction of prediction with the Q'B strategy as seen in Figure 3.7 which shows the evolution of connectivity rate per trajectory as a function of maximum coverage radius with and without starting set for the Q'B strategy. The difference is that the fixe performs better than the mobile unless there is less IRS and a radius between 30 and 90.

Handovers - Figures 3.8 and 3.9 show the evolution of the handover rate per trajectory as a function of the maximum coverage radius with and without a starting set for Q and Q'B respectively. There are more handovers for the version without a starting set of IRS for the Q strategy. We also note a decrease in the difference between fixed and mobile, which becomes more apparent for 5 and 10 IRS, although the general trend remains the same. It's much the same as for the Q'B strategy with the only difference being more changes with 5 and 10 IRS.

Connection Duration - It is much the same for Figure 3.10 which shows the evolution of connection duration per trajectory as a function of maximum coverage radius with and without starting set for Q strategy and Figure 3.11 which depicts the evolution of connection duration per trajectory as a function of maximum coverage radius with and without starting set for Q'B strategy. The average connection time also decreases as the number of IRSs

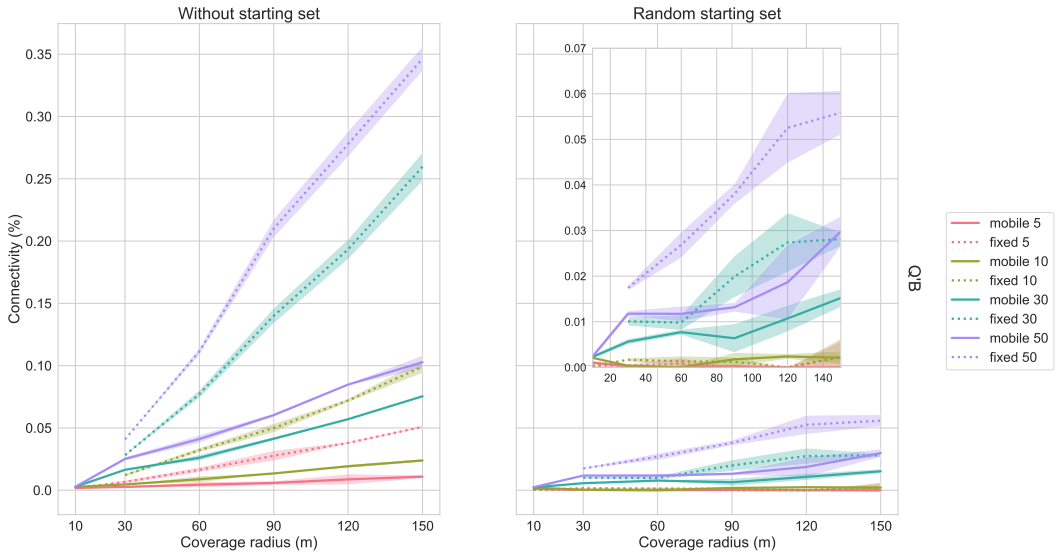


Figure **(3.7)** – *Evolution of connectivity rate per trajectory as a function of maximum coverage radius with and without starting set for Q'B strategy.*

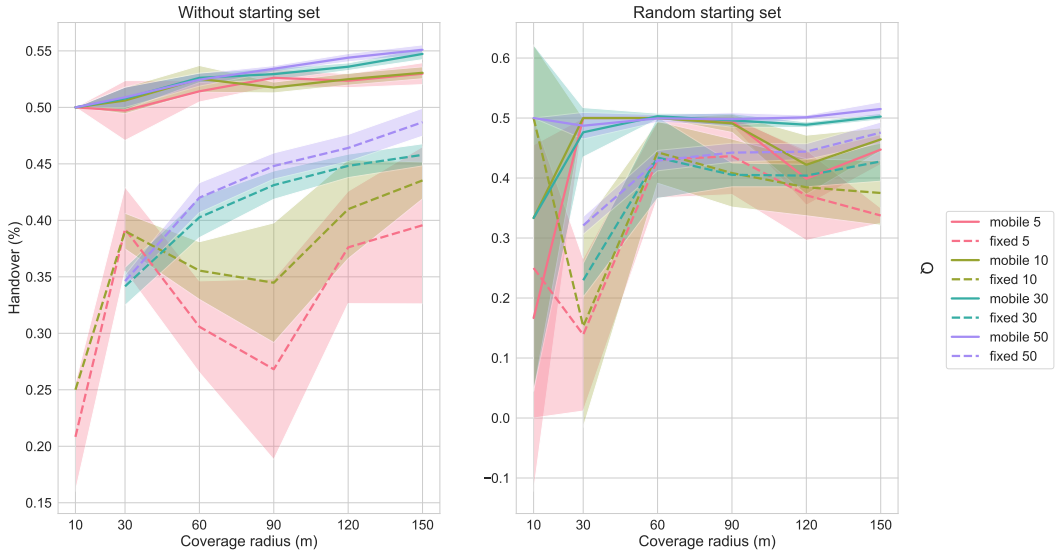


Figure **(3.8)** – *Evolution of the handover rate per trajectory as a function of the maximum coverage radius with and without starting set for Q strategy.*

decreases. For the version with a starting set, the fact that the set is chosen randomly means that these IRS may not be the optimal choice over the period, which gives a lower performance.

In general, the following observations can be made.

- Prediction gives better results than without prediction. The results demonstrate the value of prediction (connection duration, connectivity);
- The random selection of IRSs at the start of each window consistently yields sub-optimal results. This is due to the fact that the IRSs selected in this manner are not



Figure **(3.9)** – *Evolution of the handover rate per trajectory as a function of the maximum coverage radius with and without starting set for Q'B strategy.*

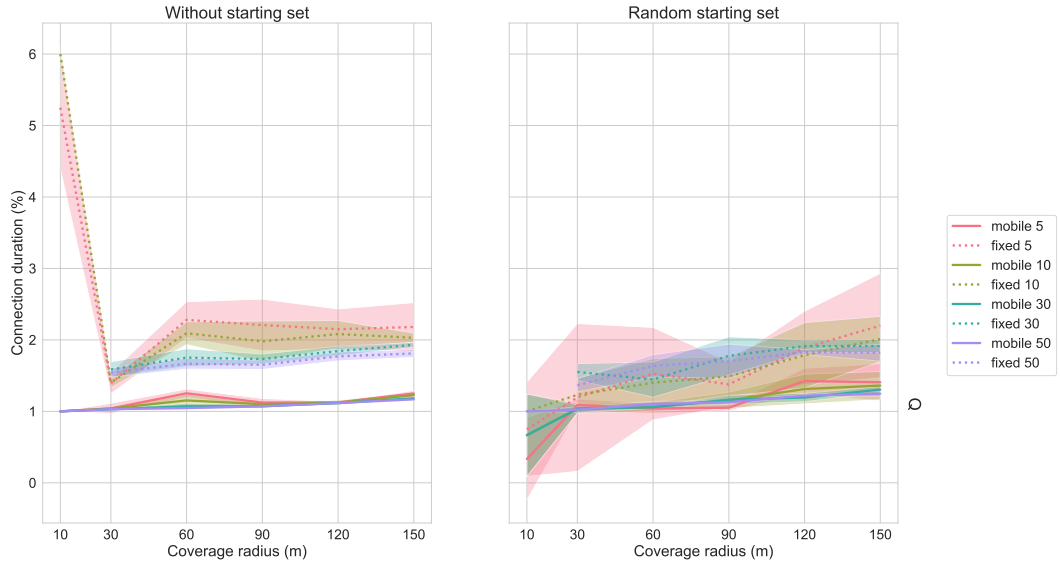


Figure **(3.10)** – *Evolution of connection duration per trajectory as a function of maximum coverage radius with and without starting set for Q strategy.*

necessarily the most optimal. However, in certain situations, mobile scenarios have been shown to yield superior results compared to fixed ones, and

- In most cases, fixed positioning is better than mobile positioning. This is because the trajectories of mobile users and the IRS do not overlap, and there are places without buses. For this reason, we propose using another dataset to evaluate the impact of these different trajectories in the fixed versus mobile comparison.

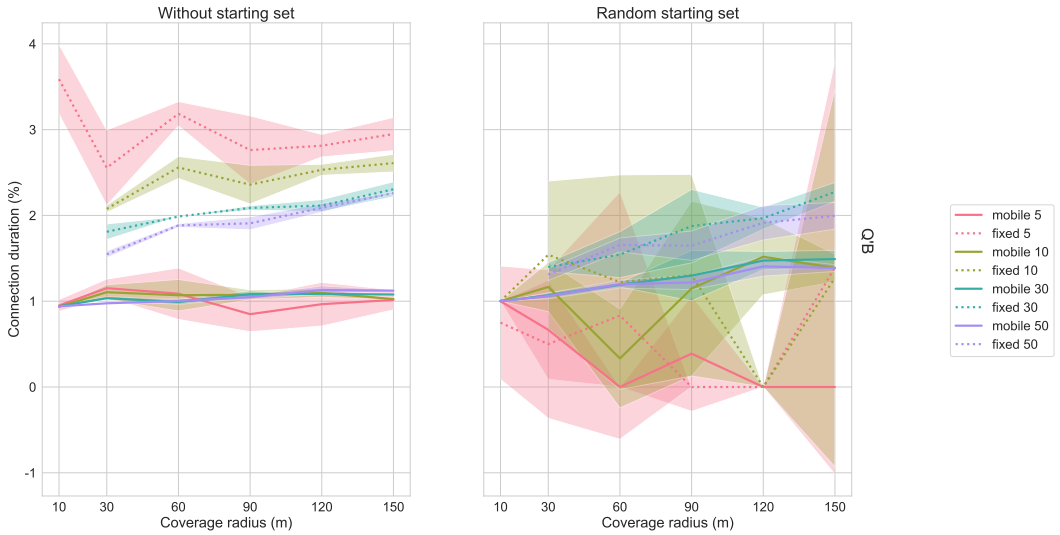


Figure **(3.11)** – *Evolution of connection duration per trajectory as a function of maximum coverage radius with and without starting set for Q'B strategy.*

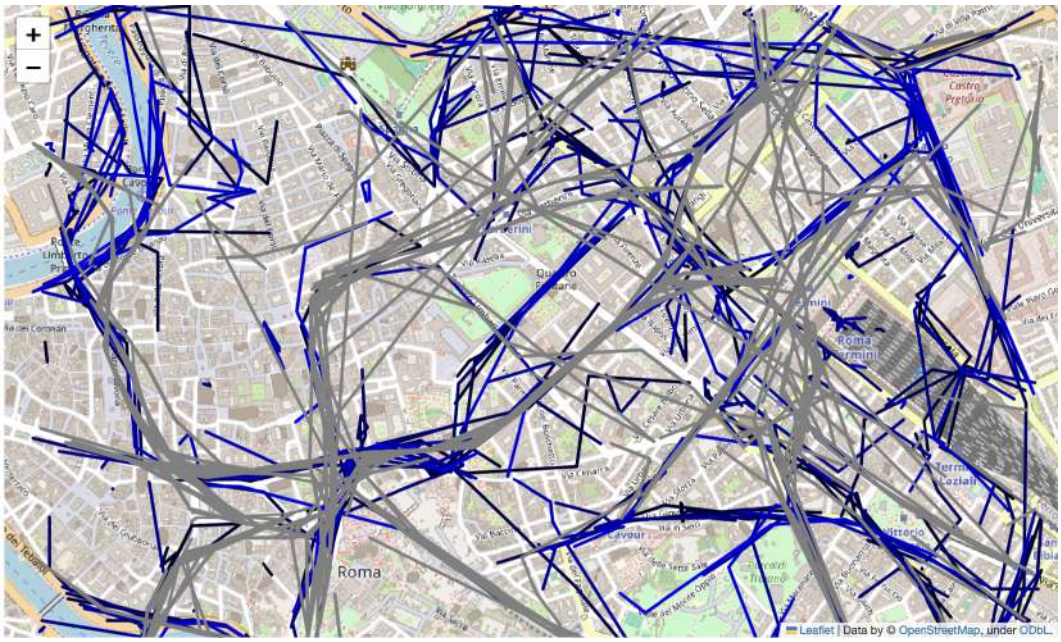


Figure **(3.12)** – *Bus trajectories in gray and taxis trajectories in shades of blue in the study area.*

3.4.3 Dataset impact

To assess the impact of the user dataset used (taxi dataset) on the calculations, we re-run the algorithm with a new dataset. In previous scenarios, taxis were considered the only users. It should be noted, however, that taxi trajectories do not overlap with bus trajectories, as shown in Figure 3.12. People often take taxis for convenience and to access areas that buses do not serve well. Furthermore, private cars and other buses can also be considered users. However, due to our lack of data on private cars, we are including a proportion of buses (80% of bus id) in the user dataset. We evaluated the results of the fixed against mobile

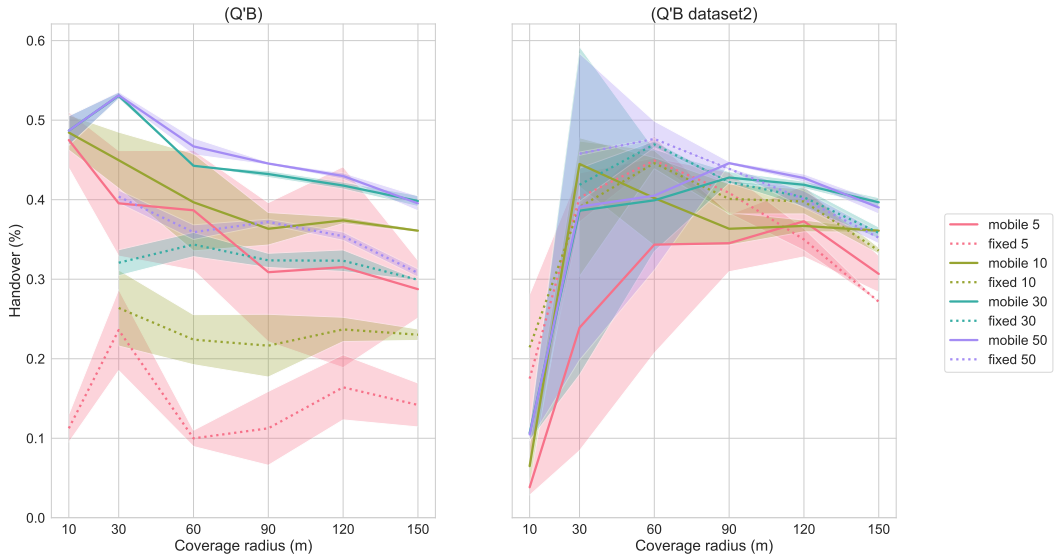


Figure **(3.13)** – *Evolution of the handover rate per trajectory as a function of the maximum coverage radius Q'B strategy.*

with the Q'B strategy.

