Deliverable 5.1: Report on the demonstration scenarios and description of testbed implementation plan

Editors:	Evangelos Pikasis, Georgia Ntouni, Dimitrios Kritharidis, ICOM	
Deliverable nature:	Document, report (R)	
Dissemination level:	Public (PU)	
Date: planned | actual	31 July 2022	29 July 2022
Version | No. of pages	1.0	29
Keywords:	D-band radios, directional links, cross-polarization interference cancellation, reflectarray antennas, metasurfaces, deep reinforcement learning, event forecasting	

Abstract

This deliverable presents the scenarios that will be showcased in the proof-of-concept demonstrators addressing key ARIADNE targets, as well as the plans for the setup of the relevant testbeds.

The two hardware demonstrators will use the development work of WP3, while the work outcomes of WP4 will be the keystone for the software demonstrator. The described scenarios and implementation plans will be the blueprint for the system integration and the demonstration activities that will follow.

Disclaimer

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 871464. This publication reflects only the author's view and the European Commission is not responsible for any use that may be made of the information it contains.

Impressum

Full project title: Artificial Intelligence Aided D-band Network for 5G Long Term Evolution

Short project title: ARIADNE

Number and title of work-package: WP5 - Demonstration of Intelligent D-Band Network

Number and title of task: Task 5.1- Definition of demonstration scenarios and performance evaluation

Document title: Report on the demonstration scenarios and description of testbed implementation plan

Editors: Evangelos Pikasis, Georgia Ntouni, Dimitrios Kritharidis, ICOM

Work-package leader: ICOM

Copyright notice

Executive summary

The deliverable “D5.1 – Report on the demonstration scenarios and description of testbed implementation plan” presents the scenarios for the three proof-of-concept demonstrators and the plans for their implementation. These demonstrators are based on the developed hardware and software from WP3 and WP4 respectively. The following 3 demonstrators and the plans for their testing activities are reported in this deliverable:

- A Point-to-point LOS Demonstrator (HW)
- A metasurface demonstrator (HW)
- An Intelligent D-Band network demonstrator (SW)

By envisioning beyond 5G networks, ARIADNE has set three key research targets: (I) development of new radio technologies using the above 100 GHz D-Band frequency range, (II) exploitation of advanced connectivity based on metasurfaces, and (III) application of Machine Learning and Artificial Intelligence techniques to network management.

The main objective of the first (HW) demonstrator is to showcase an error-free long-range outdoor communication, which will validate the capability of the developed hardware for reliable communication at the D band, addressing key target I.

The main objective tackled by the second (HW) proof-of-concept demonstrator is to showcase that an alternative propagation route can be established in which the transmitted beam is reflected in a reconfigurable manner towards the intended receiver, thus maintaining the reliability of the communication, addressing key target II.

The third (SW) demonstrator is addressing ARIADNE key target III, showing that reliability across the whole D-band network can be maintained by adjusting parameters such as power and spectrum allocation, together with reconfiguring the metasurface structures according to current channel and traffic conditions.

List of authors

Coordinator of this deliverable is ICOM. Technical contributors are all partners participating in the work package. The technical quality is assured by the Technical Manager Prof. Angeliki Alexiou, the WP Leader ICOM and the Task Leaders ICOM (Task 5.1), IAF (Task 5.2), AALTO (Task 5.3) and NCSRD (Task 5.4).

Company	Author	Contribution
ICOM	Evangelos Pikasis, Georgia Ntouni, Dimitrios Kritharidis	Editor, Input to Section 2, Final review
Aalto	Sergei Kosulnikov	Input to Section 3
NCSRD	Aris Tsolis	Input to Section 3
NCSRD	Fotis Lazarakis, Kyriakos Manganaris, Nikos Katzouris	Input to Section 4
NCSRD	Antonis Alexandridis	Review of Section 3
OULU	Joonas Kokkoniemi	Review of Section 2
Rapidminer	Rachana Desai	Input to Section 4
Nokia	Sanguanpuak Tachporn	Input to Section 4
Nokia	Korhonen, Jari K	Input to Section 4
UPRC	Alexandros-Apostolos A. Boulogeorgos	Input to Section 4
UPM	Eduardo Carrasco, Jose Manuel Riera	Review of Section 4
IAF	Thomas Merkle	Input to Section 2, Review of Section 2
UPRC	Angeliki Alexiou	Final review
EUR	Halid Hrasnica	Final review

Table of Contents

List of figures and tables

List of figures:

List of tables:

Abbreviations

Abbreviation	Explanation
AA	Azimuth Angle
AAoA	Azimuth Angle of Arrival
AAoD	Azimuth Angle of Departure
ADC	Analog-to-Digital Converter
AI	Artificial Intelligence
AP	Access Point
BER	Bit Error Rate
BBU	Baseband Unit
BS	Base Station
B5G	Beyond 5G
CER/F	Complex Event Recognition and Forecasting
DAC	Digital-to-Analog Converter
dB	DeciBel
DSA	Delay Spread Angle
DRL	Deep Reinforcement Learning
EAoA	Elevation Angle of Azimuth
EAoD	Elevation Angle of Departure
FEC	Forward Error Correction
GUI	Graphical User Interface
KPI	Key Point Indicators
LOS	Line Of Sight
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
MU-MISO	Multiple User MISO
ML	Machine Learning
Mmimo	Massive MIMO
mmWave	millimeter-wave
NLOS	Non-Line of Sight
OMT	OrthoMode Transducer
QAM	Quadrature Amplitude Modulation
RMSE	Root Mean Square Error
RF	Radio Frequency
Rx	Receiver
SNR	Signal to Noise Ratio
TE	Transverse Electric
TM	Transverse Magnetic
Tx	Transmitter
UE	User Equipment
XPIC	Cross Polarization Interference Cancellation

1 Introduction

WP5 entitled "Demonstration of Intelligent D-Band Network" focuses on the system integration, testing, and experimentation of the hardware and software solutions developed within WP3 and WP4 respectively. The outcomes of these technology development WPs, form the basis for the demonstrators of WP5, as depicted in Figure 1.

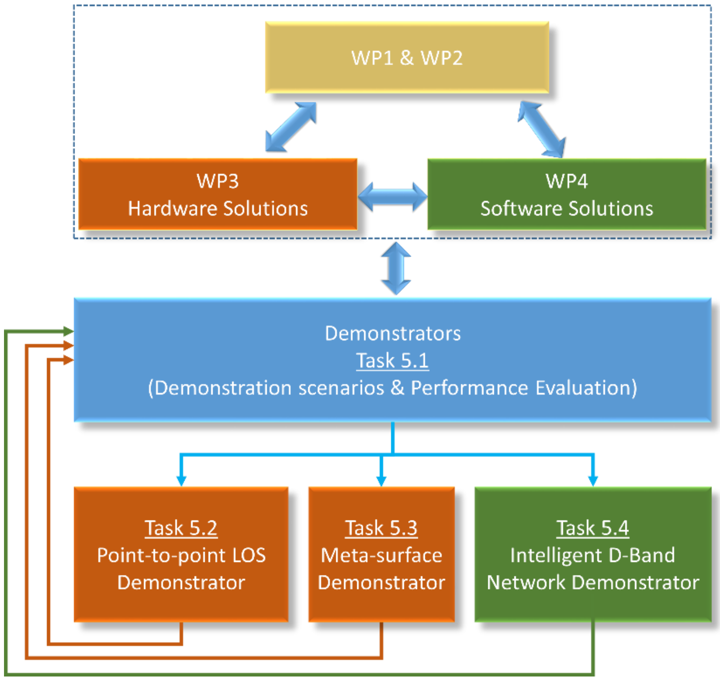

Figure 1: Interaction among the different tasks of WP5

This figure presents graphically the interaction among the different tasks of WP5, where the two hardware and one software demonstrators in tasks 5.2, 5.3, and 5.4 respectively, will be showcased.

The specific objectives of WP5 are:

- To define the demonstration and testing activities.
- To integrate the provided hardware solutions of WP3 for the final demonstration.
- To test and evaluate experimentally and by means of simulations the developed solutions and systems.
- To perform the Proof-of-Concept (PoC) demonstrations.

The basic system concept of ARIADNE revolves around three main use cases [1]. In particular, ARIADNE incorporates the following three use cases:

- **Use case 1: Outdoor backhaul/fronthaul networks of fixed topology.**
- **Use case 2: Advanced NLOS connectivity based on metasurfaces.**
- **Use case 3: Adhoc connectivity in moving network topology.**

In terms of deployment, the following main demonstrators are examined in ARIADNE:

- **Scenario 1.1: Long-range LOS rooftop point-to-point backhauling.**
- **Scenario 2.1: Indoor advanced NLOS connectivity based on metasurfaces.**

- **Scenario 3.1: Dynamic front/backhaul connectivity for mobile 5G access nodes and repeaters.**

1.1 Scope

ARIADNE aims to transform the D-band spectrum exploitation opportunity into a key enabler, leveraging novel key technologies, system concepts, and network architectures such as:

a. Radio technologies for tens of Gbit/s wireless connectivity enabled by D-band transceivers,
b. Beyond Shannon communication theory framework with ultra-high reliability in a reconfigurable environment enabled by metasurfaces,
c. Optimized network architecture based on Artificial Intelligence.

ARIADNE envisions bringing together these novel technologies and concepts into a unified framework addressing networks beyond 5G. This innovative wireless communication architecture will be demonstrated through hardware and software proof-of-concept demonstrations.

The objective of this deliverable D5.1 is to describe the scenarios for these three proof-of-concept demonstrators. The two hardware demonstrators will use the development work and outcomes of WP3, while the work outcomes of WP4 will be the basis for the software demonstrator.

