REINDEER

D2.1

Initial assessment of architectures and hardware resources for a RadioWeaves infrastructure

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Abstract:	This deliverable provides an initial assessment of the RadioWeaves infrastructure, developed in WP2 of REINDEER. Taking the description of RadioWeaves in D1.1 and the use cases and KPIs defined therein, as a starting point, a first version of the building blocks of the infrastructure are presented, together with new terminology. Architecture and topology are introduced together with a quantitative and qualitative analysis of high-level requirements on a RadioWeaves infrastructure, setting the scope for more detailed investigations and design.
Keywords:	RadioWeaves, terminology, architecture, topology, requirements, algorithm mapping

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Executive Summary

In this deliverable we perform an overview and initial assessment of how the use-cases and associated service requirements defined in WP1 translate to requirements on a RadioWeaves (RW) infrastructure. Logical and physical components for this new type of infrastructure are introduced, together with associated terminology. A central concept is tight coordination and synchronization between different parts of the infrastructure, where multiple components across the infrastructure cooperate in federations to deliver services and share the processing load in a distributed manner. These federations are dynamic and adapt to requirements of the delivered services and current conditions, such as distribution of devices and traffic load.

Use-case requirements are analyzed and critical infrastructure challenges are identified, by comparing requirements to what is ultimately possible, e.g., in terms of spatial multiplexing and localization precision, and to resulting requirements on hardware, e.g., wireless communication data rates and data rates required in back/front-hauls. Since the RW infrastructure is not yet specified in detail, the analysis is of a generic nature and conclusions are intended as a starting point for further investigations.

Aspects on topology/architecture are analyzed by performing a more detailed study of three classes of algorithms, for supporting wireless communication, localization/positioning, and wireless power transfer. It is concluded that a certain flexibility, in terms of topology/architecture, is required to find efficient balance points between parallel and sequential distributed processing strategies for different services and service requirements. A hybrid topology, mix of daisy-chain and tree, is one of the interesting cases to study in later stages of REINDEER.

Security considerations are not at the core of the infrastructure development and are not expected to have any significant impact on hardware choices, but are discussed in some detail to provide a security context to the RW infrastructure.

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Chapter 1

Introduction

At the core of RW is a new type of infrastructure, providing a much larger focus on exploiting the spatial domain than in any current wireless infrastructure, enabling entirely new services. RW is not only expected to provide various communication services, with more far-reaching capabilities than existing systems, by providing a fabric of dispersed electronic circuits and electromagnetic surfaces that collectively function as a massive, distributed resource offering hyper-diverse connectivity, positioning, wireless power transfer (WPT) and computational capabilities – it is also expected to bring the capabilities of multi-antenna systems to the next level, meeting the challenges of new interactive, real-time and real-space applications.

Designing the infrastructure of any communication system is a monumental task and the wide range of anticipated services supported by RW, see [15] for details, is only adding to the overall complexity. In this deliverable the aim is to provide an initial assessment of a RW infrastructure, in terms of its architecture and expected requirements on its hardware resources. As a starting point for this assessment we use the contents of Deliverable D1.1 *Use case-driven specifications and technical requirements and initial channel model* [15], which specifies 13 different use cases for RW with a wide range of services and associated KPIs[1].

The high-level analysis provided in this deliverable is focused on the following topics, each assigned its own chapter:

- **Terminology, network components and federations**

  Setting the stage for an initial assessment of a RW infrastructure, we start by establishing terminology, specify physical and logical network components, and outline how federations are used to assign resources when providing services.

- **Use case and deployment scenario analysis**

  The wide range of services specified in D1.1 [15], and their KPIs, are discussed qualitatively and quantitatively, to identify challenges and requirements on a RW infrastructure.

- **Energy efficiency ambitions**

  With the establishment of an infrastructure for a new wireless communication concept, that has the potential to significantly influence energy consumption, we describe the energy-

[1]For the readers reference, we reproduce the use cases and KPIs requirements in Chapter 3, Table 3.1 and Table 3.2, respectively.

efficiency ambitions of RW. These ambitions are discussed both in terms of direct energy measures and secondary environmental effects.

- **High-level architectures and topologies**

  Using distributed hardware resources cooperatively to deliver services requires establishment of high-level architectures and topologies available when designing distributed algorithms and exploiting co-processing, both for the purpose of delivering services and for fundamental network functions.

- **Algorithms and processing distribution strategies**

  Three categories of algorithms essential to services delivered by RW are discussed together with their mapping to available hardware architecture/topology. The three categories are communication, positioning/localization, and WPT algorithms.

- **Considerations for security**

  While not a main focus of the REINDEER project, security aspects are essential to any communication system and, especially, wireless systems. An overview is provided for reference and forms a basis for the overall security mindset when further developing the RW infrastructure.

The deliverable is concluded with a summary of important observations guiding the upcoming more detailed work on the design of RW. Beyond the guidelines for future work on the infrastructure itself in WP2, observations are also of value for refining use cases in WP1, algorithm development in WP3, support of energy-neutral devices in WP4, and experimental evaluations in WP5.

Chapter 2

Terminology, network components and federations

The overall vision for 6G and the analysis of a diversity of anticipated use cases in REINDEER [15], more specifically, raise the requirements beyond what is possible with a further evolution of current network architectures. Clear examples are the unperceivable latency, ultra-high reliability, and interaction with energy-neutral devices. These call for resources to be distributed in the environment to offer main utility functions:

- Local connectivity-computational resources: Many 'mixed reality' applications do to a significant extent rely on local content, and distributed processing can increase efficiency and reduce bottlenecks both regarding bandwidth and energy.
- Proximity: Interaction with energy-neutral devices essentially and realistically needs charging features to be close to these devices.
- Redundancy: Retransmissions need to be avoided to achieve unperceivable latency and ultra-reliable connections.
- Diversity: Precise and accurate indoor positioning can benefit from hyper-diversity, and favorable propagation conditions can be created to achieve consistent good communication quality and extensive spatial multiplexing.

In view of the desired utility functions, we will develop a novel network infrastructure that integrates new functional resources in distributed end-points, which we envision becoming true service points. For applications to operate herein, cooperation of these service points will require some degree of cooperation and potential extra compute power, for which we introduce the concept of synchronization anchors and edge processing units respectively.

Consequently, to design adequate RW systems, we introduce new terminology and concepts. An overview of the main components in a RW infrastructure is shown in Figure 2.1. An explicit distinction is made between logical and physical components, which we propose to call logical entities and physical elements respectively. The physical and logical structure, including its hierarchical components, are depicted in Figure 2.2. The newly introduced terms are described as general as possible to not impose any constraints on the implementation of RW systems. An overview of the terminology, including a short description, can be found in Tables 2.1 and 2.2.

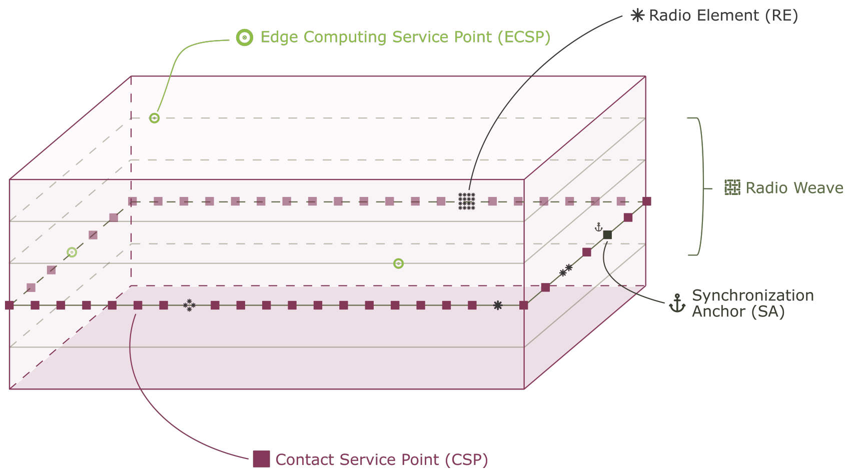


Figure 2.1: Overview of a RadioWeaves (RW) infrastructure with its main components. The RW system consists of at least one, but preferably many edge computing service points (ECSPs). This component is responsible for data aggregation and coordination of contact service points (CSPs). A CSP is the first contact point from the user equipment (UE) perspective and provides the necessary services to support user applications. A CSP can be equipped with one or several radio elements. To allow for a synchronized/coherent system, ECSP can act as a synchronization anchor to synchronize its CSPs. More details can be found in Tables 2.1 and 2.2.

2.1 Network Components

Several separate RW infrastructures can be connected through the back-haul, to be able to connect to existing cellular and other networks. A RW network consists of, at least one, but preferably several ECSPs, serving as processing units which are spatially distributed over the network. The main function of these nodes, is offloading processing power from the CSPs, coordination and aggregating data to and from the back-haul. A CSP is a node capable of serving one or multiple UEs and applications. In conventional cellular networks, a CSP is similar to an access point (AP). The term *contact service point* is introduced as in a RW system, these “APs” do not only provide communication, but also other services such as e.g., WPT and sensing. Both ECSPs and CSPs can support the novel services offered in and by the RW infrastructure.

The components in a RW system can be categorized as logical components or physical elements. The logical components, discussed in Section 2.1.1, exist of several physical elements to form one logical entity. The physical elements in the envisioned infrastructure are discussed in Section 2.1.2. The physical and logical architecture, consisting of these logical and physical elements, is depicted in Figure 2.2.

2.1.1 Logical Components

The network consist of several logical components. The first entity seen from the perspective of the UE is the *contact service point*. This logical service point allows to power the device wired or wirelessly, provide wireless communication or could host other elements (see subsection with physical components). Several CSPs are connected to one or more ECSPs. This entity can have a dedicated connection to the back-haul and other ECSPs. The task of the ECSP is to provide dedicated computing resources used for collective tasks such as, e.g., coherent channel-matched beamforming. Also, this entity can host several hardware elements besides processing/memory. A collection of CSPs coordinated by an FA to jointly serve a set of devices is called a federation.

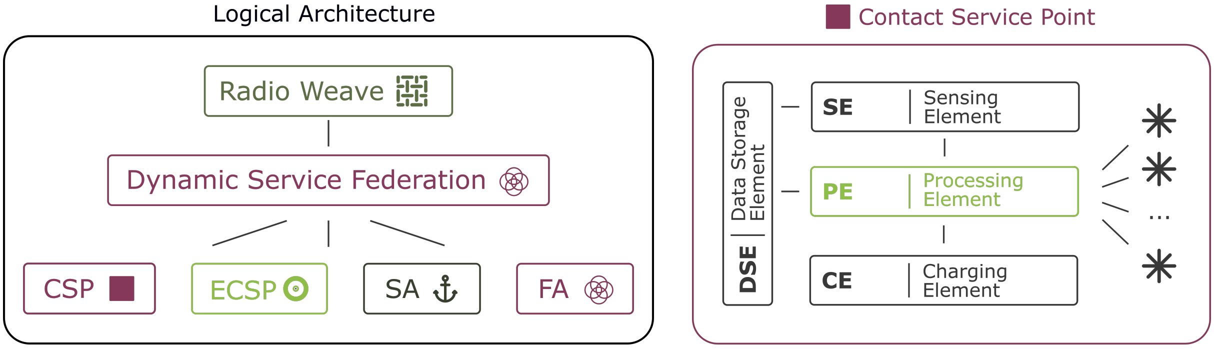


Figure 2.2: Physical and logical architecture of the RW setup. The physical architecture depicts an example implementation of a CSP including data storage, sensing, processing, charging and radio elements.

More info regarding federations can be found in Section 2.2.

2.1.2 Physical Elements

The logical components consist of several physical elements. As in a RW infrastructure the network provides not only communication but also positioning and power transfer, the service points consist of more than only radio elements. All physical components are summarized in Table 2.2. An example of the (optional) physical components hosted on a CSP is shown in Figure 2.2.

2.2 Federations

As not all CSPs will contribute equally to a given subset of users/applications, the notion of a federation is introduced. During the operation, federations will be orchestrated depending on the served UEs and their application classes, the propagation environment, and the load on the CSPs. A federation is a collection of CSPs jointly serving one or multiple UEs. A federation is typically coordinated by an ECSP acting as the federation anchor. Often, federations will consist of CSPs located closely together, but this is not mandated, nor desired in some cases.

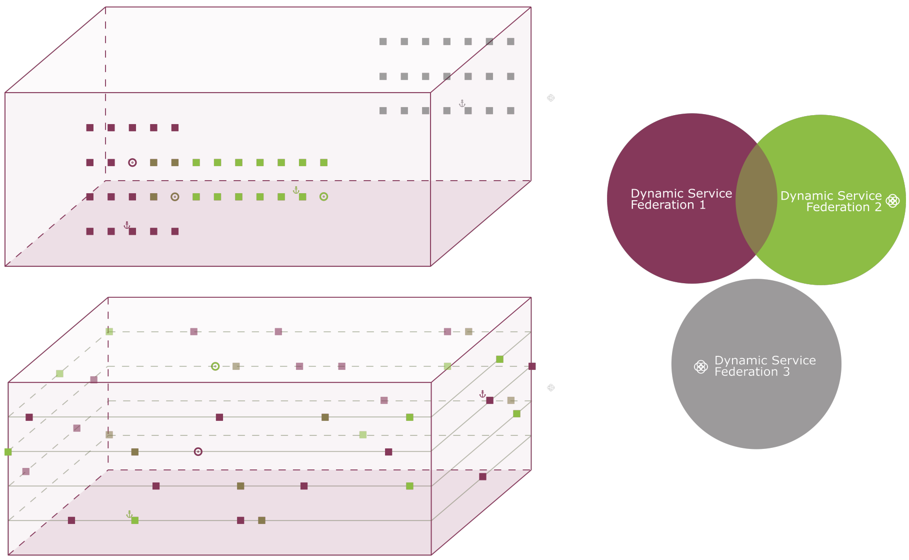


Figure 2.3: Federations in a RW infrastructure. Some CSPs are included in multiple federations. The CSPs inside one federation do not necessarily have to be in close proximity of each other.

Table 2.1: Short description of the logical components.

Term	Abbreviation	Description
RadioWeave	RW	Wireless access infrastructure consisting of a fabric of distributed radio, computing, and storage resources.
Contact Service Point	CSP	Integrates local computation and storage resources, and provides at least communication, sensing or charging functionality. It is the first contact point as seen from the UE and takes the role of an anchor in the context of position related applications.
Edge Computing Service Point	ECSP	Shared compute resources integrated in the RW that can support applications in need of substantial compute power and/or connection to the back-haul or other RW infrastructures.
(Dynamic Service) Federation	DSF	(Temporary) set of cooperating resources in the RW, working in unison, that could be more or less synchronized, and including at least CSPs and typically a synchronization anchor, and potentially edge processing unit(s), established to serve a cluster of devices and/or application(s).
Synchronization Anchor	SA	Logical function flexibly located attributed to a certain CSP to serve as a synchronization reference for a set of cooperating CSPs for some period.
Federation Anchor	FA	The FA is responsible to orchestrate and to coordinate a federation. This task will be primarily performed by an ECSP.
Energy Neutral (device)	EN	EN devices are a specific subset of UEs, housing dedicated circuitry for energy harvesting. Their main characteristic is that they are passive devices, i.e., they do not have their own power supply. All power they use for operation is harvested from incident EM fields. From a perspective of EM fields, they act as a power sink[a], as opposed to devices that have some internal power supply. EN devices rely on the WPT capabilities of the infrastructure for power provisioning. In contrast to conventional networks, RW inherently supports EN devices, requiring dedicated protocols and technologies to do so. This includes both energy harvesting techniques with intentional sources (i.e., WPT) and with unintentional sources (i.e., ambient energy harvesting).

[a] According to Poynting's theorem, a volume only enclosing an EN device would have no power delivered by sources within the volume, i.e., $P_\mathrm{s} = 0$ (compare [64]).

Table 2.2: Short description of the pool of physical components.

Term	Abbreviation	Description
Sensing Element	SE	Unit integrated in a CSP that can sense signals in the environment via radio channels or other media, e.g., a camera.
Data Storage Element	DSE	Memory resource integrated in a CSP.
Processing Element	PE	Local computational resources integrated in a CSP.
Charging Element	CE	Functionality integrated in a CSP that can efficiently charge devices in the environment, e.g., electromagnetic via antennas or inductive through coils.
Radio Element	RE	Transmit/receive units, most often including an antenna, that can serve to exchange data or charge devices using electromagnetic waves.
X-haul	X-haul	It interconnects CSPs locally (front-haul) and also provides access to remote network and cloud resources (back-haul). It can comprise both wired (including optical fibers connections) and wireless segments. In contrast to conventional networks, in RW, no clear distinction can be made between the front- and back-haul. The X-haul, thus, comprises a mix of the two.

Chapter 3

Use case and deployment scenario analysis

An in-depth study of expected use cases and derivation of main requirements has been performed in WP1 of this project, and reported on in Deliverable D1.1 [15]. The application-oriented requirements are reconsidered here from a technological perspective, and translated to resources and features that should be provided by the novel RW architectures. In the following sections we first shortly highlight the limiting use cases, among the 13 defined in D1.1 and reproduced in Table 3.1. With the wide range of use cases anticipated for RW, there will be an associated wide range of requirements on the infrastructure. In the following sections we further zoom in on the specific quantitative measures having a bearing on what we are facing in terms of topology and hardware requirements. As a starting point, we use the key performance indicators (KPIs) defined in D1.1 and reproduced in Table 3.2.

3.1 Technological perspective: limiting use cases

Three main application categories were considered: monitoring and real-time applications, AR/VR applications, and location-based information applications. These have been further analyzed with respect to their requirements, which has lead to the definition of four main clusters. We here highlight the limiting use cases from a technological perspective with their most stringent technical requirements.

1. Cluster containing AR, VR, and Mixed Reality use cases in the broader sense, that are expected in professional environments as well as entertainment and care. This cluster poses as challenging requirements the combination of high throughput for individual connections, ranging from 5Mbps to 3Gbps, and a large traffic volume, going up to $50Mbps/m^2$. They also require End-to-End (E2E) latency to be restricted to 10ms.

2. Cluster related to the ultra-reliable and low-latency communication application class in 5G, yet adding to that a requirement for accurate positioning that needs to be combined with a high reliability and latency sensitivity. Human-robot co-working and real-time digital twins require E2E latency as low as 1ms to be supported. Tracking of robots and UVs requires the packet error rate (PER) not to exceed 10^{-6}. Positioning should be achieved with an accuracy as good as 0.1m.

Table 3.1: Use cases defined in Table 1 of [15].

Use case #	Use case name
1	Augmented reality for sport events
2	Real-time digital twins in manufacturing
3	Patient monitoring with in-body and wearable sensors
4	Human and robot co-working
5	Tracking of goods and real-time inventory
6	Electronic labelling
7	Augmented reality for professional applications
8	Wander detection and patient finding
9	Contact tracing and people tracking in large venues
10	Position tracking of robots and UVs
11	Location-based information transfer
12	Virtual reality home gaming
13	Smart home automation

Table 3.2: Use case KPIs, as given in Table 18 of [15] (minor change of format).