Figure 3.13 illustrates the evolution of the handover rate per trajectory as a function of the maximum coverage radius for the Q'B strategy. We note a change in the number of handovers for fixed and mobile versions between the two datasets. In the new dataset, there are more handovers for fixed than for mobile for a radius less than 90 meters. There are also fewer handovers for the mobile positioning in the second dataset than in the first, and the opposite for fixed. The second dataset reveals a greater number of overlapping trajectories, thereby increasing the probability of prolonged usage of the same IRS when both the IRS and the user are mobile. This phenomenon does not necessarily apply to the fixed dataset.

3.5 Discussion

This work studies the deployment of mobile IRS. First, fixed and mobile deployments are compared based on several criteria, including connectivity, the number of handovers, and connection time. Then, several deployment strategies are proposed based on the current state of the network (Q strategy) or by incorporating knowledge of trajectories (Q'A and Q'B strategies).

The initial dataset of users to be covered consists of taxis, while the dataset of potential mobile IRS includes buses. For fixed IRS positioning, zones are randomly selected within the study area. Using the initial dataset, fixed placement yields better performance with various numbers of activated IRS (5, 10, 30, and 50) and radii ranging from 30 to 150 m between the IRS and users, as shown in Figure 3.2. These results improve as the coverage radius increases from 30 to 150 m. As the visibility radius expands, the number of users that the IRS can

cover increases, along with the likelihood of serving the same user despite displacement. This illustrates a high penetration rate—an ideal distribution of fixed IRS covering the study area. However, fixed systems do not produce results for radii smaller than 30 m, in contrast to the mobile system. This implies that even with their good distribution, users and fixed IRS are frequently separated by more than 30 meters. This is because fixed IRS units are usually positioned on signs, buildings, or off the road. As a result, the distance between users and fixed IRS units is typically greater than the distance between a mobile IRS unit on a bus and users. Therefore, for radii smaller than 30 m, mobile deployment performs better than fixed deployment, as shown in Figure 3.5.

We are inclined to believe that fixed positioning is less effective than mobile positioning. Vehicles often have similar proximity to one another and frequently follow the same route. However, this was not the case with the initial dataset, which consisted exclusively of taxis and IRS buses, as illustrated in Figure 3.12. As illustrated, taxis do not necessarily follow the same trajectories as buses indicating that they are operating in different areas. Taxis often provide service in areas not covered by buses. Consequently, they represent only a small proportion of users that can be served. In practice, users can include any kind of vehicle, including motorcycles and private cars, trucks, and buses. Therefore, the initial user dataset can be considered the worst-case scenario. As a result, mobile placement is negatively affected, and all other performance metrics, particularly the connectivity rate, are impacted.

To corroborate this, we have submitted a second user dataset comprising buses and taxis. Improved performance in mobile placement and overall performance improvement for both fixed and mobile placement were observed. Mobile placement outperforms fixed placement for radii of up to 90m, as shown in Figure 3.13. Including buses as users has the effect of increasing the number of users with trajectories that overlap with the mobile IRS. Incorporating other types of transportation would yield more accurate results. In urban vehicular environments, the visibility radius between two entities is often limited due to the increased presence of obstacles. This highlights the importance of short-radius reflexion results, which are better suited to this environment.

To solve these problems, we use IBM ILOG CPLEX. The optimizer is capable of solving a variety of problems, ranging from Mixed-Integer Programming (MIP) to Mixed-Integer Quadratic Programming (MIQP). The complexity of the problem is directly proportional to the number of buses and taxis, which results in a relatively extensive computation time. In certain instances, the presence of non-linearity can result in extended computation times.

Comprehension of trajectory information facilitates a more precise assessment of needs. This approach enables the identification of the optimal mobile IRS for the best mobile or fixed IRS, thereby enhancing performance. After reviewing this information and the bus schedule, the system will determine which set of IRS would provide the best connectivity over a given period. Non-predictive strategies, on the other hand, rely solely on current information to select the IRS for the period. However, the IRS selected based on current information may not be optimal for the entire duration of the period. Consequently, in the absence of prediction, performance can decline between the beginning of the period during which calculations are made and the subsequent period. In contrast, as shown in Figure 3.2, prediction ensures consistency in results over time, leading to more favorable

overall outcomes.

The present study is based on trajectory predictions to identify optimal IRS locations for activation. It can be used in different scenarios such as:

- Rapid deployment of communication infrastructure when the fixed network is down.
- Temporary Wireless Network Deployment
- Urban Mobile Broadband (5G/6G) Coverage
- Temporary Communication Networks for Large Public Events
- etc.

Furthermore, the trajectories frequently demonstrate similarity, that is, the same dynamics are observed from one day to the next, and there is a certain repetition of trajectories over the days for working days. Following a preliminary computation, the outcomes may be applicable to other days, with minor adjustments.

However, as shown in Figure 3.2, the connectivity is relatively low, covering no more than 35% of the user base. Therefore, we suggest examining the multi-hop reflection can improve coverage.

3.6 Conclusion

Faced with the problem of uneven coverage in urban and vehicle environments, we proposed the use of mobile IRS placed on buses. IRS are reflective surfaces used in networks to extend coverage, increase signal strength, and more. These functions are possible due to the reconfigurability of these elements through phase change, eliminating the need for additional power. Their integration into networks offers several advantages, including lower power consumption compared to a simple relay. This has led to a surge of interest in IRS-based approaches. However, most approaches propose fixed positioning of the IRS. This configuration allows well-defined, fixed problems to be solved. Nevertheless, in the context of vehicular networks, temporary coverage failures may occur periodically. Therefore, we propose to study mobile positioning. The problem is modeled according to three strategies and executed using IBM ILOG CPLEX.

We studied the optimal placement of mobile IRSs on buses compared to fixed placement. The impact on network performance is evaluated based on different metrics such as connectivity, connection duration, mean changement rate called handovers. The impact of the prediction was confirmed, as utilizing the prediction demonstrates a clear improvement in overall performance. With initial results indicating better fixed positioning than mobile positioning, we attempted to validate this hypothesis by randomly selecting a set of IRS to be activated at the beginning of each period, aiming to introduce fairness into the choices. Lastly, we assessed the impact of the dataset on these results by enlarging the dataset. The findings reveal that performance is contingent on the dataset used.

In summary, we can conclude that :

- Predictions produce better outcomes than without predictions.
- Random selection of IRS at the beginning of each period introduces an element of fairness but consistently generates less effective results. The issue lies in the selection process for IRS representatives, which is not always optimal. However, there are sporadic instances where mobile scenarios outperform fixed ones at specific periods.
- In most cases, fixed positioning tends to demonstrate superior performance in comparison to mobile options. This can be explained by the presence of areas without bus service and the non-overlap between IRS and mobile user trajectories.
- After examining a second client dataset that contains potential trajectories that overlap, mobile placement is determined to be the optimal solution for a narrow coverage radius (when the $radius \leq 90meters$).

This underscores the importance of thoroughly understanding the scope of the area to be covered. When the trajectories of the cover and the covered do not overlap, it appears that the fixed location produces optimal results. Conversely, when integrated with other mobile devices following a comparable trajectory, the mobile alternative demonstrates superior performance in the near field, making it particularly well-suited for this mobile urban environment.

This work aims to evaluate the possibility of optimal mobile placement of IRSs to improve connectivity. It leverages on a trajectory predictor to improve performance and therefore does not take into account phase changes, which are just as present in mobile as in fixed placement.

Chapter 4

Coverage enhancement

After considering LoRa/LoRaWAN, an energy-efficient technology, and its integration into vehicular IoT networks, we propose and study the optimal mobile deployment of IRS compared to fixed deployment. IRS are integrated into networks to transform an NLOS path between a transmitter and a receiver into a LoS path via the IRS. In this way, they improve network performance. In this chapter we explore the use of IRS to increase coverage [1].

4.1 Introduction

Mobile communications offer several major advantages, including the flexibility of wireless technology and the high-speed connectivity of internet-based services. Consequently, the current period is optimal for the rapid advancement of wireless communications. Additionally, mobile operators and developers are exploring innovative technologies to enhance bit rates and reduce power consumption beyond 5G networks. Intelligent Reflecting Surface (IRS) is one technique that can help to solve this problem. IRS promotes wireless infrastructure reduction by lowering the number of necessary BSs/gNodeB to mitigate Non Line Of Sight (NLoS) areas with the base station. It is also beneficial in a constant bit rate connection; as it boosts the intensity of the signal received.

Most of the research assumes that the IRS has a fixed location and that signals pass through a single reflection stage on the surface of the IRS, which is made of a reconfigurable meta-material.

This work presents the use of IRS devices that collaboratively reflect signals in a multi-hop fashion to regions suffering from NLoS up to the base station. Similar to multi-hop, multi-reflection is a technique used in IRS systems that use a series of reflections to increase coverage and reach more users. In networks, the word "multi-hop" is frequently used, particularly in routing, which describes the process of sending a packet from its source to its destination through intermediary nodes.

[1] This chapter has been the subject of a publication [236]

Furthermore, we propose that IRS positions be mobile and equipped with buses. We thus present different approaches that contribute to the best selection of buses that the IRS can equip to work collaboratively to form multi-hop reflectors for mobile vehicles and users in certain blind spots to improve wireless network coverage and performance. These approaches are used to select the active-passive and passive-passive network reflectors combination, and are based on heuristics. Heuristics, are a type of AI commonly defined as rules of thumb that can be utilized to speed up decision-making. They have been studied in a variety of disciplines, including economics, psychology, and computer science [237]. These approaches leverage on future knowledge of bus and taxi positions using trajectory predictions. The objective of these approaches is to ensure a superior level of service through the optimization of the number of handovers. In particular, these strategies are based on the number of times a bus will be present in the future to select the IRS.

The performance of the proposed approaches is evaluated based on the traces of taxis and the public transportation of buses [233], [234] in the city of Rome.

The rest of the chapter is organized as follows: Section 4.2 define and describe proposed approach, before presenting the results obtained in Section 4.3. Section 4.4 discusses the results. Then Section 4.5 concludes the part with an outlook for future work.

4.2 Two hops IRS

Multi-hop approaches are widely used in wireless networks: IoT networks, VANET, etc. They enable network coverage to be extended beyond the reach of individual nodes. They are often implemented at the routing level [238] and enable for sender and receiver not directly conected to use intermediary nodes to forward the packet.

The idea is to extend the signal based on multi-hop approaches and thus achieve better coverage. To achieve this, we assume the existence of areas inaccessible to antennas, known as blind zones, in our study region. Any IRS bus in these areas will need a second IRS to extend its signal to the base station. Then, a second IRS will be chosen.

Figure 4.1 describes a multihop IRS scenario for extending an antenna signal using two IRS. Assuming that a taxi or a mobile user is not in sight of the antenna, IRS technology enables these objects to be covered passively. However, if the IRS visible to the antenna is out of range of the user, it can call on another IRS to extend the signal back to the user.

