Call: H2020-ICT-2020-2

Project reference: 101015956

Project Name:

A flagship for B5G/6G vision and intelligent fabric of technology enablers connecting human, physical, and digital worlds

Hexa-X

Deliverable D3.1
Localisation and sensing use cases and gap analysis

Date of delivery:	31/12/2021	Version:	1.4
Start date of project:	01/01/2021	Duration:	30 months

Document properties:

Document Number:	D3.1
Document Title:	Localisation and sensing use cases and gap analysis
Editor(s):	Henk Wymeersch (CHA)
Authors:	Henk Wymeersch (CHA), Deep Shreshta (EAB), Kim Schindhelm (SAG), Andreas Wolfgang (QRT), Simon Lindberg (QRT), Carlos Morais de Lima (OUL), Alejandro Ramirez (SAG), Vijaya Yajnanarayana (EAB), Tommy Svensson (CHA), Hui Chen (CHA), Mohammad Ali Nazari (CHA), Hyowon Kim (CHA), Yu Ge (CHA), Musa Furkan Keskin (CHA), Traian E. Abrudan (NOF), Ali Behravan (EAB), Robert Baldemair (EAB)
Contractual Date of Delivery:	31/12/2021
Dissemination level:	PU[1]/
Status:	Final
Version:	1.4
File Name:	Hexa-X D3.1_v1.4

Revision History

Revision	Date	Issued by	Description
0.3	15/10/21	Hexa-X WP3	First inputs from all partners
1.0	17/10/21	Hexa-X WP3	Updated inputs before internal WP3 review
1.1	7/11/21	Hexa-X WP3	WP3 internal review complete
1.2	14/11/21	Hexa-X WP3	Update after internal review
1.3	28/11/21	Hexa-X WP3	Update after external review
1.4	19/12/21	Hexa-X WP3	Final

[1] CO = Confidential, only members of the consortium (including the Commission Services)

PU = Public

Abstract

This report provides the results of the gap analysis of Hexa-X work package 3: “6G High-Resolution Localisation and Sensing” as well as the initial findings towards methods, signals, and protocols for localisation and mapping and a vision of how accurate location and sensing information can enable and enrich applications as well as support communication. The report also defines research lines for future work in Hexa-X.

Keywords

6G localisation and sensing, use cases and requirements, models, and methods

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 101015956.

Executive Summary

This report is the first deliverable of the Hexa-X project work package 3: “6D High-Resolution Localisation and Sensing”. This deliverable focuses on the gap analysis between the current performance of 5G 3GPP localisation and radar and lidar sensing, and the target KPIs deduced from the Hexa-X use case families defined in [HEX20-D11] and [HEX21-D12].

Before the gap analysis is presented, the general principles of radio-based localisation and sensing are detailed in a tutorial-like manner, describing the relevant performance metrics, the basic measurement types, common localisation and sensing methods, as well as fundamental performance limitations. An overview of 5G specific localisation measurement types and methods is presented and contrasted to the potential technology enablers (including identified frequency ranges) towards 6G, as identified in [HEX21-D21]. Important challenges are identified, related to the wireless propagation channel and radio hardware impairments in the 100 GHz – 300 GHz range, to meet the target localisation and sensing KPIs, such as path loss, power amplifier nonlinearity, array calibration, and phase noise.

For the gap analysis, five use case families for [HEX20-D11] and [HEX21-D12] are interpreted from the localisation and sensing perspective and related to the key performance indicators (KPIs), so that the most challenging use cases in terms of, e.g., localisation and sensing accuracy, latency, and scalability, can be identified. A baseline evaluation is then conducted, both for 5G localisation and for radio-based sensing (including radar and lidar). From this baseline evaluation, the gap analysis is then conducted in terms of position accuracy, latency, scalability, and sensing resolution. Some of the use case families can be supported by the baseline technologies in some of the KPIs, but several important gaps have been identified, which are to be addressed through the Hexa-X work on models and methods.

Initial findings on models and methods for accurate localisation and sensing are reported. Considering 6D (3D position and 3D orientation) localisation as well as simultaneous localisation and mapping, comparisons between 5G and possible 6G systems reveal that in the 100 GHz – 300 GHz range, higher resolution in range and angle will provide superior localisation compared to 5G, despite reduced transmission power and increased path loss. Considering radio-based sensing, several methods are presented, including model-based and data-driven methods for a variety of novel scenarios, including environment classification, material sensing, joint sensing and communication, and approaches for interference mitigation. The role of sensor fusion and the trade-offs between accuracy, latency, and complexity are described. Finally, the planned demonstrators in collaboration with WP2 “Novel radio access technologies towards 6G” are detailed.

A crucial aspect of 6G, according to Hexa-X, is that localisation and sensing will not be a by-product of communication development, but instead will be integrated in the system from the start, and thus is a main design target of 6G. Toward this, an initial vision for how location and sensing information can be used to support, enable, and enrich novel applications will be sketched. In addition, potential benefits of location and sensing information for improving communication are listed.

The report concludes with an outlook on planned next steps.

Table of Contents

List of Figures

List of Tables

List of Acronyms and Abbreviations

2D	Two-dimensional
3D	Three-dimensional
5G	Fifth generation
6D	Six-dimensional
6G	Sixth generation
AGV	Autonomous ground vehicle
AI	Artificial intelligence
AMF	Access and mobility function
AoA	Angle-of-arrival
AoD	Angle-of-departure
AR	Augmented reality
BS	Base station
CDF	Cumulative density function
CEB	Clock error bound
CPI	Coherent processing interval
CRLB	Cramér-Rao lower bound
DL	Downlink
DoA	Direction-of-Arrival
DFTS-OFDM	Discrete Fourier transform spread OFDM
E-CID	Enhanced Cell-ID
EC	European Commission
EM	Electromagnetic
FFT	Fast Fourier transform
FMCW	Frequency-modulated continuous-wave
FR1	Frequency range 1
FR2	Frequency range 2
GDOP	Geometric dilution of precision
GHz	Gigahertz
GNSS	Global navigation satellite system
GOSPA	Generalised optimal sub-pattern assignment
GPS	Global positioning system
H2020	Horizon 2020
ICT	Information and communication technologies

ICI	Inter-carrier interference
IIoT	Industrial internet of things
InF	Indoor factory
IOO	Indoor open office
IoT	Internet of things
IP	Incidence point
IQ	In-phase and quadrature
JRC2LS	Joint radar communication, computation, localisation, and sensing
KDE	Kernel density estimate
KPI	Key performance indicator
lidar	Light detection and ranging
LMF	Location management function
LoS	Line-of-sight
LPP	LTE positioning protocol
LTE	Long-term evolution
MAE	Mean average error
MEB	Map error bound
MHz	Megahertz
MIMO	Multiple input, multiple output
mmW	Millimetre-wave
N/A	Not applicable
NR	New radio
NTN	Non-terrestrial networks
OEB	Orientation error bound
OFDM	Orthogonal frequency-division multiplexing
PEB	Position error bound
PRS	Positioning reference signal
QPSK	Quadrature phase-shift keying
radar	Radio detection and ranging
RAN	Radio access network
RAT	Radio access technology
RIS	Reconfigurable intelligent surface
RF	Radio frequency
RSRP	Reference signal received power
RSS	Received signal strength

RTT	Round-trip-time
RX	Receiver
SDG	Sustainable development goal
SI	Study item
SLAM	Simultaneous localisation and mapping
SLAT	Simultaneous localisation and tracking
SNR	Signal-to-noise ratio
TA	Timing advance
TDoA	Time-difference-of-arrival
ToA	Time-of-arrival
TRP	Transmission and reception point
TX	Transmitter
UAV	Unmanned aerial vehicle
UE	User equipment
UL	Uplink
UMa	Urban macro
UMi	Urban micro
UN	United nations
UWB	Ultra-wideband
w.r.t.	With respect to

1 Introduction

Hexa-X is one of the 5G-PPP projects under the EU Horizon 2020 framework. It is a flagship project that develops a Beyond 5G (B5G)/6G vision and an intelligent fabric of technology enablers connecting human, physical and digital worlds.

This document is the first deliverable of Work Package 3 (WP3) - "6G High-Resolution Localisation and Sensing". The aim of WP3 is two-fold: (i) to explore the potential of technological advances in communication systems (including from within the project) for the purpose of localisation and sensing, leveraging the geometric nature of the propagation channel at millimetre wave (mmW) frequencies (including 100 to 300 GHz); (ii) to harness high-resolution location and map information for existing (communication, security) and novel applications. The research focuses on the following key aspects related to high-resolution localisation and sensing:

- Definition of use cases and requirements, complemented with a gap analysis.
- Development of methods, signals and protocols for localisation and mapping.
- Establishment of location and mapping-enhanced service operation.

The relation of WP3 within Hexa-X, its tasks, and main interfaces are shown in Figure 1-1.

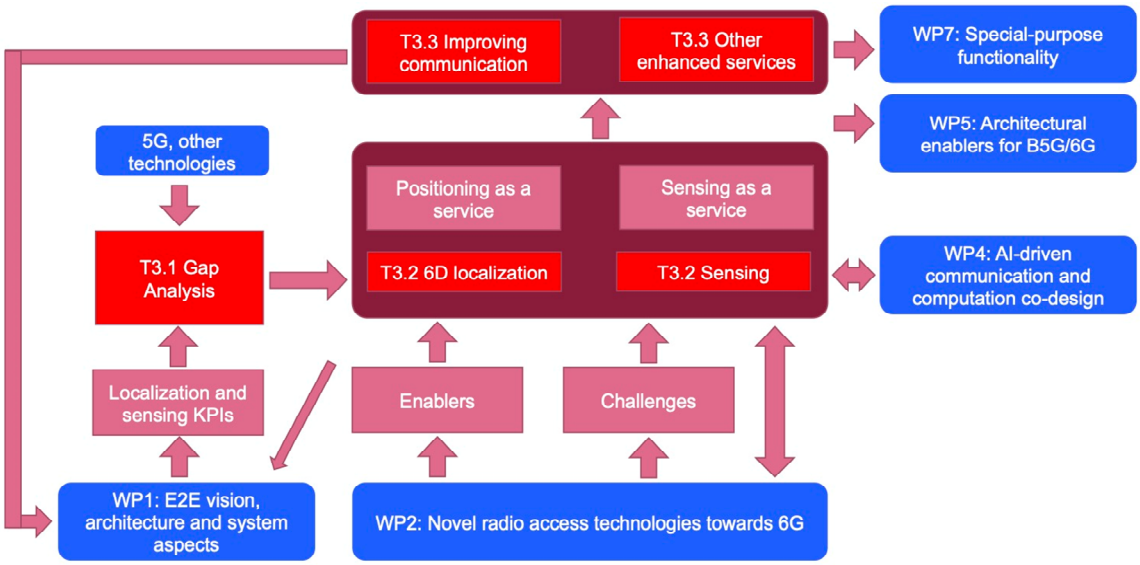

Figure 1-1 WP3 and its tasks in relation to Hexa-X.

1.1 Objective of the Document

This document reports on the finding of the use cases, requirements, and gap analysis. To support this, a basic introduction on radio localisation and sensing is provided, including the performance metrics, measurements, and methods. 5G localisation will be contrasted with localisation in the upper mmW frequency bands (here termed "6G localisation" for convenience) and also with radar, lidar, and ultra-wideband (UWB) sensing with sensing in the upper mmW frequency bands (here termed "6G sensing" for convenience).

In addition to the gap analysis, initial findings and plans related to the other key aspects are also provided: (i) localisation and sensing methods, (ii) services. These initial findings, in combination with the gap analysis will guide our future research activities.

1.2 Structure of the Document

The remainder of this deliverable is structured as follows. Section 2 provides an overview of localisation and sensing, describing the main performance metrics, the fundamentals, the measurements, and methods, in particular those related to 5G localisation. Section 2 also details the main radio and methodological enablers of 6G localisation and sensing, as well as the main challenges (visualised via the WP2 block in Figure 1-1). In Section 3, which is the main section of this document, the gap analysis is conducted. This section presents the use cases and their requirements, followed by a baseline evaluation of 5G standard and sensors (radar, lidar, UWB), as visualised through the blue block as an input to the gap analysis. The section concludes with the gap analysis itself (the left side in Figure 1-1). Section 4 presents initial results of localisation and sensing in 6G, quantifying the main benefits over 5G. The section also covers topics related to interference management and sensor fusion and ends with a presentation of the planned demonstrators. Main research questions are identified for future work. This work is visualised via 'positioning as a service' and 'sensing as a service' in Figure 1-1. Complementary to Section 4, which describes how location and sensing information is obtained, Section 5 describes how this information can be used for enabling and enriching applications as well as to support communication. It also defines network requirements. This is visualised through the WP1, WP5, and WP7 block in Figure 1-1). Our main conclusions are reported in Section 6.

The main terminology used in this document is described in Annex A.

2 Overview of Mobile Radio-based Localisation and Sensing

In this section, a brief introduction to the main concepts in radio localisation and sensing is provided, as well as the associated performance metrics, focusing on 5G scenarios. In addition, the main potentials and the associated challenges in 6G localisation and sensing are presented.

2.1 Localisation and Sensing Performance Metrics

This part presents the performance metrics for localisation and sensing, which are not limited to those used in 3GPP, considering the new use cases envisioned in 6G, as shown in Table 2-1.

Table 2-1. Performance metrics for radio localisation and sensing.

Name	Meaning	Unit
Horizontal accuracy[†]	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the location error parallel to the earth surface.	m
Vertical accuracy	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the location error perpendicular to the earth surface.	m
Orientation accuracy	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the orientation error in a global frame of reference.	rad
Range accuracy	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the ranging (distance estimation) error.	m
Velocity accuracy	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the (relative) velocity error.	m/s

[†] For a detailed discussion on accuracy and precision, the reader is referred to Annex A.

Angular accuracy	Error value corresponding to a certain percentile (e.g., 90%, 99%) or the root mean squared value of the (relative) angle error (arrival and/or departure, azimuth and elevation), within the local frame of reference.	rad
Range resolution	Minimum difference in distance between targets to have measurably different range. Equivalent to delay resolution.	m
Velocity resolution	Minimum difference in velocity between targets to have measurably different velocity. Equivalent to Doppler resolution.	m/s
Angular resolution	Minimum difference in angle between targets to have measurably different angle.	rad
Link range	Maximum distance at which an object can be located unambiguously with a certain probability of detection during sensing.	m
Velocity range	Maximum range of velocities to be measured.	m/s
Angular velocity	Rate of change of the orientation of a mobile device, relative to an external frame of reference.	rad/s
Agility	Acceleration (m/s^2), jerk (m/s^3), angular acceleration (rad/s^2) of target.	m/s^x, rad/s^x, $x \in \{2,3\}$
Latency	End-to-end localisation/sensing latency. The duration between an application or a network function requesting location and obtaining the results. Includes the physical layer latency.	s
Update rate / reporting rate	Number of consecutive localisation/sensing estimates per unit time (at most once per latency).	Hz
Availability	Fraction of the time the estimated localisation error is below the alert limit (for 1 device).	%
Integrity	Fraction of the time the true error is outside of estimate of maximum possible error (for 1 device).	%
Precision score	The ratio of correctly predicted positive observations to the total predicted positive observations.	%
Scalability	Capability to use a technique by an increasing or decreasing number user equipment (UEs) or transmit points (TRPs), given that those nodes are in coverage.	--

2.2 Radio Localisation and Sensing: An Overview

Below the fundamentals of localisation and sensing are described, addressing various aspects such as terminology, methods and limitations followed by the current localisation and sensing in 5G.