Key Performance Indicator	Unit	Use Case												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Carrier frequency	GHz	2.4 5+	2.4 3.8	0.9 2.4 5+	2.4 3.8	0.9 2.4 3.8 5+	2.4 5+	2.4 3.8 5+	0.9 2.4 3.8 5+	0.9 2.4 3.8 5+	0.9 2.4 3.8 5+	2.4 5+	5+	2.4 5+
Device density	m^{-2}	2	100	2	1	100	20	0.1	2	2	100	10	1	100
Max # of simult. Devices	1	10k	1k	20	10	50k	10k	10	50	10k	500	100	2	10k
User experience data rate	Mbps	5	1	1	5	1	1	45/3000	1	1	10	10	150	0.5
Dominant traffic direction		DL	Both	UL	Both	UL	DL	DL	UL	UL	UL	DL	DL	UL
Mobility	m/s	10	10	1	0	10	2	2	7	2	10	2	2	0
Positioning Accuracy	m	0.5	0.1	1	-	0.1	0.5	0.1	1	1	0.1	0.5	0.1	0.1
Reliability	packet loss prob.	10^{-3}	10^{-5}	10^{-4}	10^{-5}	10^{-3}	10^{-5}	10^{-2}	10^{-3}	10^{-3}	10^{-6}	10^{-2}	10^{-2}	10^{-2}
End to end latency	ms	20	1	200	1	100	1000	10	1000	1000	10	1000	10	100
Traffic volume density	$Mbps/m^2$	10	20	10	5	100	0.1	4.5	1	2	50	50	50	0.1
Power density	mW/m^2	-	-	1	-	-	0.25	10	0.1	0.1	-	-	-	0.25

3. Cluster covering massive positioning and sensing, needs the support for (very) large numbers of energy-neutral devices, generating predominantly uplink traffic. This clearly raises the requirements for energy-efficiency and the possibility to charge these devices from the RadioWeaves infrastructure. A power density of up to $1mW/m^2$ may be required for patient monitoring. The density of devices can be expected to be as high as $100/m^2$ for the case of real-time inventory and home automation, with potentially up to 10.000 simultaneous connections to be supported by the RadioWeaves infrastructure for electronic labeling.
4. Cluster comprising use cases where the user devices could demonstrate a high degree of mobility, often in complex environments. 6G use cases may require high traffic and/or high reliability to be offered in combination with a potential mobility up to 10 m/s.

The above clusters of use cases are driving the architectural concepts and design for which this deliverable reports on the first results and strategies. Furthermore, the study in WP1 revealed that it is desired that **the networking infrastructure should support new services**. Specific services that were identified include federated learning, environment mapping, localization and tracking, and edge processing and storage.

In the next sections technological requirements are considered one by one and translated to measures that relate to the communication infrastructure.

3.2 Carrier frequency requirements

Four different carrier frequency ranges are anticipated, 900 MHz, 2.4 GHz, 3.8 GHz, and 5+ GHz. To serve all these in a single radio element (RE) will require flexible radio frequency (RF) hardware, capable of receiving and transmitting at, possibly, multiple carrier frequencies at the same time and have capabilities spanning the requirements of all use cases. An alternative solution is to dedicate different RF hardware for different frequency ranges and/or service requirements, making it possible to tailor REs to a specific deployment scenario. With the second alternative, the complexity and energy efficiency of each type of RE can be kept at a minimum, at the cost of the overall architecture of RW becoming more complex. Where the best balance-point is, between the two extremes, is something that REINDEER will investigate during the course of the project.

As will be seen below, the different frequency ranges also have influence on how other requirements are interpreted, mainly through the differences in wavelength of the associated radio signals. The wavelengths associated with the carrier frequency ranges are, roughly, 33 cm (900 MHz), 13 cm (2.4 GHz), 8 cm (3.8 GHz), and, $<$6 cm (5+ GHz).

3.3 Device density requirements

RW span a three orders-of-magnitude range of device densities, from 0.1 to 100 devices/m^2, depending on use case. Taking into account that the wavelength used for a particular service has a major impact on physical device sizes, limits required spatial resolution in the case of spatial multiplexing, and governs the positioning accuracy that can be achieved, it makes sense to translate device densities in terms of devices/wavelength^2. The corresponding device densities in these terms span an even larger range, from 0.0004 to 11 devices/wavelength^2, more than four orders-of-magnitude.

Services at the low end of device densities are well suited for spatial multiplex, since the abundance of REs in RW can multiplex many RF links/signals, in the same time-frequency resource. However, the spatial resolution of any such system is limited to the scale of the wavelength, making it impossible to spatially multiplex devices spaced more densely than a few devices per wavelength^2. For this reason, we can only expect to serve a small fraction of devices with spatial multiplexing at the high end of device densities, where we have $>$10 devices/wavelength^2. A particularly challenging use case from this view is the *Position tracking of robots and UVs*, with potentially more than 10 devices/wavelength^2 for the lowest 900 MHz carrier frequency. In scenarios where devices are well spread in the remaining (vertical) spatial dimension, spatial multiplexing can support more devices/wavelength^2, such as in the *Tracking of goods and real-time inventory* use case, where we expect goods stacked high (vertically) in warehouses/on shelves to represent the highest area device densities.

An important investigation in REINDEER is to find a balance between spatial and other means of multiplexing for the different use cases, with overall system efficiency and cost in mind.

3.4 Number of devices and user data rate requirements

The combination of the number of devices and experienced user data rates determine the aggregated data traffic a RW infrastructure should be able to handle. The *Human and robot co-working* use case has the lowest aggregate data rate of 50 Mbps, while for *Augmented reality for sport events* the number can be as high as 50 Gbps. The real-time nature of the latter use case, with a 20 ms latency requirement, will put very high requirements on the RW infrastructure.

This is a critical point in the RW design, that will have to be analyzed in further detail and in combination with infrastructure design choices made.

3.5 Mobility requirements

The necessary mobility support, defined in terms of device speed, ranges from 0 to 10 m/s across use cases, where different frequency ranges and wavelengths in combination with different user data rates motivates the calculation of normalized values. Given the maximal Doppler frequency $f_{\text{d,max}} = \frac{v}{c} f_c$, where v and c are the device and light speeds, respectively, and assuming a coherence time $T_{\text{coh}} = \frac{1}{2 f_{\text{d,max}}}$ of the channel, we find that the shortest coherence times across use cases are around 3 ms. The longest coherence times are theoretically infinite when devices do not move, but in practice there will always be some changes in the propagation paths, depending on the particular environment, and synchronization drift in hardware causing changes to the equivalent channel. When using data transmission, or other services, that require channel state information (CSI) knowledge, a CSI update would be required about every 3 ms, or more frequent, in the most demanding cases.

Combining the coherence time with requirements on experienced user data rates, we find that the number of transmitted bits per coherence time can be as low as 3000 in the *Tracking of goods and real-time inventory* use case. Low number of transmitted bits per coherence interval leads to a relatively large overhead for CSI acquisition, which may point in the direction of non-coherent transmission methods.

3.6 Positioning accuracy requirements

For positioning services or positioning-based services, accuracies between 0.1 to 1 m are specified among the use cases. While there are several parameters influencing the achievable accuracy, an important measure is the wavelength. This motivates expressing positioning accuracy in terms of wavelengths, which given the different frequency ranges, give accuracies down to 0.3 wavelengths for the *Tracking of goods and real-time inventory* and *Position tracking of robots and UVs* use cases. High accuracy in absolute positioning requires advanced processing techniques, large effective apertures created by many distributed REs, long acquisition times, and high signal-to-noise ratios (SNRs) or signal-to-interference-plus-noise ratios (SINRs) as well as large bandwidth signals.

With the available signal bandwidth expected to be limited to 100 MHz in the best case, positioning algorithms will heavily rely on exploiting the large RW aperture, i.e., a large numbers of antennas and a wide spatial distribution, to compensate this limiting effect. While optimal use of the large aperture requires an accurate synchronization which is not expected to be possible due to hardware limitations, efficient data fusion of local parameter or position estimates, allowing for less stringent synchronization, will be the key to the requirements of different use cases. In addition, position information that is contained in the environment in the form of multipath propagation will be exploited to improve the robustness of positioning, stemming either from a prior available or learned floor plan in suitable (abstracted) form.

3.7 End-to-end latency requirements

Low end-to-end latency is one of the most critical and demanding requirements, that has the potential to strongly influence how RW is designed and how nodes in the infrastructure can co-operate to process and deliver services. Propagation delays are a minor contribution to the total latency, where 1 ms corresponds to about 300 km. There are, however, other inter-linked bottlenecks that need to be investigated in greater detail, and in combination, when designing the infrastructure, such as:

- Packet sizes need to be restricted to allow enough time for processing to take place. With shorter packets, everything else equal, follow higher packet loss probabilities. An initial assessment, based on the time it takes to transmit a package, shows that packets of a few hundred bits or fewer may be required to meet the most demanding end-to-en latency requirements, such as for the *Real-time digital twins in manufacturing* use case.
- The number of co-processed signals from different REs need to be restricted, to limit the processing latency incurred by exchange of processing data inside and between CSPs. With fewer available REs to take part in transmission and reception of signals, everything else equal, follow higher packet loss probabilities.

3.8 Reliability requirements

Reliability requirements are expressed in terms of *packet loss probability* and range from 10^{-2} to 10^{-6}. The most demanding use cases are *Real-time digital twins in manufacturing*, *Human and robot co-working*, and *Position tracking of robots and UVs*, where we have a combination of requirements on low packet loss probabilities ($10^{-6} - 10^{-5}$) and low end-to-and latency (1-10 ms). As indicated above, the *Real-time digital twins in manufacturing* use case is a particularly demanding one, where a relatively low data rate of 1 Mbps in combination with a strict end-to-end latency of 1 ms forces the packet length to be short, leading to an associated limitation on reliability/packet-loss probability.

Means to meet reliability requirements include

- *well distributed CSPs*, improving reliability of good signaling conditions at any point in the coverage area,
- *diversity measures*, through tight cooperation and co-processing of signals from multiple CSPs,
- *learning strategies*, adapting scheduling and federations to current conditions,
- *robust infrastructure design* with redundant components and data-paths/routing alternatives.

3.9 Traffic-volume density requirements

Traffic-volume density is expressed in terms of Mbps/m^2 and ranges between 0.1 and 100 across use cases. Designing for the worst case can lead to an over-dimensioning of the infrastructure by as much as three orders-of-magnitude, when delivering services for the least demanding use cases.

The means to handle large variations in terms of traffic-volume density are

- *densification of infrastructure* to be able to handle the most extreme traffic-volume cases, at a given maximum available bandwidth, and
- *diversify RW infrastructure capability* between different deployment locations, with different use cases/services.

3.10 Power density requirements

Requirements on power density applies to use cases where harvesting is a primary, or optional, source of energy for providing necessary functionality of devices. Energy-neutral device operation is a part of use cases *Patient monitoring with in-body and wearable sensors*, *Electronic labelling*, *Augmented reality for professional applications*, *Wander detection and patient finding*, *Contact tracing and people tracking in large venues*, and *Smart home automation*. Requirements of power density vary from 0.1 to 10 mW/m^2. Since effective antenna areas are typically given in terms of gain over the isotropic antenna we normalize power densities with $A_{\text{iso}} = 4\pi/\lambda^2$, and obtain a range of 1 to 45 μW, or -30 to -13 dBm, per isotropic antenna area. The two most demanding use cases, in this context, are *augmented reality for professional applications* and *Patient monitoring with in-body and wearable sensors*.

To deliver required power densities of use cases, the means available to the infrastructure are, alone or in combination,

- *increase transmit power*, which may require more powerful amplifiers, leading to increased hardware cost and potential violations of equivalent isotropically radiated power (EIRP) limits,

- *provide array gain*, through synchronized transmission from multiple REs and possibly from multiple CSPs, leading to tighter synchronization requirements across the infrastructure and higher hardware costs, and
- *limit the coverage area* (distance from CSPs) for energy harvesting devices.

3.11 Summary of RW challenges

Based on the above analysis of use cases and their associated KPI requirements, we make a number of initial observations about RW infrastructure design. These observations will be investigated in more detail as the project continues and the RW infrastructure is further detailed. The observations are:

1. Augmented reality for sport events

   High aggregate data rate to be supported by RW, with corresponding high requirements on the RW X-haul, including both front-haul and back-haul connections.

2. Real-time digital twins in manufacturing

   Positioning accuracy at wavelength scale puts localization/positioning performance in focus. Very tight requirements on latency, together with a large number of simultaneous devices, implies high demands on RW spatial multiplexing capacity.

3. Patient monitoring with in-body and wearable sensors

   Energy-neutral operation of devices with high power density requirement makes wireless power transfer a critical RW service.

4. Human and robot co-working

   Very low latency, combined with high reliability, is a well known and difficult challenge. Despite low per-user data rates, RW spatial multiplexing capability and channel hardening will serve this use case well. This puts high demands on synchronization between CSPs.

5. Tracking of goods and real-time inventory

   Very challenging combination of KPI requirements. This use case will have to be given particular attention in the RW design, since it stands out in terms of device density, mobility, and positioning accuracy. Some of the requirements can be made less severe by, *e.g.*, selecting an appropriate carrier frequency in combination with other requirements.

6. Electronic labelling

   A high device density and energy-neutral operation, puts WPT a the center, with relatively low requirements on other KPIs. Low requirements on latency and other KPIs allows for efficient and innovative solutions.

7. Augmented reality for professional applications

   Potentially very high per-user data rates and energy-neutral operation, in combination with tight latency requirement, makes a challenging use case to support.

8. Wander detection and patient finding

Relatively mild requirements across all KPIs. Energy-neutral operation, leading to relatively high power densities, can influence technical requirements when deployed in, e.g., hospital environments.

9. Contact tracing and people tracking in large venues

   The most critical requirement is the large number of devices, while remaining requirements are relatively mild.

10. Position tracking of robots and UVs

    Potentially very high device density will make it necessary to use a high carrier frequency for efficient spatial multiplexing and a combination with other multiple-access techniques when spatial multiplexing has reached its limit.

11. Location-based information transfer

    This use case does not stand out in comparison with the rest, with relatively mild requirements across all KPIs.

12. Virtual reality home gaming

    High requirement on user data rates that become less critical when combined with low device densities. Otherwise, relatively low requirements on all KPIs. Deployment in homes point towards low-cost infrastructure.

13. Smart home automation

    High per unit-area device densities, somewhat relaxed by an expected three-dimensional distribution of devices. High positioning accuracy that may be challenging to meet with low-cost home deployments of RW.

Chapter 4

Energy efficiency ambitions

The RadioWeaves architectures are designed to meet the performance required by new applications. Moreover, the novel concepts also open opportunities to bring considerable improvements in energy efficiency for the wireless transmission. In this chapter we first sketch the context, formulate adequate metrics, and clarify the huge challenge. Next we make the ambition in the REINDEER project explicit regarding energy reduction. Further the potential ecological benefits in reduction of harmful batteries, facilitated by the wireless charging functionality, is explained.

4.1 Context

The novel use cases to be supported require RadioWeaves technologies to offer higher Quality-of-Service levels, in terms of a.o. throughput, reliability, and latency, as elaborated in Deliverable D1.1 of the REINDEER project. Governments have defined digitization as a key enabler to address economic and societal challenges [17]. At the same time, concerns regarding sustainability are getting high, and stringent ambitions are put forward to address these, such as expressed in Europe's 'Green Deal' [16]. The novel networking concepts and architectures we develop should bring drastic changes to reduce the carbon footprint of ICT [8]. It should be noted that other Sustainable Development Goals (SDGs) also may be impacted considerably by wireless technology and infrastructure. In particular e-waste may be negatively impacted by the increasing deployment of Internet of Things (IoT) devices. The wireless charging capability of RadioWeaves could avoid the need for providing a battery, which is typically one of the most harmful components, in these devices. Even if an individual battery is small, as they are expected in massive numbers and may get distributed widely, the impact can be as significant as billions of batteries proactively saved.

Adequate metrics are required to quantify and monitor progress regarding energy efficiency of wireless technologies. A commonly used metric **at link level** is the consumed energy, including transmitted energy as well as the energy required at the transmit and the receive side, over the number of information bits in [Joule/bit]. For cellular networks, the following clarification was made and further metric was proposed in [13]: "This metric relates the total energy consumed by the entire network to the aggregate network capacity. As the measure [Joule/bit] relates the cost (in terms of energy) to the generated utility (information bits), this metric is appropriate to assess the energy efficiency at full loads. On the other hand, when the network is operated well below its capacity, the main objective is to minimize the power consumption to cover a certain area, in which case [W/m2] is deemed the most relevant energy efficiency metric." It is further noted that significant improvement in efficiency will require **progress to be made at the three main levels contributing to the total energy consumption**:

1. Hardware level: energy required by the components to transmit or receive the information. This among others includes the energy dissipated as 'overhead' in the power amplifier (PA) that often works in an operation point that is not energy efficient, potential energy to cool high-power transmitters, and (digital) signal processing functionality.

2. Link level: energy required to transport the actual message data, as well as synchronization and other network-related information that needs to be exchanged, in essence resulting from the power that is transmitted 'on the air'.

3. Network level: overhead energy required to keep the possibility to connect in the network up and assure this over the full coverage area, also in case of low traffic requirements.

'Conventional' massive MIMO technology, which has been adopted as a key technology for 5G networks, has the potential to improve energy efficiency by at least one order of magnitude with respect to the previous generation. In a recent trial, Ericsson and Vodafone have shown improvement can indeed be realized [67]. Interestingly, static power consumption of basestations has decreased in 5G New Radio (NR) with respect to 4G systems [21]. Still, reporting in the first large-scale roll-out is anything but positive [7]. The excessive consumption is explained by a combination of factors, including:

- The first installed products are not (yet) optimized for energy consumption. A higher degree of hardware integration can bring improvements in this respect.

- Operators have a tendency to select base station solutions that provide a high output power. Setting up a new base station site comes with significant complications. First of all permission needs to be acquired, which can be a very cumbersome process. Next, the installation needs to be established. Clearly, these are resource-intensive processes. Operators hence want to get the maximum out of a site and rather deploy systems that provide a high output power. The output power of a system is to some extent also regarded as a quality label.

- The complexity of the digital processing has increased in 5G systems. A rule of thumb for previous generations of mobile networks says that $\sim$80% of the energy in the access network is used in the base stations, of which $\sim$80% is consumed in the Power Amplification. In 5G it is noted that the digital processing is accounting for $\sim$50% of the power consumption in the base stations.

To make a major step towards carbon-neutral networks in 6G, a much higher ambition regarding energy consumption is needed. Even if efficiency in terms on energy/bit has improved over consecutive wireless technology generations, absolute energy consumption has still increased. To turnaround the latter in the future, we need to take into account:

- The predicted 50% yearly increase in mobile data volume [66].

- A typical 10-year interval between different mobile network generations.

A simple calculation learns that new wireless networks should improve energy efficiency by a factor of 100 just to stay 'on par' in absolute numbers.

4.2 Ambition in REINDEER

4.2.1 Energy efficiency and reduction in carbon footprint

In order to actually reduce the carbon footprint, the ambition of the REINDEER project is to explore avenues that have the potential **to improve energy efficiency by a factor of 100 to 1000.** Observing the typical power consuming components and energy inefficiency bottlenecks [13] in wireless networks, it is clear that there is a substantial potential in transforming the network to be built out of many small distributed contact service points. We propose RadioWeave technology as an infrastructure for future generation wireless networks in particular because of the great potential it bears to improve energy efficiency. Indeed, as explained in deliverable D3.1 [87] of the REINDEER project and clarified in [22], RadioWeaves-based networks allow to **drastically reduce the required transmit power** to achieve universal good service levels. This is a consequence of the distributed antenna (array) architecture that brings the twofold advantage of (i) on average reducing the path loss due to proximity to the devices and decreased probability of blocking and (ii) creating higher rank channels that enable support of many simultaneous streams efficiently. Even if gains as spectacular as 20 dB can be achieved, this advantage itself will not suffice to meet the ambition with regard to reduction of energy consumption in wireless networks stated in Section 4.1. The REINDEER project will also pursue other means to increase energy efficiency, such as constant-envelope modulation techniques. In REINDEER, we aim to progress RadioWeaves technology to achieve superior energy efficiency by consistently prioritizing that KPI in the development of the novel concepts and their implementation. At this relatively early phase in the project, we have identified main bottlenecks and specific opportunities, referring to the three levels listed above, and will pursue the following enhancements:

1. **Link Level.** Progress algorithms and architectures, such that the great theoretical improvement regarding output (transmit) power requirement in RadioWeaves-based wireless networks, can also be reached in practical deployments and implementations. As elaborated in deliverable [87] a theoretical gain of a factor of 100 could be achieved in highly loaded situations.