1.2 Structure

The organization of this document is as follows:

- **Section 2 (1st demonstrator: A point-to-point LOS demonstrator)** briefly describes the point-to-point LOS demonstrator and presents the scenarios that will be demonstrated based on the developed hardware, specifically the baseband unit, the D-band RF front-end, and the antennas.
- **Section 3 (2nd demonstrator: A metasurface point-to-point non-LOS demonstrator)** describes the two planned scenarios for the metasurface-enabled point-to-point non-LOS demonstrator.
- **Section 4 (3rd demonstrator: An intelligent D-Band network demonstrator)** describes the three demonstration use cases that have been selected based on software tools developed within WP4, bringing intelligence into a D-Band network: (i) AI/ML application for line-of-sight aware connectivity, (ii) Deep Reinforcement Learning for 5G/B5G Wireless Communications, (iii) Complex Event Forecasting for Proactive Handover and Blockage Avoidance. Each of these demonstration cases includes two scenarios.

2 1st demonstrator: A point-to-point LOS demonstrator

In this chapter, the planned scenario for a point-to-point (PtP) Line of Sight (LOS) demonstrator will be discussed. The setup is based on the hardware that was developed within WP3. The two main blocks of this hardware are (a) the baseband unit (BBU) along with the DAC/ADC boards, and (b) the RF front-end with the antennas. The main focus of this demonstrator is to showcase an error-free link in the D-band, leveraging polarization multiplexing at the Tx to increase the spectral efficiency and mitigate depolarization effects through a developed XPIC architecture at the Rx. At the same time, the developed BBU will be capable of mitigating D-band specific impairments.

2.1 Demonstrator description

The block diagram for the outdoor LOS demonstrator is depicted in Figure 2. This setup consists of the BBU including the two modems responsible for the horizontal and vertical polarizations respectively, the DAC/ADC boards for the generation/reception of data, the RF front-ends for the up and down conversion in the D-band, and the two Cassegrain antennas for the outdoor testing. This link will be bi-directional and the mitigation of the D-band specific impairments induced by the RF front-end and the performance of the developed XPIC architecture will be experimentally investigated.

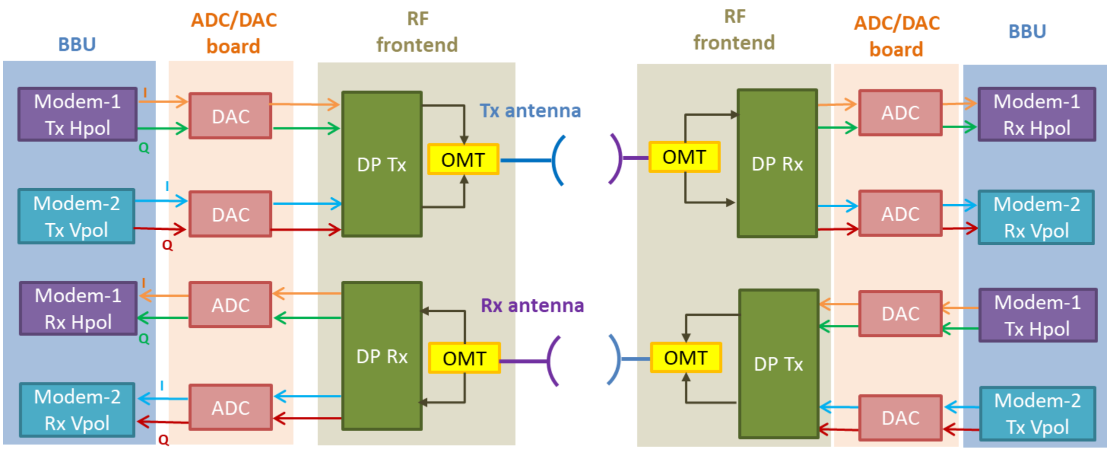

Figure 2: Block diagram of the setup of the point-to-point LOS demonstrator

2.2 Implementation details

2.2.1 FPGA-based modem and AD/DA converters

The baseband unit with the two modems (one for each polarization stream) generates the baseband signal and is one of the main building blocks for the PtP LOS demonstrator. These baseband sub-systems consist of the baseband unit (BBU) with the FPGA-based modem, the digital-to-analog (D/A) and analog-to-digital (A/D) converters board as depicted in the simplified block diagram of *Figure **3***.

A specific FPGA board has been utilized to support the demanding digital signal processing (DSP) algorithms. ICOM has evolved its DSP methods (related to impairment cancellation as phase noise, carrier frequency offset, non-linearities) to combat the expected D-Band specific impairments induced by the RF Front end. Moreover, this baseband system offers increased spectral efficiency through the use of the polarization multiplexing technique. Towards this end and based on the existing know-how, the receiver part of the baseband module was designed so that it would be capable of mitigating the depolarization effects in D-Band through the developed XPIC architecture [1].

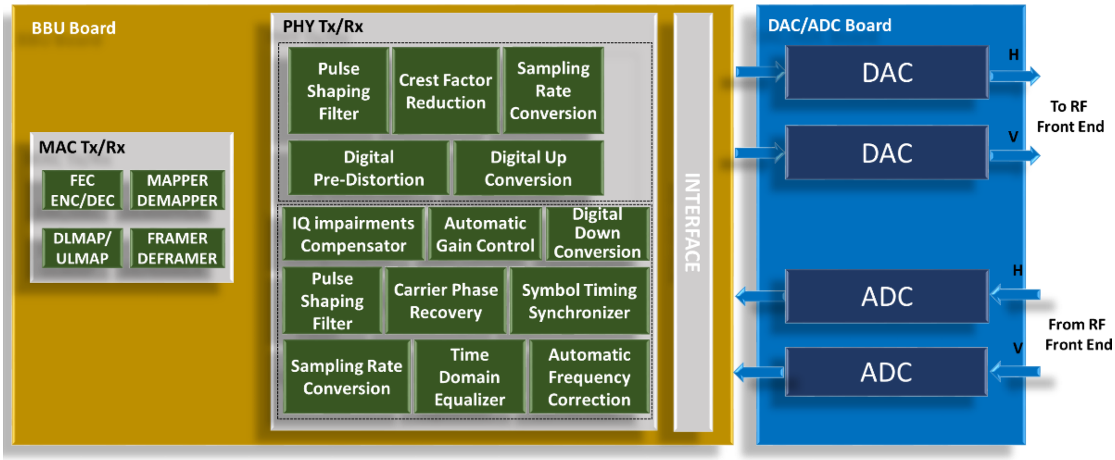

Figure 3: The basic baseband components (BBU & DAC/ADC modules)

ICOM designed and implemented the board with the required DA/AD converters to generate/acquire the in-phase and quadrature (I-Q) data streams, satisfying the requirements of the polarization multiplexing technique for the PtP LOS demonstrator. This board hosts two DAC and two ADC modules supporting the two transmit (Tx) and the two receive (Rx) parts of the modems.

The implemented baseband unit and DA/AD converters board can be seen in Figure 4. As can be observed from the DA/AD board there are eight SubMiniature version A (SMA) type connectors corresponding to the in-phase and quadrature (I/Q) paths of each DAC (or ADC), which are fed separately to (or by) the specific D-Band frontend.

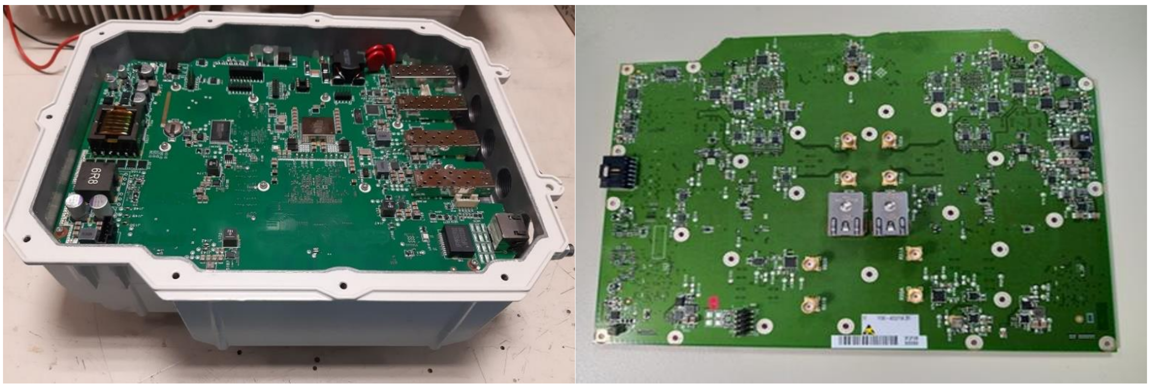

Figure 4: The implemented baseband unit inside its housing and DA/AD converters board

The Table 1 summarizes the main parameters of the baseband and signal converter units.

Table 1: The main parameters of the baseband and DA/AD converter units

Parameter	Value
Bandwidth	up to 2GHz
Single Carrier Modulation	up to 256QAM
Bit Rate	up to 30 Gbps
DAC resolution	12-bit

ADC resolution	12-bit
Sampling rate	2.5 Gsps
Input/Output Z_0	50 ohm

The bandwidth of the generated single carrier streams will be up to 2 GHz for each polarization, with QAM constellation size up to 256, achieving a total bit rate of up to 30 Gbps. The resolution of the DAC and ADC are 12-bit. These QAM data streams will modulate the D-band carrier frequency through the RF front-end and the two cross-polarized signals are combined before the antenna through the orthogonal mode transducer (OMT).