The choice of an IRS is made by election. Each mobile will elect an IRS called IRS1. If IRS1 is in a blind zone, it will hold an election to choose its potential IRS, called IRS2. Figure 4.2 shows the IRS election process for a taxi in a blind zone. Initially, we looked for all the buses that could cover the taxi. If at least one bus covers the taxi, a bus is chosen according to strategies Q, Q'A, Q'B, or Q". For each selected bus, one is elected per zone. The bus with the most votes becomes the IRS for a zone. Next, we check whether the chosen IRS is in LoS with the antenna or whether it is also in a blind area. If the former, the election is over. However, in the second case, the process continues with the search for buses in LoS that can cover the IRS level 1 or IRS1. If there are any, as in the case of the taxi, one bus is

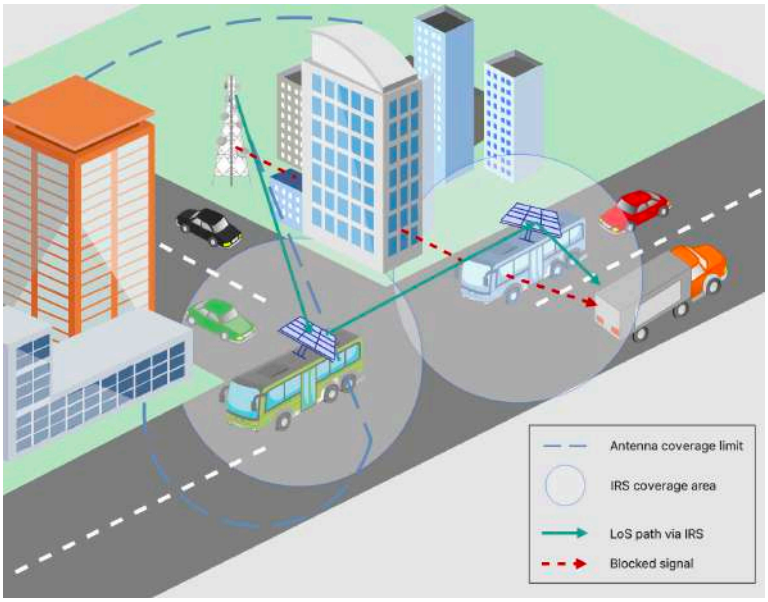


Figure **(4.1)** – *Usage scenario.*

chosen according to the strategy, and then one bus is elected from among those selected in the zone to reduce the number of buses used.

This work aims to show the difference between one and two hops, so the management of reflection angles is just as present in a single hop as in two hops. Given this, we have assumed that the IRSs are randomly configured, which, according to [239], offers better performance than without the IRS.

4.2.1 Settings

This work exploits taxis [233] and bus records from Rome's public transport system [234]. Bus information includes line numbers, stops, and schedules. We also use taxi traces for one day, between 10 a.m. and 11 p.m., with about 1,535 trajectories in the historic center of Rome. Each trajectory contains ten positions. We then used the trajectory prediction results obtained in [210] for that day. This prediction model is based on LSTM and predicts, at each time t, the position of a taxi at times t+1,t+2,t+3 and t+4. The coverage area is restricted to the following coordinates: latitude 41.8 - 42.0 and longitude 12.4 - 12.6, representing an approximate area of 22.239 km x 16.576 km. This area is divided into small zones of around 250 x 200 meters, with randomly distributed blind zones. The percentage of blind zone is set at 40%. In the next section, we set the coverage radius between 100 and 600 meters.

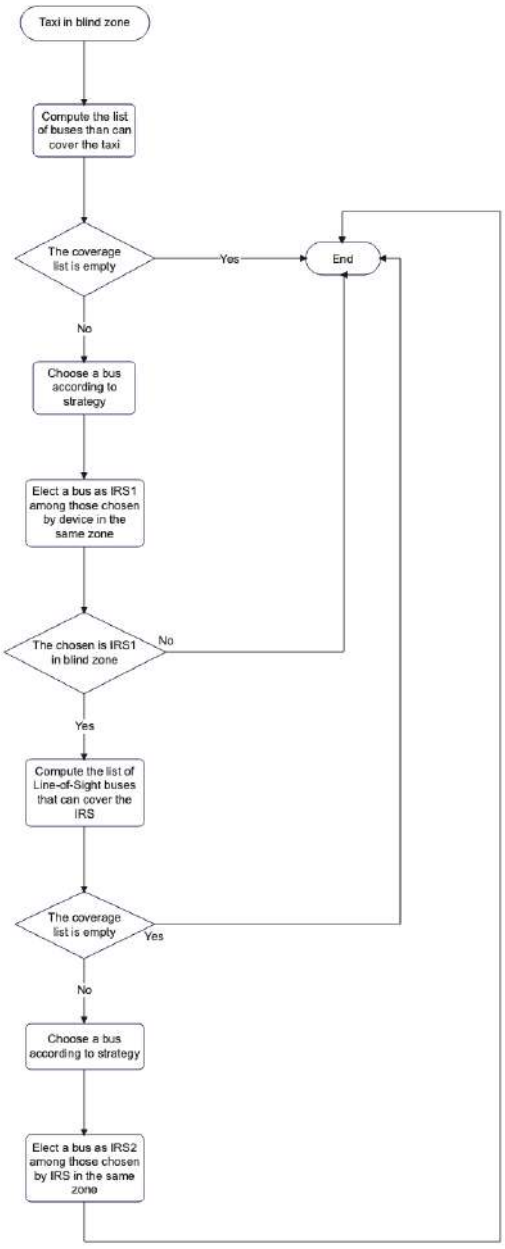


Figure **(4.2)** – *Flowchart of IRS election algorithm.*

4.2.2 Strategies

First, a taxi in a blind area will elect its IRS bus, and then each zone - a zone represents the subdivision of the study area into smaller zones - will elect an IRS1 for the zone according to each strategy. If the chosen IRS1 is in a non-blind area, the election stops. Otherwise, the blind IRS1 will repeat the election process to select a non-blind IRS in its vicinity.

Four strategies based on IRS selection are studied.

- Q: A bus is randomly chosen from the list of available buses.

Strategy	Principle	Based prediction
Q	A bus is randomly chosen from the list of available buses	No
Q'A	The bus most likely to appear most often in the future is chosen as the IRS	Yes
Q'B	Similarly to the Q'A strategy, except that the taxi retains its previous IRS if it is still under its coverage	Yes
Q"	Identical to Q'A except that the previous disconnected IRS is not considered.	Yes

Table **(4.1)** – *Strategies presentation.*

- Q ' A: The bus most likely to appear most often in the future is chosen as the IRS.
- Q ' B: Similarly to the Q ' A strategy, except that the taxi retains its previous IRS if it is still under its coverage.
- Q": Identical to Q ' A except that the previous IRS is not considered.

Table 4.1 summarizes the main principles of each strategy.

The following equations define the different strategies Q, Q', and Q" with :

- i: a taxi identifier
- n: a time slot, set at one minute considering the dynamic nature of vehicular networks.
- j: an IRS j
- $d_{i,n}(j)$: distance between taxi i and IRS bus j
- ρ : the coverage radius

$$q_{i,n}(j) = \begin{cases} 0 & \text{if } d_{i,n}(j) > \rho \\ 1 & \text{otherwise.} \end{cases} \tag{4.1}$$

$$q'_{i,n}(j) = \sum_{k=0}^{T} 1_{\{d_{i,n+k}(j)<\rho\}} \tag{4.2}$$

$$q"_{i,n}(j) = \sum_{k=0}^{T} \prod_{l=0}^{k} 1_{\{d_{i,n+k}(j)<\rho\}} \tag{4.3}$$

The last three strategies are based on predictions of taxis and bus positions, while the Q strategy is without predictions.

The following criteria are used to evaluate the different strategies:

- ***Disconnectivity***: It represents the number of times a mobile is not covered (no IRS) or covered by an IRS1 in a blind zone without an IRS2.
- ***Number of handovers***: This is the average number of times that a device changes IRS. Changing one of the IRS in the case of a multi-hop is considered a handover.
- ***Average connection duration***: This is the average period for which a taxi retains the same IRS. Changing one of the IRS (if applicable) is a change of connection.

4.3 Results

The results are collected for each criterion: disconnectivity, number of handovers, and connection duration. For each strategy, we compare the 2-hop results with the single-hop results. Figure 4.3 shows the coverage, that is, the average number of buses present as a function of the coverage radius. It is strategy-independent and, thus, identical to all strategies. It shows that just over half the taxis are covered for a radius of R=100m and that almost all taxis are covered for R=600m, indicating good coverage.

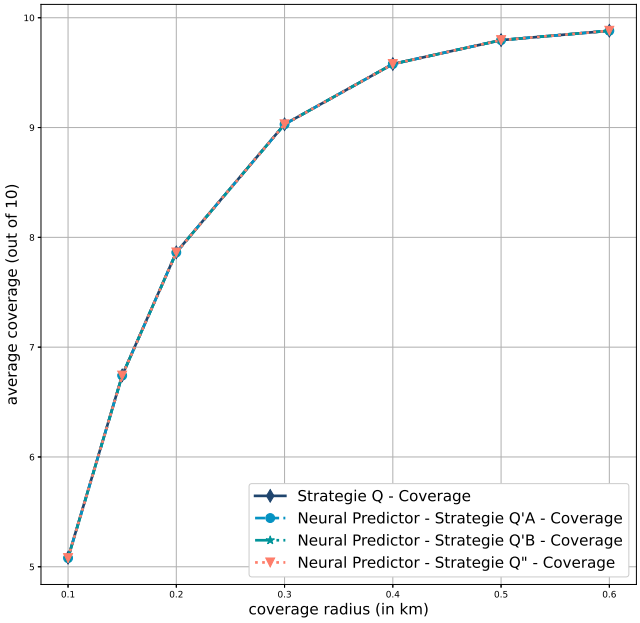


Figure **(4.3)** – *Taxis coverage by coverage radius.*

4.3.1 Disconnectivity

Figure 4.4 shows the average number of disconnections for the strategies Q, Q'A, Q'B, and Q". First, we note that disconnections decrease as the coverage radius increases. It goes from

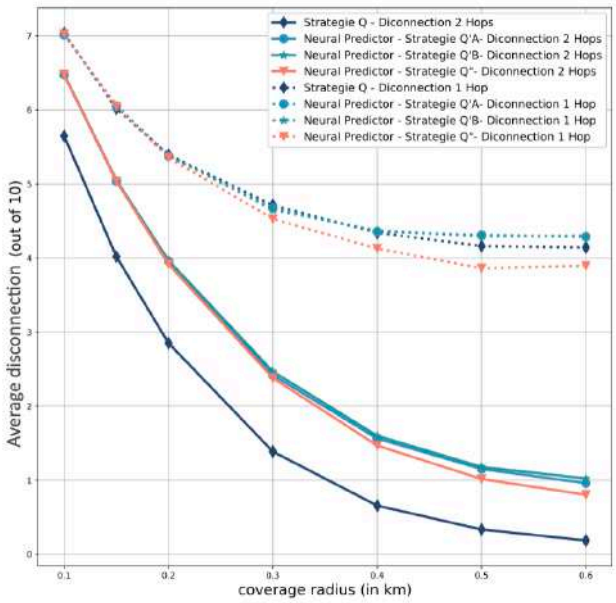


Figure **(4.4)** – *Taxis disconnection 1-2 Hops by coverage radius.*

around 70% disconnections to less than 10%. This is logical because increasing the radius increases the number of IRS candidates with the taxi under their coverage. Furthermore, it is observed that the three strategies, denoted as Q' and Q" in this study, demonstrate a high degree of similarity within a radius of 100 to 230m. At around 300m, the Q" strategy performs slightly better than the Q'A and Q'B strategies. The Q strategy performs better than the Q' and Q" strategies. These results can be explained by the fact that within a radius of 200 meters, there are few buses to cover the taxis: 1 out of 2 taxis without a bus as shown in Figure 4.3. Given the nature of these strategies, which are designed to function effectively in scenarios where there are multiple candidates — typically in situations with small lists — the outcomes tend to be nearly identical. The Q' and Q" strategies aim to retain the bus with the highest future occurrence. In other words, the bus selected as IRS1 may be in a blind zone and not have an IRS2, or the taxi may temporarily leave its coverage area before returning.

The red curve illustrates the disconnection for the Q strategy for one hop. The dotted lines represent the disconnection of strategies for a single hop. There is an increase in single-hop disconnections, observed regardless of the value of the coverage radius, R. From 400 meters up, the difference is more than 30%. As illustrated in the Figure 4.4, which shows the average number of disconnections for the strategies in 1 hop and 2 hops versus the coverage radius, the other single-hop strategies demonstrate a similar pattern. This illustrates the effectiveness of multi-hop for achieving comprehensive coverage.