2. **Hardware Level - PA stage** Improve the efficiency of the power amplification. Next to reduction of required transmit power, this is a key factor as efficiency is often as low as 30%. It is important to note that the gain that could be achieved will be fully on top of the gain on the link level. Progress can be achieved by operating Power Amplifiers (PAs) with less back-off from their more efficient saturation point. This requires non-linear distortion terms to be managed, in particular with respect to out-of-band radiation. Many researchers in the REINDEER consortium have contributed to this domain for massive MIMO systems e.g. [72] and have the ambition to also address this for RadioWeaves deployments.

3. **Hardware Level - DSP** Design of low complexity digital processing, and a co-design of algorithms and architectures in that respect, is a key priority. Thereto, an initial analysis of hardware requirements is provided in an early phase, as exemplified in Chapter 6. This will be a crucial contribution, as increased DSP complexity **may jeopardize the gains** made at link level and in the PA stage.

4. **Network Level.** The many components in the full RadioWeaves should cooperate dynamically, and selectively switch to low power and sleep modes whenever possible, to achieve a lean operation. This should in particular reduce static power consumption, which can be a key contributor to the energy consumption in low load situations. We intend to develop

energy saving strategies based on the concepts of dynamic federations as logical entities in the RadioWeaves, which are introduced in Chapter 2 of this deliverable.

5. Reduce the energy consumption in the fronthaul and backhaul of wireless networks by providing decentralized compute power and storage capacity to allow for application to (partially) run locally in the RadioWeaves. The energy consumption on this level is not clearly modeled and accounted for so far.

Last but not least, **eventual network infrastructure implementation and deployment will need to be driven by sustainability targets, and rely on highly integrated and efficient platforms**. Clearly, the eventual implementation and deployment are beyond the scope of the REINDEER project. However, we can provide estimates on opportunities in implementing the RadioWeave infrastructure based on highly integrated, low power platforms that are typically used in mobile devices. Today, the digital processing in basestations is to a large extent implemented based on FPGAs, featuring specific accelerators [49], and software. While this 'adaptive computing' approach allows for upgrading towards new standard releases smoothly, it can not offer the energy efficiency achieved with full ASIC implementations. The migration of FPGA-based DSP implementation to ASIC may in itself bring an order of magnitude improvement. However, memory access also accounts for an important part of the energy consumption in the digital processing, which is not easily reduced.

Summarizing, in REINDEER we see a great potential in the development of RadioWeaves-based wireless networks to improve energy efficiency. The ambition to achieve a factor of 100 improvement is very high, and the possibilities to get there are not (yet) fully identified at this stage of the project. Furthermore, it is clear that we have been pursuing a moving target in the development of consequent generations of wireless technologies, attempting to improve beyond the energy efficiency at a higher pace than the increase in mobile traffic. The exponential evolution to some extent also should be questioned, as there are physical limits that even radical new transmission paradigms (link level) and excellent implementation in deeply scaled technologies (hardware level) can not overcome. Ultimately, the increase in mobile data will need to be slowed down. While applications are even more demanding, one way to save on total energy is to be smart about what we transmit and when. For example, the edge computing infrastructure in REINDEER can be exploited to reduce the data that actually needs to be transmitted. This could be for example by doing transcoding of video and other content, local processing of sensor data to determine when measurements are actually needed, rather than just measuring at a regular rate, identifying redundant data and combining it or dropping it, etc. While these data reduction measures mostly reside on application level and networking layers beyond the scope of REINDEER, we will identify opportunities where possible. Moreover, we will consider **the need to be able to achieve data reduction in the RadioWeave infrastructure** as a key requirement.

We will articulate the energy efficiency concerns and opportunities, and the priority it should be given in implementation and deployment, in our dissemination and communication activities.

4.2.2 Sustainability beyond efficient communication

It is clear that the ecological footprint of ICT networks is determined by several components, whereby energy efficient communication is one important contribution. Other parts to be assessed and taken into account in the future are e.g. the energy and materials required for establishing the infrastructure. While we acknowledge this is an important facet to consider, this is beyond the scope of this project. In this subsection we zoom in on the specific sustainabil-

Table 4.1: LCAs conducted in research to analyze the environmental impact of batteries. The cumulative energy demand (CED) and energy storage capacity E_c computed by the authors are used to compare the energy efficiency, i.e., E_c/CED, of battery usage in for non energy neutral devices.

Year	**Ref.**	**Type**	E_c	**CED**	E_c/**CED**
2015	[42][a]	LMO	$1\,\mathrm{W\,h}$	$0.85\,\mathrm{MJ\,eq}$	4.2×10^{-3}
2016	[14][b]	alkaline	$1.68\,\mathrm{W\,h}$	$0.7\,\mathrm{MJ\,eq}$	8.6×10^{-3}
2017	[62][c]	Li-ion	$1\,\mathrm{W\,h}$	$328\,\mathrm{W\,h}$	3.0×10^{-3}

[a] Parameters used in the table were taken from plotted data of the environmental impact comparison for solid state and laminated cells.
[b] Parameters used in the table come from the analysis for a AAA battery collected with a car.
[c] Contrary to the others, these batteries are rechargeable but only one charge cycle is considered here. Multiple charge cycles reduce the CED.

ity aspect of reduction of batteries typically containing toxic materials, for low-power connected devices. The REINDEER project through WPT will contribute to reducing the dependency on batteries for many connected nodes. However, it should be noted that this comes at an overall energy penalty in charging of these devices, as the efficiency of WPT is typically low. This is due to basic laws of physics, which restrict the mechanism to small energy budgets in absolute values.

The potential of RadioWeaves in terms of energy efficiency and sustainability hence extends beyond the domains of communication and computation. As indicated in Table 2.1, RadioWeaves inherently supports the wireless power supply of EN devices. These devices can be built batteryless and powered solely through RF WPT. By offering WPT as a service to its devices, RadioWeaves will make a tremendous difference to existing use-case scenarios as, for instance, enabling simultaneous communication and WPT to thousands of electronic shelf labels in supermarkets, and further pave the way for a sustainable, yet cost-effective IoT deployment.
Dolci et al. [14] conducted life cycle assessments (LCA) to analyze the environmental impact of battery usage. The significance of their findings is manifold, when comparing an IoT deployment of battery-powered devices with a deployment of EN devices:

1. The toxicity of batteries and their manufacturing and recycling processes have an impact on the environment in several ways including climate change, ozone depletion, freshwater eutrophication, human toxicity, etc. The aggravating fact that the overall collection rate of batteries within the EU lies around $50\,\%$ [18] and most of the not collected batteries are incinerated or landfilled adds significance to their environmental impact.

2. It has been found that rechargeable batteries outperform primary (non-rechargeable) batteries in terms of sustainability only, if they are used for at least 20 charge cycles[1] [14]. In either case, battery lifetime will always be limited. Battery-less EN devices, however, possess a virtually unconstrained lifespan[2] [2].

3. Several authors have found the overall energy efficiency of using batteries to be quite low: Table 4.1 shows a comparison of several works that analyzed the cumulative energy density (CED) of different types of batteries for various energy storage capacities E_c. We compute the ratio of usable energy that can be taken out of a battery, i.e., E_c, to energy that had to be spent to make, transport, and recycle the battery, i.e., the CED. Although the works have

[1] This is justified through the higher toxicity of the examined rechargeable NiMH batteries and additional waste generation due to the needed charger, compared with primary alkaline batteries [14].

[2] The authors in [2] mention the unconstrained lifespan when refering to passive RFID tags. According to our definition of EN devices, RFID tags are a type of EN device themselves.

been performed against different backgrounds, they reveal that the use of batteries is not energy efficient.

Historically, RF WPT systems were relying on forming narrow beams to transmit power efficiently [10], which conflicts with radiation exposure regulations for indoor use cases. Large, distributed apertures with large numbers of antennas will enable safe, regulatory compliant WPT at efficiency levels which are close to those computed in Table 4.1, as will be demonstrated in the REINDEER deliverable D4.1 [68]. In Section 6.3.1 we show that an RW panel could supply an EN device at $6\,\mathrm{m}$ distance through WPT with an efficiency level of 5.6×10^{-3} (i.e., a pathloss of $-22.5\,\mathrm{dB}$). Thus, EN devices have an efficiency comparable to battery usage (see Table 4.1) while having a much longer lifespan, and greatly reduced toxicity and waste generation.

Chapter 5

High-level architecture/topology

Architecture and topology are closely related concepts and here we use topology to describes how different network components are connected physically, which thereby acts as a limitation on the potential architectures that can be implemented on top of a certain topology. Both architecture and topology will influence network properties, with ramifications on necessary hardware requirements and associated costs. Considering the targeted modus operandi of RW, there are a multitude of new aspects that have to be taken into account, compared to traditional networks. Many of them emanate from the particular focus on exploiting the spatial domain with tight, synchronized, cooperation between CSPs.

To give a high-level illustration of some of the concerns related to RW, Fig. 5.1 shows how a set of CSPs are connected using four different basic topologies. The four topologies are Star, Tree, Ring, and Mesh. Four of the CSPs are in a federation to deliver a service, where tight cooperation with exchange of processing data and/or synchronization information is necessary. Some of the observations that can be made are:

- **Tight latency requirements** for a delivered service are directly translated to (even tighter) requirements on latency in the exchange between the federated CSPs. Making a reasonable assumption that the number of hops or potential congestion[1] are dominating latency-limiting factors, we see that all but the Mesh topology may lead to issues under tight latency requirements.
- **High reliability requirements** for a delivered service, where a high robustness of the interconnect between federated CSPs is required[2], is also influenced by the chosen topology. Both the Star and Tree topologies suffer from single point of failure, while the Ring topology has a certain robustness, where two points of failure are needed to bring down the federation. Again, the Mesh topology has an advantage, with two points of failure in the part of the network inside the federation needed to bring it down.

The above examples of topology considerations for RW are discussed in general terms, without any concern for the particular network architectures implemented on top of a physical network topology. Network architectures for synchronization and processing are discussed next, followed by a more in-depth discussion of topologies suitable for RWs.

[1] Congestion may originate both from the exchange between nodes in the illustrated federation or from exchange in other federations, not shown in the illustration.

[2] In addition to the reliability of the wireless links created by the federated CSPs.

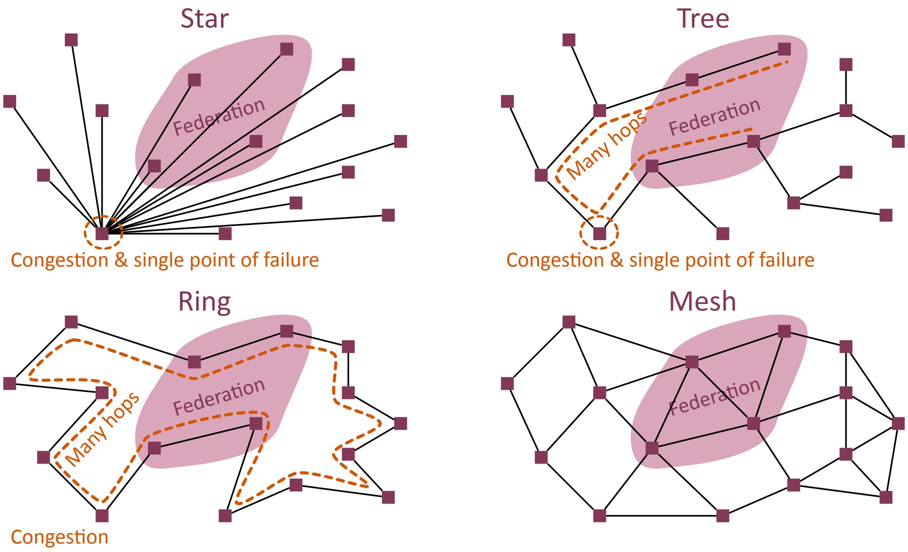


Figure 5.1: Four basic example topologies, Star, Tree, Ring, and Mesh, connecting a set of CSPs. Four of the CSPs are acting in a federation to jointly deliver a service.

5.1 Topology benefits and limitations

In the context of RW infrastructure, we are interested in evaluating different topologies to organize and connect different nodes or service points, such as CSP and ECSP. Each of these topologies, will offer different benefits and impose limitations to the overall infrastructure. One key limitation is directly connected to reliability, as in certain topologies, such as daisy-chain or a tree, the loss of one node due to a hardware failure or other problem could effectively take out the whole deployment. For use cases requiring a high level of reliability, this is a key consideration.

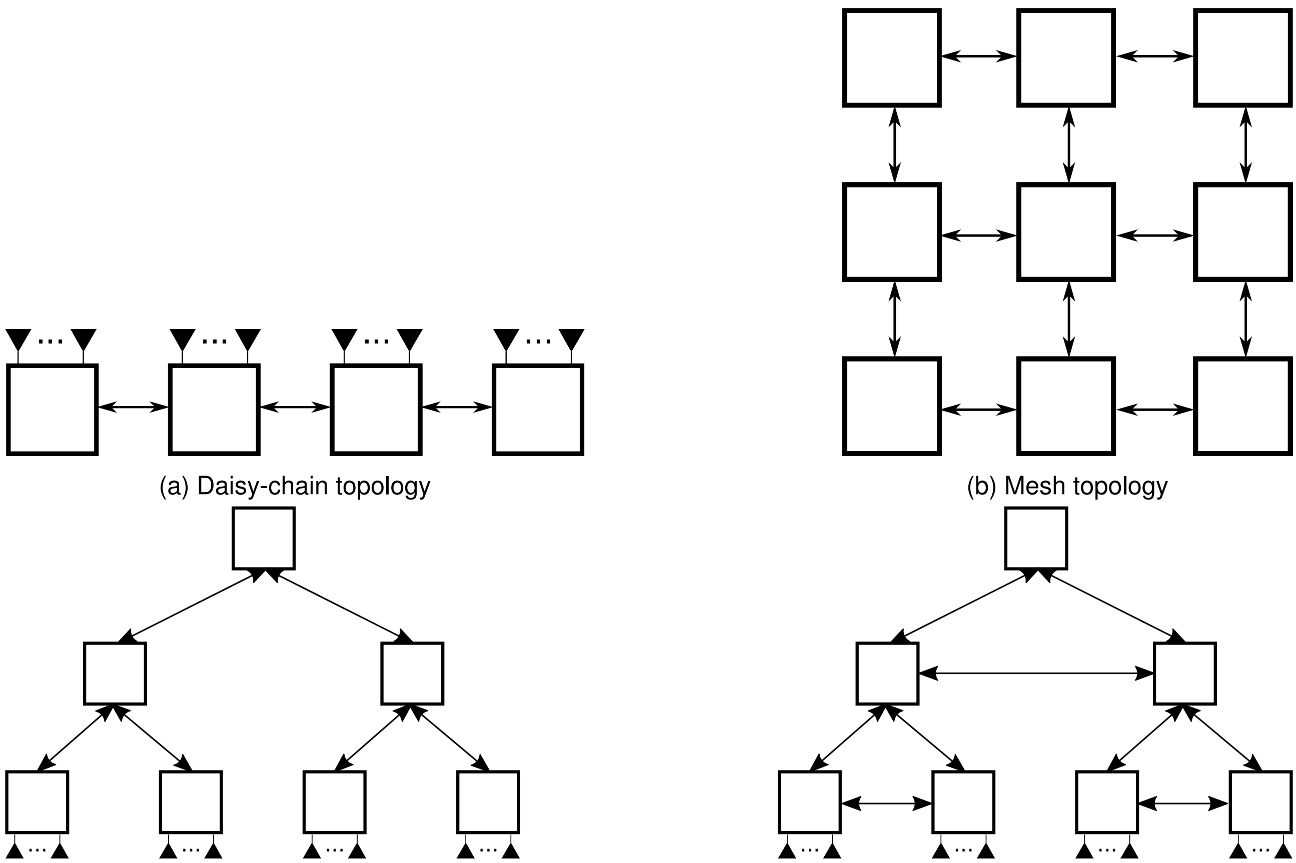
In this section we list and briefly describe some of the specific topologies available in the literature that are of consideration for RW infrastructure.

5.1.1 Daisy-chain

In the daisy-chain topology, shown in Fig. 5.2a, each service point is connected to two neighboring ones (except both ends) with bidirectional links.

Here we briefly describe the benefits of choosing this topology:

- Design reuse: Daisy-chain simplifies the design and deployment of the system, since all nodes have the same number of inputs/outputs and are required to support the same functionality (except probably one with back-haul access) and have the same inter-connection data-rates. This allows reuse of the same design for all of them. This reduces design and verification times.
- Easy to scale: Another advantage of this topology is that adding one more node into the system should be very straightforward, since it only requires the establishment of one (if an edge node) or two (first unlinking existing ones and link to new node) connections.
- Fully distributed: Daisy-chain is also appropriate in cases where a fully processing distribution wants to be achieved. This may be the case of a expected high processing demand (i.e. serving large number of spatially multiplexed users with high throughput demand) or/and lack of a *centralized* processing unit with enough resources.



(a) Daisy-chain topology

(b) Mesh topology

(c) Tree topology

(d) Hybrid topology

The topology also shows relevant limitations that we describe here:

- Latency: The number of hops required to go from one node to any other one scales linearly with the total number of them (N), which may limit its use in low-latency applications. Furthermore, applications with relatively high mobility could also be impacted by this limitation, as the wireless channel estimates need to be updated more often, including potential exchange of data between nodes for joint interference cancellation, as will be seen in Chapter 6.
- Reliability: A failure in any of the nodes in the chain may lead to a partial or total outage of the infrastructure.

As a summary, daisy-chain represents a solid candidate in use-cases where latency is not critical, mobility is not relatively high, deployment needs to be easy (minimum reconfiguration if new node is added), and maximum processing distribution wants to be achieved to accommodate for large processing demand.

5.1.2 2-D mesh

2-D mesh topology, shown in Fig. 5.2b, can be seen as the natural extension of daisy-chain in the 2-D world, where each node is connected to four neighbors, except the ones on the sides. By using the second dimension, the number of hops between any pair of nodes scales with $\sqrt{N}$, which is a significant improvement compared to the 1-D case. Additionally, the second dimension allows to overcome the reliability issue presented in daisy-chain, as if a node fails, re-routing is possible.

On the other hand, real implementation can become more complicated as each node may receive data from up to four neighbors, which may require a special attention to the synchronization among all nodes. Another disadvantage is the relatively large number of connections needed, which can limit the deployment over large areas, making this topology more preferable when nodes are physically co-located.

5.1.3 Multi-level tree

While in daisy-chain and 2D mesh all nodes are organized in a flat structure, multi-level tree introduces hierarchical levels. Tree topology, shown in Fig. 5.2c, establishes a single node as root node, which is connected to a certain number of nodes, which are also connected to other nodes in a recursive fashion.

One of the potential benefits of the multi-level tree is the reduction in the number of hops between two nodes, now scaling as $\log N$. This has potential benefits in term of latency.

As a potential limitation, we remark the existence of a root node, that may serve as *fusion node* or *aggregating point*, depending on the algorithm. This node may have a high computational demand in certain scenarios, leading to potential computational and inter-connection bottlenecks if the algorithm and implementation is not carefully selected for this topology.

As a summary, multi-level tree is an appropriate candidate in use cases where latency is also critical. The algorithm selection is crucial, as it needs to distribute processing across the nodes and limit the dependence on the root node. Examples of such algorithms are shown in next chapter.