2.2.1 Localisation and Sensing Fundamentals

2.2.1.1 Localisation

As defined in Annex A, (radio) localisation is the process of estimating the location of a device from (radio-based) sensor measurements. The location can be in 2D (horizontal plane), 3D (including altitude) and 6D (including pose or orientation). Base stations (BSs) commonly serve as location and time reference, while UEs have unknown and time-varying locations, which should be estimated through the exchange of signals (in uplink (UL) or downlink (DL), or a combination of both) with the BSs. In the case of non-terrestrial networks (NTNs), the BS is itself mobile and, thus, has a dual role in localisation. Firstly, an NTN BS can serve as a location and time reference. In this case, connected UEs are localised in the coordinate system of the NTN BS. Secondly, the NTN BS has a time-varying

location and may itself need to be localised through the exchange of signals with terrestrial BSs, like a UE. The remainder of this deliverable considers only the terms BSs and UEs. It should be noted that the term UE should here be considered to include conventional UEs, but also complexity-constrained tags and reduced capacity (so-called 'RedCap') devices.

The signals used for localisation are generally pilot signals. The received signals at the BS or UE are a function of (i) the unknown UE state (e.g., location, orientation, velocity); (ii) the known state of the infrastructure (e.g., location, orientation, and velocity in the case of a mobile BS on an unmanned aerial vehicle (UAV)), and (iii) nuisance parameters (e.g., channel gains, clock bias). From the observed signals, different types of measurements can be obtained. The most common measurements are listed below in Table 2-2, and rely on the resolvability of the line-of-sight (LoS) path. Several conditions may exist:

- *The LoS path with respect to (w.r.t.) a BS is present and resolvable:* This is the preferred condition; in which case the quality of the measurement is limited by the measurement noise.
- *The LoS path w.r.t. a BS is present but not resolvable:* In this case, other paths will interfere with the LoS path, thus limiting the accuracy of the measurement and the localisation. Resolvability can be improved using larger bandwidth (delay/range resolution), longer coherent processing times (Doppler/velocity resolution), or larger antenna apertures (angle resolution).
- *The LoS path w.r.t. a BS is blocked:* In this case, the localisation method should ensure that the corresponding measurements are not used as if they were the result of LoS paths. Hence, some form of LoS detection is needed.

Table 2-2. Common measurements for localisation. Measurements can be performed by the UE (DL) or BS (UL).

Measurement type	Relation to location	Geometric constraint	Performance limitations
Cell identifier	Coarse indicator of distance to the base station	Ball around the BS	Accuracy depends on cell size
Received signal strength (RSS)	Coarse indicator of distance to the base station	Circle (2D) or sphere (3D) around BS under simplified propagation assumptions	Affected by multipath and shadowing, and antenna patterns
Time of arrival (ToA) of the first path	Distance to BS with clock bias	Circle (2D) or sphere (3D) around BS	Depends on signal-to-noise ratio (SNR) and bandwidth
Time-difference-of-arrival (TDoA) of the first paths	Difference of distances with respect to several BSs	Hyperbola (2D) or hyperboloid (3D)	Depends on SNR and bandwidth, synchronisation among BSs.
Round-trip-time (RTT) of the first path	Distance to BS	Circle (2D), sphere (3D) around BS	Depends on SNR and bandwidth
Angle-of-arrival (AoA) of the first path	Direction of transmitter to the receiver	Direction of the line between transmitter to the receiver in receiver reference frame	Depends on SNR and array aperture
Angle-of-departure (AoD) of the first path	Direction of transmitter to the receiver	Direction of the line between transmitter to the receiver in transmitter reference frame	Depends on SNR and array aperture
Doppler of the first path	Radial velocity of the UE	N/A	Depends on coherent processing time

Once enough measurements are obtained, the UE location can be estimated. Examples are shown in Figure 2-1 and further elaborated in Section 2.2.2.1.

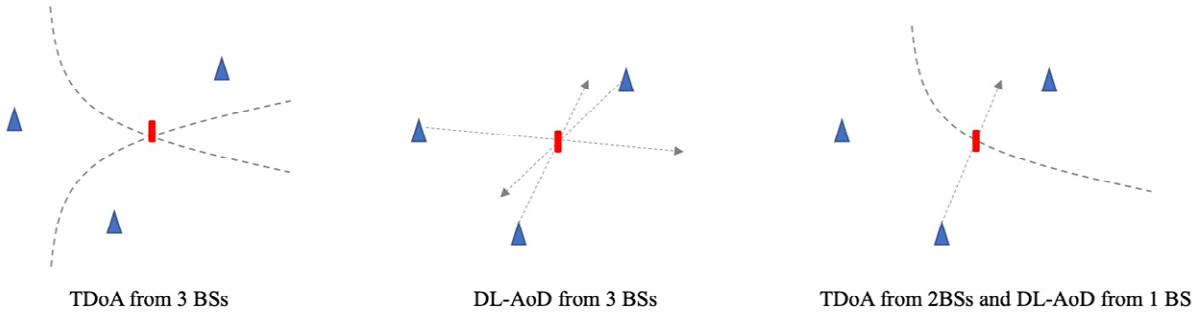

Figure 2-1 Localisation of a UE (red rectangle) with 3 BSs (blue triangles) using TDoA, AoD or a combination thereof.

The accuracy of the location estimate depends on (i) the accuracy of the underlying measurements from Table 2-2; (ii) the relative position of the BSs w.r.t. the UE. Hence, localisation performance can be improved by improving the measurements and the geometric placement of the positioning infrastructure.

2.2.1.2 Sensing

As defined in Annex A, sensing is the operation of the sensor, which is any device, module, machine, or subsystem that detects events or changes in its environment. Goals of sensing include to localise and track passive objects or targets (including unconnected users), extract features from objects (e.g., material sensing), and classify states of the environments (e.g., indoor and outdoor). In this section, our description is limited to radar-like sensing, which is often the first step for other sensing modalities. Sensing can be performed by a UE or one or more BSs, as described in Table 2-3. For monostatic sensing, it is important to mention that the transmitted signals need not be pilot signals, as the transmitter and receiver are co-located. Hence data-carrying communication signals can be used for monostatic sensing (see Section 2.3.2).

Table 2-3. Sensing modes.

Operation	Transmitter	Receiver	Description
Monostatic	UE	Same UE	When there is no infrastructure, and the transmitter and the receiver are co-located on the UE with full-duplex capability, the measurements of ToA, AoA, AoD, and Doppler of each of the resolved paths corresponds to the detection of a target, where the location is relative to the coordinate system of the UE.
Monostatic	BS	Same BS	When the BS acts as full-duplex transmitter and receiver, the measurements of ToA, AoA, AoD, and Doppler of each of the resolved paths corresponds to the detection of a target, where the location is absolute, in the coordinate system of the BS.
Bi/multi-static	BS	UE	When there is a BS, the signal to the UE can be used to estimate ToA, AoA, AoD, and Doppler of each of the resolved paths, which in turn can be used to localise the UE and detect the targets, all in a global frame of reference.
Bi/multi-static	BS	BS	When the transmitter and receiver are BSs, the targets are detected, and their location estimated in the absolute joint coordinate system of the BSs.

Generally, targets or objects are tracked over time, a method known as multi-target tracking or multi-object tracking. When the UE location is involved in the process, this becomes a *simultaneous localisation and mapping* (SLAM) or a *simultaneous localisation and tracking* (SLAT) problem, where SLAM considers static objects, while SLAT considers also moving targets. SLAM and SLAT can be performed in a relative or absolute frame of reference. Examples of sensing are shown in Figure 2-2.

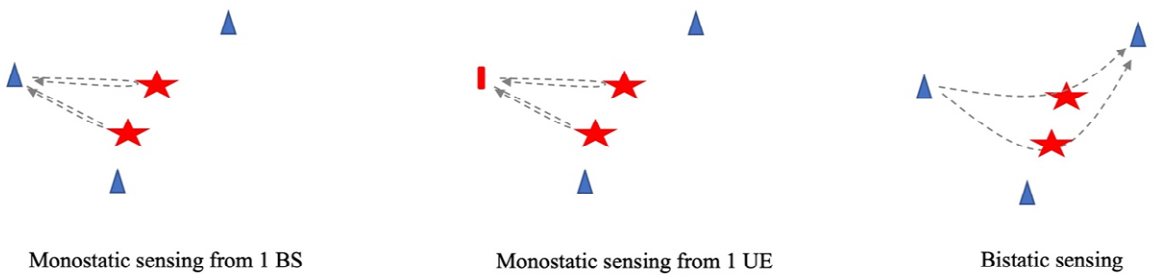

Figure 2-2 Sensing of targets (red stars) with a BS (blue triangle) or a UE (red rectangle). Measurements are not specified, but may include ToA, AoA, AoD, and Doppler.

2.2.1.3 Localisation and Sensing Methods

Localisation and sensing involve the iterative application of several processes:

- *Signal design:* the design of signals in time, frequency, and space to support positioning and sensing. The signals are ideally designed to be orthogonal among different transmitting sources to avoid interference. In 5G, the signals are generally broadcast signals with a predetermined structure. Examples include the positioning reference signals (in time and frequency) and the spatial signals generated at BSs for angle estimation [38.305]. When a priori information about the UEs or environment is available, signals can be designed to optimise the localisation or sensing performance of a specific UE or group of receivers [KWS+21].
- *Signal transmission and reception:* The designed signal is transmitted over the radio channel and acquired at the receiver. The signal is subjected to analogue and digital impairments. The receiver obtains in-phase and quadrature (IQ) samples of the received signals, which are used for further processing. This process involves synchronisation, phase noise tracking, and filtering.
- *Channel parameter estimation:* The sampled signal is applied to a parametric channel estimation routine, which returns estimates of the ToA, AoD, AoA, and Doppler, of the LoS path and possibly also of multipath components. When estimating these parameters jointly, the computational complexity becomes an important bottleneck. There is a rich literature on ToA estimation [PRL+17], while AoA and AoD estimation have appeared more recently in sparse mmW channel estimation [AEL+14]. Approaches can be divided into search-based (e.g., maximum likelihood, orthogonal matching pursuit, expectation-maximisation) and search-free (e.g., ESPRIT - estimation of signal parameters via rotational invariance techniques [RK89]). The output of the channel estimator is a set of tuples, where each tuple in the set corresponds to the channel parameters of a single propagation path. The estimates may also be tagged with corresponding reliabilities, e.g., in the form of a covariance matrix per tuple.
- *Localisation, sensing:* The channel parameters are provided to the localisation, mapping or tracking routine. The purpose of this routine is to solve the inverse problem of inferring the state of the UE or the environment from the estimated channel parameters [ZB11]. Methods can be classified as geometric or statistical, depending on whether uncertainty information is available. Geometric methods aim, for instance, to determine the intersection (in a least squares sense) of circles, spheres, or lines. Statistical methods include maximum likelihood or maximum a posteriori estimation. Methods may provide a point estimate or a distribution of the state. Estimates across time are connected by Bayesian filters, such as the Kalman filter. This inference can rely on prior information from previous time steps or from external sensors, such as global navigation satellite systems (GNSS) or UWB. Sensor fusion, which involves fusing information from multiple sensors to reduce the uncertainty in localisation or sensing, can then be performed at the level of the channel parameters (tight coupling) or at the level of the position estimates (loose coupling).

2.2.1.4 Performance Limitations

The performance of localisation and sensing is limited by several factors:

- **Resolution:** To estimate the parameters of a signal path during channel estimation, the path should be resolvable (separable) in at least one domain among delay, AoD, AoA, or Doppler. Paths with similar values in all domains will interfere, affecting the resolution. The resolution can be improved by larger bandwidth (delay resolution), larger aperture of the transmit array (AoD resolution), larger aperture of the receive array (AoA resolution), longer coherent processing interval (CPI) (Doppler resolution). To support the use cases from Section 3.1, bandwidths on the order of 1 GHz to 4 GHz will be needed. When a contiguous band is not available, but only several smaller sub-bands (which are employed either in parallel through carrier aggregation or sequentially through frequency hopping), two cases are distinguished:
    - There is phase-coherence between the sub-bands: in this case, resolution is not affected, but the ambiguity function (refer to Annex A) may exhibit significant side-lobes, adversely affecting localisation and sensing performance.
    - There is no phase-coherence between the sub-bands: in this case, the delay resolution is limited by the bandwidth of the largest sub-band.
- **Accuracy:** Even under sufficient resolution, paths may be weak, thus limiting the accuracy of the estimated parameters. Accuracy depends on the SNR which depends on the received signal power and the receiver noise figure of the receiver. The received power depends on the transmit power, antenna patterns (including beamforming, if used), and propagation.
- **Environment:** The propagation environment plays an important role in the localisation and sensing performance. Environments with many objects that can block radio signals lead to interruption of the LoS path and reflections / scattering can increase the number of interfering signal paths, as well as clutter. At sub-THz frequencies, signals are also affected by molecular absorption.
- **Mobility and frequency offsets:** Since delay, angle, and Doppler information is generally extracted via the phase of the received signal, additional variations in phase are undesirable. When Doppler information is not extracted from the received signal, the CPI is limited to the time during which UEs or objects move a fraction of a wavelength. A short CPI implies a reduced SNR and thus degraded accuracy. A similar behaviour is induced by frequency drift of local oscillators. The residual phase drift due to the oscillator should be negligible during the CPI.
- **Range:** the maximum distance depends on the SNR at the receiver. Which in turn depends on the CPI and the pathloss.
- **Model mismatch:** In general, unmodeled effects due to radio hardware impairments (e.g., array calibration, coupling, power amplifier nonlinearities) or propagation effects will lead to reduced localisation and sensing performance. The impact of unmodeled effect is largely unknown but expected to be more significant for localisation and sensing, as compared to communication.

2.2.2 Localisation and Sensing in 5G

Positioning has become an integral part of cellular system standardisation since 4G. Initial positional requirements for 4G systems are dominated by the regulatory agencies such as Federal Communications Commission (FCC) [FCC15]. The target accuracy of 4G systems is in the order of 50 meters to meet these regulatory agencies' requirements. However, in 5G, guided by the new requirements from the use cases such as indoor factories, vehicle to everything (V2X), etc., the required positional accuracy targets are in the order of a few decimetres [22.261]. The key enablers to support these requirements include high dimension multiple input multiple output (MIMO) in mmW band and support for wideband positioning signals.