4.3.2 Numbers of handovers

The notion of handover here refers to a change in the IRS. In the case of two hops, a handover occurs when one of the two IRS changes. Figure 4.5 represents, on average, the number of handovers as a function of the coverage radius for the strategies for one and two hops. The number of handovers is similar for a small coverage radius and generally lower

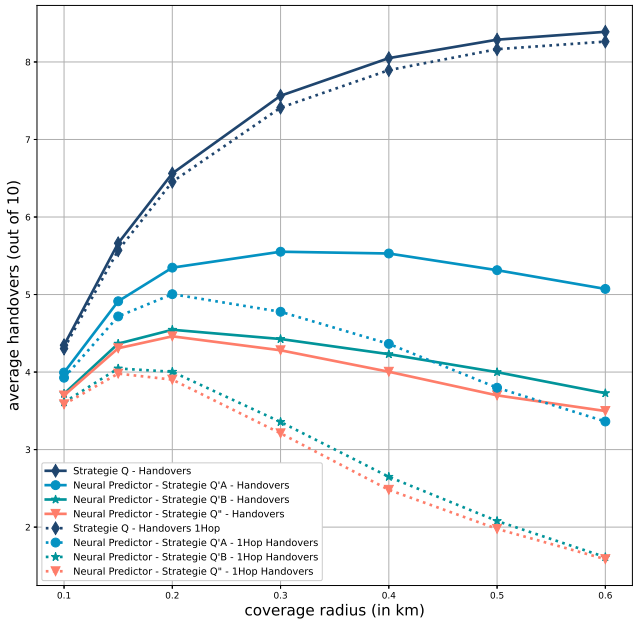


Figure **(4.5)** – *Average number of handovers by coverage radius.*

between 100 and 150 meters. The reasons for this are low coverage, with few IRS available and, as a result, no change. Then, this number increases for strategy Q and increases and decreases for strategies Q' and Q" as the radius increases. As the radius increases, the number of candidates' buses and connections increases, and the handover phenomenon becomes more apparent. But at a certain point, for strategies such as Q", Q'B, and even Q'A, which aim to keep the same bus for as long as possible, increasing the radius enables it to continue a little longer with the same IRS bus, even if the trajectories start to diverge, and hence the decrease after a certain threshold. This approach contrasts with the Q strategy, which operates in a more opportunistic manner.

The dotted curves represent one-hop strategies. For the Q' and Q" strategies, there are fewer handovers with the single hop than with two, as there are half as many IRS in some cases. Finally, we note that for the Q strategy, the number of hops has no impact on the number of handovers. This means that the IRS changes as much in one jump as it does in two due to the random draw. Another aspect is the behavior of the strategies. The Q'B and Q" strategies are relatively similar in one- and two-hops. In addition, there are always fewer handovers for these two-hop strategies, up to a coverage radius of 400 meters, than

for the single-hop Q'A strategy.

4.3.3 Connection duration

The trend is the opposite for connection duration, as shown in Figure 4.6, which illustrates the average duration a taxi stays with the same IRS or IRS pair in the case of a double hop. The connection duration is nearly equivalent to 1 for the Q strategy. This is logical, considering the high number of handovers (100%). It is important to note that, in addition to

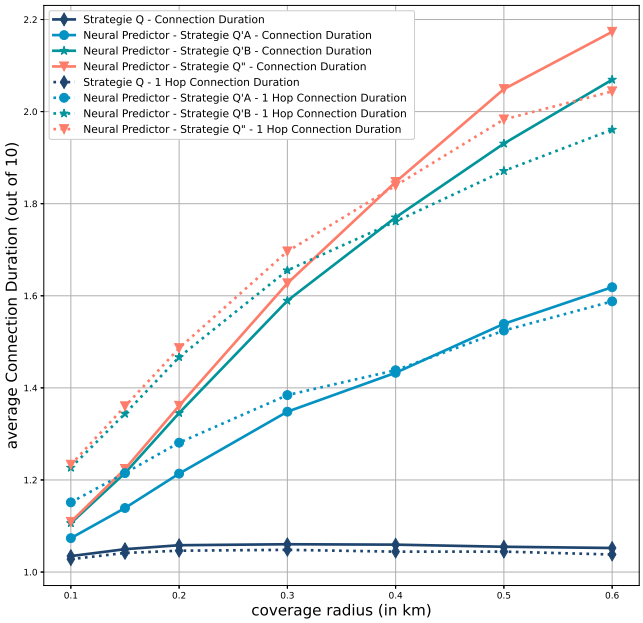


Figure **(4.6)** – *Average connection duration by coverage radius.*

this separation of strategies, which confirms the previous findings, the connection duration is higher with one hop than with two up to a radius of 400 meters and vice versa beyond that. Retaining a single IRS is often more feasible than managing multiple IRSs, particularly when coverage is limited. The duration for which a taxi can remain with a given pair of IRS also increases as the coverage radius increases.

In terms of connectivity, the connection/disconnection curve increases/decreases with the coverage radius. This is logical because as the coverage area increases, a taxi or bus is more likely to find an IRS bus to cover it, depending on whether it is a Level 1 or Level 2 election. As the radius increases, the number of handovers decreases because the probability of being covered by the same IRS remains constant, regardless of movement. An exception is made for the Q strategy, which offers a superior connection rate and equivalent handovers and connection duration for both single-hop and double-hop scenarios. It is also important to note that a temporary loss of connectivity is not considered a handover,

Route	MSE	MAE	RMSE
1	0.0014	0.00775	0.038
2	0.00004	0.00337	0.006
3	0.00032	0.0119	0.041

Table **(4.2)** – *Neural Predictor Indicator. [210]*

meaning there is no strict relationship between the connection duration and handover criteria. However, it is important to note that connectivity also influences the duration of the connection. Then there is a classification of strategies, with the Q" and Q'B strategies giving better results than the Q'A strategy regarding the number of disconnections, handovers, and connection duration. Finally, and most importantly, the impact of the double hop in increasing coverage capacity should be noted.

4.3.4 Prediction quality

In this chapter, as in the previous chapters, we used information on trajectory prediction from [210]. The predictor, based on LSTM, predicts four positions for the taxi for each time interval corresponding to t+1, t+2, t+3, and t+4. In this section, we compare the results obtained with the LSTM-based neural predictor with the perfect predictor. The Perfect Predictor uses the real-time positions of taxis as a forecasting mechanism, enabling us to validate the efficacy of our model. As indicated in table 4.2 which resume the results for Mean Square Error (MSE), Mean Absolute Error (MAE) et Root Mean Square Error (RMSE) for three predicted routes, the used LSTM predictor is not perfect. Therefore, we aim to assess the reliability of our results by investigating the impact of prediction accuracy on our findings. The curves show the results for each strategy Q'A, Q'B, and Q" in the Perfect and Neural predictors for the average disconnection (Figure 4.7), number of handovers (Figure 4.8) and the average duration of connections (Figure 4.9).

The findings indicate comparable outcomes for both predictors. This can be explained by the fact that the neural predictor used also has relatively good accuracy and that we are considering short-term predictions.

4.3.5 Max First vs. SINR First

In wireless networks, some metrics are used to estimate signal quality, such as RSSI (Received Signal Strength Indicator), SNR (Signal-to-Noise Ratio), SINR (Singal-to-Interference plus Noise Ratio), etc. In this section, we propose the integration of SINR into the IRS bus election.

The Signal to Interference Noise Ratio (SINR) is a crucial metric to measure signal quality in wireless communication systems. It is a metric that has a direct impact on the system's performance and dependability. The SINR serves to quantifie the signal strength in relation to background noise and other signal interference. It represents the power of the desired

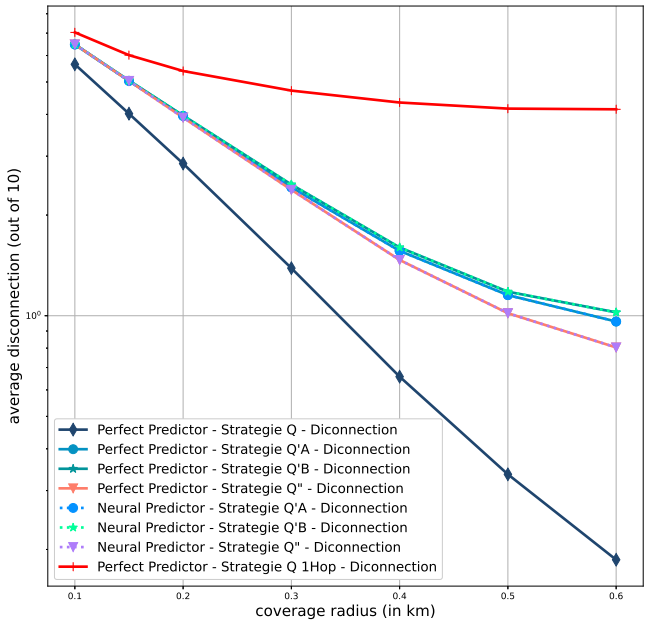


Figure **(4.7)** – *Average number of disconnections for Perfect and Neural predictors for the three strategies.*

signal divided by the power of the noise and interference. A low SINR value suggests that the signal is weak and might be obscured by noise. A high SINR value suggests that the signal is powerful and easily detectable. SINR is used to optimize wireless system performance as well as to assess the coverage and capacity of wireless networks [240].

We propose to elect the bus with the best SINR as IRS while always based on predictions and strategies. The SINR is, therefore, calculated for each prediction, and the device with the highest SINR is chosen as the IRS. However, optimizing the SINR contradicts most of the performance criteria selected, for instance, optimizing the number of handovers and connection time. Choosing the candidate IRS with the best SINR at each stage does not guarantee that the same IRS will be maintained. We therefore tested two cases:

- ***Max First***: First, we will examine the bus that is most likely to appear according to the prediction. In the event of a tie, the bus with the best SINR is selected.
- ***Sinr First***: In the second case, the roles are reversed. The bus with the best current and future SINR is selected and in the event of a tie, the number of occurrences of the bus is used to determine the final result.

We use the generic formula of the SINR.

$$SINR = \frac{SignalPower}{Noise + Interference} \tag{4.4}$$

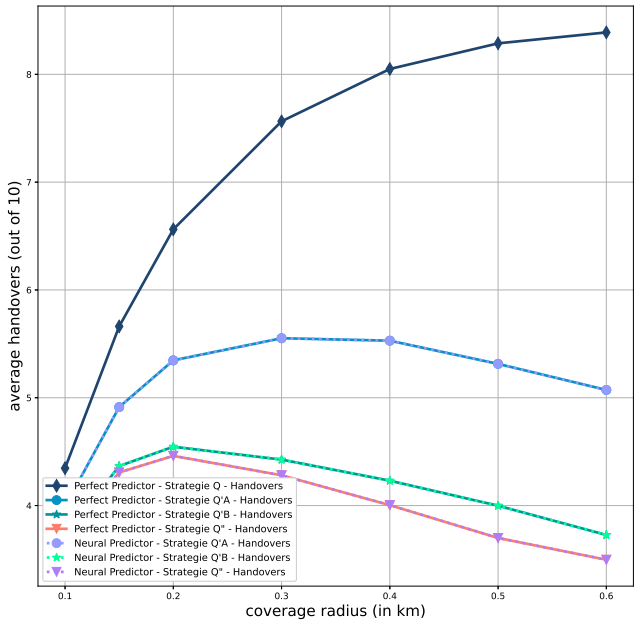


Figure **(4.8)** – *Average number of handovers for Perfect and Neural predictors for the three strategies.*

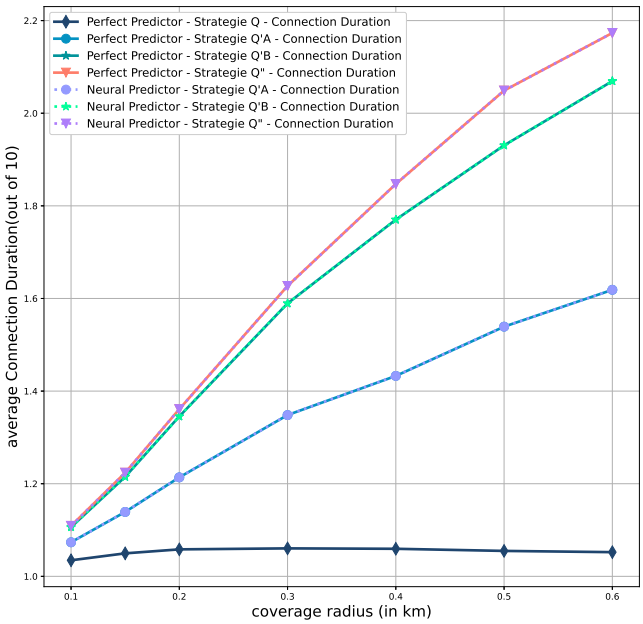


Figure **(4.9)** – *Average connection duration for Perfect and Neural predictors for the three strategies.*

Where:

- **Signal Power** refers to the desired signal's power;
- **Interference** represents undesirable signals' power; and
- **Noise** refers to the background noise's power.

SINR is commonly measured in decibels (dB).

We have tested these mechanisms for each strategy. Figures 4.10, 4.11, and 4.12 show, respectively, the number of disconnections, the number of handovers, and the average connection time, with minimal variation between the two mechanisms for single and double hops. This may be due to the method by which the SINR is calculated. In this section, we aggregate the SINRs, incorporating predictions to ensure a comprehensive analysis. The bus with the most occurrences is more likely to be chosen if the SinrFirst strategy is also used.