5.1.4 Hybrid topology

Hybrid topology is essentially a multi-level tree topology with direct connections between nodes of the same level, creating local daisy-chains, which may be helpful for certain algorithms. Additionally, the number of hops is reduced compared to a multi-level tree. This is illustrated in Fig. 5.2d.

Hybrid topology presents benefits from daisy-chain, in terms of processing decentralization, and multi-level tree, to minimize processing latency, which makes it a solid candidate in a wide range of use cases.

5.2 Federations and ECSPs

The different topologies described above also have implications for the formation of federations and the placement and use of ECSPs. The same issues regarding latency and reliability that apply to interconnections between CSPs for coherently processing channel information also apply to communication between CSPs and ECSPs. Considering ECSP placement, congestion becomes an even larger concern, since ECSPs will function as aggregation sinks and distribution sources for application data as well as internal signalling for the infrastructure itself.

The formation of federations is limited (or conversely enabled) by the topology chosen, since a federation will need tight synchronization between all of its CSPs, as well as the FA (likely colocated with an ECSP), and in most cases also coherent processing of channel data from the CSPs. Depending on the purpose of the federation, i.e. the applications or users served, the latency constraints may be more or less stringent. For low latency applications, topologies with lower latencies such as mesh or tree topologies may be needed. Meanwhile, other applications may require a high degree of spatial diversity in the CSPs in the serving federation, for example to provide a large aperture for positioning. In such cases, if a low latency is not needed, a daisy chain or ring topology may be more feasible for connecting CSPs spread out over a larger area.

Chapter 6

Algorithms and processing distribution strategies

In the previous chapter we presented different topologies that dictate how the elements in the system are connected, and therefore how data is exchanged between them. In this chapter we introduce the techniques and processing considerations that fuel the different elements of the system, and enable the numerous applications and use cases described in Deliverable D1.1 [15].

Algorithms are a critical part of the system, and their selection will impact many system level parameters and KPIs. They formulate the instructions, for example, on how to operate, how to process the received signal, what data to share with peer nodes, how to aggregate information. Algorithms and topologies are not independent. The same algorithm in different topologies may yield different results. An adequate co-design of topology and algorithm is therefore important to achieve a highly efficient use of hardware resources and energy. Furthermore, as the system becomes physically large, and the demand for processing grows, there is a need to apply processing distribution strategies that aim to reduce interconnection data-rate and balance processing requirements across different nodes in the system.

In this chapter, we will start by introducing algorithms used specifically for communication purposes, including an algorithm-topology co-design discussion, followed by a selection of different methods for positioning. Finally, we will introduce the concept of wireless power transfer (WPT), first from a system point of view, to follow with a consideration about mapping to a RW infrastructure. These three fields of application are related to the RW infrastructure on different levels. Communication systems need to relay data between the different network entities, with specific requirements on, e.g., latency or data-rate, where the network topology has a direct influence, while also analyzing detection and precoding strategies which are of general interest. For positioning applications, the initial point of interest is on the measurement level, dealing with the, e.g., scaling behavior regarding the topology and identifying generally applicable parameters, i.e., position related measurements, that will be of interest in algorithm development. Similarly, wireless power transfer is analyzed on an application-oriented level, where the focus is initially put on the system capabilities in relation to the scaling behavior, e.g., with the aperture of the CSP or regarding the influence of the propagation environment.

6.1 Communication algorithms

As we contemplate the implementation of the RadioWeaves infrastructure, probably the first solution to consider consists of CSPs with antennas and ADC/DAC converters only. In uplink, baseband samples are then to be sent directly to one (or some) ECSP, that aggregates the incoming data, and performs baseband processing for detection and further decoding. While perfectly valid, this approach may lead to high interconnection bandwidth (and therefore high energy consumption), poor scalability properties, and excessive workload for such a node. Hence, performing local dimensionality reduction in the CSP by the use of baseband processing techniques seems as the right direction to alleviate these implementation issues. This approach can be combined with the data locality principle, by which data should be consumed as close as possible to where it is generated. These principles, that can be applied to CSP baseband processing, can be summarized as follows:

- Per-user processing: Performing per-user processing (apart from per-antenna processing) is the first step to reduce dimensionality and enable scalability. While in common massive multiple-input multiple-output (MIMO) systems we can expect a ratio of 10 between number of antenna elements and users, we foreseen even larger ratios for RW, leading to substantial potential reductions in dimensionality. Moving from antenna domain to user domain processing requires an equalization or detection method. Some of the existing detection methods in literature are presented in this section.
- User-locality: In spatially distributed and very large arrays as RW, the system may cover a large geographically area. Then, it is expected that a part of it (i.e. an RW) only receives sufficient signal level from a limited number of users, generally the ones closest. Therefore, an energy-efficient strategy for resources allocation should focus exclusively on those users.

The data locality principle and local per-user processing introduced before also implies that each CSP has knowledge of local channel information exclusively, and no element in the system has full knowledge of the complete channel information. Same approach is applied to the uplink filtering and precoding weights, where only local weights are needed to be stored. This assumption is key to ensure scalability and efficient use of resources.

In this section we introduce different existing methods in the literature for downlink precoding and uplink detection. Furthermore, we explore how these methods are mapped onto the existing topologies presented in previous chapter. For simplicity we will reduce our scope to linear methods, including maximum ratio transmission (MRT) and maximum ratio combining (MRC), zero forcing (ZF), and minimum mean square error (MMSE).

6.1.1 System model

In this document we consider a MU-MIMO system with a RW infrastructure (or corresponding federation) with M antenna elements serving to K single-antenna users. The system is made of N CSPs, and for simplicity we assume all have same number of antennas, this is: $M_{\text{CSP}} = \frac{M}{N}$.

The communication between RW and users is assumed to be based on time division duplexing (TDD) and orthogonal frequency-division multiplexing (OFDM) [1]. The $M \times K$ channel estimate

[1]Further exploiting the spatial domain is a main goal of RW, and OFDM-TDD is the preferred solution under this assumption.

matrix $\mathbf{H}$ can be written as $\mathbf{H} = [\mathbf{H}_1^T, \mathbf{H}_2^T, \cdot, \mathbf{H}_\mathsf{N}^T]^T$, where $\mathbf{H}_i$ is the $M_{\mathsf{CSP}} \times K$ channel estimate matrix of the i-th CSP.

In case of uplink, the signal received by antennas is

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{6.1}$$

where $\mathbf{x}$ is the $K \times 1$ users transmitted data vector, that we assume $\mathbb{E}\{\mathbf{x}\mathbf{x}^H\} = \mathbf{I}$, $\mathbf{n} \sim \mathcal{CN}(0, \sigma_n^2\mathbf{I})$ is an $M \times 1$ noise vector with Gaussian i.i.d. elements.

6.1.2 Detection and precoding

In case of uplink, for linear detection methods, the data vector estimated is obtained as

$$\widehat{\mathbf{x}} = \mathbf{W}\mathbf{y}, \tag{6.2}$$

where $\mathbf{W}$ is a $K \times M$ complex matrix, which can be written as $\mathbf{W} = [\mathbf{W}_1, \mathbf{W}_2, \cdots, \mathbf{W}_\mathsf{N}]$, where $\mathbf{W}_i$ is the $K \times M_{\mathsf{CSP}}$ filtering matrix corresponding to the i-th CSP. Similarly for $\mathbf{y}$, it can be written as $\mathbf{y} = [\mathbf{y}_1^T, \mathbf{y}_2^T, \cdots, \mathbf{y}_\mathsf{N}^T]^T$.

For downlink precoding, the $M \times 1$ array $\mathbf{y}$ at the antennas is given by

$$\mathbf{y} = \mathbf{P}\mathbf{x}, \tag{6.3}$$

where $\mathbf{x}$ is the $K \times 1$ data vector to transmit, $\mathbf{P}$ is the $M \times K$ precoder matrix, which can be also written as $\mathbf{P} = [\mathbf{P}_1^T, \mathbf{P}_2^T, \cdots, \mathbf{P}_\mathsf{N}^T]^T$, where $\mathbf{P}_i$ is the $M_{\mathsf{CSP}} \times K$ precoding matrix corresponding to the i-th CSP.

Each CSP is assumed to estimate the channel locally based on orthogonal pilots sent by users. This channel information is used to compute the filtering matrix for uplink detection and downlink precoding matrix. A priori we do not assume a block-fading channel model, rather we will assume interpolation in frequency domain to estimate channel response between subcarriers, and maybe across OFDM symbols. This may impose more severe constraints from computation time point of view when calculating the precoder weights [39]. In that sense, there is a need to verify the model with real measurements.

We now revise some of the most common methods for detection and precoding, followed by different processing strategies, including different algorithms available in the current literature.

6.1.2.1 Maximum Ratio Transmission (MRT) and Maximum Ratio Combining (MRC)

MRT/MRC is a technique for downlink precoding and data filtering in uplink respectively, where the goal is to maximize SNR at UE (case of MRT), and in the base station receiver (case of MRC). The vector of weights used is obtained directly from the channel estimate, more formally $\mathbf{W}_i = \mathbf{H}_i^H$, and $\mathbf{P}_i = \alpha\mathbf{H}_i^*$, where α is an scalar for meeting transmit power constraint.

MRT/MRC is suitable for distributed processing as there is no exchange of data for interference cancellation. That makes it possible for all baseband processing to be performed locally in the CSP, including detection and precoding.

Even though this method is well suited for distributed processing schemes, it shows limitations to cope with inter-user interference, which is critical in the case of scenarios with large number of users. On the other hand, having no data to exchange for interference cancellation reduces baseband processing latency and interconnection bandwidth. As a summary, we can conclude that this method is attractive in use cases with low latency constraints and reduced number of users.

6.1.2.2 Zero-forcing (ZF)

Zero-forcing (ZF) is another linear method for uplink detection and downlink precoding, that aims to cancel user interference. Having no interference makes the system capable of operating with a larger number of users and, therefore, considerably increase the capacity of the infrastructure to transmit and receive information by using RWs. To achieve that, CSPs need to exchange data (in contrast to MRT/MRC) with the consequent implications in terms of latency and interconnection bandwidth.

The filtering matrix is defined as $\mathbf{W} = (\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H$, while the precoding matrix is defined as $\mathbf{P} = \alpha\mathbf{H}^*(\mathbf{H}^H\mathbf{H})^{-1}$.

6.1.2.3 Minimum mean square error (MMSE)

While a ZF detector is able to cancel user interference, it may enhance the received noise during uplink filtering. To mitigate this issue, MMSE[2] can be used, as it presents the best trade off between interference cancellation and noise enhancement, by maximizing post-filtering SINR.

The filtering matrix is defined as $\mathbf{W} = (\mathbf{H}^H\mathbf{H} + \sigma_n^2\mathbf{I})^{-1}\mathbf{H}^H$, while the precoding matrix is defined as $\mathbf{P} = \alpha\mathbf{H}^*(\mathbf{H}^H\mathbf{H} + \sigma_n^2\mathbf{I})^{-1}$.

Different processing strategies can be used to realize the same method for detection or precoding. We differentiate two main classes of algorithms attending to the time relation and processing order of required operations: parallel processing and sequential processing. We describe both in more detail next.

6.1.3 Parallel Processing

Inside of this processing strategy we include algorithms that lead to a parallel processing approach during the filtering/precoding phase. The idea is to calculate the weights first by a procedure called *formulation*, and use those during filtering/precoding. In the case the block-fading channel model is of application in the context of RW, we could reuse the same weights for all transmitted signals under the same channel coherence block (time-frequency). As mentioned previously, this is left for further real measurements in order to validate the model. In case the block-fading model is valid, this would lead to a significant reduction in computational complexity, as shown in next section. Following this approach, the estimate (in case of uplink filtering) can be computed as

$$\widehat{\mathbf{x}} = \sum_i \mathbf{W}_i\mathbf{y}_i = \sum_i \Delta\widehat{\mathbf{x}}_i, \tag{6.4}$$

where $\mathbf{y}_i$ is the corresponding received vector at the antennas of the i-th CSP. This means that all CSPs can perform filtering with local data simultaneously in time, where the partial results are to be added throughout the infrastructure until the corresponding ECSP or *root* node, that performs final detection and decoding.

[2] It is worth to mention that when data vector $\mathbf{x}$ is assumed to follow a multivariate Gaussian distribution then the linear MMSE estimator described here is actually the MMSE estimator.

In case of precoding, user data (in the form of QAM symbols) are sent from root node to CSPs, which perform parallel precoding with local weights, this is

$$\mathbf{y}_i = \mathbf{P}_i \mathbf{x}. \tag{6.5}$$

We list below a number of relevant algorithms available in the literature within this processing strategy:

6.1.3.1 Channel Gram matrix adder

One algorithm that achieves exact ZF/MMSE solution requires of each CSP the computation of the Gram matrices based on local channel estimates.

For example, for the i-th CSP we have $\mathbf{G}_i = \mathbf{H}_i^H \mathbf{H}_i$. These matrices can be aggregated through the infrastructure and reach the root element for further matrix inversion as follows

$$\mathbf{D} = (\mathbf{H}^H \mathbf{H} + \mathbf{G}_0)^{-1} = \left(\sum_{i=1}^{N} \mathbf{G}_i + \mathbf{G}_0 \right)^{-1}, \tag{6.6}$$

where $\mathbf{G}_0 = \mathbf{0}$ in case of ZF, and $\mathbf{G}_0 = \sigma_n^2 \mathbf{I}$ in case of MMSE.

The resulting matrix $\mathbf{D}$ is broadcasted to all CSPs, which perform the following local computation to update filtering weights

$$\mathbf{W}_i = \mathbf{D}\mathbf{H}_i^H. \tag{6.7}$$

During filtering, the data vector estimate is computed as in (6.4), while for precoding (6.5) is used, and $\mathbf{P}_i = \alpha \mathbf{W}_i^T$ is assumed.

This algorithm can be mapped to all the presented topologies. For the particular case of tree, the authors in [9] identify the computational tasks, their cost, data dependencies, and communication requirements.

6.1.3.2 Lossless dimensionality reduction

One variant of the previous algorithm consists of the computation of matrix $\mathbf{D}$ as explained before, and not sending back to the CSPs. Then these perform MRC in distributed form, and the filtered signals are aggregated through the infrastructure to the root element, where multiplication with $\mathbf{D}$ occurs. It is worth to mention that this approach is based on the fact that the MRC (also known as matched filter) output consists of sufficient statistics for the estimation process, therefore reduction in dimensionality from M down to K is achievable without information loss. The resulting data can then be used for detection, achieving optimal performance if maximum likelihood method is used, or employing any available linear method such as MMSE.

6.1.3.3 Coordinate descent (CD)

In [71], authors introduce an approximate zero-forcing method based on coordinate descent (CD) for daisy-chain topology in Massive MIMO scenarios. With a very low computational complexity formulation, this algorithm achieves very good interference cancellation properties without the need of matrix inversion. Multiple iterations through the array improve the performance, closing the gap to ZF, but at the expense of an increment in latency.

6.1.3.4 Approximate ZF precoder

A novel approximate decentralized Massive MIMO ZF precoder for daisy-chain is presented in [75]. In scenarios where the number of antennas involved is large, the algorithm performs close to ZF. Main difference compared to CD algorithm is the constraint of same mean transmitted power at all antennas.

6.1.3.5 Adaptive interference cancellation

In [73] authors introduce a distributed processing architecture for uplink processing intended for large intelligent surface (LIS). The architecture consists of a hybrid topology, where a daisy-chain is used only during formulation of the filtering weights, and a tree is used during the filtering phase to reduce processing latency. A novel algorithm for dimensionality reduction is also presented in this work, which is based on singular value decomposition (SVD). The number of filtering weights per CSP is adaptive, therefore the algorithm is flexible enough to provide a rich number of working points depending on the performance/interconnection data-rate/computational resources requirements.

6.1.3.6 Fully-decentralized feedforward architecture

The fully-decentralized feedforward architecture presented in [37] is not an algorithm, but a framework to support mapping of different algorithms to different topologies during uplink equalization, aiming for low consumption of computational and interconnection resources. Under this framework, each CSP computes a point-estimate of the users transmitted data vector together with a post-equalization error variance vector. This soft-information allows for fusion of different estimates coming from different CSPs in an optimal way from a post-equalization SINR point of view. This fusion approach, despite being efficient from an interconnection data-rate point of view, incurs a performance penalty, as shown in [37].

6.1.4 Serial processing

The algorithms under the category of serial processing aim to achieve a sequence of estimates during the uplink filtering process. One CSP provides an estimate based on local observations, $\widehat{\mathbf{x}}_1$, which is then passed on to another CSP, that updates this estimate based on its local observations, this is $\widehat{\mathbf{x}}_i = f(\mathbf{y}_i, \mathbf{H}_i, \widehat{\mathbf{x}}_{i-1})$. This can be repeated as many times as nodes in the system, therefore generating the sequence $\widehat{\mathbf{x}}_1 \rightarrow \widehat{\mathbf{x}}_2 \rightarrow \cdots \rightarrow \widehat{\mathbf{x}}_{N_{\text{CSP}}}$. Typically we look for linear combiners of the form $\widehat{\mathbf{x}}_i = \mathbf{A}_i\mathbf{y}_i + \mathbf{B}_i\widehat{\mathbf{x}}_{i-1}$.

During the formulation phase, the CSPs obtain the matrices $\mathbf{A}$ and $\mathbf{B}$, which may or may not require data exchange between nodes. Additionally there is no need to explicitly share local observations between CSPs (only the estimates) during filtering, therefore saving important communication resources and energy. The main limitation of this approach probably lies in the sequential dependency of the estimates, which impose a latency overhead. This dependency also plays an important role during the mapping to the topology as we will see in the next section. We list some of the available algorithms in literature under this category.

6.1.4.1 Recursive Least Squares (RLS) and sequential LMMSE (S-LMMSE)

As the ZF method can be seen as the Least Squares (LS) solution to the problem $\min_{\mathbf{x}} \|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2$, its recursive version (RLS) can be used for a distributed processing scheme by unrolling the processing tasks as shown in [74]. A similar approach can be applied with the sequential version of LMMSE (S-LMMSE), described in [40] and defined as follows

$$\widehat{\mathbf{x}}_i = \widehat{\mathbf{x}}_{i-1} + \mathbf{K}_i(\mathbf{y}_i - \mathbf{H}_i\widehat{\mathbf{x}}_{i-1}), \tag{6.8}$$

where

$$\mathbf{K}_i = \mathbf{M}_{i-1}\mathbf{H}_i^H(\sigma_n\mathbf{I} + \mathbf{H}_i\mathbf{M}_{i-1}\mathbf{H}_i^H)^{-1}, \tag{6.9}$$

and

$$\mathbf{M}_i = (\mathbf{I} - \mathbf{K}_i\mathbf{H}_i)\mathbf{M}_{i-1}, \tag{6.10}$$

where $\mathbf{K}_i$ and $\mathbf{M}_i$ are matrices. To initialize we take $\widehat{\mathbf{x}}_0 = \mathbf{0}$, and $\mathbf{M}_0 = \mathbf{I}$. This algorithm has been applied to Cell-Free Massive MIMO networks in [77], where non-ideal CSI and colored noise is considered. This algorithm is also the base of the one proposed in Deliverable D3.1, under the name *Kalman Filter*, which also includes support for fusion of estimates.

6.1.4.2 Serial Coordinate Descent

The CD algorithm described before can be expressed in a serial form as shown in [71]. The key idea of this algorithm is to replace the matrix $\mathbf{K}_i$ in (6.8) with another one, which does not require matrix inversion. This provides a significant reduction in computational complexity, in exchange of a performance loss compared to the MMSE method.