2.2.2 D-band RF Front end

The RF outdoor unit includes the RF front-end supporting two polarizations for the up-link and down-link each, with an integrated polarization multiplexer, two Cassegrain antennas with circular waveguide feed horn, a DC power supply unit (7V), a switched dual-PLL local oscillator for generating the up-link and down-link carrier frequencies, and an RF controller unit with a TCP/IP interface and a serial interface (Figure 5).

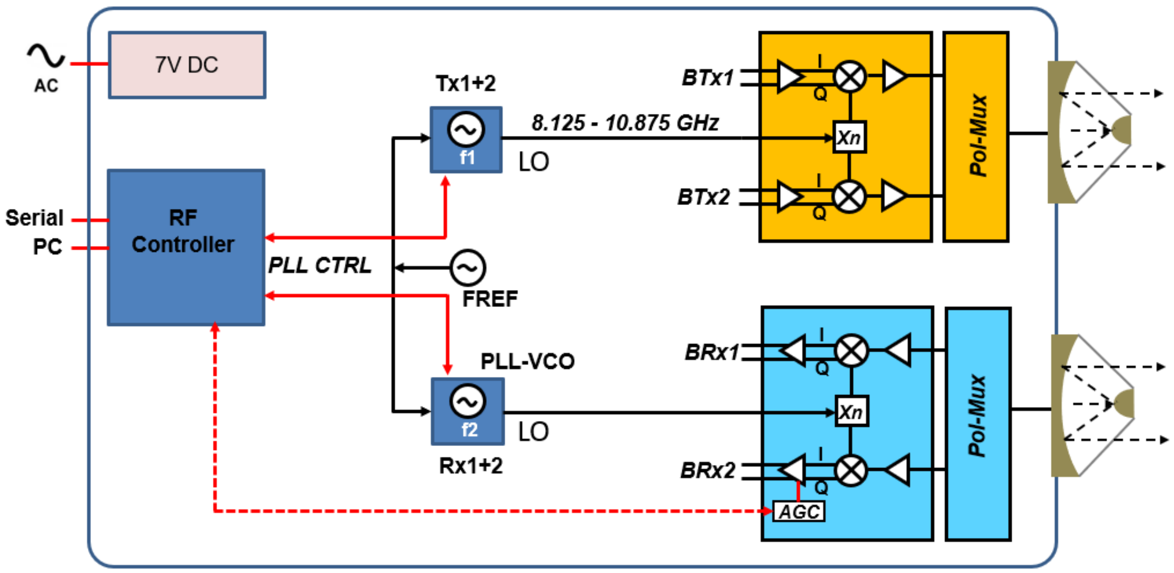

Figure 5: Block diagram of the RF outdoor unit for the D-band LoS demonstrator

Some of the main parameters for the RF Front end demonstrator are summarized in **Table 2**.

Table 2: Main parameters of the RF front end package (referred to circular waveguide flange)

Parameter	Value
3-dB bandwidth (baseband)	>4 GHz
Carrier frequency (programmable)	142 - 172 GHz
Power level per polarization (P-1dB)	>10 dBm
Receiver noise figure per polarization (SSB)	<7 dB

SSB Phase noise values for 160 GHz carrier frequency @ (1KHz, 10KHz, 1MHz offset)	(-71, -76, -96) dB

2.3 Testbed implementation plans

Figure 6 shows the two integrated systems consisting of the baseband units with the DAC/ADC boards inside the environmentally-hardened housing. The systems have successfully completed both electrical and functional verification in ICOM's labs, while measurements in loopback mode have been reported in D3.3. These systems with the RF front end will be mounted on a pole, as depicted in the graphical illustrations of Figure 7**Error! Reference source not found.**. This figure, shows also the eight SMA connectors for interfacing with the RF front-end (blue line) and the connectors for the Data/Power Supply interfaces (yellow line). The same pole will host the RF front-end and the Cassegrain antennas from IAF with an estimated gain of 52 dBi, for the final demonstrator setup.

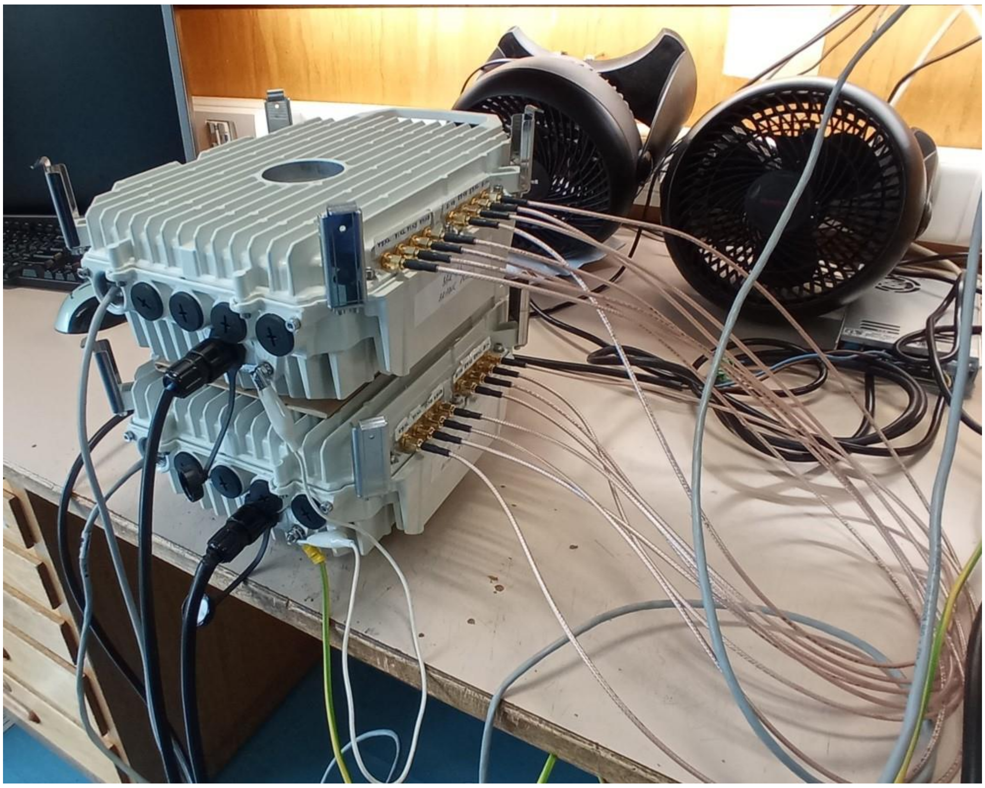

Figure 6: The two integrated systems including the BBUs with DAC/ADC boards inside the cooling housing

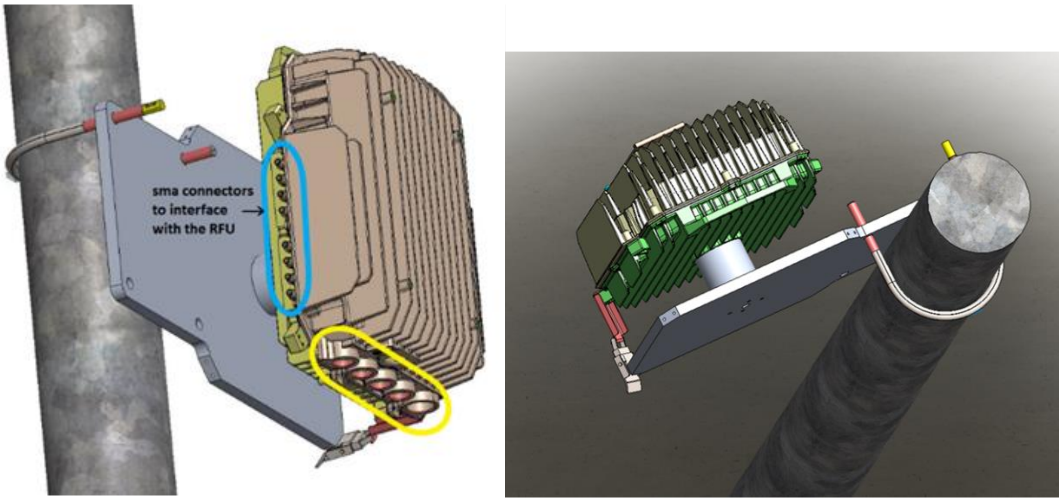

Figure 7: ICOM's integrated systems' mounting plan

2.4 Demonstration scenarios

The initial plan is that a link will be set up between the rooftops of two buildings at Intracom Telecom premises, as depicted in Figure 8. The link distance based on our current plans is about 185 m. However, it will be precisely defined after the final testing of the RF front-end at IAF, because the achieved RF transmitted power and the noise level of the Rx part are critical parameters to be considered.