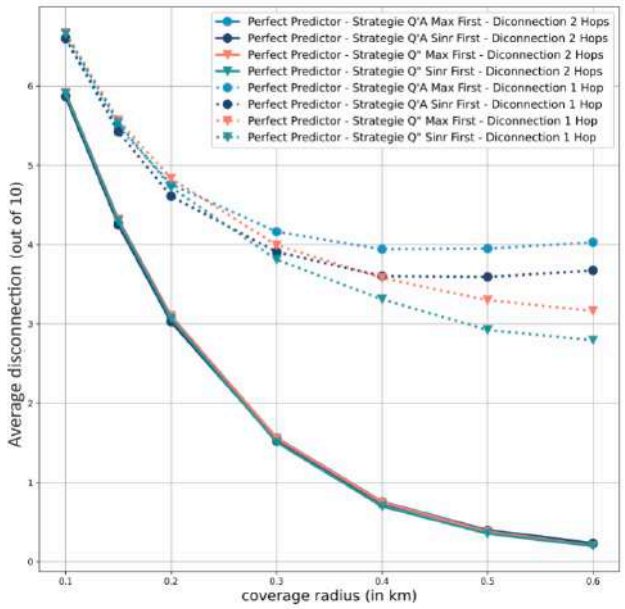


Figure **(4.10)** – *Average numbers of disconnections for MaxFirst and SinrFirst election for strategies Q'A and Q".*

4.3.6 Impact of N

Another parameter impacting these results is granularity. In other words, the number of zones in the study area. If N is small, the zones are large, while the zones are small if N is large. A blind zone is defined as a rectangle of size L/N x l/N where l and L represent the dimensions of the study area.

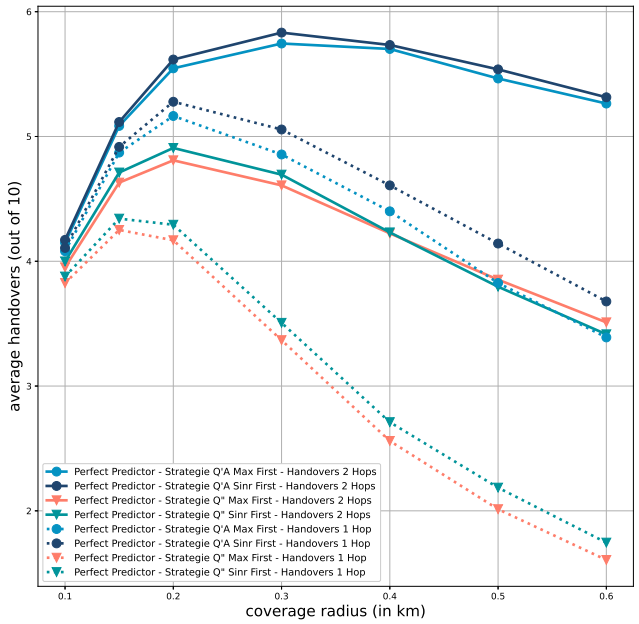


Figure **(4.11)** – *Average numbers of handovers for MaxFirst and SinrFirst election for strategies Q'A and Q".*

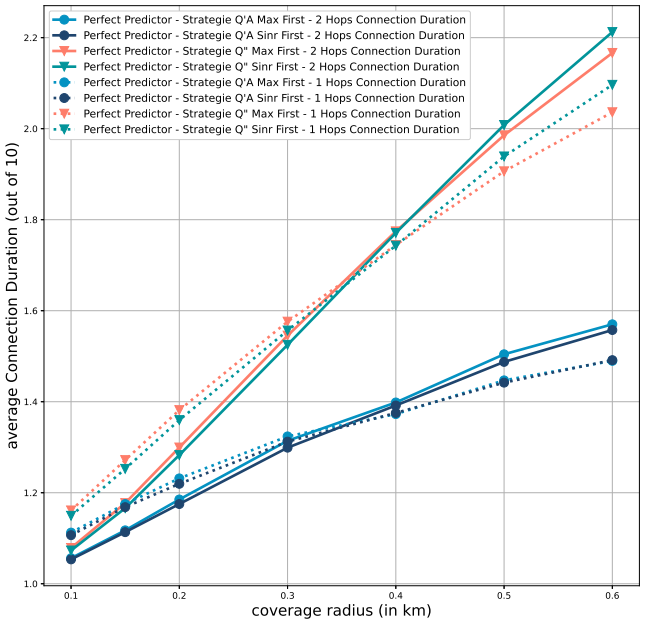


Figure **(4.12)** – *Average connection duration for MaxFirst and SinrFirst election for strategies Q'A and Q".*

Figures 4.13 and 4.14 illustrate the average number of disconnections for a coverage radius of 100 and 600 meters, respectively. This number decreases as a function of N, indicating that there are fewer disconnections when the zones are smaller. This phenomenon can be attributed to the increased likelihood of encountering an IRS in a non-blind zone. In the event of a larger blind-tagged area, all nearby buses may be susceptible to blind IRS1 and may not have IRS2. Conversely, in scenarios where the zones are small, some of these buses may be in non-blind zones, and the probability of having an IRS2 is higher.

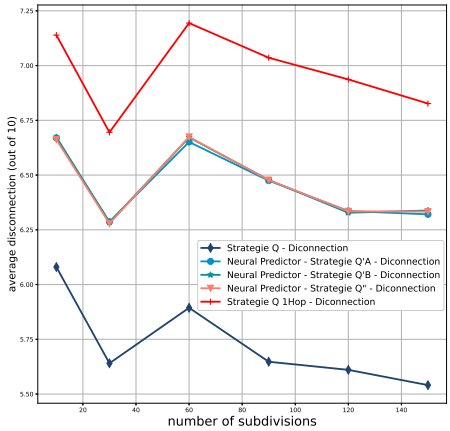


Figure **(4.13)** – *Taxis disconnection for R=100m by N.*

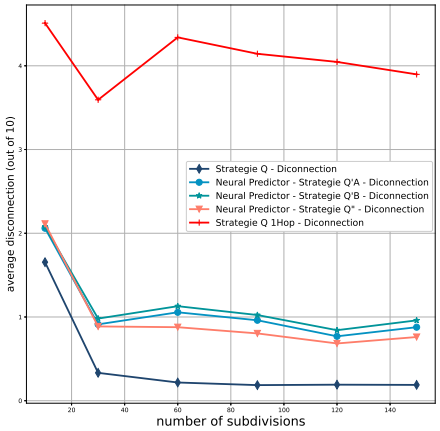


Figure **(4.14)** – *Taxis disconnection for R=600m by N.*

The number of handovers increases as a function of N, especially for a small radius (Figure 4.15). A small radius and small area result in limited coverage, with alternating blind and gray spots. This allows for potential change of IRS on level 2 IRS, if necessary. As the radius increases (Figure 4.16), the effect of granularity become less noticeable and the results tend to stabilize. However, there is generally an increase in handovers for a small radius. This may be due to the high number of handovers from extended coverage.

4.4 Discusion

This chapter examines multi-reflection as a means of enhancing the connectivity rate. Three strategies for selecting mobile IRS in double hop are proposed under the same previous strategies. The first strategy is strategy Q, which does not utilize prediction. The second strategy is strategy Q', which is subdivided into Q'A and Q'B. The third strategy is strategy Q". The results demonstrate the impact of multiple reflections on coverage, as shown in Figure 4.4. The same applies to the effect of the number of subdivisions in the study area, as shown in Figures 4.13 and 4.13, which is related to the number of activated IRSs. As the number of subdivisions increases, the zones decrease in size, and the number of IRSs is increased. This leads to a performance improvement similar to that observed when visibility increases. The best performance is noted for the Q" strategy, followed by the Q'

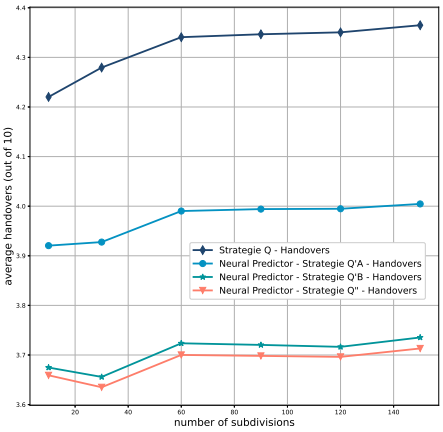


Figure **(4.15)** – *Average number of handovers for R=100m by N.*

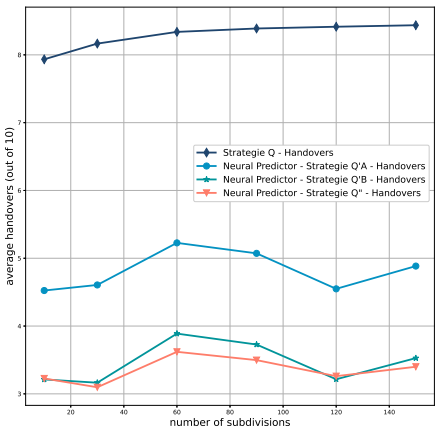


Figure **(4.16)** – *Average number of handovers for R=600m by N.*

strategies, and finally, the Q strategy. Unlike the Q' and Q" strategies, the Q strategy does not incorporate predictive information. The Q' and Q" strategies use a trajectory predictor that provides insights into the user's potential future positions.

The accuracy of the used predictor is confirmed by comparing it with the actual position data. As demonstrated by the Figures 4.7, 4.8, and 4.9 there is minimal distinction between the neural predictor and a perfect predictor composed of real data element.

Given that this mechanism is dependent on trajectory prediction, it is imperative that the predictor employed ensures the minimum possible error. High error rates can lead to inaccuracies, potentially compromising the validity of the results and performance. Consequently, it would be worthwhile to assess the impact of increased prediction error or bus delays on the outcomes. This is with a view to studying mechanisms for real-time optimization.

4.5 Conclusion

IRS surfaces consist of multiple reflecting elements that can direct signals in the intended direction. This suggests that they can function in scenarios where there is no direct connection between the antenna and the user. These devices help improve coverage.

Multi-reflection is a process in IRS systems that uses a sequence of reflections to extend coverage and reach more users, similar to multi-hop. Multi-hop is a common term in networks, notably in routing, which refers to the process of forwarding a packet from source to destination through intermediate nodes.

This chapter proposes a novel approach that integrates mobile IRS and multi-hop techniques. We assumed the presence of blind zones to validate our scenario and demonstrated

the benefits of multi-hop to increase network coverage.

We then compared different IRS election strategies based on the number of handovers and connection duration. The results demonstrate the efficacy of the multi-hop strategies we propose to ensure minimal disconnection rates. We also examined the evolution of different performance criteria as a function of the coverage radius and zone size.

Finally, we examined the impact of SINR integration on IRS selection. With regard to SINR, enhancing precision is possible through the inclusion of additional radio factors. Furthermore, the system's robustness can be enhanced through the integration of diverse traffic patterns, the incorporation of additional errors in prediction, and the introduction of specific delays in bus scheduling.

Conclusion

Many of the problems currently facing the transport sector could be solved by ITS. These challenges include growing congestion in cities, which is forcing people to travel further and putting a strain on infrastructure. Billions of dollars are spent each year on maintenance, accidents and fatalities, demonstrating the significant financial impact of these issues. As evidenced by the rise of applications such as electronic toll collection, ramp metering, traffic light cameras, traffic signal coordination, transit signal priority and traveller information systems, the field of ITS has already begun to have a major impact on the transport sector. Reduced environmental impact and financial gain are just two of the benefits that public and commercial users can enjoy from the deployment of these systems.

ITS are enabled by VCN. It refers to the use of memory, computational resources and communication systems to facilitate ITS. To achieve these goals, members of a VCN need to collect, exchange and communicate data. Examples of these communications include V2V, V2I, vehicle-sensor, vehicle-passenger, vehicle-pass-by, etc. V2X.

This thesis presents the study of QoS optimization in vehicular network based on predictive AI.

VCNs are designed to enhance traffic safety, maintenance, and user experience. This includes improving vehicle functionality for environmental awareness through sensors and wireless communication technologies. Different short-range wireless technologies like Bluetooth, Wifi, and DSRC are used, while cellular options can be expensive. The challenges in providing connectivity arise from fluctuating node density, vehicle speeds, and quick topological changes. One solution is the placement of RSU antennas or more BS to improve coverage, though extensive antenna deployment can cause interference and lead to high costs. These costs may reduce with relay usage, similar to traditional networks, but their placement for performance and cost-effectiveness is critical. Promoting heterogeneity in VCNs by integrating various wireless network cards in vehicles increases network access opportunities through combined communication protocols and secure handover mechanisms. This is crucial with IoT in vehicles, enabling intelligent traffic management, dynamic services, and vehicle control.

The incorporation of AI has yielded favourable results in the search for solutions in various fields. Predictive AI accelerates and improves the statistical analysis that has long been used to predict the future, using machine learning algorithms and vast amounts of data.

Then, QoS ensures that users, applications, etc. receive a certain level of service. It

encompasses a number of factors in the communications domain, including coverage, delay, security, and accessibility of resources.

This thesis addresses some of these issues in three sections: the optimal deployment problem, increasing coverage through multi-hop reflection, and the resource allocation problem in a vehicular IoT network.

In the first part, a resource reservation mechanism for LoRaWAN-based IoT devices in a vehicular environment is presented. LoRa/LoRaWAN, an LPWAN technology that uses ISM frequency bands and is known for its long-range coverage, energy efficiency and ease of implementation. It is one of the most widely deployed IoT technologies. In addition, LoRa's chirp-based modulation provides a degree of immunity to interference.