The 5G standards provide new architecture, protocols, signalling, and measurements to support these requirements. The 5G positioning architecture is shown in Figure 2-3 [38.305]. Typically, the UE receives the necessary radio resource configuration (RRC) through the so-called NR-Uu or LTE-Uu interface, for performing required positional measurements. The gNodeB (gNB)/ non-standalone enhanced NodeB (eNBs) exchange these measurements with the location management function (LMF) via access and mobility management function (AMF) through positioning protocols such as NR

positioning protocol annex (NRPPa) and LTE positioning protocol (LPP) for estimating the position of the UE [DSM+21].

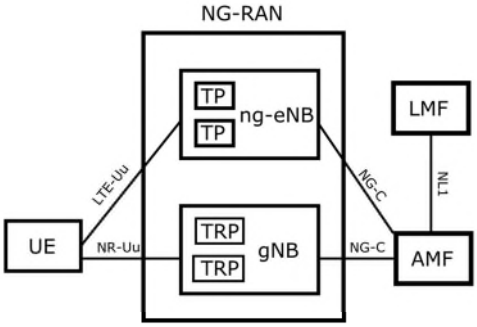

Figure 2-3: NR positioning Architecture

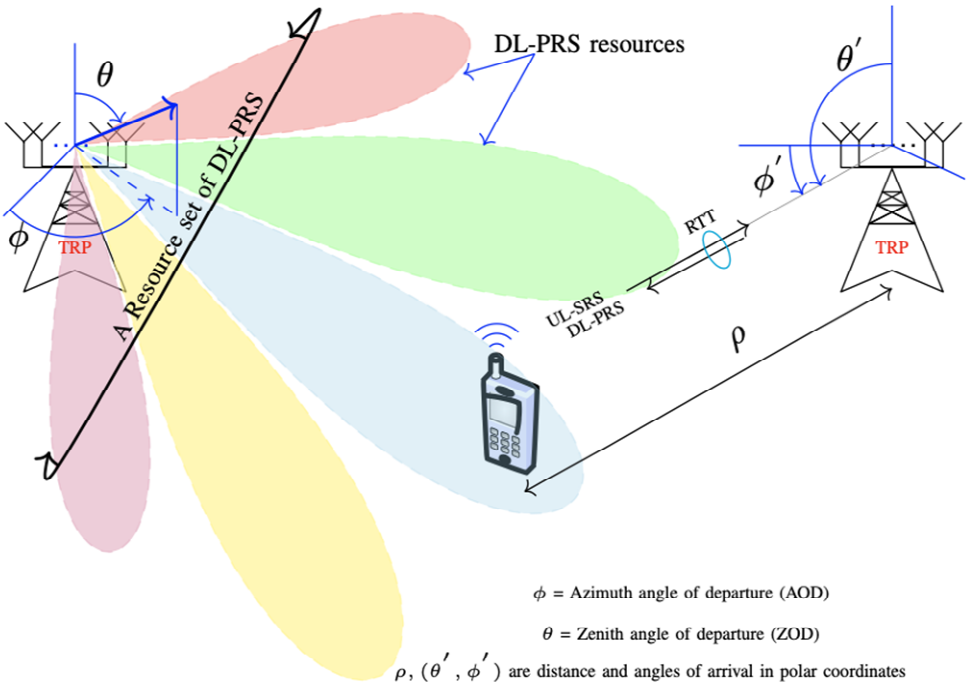

Figure 2-4: 5G Positioning signals and methods. Reproduced with permission from [DSM+21].

The different positional signals and measurements involved in 5G positioning are as shown in Figure 2-4 and are listed below:

- Downlink positioning reference signal (DL-PRS)
- Uplink sounding reference signal (UL-SRS)
- Downlink angle-of-departure (DL-AoD)
- Uplink angle-of-arrival (UL-AoA)
- Multi-cell roundtrip time (Multi-RTT)

To arrive at the positioning information in 5G networks, two different strategies are employed. The first set of methods are those where UEs perform measurements and transfer the results of the measurements to the BS or LMF which, in turn, calculates the position of the UEs. In another set of methods, the UEs calculate their position from assistance data provided by the network, for example, a BS can provide information regarding list of visible satellites, Doppler shift corrections needed for those satellites, etc. to the UE, thereby reducing the time required for location estimation using GPS. Below, a few

positioning methods, which use the positioning signals and measurements discussed above, are described.

2.2.2.1 Positioning using 5G signals

TDoA based methods

This method is based on hyperbolic multilateration using the TDoA of reference signals between a node and a reference node. TDoA between each pair of reference nodes will yield a locus of points along a hyperbola in which the UE location might be present. To unambiguously identify the location, multiple TDoA from several reference nodes (at least four) is needed. The TDoA measurements are performed on PRS signals. In DL-TDoA method, UEs perform DL PRS received signal time difference (RSTD) per beam and report the measured RSTD including DL PRS resource id (beam id) to the LMF, which computes the position of the UE using hyperbolic multilateration. In UL-TDOA, the UL relative time of arrival (UL-RTOA), is computed at the gNBs and is reported to the LMF along with the azimuth and zenith AoAs. The LMF computes the position of the UE from this information.

Angle based methods

Due to the mmW operation with large dimension MIMO, high angular resolution is theoretically possible in 5G. Two new methods which exploit this in UL and DL, respectively, are proposed in 5G [DSM+21]. With the downlink-direction of arrival (DL-DoA) method, the gNB creates a narrow DL-PRS beam on which the UE will perform measurements and reports these to the LMF. The LMF combines these measurement results with the beam angles provided in the azimuth and elevation directions by the gNB and estimates the UE position. In the UL-AoA method, the UL-SRS signal is captured from multiple TRPs to estimate the angular measurements. This is transferred to the LMF which will use this together with the deployment information to arrive at the UE's position.

E-CID based approach

In the enhanced Cell-ID (E-CID) method, the UE location is estimated based on the geographical coordinates of the serving cell antennas. These methods use the readily available parameters such as timing advance (TA) along with reference signal received powers (RSRPs) on reference signals. This method typically is less accurate, but it is obtained for free without the need for dedicated localisation specific signalling or measurements.

Multi-RTT based methods

One of the newer methods proposed in 5G for position estimation is based on multi-cell round trip time (multi-RTT). Multiple TRP's PRS data is typically multiplexed into a comb formation. The LMF provides the DL-PRS configuration to the UE using LPP. The UEs perform the measurements on the DL-PRS from multiple transmit TRPs and report them to the LMF for position estimation. This method does not require tight network synchronisation.

2.2.2.2 Sensing using 5G signals

Sensing using 5G cellular networks has received some attention especially for indoor sensing. Even though the 5G standard does not explicitly specify methods, signals, and architectures for sensing, there have been some attempts in research for using 5G signals for sensing. These methods typically sense environment stimuli by using the fluctuations in radio parameters such as Doppler signature, channel state information (CSI) envelope and Fresnel zones. Indoor sensing, such as device-free passive sensing of human activity such as walking is an interesting area, as it does not require users to wear any bands for measuring vital statistics for various human activities such as sleeping, running, etc. [GSS17]. Emergence of new sensing use cases in 6G has the potential to bring about changes in standardisation to specify methods, signals, and architectures for sensing.

2.3 Potential for Localisation and Sensing in 6G

In this section, the main potentials, according to Hexa-X, for localisation and sensing in 6G are highlighted, namely *extreme performance* and *joint radar, communication, computation, localisation, and sensing* (JRC2LS). Then, the main enablers are described from a radio perspective followed by the main challenges, which will drive the work in WP3, depicted in Figure 2-5.

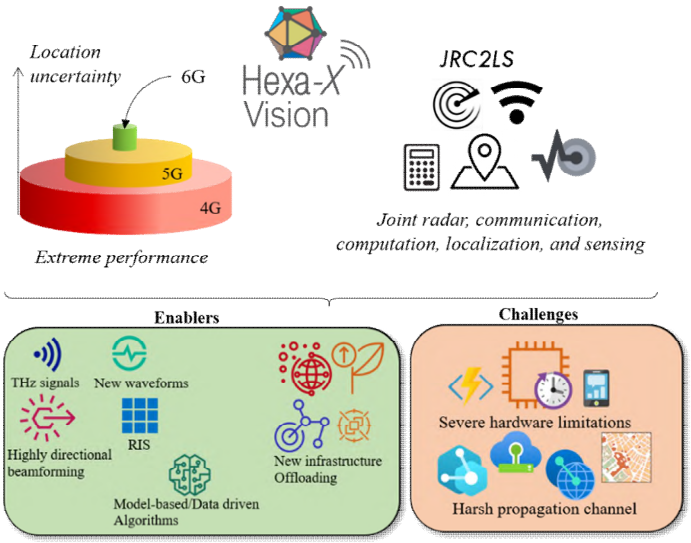

Figure 2-5. The Hexa-X vision for localisation and sensing, including the main enablers and challenges [WSM+21].

2.3.1 Extreme Performance

As pointed out in [HEX21-D21], the 6G RAT will operate at a variety of frequency ranges encompassing not only present-day 3GPP NR FR1 and FR2, but upper mmW and sub-THz ranges as well. By operating at high carrier frequency and providing large bandwidths, the 6G radio access interface permits small form factor, highly dense antenna arrays which enable pencil-like beamforming, as well as very fine delay resolution which, in turn, permit resolving and then harnessing multipath components on the spatial and temporal domains. As a result, new use case families which require or benefit from highly accurate localisation and sensing will also become possible. Such use case families will require very low latency, high reliability, and availability in addition to traditional accuracy and resolution requirements (see Section 2.1 for a discussion on the localisation and sensing performance metrics). Thus, next generation RF-based localisation and sensing are expected to match the performance of available sensor technologies, such as lidar and high-definition cameras. Compared to light-based imaging, lower and upper mmW frequency ranges are less susceptible to ambient illumination and weather conditions. It is worth noticing that alternative RF-based solutions, such as Bluetooth Low Energy and UWB technologies, would still demand separate/extra infrastructure and additional maintenance expenses.

By exploiting the high spatial and temporal resolution and considering the upper mmW and sub-THz propagation features, it becomes possible to capture and identify relevant properties of the environment and map the surroundings at very short intervals. Such environment mapping can also be used to leverage accurate positioning even in NLOS situations. For instance, in [RXK+19] authors show an experiment where cm-level accuracy is achieved through mmW imaging without requiring any prior knowledge of the deployment scenario. This procedure can create real-time 6D maps (3D position and 3D orientation) with fine details and, conditional on the network infrastructure (e.g., edge computing), can be quickly stored and shared on demand between communicating nodes, thus enabling advanced use cases (as discussed in [HEX21-D12] and [HEX21-D21]), such as immersive telepresence, digital twinning, and collaborative robots. At mmW operation range, it also becomes viable to detect certain materials (including, for example, hazardous gases) by implementing frequency scanning spectroscopy.

The shorter wavelength and the corresponding small form factor antennas allow very directive applications, such as miniaturised radars capable of detecting gestures and thus enabling touchless interactive user interfaces.

The technical activities reported in this deliverable will determine localisation and sensing KPIs for the most challenging use cases and assess the technology gap w.r.t. 5G.

2.3.2 Joint Radar, Communication, Computation, Localisation, and Sensing (JRC2LS)

Successive generations of cellular standards have seen an increase in operating frequency and bandwidth. 6G will continue to see the same trend, resulting in the potential use of radio communication bands for sensing applications (e.g., like automotive radar). This creates a new opportunity for using cellular infrastructure for sensing and mapping applications. The traditional radar type of sensing requires detecting and estimating the range and Doppler signature of the target [Sko08]. The range and angular resolutions are significant KPIs of any sensing system. High frequency operations of 6G will enable deploying massive antenna arrays into compact dimensions aiding in resolution, while the large operating bandwidths can provide better range resolution [SGB+21]. Joint sensing, mapping and communication systems can be categorised into monostatic and bi/multi-static systems (see also Section 2.2.1.2).

- In monostatic operation, the transmitter and receiver are co-located. This mode of operation needs a high degree of isolation between transmitter and receiver to overcome the self-interference and typically the transceivers need to operate in full-duplex mode [BRT+19]. How the spectrum, hardware and waveforms are shared between communication and radar functionality have attracted considerable attention in the 6G context [LMP+20] [WBV21].
- In bi/multi-static setup, the transmitter and receiver are physically separated. There is no need for further isolation between transmitter and receiver, leading to cost-effective transceiver hardware. The high frequency operation of 6G systems in sub-THz bands, will lead to densely deployed cellular systems with wide bandwidth having small cells which can, in turn, aid in distributed co-operative network sensing. The choice of waveform [DMM+19], sensing resource allocation [WBV21], co-operation and multiplexing between multiple nodes [YHS+21] have received particular interest in the multi-static mode of sensing operations.

Future 6G networks are expected to involve large dimension wireless channels in terms of increased number and density of connected devices, greater antenna array size, as well as wider bandwidth usage, when compared to present day cellular systems. This characteristic imposes formidable computational challenges to estimate and track channel parameters in very high dimensions, it also imposes high overhead if real time CSI needs to be acquired relying solely on typical pilot-based channel training and feedback techniques. As an alternative, detailed environment mapping of channel (parameter) features together with main aspects affecting the wireless channels (such as blockages, reflectors, and scatterers) can support communication procedures, such as beam alignment, system capabilities adaptation, channel features and location of communicating transceivers prediction, with reduces overheads. While such ideas were already present in 5G, they are largely optional [TMR+14]. In 6G, in contrast, harnessing *location and sensing information will be critical to support efficient communication***.**

2.3.3 Radio Enablers

The potential of extreme performance and JRC2LS is enabled by a variety of technical developments, which are studied and advanced in Hexa-X, as collaboration between WP2 (Novel radio access technologies towards 6G, see [HEX21-D21] for more details) and WP3. Below, these enablers are described.

2.3.3.1 High-resolution Sensing with Large Bandwidths and Large Arrays

Localisation, radar, and sensing all rely on the resolvability of multipath components using, for example, angle, range, or Doppler dimensions (as discussed in Section 2.2.1.1). Resolution in angle is

obtained by massive antenna arrays [SGB+21], where lower carrier frequencies can provide extended range (due to smaller propagation losses) at the cost of physically larger arrays, while mmW and sub-THz frequencies allow for progressive miniaturisation of components. Range resolution relies on large bandwidths, which are mainly obtained at higher carrier frequencies. Especially, signals in upper mmW bands with much shorter wavelength support massive antenna arrays with fine spatial (angle and delay) resolution, thus enabling highly directional sensing and imaging applications (e.g., gesture detection, 3D mapping), while being less susceptible to ambient light and weather conditions than light and infrared technologies [RXK+19], [DBB+21]. Harnessing this resolution will require careful synchronisation and antenna calibration. Additionally, the channel coherence time at upper mmW frequency range decreases, which causes the channel state to change much faster. Consequently, this requires much more frequent estimation to properly follow channel variations. The corresponding Doppler shift significantly increases in such circumstances, which requires the development of new estimation algorithms to properly compute position and velocity.

Narrow beams also provide high resolution scanning in the beam space domain enabling on-the-fly creation of highly accurate 3D maps. A personal radar using 6G UEs can enable several mapping applications. UEs can scan the environment at each position using narrow beams in many directions and the backscattered accumulated signal over time can be used to generate a map of the environment. Several UE measurements can be crowdsourced to build a high-resolution 3D map of the environment [GDD16].