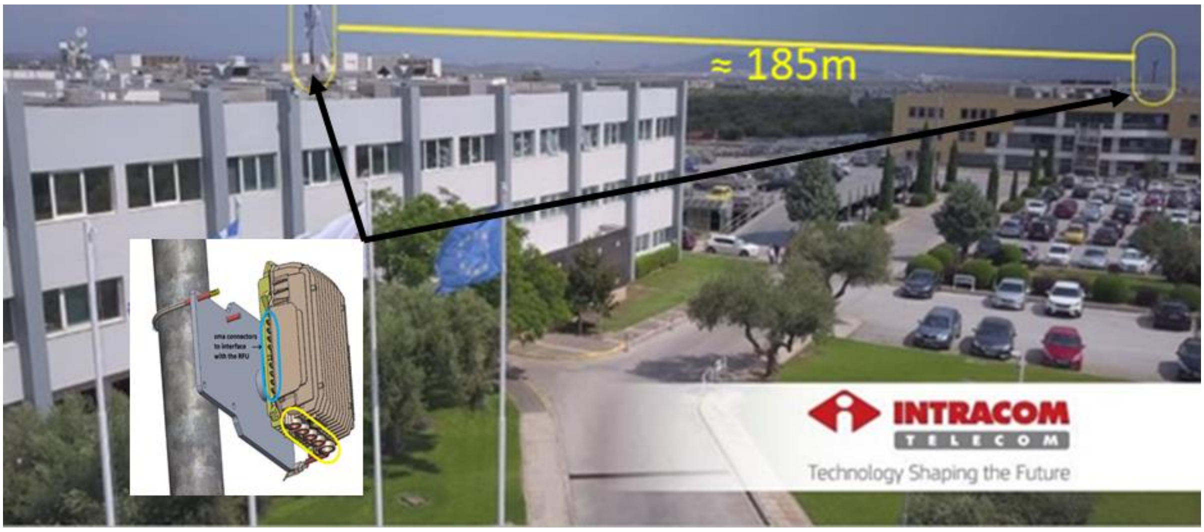

Figure 8: The planned outdoor LOS link between the two rooftops of ICOM buildings

Figure 9 shows the input and output parameters for the BBU and the RF front-end that will be used as the basis for the different demonstration scenarios. The tunable parameters for the BBU are the channel bandwidth (BW) which can be scaled up to 2 GHz and the constellation size of the single carrier QAM modulation with values up to 256 QAM.

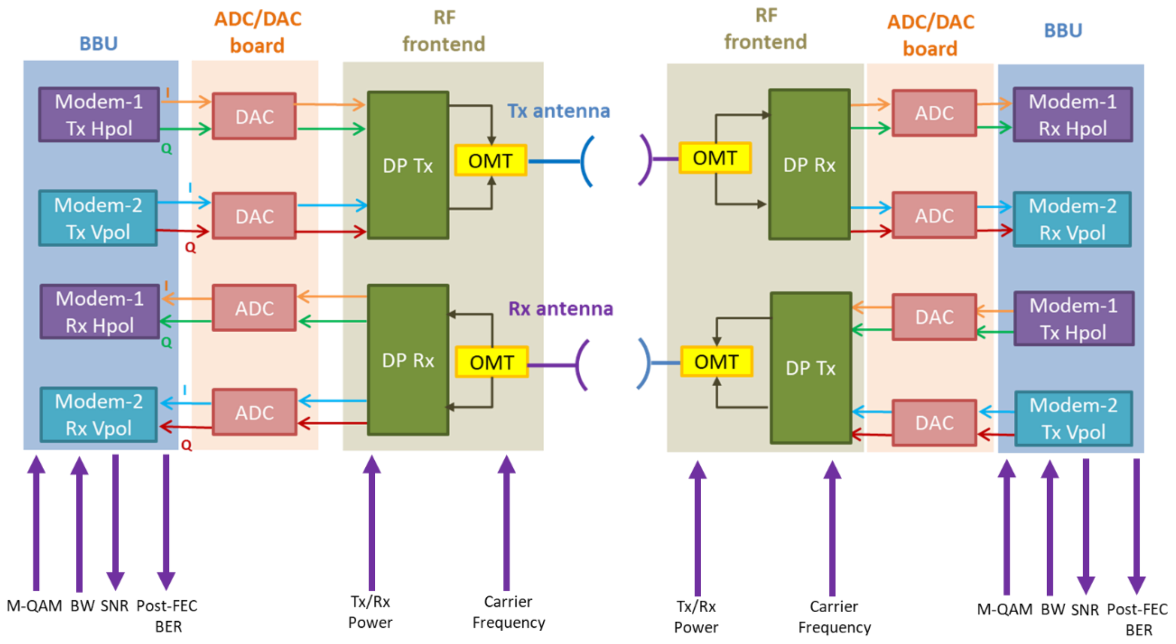

Figure 9: Input and output parameters for the BBU and the RF front-end

On the Rx side of the Modems, the values of the Signal to Noise Ratio (SNR) and the post-Forward Error Correction (FEC) Bit Error Rate (BER) can be measured. Regarding the RF front-end, the carrier frequency and the received signal power at the baseband can be tuned. The Tx power must be adjusted at the baseband (coarse) but there will be also an RF variable gain stage that may be used for fine tuning the RF power via the RF controller.

For different values of the channel BW and QAM constellation size at the BBU, while tuning in parallel the RF-carrier frequency at the RF front-end to a set of different values, measurements of SNR and post-FEC BER vs frequency can be obtained as depicted in Figure 10**.**

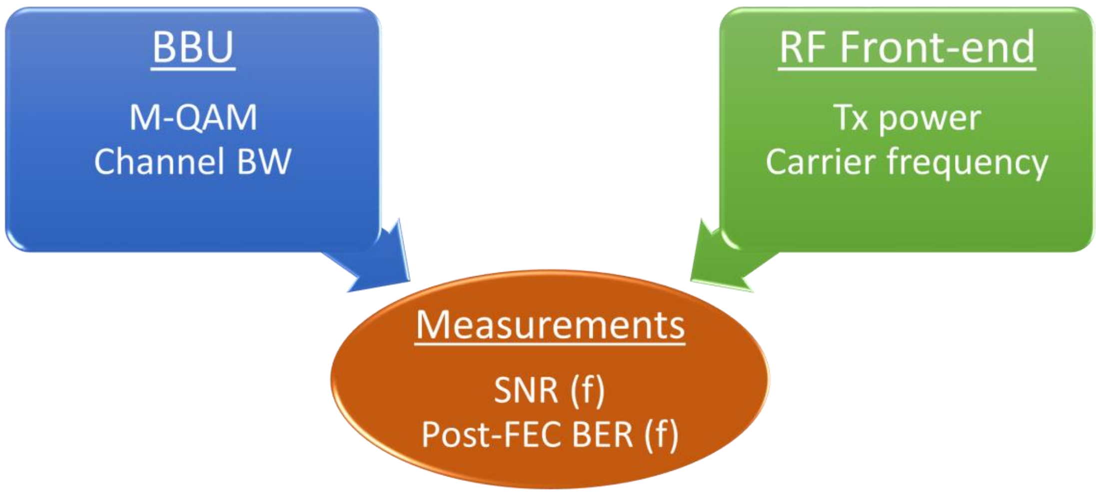

Figure 10: Measurements of SNR and post-FEC BER vs frequency

3 2nd demonstrator: A metasurface point-to-point non-LOS demonstrator

In this chapter, we describe two planned scenarios for a metasurface-enabled point-to-point non-LOS demonstrator. It utilizes tools that are being developed within WP3, namely metasurfaces for anomalous reflection and directive lens antennas. The focus of the demonstrator is to show a stable additional wireless channel between two sources via anomalous reflection from a specifically designed environment – a metasurface mounted on a wall.

3.1 Demonstrator description & testbed implementation plans

A non-LOS channel should be established with two sources, separated by an obstacle, via an anomalously reflecting metasurface. The main blocks of the demonstrator are presented in Figure 11. Directive lens antennas emit waves of horizontal polarization. This corresponds to TE polarization with respect to the metasurface plane. An anomalous reflection channel will be established between two sources, oriented normally and at the angle of 50 degrees with the respect to the metasurface, see Figure 11.

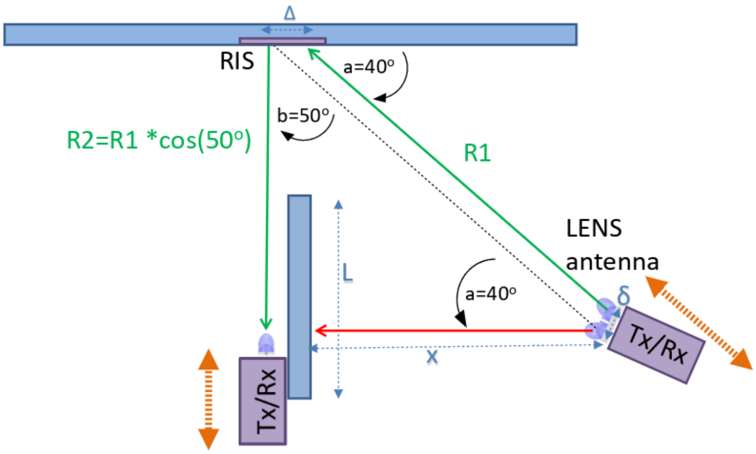

Figure 11: Topology of the indoor non-LOS demonstrator.

Demonstration is planned with the estimated distance $R_1 \approx 3 \; up \; to \; 6$ m (and the corresponding R_2 , as defined at Figure 11) to be applicable for a common room sizes. Metasurfaces were designed for particularly defined frequencies 144.75, 157.75, 170.90 GHz (D-band Ch2, Ch3 and Ch4) with a possible slight shift of the central frequency (up to 5%) if the final manufactured metasurface design will require it. Note here, that only one design (144.75 GHz) is fully implemented at the moment of this deliverable compilation, but still has not been manufactured. Two other designs are under implementation and will be realized in the near future. All three metasurfaces will be fixed at a single panel without any specific requirements for their mutual positions, forming a “metasurface collage”. This planned layout is presented in Figure 12.

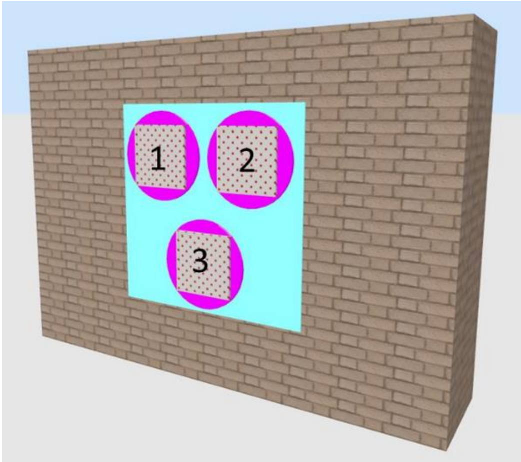

Figure 12: Collage of three metasurfaces mounted on a wall.