LoRaWAN is appropriate for non-critical applications—that is, applications that are not delay-sensitive. We suggest a resource reservation method for LoRaWAN-based IoT devices operating in a vehicle context to lessen this latency issue. The proposed mechanism is an advanced reservation of available resources, which is based on a prefetching method. Web services and caching systems like DNS make extensive use of this prefetching technology. Since the concept of reservation, as described here, is relevant throughout the process of rejoining a new NS, which consists of just two states—acceptance or rejection—the metric used is the number of rejections.

A series of simulations were performed with different parameters to assess the evolution of the number of rejections. The non-nominative mechanism is the most optimal, offering service differentiation between subscribers and others with fewer rejections. It is also the most computationally effective. In contrast, the nominative mode is more stable than the non-nominative mode, although it offers a more pronounced service differential and experiences more rejections during congestion. Traffic differentiation is useful in QoS management. In this work, it was used to privilege primary subscribers in roaming states, but it can also be applied in other directions, such as the need for QoS differentiation between different application flows.

We suggested using a mobile IRS mounted on buses to address the issue of uneven coverage in automobile and urban areas. IRS is a type of passive relay technology. It can be used in coverage gaps - areas with little or no coverage - to increase coverage or boost the signal. IRS, also called "passive relay", has gained popularity due to its reconfigurability and, most importantly, its energy efficiency compared to traditional relays. The majority of methods, however, suggest that the IRS be positioned fixedly. This setup makes it possible to solve clearly defined, fixed problems. However, there may occasionally be brief coverage failures in the context of vehicular networks. Thus, in contrast to fixed installation, the second contribution investigates the optimal location for mobile IRSs aboard buses.

The problem is modeled using three different approaches, and it is then executed using IBM ILOG CPLEX. The impact on network performance is evaluated using a number of parameters, such as connectivity, connection duration, and the average change rate, or handovers. When the prediction is used, overall performance noticeably improves, demonstrating the forecast's impact. Preliminary findings indicated that fixed positioning was better than mobile positioning. We, therefore, attempted to test this notion by selecting a set of IRS at random to be activated at the beginning of each period to ensure selection fair-

ness. Lastly, we assessed the impact of the dataset expansion on these results. The findings indicate that performance is impacted by the dataset used.

To increase coverage, the third contribution suggests a strategy that combines mobile IRS with multi-hop. Similar to multi-hop, multi-reflection is a technique used in IRS systems that uses a series of reflections to increase coverage and reach more users. In networks, the word "multi-hop" is frequently used, particularly in routing, which describes the process of sending a packet from its source to its destination. We assumed that there were blind zones in the area to test our scenario.

We also demonstrated how network coverage can be enhanced by multi-hop. Next, we analyzed several IRS election procedures based on connection time and the number of handovers. The outcomes show the advantages of the multi-hop methods to guarantee a low number of disconnections. We also looked into how zone size and coverage radius affected certain performance measures. Lastly, we looked at the impact of SINR integration on IRS selection.

The integration of two energy-efficient technologies in vehicular networks is the focus of this work. Prefectching has shown positive results in reducing NS-level rejection and promoting service differentiation in the context of IoV. In addition, the issue of IRS deployment is examined from many angles. It is shown that the proposed mobile deployment outperforms the stationary one when there are fewer IRS, when trajectories are similar, and when the LoS distances between the IRS and the user are small. Coverage was increased by using multiple IRS in multi-hop mode.

The use of IA prediction in the form of trajectory prediction has consistently shown an improvement in overall performance.

The use of an enhanced dataset, encompassing diverse types of vehicles among the user population, can lead to substantial advancements in the optimization function. Precision can be enhanced by including additional factors, such as the Doppler effect and fading. Furthermore, the adoption of artificial intelligence (AI) as a replacement for the conventional optimizer can yield notable improvements. Real experiments can help analyze the feasibility and accuracy of the system. A subsequent stage of the process would entail the assessment of energy consumption, signal quality and interference (SNR, SINR, etc.).

Finally, Predictive AI is not limited to trajectory prediction; it involves a computer program's capacity to recognize patterns, anticipate behavior, and forecast future occurrences using statistical analysis and machine learning. It can thus be used to reconfigure the IRS. In this case, it should be able to anticipate CSI information in order to better cover the various users or secure transmissions.

Appendices

Appendix A

List of publications

1. Fall, N. P., Said, A. M., Marot, M., Diallo, C., Afifi, H., & Moungla, H. (2023, October). Two Hops IRS Optimization in Urban Mobile Environment. In Proceedings of the Int'l ACM Symposium on Mobility Management and Wireless Access (pp. 83-90).

2. Fall, N. P., Marot, M., Diallo, C., Bernard, A., & Roujanski, G. (2023, December). Optimizing mobility in LoRaWan: A resource reservation approach. In GLOBECOM 2023-2023 IEEE Global Communications Conference (pp. 7562-7567). IEEE.

3. Fall, N. P., Diallo, C., Said, A. M., Marot, M., Afifi, H., & Moungla, H. Fixed and Mobile IRS Placements. 2025 10th International Conference on Frontiers of Signal Processing (ICFSP), 10-12 September 2025. Accepted.

4. Fall, N. P., Diallo, C., Said, A. M., Marot, M., Afifi, H., & Moungla, H. (Submitted on April 27 2025), Exploring The Use of Mobile IRS in a Vehicular Context. In Vehicular Communications, Elsevier.

Appendix B

Résumé de la thèse en Français

This chapter presents a summary of this thesis in French.

Titre : Optimisation de la qualité de service dans les réseaux véhiculaires basée sur l'IA prédictive.

B.1 Introduction

Un réseau de communication véhiculaire (VCN) fait référence à l'utilisation de systèmes de communication, d'installations informatiques et de stockage dans un contexte véhiculaire pour permettre la mise en œuvre d'un système de transport intelligent (Intelligent Transport Systems (ITS)). Son principal objectif est de réduire les accidents et d'assurer la sécurité routière.

En 2021, le nombre d'accidents de la route était estimé à 1,19 millions, soit 15 accidents pour 100 000 habitants. L'Afrique représentait 19% de ces incidents, tandis que le Sénégal en comptait 24 pour 100 000, malgré une baisse de 5% depuis 2010 [1]. Outre les impacts de la pollution atmosphérique et sonore, la congestion routière a également des conséquences économiques, en provoquant des retards. Au vu de ces chiffres, des politiques internationales, nationales et locales ont été mises en place pour réduire les accidents de la route. Il s'agit notamment d'introduire des législations, d'accroître la sensibilisation, d'améliorer l'infrastructure routière et d'intégrer les technologies de l'information et de la communication dans les transports par le biais des ITS, entre autres mesures. L'intégration des technologies de l'information et de la communication dans les infrastructures de transport et les véhicules est connue sous le nom de ITS [3].

Les ITS ont été présentés comme une solution potentielle à de nombreuses difficultés auxquelles est confronté le secteur des transports aujourd'hui. Ces difficultés comprennent l'augmentation de la congestion urbaine, qui allonge les temps de déplacement des individus et sollicite considérablement les infrastructures. Ces problèmes ont un impact financier important, avec des milliards de dollars dépensés chaque année pour l'entretien des infrastructures routières, les accidents de la circulation et les décès.

Le domaine des ITS a déjà commencé à exercer une influence considérable sur l'industrie des transports, comme en témoigne l'émergence d'applications telles que le télépéage, les caméras des feux de circulation, la coordination des feux de circulation, la priorité des feux de transit et les systèmes d'information des voyageurs. La mise en œuvre de ces systèmes offre une série d'avantages au grand public et aux utilisateurs commerciaux, notamment une réduction de l'impact sur l'environnement et des gains économiques.

Cette mise en oeuvre implique la collecte, le partage et la communication de données entre les différents participants qui composent un réseau de communication véhiculaire. Les communications véhicule-à-véhicule (V2V), vehicule-à-infrastructure (V2I), véhicule-capteur, véhicule-passager, et véhicule-à-tout (V2X), qui englobe toute communication intégrant un véhicule et une autre entité, sont des exemples de ces communications.

Avec l'avènement de la 5G et la tendance vers la 6G, de nouveaux cas d'utilisation apparaissent, tels que la communication et détection intégrées ou Integrated Sensing And Communication (ISAC) en anglais, avec l'intégration massive de l'internet des objets (IoT), l'intégration et le déploiement de multiples techniques d'accès radio pour évoluer vers un réseau d'accès radio ouvert (ORAN) [6]. A cela s'ajoute les tendances vers des solutions et des pratiques respectueuses de l'environnement ou des approches VERTES. Cela entraîne de nouveaux défis tels que: la couverture en raison de l'augmentation constante de la demande, la prise en charge de la mobilité et du transfert dans un contexte multi-opérateurs, l'allocation des ressources, la sécurité, le routage, les systèmes basés sur la localisation, etc. L'énergie est également un aspect important, bien qu'elle ne soit pas la préoccupation première des réseaux véhiculaires. Assurer la connectivité dans un réseau de véhicules avec une densité de nœuds fluctuante, une vitesse de véhicule aléatoire et des changements topologiques rapides présente de nombreuses difficultés.

La première solution consiste à utiliser des antennes appelées RSU [7] pour rapprocher les utilisateurs des antennes et améliorer la couverture. Toutefois, le déploiement massif d'antennes peut entraîner des interférences. En outre, les coûts de déploiement et de maintenance risquent d'être élevés. Il est possible d'améliorer ces coûts tout en augmentant la couverture en utilisant des relais, comme dans un réseau de communication traditionnel. Cependant, leur emplacement reste une préoccupation majeure lorsqu'il s'agit d'augmenter les performances tout en minimisant les dépenses.

Une autre solution consisterait à promouvoir l'hétérogénéité dans les VCNs en intégrant différentes cartes de réseau sans fil dans les véhicules pour augmenter les chances d'accéder à un réseau [7]. Ce dernier point est encore plus essentiel avec l'introduction de l'internet des objets dans les véhicules et leur environnement. Cette introduction rend possible la gestion intelligente du trafic, les services d'information dynamiques et le contrôle des véhicules.

D'un autre coté, les tendances actuelles penchent vers une sobriété numérique, qui est un ensemble d'approches d'amélioration continue qui tentent de réduire les effets négatifs de la technologie numérique sur l'environnement, la société et l'économie. Avec une part comprise entre 6 et 32% de la consommation globale d'énergie prévue pour 2025, dans des systèmes tels que les réseaux, il s'agit principalement de réduire la facture énergétique. Les frais généraux du réseau sont les données et les ressources supplémentaires néces-

saires pour gérer et contrôler la connexion au réseau. Il se compose de différents éléments, tels que:les entêtes de protocole, les mécanismes de correction d'erreur, les numéros de séquences, etc. Il est donc, essentiel de trouver des solutions pour réduire la consommation d'énergie tout en maintenant un minimum de qualité de service. L'utilisation de technologies efficiente en energie permet d'améliorer la consommation énergétique. Cependant, cette efficience energétique vient souvent avec certaines limitations : faible couverture, faible débit, longue latence, etc. C'est le cas des technologies Bluetooth Low Energy (BLE), Zigbee, ou des LPWAN qui combinent longue portée et faible consommation d'énergie.

Ainsi dans cette thèse, nous nous basons sur des technologies économes en énergie pour tenter de résoudre des problèmes de connectivité spécifiques dans les VCNs.

Dans cet élan, notre premier objectif est motivé par le nombre toujours croissant d'objets connectés. Ces objets peuvent être éloignés des RSUs ou des passerelles. De plus pour réduire autant que possible le nombre d'intermédiaires, nous proposons d'utiliser une technologie à longue portée. LoRaWAN a été choisi pour sa couverture et son efficacité énergétique. L'objectif est de proposer une solution basée sur LoRaWAN qui résout le problème de connectivité dans l'IoT véhiculaire tout en atténuant les limites de LoRaWAN. Ensuite nous étudions le déploiement des IRS, un type de relais passif pour améliorer la couverture, avant d'explorer la multi-reflexion au multi-saut avec les IRS dans le bus d'étendre la couverture.

L'intelligence artificielle (IA) permet aujourd'hui d'améliorer les performances dans plusieurs domaines. Ainsi ce travail se base sur l'utilisation d'une IA prédictive pour optimiser la QoS dans les VCNs.

B.2 Mécanismes de réservation de ressources LoRawan dans les VCN

La technologie de communication LoRa/LoRaWAN appartient à la famille des LPWANs (Low Power Wide Area Network), caractérisée par une longue portée et une faible consommation d'énergie. Dans le cadre de l'Internet des objets, cette technologie est employée de manière extensive en raison de plusieurs facteurs. En premier lieu, sa mise en œuvre s'avère aisée et peu onéreuse, ce qui la rend accessible à un large éventail d'utilisateurs. En outre, elle fonctionne sous licence ISM (Industriel Scientifique et Médicale), qui est une licence libre. Enfin, elle propose un éventail d'options de déploiement, permettant une personnalisation et une adaptabilité optimales selon les besoins spécifiques. Des expérimentations ont été élaborées dans le secteur véhiculaire. Il a été constaté que ce dispositif était adapté aux applications non critiques, c'est-à-dire aux applications non sensibles au temps de latence, en dépit des difficultés rencontrées en matière d'intégration de la mobilité.