Lower and especially upper mmW signals are affected by high propagation attenuation, power constraints, and blockage. Thus, highly directional pencil-like antenna beams are needed to compensate for the channel impairments. As a result of such high gain antennas, very directional sensing applications become a viable solution to create high-definition images of the surroundings [RXK+19]. As mentioned earlier, by implementing such high-resolution scanning in the beam space domain, it becomes possible to create on the fly detailed 3D maps of the surroundings which can then enable, e.g., elaborated digital twin applications in industrial use cases; or, at a smaller scale, innovative sensing applications capable of implementing touchless interfaces by tracking hand gestures, e.g., for telepresence use case. Moreover, this high-resolution beam space domain (note that, as addressed in [ATL+18], there are still problems related to beam point errors which degrade overall performance) permits imaging to be employed in conjunction with traditional time-based (range) metrics to support precise localisation without requiring prior knowledge of the environment. Large arrays have additional properties relevant for localisation, including near-field effects and beam-squint. Beamforming also forms an important connection between localisation and communication: pencil-like beams can benefit immensely from accurate location information, to track array locations over time, and harnessing proactive resource allocation methods with extremely low overhead [ZX21].

2.3.3.2 Intelligent Surfaces

Reconfigurable intelligent surfaces (RIS) are a developing technology that has the capability of modifying how an incoming electromagnetic signal is reflected by controlling its surface physical properties through electronic means [WZZ+21]. A RIS is largely passive and will thus have a lower cost (both for deployment and operation) than a BS or a relay [DKJ+20]. In more complex configurations, hundreds of elements on a single RIS will be able to be controlled individually (though at a relatively low rate of 10–60 Hz), which can be used to steer a beam's reflection in an unprecedented fashion. RIS can be mainly implemented through two techniques, i.e., reconfigurable metamaterials and conventional discrete antennas. Metamaterials exploit the possibility of dynamically and artificially adjusting their physical properties, such as permittivity and permeability, with respect to the transmitted/received electromagnetic (EM) waveforms to obtain some desired electrical or magnetic characteristics that, in principle, are not available in nature. Discrete antenna solutions entail the adoption of antenna elements and act as an independent unit that modifies the behaviour of the wave in the desired manner. When large intelligent surfaces are used actively and with the adoption of many tiny antennas, they represent a natural evolution of massive MIMO technology [EGG+21]. A RIS can be used to allow a signal to reach its destination when no LoS can be achieved. Whenever the position

of the RIS is known in advance, reception of the signal through an RIS will provide additional information relevant to localisation [WHD+20].

2.3.3.3 Joint Hardware and Joint Waveform

From a waveform perspective, communication waveforms, such as orthogonal frequency-division multiplexing (OFDM) combined with MIMO, are well-suited for localisation and sensing in terms of resolution. On the other hand, in terms of accuracy, optimisation of these waveforms (e.g., the use of dedicated sequences, power allocation, and precoding) for localisation and sensing may be conflicting with communication requirements. For localisation and bi/multi-static sensing, the signals are generally pilot signals (e.g., PRSs) and can thus not be used for conveying data. While such trade-offs are unavoidable, there are also important synergies, which will be further described in Section 5.2.

From a radio hardware perspective, localisation and sensing will have to work with the network and UE hardware deployed and used for communication to avoid additional installation effort and costs. Nevertheless, for some scenarios, a denser deployment will be necessary to achieve the required accuracy. Overall, if localisation builds on existing hardware, it can rely on a large-scale infrastructure that is available almost everywhere.

Given that the radio hardware is shared between communication, localisation, and sensing, an even deeper integration of the two services could be envisioned, where communication signals are reused for monostatic sensing. In such as case, data-bearing signals will be transmitted to communicate with users, while targets will be detected using the backscattered signals [LMP+20], [HAA+19], [LZM+18], [MBK+19]. However, variations can also be envisioned, where dedicated signals for each service (communication, localisation, and sensing), as well as dedicated hardware for each service are utilised. The trade-offs and practical realisation of these different approaches are yet unclear. For instance, for mono-static deployments with full-duplex mode, self-interference cancellation poses a significant challenge that requires the use of digital and radio frequency (RF) cancellers to provide sufficient transmitter/receiver (TX/RX) isolation [BRT+19], which may prove impossible at higher mmW frequencies. Nevertheless, significant academic effort has been devoted to designing feasible joint waveforms for both communications and sensing with limited time-frequency resources. For downlink communications, BSs with monostatic sensing capability can serve multiple UEs and estimate target parameters using a dual-functional waveform jointly optimised for both functionalities [LZM+18]. Multi-carrier waveforms are attractive, due to their high flexibility and wide prevalence in modern wireless communication systems [BK16], [KKW21], [GKC+20], [KWA21], [SW11], [KWSG+21]. In high-mobility scenarios (e.g., automotive, drones), one of the most significant challenges for OFDM radar will be inter-carrier interference (ICI), which destroys the orthogonality of subcarriers and degrades the performance of conventional fast Fourier transform (FFT)-based algorithms [HY17], [KWK21]. Single-carrier waveforms (e.g., IEEE 802.11ad) are more attractive from a hardware perspective but should be carefully designed [GLV20].

In general, all waveforms should be evaluated in terms of range-Doppler ambiguity function, which reveals waveform characteristics regarding resolution, accuracy, and clutter rejection [TSV+97].

Although the focus of this section is on the re-use of transceiver hardware and signalling between communication, localisation, and sensing, this concept can also be extended to the reuse of computational hardware. All three applications can have similar building blocks in the algorithm designs, which could be reused, especially on the infrastructure side. This is however beyond the scope of this document.

2.3.3.4 Algorithmic Developments

The envisioned large bandwidth of 6G systems will allow better multipath resolution, resulting in a rich path diversity. The possibility for high-frequency operation complemented with large-dimensional MIMO, can provide higher delay/angular resolution and rich information about the geometrical perspective of the scatterers in the environment, possibly even estimating the EM properties (roughness, permeability, etc.) of materials. At these high frequencies, the channel response will be highly site-

dependent, based on the local geometry and material EM properties, making the radio channel models using predefined parameters (e.g., depending on macro, micro, rural) ineffective.

Two complementary tracks are foreseen in terms of algorithms: *model-based* methods harnessing geometric optics, statistical signal processing, and optimisation theory (e.g., [KHC+17], [WML+16], [GWK+20], [WHC21]) and *model-free* methods harnessing data-driven machine learning and artificial intelligence (AI) (e.g., [WXC+18], [AK21], [KWP+20], [GFS20], [MSR+19]). While model-based methods are attractive, due to their rigorous foundation, performance guarantees, ability to optimise designs, and explainability, AI-based methods will prove useful when dealing with concatenated hardware impairments (see Section 2.3.4.1), or, when the functional mapping between the fingerprint of the channel and the position is intractable. Algorithms that exploit data, while also being capable of quickly adapting and coping with limited training, will play a central role in 6G systems. Examples of these methods include radio analytics based on the multipath channel profiles to capture the subtle environment changes for sensing [WXC+18], loop closure and data association procedures in SLAM [AK21], and location and orientation estimation from fingerprints [KWP+20].

2.3.4 Challenges for Attaining 6G JRC2LS

To fully harness the radio enablers for extreme performance and JRC2LS, two fundamental challenges have been identified:

1. *Hardware impairments*, which affect localisation and sensing more severely than communication; and
2. *Lack of channel models*, which also affects localisation and sensing more severely than communication, as WP3 activities rely explicitly on the geometric properties of the channel and thus require a deep and detailed understanding of the propagation phenomena.

These two challenges are further elaborated below.

2.3.4.1 Hardware Impairments

The accuracy of localisation systems using TDoA and RTT methods is mainly determined by the timing accuracy of the devices and the network. Moving towards higher accuracy means taking into consideration additional signal information such as AoD, AoA, multipath components, etc. The estimation of all these additional signal parameters is impacted by hardware imperfections. For accurate sensing and localisation, estimation of channel parameters needs to be robust towards hardware imperfections, and the estimation process needs to be able to extract the physical channel parameters from the receiver-side observation affected by the transmitter and receiver hardware. Examples of hardware imperfections that can affect localisation and sensing are listed below [RKL+20]:

1. Phase noise, which is more prominent at lower and upper mmW frequencies (when compared to 5G frequency range), will affect Doppler-processing and reduce coherency needed for integration [SHPW18].
2. Non-linearities and mutual coupling between antenna elements will affect angle estimation [WWS+20].
3. High-bandwidth signals used for range resolution will be impacted by non-linear distortion with memory effects and by linear distortion [Coo17].
4. Frequency-dependent IQ imbalance [CST+09] degrades the SNR and can affect AoD/AoA estimation.

While some of the hardware impairments can be compensated for by calibration (antenna calibration, linear distortion calibration), others, such as phase noise, will have to be compensated for dynamically during operation. The research challenge is to understand how hardware imperfections impact the localisation and sensing accuracy, and how signals should be designed to make estimation robust towards hardware imperfections.

2.3.4.2 Channel Modelling

In [HEX21-D21], potential enabling technologies and physical layer aspects for future wireless communication systems operating in the frequency range of 100 up to 300 GHz are discussed. Channels at different frequencies lead to different propagation effects, depending on the relation of the wavelength and the size of objects. At sub-6 GHz, the channel has a very complex relationship to the environment and small movements lead to large power fluctuations due to small-scale fading. At mmW bands, obstacle penetration is reduced, and reflection and scattering become more important phenomena. There is a higher degree of multipath resolvability due to a sparser channel (characterised by a limited number of propagation clusters), larger bandwidths (considering, e.g., 5G NR FR2 bandwidth of 400 MHz), and large antenna arrays, being more conducive to accurate localisation [STT+19]. Nevertheless, the presence of diffuse multipath leads to objects being intermittently visible, which deteriorates mapping abilities. Diffuse multipath tends to decrease its contribution to the total power as the radio frequency increases, as demonstrated at 60 GHz in [WML+16]. Finally, at 100 GHz and above, with wavelengths in the mm- and sub-mm- range, mainly multipath due to metallic objects will be visible, either in the form of large surfaces (described by moving incidence points or virtual anchors) or (groups of) smaller objects (e.g., pillars), behaving as static points.

It is evidenced by exemplary channel sounding at 140 GHz that both planar and cylindrical objects produce specular reflections. Cylindrical pillars would have caused a smaller number of reflections in sub-6 GHz because their cross-section becomes electrically small. From [NJK+18], there are fewer weak paths at 140 GHz resulting in a smaller number of clusters and fewer multipath components per such cluster when compared to 28 GHz. Additionally, the Doppler shift will be much more severe at the upper mmW frequency range. At such high frequencies, the channel state changes faster and thus needs to be updated more frequently which demands better spatial consistency of the developed channel models so that consecutive channel impulse response samples are accumulated as time evolves. These properties make sub-THz signals promising for localisation and sensing, as well as spectroscopy applications. However, characterisation of the angular, delay, and Doppler spreads due to extended objects, molecular absorption, link gains, and behaviour under mobility are important challenges to be addressed in the coming years based on, e.g., measured evidence and channel models. As it seems, a promising approach to obtain a channel model for localisation would be to relate physical objects in the environment with link gains, making site-specific models with full temporal and spatial consistency, e.g., [PMM+16], [JKH16], [FHZ+17]. Such an approach seems more appealing than partially stochastic models, e.g., [38.901]. Studies of influential scattering objects in propagation environments along with calibration of ray-based site-specific propagation models based on measured channels are on-going.

In [HEX21-D21], the propagation models for above-100 GHz radios are addressed. Therein, the most influential features for the key performance indicators are identified, i.e., pathloss, multipath richness, multi-user spatial correlation, wave polarisation characteristics, and channel dynamics.

3 Gap Analysis for High-Resolution Localisation and Sensing

In this section, a gap analysis to achieve high resolution localisation and sensing is presented. As a first step, high-level requirements for localisation and sensing in different use cases are studied. In the latter part of this section, the achievable accuracies for the existing solutions are explored. Finally, the gap analysis is provided, which gives an understanding of use cases and areas that need improvements.

3.1 Use Cases and Requirements

To address the needs of eventual evolution of the society, Hexa-X envisions five families of use cases for which 6G will be needed. An overview of these use case families is presented in Figure 3-1 and further elaborated in [Hexa-X-D11], [Hexa-X-D12]. In this section, scenarios defined by WP3 under

each use case family (specified in [Hexa-X-D12]), which benefit from sensing and localisation, are defined. To support these use cases, the next generation of radio access technology (RAT) must meet requirements of relevant KPIs for sensing and localisation. The identified KPIs are either supported by references or are based on internal documentation The actual values for each KPI in each scenario should be interpreted as strictest requirement. For many scenarios flexible adjustment of KPIs is relevant, as the requirement, e.g., for position accuracy, may change over time.

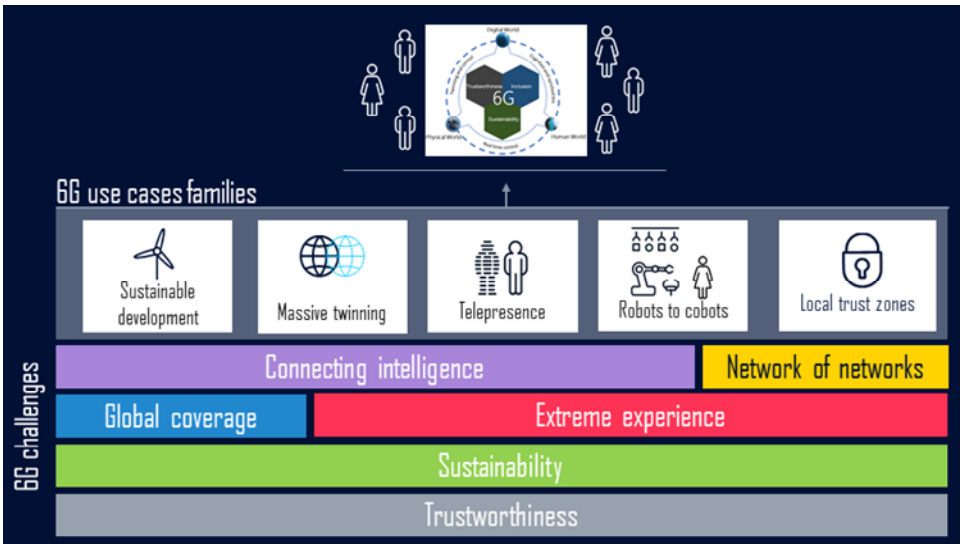

Figure 3-1. Hexa-X use case families.

3.1.1 Sustainable Development

The evolution of RAT towards 6G needs to address both environmental sustainability and sustainable development of humans and society to address the UN sustainable development goals (SDGs) and to also help verticals reduce their environmental footprint. To address these two key aspects, the next generation of RAT is envisioned to support clusters of use cases that are identified, for example, as E-health for all, Earth monitor, institutional coverage, and autonomous supply chain. All these use cases, as will be elaborated in the sections to follow, will require sensing and localisation capabilities for which requirements on relevant KPIs must be met.