We have derived analytical expressions for a qualitative estimation of the link budget. The ratio between the transmitted and received powers can be found as

$$|S_{21}|^2 = \frac{P_r}{Pt} = G_t G_r \left(\frac{S_{\mathrm{MS}}}{4\pi R_1 R_2}\right)^2 |\cos\theta_i| \eta_{\mathrm{eff}} \qquad (3.1).$$

The main parameters that define the metasurface-enabled channel are the gains G_t and G_r of the transmitter and receiver antennas, positions of the transmitter and receiver (R_1, R_2 and $\cos\theta_i$), the metasurface area (S_{MS}) and the power reflection efficiency (η_{eff}) of the metasurface. The estimated pathloss of the metasurface channel is presented at Figure 13 for the distances $R_1 = R_2 = 5$ m , ϑ_i = 50 degrees and the metasurface side size $a = 70.71$ mm.

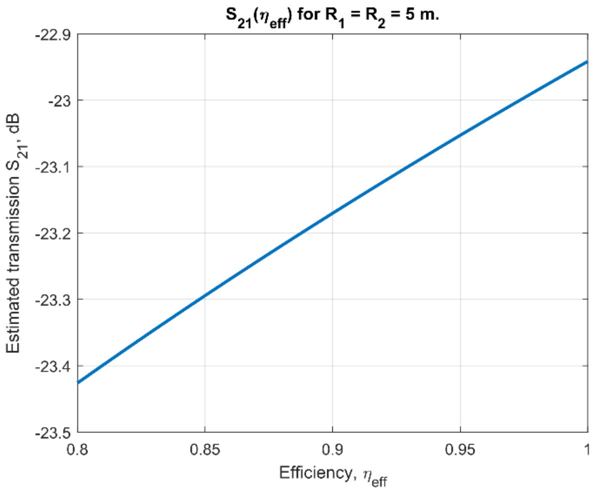

Figure 13: Demonstrator path loss in accordance with the link budget model for various efficiencies of the metasurface.

3.2 Demonstration scenarios

We plan to realize two main scenarios: with single (test case-1) and double (test case-2) lens antennas of the Rx/Tx block. Thus, one can implement both mechanical and electronic switch between the direct and non-LOS modes. At the first step of both scenarios the Rx/Tx antennas are installed at the desired initial points, as shown in Figure 14(top) for both a) and b) panels. In accordance with the first scenario, the direct, free-space channel is to be measured as a reference case. After this measurement, the obstacle will be installed to block the direct channel, as shown in Figure 14a (top). Then both antennas will be reoriented (mechanical) towards the metasurfaces, and the non-LOS channel signal will be measured (Figure 14a, bottom).

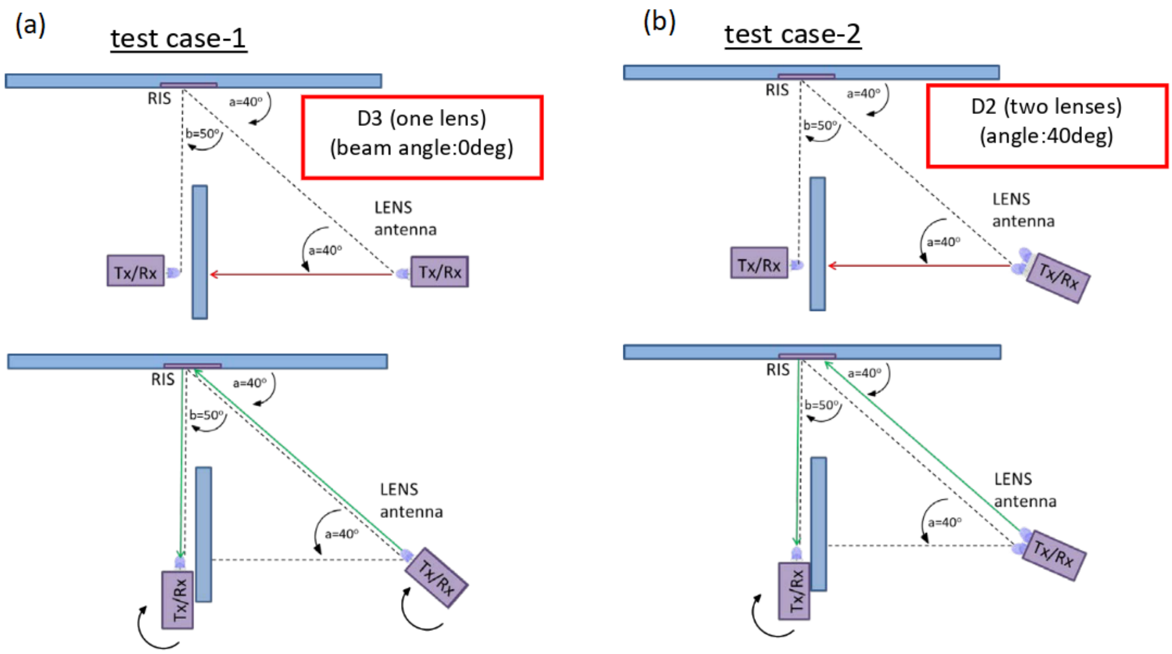

Figure 14: Demonstration scenarios.

In test case 2, first we will realize a direct channel, removing the obstacle (Figure 14b, top). Then, using an electronic RF-switch the normally oriented antenna will be reoriented towards the wall with the metasurface, the source activates the beam towards the metasurfaces and the non-LOS channel signal will be measured.

In summary, we have developed complete plans for the indoor demonstrator, where the metasurface will direct the reflected waves towards a non-LOS Rx position at three different frequency channels of D band. The metasurface performance has been estimated and surface topology has been designed (fully tested for one of the target frequencies). Using the developed theory of far-field scattering from anomalous reflectors, the proper metasurface size has been selected in order to ensure the required field strength at the receiver position. It was decided what antennas will be used at the Tx and Rx sites, and two alternative measurement scenarios planned in detail. It is expected that the metasurface will dramatically enhance the signal behind a large solid wall due to its focusing gain capabilities.

4 3rd demonstrator: An intelligent D-Band network demonstrator

5G and B5G networks are expected to support a variety of applications with diverse requirements, including higher peak and user data rates, very low latency, and enhanced system capacity. To achieve this goal, a series of emerging wireless technologies have been proposed and especially their exploitation in millimeter-wave (mmWave) and sub-THz communications. Towards B5G networks, ARIADNE objectives have been organized through three main pillars, i.e., (i) development of new radio technologies using the above 100 GHz D-Band frequency range, (ii) exploitation of advanced connectivity based on metasurfaces and (iii) application of Machine Learning and Artificial Intelligence techniques to network management. Accordingly, three use cases were defined to depict ARIADNE system concept: (i) Use case 1: Outdoor backhaul/fronthaul networks of fixed topology, (ii) Use case 2: Advanced NLOS connectivity based on metasurfaces, (iii) Use case 3: Ad hoc connectivity in moving network topology. As analysed in [1], optimum resource management, establishment of LOS connectivity and/or blockage avoidance are major topics of interest where ARIADNE develops innovative solutions incorporating Artificial Intelligence/Machine Learning techniques.

Based on the above, three demonstration use cases have been selected based on software tools developed within technical WPs bringing intelligence in a D-Band network: (i) AI/ML application for line-of-sight aware connectivity, (ii) Deep Reinforcement Learning for 5G/B5G Wireless Communications, (iii) Complex Event Forecasting for Proactive Handover and Blockage Avoidance. Each demonstration case includes two scenarios as described below.

4.1 AI/ML application for line-of-sight aware connectivity

B5G systems are expected to integrate AI/ML algorithms/techniques in various layers of the network management stack. In order to create customized AI/ML solutions, we present this approach in the context of LoS-aware backhaul and fronthaul connectivity scenarios that are part of the ARIADNE use cases. The approach employs Metaheuristics and Machine Learning algorithms –initially in a joint constellation and later in a parallel manner to establish reliable connectivity. Considering important challenges inherent in dynamic planning problems, we devised an approach to deliver hybrid solutions (an optimization outcome and a predictive outcome). We further distinguish two aspects of using the presented approach: i) Design Time: this is when a solution is engineered to understand the dimensions of the problem and estimate the quality of the solution using experimental frame/GUI developed using React (Java script) and RapidMiner Studio for interactive exploration of predictive models, and ii) Deployment/Online optimization Time: this deals with making the solutions operational for productive use, by producing real time solutions tailored to the different deployed scenarios. The latter contributes mainly as an extension of the current work by demonstrating GUI Framework. However, herein we also provide references to the software platforms that may be used for making these solutions operational in real time.