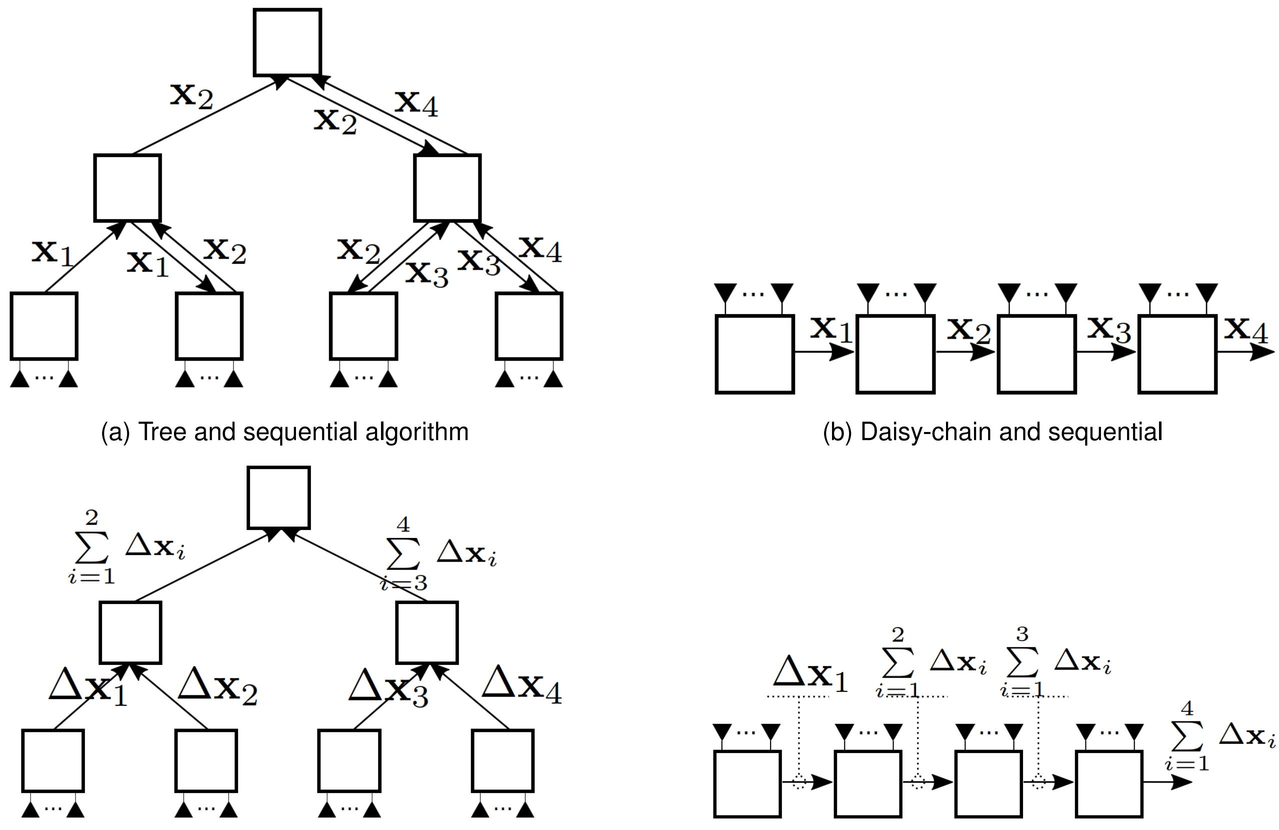
6.1.5 Mapping to the architectures

In order to map algorithms to topologies, a distribution of the processing resources in the system must be defined. The processing capabilities of each node in the system are vital to make sure we are able to map certain processing onto it. In general we assume that each node contains baseband processing, memory and inter-connection resources. They may or may not contain antenna elements depending on the topology and the role of the node.

Each of the algorithms listed before can be mapped to any of the presented topologies (assuming the nodes are able to support it). However, the impact on computational complexity and interconnection data-rate at each processing element and link respectively is different, making some topologies more appropriate for certain algorithms and viceversa.

Algorithms under the parallel processing category allow all processing elements to perform filtering (or precoding) at the same time, which means that their results are also ready at the same time. A tree-based topology can be used to aggregate such results at low latency, while requiring more links than other topologies, like daisy-chain, where the accumulation is done throughout the elements in the chain as shown in Fig. 6.1c and Fig. 6.1d respectively. A combination of both topologies, i.e. a tree with chains as leaves, is perfectly supported under this category. In the case of the mesh topology, aggregation routes need to be defined and the abundant number of links offer higher reliability against hardware failures. A hybrid topology can be treated as a tree topology during the filtering/precoding phase.

For algorithms in the serial processing category, the suggested approach is to map each iteration (computation of each element in the sequence of estimates) to a different physical node (such



(a) Tree and sequential algorithm

(b) Daisy-chain and sequential

(c) Tree and parallel algorithm

(d) Daisy-chain and parallel algorithm

Figure 6.1: Result of mapping sequential and parallel algorithms onto different topologies, such as tree and topology. Four panels process received signal from users to provide a estimate of the transmitted symbols.

as CSP). Doing that, channel state information and received antenna data remains in the node and does not have to be exchanged, therefore reducing inter-connection data-rate in the system. During filtering, the estimates are the ones that are passed from one node to the following, while during formulation (if existing), data for interference mitigation is exchanged. Certain topologies are more suitable than others for this type of algorithms as shown in Fig. 6.1. While daisy-chain represents the natural fit for them, other ones like the tree may suffer from an increase in inter-connection data-rate and latency as shown in Fig. 6.1a, as the estimates need to be routed in a sequential fashion that may imply multiple hops to reach to the next processing node.

6.1.6 Initial analysis of hardware requirements

In this subsection we present an initial analysis of the presented algorithms and topologies based on their hardware requirements. Results for uplink filtering are shown in Table 6.2, where no dimensionality reduction is assumed (panels process all users, K). Dimensionality reduction techniques such the ones proposed in [73] reduces computational complexity and interconnection data-rate in exchange of potential performance loss.

For simplicity we only cover two topologies, daisy-chain and tree. System parameters used in the analysis are listed in Table 6.1. From table 6.2 we can observe that sequential algorithms imply twice as much computational complexity as parallel ones, making computational complexity the main drawback of sequential approaches. Additionally, the sequential tree requires twice as much

Table 6.1: System parameters.

Parameter	Definition
M_{p}	number of antennas per CSP
N	number of CSPs
n_{b}	bit-width of each element (real + imag) of $\widehat{\mathbf{x}}$ and $\Delta\widehat{\mathbf{x}}$
K	number of users
f_{B}	signal bandwidth (Hz)

Table 6.2: Analysis of hardware requirements for sequential and parallel algorithms in daisy-chain and tree topologies. Only uplink filtering considered. Computational complexity refers to a panel, while interconnection data refers to any link in the system. No dimensionality reduction assumed. N: number of panels. d: maximum number of children per node in the tree. a: Assuming baseband processing latency much larger than routing latency. For the number of links in the tree, N is assumed large. Units: Computational complexity [MAC/s], interconnection data-rate [bps], processing latency [s].

Algorithm - Topology	seq. daisy-chain	parallel daisy-chain	sequential tree	parallel tree
Comp. complexity	$2KM_{\mathsf{p}}f_{\mathsf{B}}$	$KM_{\mathsf{p}}f_{\mathsf{B}}$	$2KM_{\mathsf{p}}f_{\mathsf{B}}$	$KM_{\mathsf{p}}f_{\mathsf{B}}$
Inter. data-rate	$n_{\mathsf{b}}Kf_{\mathsf{B}}$	$n_{\mathsf{b}}Kf_{\mathsf{B}}$	$\approx 2n_{\mathsf{b}}Kf_{\mathsf{B}}$	$n_{\mathsf{b}}Kf_{\mathsf{B}}$
Processing latency	$\mathcal{O}(N)$	$\mathcal{O}(N)$	$\mathcal{O}(N)^a$	$\mathcal{O}(\log N)$
Number of links	N	N	$\approx N\left(\frac{d}{d-1}\right)$	$\approx N\left(\frac{d}{d-1}\right)$

interconnection data rate as the parallel version due to the links being used in both directions, as illustrated in Fig. 6.1a.

Daisy-chain and corresponding algorithms seem a reasonable choice when latency is not critical, as it simplifies control and enables easy scalability. For use cases where latency is the main concern, the number of elements in the chain has to be kept below a certain value, or a tree topology can be used instead, as we explain next.

In general, a parallel tree (and a hybrid) seems very attractive for latency critical applications with a large number of nodes. It shows the lowest hardware requirements, except for the number of links, which is larger than daisy-chain. However, as the number of children per node increases in the tree (d in Table 6.2), the number of links becomes the same as for a daisy-chain.

6.2 Algorithmic requirements for positioning and localization

Section 6.2.1 gives an overview of potential position related measurements and Section 6.2.2 relates these to the envisioned RW architecture to evaluate potential use in positioning algorithms. Section 6.2.3 treats aspects that are specific to the envisioned RW hardware.

Positioning and localization algorithms rely on position related measurements to estimate the position of radio devices. These measurements are obtained from received signals by means of suitable estimation procedures based on dedicated measurement models describing the relation to the propagation delay and direction of arrival of the signals and are the input of positioning algorithms. The accuracy of these algorithms is related to the accuracy of the measurements, which in turn depends on different system parameters such as bandwidth or the number of available antenna elements in an antenna array, and on environment properties such as multipath propagation characteristics or the geometric configuration of the radio devices.

Development of new estimation procedures and models of the measurements and radio channels are of interest in performance and accuracy considerations of algorithms for parameter estimation, environment estimation and learning as well as in the final channel model.

In positioning literature, the interacting radio devices are commonly termed anchors and agents[3]. The anchors located at known positions $\mathbf{a}_l = [x_{\mathrm{a},l}, y_{\mathrm{a},l}, z_{\mathrm{a},l}]^\mathsf{T}$ and the agent at $\mathbf{p} = [x, y, z]^\mathsf{T}$ in standard positioning applications. With respect to the terminology described in Sec. 2.1 an anchor suitable for positioning can be any device at a known position capable of transmitting and receiving signals, with the resulting position-related measurements either obtained from the signals directly at the anchor or obtained, i.e., estimated, by another device and passed along to the processing unit. In the RW infrastructure an anchor is a CSP that interacts with other CSPs, either to relay the received signals to a processing unit in form of an ECSP or a federation, by performing local computations to extract the measurements which are then relayed to a processing unit or by directly performing positioning tasks. Combing the measurements of different anchors requires a certain level of synchronicity to allow correct measurement fusion, which ultimately depends on the position-related measurements and the mobility of the agent. Beamforming with a large panel for example requires phase coherency over the full panel, while data fusion of the measurements of distributed smaller panels requires less stringent time synchronization on the level of the channel coherence time. The latter approach also has the advantage of distributing the processing resources. These synchronization tasks between separate CSPs are performed by a synchronization anchor (SA) while generation and termination of federations is orchestrated by a FA. The agent is the UE and can belong to different device classes [15], which results in different measurements being of interest for each class. The different levels of mobility furthermore have an effect on the choice of positioning algorithm.

Regarding the co-existence of communication and positioning, it is expected that pilot signals used for communication are also suitable for position related tasks. An example thereof can be found in [32] where an iterative-receiver for an OFDM system is proposed that employs a parametric channel estimator. Still, certain trade-offs are expected to be necessary, with the initial analysis presented in this deliverable functioning as a starting point to investigate possible issues.

[3]Alternative terms are *base station* and *mobile device* respectively

6.2.1 Position related measurements

This section presents a discussion of basic position related measurements that can serve as input to positioning algorithms. Measurements of interest obtained from channel estimators are time-of-arrival (TOA), time-difference-of-arrival (TDOA), angle-of-arrival (AOA)/angle-of-departure (AOD) or received signal strength (RSS) which are then used to estimate the UE position, either as point estimates or as posterior distributions in Bayesian algorithms. Alternatively, one can use the full signals to directly estimate the UE position in direct positioning approaches.

6.2.1.1 Received signal strength (RSS)

RSS measurements can be used to estimate the propagation distance when an accurate path loss (PL) model is available. A simple model for received RSS values r_{RSS} including only distance dependent components is

$$r_{\mathrm{RSS}} = P_0 - n \cdot 10 \log(d) \tag{6.11}$$

where d is the distance between transmitter and receiver in m and n is the path loss coefficient. P_0 denotes the reference power at a distance of $1\,\mathrm{m}$ and is assumed known.

The path loss exponent n is usually assumed $n = 2$ for free space, but it is often $n \leq 2$ in indoor environments. A positive aspects of RSS measurements is the relative robustness with respect to imperfect synchronization. A downside is the strong sensitivity towards amplitude fading introduced by multipath propagation and shadowing which is present in practically all environments.

The resulting distance estimation accuracy for the model in (6.11) can be quantified by means of the Cramér-Rao lower bound (CRLB) as [3]

$$\mathrm{var}(\hat{d}) \geq \frac{\sigma_n^2 d \log(d)}{n^2 + 2\sigma_n^2} \tag{6.12}$$

where σ_n^2 is the variance of the path loss exponent estimation error. While RSS measurements are of interest in low-cost hardware with limited processing power, the accuracy is usually in the range of a few meters [25] which can be insufficient in many applications of interest.

While small scale fading effects can be countered by time-averaging of the RSS measurements, shadowing can only be countered by performing spatial averaging, e.g., by using distributed CSPs or when tracking a moving UE. RSS measurements in the context of distributed (massive-)MIMO systems are treated in [65] where machine learning methods were used in positioning of UEs when shadowing effects are distorting the RSS measurements.

In addition to shadowing, directional properties of the antennas can be included and exploited in positioning algorithms [91, 83] as well as unknown channel characteristics [26]. In terms of robustness, Bayesian approaches usually are preferable [11, 53, 12], which are applicable independent of the type of measurement.

6.2.1.2 Time-of-arrival (TOA) and Time-difference-of-arrival (TDOA)

A popular approach to estimate distances between transmitter and receiver are time based measurements. While these require accurate time synchronization, a high accuracy can be achieved at low computational complexity. The distance estimates are either extracted directly from the received signal using parametric model based algorithms (e.g., likelihood-based estimators or matched filtering) or based on transmitted time codes (e.g., one-way-ranging or two-way-ranging). The synchronization requirements can be relaxed by using TDOA measurements, i.e., relating all TOAs to a chosen common reference TOA.

A simple model for the discrete time-domain received signal $\boldsymbol{r}$ consists of a single delayed and scaled transmit waveform representing the line-of-sight (LoS) as

$$\mathbf{r} = \alpha \mathbf{s}(\tau) + \mathbf{w} \tag{6.13}$$

with complex amplitude $\alpha \in \mathbb{C}$, time delay τ related to the distance d via the propagation speed c as $d = c\tau$ and delayed signal vector $\mathbf{s}(\tau) = [s(-\tau), s(T_s - \tau), \ldots, s((N-1)T_s - \tau)]^\mathsf{T}$ containing the sampled transmit waveform $s(t)$. The noise vector $\mathbf{w}$ can either be modeled as zero mean additive white Gaussian noise (AWGN) or as colored noise, representing diffuse multipath and AWGN by a suitably structured covariance matrix. From analyzing the CRLB the achievable ranging accuracy is known to depend on the bandwidth of the transmitted signals and on the SNR for AWGN channels and on the SINR in diffuse multipath channels, where in the latter interference is modeled by means of colored noise with exhibiting a double exponential power delay profile (PDP). The CRLB for the LoS delay is found in closed form as [86]

$$\mathrm{var}(\hat{d}) \geq \frac{c^2}{8\pi^2\beta^2 M \widetilde{\mathrm{SINR}}} \tag{6.14}$$

where M denotes the number of receive array elements, β^2 is the root mean square (RMS) bandwidth and $\widetilde{\mathrm{SINR}}$ is the effective SINR for delay estimation, quantifying the joint effect of AWGN and diffuse multipath propagation. In dense multipath environments, the effective SINR is usually lower then the SNR that takes only AWGN into account, i.e., $\widetilde{\mathrm{SINR}} \leq \mathrm{SNR}$ [34]. The bound for an AWGN-only channel is obtained by exchanging $\widetilde{\mathrm{SINR}}$ with SNR [69, 79].

When using TOA measurements for positioning, the accuracy is independent of the propagation distance and the distance information that influences the positioning accuracy points in propagation direction [79] (c.f., the following section dealing with AOA measurements). Extending the model in (6.13) to include multipath propagation allows to exploit position information contained in the environment when using suitable multipath channel estimators [20, 32] to improve the positioning accuracy [44] as well as the communication performance [48, 50]. In addition, simultaneous localization and mapping (SLAM) approaches allow to learn an environment map while simultaneously localizing the agent based on the obtained multipath delay measurements [52, 24]. A difficulty arising in multipath channels is the negative effect of path overlap on the estimation accuracy of the path delays as well as resulting position estimates [78].

6.2.1.3 Angle-of-arrival (AOA)

Estimating the AOA of signals requires the use of antenna arrays consisting of multiple sensors that can be processed coherently. Depending on the signal bandwidth and array size different types of signal models are used: narrowband (NB) and wideband (WB) models both exploit phase differences at the array elements in combination with the far-field plane-wave assumption and ultrawideband (UWB) models take the propagation delay of the receive signal along the array aperture into account, in combination with the plane wave or spherical wave assumption. For the latter case this is necessary as the inverse bandwidth (representing a measure for the signal duration) being in the same order of magnitude as the array aperture.

A standard (2-dimensional) parametric array model for time-delay τ and angle φ stored in the parameter vector $\boldsymbol{\theta} = [\tau, \varphi]^\mathsf{T}$ for an array with M elements can be written in form of the sampled received signal at the mth element as [38]

$$\mathbf{r}_m = \alpha e^{i2\pi f_c \tau_m(\boldsymbol{\theta})} \mathbf{s}(\tau - \tau_m(\boldsymbol{\theta})) + \mathbf{w}_m \tag{6.15}$$

where τ is the delay from anchor to the array reference point $\mathbf{p}$ as defined in the previous section and the phase change due to the array geometry is represented by $\tau_m(\theta)$. Assuming plane wave propagation, this becomes $\tau_m(\boldsymbol{\theta}) = \mathbf{p}_m^\mathsf{T}\mathbf{u}(\varphi)/c$ which is the relative delay of the mth array element w.r.t. to the array reference point. The incidence direction is represented by a unit direction vector $\mathbf{u}(\varphi)$, while $\mathbf{p}_m$ denotes the mth array elements position relative to the array reference point. Equation (6.15) is suitable for ultrawideband systems. A wideband model is obtained by neglecting the relative delay in the transmitted waveform using only $\mathbf{s}(\tau)$, while narrowband models simply assume a constant waveform. Assuming that the noise vector $\mathbf{w}_m$ includes AWGN and colored noise, with the latter representing diffuse multipath propagation, the CRLB for the AOA for the above array model is found to be [86]

$$\mathrm{var}(\hat{\varphi}) \geq \frac{1}{8\pi^2 D^2(\varphi) M \mathrm{SINR}} \tag{6.16}$$

where $D^2(\varphi) = \frac{f_c^2}{M}\sum_{m=1}^{M}\left(\frac{\partial \tau_m(\boldsymbol{\theta})}{\partial \varphi}\right)^2$ is the normalized squared array aperture and SINR is the SINR for AOA estimation in diffuse multipath channels [86]. For the case of a uniform linear array (ULA), the normalized squared array aperture becomes $D^2(\varphi) = \frac{1}{M}\sum_{m=1}^{M}\frac{p_m^2}{\lambda^2}\sin^2(\varphi - \varphi_m)$ where p_m and φ_m are distance and angle of the array element position in (local) polar coordinates. The SINR is related to the SNR arising in the CRLB for an AWGN-only channel [51, 27, 31] and the effective SINR for ranging in diffuse multipath channels and generally fulfills $\kappa \leq \mathrm{SINR} \leq \widetilde{\mathrm{SINR}} \leq \mathrm{SNR}$ where κ denotes the power ratio between the LoS and the diffuse multipath.