3.1.1.1 E-Health for All

Exploiting a cost-efficient 6G connectivity, it is possible to enhance availability of health services to a large part of the world's population. A physical visit to a doctor can be effectively replaced by interaction between a patient and a doctor by means of augmented reality, virtual reality, and or extended reality. Drones can be deployed to remote areas to facilitate sample collection for examination. To ensure a reliable sample collection by deploying drones to enhance remote health care, stringent requirement on localisation accuracy (0.1 m - 0.5 m in horizontal plane and 0.1 m – 0.3 m in vertical plane) must be met. These strict requirements must be maintained with high availability of up to 99.99% and an update rate of acquiring new position estimated every second for the purpose of tracking, mainly when landing and sample collection/delivery procedures are ongoing.

Table 3-1. KPIs and requirements for drone deployment to enhance remote healthcare [22.261].

KPIs (localisation)	Requirements
Location accuracy	0.1 m – 0.5 m horizontal, 0.1 m – 0.3 m vertical
Orientation accuracy	N/A
Update rate	At least once per second
Availability	99.99%

Scalability	N/A

3.1.1.2 Earth Monitor

One of the goals in UN SDGs is to monitor Earth in real-time. To achieve this goal, a high density of very low cost and bio-degradable devices will be deployed to sense weather conditions, perform climatic measurements and keep an account of biodiversity in different parts or regions of Earth. To map the collected measurements from such a large deployment of zero-cost or bio-degradable sensing devices to the location where the measurements are taken, a robust and autonomous positioning will be needed. In this regard, KPIs and requirements for remote-sensing and monitoring are formulated as presented in Table 3-2. The target accuracy is in the range of 1 m to 30 m, obtained at a rate where a new position estimate is acquired every second with availability of 99%. Depending on the sensor to be localised, for example a sensor for weather condition monitoring, the update rate and availability may be subjected to lower values.

Table 3-2. KPIs and requirements for localisation for remote sensing and monitoring [22.261].

KPIs (localisation)	Requirements
Location accuracy	1 m - 30 m horizontal
Orientation accuracy	N/A
Update rate	Once per second (or even less frequent)
Availability	99%
Scalability	N/A

3.1.1.3 Institutional Coverage

6G aims to provide wireless connectivity for digital inclusion of institutions and organisations in both developing countries, as well as remote rural areas of the developed countries. By ensuring such an extensive outreach of high-grade wireless connectivity, services such as telepresence for remote virtual education can be effectively delivered. To ensure timely and efficient delivery of telepresence as a service, relevant KPIs and requirements on sensing and localisation must be met. The KPIs and requirements for telepresence can be mostly derived from the immersive telepresence for enhanced interactions use case family and will be elaborated in Section 3.1.2.

3.1.1.4 Autonomous supply chain

Autonomous supply chain ensures high resource efficiency and reduces material and energy consumption by tracking the end-to-end life cycle of goods during their production, shipping, distribution, usage, and recycling. In this regard, 6G connected micro tags can be used: to connect each product to the network, to enable an autonomous global asset tracking and management system, to monitor location and status of goods, as well as to facilitate a dynamic and responsive supply chain. To realise such a system, requirements on localisation KPIs (reported in Table 3-3) must be met.

Table 3-3. KPIs and requirements for asset tracking and management [22.872].

KPIs (localisation)	Requirements
Location accuracy	1 m horizontal
Orientation accuracy	N/A
Update rate	Once per second
Availability	99%
Scalability	several dozen per cubic meter.

3.1.2 Immersive Telepresence for Enhanced Interactions

Immersive telepresence outlines a capability that allows a person to be present anytime anywhere and interact with another remote person, object, or devices using all the senses, if desired. Such a capability will enhance mixed reality and holographic experience that are foundations of a fully merged cyber-physical world. Immersive telepresence will also facilitate mixed reality co-design by supporting remote collaboration to experiment configurations before prototyping a reality. Moreover, immersive sport events and merged reality games/work will significantly benefit from this new capability. At the core of scenarios that fall under this family of use case clusters is a need of sensing and localisation capabilities for enabling, for example, gesture recognition and augmented reality. In the following sub-sections, the requirements of KPIs for these use cases are introduced.

3.1.2.1 Gesture Recognition for Human-machine Interface

Gesture recognition can be used to feed in input for human-machine interface, specifically when the person and the machine are in two different worlds (digital and physical). For effective gesture recognition, requirements on sensing KPIs presented in Table 3-4 must be met.

Table 3-4. Sensing KPIs and requirements for gesture recognition for human-machine interface [LLA+19].

KPIs (sensing)	Requirements
Location (range + angular) accuracy	cm-level
Range resolution	cm-level
Maximum link range (unambiguous range)	~0.4 m
Angular resolution	~15 degree
Velocity range	-10 m/s to 10 m/s
Velocity resolution	0.3 m/s
Update rate	Once per 100 ms
Availability	99.99%

3.1.2.2 Augmented Reality

Augmented reality (AR) is vital when experimenting on a prototype before making an actual product and to provide context aware services to the end users. To deliver an augmented experience that is close to reality and is relevant where the user is located, 6D localisation of the device that is used to provide the service is a must. In one scenario where a user has an augmented reality device, to feed in the appropriate data, the device needs to be localised with the accuracies as in Table 3-5 [22.261]. An example is a user in a shopping mall, which provides AR-enhanced advertisement.

Table 3-5. Localisation KPIs and requirements for augmented reality for context aware services [22.261].

KPIs (localisation)	Requirements
Location accuracy	1-3 m (horizontal), 0.1-3 m (vertical)
Orientation accuracy	10 degrees (roll, pitch, and yaw)
Update rate	Once per second – once per 0.1 s
Availability	99%
Scalability	N/A

Another scenario for augmented reality is to place virtual object(s) into the real world. This specific scenario requires a significantly higher accuracy, as described in Table 3-6.

Table 3-6 Localisation KPIs and requirements for augmented reality for placing virtual objects in the real world [DGS+20,Azu93,PJ99].

KPIs (localisation)	Requirements
Location accuracy	<0.5 cm
Orientation accuracy	1 degree
Update rate	At least once per 10 ms
Availability	99.9%
Scalability	several dozen per cubic meter

3.1.3 Local Trust Zones for Human and Machine

This family of use case clusters identifies the need for a framework that requires the next generation RAT to support flexible architectures that allow sensitive information of organisations or services to remain on premises as in private networks. To exemplify scenarios under this family of use case clusters, the following are mentioned:

- Precision healthcare,
- Sensor infrastructure web,
- 6G-IoT micro-networks for smart cities,
- Infrastructure-less network extensions and embedded networks,
- Automatic public safety,
- Local coverage for temporary usage,
- Small coverage, low power micro-network in networks for production and manufacturing.

Use case clusters, apart from 6G-IoT micro-networks for smart cities, and small coverage, low power micro-network in networks for production and manufacturing use case clusters, greatly benefit from sensing and localisation capabilities. In the following sub-sections, an overview of the requirements of sensing and localisation KPIs is given.

3.1.3.1 Precision Healthcare

Precision medicine is an emerging initiative that takes an individualistic approach for disease treatment and prevention. Unlike the conventional one-size-fits-all approach, the individualistic treatment is governed by health-related data collection and dispensing medicine using wireless milliscale robots that navigate inside soft tissues of the human body [SUS21]. For example, 6G connectivity can be exploited to collect sensor-based measurements to keep track of patients' vital signs. Individual patient tracking and monitoring can be used to enhance patients' security, prevailing to the health condition or type of sickness a person seeking medical assistance is in need by exploiting the wide area connectivity that 6G can provide. All these different use cases, which play a pivotal role when it comes to improving healthcare, benefit from the envisaged 6G sensing and localisation capability. In the following sub-sections, the requirements on relevant KPIs are elaborated for telesurgery, patient tracking and monitoring, milliscale robots, and placement of equipment.

Telesurgery

One distinct use case in cutting-edge E-health is telesurgery, or remote surgery [MWS+21, SCA+21], which involves one or more robotic arms controlled by a surgeon and a master controller located in a remote area. All the controlling and feedback information must be transferred reliably between the remote areas. The 6G technology shall enable URLLC wireless connectivity such that the robotic arms mimic the natural hand movements of the surgeon and provide haptic feedback for further sensory and dexterity enhancement. Cooperative surgical systems go one step further and enable humans and machines to combine their individual strengths to improve the surgical outcome [SVH+21]. To be able to perform remote surgery, accurate location of the tissues as well as the instruments used in surgery is required. The following table shows the required accuracy for such accurate surgery.

Table 3-7 KPIs and requirements for telesurgery [MWS+21, SCA+21].

KPIs (localisation)	Requirements
Location accuracy	< 1 mm
Orientation accuracy	< 1 deg
Update rate	At least once per 100 milliseconds
Availability	99.99999%
Scalability	N/A

Patient tracking and monitoring

For effective patient tracking and monitoring, location accuracy of <10 m in horizontal plane and accuracy of <3 m in vertical plane (to identify floor level location of the patient) must be achieved. To ensure reliable tracking, an update rate of 1 new position estimate per second with availability of up to 99.99% is needed as well.

Table 3-8. KPIs and requirements for patient tracking and monitoring [22.261].

KPIs (localisation)	Requirements
Location accuracy	3 m – 10 m horizontal, <3 m vertical
Orientation accuracy	N/A
Update rate	Once per second (can be relaxed)
Availability	99.99%
Scalability	N/A

Localisation of milliscale robots

Combined with imaging techniques, milliscale robots can follow complex paths within human tissue with sub-millimetre accuracy, to perform various of tasks such as: hyperthermia, cauterisation, stimulation of nerves, taking biopsies, and drug delivery.

Table 3-9 KPIs and requirements for localisation of milliscale robots [SUS21].

KPIs (localisation)	Requirements
Location accuracy	< 1 mm
Orientation accuracy	< 1 deg
Update rate	At least once per 100 milliseconds
Availability	99.999%
Scalability	N/A

Placement of medical equipment on the body

Very often medical equipment is brought up onto or right next to the patient's body, and its exact position is crucial for the measurements to be collected. An example is the placement of digital x-ray detectors behind a patient's body, for which the position and orientation must be accurately calculated.

Table 3-10. KPIs and requirements for localisation of medical equipment on the body. [SWG+02][MSP+19]

KPIs (localisation)	Requirements
Location accuracy	< 1 cm

Orientation accuracy	< 1°
Update rate	Once per 0.1 second
Availability	99.9%
Scalability	Up to a couple dozen per cubic meter

3.1.3.2 Sensor Infrastructure Web

To support this use case, 6G should support devices with limited or no sensing capability with sensing information, for example navigating a vehicle that has insufficient onboard sensors (like radar, lidar) to understand its surrounding environment. To support such use cases, accurate localisation of devices without sensing capability is needed to pass sensing information of relevance. In Table 3-11, the relevant localisation KPIs and requirements for the device to be assisted are presented.

Table 3-11. KPIs and requirements for localisation for sensor infrastructure web [5GP19].

KPIs (localisation)	Requirements
Location accuracy	10 cm (pedestrian), 30 cm (vehicle)
Orientation accuracy	N/A
Update rate	Once per 100 ms (pedestrian) or 10 ms (vehicle)
Availability	99.99%
Scalability	N/A

3.1.3.3 Infrastructure-less Network Extensions and Embedded Networks

Use cases in this cluster require a temporary extension of the network coverage, especially when the target devices are at the network edge. One of the illustrative use cases that fall under this cluster is the deployment of a platoon of autonomous vehicles for agriculture harvesting. In such a deployment, vehicles in platoon are expected to maintain a safe distance among themselves to avoid collision and coordinate for navigation through the area of operation. The safe operation of such vehicles must also be ensured even when they are partially in out-of-coverage area. To support this type of use case, Table 3-12 outlines localisation KPIs and requirements for the vehicle platooning use case. This use cases are sometimes labelled under the umbrella of “cooperating localisation”. The update rate mandated by the application will be dependent on the current movement speed of the vehicles; the faster the movement the higher the update rate required.

Table 3-12 KPIs and requirements for co-operating localisation [ZGG+09, 5GP19].

KPIs (localisation)	Requirements
Location accuracy	1 cm (agriculture), 30 cm (automotive)
Orientation accuracy	<1° (agriculture)
Update rate	Once per 10 ms (depending on velocity)
Availability	99.99%
Scalability	Hundreds of devices in the coverage area

3.1.3.4 Automatic Public Security

Radio waves at different frequencies show different behaviour when interacting with different objects. This behaviour becomes more prominent at higher frequencies. Owing to the deterministic nature of interaction of the radio signals, and the fact that 6G will potentially exploit higher frequency spectrum, it is possible to use radio signal-based spectroscopy technology for threat detection (detection of weapon, harmful substances, explosives etc.) and localisation to enable autonomous security in public

places. In this regard, Table 3-13 outlines requirements on sensing KPIs for threat localisation. Requirements on key KPIs can be observed to have values similar to environment mapping use case (presented later in Section 3.1.5) where the difference lies in the fact that the localisation of threat refers only to localising objects in and around the radio environment that impose threats.

Table 3-13. KPIs and requirement for threat localisation use case.

KPIs (sensing)	Requirements
Location (range) accuracy	cm-level
Range resolution	1 cm
Maximum link range (unambiguous range)	~120 m
Angular resolution	sub-degree level
Velocity range	-30 km/h to 30 km/h
Velocity resolution	0.5 m/s
Update rate	Once per 100 ms to once per 0.1 ms
Availability	99.99%

3.1.3.5 Local Coverage for Temporary Usage

This use case family includes scenarios and use cases that require local networking coverage to fulfil high communication requirements or to ensure cellular coverage when the deployed terrestrial network is not enough. When the terrestrial network is insufficient or not available, the next generation RAN should commission a local coverage on a semi-permanent or temporary basis by deploying nodes that are mounted on autonomous vehicles, such as drones. Table 3-14 outlines localisation KPIs and requirements that must be satisfied to commission a network by deploying network nodes on autonomous vehicles.

Table 3-14. KPIs and requirements for autonomous deployment of network nodes for communication [22.289].

KPIs (localisation)	Requirements
Location accuracy	<2 m (horizontal), <2 m (vertical)
Orientation accuracy	0.5 degree (3D)
Update rate	Once per need to move to a new location
Availability	90%
Scalability	N/A

3.1.4 Massive Twinning

One of the primary objectives of future generation of RAN is to bring the digital and physical worlds together by bridging the gap between them, thus, creating a digital twin of everything in the physical world in digital world. The possibility of creating a reliable, effective, and efficient digital twin of everything (objects and events) in the physical world will facilitate new possibilities: for example, *i*) available resources are more efficiently used impacting sustainability of food production, *ii*) a 4D spatio-temporal interactive map of a city is created to enable immersive smart city, and *iii*) a real-time digital map of an industrial environment is created to monitor and keep track of events taking place at different parts of a factory floor.