4.1.1 Demonstration scenario 1.1: ML model for environment-specific channel modeling:

5G communication networks have numerous new requirements and face new challenges for channel modelling in the context of massive multiple-input multi-output (mMIMO). In the following, we present an initial analysis of the challenges and opportunities for Machine Learning in the channel modelling domain for both LoS and NLoS scenarios followed by predictive exploration with environmental and geometrical conditions of channel modelling links. The objective here is to understand the feasibility of predicting various properties of the wave at the physical layer and to analyze the statistical relation between condensed parameters of multi-dimensional mobile channels and geometrical link condition((using the data supplied by Ariadne project partner-Aalto University)

Starting with the preliminary stage, data was collected for various routes where the UE moves. The transmitter (Tx) and receiver (Rx) information from the different locations (between the start and end location of the route of the moving UE) were interpolated and fed into the machine learning model, along with the channel attributes of Multipaths, including complex amplitude, delay, departure angle azimuth (AAoD) and elevation (EAoD), arrival angle azimuth (AAoA) and elevation (EAoA), Delay spread angle (DSA), Azimuth angle (AA). After pre-processing the data, the statistical characteristics of the channel (including expectations and the extension of these parameters) were obtained to train ML algorithms. Since the currently available datasets have a limited feature set and observed error margins using statistical distribution methods such as root mean square error(RMSEs) were not optimal, our approach relies on investigating the existence of pattern within the available features as well as bringing geographic location as a first step to include environmental features to examine the density according to the user mobility.

Initial analysis reveals a certain degree of correlations among attributes when location information is included, but the predictive modelling aspects require further engineering of features for developing and deploying various KPI's focusing on accuracy, fading statistics, correlations, complexity, and versatility which can find the hidden non-linear relationships among different features and can indeed improve the feasibility and viability of the model.

In general, we aim to deliver more dynamic settings that change over user mobility and can be incorporated in the form of real-time simulations. In particular, real-world scenarios have users moving towards certain directions resulting in loss of connectivity approaching an object or wall. So the data generated will be used by AI-based techniques to access the efficacy of LOS connectivity. Gradually this process will trigger a pro-active handover process in order to identify the patterns depending on user mobility on different routes under outdoor/indoor environments. Furthermore, by providing the predictive GUI framework as shown in Figure 15, it will allow us to map out many options such as risks, objectives, profits and finally evaluate which course of action has the best chance of success while avoiding unnecessary risks or unpleasant outcomes.

The basic proposed pipeline for steps and decisions involved in the simulation will include but is not limited to: pre-processing, running of a simulation, and post-processing. Pre-processing will involve model settings and input data to prepare data for further training so that the data can be used easily and effectively. This step often ends when a simulation is ready to launch. The simulation phase will allow interactive visualization to be performed at each time step. Here, based on user mobility on certain routes under a specific environment, it will show whether the route on which the user is moving will have LOS connectivity or NLOS connectivity. Moreover, the simulations will also help to tailor down how the model performs with respect to reality. The last step of post-processing will extract the results and put them in usable form. It will lead into further investigation or tuning of parameters to achieve reliable results and further converting predictive modeling into prescriptive modeling. However, the main objective of this experimental GUI design-based concept as depicted in Figure 15, for simulation is to target various outcomes for, e.g., most likely predictions, confidence distribution, influencing features set along with accuracy and interpretations of results which will eventually help users to get a better understanding of how the model draws conclusions for LOS connectivity on different routes.

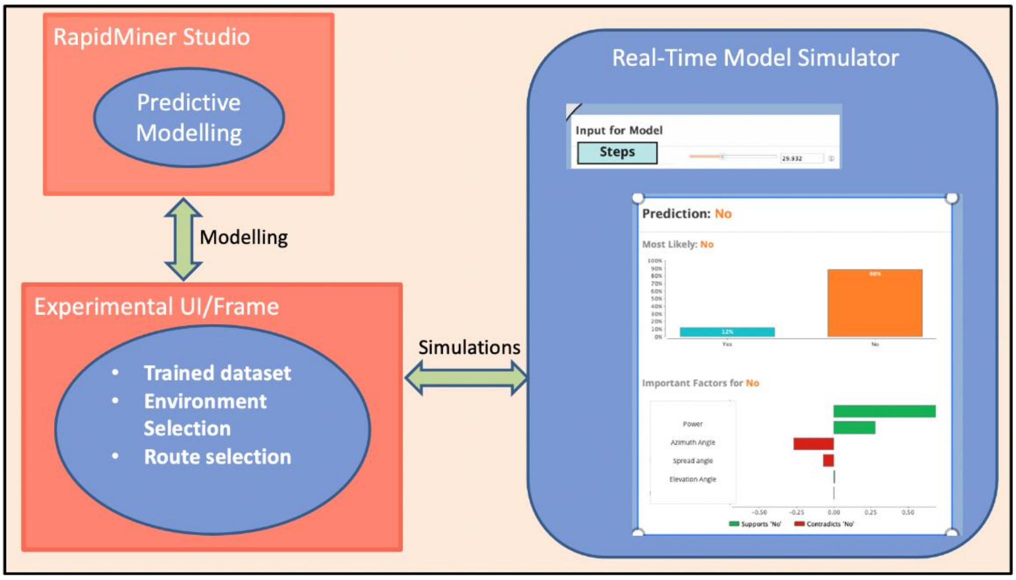

Figure 15: **Predictive exploration GUI/framework design**

4.1.2 Demonstration scenario 1.2: UE-AP optimal resource allocation in dense networks

Another promising but under-explored approach for a deployable solution to a changing problem lies in online optimizations. The basic concept is that, given a recurring optimization problem such as the joint UE-to-AP association and resource allocation problem, the problem instance is fed to a solver which solves it in a continuous fashion, while taking into consideration any trigger events that may change the problem instance being solved. This approach offers several benefits. Firstly, the best solution can be fetched within a desired time period after a change event is triggered, e.g., after new UEs appear in the network or locations of UE(s) change due to user mobility. Secondly, the network assignments can be consolidated for optimal resource usage at frequent intervals, in what can be referred to as 'resource consolidation'. Thirdly, a set of best solutions retrieved from the solver at regular intervals or after a change event is triggered, can be labeled as described in [2] to generate training datasets for ML. These situation-rich training datasets can be used in parallel to update the ML model from time to time, where the ML model aims to predict the assignment and resource allocation as a secondary solution. Hence, online optimizations can provide just-in-time solutions as well as frequent snapshots of the network, which are leveraged for (re)training of the ML predictive models in a hybrid scheme, until the ML model achieves the desired predictive quality and stability - at which point, online predictions can replace online optimizations.

The vision behind the proposed framework is to:

1. Identify a reusable, common, and configurable approach that can deliver highly customized AI/ML models to solve a specific problem scenario,

2. Enable the operator to evaluate and compare optimization and prediction-based outcomes,

3. Study the transformation of different constraint-based optimization problems into a Machine Learning-based predictive paradigm,

4. Solve the problems under dynamic settings, i.e., the framework should possess the technical foundations that enable continuous updates of the ML models by discovering more and more solutions given different data instances of the problem being studied. For this, the proposed approach is to use

the optimization phase to get multiple best solutions, each of which provides the ground truth needed to generate a training dataset. This allows to retrain or update the model till an acceptable performance level is reached.

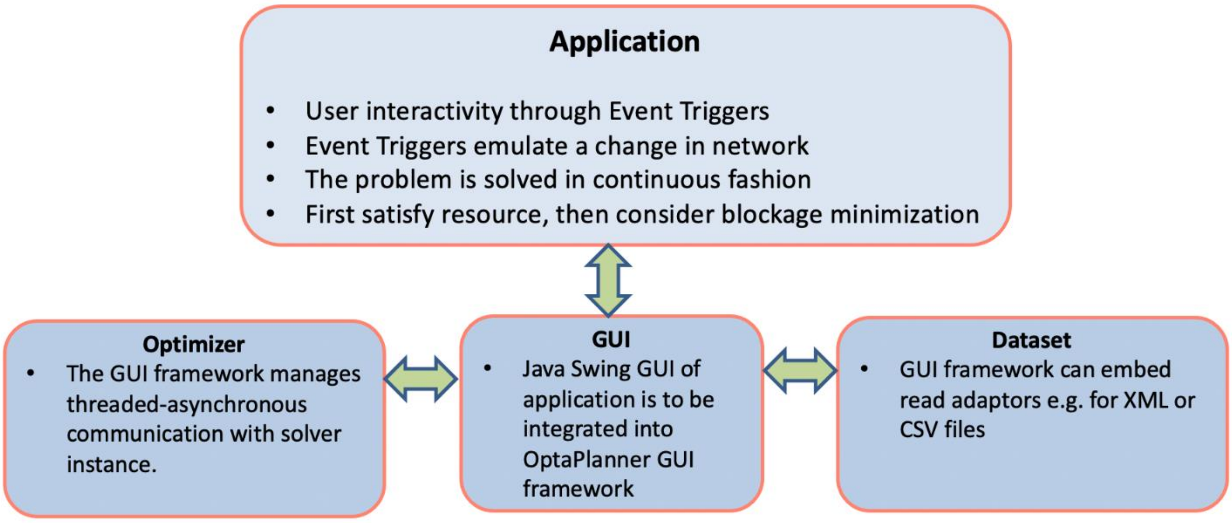

Figure 16: **Application design: OptaPlanner GUI/Solving framework**

Figure 16 shows the overall design of the application to be developed including its pillar and interactions. Green arrows are interactions, while the blue boxes at the bottom are pillars of the application. Application is mainly focused on event triggers and 2-step plan to implement the constraints for solving. First, focusing on resource satisfaction and in next steps, it will focus on bringing blockage minimization which needs more implementation work.

4.2 Deep Reinforcement Learning for 5G/B5G Wireless Communications

Multiple network entities are involved in 5G and B5G systems, e.g., BSs of different types and UEs with different QoS requirements. It is challenging to achieve optimized resource and service management in the presence of the wide variety of service requirements as well as uncertainty in mobile 5G and B5G network environments, such as fast time-varying wireless channels.

In such time-varying and unpredictable network environments, deep reinforcement learning (DRL) is a powerful tool to tackle real-time dynamic decision-making problems. The DRL naturally incorporates long-term system evolution when making decisions, which is very essential for time-variant 5G/B5G. The DRL can update decision policies to reach optimal system performance through the reward feedback of the previous decisions and therefore, provides an excellent option for solving resource management/resource allocation problems in mobile networks.