When using AOA measurements for positioning, each measurement contributes position information that is inversely proportional to the propagation distance and oriented perpendicular to the direction of the AOA [31, 86]. Antenna selection strategies are analyzed in [4] showing the trade-off in terms of accuracy when the received power is normalized, allowing to find an optimum point of the used number of array elements. While investigating a different frequency range than targeted with RW, theoretic results from millimeter wave (massive-)MIMO systems are expected to scale to lower frequency bands to some extent. Considering systems with arrays employed at both the anchor and the agent, analysis of the scaling behavior with respect to the number of transmit and receive antennas M_T and M_R respectively shows that uplink positioning, i.e., with the agent transmitting, benefits much more from increasing M_R than for the downlink case [1]. While increasing the number of antenna arrays improves the accuracy of AOA estimation, the number of beams necessary to cover a certain region where the target could be located also increases, as the beamwidth is inversely proportional to the number of array elements [76].

6.2.1.4 Direct positioning

The above approaches commonly make use of the simplifying assumption of plane wave propagation for computational efficiency (especially for the case of AOA estimation) and due to the sufficiently accurate approximation when all devices are located in the far-field [38]. When using large arrays the far-field plane wave assumptions is often not fulfilled, resulting in a model mismatch inducing errors [30]. This problem is overcome by a direct positioning approach which works on the signal level, i.e., without prior estimation of separate position-related parameters [90].

The models in use are similar to the ones introduced above, with the main difference that the model parameters are expressed using the UE and CSP positions $\mathbf{p}$ and $\mathbf{a}_l$ respectively [23, 29, 61], e.g., as $\tau_l(\mathbf{p}) = \|\mathbf{p} - \mathbf{a}_l\|/c$ for the delays. While inherently similar, it can be shown that direct positioning results in improved performance in positioning using MIMO radar [6] or in multipath-assisted positioning where the necessity for association of estimated parameters, e.g., delays, and environment features is overcome by directly evaluating the model likelihood at the hypothesized positions [41]. Apart from positioning of the UE, also scatterers can be localized by exploiting the spherical wavefront that is observed over large arrays [89]. When employing narrowband sources it can furthermore be shown that in the far-field of the array distance estimation from the wavefront curvature fails as the curvature decreases [29]. Transitioning from large arrays to LISs, the scaling behavior of the CRLB for positioning using LIS shows a thresholding effect that limits the effective usable size of the LIS [36, 33].

6.2.2 Mapping to the architecture

The RW infrastructure as described in Sec. 2.1 can be related to positioning algorithms based on estimated position-related measurements using the models described in Sec. 6.2.1, with the main characteristics of the RW infrastructure analyzed in this section.

The RW architecture is envisioned to provide a large spatial aperture, e.g., either due to a large number of array elements M or due to the distribution of the panels in a large spatial region. This large effective aperture will in theory yield a high accuracy, assuming perfect synchronization and coherency. The accuracy is expected to be degraded by the non-stationary environment but also by the fact that different panels are not expected to be perfectly phase coherent due to the high cost this would place on the hardware. Due to the wide distribution of the sensing devices the channels between devices have different statistical properties, which needs to be accounted for on the algorithm level. In the simplest form, this can be achieved by applying algorithms to subsets of the available panels and perform data fusion on a higher level, e.g., by forming federations based on the similarity of the environment that is sensed by the panels. Regarding array processing, it is assumed that only a small portion of the large panels can be processed within the stricter bounds of phase coherency that is necessary for array processing. In combination with the relatively limited bandwidth which is assumed to be in the range of $100\ \mathrm{MHz}$, the data processing can be performed directly at local processing units, at ECSPs or at other units in the federations. This separation into smaller processing groups or federations is based on the architectures and topologies introduced in Chapter 5, where only a limited number of CSPs is directly connected. With different topologies expected to introduce different levels of latency, the effects on the positioning accuracy need to be analyzed in detail. Exemplary for the daisy chain topology, similarities to standard tracking filters can be drawn, with each node performing a local fusion step and passing the obtained result to the next node. This would allow to consistently incorporate more knowledge and refine the obtained (position) estimates, while allowing each node to perform the same computations without an increase in complexity. Similar approaches are envisioned for the other topologies, with each node performing local data fusion, whereas more connections require to optimize the scheduling. The key to the required high positioning accuracy is seen in exploiting the large aperture as well as an efficient data fusion of channel estimates obtained locally at each (or possibly a small subset) of panels or nodes.

With devices of different device classes [15] being part of the infrastructure the selection of position-related measurements that are usable for positioning will strongly depend on the communication capabilities of the devices to localize. Low-power devices without any or with only limited power supply or storage have to be powered or charged wirelessly, without excessive communication or channel sounding possible beforehand. Thus, combinations of RSS-, TDOA- or AOA-based procedures with the main processing performed at the CSP will be of interest. For the case of RSS-based positioning, the wide distribution of the RW infrastructure can provide a good coverage and the possibility to obtain environment maps for the necessary path loss models, which can be used either for an initial coarse position or when only low accuracy position estimates are required. Devices capable of synchronization over the infrastructure allow to exploit the higher accuracy that can be achieved with TOA-based procedures and high-level channel estimation from the signals received from transmitted pilots or similar channel sounding procedures. As the CRLB for distance estimation (6.14) is inversely proportional to the signal bandwidth and the number of receive elements (while being directly related to the achievable positioning accuracy [79, 31]) maximizing both is desirable. While AOA estimation in AWGN-only channels is bandwidth independent, diffuse multipath channels show an increased overlap between diffuse multipath components and the direct path or multipath components, which results in a bandwidth dependency of the SINR and consequently the AOA estimation accuracy.

In both time and angle based positioning, specular multipath components can be exploited to improve the positioning accuracy by using floor plan information [44, 88, 84, 85, 55], which is seen as another main field of interest for RW, as the large aperture is expected to allow resolving and exploiting multipath components by using environment maps. When environment maps are not available with suitable accuracy or not at all, the environment can be learned by exploiting common information extracted from the signals received at different spatial locations using suitable SLAM approaches [45, 24, 46, 43].

6.2.3 Initial analysis of hardware requirements

The main limiting factors for positioning are expected to be the bandwidth of the transmitted signals used for channel estimation, the number of radio/antenna elements per panel, i.e., the number of antennas per panel that can be used phase coherently, and the total number of CSPs that can perform measurements with the agent. Note that the latter is on the one hand related to the environment, e.g., with shadowing being a limiting factor, but also by communication limitations such as the number of devices that can be served simultaneously. For combining separate measurements of different anchors, the synchronization and the correct association of measurements from different panels will be essential which needs to be dealt with on the algorithm level, i.e., when exploiting an environment model for positioning or in the learning phase of the environment model.

Due to the large RW aperture or wide spatial distribution of the panels, a spherical wave model should be employed and consequently direct positioning approaches when the target device is in the aperture near field. In addition, larger distances between panels can result in a degradation of the synchronization accuracy of the panels, e.g., due to different synchronization anchors being responsible. Depending on the severity of the synchronization error, this needs to be considered in the employed estimation algorithms [54] to support or relieve the hardware. Assuming that cooperating CSPs share a common SA, algorithms for network wide synchronization can be employed [70, 80], requiring only a limited number of devices cabale of high accuracy synchornization. For use cases where tight synchronization between CSPs is necessary, e.g., in high mobility tracking, the RW architecture should allow incorporating the results obtained by joint positioning and synchronization algorithms to refine the synchronization of CSPs. Imperfect synchronization between CSPs and the UE requires to estimate the clock offset which will result in a deterioration of the achievable positioning accuracy, with the geometric setup of CSPs and UE can be used to counter this effect as well as coarse synchronization information that can used as prior information [79].

Depending on the positioning method, transferring either the full recorded data on the signal level or the locally estimated position related measurements from each panel to a processing unit will be the main bottleneck regarding data transmission bandwidth. The former is required by direct positioning and is expected to require a larger transmission bandwidth while allowing a generally higher accuracy. The latter allows for a more efficient use of transmission bandwidth as well as initial position estimates that can be obtained directly at the CSP by the processing units while estimation inaccuracies due to the smaller aperture compared to the full data might yield sub-optimal results. Forming federations can in turn exploit the already existing local channel estimates, e.g., choosing only CSPs that received signals from a specific spatial region for data fusion.

6.3 Wireless power transfer

RadioWeaves, being an infrastructure with distributed radio elements, offers unforeseen potential for wireless power transfer (WPT): large numbers of antennas that coherently transmit power to desired points in space can yield a large array gain that will enable RF WPT at unmatched efficiency levels. The use of sub-10 GHz frequencies allows to form physically large apertures that are spaced at Nyquist distance[4]. An aperture being physically large results in power coherently adding up in a focal point rather than a beam, which in turn yields in a high receivable power within the focal point and a low radiation exposure everywhere else[5]. A spacing at Nyquist distance results in power being focused in a single focal point. Antennas uniformly spaced at distances greater than Nyquist distance would result in grating focal points that are not desired. Indoor RadioWeaves deployments benefit from the strong multipath propagation present. As is shown later in this section, specular reflections along walls can effectively be used to focus energy via walls to the position of an EN device and thereby even increase the power budget over what is achievable in free space. We envision environment-awareness an important tool that can help with the initial access for EN devices: knowing the environment surrounding an RW panel, a focal point can be swept across spaces where EN devices may possibly be located (e.g., on shelves, along walls, floors and ceilings). In this search procedure, the array gain can be used to extend the initial access distance significantly.

A range of uplink combining and downlink precoding schemes with possible applicability for a RadioWeaves architecture have been analyzed in the REINDEER deliverable D3.1 [87]. For an initial analysis of the potential of RadioWeaves regarding WPT, we use perfect channel state information (CSI) and maximum ratio transmission (MRT) for power focusing. Together with additional assumptions on idealizing conditions, the results presented in this section may hint at the upper bound of the possible power budget for RadioWeaves.

6.3.1 WPT for RadioWeaves

6.3.1.1 System description

This section will demonstrate the potential of RadioWeaves in the context of WPT. For simplicity, the RW panel used is a single uniform rectangular array (URA) spaced at $\lambda/2$, which is mounted on a wall parallel to the xz-plane (see Fig. 6.2). It has dimension l_x and l_z, respectively, which define its physical aperture A. A multiple-input single-output (MISO) system model is considered in this section where a number of L_t antennas within the RW panel are transmitting power wirelessly to a single receiving EN device. Looking at two arbitrary antennas ℓ_i and ℓ_j within the panel, their individual distances $d_{\ell,i}$ and $d_{\ell,j}$ to the EN device are computed. This is necessary because RadioWeaves employs physically large apertures and distributed architectures. A physically large aperture results in a large Fraunhofer distance (i.e., the boundary that separates near field and far field), such that the EN device is located well within the array near field[6]. Computing the individual distances $d_{\ell,i}$ and $d_{\ell,j}$ to the EN device, spherical wave fronts are modeled to focus power at the device location[7].

[4] The distance $\Delta_{i,j}$ between the two closest neighboring antennas ℓ_i and ℓ_j within a panel is at most $\Delta_{i,j} \leq \frac{\lambda}{2}$.
[5] This substantial feature of RadioWeaves can be observed in Figure 6.4, later in this section.
[6] Having an aperture width of $l_x = 2.5\,\mathrm{m}$ as the largest dimension D of the array would yield a Fraunhofer distance $d_\mathrm{F} = \frac{2\,D^2}{\lambda} \approx 100\,\mathrm{m}$ at a frequency of $2.4\,\mathrm{GHz}$.
[7] This is done in contrast to conventional beamforming in the array far field, where planar wavefronts are assumed across the entire aperture.

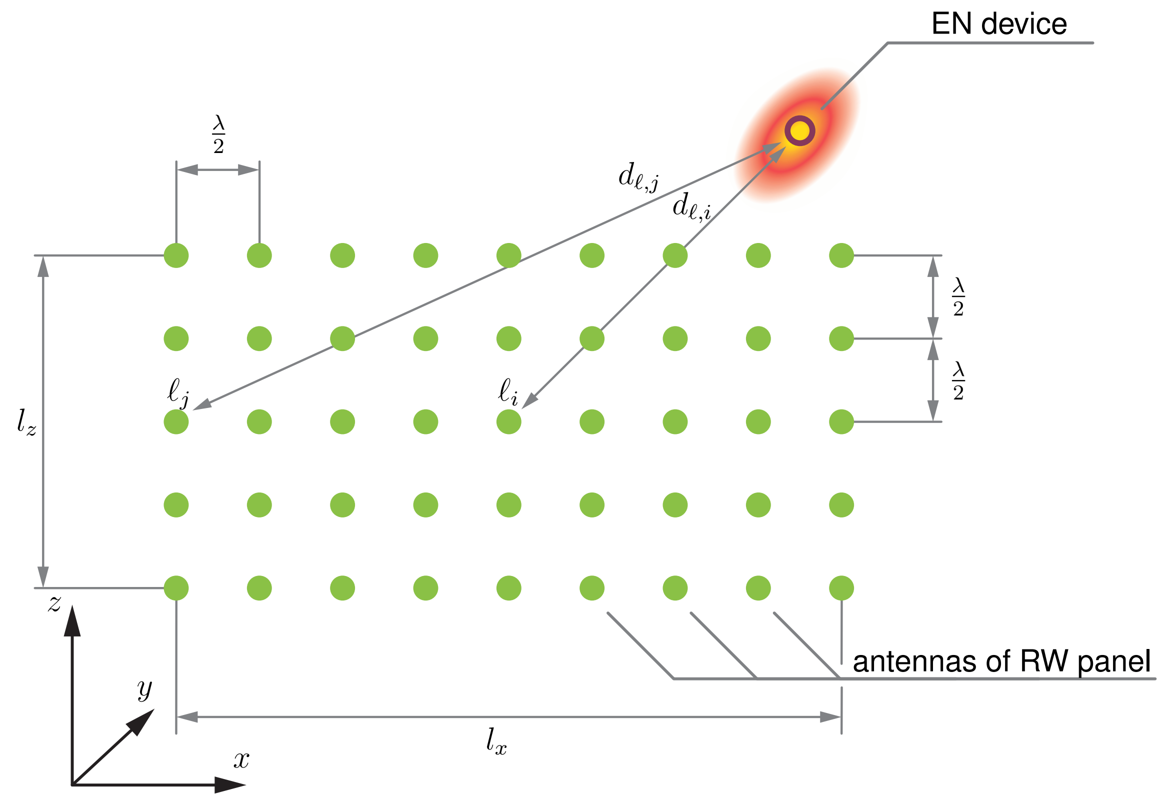


Figure 6.2: Schematic drawing of an RW panel and an EN device used for the WPT analyses in this section.

In the subsequent analyses, the power budget at the EN device location is computed by focusing power from a single RW panel. Note that this is just an exemplary demonstration of the capabilities of RadioWeaves that may be mapped to other architectures. What WPT particularly benefits from in the context of RadioWeaves is the spatially distributed architecture. Having a more distributed architecture may be even more beneficial for the resulting power budget and the spatial distribution of radiated power.

6.3.1.2 Power budget analysis - free space LoS model

For a single-input single-output (SISO) system, the *Friis transmission equation* can be used to compute the available power budget at a certain distance between two antennas in free space:

$$\frac{P_\mathrm{r}}{P_\mathrm{t}} = \underbrace{\left(1-|\Gamma_\mathrm{t}|^2\right)}_{\text{TX matching}} \underbrace{\left(1-|\Gamma_\mathrm{r}|^2\right)}_{\text{RX matching}} \underbrace{\left(\frac{\lambda}{4\,\pi\,d}\right)^2}_{\text{path loss}^a} \underbrace{G_\mathrm{t}\,G_\mathrm{r}}_{\text{antenna gains}} \underbrace{|\boldsymbol{\rho}_\mathrm{t}\cdot\boldsymbol{\rho}_\mathrm{r}|^2}_{\text{polarization loss}} \quad . \tag{6.17}$$

P_r	...	received power.
P_t	...	transmitted power.
Γ_r	...	reflection coefficient at receiver load.
Γ_t	...	reflection coefficient at transmit antenna.
λ	...	wavelength.
d	...	distance between transmit and receive antenna.
G_r	...	receive antenna gain.
G_t	...	transmit antenna gain.
$\boldsymbol{\rho}_\mathrm{r}$	...	receive antenna polarization vector.
$\boldsymbol{\rho}_\mathrm{t}$	...	transmit antenna polarization vector.

[a] The way it is described here, it is actually a *path gain*, but will be denoted *path loss* for the rest of this section.

The path loss (PL) exponent in free space is 2 because the radiated power propagates as a spherical wave, i.e., the power is distributed over the surface $4\,\pi\,d^2$ of the sphere[8]. In a perfectly matched system, i.e., $\Gamma_\mathrm{t} = \Gamma_\mathrm{r} = 0$, with perfectly aligned antenna polarization, i.e., $|\boldsymbol{\rho}_\mathrm{t}\cdot\boldsymbol{\rho}_\mathrm{r}| = 1$, and under an isotropic antenna assumption $G_\mathrm{r} = G_\mathrm{t} = 1$, the power budget of a SISO system merely depends on the PL. Performing WPT from an RW panel to an EN device makes it possible to exploit the array gain such that the signal amplitudes from L_t transmit antennas constructively interfere at the location of the single receive antenna. Such a multiple-input single-output (MISO) system exhibits a superior performance when compared with a SISO system and has particular benefits in the context of RadioWeaves which will be elaborated later in this section.

For MISO WPT systems, we summarize a range of equations that let us approximate the available power budget under certain assumptions: We denote the SISO PL as

$$PL_\mathrm{SISO} = \left(\frac{\lambda}{4\,\pi\,d}\right)^2 . \tag{6.18}$$

For a URA spaced at a distance of $\lambda/2$, the panel comprises a total number of antennas

$$L_\mathrm{t} \approx \frac{A}{\left(\frac{\lambda}{2}\right)^2} , \tag{6.19}$$

where A is the physical antenna aperture in m^2. For a phase-coherent transmission, the array gain G_array equals the number of transmit antennas, i.e.,

$$G_\mathrm{array} = L_\mathrm{t} \, . \tag{6.20}$$

[8] Note that the remaining term $\frac{\lambda^2}{4\,\pi}$ in the path loss models the effective aperture of the receiving antenna [5].

Table 6.3: Back-of-the-envelope power budget estimation for a $\lambda/2$-URA with physical dimensions along the x and y axes of $l_x \times l_z = 2.5\,\mathrm{m} \times 1.5\,\mathrm{m}$ evaluated at a distance $d = 6\,\mathrm{m}$ from the RW panel.