Fundamentally, digital twin creation can capitalise on information on events taking place in the physical world at a given location and time as shown in Figure 3-2. In many use cases, 6G-connected tags can be attached to physical objects to create their digital twin with the potential of collecting sensing information that can be coupled with time instances indicating when the sensing information were

collected. However, there are challenges associated with precisely localising these devices, especially when they are deployed in GPS denied areas. To solve this problem, wide area 6G networks that are deployed to support communication needs of digital twins can be exploited also for localisation. In some other use cases, localisation of passive objects (detection and localisation of objects that are not connected to the digital world through 6G-connected tags or similar devices) such as scatterers of different types are needed. In that regard, radio signal-based sensing can be used to collect information on passive objects in terms of their location and time when they were present. This information on passive objects can be used to complement digital twin that otherwise would contain digital replica of objects that can only be connected to the network. In the next sub-sections, an overview of the requirements of sensing and localisation KPIs for use cases that benefit from twinning the physical world to digital world are elaborated.

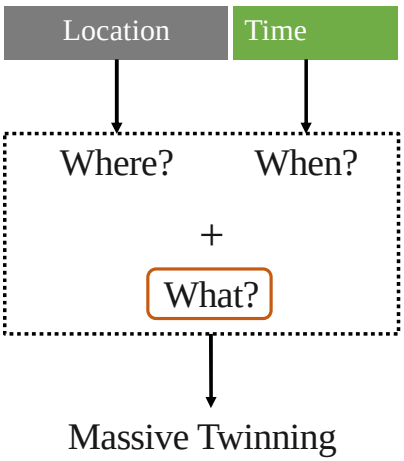

Figure 3-2. Fundamentals of twinning.

3.1.4.1 Digital Twins for Manufacturing

In order to enable a complete digital representation of the physical manufacturing environment, an accurate localisation and mapping of the scatterers which can be any object, moving or stationary, in a factory floor, is needed; for example, industrial tools whose configuration is dynamically selected depending on their accurate location. To achieve this, the requirements of KPIs listed in Table 3-15 must be met.

Table 3-15. KPIs and requirements for mapping an industrial environment [WSM+21,VDD+16].

KPIs (sensing)	Values
Location (range + angular) accuracy	cm-level
Range resolution	cm-level
Maximum link range (unambiguous range)	~130 m (industry floor of dimensions 120 m x 50 m)
Angular resolution	sub-degree level
Velocity range	-30 km/h to 30 km/h
Velocity resolution	0.5 m/s
Update rate	Once per 100 ms to once per 0.1 ms
Availability	99.99%

3.1.4.2 Immersive Smart City

An immersive smart city, which encompasses a digital replica of the city that contains real-time information on traffic, pollution maps, control utilities, etc., needs to provide a rich data set to enhance

liveability of the city. In this regard, KPIs and requirements for localisation of control utilities and sensing for traffic monitoring at different parts of the city are presented.

Localisation of control utilities

One of the primary objectives of immersive smart city is to enable interactive 4D map that can be used to plan and optimise utility services such as transportation, garbage, piping, cabling etc. To facilitate such an interactive map, the localisation of sensors deployed to track, monitor, and update status of these services is vital and the requirements of localisation KPIs listed in Table 3-16 must be met.

Table 3-16. KPIs and requirements on localisation for control utilities. [FAA+19]

KPIs (localisation)	Requirements
Location accuracy	<1 m (horizontal and vertical)
Orientation accuracy	N/A
Update rate	Once per second
Availability	99.99%
Scalability	several dozen per cubic meter.

Traffic monitoring

Roadside or track side units that are deployed to support communication can also be used to monitor traffic status in different parts of the city. Relevant requirements of the sensing KPIs that must be met for effective realisation of the use are listed in Table 3-17.

Table 3-17. KPIs and requirement for traffic monitoring [Nok21].

KPI (sensing)	Requirement
Range resolution	0.5 m
unambiguous range	100 m
Velocity resolution	0.5 m/s
Velocity range	-20 m/s to 20 m/s
Update rate	Once per second
Availability	99.99%

Landscape sensing

At a given geographical location, a UE receives radio signals that are deterministically (in terms of attenuation due to presence of scatterers of different types, shapes, and material) affected by the characteristics of the surrounding environment. For example, a UE in deep street canyon receives signal that propagates via multiple reflections due to the presence of buildings and other urban infrastructures. At forest, the radio signals are reflected due to the presence of trees around the target UE. These deterministic effects on radio signals can be used to identify type of landscape at the UE location; then, making this type of inferencing a tool to map landscapes within the area of cellular network deployment. Requirements on sensing KPIs for landscape sensing are outlined in Table 3-18.

Table 3-18. KPIs and requirement for landscape sensing [YHS+21].

KPIs (sensing)	Requirements
Precision Score	90%
Orientation accuracy	N/A
Update rate	Once per minute

Availability	99%

Digital twins of smart buildings

Future smart buildings can benefit from massive digital twining through a virtual representation of each infrastructure element. This requires obtaining an accurate position of each light switch, lamp, heater, and any other controllable element in the building. This will be used not only for the regular operation of the building, but it can also provide a huge reduction of commissioning costs through intelligence and automation.

Table 3-19. Positioning KPIs and requirement for digital twins of smart buildings use case [Azh11].

KPIs (localisation)	Requirements
Location accuracy	< 2.5 cm (half thickness of typical wall)
Update rate	Once per hour
Availability	99%
Scalability	Average of 1 per m²

3.1.4.3 Digital Twins for Sustainable Food Production

For a sustainable food production, it is essential to perform real-time monitoring of conditions at locations to optimise disease combat strategies. In this regard, semi-autonomous vehicles can be deployed to collect measurements from the locations of interest. To map the measurements to the respective locations, an accurate localisation of autonomous vehicles is needed. To support such a use case, the requirements of localisation KPIs listed in Table 3-20 must be met.

Table 3-20. KPIs and requirements for semi-autonomous ground vehicle localisation [22.261].

KPIs (localisation)	Requirements
Location accuracy	<1 m horizontal
Orientation accuracy	N/A
Update rate	Once per second (can be relaxed)
Availability	99.99%
Scalability	N/A

3.1.5 Robots to Cobots

6G systems are expected to provide tools and methods to layout a technical foundation that can enable collaboration among robots (referred to as cobots) and humans to accomplish a common goal or task. Cobots will be widely exploited both in consumer and industrial domains. In the consumer domain, cobots will be an integral part of our future living and will take forms beyond automated vacuum cleaners and lawn mowers that are widely used today. In the industrial domain, cobots will be exploited for modular production of goods and to also support high degrees of customisation and individualisation of the product being manufactured. To enable efficient operation of cobots, capabilities to sense and perceive the environment, on top of accurate absolute 3D and relative localisation of collaborating robots, are needed as well as high update rates specially to allow for smooth and uninterrupted synchronised collaboration. This information can then be taken as inputs by cobots to plan and act independently or synchronously to meet the common objective.

Sensing in the context of cobots and robots can be divided into two different applications:

- Sensing the environment and mapping it. This information is used by robots/cobots to position and orient themselves relative each other and the environment.
- Sensing of objects robots/cobots execute certain tasks on.

This information can then be taken as inputs by cobots to plan and act independently or synchronously to meet the common objective. In this regard, the KPIs and requirements when it comes to sensing and mapping passive objects in and around the environments where cobots are deployed are presented in Table 3-21 and Table 3-22. KPIs and sensing/localisation capabilities relevant to consumer robots/collaborative robots/interacting and cooperative mobile robots use cases also apply to use cases under flexible manufacturing cluster. If humans are also involved in the collaborative tasks in industrial environments, special attention must be paid to the topic of safety. This case is highlighted in Chapter 5.

KPIs regarding object sensing are presented in Table 3-23. Although these KPIs are very application dependent, typically a high accuracy, high update rate but low range are required.

Table 3-21. KPIs and requirements for collaborative robot localisation [HEX21-D71].

KPIs (localisation)	Requirements
Location (horizontal + vertical) accuracy	<1 cm
Orientation accuracy	sub-degree (3D)
Update rate	Once per 100 ms to once per 0.1 ms
Availability	99.99%
Scalability	>5 devices per m^3

Table 3-22. KPIs and requirements for environment mapping [WSM+21,VDD+16].

KPIs (sensing)	Requirements
Location (range + angular) accuracy	cm-level
Range resolution	cm-level
Maximum link range (unambiguous range)	~120 m
Angular resolution	sub-degree level
Velocity range	-30 km/h to +30 km/h
Velocity resolution	0.5 m/s
Update rate	Once per 100 ms to once per 0.1 ms
Availability	99.99%

Table 3-23. KPIs and requirements for object sensing

KPIs (sensing)	Requirements
Location (range + angular) accuracy	sub cm-level
Range resolution	sub cm-level
Maximum link range (unambiguous range)	~10 m
Angular resolution	sub-degree level
Velocity range *	10 km/h
Velocity resolution *	0.1 m/s
Update rate	Once per 100 ms to once per 0.1 ms
Availability	99.99%

*Typically only needed if operations are executed on moving targets.

An accurate position of vehicles is required to be able to control them for the purpose of automation and interaction with other elements or people in a safe and effective way.

Table 3-24. KPIs and requirements for fine localisation of vehicles use case [HKK17,Zho11].

KPIs (localisation)	Requirements
Location accuracy	0.1 m to 1 m
Orientation accuracy	N/A
Update rate	1 to 10 times per second
Availability	99.9%
Scalability	N/A

3.2 Baseline Evaluation

In this section, the baseline evaluation is presented. For localisation, 3GPP Release 16 simulations using 5G signals and methods are provided in Section 3.2.1. For sensing using radar and lidar sensors, performance based on the specification of commercial devices is listed in Section 3.2.2. This evaluation will then be combined with the use case requirements from Section 3.1 for the gap analysis in Section 3.3.

3.2.1 Localisation

3.2.1.1 Reference Signal for Positioning

Section 2.2.2.1 outlines positioning methods that are currently supported by NR. These methods rely on reference signals that are specifically designed to support positioning measurements. These reference signals are called positioning reference signals (PRSs) and can be transmitted in both UL and DL directions to perform positioning measurements depending on the positioning method being realised. In DL, PRS is transmitted by a transmission and reception point (TRP) for positioning measurements to be performed by UE. For the UL measurements during a positioning occasion, PRS is then transmitted by UE and the measurements are done by TRP. Depending on the UE capability, NR RAN configures DL and or UL PRSs to support distinct positioning methods.

DL-PRS

NR supports DL-PRSs with different configurations. A typical DL-PRS configuration is defined in terms of comb-factor and number of symbols, where comb-factor denotes frequency re-use for PRS and the number of symbols that are either staggered or permuted during the respective PRS transmission. The multi-symbol PRS is combined during a positioning measurement. Table 3-25 shows different configurations of DL-PRS signal that are supported by NR PRS architecture.

Table 3-25. DL-PRS configuration.

Frequency reuse	Number of symbols
Comb-factor 2	At least 2 symbols
Comb-factor 4	At least 4 symbols
Comb-factor 6	At least 6 symbols
Comb-factor 12	At least 12 symbols

Typically, a single TRP can be configured to transmit multiple PRSs. In this case, a single configuration of PRS is called a PRS resource and a collection of PRS resources that are allocated to a TRP is called PRS resource set. An example of a PRS resource is shown in Figure 3-3.

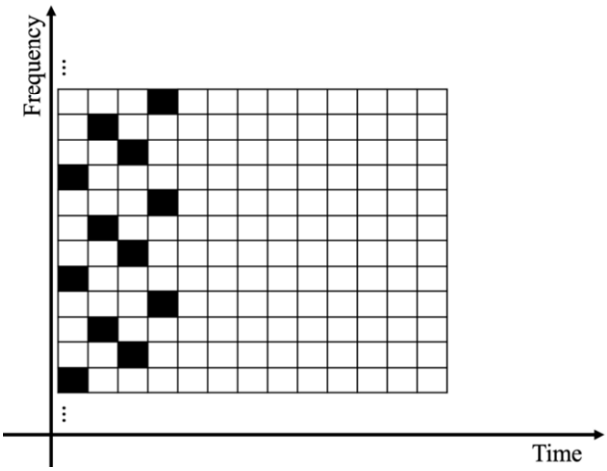

Figure 3-3. An example of comb-4, 4 symbol permuted DL-PRS configuration. Each tile in the grid of this figure denotes one resource element. Black tiles denote resource elements that are configured with PRS.

UL-PRS

Similar to DL-PRS, NR also supports PRS configuration for UL transmission. For the UL measurement-based positioning methods, the network configures the UE with sounding reference signals values shown in Table 3-26. An example of such a signal is shown in Figure 3-4.

Table 3-26. UL-PRS configuration.

Frequency reuse	Number of symbols
Comb-factor 2	At least 2 symbols
Comb-factor 4	At least 4 symbols
Comb-factor 8	At least 8 symbols

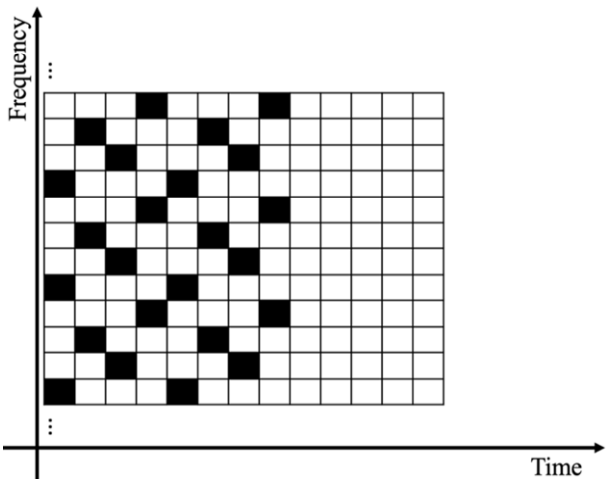

Figure 3-4. An example of comb-4, 8 symbol permuted UL-PRS. Each tile in the grid of this figure denotes one resource element. Black tiles denote resource elements that are configured with PRS.

3.2.1.2 Interference Handling

To minimise interference among TRPs transmitting DL-PRS and UEs transmitting UL-PRS, The NR Release 16 positioning specification supports multiple interference management techniques. The PRSs, on both UL and DL directions, are orthogonalised in code, frequency, and time domains. For the code domain orthogonality, the quadrature phase shift keying (QPSK) modulated PRS is initialised by the standard 31-bit Gold code sequence in the DL and by standard Zadoff-Chu sequence in the UL. To maintain frequency domain orthogonality, both UL and DL PRSs can be configured (among interfering

nodes) using different comb-factors listed in Table 3-25 and Table 3-26. To orthogonalise PRS in time domain, cyclic shift configurations (as shown in Figure 3-6) are used for UL-PRS and muting configurations (as shown in Figure 3-5) are used for DL-PRS.

Figure 3-5. TRP muting during comb-2, 2 symbol PRS transmissions.

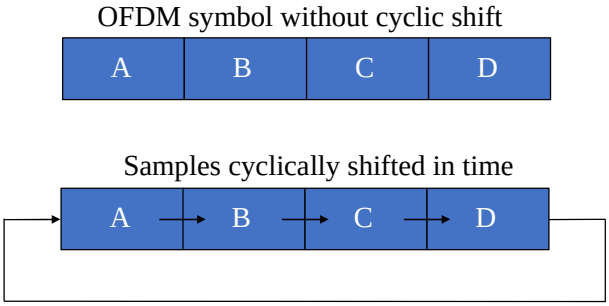

Figure 3-6 Cyclic shift in an OFDM symbol.