4.2.1 Demonstration scenario 2.1: Beamforming Optimization with MU-MISO scheduler for Mobility Users based Deep Reinforcement Learning

In this scenario, we focus on using DRL to solve beamforming optimization with carrier aggregation (resource management) problem. We consider a downlink scenario where a multi-antenna base station (BS) is transmitting signal to multiple moving UEs.

Two examples will be demonstrated: (i) The BS serves multiple UEs and (ii) When there is a blockage between the BS to UEs, we deploy RIS to redirect the signal from the BS to UEs. In both cases, the BS serves UEs and the BS connects to RIS using mmWave channel. We also use Ray-tracing based Nokia internal ray-tracing tools to provide realistic channel realizations between BS-UEs link connections as well as BS-RIS-UEs link connections.

In the 1st example, we activate DRL based multi-user multi-input-single-output (MU-MISO) scheduler on the fly to find the best beam to allocate to multiple moving UEs at the same time. In the 2nd example, we activate DRL based MU-MISO scheduler on the fly to find the best beam at BS and best analog phase shifter angles at RIS to serves multiple moving UEs at the same time. Figure 17 shows DRL model implementation with a wireless environment according to our scenario.

Note that "Reward" and "State" in Figure 17 can be defined based on different system objectives in 5G/B5G, i.e., throughput maximization or outage probability minimization or minimization of power consumption at the BS. The DRL will store and sample historical rewards, actions, and state transitions into mini-batches. Then, DRL uses the stored historical data to train the deep network weight factors. Therefore, the training process can be accelerated with the assistance of system and environment knowledge.

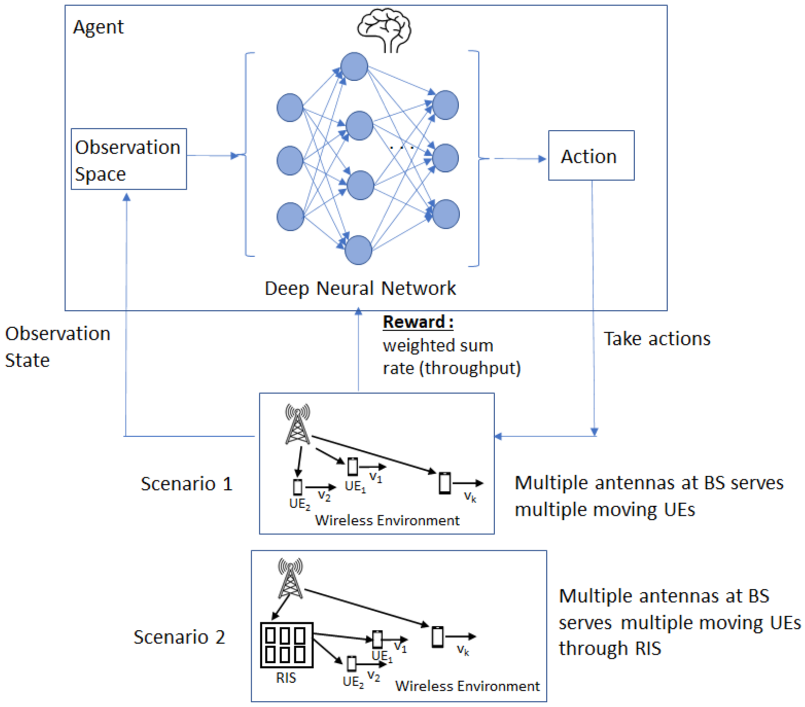

Figure 17: **DRL model implementation with wireless environment according to our scenarios**

4.2.2 Demonstration scenario 2.2: Deep learning empowered blockage avoidance for RIS-assisted communications

Reconfigurable intelligent surface (RIS) has been speculated as one of the key enabling technologies for the next generation wireless communication systems. The RIS scaled up beyond Massive-MIMO (mMIMO) to achieve a smart radio environment since they can be made of low-cost passive elements that do not require any active power sources for transmission.

Wireless D-band systems have a significantly high penetration loss that results in almost fully signal loss. This phenomenon is called blockage. In a time-varying and unpredictable wireless network environment, the impact of blockage is considered detrimental. Motivated by this, UPRC & NOKIA designed a deep reinforcement learning (DRL) based framework for proactive blockage avoidance and real-time dynamic resource allocation for wireless D-band networks.

Specifically, we focus on using DRL to solve beamforming optimization with carrier aggregation (resource management) problem where we consider a downlink scenario where a multi-antenna base station (BS) is transmitting signal to multiple moving UEs. Two examples will be demonstrated: (i) The BS serves multiple UEs and (ii) When there is blockage between the BS to UEs, we deploy RIS to redirect signal from the BS to UEs. In both cases, the BS serve UEs and the BS connect to RIS using 3.5GHz, mmWave channel, sub-THz (90 GHz) and D-band for performance comparison. We also use Ray-tracing based Nokia internal ray-tracing tools to provide realistic channel realizations between BS-UEs link connections as well as BS-RIS-UEs link connections.

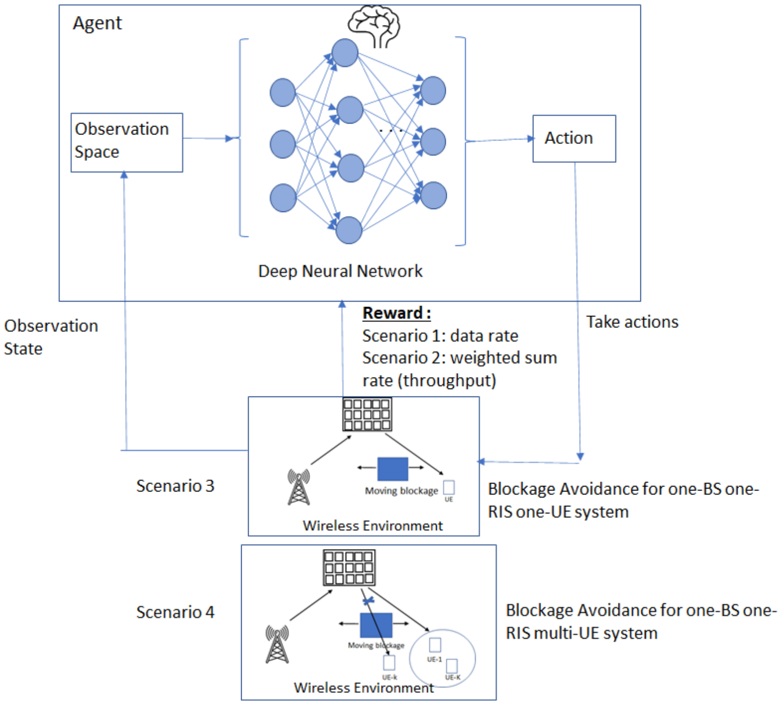

Figure 18: DRL model implementation for (i) Blockage avoidance for one-BS one-RIS one UE system and for (ii) Blockage avoidance for one-BS one-RIS and multi-UE system

In the 1st example (denoted as Scenario 3 in Figure 18), we activate DRL-based single-user multi-input-single-output (SU-MISO) with RIS on the fly to maximize the capacity of end-to-end connection while avoiding blockage. In the 2nd example (denoted as Scenario 4 in Figure 18) we activate DRL based multi-user MISO (MU-MISO) scheduler with RIS on the fly to maximize weighted sum rate of end-to-end connections while avoiding blockage. Figure 18 shows DRL model implementation with proactive blockage avoidance and real-time dynamic resource allocation.

4.3 Complex Event Forecasting for Proactive Handover and Blockage Avoidance

Complex Event Recognition and Forecasting (CER/F) techniques aim to detect, or even forecast ahead of time, the occurrence of some special events of interest. Such target events are called complex events since they are defined as spatio-temporal combinations of lower-level, time stamped pieces of information in the input data, which, in turn, are called simple events. A set of complex event patterns explicitly defines such spatio-temporal simple event combinations in some event specification language/formalism and the purpose of a CER/F system is to efficiently detect, or forecast, matchings of such patterns in the incoming data.

In ARIADNE we treat the blockage avoidance problem as a complex event forecasting one, where the goal is to timely detect imminent blockage incidents from early signs (e.g. signal strength deterioration) and trigger an AP/UE reallocation process (i.e., handover negotiation) in a proactive fashion. The realization of this approach involves two discrete steps: The first step is concerned with learning patterns of blockage from a set of labeled data, in the form of sequences, each of which contains the evolution of some domain-specific features in time and carries a blockage/non-blockage label. The second step is the actual forecasting task. We use a dedicated event forecasting engine for that, called Wayeb, developed by the NCSR team. Wayeb receives a complex event pattern in the form of a symbolic automata (deterministic finite state machine) and based on that, it learns a probabilistic model, typically a Markov chain, that encodes dependencies among the events in an input stream, in terms of statistical correlations between event occurrences. By means of this probabilistic model, Wayeb is able to output forecasts on the occurrence of a target complex event (e.g. a blockage incident) in the future, along with its likelihood and an estimate of the “horizon” when the event is expected to occur. Since Wayeb relies on an automata-based event specification language the ML techniques employed in ARIADNE to learn the complex event patterns also aim at learning automata structures from multivariate time series input.