Quantity Name	**Symbol**	**Unit**				
Carrier frequency	f_c	GHz	0.9	2.4	3.8	5.2
Aperture size	A	m^2	3.75	3.75	3.75	3.75
Distance to EN device	d	m	6	6	6	6
Number of transmit antennas	L_t	-	135	960	2407	4507
SISO PL	PL_SISO	dB	-47.1	-55.6	-59.6	-62.3
Array gain	G_array	dB	21.3	29.8	33.8	36.5
MISO PL	PL_MISO	dB	-25.8	-25.8	-25.8	-25.8

Under the assumption[9] that the distances from the EN device to any antenna of the RW panel are approximately equal (i.e., $d_{\ell,i} \approx d_{\ell,j}\,\forall\, i,\, j\, \in \{1 \ldots L_\mathrm{t}\}$), we compute the MISO PL as

$$PL_\mathrm{MISO} \approx G_\mathrm{array}\, PL_\mathrm{SISO}\,. \tag{6.21}$$

Example:
Evaluating the MISO PL equation in (6.21) for a fixed aperture of $A = l_x \times l_z = 2.5\,\mathrm{m} \times 1.5\,\mathrm{m} = 3.75\,\mathrm{m}^2$ yields the results in Table 6.3. Note that the MISO PL PL_MISO gets *independent of the carrier frequency*. For the chosen parameters, transmitting only $P_\mathrm{t} = 1\,\mathrm{W}$ of power (distributed over all antennas, i.e., $\sum_{\ell=1}^{L_\mathrm{t}} P_\ell = 1\,\mathrm{W}$) to an EN device located $d = 6\,\mathrm{m}$ away from the RW panel results in a received power of $P_\mathrm{r} \approx 4.2\,\mathrm{dBm} \approx 2.6\,\mathrm{mW}$. In comparison with other WPT technologies, this is quite a significant amount of power that can be delivered to an EN device at such a distance. State of the art ultra-low power EN device frontends have a sensitivity, i.e., a minimum required power for wake-up and backscatter communication, of about $-23\,\mathrm{dBm}$ [60]. That is approximately 1000 times lower than the power available[10] at the EN device position. Although the computed MISO PL of $-25.8\,\mathrm{dB}$ may seem low if seen in absolute numbers, the use of batteries is comparable in terms of energy efficiency, as demonstrated in Section 4.2.2.

6.3.1.3 Power budget analysis - Rayleigh model

In an indoor radio environment, in contrast to free space, specular reflections and diffuse scattering of electromagnetic waves are interfering constructively and destructively with the line-of-sight (LoS) and with each other. For a SISO system, multipath propagation results in Rayleigh or Ricean fading channels, where an EN device (i.e., the receiver) may be located at a distance from the transmitter where a deep fade occurs. At such unfavorable positions, a sufficient WPT supply is hardly possible. In a MISO setup, however, unfavorable propagation paths can be avoided and constructive, phase-coherent summations of signals exploited, such that the array gain severely boosts the power budget.

The frequency-flat MISO signal model describes the received signal y depending on a transmitted signal s:

$$y = \sqrt{P_\mathrm{t}}\,\mathbf{h}^\mathsf{T}\,\mathbf{w}\,s + n \tag{6.22}$$

[9]Note that this is a reasonable approximation for RadioWeaves. The results computed under this assumption are still in good agreement with the simulations presented in this document.
[10]Note that the RF-to-DC conversion efficiency is disregarded here for simplicity.

P_t	...	transmitted power.
$\mathbf{h}$	...	$(L_\mathrm{t} \times 1)$ MISO channel vector.
$\mathbf{w}$	...	$(L_\mathrm{t} \times 1)$ weight vector.
s	...	transmit signal phasor with $\|s\|^2 = 1$.
n	...	additive noise.

For optimal preprocessing using MRT, the weight vector is chosen as the complex conjugate of the normalized channel vector

$$\mathbf{w} = \frac{\mathbf{h}^*}{\|\mathbf{h}\|} \,. \tag{6.23}$$

The mean received power for a SISO system is

$$P_{\mathrm{r,\,SISO}} = \mathbb{E}\left\{|y|^2\right\} = P_\mathrm{t}\,\mathbb{E}\left\{|h|^2\right\} = P_\mathrm{t}\,\sigma_h^2 \,, \tag{6.24}$$

where $\mathbb{E}\left\{|h|^2\right\} = \sigma_h^2$ models the SISO path loss.

The mean received power for a MISO system is

$$P_{\mathrm{r,\,MISO}} = P_\mathrm{t}\,\sigma_h^2\,L_\mathrm{t} \,. \tag{6.25}$$

In a case of optimal preprocessing, the output power of a MISO system is increased over the output power of a respective SISO system by the array gain

$$G_\mathrm{array} = \frac{P_{\mathrm{r,\,MISO}}}{P_{\mathrm{r,\,SISO}}} = L_\mathrm{t} \,. \tag{6.26}$$

Even for a Rayleigh fading channel, typically present in indoor radio environments, a RadioWeaves deployment with a large number of transmit antennas L_t can be used to overcome the negative impacts of fading and make the full array gain achievable with optimal preprocessing.

6.3.1.4 Power budget analysis exploiting multipath propagation

We employ a simulator to compute the power budget in an exemplary indoor environment with strong specular multipath components and diffuse scattering. Figure 6.3 depicts the simulated environment with an RW panel as described in Table 6.3. Virtual mirror panels model specular reflections at the walls. Note that only the front wall and left wall, i.e., parallel to the yz-plane, as well as the floor are modeled in this initial simulation. Furthermore, a cloud of scatter points is randomly drawn on the front wall in the direction of LoS to the EN device. In Figure 6.4, the power budget is evaluated at a frequency of $f_\mathrm{c} = 2.4\,\mathrm{GHz}$ on a cutting plane parallel to the xy-plane.

We compute the complex-valued signal amplitudes y from all sources over a chosen grid across the cutting plane. Specular reflections at plane walls are modeled through the virtual mirror panels where an attenuation[11] of $3\,\mathrm{dB}$ is associated with each reflection. Diffuse reflections are considered through scatter points modeled as pinhole channel. In this initial analysis, only a small range of scatter points is included in the analysis to qualitatively assess their influence on the power budget. The EN device is located at a position $\boldsymbol{p}_\mathrm{EN} = [p_x, p_y, p_z]^\mathsf{T} = [5\,\mathrm{m}, 6\,\mathrm{m}, 1\,\mathrm{m}]^\mathsf{T}$. Power focusing has been simulated using MRT to the EN device assuming perfect CSI. At its location, the computed MISO PL is $PL_\mathrm{MISO} = -22.5\,\mathrm{dB}$, which is even $3\,\mathrm{dB}$ higher than the

[11] The attenuation of $3\,\mathrm{dB}$ is only an initial choice for simulation purposes.

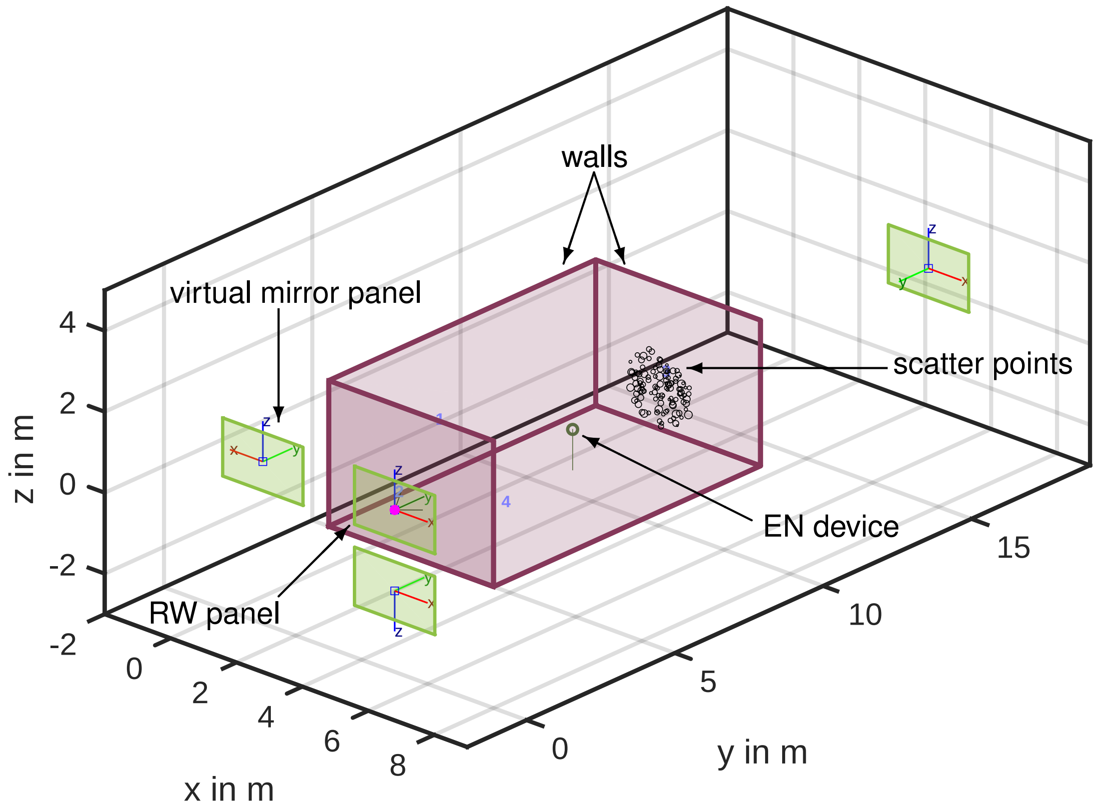


Figure 6.3: Simulation setting with a left and front wall, as well as a floor. A $(5\,\mathrm{m} \times 9\,\mathrm{m} \times 3.5\,\mathrm{m})$ large room is simulated. Virtual mirror panels are indicated in the figure along with the EN device. Scatter points are distributed along the front wall in the direction of LoS to the EN device.

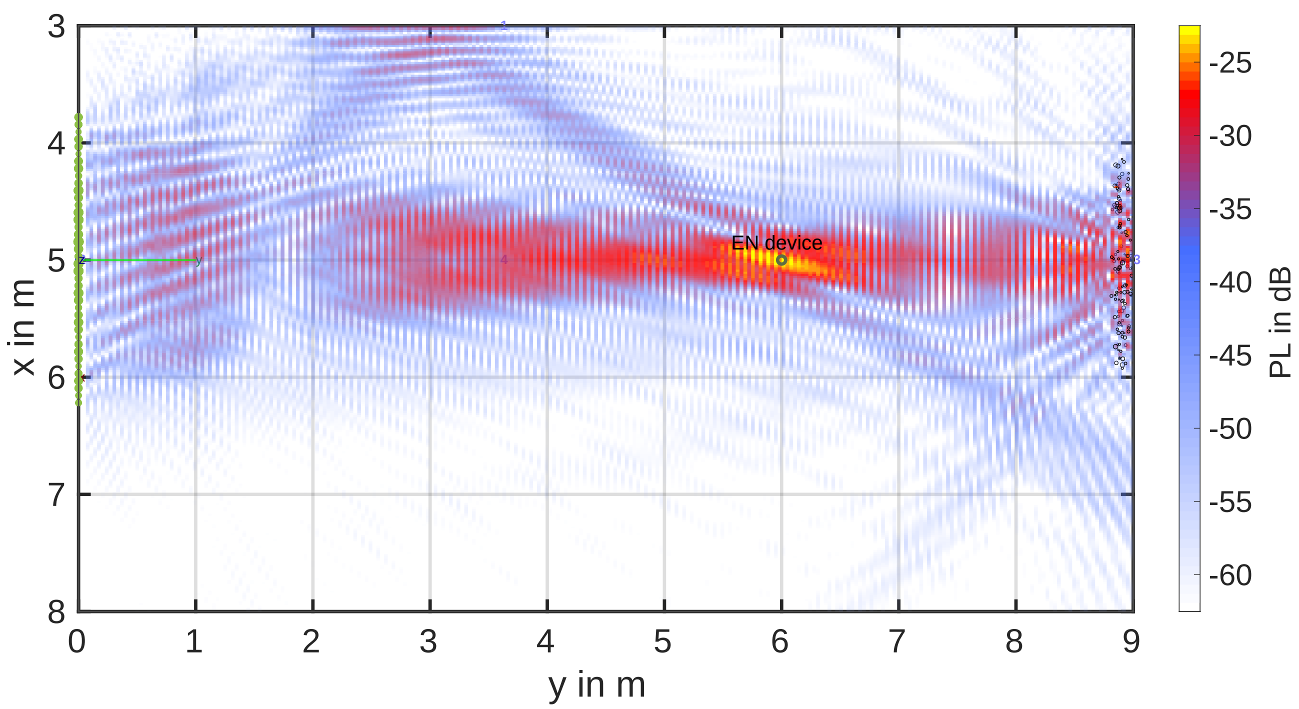


Figure 6.4: Initial analysis of the MISO PL PL_{MISO} evaluated on a cutting plane (at $z = 1\,\mathrm{m}$, perpendicular to the center of the RW panel) through the simulated room. The parameters from Table 6.3 have been used and evaluated at a carrier frequency $f_{\mathrm{c}} = 2.4\,\mathrm{GHz}$ with perfectly known CSI.

approximate free space estimate in Table 6.3 ($-25.8\,\mathrm{dB}$). This shows that RadioWeaves is capable of exploiting multipath propagation to increase the power budget over the free space case. Furthermore, the picture shows another significant feature of using RadioWeaves for WPT: the power levels close to the RW panel are smaller than at the focal point, i.e., the EN device. This allows to keep the overall exposure to electromagnetic radiation low in the environment and efficiently focus power to points where it is needed. Note that more distributed architectures will further decrease the spatial correlation of transmitted signals and thus further decrease radiation exposure outside the focal point (compare [81]). However, apertures with uniform antenna spacing larger than the Nyquist distance may exhibit grating focal points (i.e., aliasing may occur due to ambiguities of spatial signal correlations).

6.3.2 Initial access for EN devices

To operate an EN device for the first time, it has to be supplied with power wirelessly under the constraint that its position and channel are unknown. Without CSI, preprocessing using MRT cannot be done and the array gain G_{array} is generally not exploitable. For initial access, the EN device has to be woken up for the first time and a backscattered signal at the RW panel has to be received. In the downlink, i.e, transmitting power and information wirelessly from the RW panel to the EN device, the received power has to exceed the device sensitivity[12]. In the uplink, i.e, transmitting a backscattered signal wirelessly from the EN device to the RW panel, the received power has to exceed the RadioWeave sensitivity[13].

For EN devices in a RadioWeaves infrastructure we envision RF front ends that feature a class 1 mode[14], i.e., a mode with a low device sensitivity, for initial wake-up and the start of backscatter communication, which can be performed energy efficiently. Receiving a backscattered signal at an RW panel, channel estimation can be performed. With CSI available, power can be intentionally focussed at the EN device location. As soon as the device receives sufficient power, the front end can switch its mode of operation from the class 1 mode to full functionality and request power from the RW infrastructure according to its current demands. The infrastructure can in turn grant power requests to the devices adaptively, depending on their individual needs and thereby efficiently supply power wirelessly.
In addition to EN devices featuring a class 1 mode, more distributed architectures will aid a successful initial access. Generally, any of the considered topologies in Chapter 5 (compare Figure 5.1) may be used for WPT. However, the latency associated with a specific topology must meet constraints of the mobility model imposed by a certain use case (compare Table 3.2).

6.3.2.1 Reciprocity-based WPT

The above described procedure, in particular the estimation of CSI from pilot signals transmitted from the EN device to the RW panels via backscatter communication and subsequent MRT for

[12] The device sensitivity is the minimum power required by the EN device to be activated. In the realm of ultra high frequency (UHF) RFID this quantity is known as the tag chip sensitivity [28] defined as the minimum RF power necessary to power the chip [59]. For simplicity, we assume perfect impedance matching between chip and antenna in this document, such that all power incident at the antenna is accepted by the chip, or EN device, respectively.

[13] The RadioWeave sensitivity is the minimum power required by the infrastructure for a backscattered signal to be received without errors. In the realm of UHF RFID this quantity is known as the receiver sensitivity [19].

[14] According to the RadioWeaves device classification in the REINDEER deliverable D1.1 [15], devices of class 1 have the lowest power consumption of all defined classes. They communicate via backscatter communication only.

power focusing, is denoted as reciprocity-based WPT in this document. Without awareness of its environment, an RW panel may illuminate its surroundings without coherently focusing power at a certain point to wake up an EN device and receive a first backscattered signal. Two distinct phases can be identified [57]:

Phase 1: (CE phase)
The phase where CSI is unknown, a device is woken up and backscatters a signal for the first time is called channel estimation (CE) phase. In this phase, with unknown CSI, the coherent focusing is not possible. Instead, the environment has to be illuminated by uncorrelated transmission and the power harvested in the downlink has to exceed the EN device sensitivity without exploitable array gain. That is, the received power P_{r} has to exceed the device sensitivity $P_{\mathrm{d,min}}$ (e.g., -23 dBm) if, for simplicity, perfect antenna matching was assumed. After waking up, the EN device transmits pilots via backscatter communication which are detected and received by infrastructure if the power received in the uplink exceeds the RadioWeave sensitivity. CSI is estimated by the RadioWeave. Mishra and Larsson [57] have found that the optimal number of pilots, i.e., the pilot count (PC) K, for channel estimation depends on the SNR at the receiver, i.e., the RadioWeave: For low SNR, it is better to allocate the full transmit power to a single antenna and estimate the channel to the EN device from a single pilot, thus $K = 1$. For high SNR, it is better to distribute the transmit power over all L_{t} available antennas and estimate the channel to the EN device from L_{t} pilots, thus $K = L_{\mathrm{t}}$.

Phase 2: (ID phase)
After CSI has been estimated from backscattered pilots received by the RW panels, MRT can be used to transmit signals coherently to an EN device location. This phase is denoted the information decoding (ID) phase. If perfect CSI was known, coherent summation of transmitted signals at the position of the EN device would be possible. Contrary to the CE phase, where only the signal powers would sum up at the EN device position, the signal amplitudes would sum up coherently in the ID phase. Thus, the full array gain could be leveraged. In a real implementation, however, the CSI cannot be estimated perfectly. In [57] it is demonstrated how the power received by the EN device decreases depending on the quality of CSI estimates.

The two phases are schematically depicted in Figure 6.5, where the tag would be replaced by an EN device in the context of RadioWeaves. Furthermore, no full-duplex backscatter communication is envisioned for RadioWeaves. In a bistatic setup, for instance, one RW panel supplies the EN device with power and another panel receives its backscattered signals.

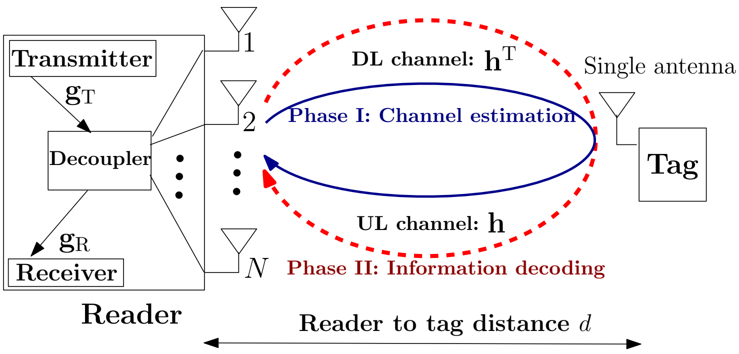


Figure 6.5: Channel estimation scheme for a monostatic backscatter communication model with a full-duplex antenna array proposed in [57]. Note that full-duplex communication is not envisioned for RadioWeaves, thus a bistatic setup may be used. The tag would be replaced by an EN device in the context or RadioWeaves.

6.3.2.2 Environment-aware WPT

Environment-awareness, i.e., incorporating information about the geometry of the radio environment, can help to wake up EN devices at greater distances: Power may be focused at possible (a priori unknown) device locations with methods like sweeping focal points across walls while listening for backscattered signals. Thereby, some array gain may be leveraged to initially access devices at much greater distances although CSI is not available.

Knowing the exact paths (e.g., specular reflections) that are useful to focus energy in the environment, can make WPT more robust: Moving objects or people in the environment may temporally block the LoS or other reflections that are used to transmit power to the EN device. By tracking these moving targets, obstructions of WPT paths can be predicted and bypassed early by illuminating affected EN devices via alternative paths.