3.2.1.3 Numerical Validation

In this section, simulation results that show achievable horizontal positioning accuracy in 3 different scenarios: urban macro (UMa), urban micro (UMi), indoor open office (IOO) are presented (a detailed description of these scenarios can be found in Annex B). As positioning methods such as DL-TDoA, UL-TDoA, and multi-RTT positioning rely heavily on the PRS design, the numerical validation of only these methods is reported. PRS configurations of comb-12, 12 symbols and comb-2, 2 symbols are respectively considered for DL and UL transmissions. In terms of bandwidth, 100 MHz PRS is transmitted in the frequency range 1 (FR1) and 400 MHz PRS is transmitted in the frequency range 2 (FR2). Apart from these, effect of interference is not considered in the simulations and other parameters and assumptions are elaborated where necessary.

Figure 3-7 shows positioning accuracy of DL-TDoA in FR1 and FR2 in UMa, UMi, and IOO scenarios. To show the effect of an unsynchronised network, the simulation results when the network synchronisation error is 50 ns is also shown. It is evident that with large bandwidth PRS and a synchronised network better positioning accuracies can be achieved in all three scenarios.

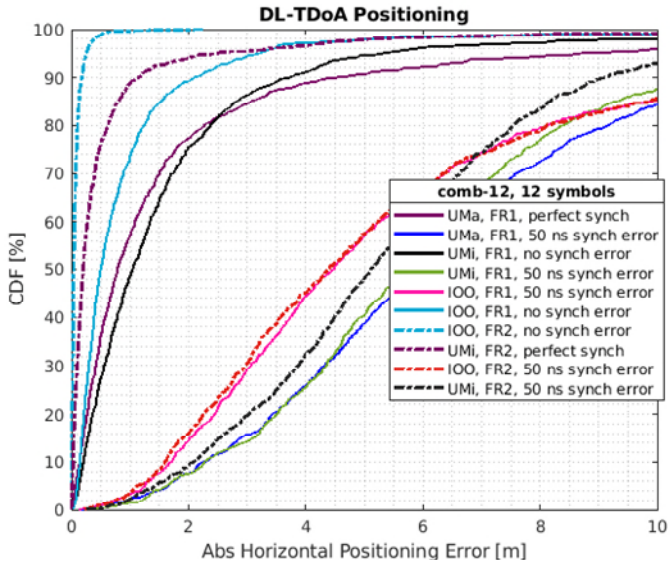

Figure 3-7 Positioning accuracy of DL-TDoA (FR1 and FR2) method in UMa, UMi, and IOO scenarios.

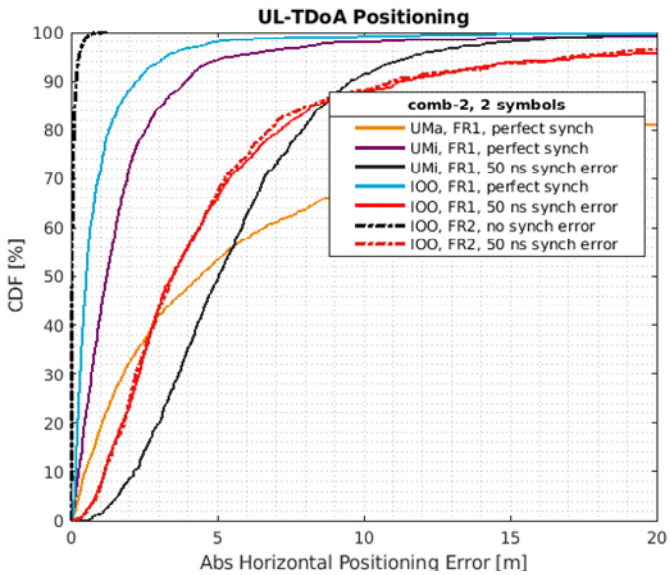

Figure 3-8. Positioning accuracy of UL-TDoA (FR1 and FR2) method in UMa, UMi, and IOO scenarios.

The achievable positioning accuracies of UL-TDoA method in all three scenarios in FR1 and FR2 are shown in Figure 3-8. Due to bad coverage in UL, the UL-TDoA accuracy in large area deployments such as UMa and UMi is worse in comparison to small area IOO deployment. In FR2 the UL coverage becomes even more limited therefore only IOO results are reported for FR2. Similar to what has been observed for DL-TDoA, improvement in accuracy due to large bandwidth in FR2 and the degradation of achievable positioning accuracy when the network is unsynchronised is evident also for UL-TDoA method as shown in the results in Figure 3-8.

The achievable positioning accuracy of multi-RTT positioning method is reported in Figure 3-9. Due to bad UL coverage in UMa and UMi scenarios, the multi-RTT positioning accuracy is worse than in

IOO. In IOO scenario, multi-RTT performs better than in the UMa and UMi scenarios and shows significant improvement in FR2.

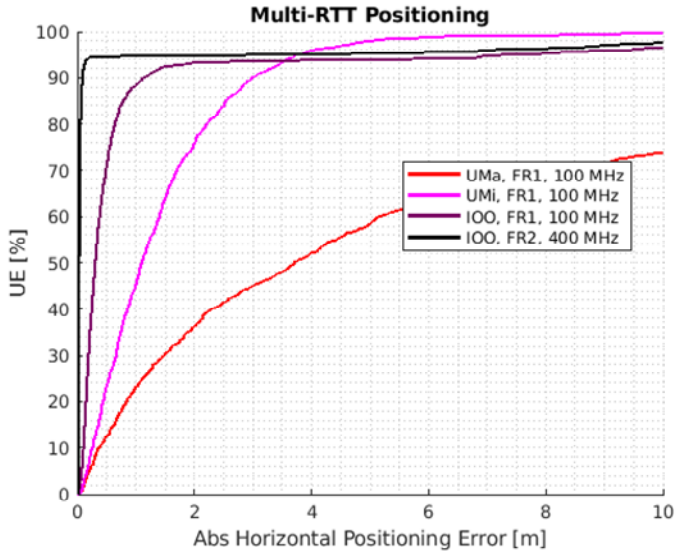

Figure 3-9. Positioning accuracy of multi-cell RTT method in UMa, UMi and IOO scenarios for bandwidths of 100 MHz and 400 MHz.

In scenarios where UL coverage is not an issue, multi-RTT positioning provides unparalleled advantage over other positioning methods and solutions. That is, the multi-RTT positioning method is robust to network synchronisation error. Unlike in TDoA methods, where a synchronised network is needed to measure meaningful positioning measurements, for multi-RTT positioning measurements can be done on individual TRPs. Since TRP pair is not considered during positioning measurement collection, unsynchronised network does not impose a bottleneck to achieve high accuracy UE position estimate. The achievable positioning accuracy in an unsynchronised network is reported for UMi and IOO in Figure 3-10 and Figure 3-11, respectively. To conclude this simulation evaluation section, a summary of achievable positioning accuracies of the evaluated methods and scenarios is given in Table 3-27.

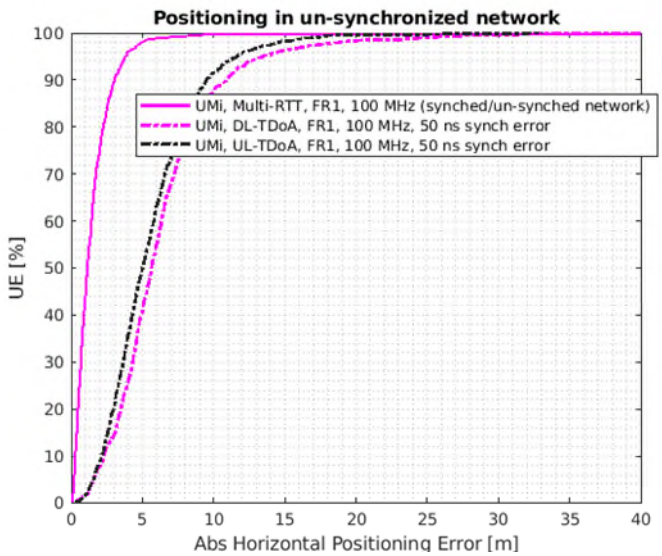

Figure 3-10 Positioning accuracy in an unsynchronised UMi network.

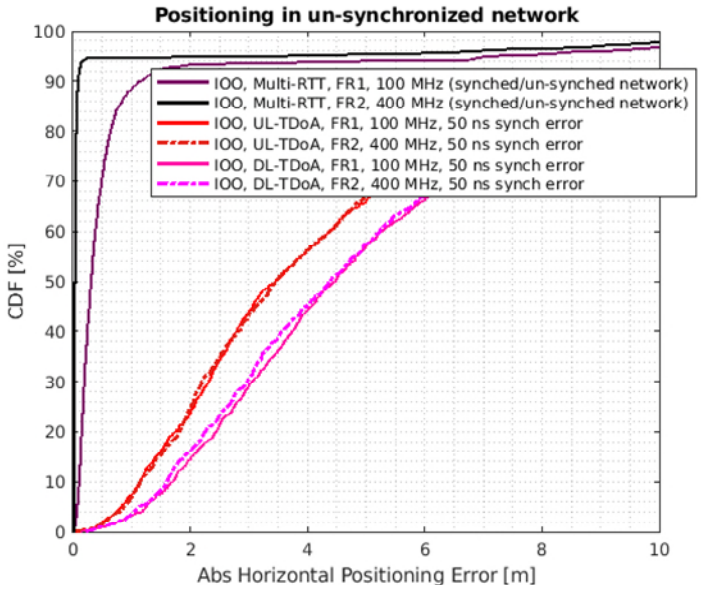

Figure 3-11. Positioning accuracy in an unsynchronised IOO network.

Table 3-27. Summary of achievable positioning accuracies of DL-TDoA, UL-TDoA, and multi-RTT methods. Reported values correspond to 90 percentiles from the simulation results shown above.

Method	UMa	UMi	IOO
DL-TDoA	FR1: 4.37 m (synched) 11.81 m (un-synched)	FR1: 3.48 m (synched) 10.9 m (un-synched)	FR1: 2.10 m (synched) 11.48 m (un-synched)
	FR2: N/A (coverage issue)	FR2: 1.11 m (synched) 9.11 m (un-synched)	FR2: 0.17 m (synched) 11.93 m (un-synched)
UL-TDoA	FR1: 35.14 m (synched)	FR1: 3.88 m (synched) 9.51 m (un-synched)	FR1: 2.19 m (synched) 11.24 m (un-synched)
	FR2: N/A (coverage issue)	FR2: N/A (coverage issue)	FR2: 0.18 m (synched) 10.97 m (un-synched)
Multi-RTT	FR1: 30.29 m (synched and un-synched)	FR1: 2.99 m (synched and un-synched)	FR1: 1.11 m (synched and un-synched)
	FR2: N/A (coverage issue)	FR2: N/A (coverage issue)	FR2: 0.07 m (synched and un-synched)

3.2.2 Sensing

The commercially most widely deployed sensing techniques are not based on 5G but rather on radar (ranging from ultra-wideband up 80 GHz) as well as optical sensing based on lidar. Both techniques are

typically tailored towards specific applications. In the tables below typical performance of today's sensors is provided, which are relevant for the considered use-cases in Section 3.1.

3.2.2.1 Radar

There exists a wide range of different radars specialised for different use cases. The UWB system has a high penetration level and good accuracy, which makes it useful in indoor use cases. With increased frequency, the range of the radar increases, but at the cost of accuracy. For the 10-30 GHz range radars, a typical use case could be obstacle detection on a runway. With the 60-80 GHz radar it is possible to generate a complete image of the surroundings, detecting both static and moving objects. In Table 3-28, some values of the performance of different radars are listed. There are large variations on the performance level between different radars within each category, thus the values used in the table should be seen just as examples for comparisons between the different categories.

Table 3-28 Performance of existing radar sensors.

	UWB [Nov20]	**10-30 GHz [Mor17]**	**60-80 GHz [Arb19]**
Angular resolution	-	-	1 deg azimuth 2 deg elevation
Field of view	-	120 deg az 15 deg el	100 deg azimuth 30 deg elevation
Range resolution	0.1 m (based on bandwidth)	0.75 m	0.5 m
Range	10 m	200 m	300 m
Velocity resolution	-	-	0.1 m/s

3.2.2.2 Lidar

The lidar technology is a bit more limited in its use cases as it is mainly based on time measurements of reflected laser beams. As of today, there are essentially two different types of lidars, mechanical and solid state. The working principles of them are very similar, but the difference is that in the solid state lidar there are no moving parts, making it cheaper to manufacture. The mechanical lidar usually has a stronger laser and has the capability of directing it easier compared to the solid state lidar. These differences are the main reasons to the difference seen in Table 3-29, where the performance levels of two different lidars are shown. As there exists many different lidars, these numbers should only be seen as example values and used for comparisons between the two categories.

Table 3-29 Performance of existing lidar sensors.

	Mechanical [Hes20]	**Solid state [Liv19]**
Angular resolution	0.2 deg	0.05 deg
Field of view	360 deg azimuth 40 deg elevation	81.7 deg azimuth 25.1 deg elevation
Range accuracy	0.02 m @ 200 m distance	0.02 m @ 20 m distance
Range	200 m @ 10% reflectivity	90 m @ 10% reflectivity
Velocity resolution	-	-

3.2.2.3 Radar and Lidar Performance in Non-ideal Conditions

The performance levels listed in the tables are under good conditions for each detector. In reality, this will most likely not always be the case, thus it is important to also know how each detector is affected in different scenarios. The most common problem is precipitation and fog. How much the performance level is affected, depends in general on the wavelength of the signal. Shorter wavelengths will be more sensitive to precipitation. This means that lidars will be more affected than radars. Several studies have been done on the performance of lidars in non-ideal conditions. One example is [WZK+14], where it was shown that the range of the lidar does depend on rain amount, but it was even more affected by fog where the range could drop by 90%. Also, the effect of rain and fog of radars has been investigated. In [ZDS+19] these effects are studied, and the conclusion is that in contrast to lidars, radars are more sensitive to rain than fog. The range does also not drop as much as for the lidars. In very heavy rain the range drop is around 30% for radars operating in the mmW region.

3.2.2.4 Interference Mitigation

Sensor evaluation and KPIs are often evaluated on a single sensor basis. Deploying sensors on a massive scale, while requiring a high update rate can however cause interference which will impact on the availability and outage of sensors. Different strategies can be pursued to combat interference. The main three strategies are:

- Use waveforms that are robust to interference.
- Minimise probability of interference.
- Avoid interference by resource allocation.

Robust Waveforms

A robust radar waveform is a waveform which gracefully degrades the detection performance, as the interference level (sensor density) increases. Such waveforms are typically based on wideband radar signals. The effect of interference on wideband radar signals is, that the detection performance is degraded, i.e., accuracy is reduced if interference is present. This is because interference will appear as an increased noise-floor. In contrast, a waveform that is sensitive to interference is the commonly used frequency-modulated continuous-wave (FMCW). If an FMCW interfering signal is within the receiver bandwidth of an FMCW receiver, false detections can be created. An interfering signal could be classified as a non-existing object for example.