4.3.1 Demonstration Scenario 3.1: Decentralized Proactive Handover Negotiation

The purpose of this scenario is to showcase the capabilities of our event forecasting-based approach to blockage avoidance, while paving the way for a lightweight, decentralized approach for dynamic, proactive handover negotiation. The demonstrator is based on simulation data from a monitored region, as shown in the figure below:

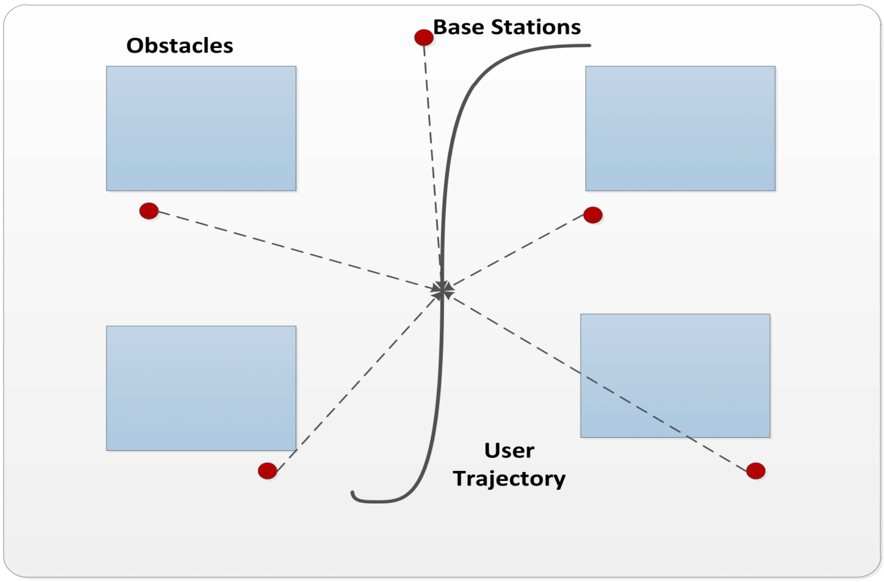

Figure 19: **Example of simulated area for the data production for CER/F**

The simulated region features a set of obstacles, a moving user and a number of base stations (access points - APs) that transmit signal to the user’s device (user equipment - UE), where it is assumed that the obstacles impose a line of sight blockage between APs and UEs in certain areas of the region.

As the user moves around the region, the user's device monitors the evolution of the strength of the signal received from each AP in the region at each point in time, in addition to other potentially informative domain features, such as the user's coordinates, direction, and speed. It is assumed that the user's device runs our event forecasting tool, equipped with a model of blockage patterns for the particular region, learnt beforehand by the machine learning techniques that support the event forecasting engine. Furthermore, the user is initially assigned to some particular AP in the region. As the user moves around, the event forecasting engine continuously attempts to forecast two complex events, in parallel: (i) imminent blockage incidents for the AP the user is currently assigned to; and (ii) "signal improvement" events for each other AP in the region. When a blockage event is forecast for the current AP with high probability, the application selects another AP to connect to, from those that look most "promising" w.r.t. signal evolution. The goal of this process is twofold: first, the handover in this scenario takes place in a decentralized fashion, based on processing that takes place in the user's device only. Second, the handover negotiation process takes into account the future signal evolution of all APs in the region, potentially enhanced by mobility-related information, rather than simply choosing an AP in a "greedy" fashion, i.e. picking the AP with the best signal at the current time point. This has the potential of resulting in fewer handover events, by selecting an AP that is less likely to be blocked in the near future, as opposed to the "greedy" approach.

The demonstrator will aim to show the merits of the approach by extracting sequences of handover incidents from simulated runs and comparing such "plans" to optimal ones, for the particular scenarios, which will be known beforehand. A description of the data generation process for such simulations follows. Note that modifications to the general methodology described below might be implemented, in order to derive informative baseline simulations with clear "ground truth" handover sequences.

The system-level simulation model which is exploited consists of a square geographical area within which four rectangular obstacles have been set. Moreover, we assume the presence of one mobile user node and a specific number of access points which are placed in predefined coordinates inside the simulated area. Time evolution is incorporated in the simulation model, as the coordinates of user node change over time according to a specific mobility model and its received power from every access point is tracked during the whole simulation session.

Finally, we have to mention that the types of data which are exploited for the CER/F techniques are the user's coordinates and velocity, as well as the received power of the user from every access point for every time slot of a simulation session, respectively. For this purpose, a suitable Path Loss model is applied for D-band networks.

4.3.2 Demonstration Scenario 3.2: The Multi-User Case

The purpose of this second scenario is to monitor an area where multiple users move around and attempt to forecast BS "overloading" events. Such events occur when a single BS is assigned to too many UEs, which causes the quality of the communication that each UE receives to deteriorate. The scenario is illustrated in the figure below:

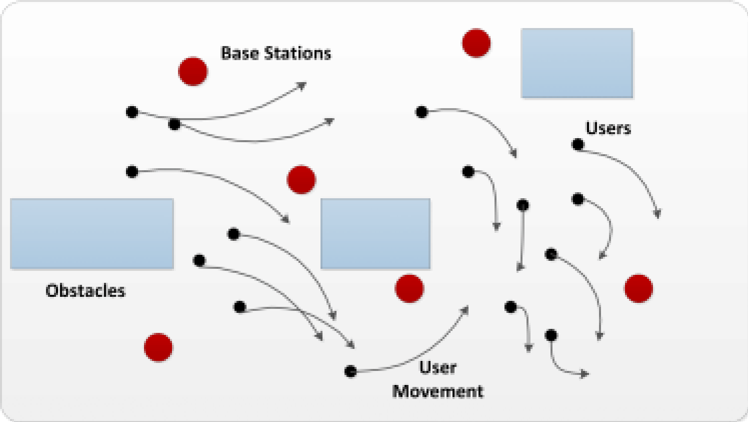

Figure 20: **Example of simulated area for the data production for CER/F in the multi-user case**

As previously, the simulated region features a set of obstacles and a number of base stations, which serve multiple users moving around the region. Initially, each user is assigned to a particular BS, based on the user's initial position in the region (e.g. initially the user is assigned to the BS with the closest line-of-sight proximity). Some mobility scenarios will be defined, e.g. moving towards a metro station, walking around a park/square, visiting a mall, and so on, and simulations will be generated where the users move across some typical trajectories in these mobility scenarios. Such trajectories may vary, depending on conditions such as time of day, weather, and so on.

An overloading event for some BS will be defined as occurring when that particular BS is simultaneously assigned to users whose number exceeds a given threshold. The goal of this application scenario will be to timely forecast such events, using event forecasting techniques that will depend on a "user mobility model", obtained via machine learning techniques, from sets of typical trajectories.

In more detail, the setting will be as follows: The monitored region will be divided into "sectors", each of which is assumed to be served by a particular BS. The training data that will be used to learn the mobility model, will consist of typical user trajectories, under various circumstances. The learnt model obtained from such data will be able to generate a probability distribution over the region's sectors, at each point in time, assigning a larger probability mass to regions that are more likely to be reached by a particular user in the near future. Once the model is adequately trained it will be used to monitor users' mobility for each user that appears in a region. The model's predictions for each user's future location will be combined in time to infer situations where an imminent overloading event is likely to occur, based on whether the number of users that are likely to reach a particular region exceeds the given threshold that defines the overloading event. Once such a forecast is made, a "snapshot" of the region in the time of the forecast may be used by other tools that are being developed in ARIADNE to infer a different BS/UE allocation, which "overrides" the default, region-based one and avoids the overloading event.

The scenario will be evaluated in terms of accuracy (its capacity of correctly forecasting overloading events), as well as in terms of efficiency/scalability, by varying the number of users that appear in the region.

5 Conclusions

In this deliverable D5.1, “Report on the demonstration scenarios and description of testbed implementation plan”, we have presented the individual scenarios for each demonstrator. These proof-of-concept demonstrators were designed to showcase the key technologies, system concepts, and network architectures of the ARIADNE approach:

- Novel radio technologies for tens of Gbit/s wireless connectivity in D-band frequency
- Beyond Shannon communication theory framework with ultra-high reliability in a reconfigurable environment enabled by metasurfaces
- Network intelligence is provided by machine learning techniques.

At first, the plan for the point-to-point Line of Sight (HW) demonstrator was presented. Its main focus is to showcase an outdoor error-free link in the D-band leveraging the polarization multiplexing technique, based on the main hardware blocks (baseband unit, RF Front end and antennas) that were developed within WP3. The BBU will be capable of mitigating D-band specific impairments.

Regarding the second (HW) demonstrator, the two planned scenarios for a metasurface-enabled point-to-point non-LOS demonstrator were presented. This demonstrator utilizes hardware tools that are being developed within WP3, namely metasurfaces for anomalous reflection, directive lens antennas, and the RF front-end. The target of this demonstrator is to show a stable additional wireless channel between two sources via anomalous reflection from a specifically designed environment addressing ARIADNE Pillar II.

The software demonstrations aim at highlighting how ARIADNE incorporates intelligence into various aspects of network management. Thus, three main use cases have been selected and presented, namely, (i) AI/ML application for line-of-sight aware connectivity, (ii) Deep Reinforcement Learning for 5G/B5G Wireless Communications, and (iii) Complex Event Forecasting for Proactive Handover and Blockage Avoidance. Each case addresses a small number of scenarios focusing on the application of AI/ML techniques to optimize certain aspects of resource management, LOS connectivity, and/or blockage avoidance in D-band networks. It is noted that the corresponding research topics are investigated within WP4 where more results will be produced by the end of the project. In that sense, software demonstration plans will be further elaborated and revisited in the forthcoming deliverables of WP5.

6 Bibliography

[1] Deliverable D1.1, “ARIADNE use case definition and system requirements”, ARIADNE project

[2] Deliverable D4.1, “Initial results on adaptive directional LOS and NLOS reliable connectivity:” ARIADNE project.