Afin de pallier cette difficulté, la section suivante propose une approche méthodique de la réservation de ressources dans un contexte véhiculaire pour les dispositifs IoT basée sur LoRaWAN. L'approche est basée sur le mécanisme de préchargement ou prefetching en anglais qui permet la récupération anticipée des ressources. Le prefetching est une pratique courante dans les systèmes de mise en cache, tels que le DNS (Domain Name System) ou le

web, entre autres.

L'objectif de cette étude est de maximiser l'allocation des ressources dans un scénario mobile multi-opérateurs utilisant le protocole de communication LoRaWAN. Dans le cadre de cette analyse, il est supposé que les antennes sont partagées entre cinq opérateurs, une hypothèse qui vise à refléter la réalité observée. Afin d'illustrer le phénomène de l'itinérance, chaque antenne ou passerelle dispose d'un serveur réseau ou NS. Les antennes sont attribuées aux opérateurs de manière alatoire. La stratégie préconisée repose sur deux mécanismes principaux : la distinction ou différentiation du trafic et la réservation.

La différenciation de services se fait par une séparation du trafic en deux catégories prioritaire et non prioritaire. Un trafic est considéré comme prioritaire lorsque l'opérateur auprès duquel l'appareil est abonné, désigné par l'acronyme « hO », correspond à l'opérateur propriétaire de l'antenne. Le trafic est non prioritaire, si l'opérateur du dispositif mobile est distinct de l'opérateur propriétaire de l'antenne. Cette différenciation vise à garantir que la réservation de ressources soit exclusive pour l'appareil en situation de trafic prioritaire. Cette mesure devrait favoriser les clients de l'opérateur actuel au détriment des autres utilisateurs itinérants.

Dans le cadre de cette étude, on suppose que chaque dispositif part de son réseau domicile (ses hNS et hO). La première position de chaque appareil permet de déduire le hO. Dans un second temps, pour les positions suivantes, l'opérateur propriétaire de l'antenne est récupéré et comparé au hO de l'appareil mobile afin de déterminer le type de trafic (prioritaire, non prioritaire). Cette opération permet de décider si une réservation est nécessaire ou non.

Les ressources destinées au vehicule sont fournies aux stations de base adjacentes à celle où la jointure est réalisée, en prévision d'un déplacement et, par conséquent, d'une future connexion. L'utilisation des résultats de l'algorithme de prédiction de la mobilité permet, lorsque cela est possible, la réservations sur les antennes candidates.

Nous avons aussi testé deux mécanismes de réservation. Le modèle de réservation nominative implique l'enregistrement de chaque réservation avec l'identifiant du réservataire et la date d'expiration. L'identifiant, désigné par le terme numTraj, est une référence unique qui identifie le véhicule par sa trajectoire. La date d'expiration d'une réservation correspond à la durée de validité de ladite réservation. Avec la réservation non nominative, les réservations ne sont enregistrées qu'avec leur date d'expiration. Par conséquent, tout vehicule étant en situation prioritaire peut utiliser cette réservation.

Notre analyse se concentre sur le nombre de jointures rejetées, appelées « nombre de rejets ». La notion de réservation intervient lors du processus de jointure avec un nouveau NS. Ce dernier ne comporte que deux états : l'acceptation ou le rejet. Par conséquent, l'évaluation du nombre de rejets apparaît comme le critère le plus pertinent pour évaluer la qualité du service.

La figure B.1 représente les ratios de rejets au total, prioritaires et non prioritaires, pour les mécanismes de réservation nominative et non nominative. Ces ratios sont calculés pour une capacité égale à 400, un temps de jointure de 17 minutes et un temps de réservation de 4 minutes. Le seuil de 0 indique une réservation correspondant à 0% de la capacité totale,

c'est-à-dire sans réservation. Il est considéré comme le scénario de référence.

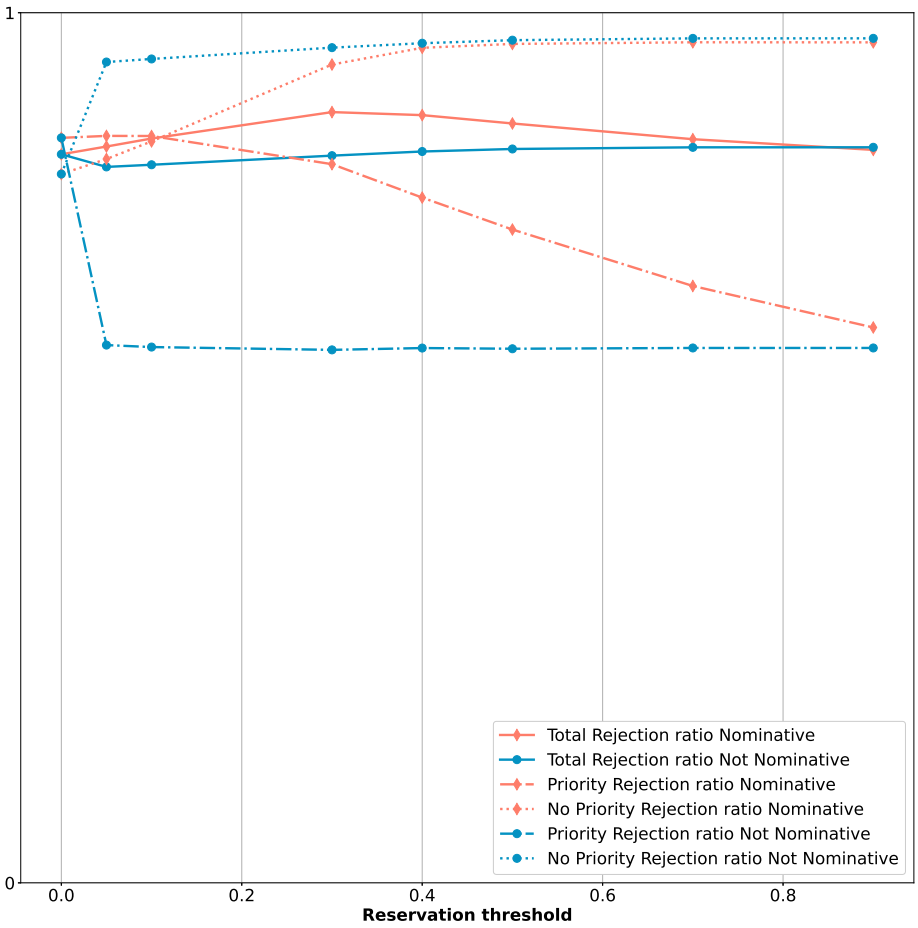


Figure **(B.1)** – *Taux de rejet total, prioritaire et non prioritaire pour les mécanismes de réservation nominative et non nominative en fonction des seuils de réservation, capacité*=400*, intervalle de jointure* =17$minutes$*, durée de réservation*=4$minutes$

Il est intéressant de constater qu'au début des courbes, le trafic prioritaire présente un nombre de rejets supérieur au trafic non prioritaire. Cette différence est particulièrement marquée jusqu'à 10% de la capacité. À ce stade, on observe une diminution des rejets pour le trafic prioritaire, tandis que le trafic non prioritaire affiche des rejets supplémentaires. Cette situation peut être attribuée au fait que moins de 10% du trafic est réservé et, par conséquent, traité comme prioritaire, tandis que la proportion restante, soit plus de 90%, est traitée comme non prioritaire. Il a été constaté que les rejets sont partagés, mais qu'ils sont majoritairement attribuables aux réservations non utilisées. Il convient de noter que la réservation est nominative, ce qui implique que cette réservation ne peut être utilisé que par le dispositif ayant effectué la réservation. Cette dynamique conduit fréquemment à des

taux de rejets supérieurs à la référence, notamment lorsque le seuil de réservation est élevé.

La version non nominative permet de minimiser ces réservations inutilisées et, par conséquent, de réduire les erreurs de prédiction. En effet, un dispositif prioritaire peut bénéficier d'une réservation sans pour autant en avoir fait une. On note une distinction significative entre le trafic prioritaire et non prioritaire. Cette différence s'accentue de manière significative à mesure que le seuil augmente. Cependant, pour des seuils très élevés, ce type de réservation engendre des pertes plus importantes et présente une convergence similaire à celle observée pour la version nominative. Le seuil à partir duquel ces deux mécanismes convergent ou commencent à générer plus de rejets dépend du nombre de requêtes, de la capacité des passerelles, mais aussi de la durée de jointure et de la durée des réservations. Cette approche méthodique nous conduit à examiner les fluctuations de ces paramètres.

La différenciation du trafic est une méthode couramment utilisée pour gérer la qualité de service. Dans le cas présent, elle est utilisée pour privilégier les abonnés principaux en situation d'itinérance. Elle peut toutefois être appliquée à d'autres fins, par exemple pour différencier la qualité de service entre divers flux d'application.

Les deux méthodes de réservation présentées ici ont chacune leurs avantages et leurs inconvénients. Le mécanisme non nominatif est le plus optimal, car il permet de réduire les rejets tout en offrant une différenciation du service entre les abonnés et les autres utilisateurs. C'est également la méthode la plus efficace en termes de calcul. Le mode nominatif est plus stable. Il offre une différenciation de service plus limitée que le mode non nominatif, mais provoque davantage de rejets en cas de congestion.

B.3 Optimisation du déploiement

Les IRS, ou surfaces réfléchissantes intégrées, sont des dispositifs stratégiques dans les réseaux de communications. Ils permettent d'étendre la couverture réseau, d'amplifier le signal et d'améliorer la performance des systèmes de communication. La reconfigurabilité de ces éléments par changement de phase permet la réalisation de ces fonctions, éliminant ainsi la nécessité d'une alimentation supplémentaire. L'intégration de ces dispositifs dans les réseaux de communication présente plusieurs avantages notables, dont une consommation d'énergie significativement inférieure à celle d'un simple relais. Cette évolution a suscité un intérêt renouvelé pour les approches fondées sur les IRS. Néanmoins, la majorité des approches préconisent un positionnement fixe de l'IRS. Cette configuration permet de résoudre des problèmes fixes et bien définis. Néanmoins, dans le contexte des réseaux de véhicules, des problèmes de couverture temporaires peuvent se produire de manière ponctuelle. L'approche méthodologique proposée dans le cadre de cette étude consiste à examiner le positionnement mobile. Le problème est modélisé sous forme de système de programmation linéaire (MILP) selon trois stratégies et exécuté à l'aide du logiciel IBM ILOG CPLEX.

Notre étude s'est concentrée sur l'optimisation de la disposition des IRS mobiles placés sur des bus en comparaison avec une configuration fixe. L'évaluation de l'impact sur la performance du réseau s'effectue à l'aide de diverses mesures, parmi lesquelles la connec-

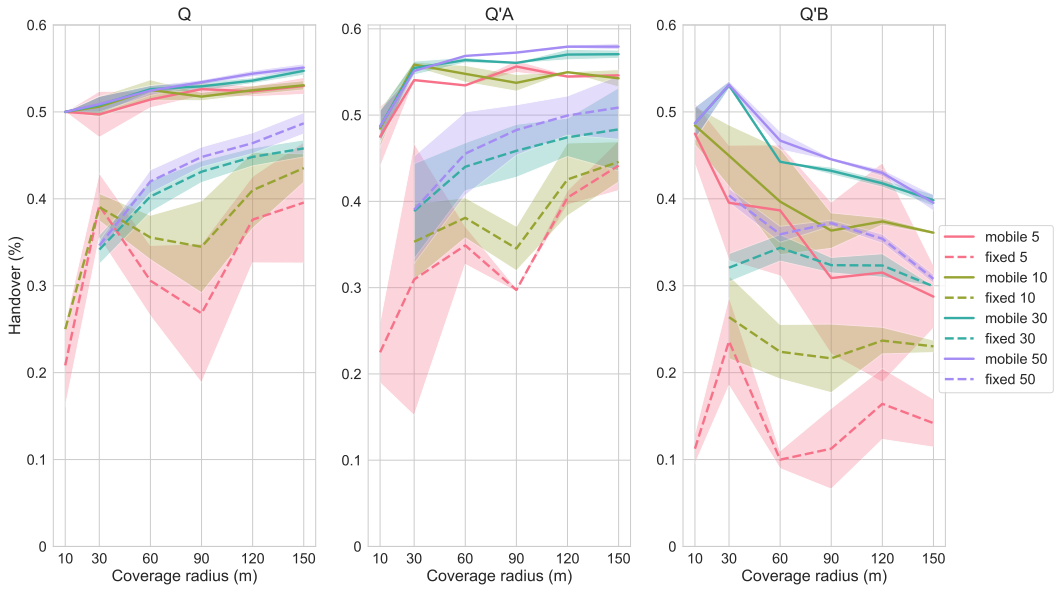


Figure **(B.2)** – *Evolution du nombre de handovers par trajectoire en fonction du rayon de couverture pour les stratégies Q, Q'A et Q'B*



Figure **(B.3)** – *Evolution du nombre de handovers par trajectoire en fonction du rayon de couverture avec et sans ensemble d'IRS de départ pour la stratégie Q'B*

tivité, la durée de connexion ou encore le taux de changement moyen ou « handover ». L'efficacité de la prédiction a été validée avec une amélioration significative des performances globales. Les premiers résultats obtenus indiquent un meilleur positionnement fixe que mobile. Afin de valider cette hypothèse, nous avons procédé à une sélection aléatoire des IRS à activer au début de chaque période. Cette démarche a pour objectif d'introduire de certaine forme d'équité. Ensuite, nous avons procédé à une extension de l'ensemble du dataset initial. Les résultats de cette étude mettent en évidence une corrélation entre les performances observées et le dataset utilisé pour l'analyse.