6.3.3 Mapping to the architecture

Cooperative WPT from multiple RadioWeaves panels can be achieved in the following ways:

Option 1:
One federation, i.e., one DSF, (or panel) serves one EN device at a time. This way, no phase synchronization is required between DSFs, the infrastructure has to choose the best suited set of REs (e.g., closest, or with LoS conditions, etc.) to serve an EN device. This comes at the price of not using the full power transfer potential of the infrastructure.

As has been demonstrated throughout this section, a high number of antennas and the resulting array gain severely boost the power budget. To make the power budget available, a complete DSF or set of REs that supplies an EN device through WPT has to be synchronized in frequency and exhibit a stable phase.

Option 2:
Multiple DSFs (or panels) serve an EN device at the same time and use the full power transfer potential of the infrastructure. Each DSF is capable of supplying multiple EN devices through WPT simultaneously. Sychronization in frequency and phase has to be accomplished between the individual DSFs. Furthermore, the individual DSFs have to work together cooperatively: For constructive interference of the transmitted signals of different DSFs, phase alignment has to be achieved at the location of the EN device. That is, agreements have to be found (through cooperative algorithms) between the DSFs such that adaptive power focusing is achieved in a cooperative manner. Otherwise, destructive interference of the transmitted signals of individual DSFs may occur at the location of the EN device.

6.3.4 Initial analysis of hardware requirements

Some of the hardware requirements necessary for successful WPT using RadioWeaves have already been mentioned throughout this section.
On the device side, for initial access, EN devices must be capable of backscatter communication. An ultra-low power for wake-up, i.e., EN device sensitivity, is crucial for initial access at far distances, thus we envision all EN devices to have a front end featuring a Class 1 mode, as mentioned in Section 6.3.2.
Synchronization plays a significant role on the side of RadioWeaves (as already mentioned in Section 6.3.3). In a distributed architecture like RadioWeaves, few centralized clock signals may

be distributed to a large number of REs or a multitude of very accurate, i.e., having a very low drift, distributed clocks (see Section 6.3.3) may be distributed among smaller DSFs which are synchronized over-the-air (OTA).

6.3.4.1 Performance considerations

The upper power levels that can be expected from an RW panel of a given size were investigated in Section 6.3.1. In the analysis, the power budget was analyzed at a given distance d between the EN device and the RW panel. However, we only evaluated the path loss being merely the ratio of received power P_r and transmitted power P_t. The maximum power P_t that can could be transmitted has not been discussed yet. The received power P_r would linearly scale with the transmitted power but it is subject to regulatory limits.

The maximum transmissible power that can be used for WPT with distributed antennas or physically large apertures will be discussed in the REINDEER deliverable D4.1 [68]. The document will furthermore reveal the technical requirements neccessary by the RadioWeaves architecture to achieve the maximum receivable power in compliance with regulatory standards.

6.3.4.2 Complexity and scalability

A comprehensive performance comparison of different algorithms, and uplink combining and downlink precoding schemes have been analyzed in the REINDEER deliverable D3.1 [87]. The algorithms have been compared in terms of computational complexity, which can serve as a starting point for analyzing their suitability for WPT using RadioWeaves. Most of the analyzed algorithms cover potential reciprocity-based WPT schemes for RadioWeaves. Additionally, algorithms for environment-aware WPT are yet to be developed. The incorporation of environment information may bear high potential but also high computational complexity due to the large number of antennas and large amounts of data involved. Eventually, the design of computationally tractable algorithms for large antenna arrays plays a significant role as has already mentioned in the context of positioning (refer to Section 6.2.2). This is particularly crucial for the envisioned real-time use cases that demand very low latencies [15] but also to keep the power consumption due to digital signal processing low as mentioned in Section 4.1. Furthermore, algorithms for collaborative WPT using multiple DSFs will be developed.

Chapter 7

Considerations for security

In this chapter relevant security considerations are being addressed with a focus on future 6G environments. These security topics have been also identified in the definition of the REINDEER use cases in WP1. However, 6G security mechanisms are not an integrative part of the REINDEER RW architecture, as they need to be considered in the higher levels of the network topology. The following sub-chapters are a summary of existing papers and deliverables dealing with security in 6G networks.

7.1 Confidentiality

Confidentiality is maintaining the privacy/secrecy of another person or entity's information. Compared to the technology used to create the 5G network, 6G will allow the realisation of applications that require more complexity to create, such as holograms and augmented reality. Human mobile communications are other important points of 6G connectivity, ranging from wireless networks in the body area, to small (or nano) external devices, internal devices, and even communications in the biochemical industry. The human body will be seen as a point or a set of points that collect confidential information to be studied and worked on in order to establish a database, in other words, the human body will be part of a network architecture [63]. With the growing worldwide demand for the use of data collected by sensor networks, as well as the mobility features of most scenarios, this data needs advanced security techniques that take into account information security solutions and technologies.

7.1.1 Physical Layer 3, security solutions

In order to handle information securely, three main points have been taken into account: the resources that the device has, the network environment in which this device is inserted and, finally, the dynamics of this network. Since the physical layer is also the foundation of wireless communications in 6G RadioWeaves networks, protecting physical layer information can prevent many conventional attacks on radio waves signals that affect almost all applications for future 6G network. The premise of physical layer 3 security is to exploit the characteristics of wireless channels to improve confidentiality and perform authentication [56]. The concept of physical layer 3 security will be particularly beneficial to low-cost 6G IoT devices, which often lack the power and computing power to run advanced authentication mechanisms. In addition, physical layer security is robust against cryptanalysis, which has been the main concern of conventional cryptographic algorithms. Physical layer security can be implemented in the base stations of IoT gateways of operator nodes or in signal modulation algorithms.

7.1.2 Artificial intelligence algorithms

This method advances computing architectures to improve cryptographic techniques and also to meet information security requirements that they are sometimes unable to use cryptographic methods. The 6G network on RadioWeaves systems must be an "AI enabled" network, meaning that Artificial Intelligence (AI) is both its driver and most prominent feature [56]. It will be able to create new opportunities in 6G networks for technological innovation furled by many different types of machine learning. AI capability and 6G security in RadioWeaves systems are key success factors in future AI based wireless networks.

7.1.3 Physical key generation

public key infrastucture (PKI) serves to protect the confidentiality of communications between UEs and stations against interception, which is an approach used to exploit the entropy of randomness in transmit and receive channels to create so-called secrecy keys in communications. Theoretically, the information is identical when two terminals are connected over the same wireless channel, but it could be different if the responder is located half a wavelength away from the sender [58].

7.1.4 Encryption

Preventing unauthorized interceptors from accessing communications is an essential requirement for secure data transmission for the 6G technology, since preventing unauthorized interceptors from accessing communications is an essential requirement for the encryption step in the RadioWeaves system. Quantum communication can significantly increase the reliability and security of data transmission. This technology can be considered as a huge potential in 6G networks. The quantum state is directly affected when a hacker tries to pass the security criteria of this communication, therefore, this state will be affected and the recipient cannot refuse this message. In theory, quantum communication can be efficient in the matter of information security and can be suitable cyber security, confidentiality, integrity and privacy of personal information. A caution to be taken with quantum computers when using 6G networks is that these computers may be able to break complex algorithms such as elliptic curve cryptography and such as RSA [56]. Therefore, this matter should be discussed widely so that this threat does not affect information security on 6G networks. Roughly speaking, the overall goal is to develop quantum-resistant cryptographic suites as quickly as possible.

7.2 Authentication

Authentication technology provides access control for systems by verifying a user's credentials in an authorized user database or on a data authentication server. In the context of 6G, it will be important to take quantum computing into account. The current 5G standard does not address the issue of quantum computing, but relies on traditional cryptography such as elliptic curve cryptography (ECC) technology, which consists of a discrete logarithm with problems that can be solved with the question of quantum computation [63]. As the 6G coverage studies indicate that it will address all network nodes, which can range from the satellite to the inside of the human body, the 6G network architecture will be much more complex and will depend even more on the PKI layers of protection for its use.

7.2.1 ECC and ECDLP

Elliptic curve cryptography (ECC) is an approach to public-key cryptography based on algebraic structure of elliptic curves over finite fields. It's important to use a strong, encrypted public key, such as one based on ECC networks, dealing with the underlying elliptic curve discrete logarithm problem (ECDLP) [58]. The 6G security architecture will be more complex compared to 5G networks, so the structures for cloud and state-of-the-art infrastructure must be enhanced in future RadioWeaves technologies.

7.2.2 Mutual authentication

6G authentication and key management is being designed for mutual authentication between subscriber and network. These are aspects to prevent attacks such as fake operators and traceability attacks. To provide better support and a unified authentication model in RadioWeaves networks, authentication protocols for open interfaces can be implemented with algorithms that are more resistant to these attacks [58].

7.2.3 Distributed ledger technologies (DLT)

Distributed Ledger Technology (DLT) can improve the reliable communication of 6G key entities such as authentications servers or between the servers network and the home network. This is a possible solution to evolve and build a reliable 6G network. A DLT review will ensure key security and privacy such as traceability, immutability, transparency, data integrity, verifiability, anonymity and pseudonymous, authentication and monitoring [58]. For RadioWeaves 6G vision, using distributed consensus and encryption to provide resource management for spectrum sharing can generate a level of secure autonomy in 6G networks, such as: immutable, transparent and autonomous, ledgers using distributed consensus and encryption to provide a security transaction logging authority.

7.3 User Access Control

A User Access Conrol protocol allows a database owner to control the "Entry and Exit" of users into their database. This purpose has privacy and consent implications in Block chain, differencial privacy (DP) and federated learning (FL) technologies. The use of an artificial intelligence block chain is an option that can be taken into consideration for 6G networks, where this architecture can offer data security, anonymity, privacy, verifiability, among others. FL is an important technique for the 6G network, as this technique allows different model training, where bringing the code to the database is more important than the database to the code [63]. In this way, it is able to meet the security requirements such as data privacy, data ownership and database integrity.

7.3.1 Transparency and Anonymity

To satisfy a user's demand on high privacy, anonymity and transparency, the most suitable solution should address conditional anonymity to suit the applications and a lower cost of implementation. Methods such as cryptography for the preservation of privacy can and should be applied in these areas [58].

7.3.2 Federated Learning (FL)

FL is another potential solution that allows the training of algorithms in edge equipment, where each device keeping its data locally. These privacy-aware networks on 6G will need to operate around zero-reliability models in RadioWeaves technologies [56].

7.4 Data Integrity

Data integrity refers to the accuracy and reliability of data throughout its life cycle. After all, compromised data is of little use to businesses, not to mention the dangers posed by the loss of sensitive data. For this reason, maintaining data integrity is crucial to the future development of 6G networks. Compared to 5G networks that support IoT, 6G networks will also need to be aligned with Internet of Everything (IoE), meaning the 6G network will be able to manage the best decisions in different layers of protection. Artificial intelligence that meets information security requirements will certainly be necessary, since everything at IoT is connected to the internet. This way of working will improve information security and even the privacy of the network [82]. machine learning (ML) is another tool that can benefit from 6G technologies, once this tool is improved, it can easily ensure the end-to-end security of communications and hence the integrity of the database.

It will require distributed artificial intelligence that must meet various requirements. In the RadioWeaves era, end equipment with various AI features will work with a variety of cutting-edge and cloud features. This service architecture can provide dynamic and extremely refined service capabilities on demand as data integrity compliance. Access controls are sets of training data that must be unevenly distributed across most edge devices, while each edge device must have an ability to access and control some of the data [47]. It can easily ensure the end-to-end security of communications and therefore the integrity of the database. ML's vulnerability to adversary contributions has led to a field of research focused on better assessing its robustness and developing defences against potential attacks.

7.5 Privacy

Privacy is related to security, but it is a different matter. Privacy concerns an individual's rights to own the data generated by their activities, to restrict the flow of that data, to determine who can have access to that data, and to determine how the data can be used. Privacy in IT systems exists to protect the personal information of a human being or a company. Differential privacy, data anonymization, homomorphic encryption and calculations are the best-known examples of privacy. Those technologies that are used to enhance privacy refer to the building blocks that can be used as privacy requirements arising in 6G technology. The general data protection regulation (GDPR) that says that anonymous data may be processed for statistical or research purposes free of charge and data protection processes are not required for anonymous data. Therefore, the anonymous data is powerful because with that statement, it does not require the security procedures expected for the non-anonymous data. In other words, anonymization consists of removing private data that prevents intruders from linking between the database and the private party that owns that database [35]. Quantifiable privacy is the limit of the probability that two sets of databases can be recognized and distinguished. Differencial privacy DP is the database anonymization for quantifiable privacy; this tool is widely used to ensure protection and privacy of beings whose database is in a dataset. To address differential privacy in 6G environments when talking in ML context, random noises can be used for the input data (the noise is added to the data itself), and the output data (the noise is used for the resulting parameters) of the algorithm.

7.5.1 Privacy Preservation

Can be categorized into three groups: (1) security and privacy preservation for IoT networks and their subsidiaries, e.g. wireless sensor networks, vehicular networks, etc. (2) security and privacy issues for existing 4G and 5G cellular networks, and (3) security and privacy in 6G by analysing issues around specific key technologies, such as machine learning [56].

7.5.2 Privacy Enhancing Technologies (PETs)

Employ specific principles such as minimizing personal data, maximizing data security and training is obligatorily general items of privacy enhancing technology (PET), which also encompass practices such as privacy in the collection, processing and use of the database to meet the requirements [58]. These requirements characterize PETs in three stages: learning, semi-reliable and unrefined.

7.5.3 Differential Privacy (DP)

Differential privacy (DP) works using functions with some kinds of artificial design noise before allowing its final output to the attacker's server, so that an attacker can be prevented from accessing the database in question due to this protocol and, thus, a protection of privacy is guaranteed [56]. The idea of differential privacy is to create aggregated information within a dataset, where a search for any item can be identified without any noise and also in the aspect that aims to maintain the accuracy of the query in the database, while minimizing leakage or identification of the database.

7.5.4 AI and ML

In AI and ML technologies, random noise can be used for the input data (noise is added to the data itself), and the output data (noise is used for the included parameters) of the algorithm to satisfy the privacy problem, thus secrecy is specified and consequently this solution will decrease the chances of interruption [58]. This technology integration can also be used to improve the performance of key physical generation in RadioWeaves systems.

Chapter 8

Summary and Conclusion

This deliverable has taken a broad perspective on architecture and hardware requirements for a RW infrastructure by first establishing logical and physical network components, specific to RW, and in the same process establishing a new terminology. While important for clarity of initial discussions and evaluations, we expect both terminology and network components to develop further throughout the project, as new solutions and approaches are studied in more detail.

Use cases defined in WP1 have been put into an RW infrastructure context in a high-level analysis of how KPI requirements translate to various challenges. Critical challenges are identified and their influence on the infrastructure design have been discussed on a high level. These challenges collectively put extreme requirements on an RW infrastructure, capable of handling all use cases, with high deployment costs and over-dimensioning as a consequence. Over-dimensioning also limits the possibilities to minimize energy consumption, an important objective of REINDEER. This all points to a flexible infrastructure design, where each individual deployment is to be tailored to a particular set of use cases, while still being a fully integrated, yet distinctive, part of a larger RW infrastructure.

As a first step in the direction of establishing an RW infrastructure design, we have focused on a set of three basic RW services - communication, positioning/localization and wireless power transfer. They share the same set of technical requirements on the infrastructure, but with different characteristics. They all benefit from the spatial resolution that can be provided by an RW infrastructure, but exploit it in different ways and therefore lead to different requirements and strategies for distributing the associated algorithm processing across RW. The overall study performed on the three basic services leads to the following high-level conclusions about the infrastructure:

1. Both parallel and serial execution of algorithms across the infrastructure should be supported, since they serve different purposes. This leads to a hybrid form of topology, with a combined tree/daisy-chain structure that can provide different balance-points, depending on requirements of the provided service.
2. Exploiting the spatial dimension has the potential to improve quality and/or efficiency of the studied basic services. Increased use of the spatial dimension, however, makes the system more complex and will have an impact on energy consumption of the infrastructure. The means of synchronization of CSPs needs to be further studied.

All wireless communication systems also need to take security considerations into account and, while not at the core of the REINDEER project, we have provided an overview of these. The security topics covered include, confidentiality, authentication, user access, data integrity, and privacy. The influence of these on the RW infrastructure is not significant, but needs to be considered for a complete infrastructure design.

At this early stage of the REINDEER project the above summary and conclusions are preliminary and are to be seen as a starting point for the more detailed studies performed hereafter.

List of Abbreviations

AI Artificial Intelligence. 55, 58

AOA angle-of-arrival. 38, 39, 40, 42

AOD angle-of-departure. 38

AP access point. 4

AWGN additive white Gaussian noise. 39, 40, 42

CE channel estimation. 51

CED cumulative energy density. 21

CRLB Cramér-Rao lower bound. 38, 39, 40, 41, 42

CSI channel state information. 12, 44, 48

CSP contact service point. V, 4, 5, 6, 7, 8, 13, 14, 15, 23, 24, 26, 27, 28, 29, 30, 31, 32, 33, 35, 36, 37, 38, 41, 42, 43, 59

DLT Distributed Ledger Technology. 56

DP differencial privacy. 56, 58

E2E End-to-End. 9

ECC elliptic curve cryptography. 55

ECDLP elliptic curve discrete logarithm problem. 56

ECSP edge computing service point. 4, 5, 7, 24, 26, 29, 31, 37, 41

EIRP equivalent isotropically radiated power. 14

EM electromagnetic. 7

EN energy neutral. 7, 44, 46, 47

FA federation anchor. 4, 5, 7, 26, 37

FL federated learning. 56, 57

GDPR general data protection regulation. 57

ID information decoding. 51

IoE Internet of Everything. 57

IoT Internet of Things. 17, 21

KPI key performance indicator. VI, 1, 9, 10

LCA life cycle assessment. 21

Li-ion lithium-ion. 21

LIS large intelligent surface. 33, 41

LMO lithium ion manganese oxide. 21

LoS line-of-sight. 39, 40, 47

MIMO multiple-input multiple-output. 29, 33, 38, 40, 41

MISO multiple-input single-output. 44, 46, 47

ML machine learning. 57, 58

MMSE minimum mean square error. 29, 31, 32, 34

MRC maximum ratio combining. 29, 30, 31, 32

MRT maximum ratio transmission. 29, 30, 31, 44, 48

NB narrowband. 39

NR New Radio. 18

OFDM orthogonal frequency-division multiplexing. 29, 30, 37

OTA over-the-air. 53

PA power amplifier. 18, 19

PC pilot count. 51

PDP power delay profile. 39

PER packet error rate. 9

PET privacy enhancing technology. 58

PKI public key infrastucture. 55, 56

PL path loss. 38, 46

RE radio element. 11, 12, 13, 15

RF radio frequency. 11, 12, 21, 44, 50

RFID radio frequency identification. 50

RMS root mean square. 39

RSS received signal strength. 38, 42

RW RadioWeaves. II, V, 1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 23, 24, 28, 29, 31, 37, 40, 41, 42, 54, 59, 60

SA synchronization anchor. 37, 42

SDG Sustainable Development Goal. 17

SINR signal-to-interference-plus-noise ratio. 13, 31, 39, 40, 42

SISO single-input single-output. 46

SLAM simultaneous localization and mapping. 39, 42

SNR signal-to-noise ratio. 13, 30, 39, 40

SVD singular value decomposition. 33

TDD time division duplexing. 29

TDOA time-difference-of-arrival. 38, 39, 42

TOA time-of-arrival. 38, 39, 42

UE user equipment. 4, 5, 7, 30, 37, 38, 41, 43

UHF ultra high frequency. 50

ULA uniform linear array. 40

URA uniform rectangular array. 44

UWB ultrawideband. 39

WB wideband. 39

WPT wireless power transfer. 1, 2, 4, 7, 21, 28, 44, 47

ZF zero forcing. 29, 31, 32, 33, 34

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