En somme, il est possible de conclure que :

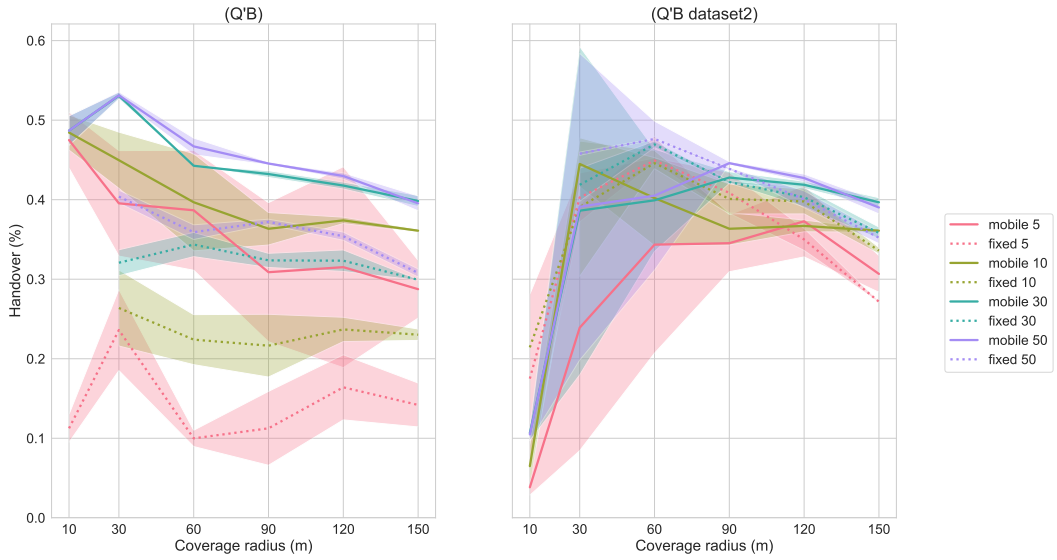


Figure **(B.4)** – *Evolution du nombre de handovers par trajectoire en fonction du rayon de couverture pour la stratégie Q'B (dataset2)*

- Les approches basées sur la prédiction produisent de meilleurs résultats.
- La sélection aléatoire des IRS au début de chaque période introduit un certain degré d'équité, mais produit systématiquement des résultats moins performants. La raison de cette baisse de performance proviendrait du fait que les IRS sélectionnés de cette manière ne donnent pas forcément le résultat le plus optimal. Néanmoins, avec cette sélection, il convient de noter l'existence de points où les scénarios mobiles peuvent démontrer une performance supérieure aux scénarios fixes, bien que cela demeure limité à des périodes spécifiques.
- Un changement de dataset avec plus de trajectoires qui se ressemblent montre un placement mobile opérerant de manière plus efficace pour un rayon de couverture restreint inférieur à 90 mètres.

B.4 Amélioration de la couverture

Ce travail présente l'utilisation de dispositifs IRS qui réfléchissent ensemble les signaux en plusieurs reflexions vers des régions souffrant de non visibilité directe ou NLoS jusqu'à la station de base. Tout comme le multi-saut, la multiréflexion est une technique utilisée dans les systèmes IRS qui utilisent une série de réflexions pour augmenter la couverture et atteindre plus d'utilisateurs. Dans les réseaux, le terme « multi-saut » est fréquemment utilisé dans le routage qui décrit le processus d'acheminement d'un paquet de sa source à sa destination.

Sur cette lancée, nous proposons d'explorer le multi-saut mobile. Nous présentons différentes approches qui contribuent à la meilleure sélection des bus pour lesquels activer l'IRS. Le but est de former une collaboration de réflecteurs multi-sauts pour les véhicules

et les utilisateurs dans certains angles morts, afin d'améliorer la couverture et les performances des réseaux sans fil. La présente approche est basée sur les heuristiques et permet de sélectionner la combinaison de réflecteurs actifs-passifs et passifs-passifs. Les heuristiques sont un type d'intelligence artificielle communément défini comme des règles empiriques permettant d'accélérer la prise de décision. Elles ont été étudiées dans diverses disciplines, notamment l'économie, la psychologie et l'informatique [237].

Les approches multi-sauts sont largement utilisées dans les réseaux sans fil, tels que les réseaux IoT et VANET. Elles permettent d'étendre la couverture du réseau au-delà de la portée des nœuds individuels. Elles sont souvent mises en œuvre au niveau du routage [238].

L'objectif est d'étendre le signal, sur la base d'approches multi-sauts, pour obtenir une meilleure couverture. Pour ce faire, nous supposons l'existence de zones inaccessibles aux antennes, appelées zones aveugles, dans notre région d'étude. Tout bus IRS de ces zones nécessitera un deuxième IRS pour atteindre la station de base.

Le choix d'un IRS se fait par élection. Chaque mobile choisira un IRS appelé IRS1. Si l'IRS1 se trouve dans une zone aveugle, il organise une élection pour désigner l'IRS qui va le servir, appelé IRS2.

La figure B.5 montre le processus d'élection d'un IRS pour un taxi dans une zone aveugle. Dans un premier temps, nous recherchons tous les bus susceptibles de couvrir le taxi. Un bus, s'il existe, est alors choisi selon les stratégies Q, Q', A, B ou Q', parmi les bus couvrant le taxi. Un bus est élu par zone pour chaque bus sélectionné. Le bus ayant obtenu le plus grand nombre de voix devient l'IRS pour cette zone. Ensuite, nous vérifions si l'IRS choisi se trouve dans la zone de couverture (LoS) de l'antenne ou s'il se trouve également dans une zone aveugle. Dans le premier cas, l'utilisateur a un chemin LoS avec l'antenne à travers l'IRS. Toutefois, dans le second cas, le processus se poursuit avec la recherche de bus en LoS pouvant couvrir l'IRS1. S'il y en a, comme dans le cas du taxi, un bus est choisi conformément à la stratégie, puis un bus est sélectionné parmi ceux de la zone afin de réduire le nombre de bus utilisés.

Nous avons ensuite comparé différentes stratégies d'élection de l'IRS en fonction du nombre de transferts et de la durée de la connexion. Les résultats montrent que les stratégies multi-sauts présentent l'avantage de garantir un faible nombre de déconnexions. Nous avons également étudié l'évolution des différents critères de performance en fonction du rayon de couverture et de la taille de la zone.

Enfin, nous avons étudié l'effet de l'introduction du SINR sur le choix de l'IRS. Pour la version MaxFirst, nous examinons le bus susceptible d'être le plus présent sur la base des prévisions. En cas d'égalité, le bus ayant le SINR le plus élevé est sélectionné. En ce qui concerne la version SinrFirst, le bus ayant le meilleur SINR actuel et futur est sélectionné, et, en cas d'égalité, le nombre d'occurrences du bus est utilisé pour déterminer le résultat. Les résultats présentent des performances similaires pour les deux versions.

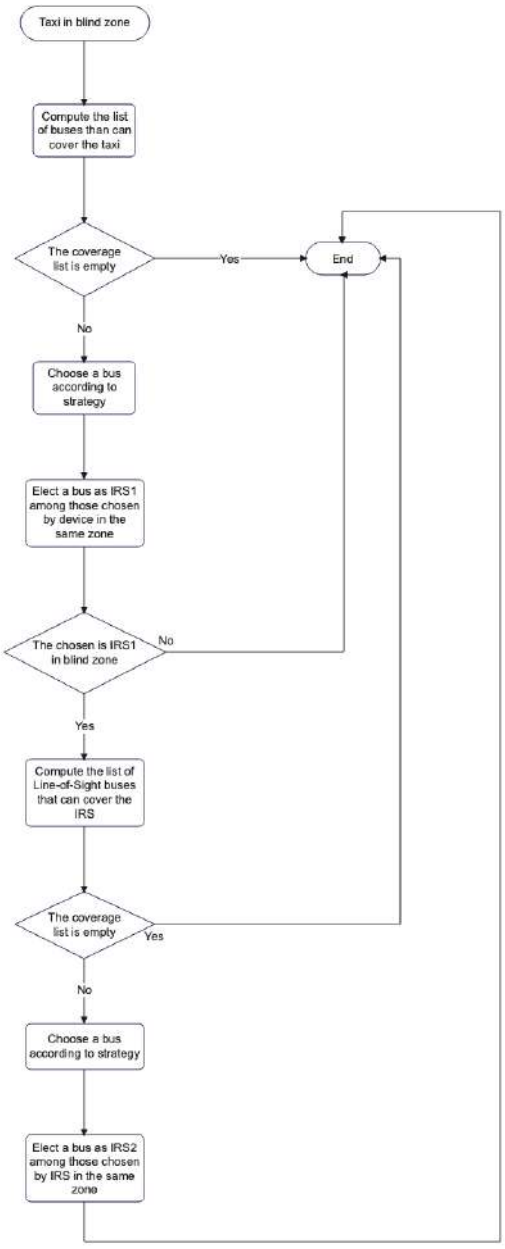


Figure **(B.5)** – *Flowchart of IRS election algorithm*

B.5 Conclusion

La qualité de service garantit que les utilisateurs, les applications, etc. reçoivent un niveau de service requis. Elle englobe un certain nombre de facteurs dans le domaine des communications, notamment la couverture, le délai, la sécurité et l'accessibilité des ressources. Cette thèse aborde certaines de ces questions en trois parties : le problème du déploiement optimal, l'augmentation de la couverture grâce à la réflexion multi-sauts et le problème de l'allocation des ressources dans un réseau IoT véhiculaire.

Dans la première partie, un mécanisme de réservation de ressources pour les appareils

LoRaWAN basés sur l'IoT dans un environnement véhiculaire est présenté. Une série de simulations a été réalisée avec différents paramètres afin d'évaluer l'évolution du nombre de rejets. Deux méthodes ont été comparées. Le mécanisme non nominatif s'est révélé le plus optimal, car il permet de différencier les services entre les abonnés et les autres, avec moins de rejets. De plus, il s'agit de la méthode la plus efficace sur le plan computationnel. Le mode nominatif est plus stable, mais offre une différenciation de service plus accentuée, avec plus de rejets en cas de congestion, que le mode non nominatif. La différenciation du trafic est utilisée pour gérer la qualité de service et privilégier les abonnés principaux en situation d'itinérance, mais elle peut également être appliquée à d'autres situations. Par exemple pour différencier la qualité de service entre les différents flux applicatifs.

La deuxième contribution examine le placement mobile IRS, par rapport à une installation fixe. Un certain nombre de paramètres a été utilisé pour évaluer l'impact sur les performances du réseau. Les résultats indiquent que si l'utilisation de la prédiction améliore clairement les performances globales, celles-ci dépendent de l'ensemble de données utilisé.

La troisième contribution propose une méthode combinant multi-saut et IRS mobile pour étendre la couverture. Pour tester notre scénario, nous avons supposé l'existence de zones aveugles dans la région étudiée. Le résultats montrent comment le multi-saut peut améliorer la couverture du réseau. Nous avons ensuite comparé différentes stratégies d'élection de l'IRS en fonction du nombre de changements et de la durée de connexion. Les résultats démontrent les avantages des techniques multi-sauts pour garantir un nombre minimal de déconnexions. Nous avons également étudié l'évolution de divers critères de performance en fonction du rayon de couverture et de la taille de la zone. Enfin, nous avons étudié l'impact de l'intégration du SINR sur la sélection de l'IRS.

Ce travail est axé sur intégration de deux technologies efficient en energie, LoRaWAN et les IRS, dans les réseaux véhiculaires. Le « Prefectching » a montré des résultats positifs en réduisant les rejets au niveau du NS et en favorisant la différenciation des services dans le contexte de l'IoV. En outre, la question du déploiement des IRS est examinée sous plusieurs angles. Le déploiement mobile proposé s'est plus performant que le déploiement stationnaire dans les situations où il y a moins d'IRS, les trajectoires sont similaires ou lorsque les distances entre l'IRS et l'utilisateur sont faibles. De plus la couverture a été améliorée par l'utilisation de plusieurs IRS en mode multi-sauts.

L'utilisation l'IA prédictive sous forme de prédiction de trajectoire a constamment montré une amélioration de la performance globale. L'IA prédictive ne se limite pas à la prédiction des trajectoires ; elle permet de la reconnaissance de modèles, d'anticiper des comportements et de prévoir des événements futurs grâce à l'analyse statistique et à l'apprentissage automatique. Elle peut donc être utilisée pour reconfigurer l'IRS. Dans ce contexte, elle devrait être capable d'anticiper les informations d'état du canal (Channel State Information (CSI)) afin d'optimiser la couverture des différents utilisateurs ou de sécuriser les transmissions.

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