Minimising Probability of Interference

Another strategy is to minimise the likelihood that interference will be present on the time/frequency resource used by the sensor. Typically, this is achieved by choosing the frequency and time used for transmitting the sensing signal in a random manner. A sensor using this technique can use random frequency (sub-band) or randomised pulse-start time. Randomised pulse-start times can be used in both lidar and radar applications, while changing frequency is mostly used by radars. Also, minimising spatial overlap between sensors can be used to minimising the risk for interference.

Resource Allocation

Radar systems using resource allocation are mostly implemented in proprietary solutions. In such systems each sensor uses an assigned frequency/time for transmitting the sensing signal and a (central) control device ensures that only one sensor at a time in the system uses a certain time-frequency resource. Note that resource allocation can be static (configured during setup), or dynamic which requires communication with the sensor.

3.3 Gap Analysis

3GPP Release 16 specification outlines localisation technologies to support both regulatory and commercial use cases. For commercial indoor use cases, the considered target is to localise at least 80%

of the UEs with <3 m horizontal accuracy [38.855]. For commercial outdoor use cases, the target is to localise at least 80% of the UEs with <10 m horizontal accuracy. To address higher accuracy requirements of new applications and industrial verticals, Release 17 work aims to achieve <1 m horizontal accuracy for 90% of the UEs to support indoor commercial use cases, and <0.2 m horizontal accuracy for 90% of the UEs to also support Industrial internet of things (IIoT) use cases. Apart from achievable accuracy, Release 17 work also mandates latency requirements of <100 ms (end-to-end latency) and < 10 ms (physical layer latency) [38.857].

In order to support use cases identified in Section 3.1, the next generation of mobile networks must support enhanced localisation and in addition should also be able to comprehend sensing capability. In this Section, an overview of the requirements on sensing and localisation KPIs that can be met by 5G localisation, and sensing technology is provided. Based on the presented overview, a gap between what KPIs can be met today and what KPIs must be achieved by the future RAN will be established.

3.3.1 Localisation

3.3.1.1 Position accuracy

The use cases identified in Section 3.1 require positioning accuracies ranging from <1 cm to 30 m as shown in Table 3-30. Based on the identified requirements, the elaborated use cases in Section 3.1 can be generalised as use cases that demand stringent, moderate, and relaxed accuracy.

Table 3-30. Positioning accuracy requirements of localisation use cases and their requirement class.

Use case	6G requirement	Class
Drone deployment for enhanced remote health care	0.1 m – 0.5 m	stringent
Remote sensing and monitoring	1 m - 30 m	relaxed
Asset tracking and management	1 m	moderate
Augmented reality for context aware services	1-3 m	moderate
Augmented reality placing virtual objects in the real world	5 mm	(very) stringent
Telesurgery	< 1 mm	(very) stringent
Patient tracking and monitoring	3 m – 10 m	relaxed
Localisation of milliscale robots	1 mm	(very) stringent
Placement of medical equipment on the body	1 cm	(very) stringent
Sensor infrastructure web	10 cm	stringent
Cooperating localisation	1 cm – 30 cm	stringent
Autonomous deployment of network for coverage	2 m	moderate
Localisation of control utilities	1 m	moderate
Digital twins of smart buildings	< 2.5 cm	stringent
Localisation of semi-autonomous ground vehicle	< 1 m	(very) stringent
Localisation for collaborative robots	< 1 cm	(very) stringent
Fine localisation of vehicles	0.1 m – 1 m	stringent

The positioning requirements of **relaxed accuracy** use cases can be met by most of the evaluated 5G localisation techniques (see positioning accuracies of each method reported in Table 3-27 and elaborated in Section 3.2.1.3). The limitations of the reported 5G localisation techniques to support relaxed accuracy use cases occur when using UL based method in scenarios where coverage is an issue. In other scenarios, the requirements are met even when the network synchronisation error is 50 ns (check Annex A for definition). Use cases that demand **moderate localisation accuracies** can be

supported by 5G localisation methods mainly in IOO like scenario. For methods other than multi-RTT, the required accuracies however cannot be met when the PRS transmitting nodes are unsynchronised.

The **stringent accuracy** requirement imposed by drone deployment for enhanced remote health care use case can be met by the evaluated methods and scenarios in FR2 only. However, network synchronisation error affects achievable positioning accuracies of DL-TDoA and UL-TDoA methods such that the required accuracy cannot be met. Localisation for collaborative robots demands the most stringent positioning accuracy requirement. For its effective realisation, the collaborative robots are required to be localised with an accuracy of less than 1 cm. None of the evaluated methods in the considered scenarios can meet this requirement. In the considered scenarios, the likelihood of finding a UE in LoS with majority of the TRPs within the deployment area creates a bottleneck and limits the achievable positioning accuracy to 0.07 m (90% of the UEs can be localised with less than 0.07 m positioning accuracy error) in IOO (FR2). To elaborate the effect of LoS on the achievable positioning accuracy, the positioning error of DL-TDoA and UL-TDoA methods in FR2 is shown in Figure 3-12. The numerical validation is done considering a DL-PRS of bandwidth 400 MHz and the observed 90 percentile accuracies are reported in Table 3-31.

Table 3-31. DL-TDoA and UL-TDoA achievable positioning accuracies in Indoor Factory Sparse-High scenario.

Positioning method	90% accuracy
DL-TDoA, convex hull UEs	0.017 m
UL-TDoA, convex hull UEs	0.016 m

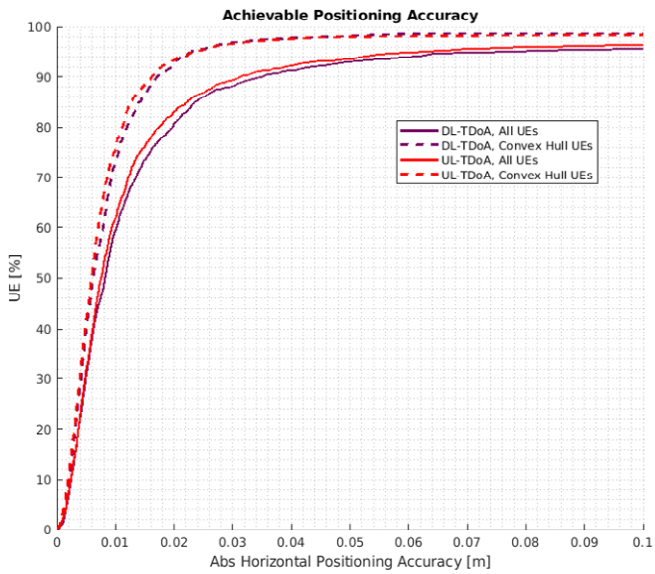

Figure 3-12. DL-TDoA and UL-TDoA achievable positioning accuracies in Inf-SH scenario.

3.3.1.2 Latency

End-to-end localisation latency in 5G depends on the employed positioning method, processing latencies, and signalling propagation delays between the participating nodes (UE, TRP, AMF, and LMF) during a positioning procedure. In the following sub-sections, latency evaluations of positioning methods considered in the baseline evaluation are presented to outline the capabilities of 5G localisation methods in terms of meeting the latency requirements of the use cases reported in Section 3.1. The presented latency evaluation is then used to identify potential gaps that future RAN should fill in to support use cases that demand latencies lower than what can be achieved today.

DL-TDoA

Interaction between UE, TRP, AMF, and LMF nodes during a DL-TDoA positioning procedure is shown in the sequence diagram of Figure 3-13. In the beginning of the procedure, LMF sends a *request capabilities* request message to the UE, UE then responds to this request by providing its capabilities to LMF. After receiving a response to its capabilities request, the LMF then provides assistance data followed by location information request to the UE. UE then performs the positioning measurements and reports them as *provide location information* signalling to LMF. The LMF after receiving location information from UE estimates the corresponding UE location. During each of these interactions, processing delays and signalling delays contribute to the overall latency during the positioning procedure. An overview of such latencies is given in Table 3-32.

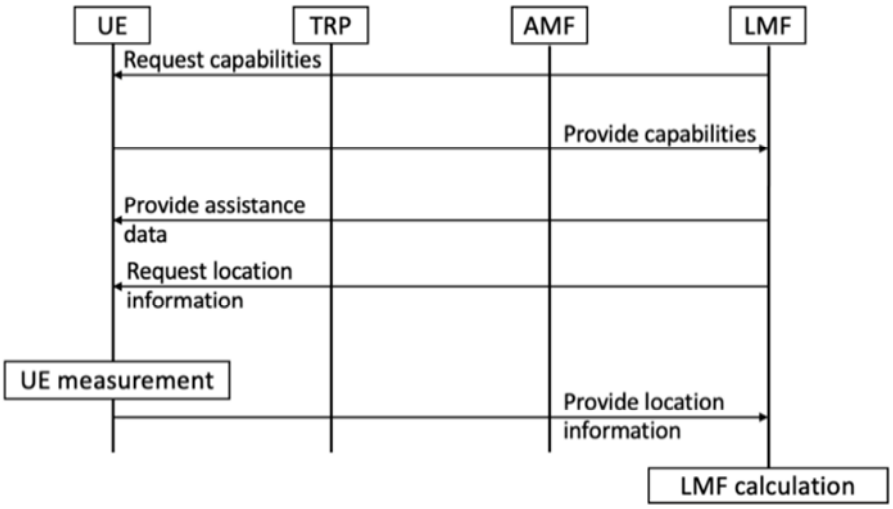

Figure 3-13. UE-assisted DL-TDoA positioning procedure.

Table 3-32. Latency budget calculation of UE-assisted DL-TDoA positioning procedure [38.857].

Step	Delay values
Request capabilities	Processing delay: 14 ms Signalling delay: 4 ms – 20.5 ms
Provide capabilities	Processing delay: 21 ms – 34 ms Signalling delay: 4 ms – 20.5 ms
Provide assistance data	Processing delay: 24 ms Signalling delay: 4 ms – 20.5 ms
Request location information	Processing delay: 19 ms Signalling delay: 4 ms – 20.5 ms
UE measurement (including RRC delays)	Processing delay: 106.5 ms – 109.5 ms Signalling delay: 1 ms
Provide location information	Processing delay: 16 ms – 19 ms Signalling delay: 4 ms – 20.5 ms
LMF calculation	Processing delay: 2 ms – 30 ms
Total delay	**223.5 ms – 353 ms**

UL-TDoA

UL-TDoA positioning measurements are done by TRP(s) on the UL-PRS transmitted by a UE. As a first step, similar to the DL-TDoA method, the LMF requests a UE to report its capability to support the UL-TDoA method. After receiving the response to the capability request, the LMF then requests TRP to provide positioning information. Since the positioning measurements are done by TRPs on UL-PRS transmitted by the UE, the serving TRP sends the SRS configuration to UE and also responds to positioning information request received from the LMF. After receiving a response to its positioning information request, the LMF sends a measurement request to TRPs. These TRPs report their positioning measurements to the LMF when they are ready. The LMF then calculates the UE position based on the received measurements. All these interactions are shown in Figure 3-14 and an overview of latencies due to processing and signalling delays during each of these interactions is given in Table 3-33.

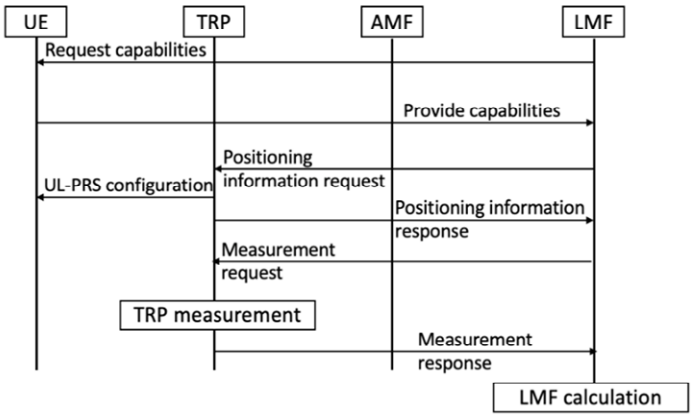

Figure 3-14. UE-assisted UL-TDoA positioning procedure.

Table 3-33. Latency budget calculation of UE-assisted UL-TDoA positioning procedure [38.857].

Step	Delay values
Request capabilities	Processing delay: 14 ms Signalling delay: 4 ms – 20.5 ms
Provide capabilities	Processing delay: 21 ms – 34 ms Signalling delay: 4 ms – 20.5 ms
Positioning information request	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
UL-PRS configuration	Processing delay: 13 ms Signalling delay: 0.5 ms
Positioning information response	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
Measurement request (including SRS activation)	Processing delay: 19 ms – 21 ms Signalling delay:12.5 ms – 60.5 ms
TRP measurement	Processing delay: 12 ms
Measurement response	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
LMF calculation.	Processing delay: 2 ms – 30 ms
Total delay	**141 ms – 313 ms**

Multi-RTT

Multi-RTT positioning is done by exploiting both UL and DL measurements. After receiving the response to capability request from a UE, the LMF sends positioning information request to TRP. To perform UL positioning measurements, the serving TRP configures a UL-PRS to the target UE and then sends a positioning information response to the LMF. This signalling is then followed by the measurement request to TRP from the LFM and sending the assistance data to the UE with a request to provide location information. Both UE and TRP after completing their positioning measurements report them to the LMF where the UE position estimation calculation is done. During each of these interactions (also shown in Figure 3-15), processing and signalling delays contribute to the overall latency during the positioning procedure. An overview of such latencies is given in Table 3-34.

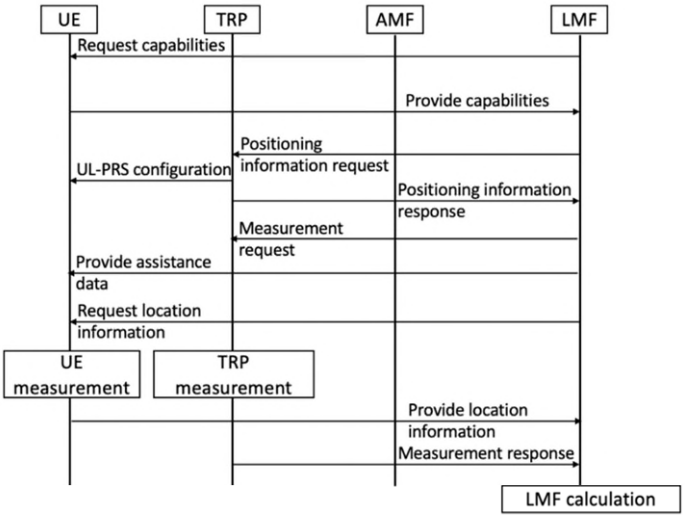

Figure 3-15. UE-assisted multi-RTT positioning procedure.

Table 3-34. Latency budget calculation of UE-assisted multi-RTT positioning procedure [38.857].

Step	Delay value
Request capabilities	Processing delay: 14 ms Signalling delay: 4 ms – 20.5 ms
Provide capabilities	Processing delay: 21 ms – 34 ms Signalling delay: 4 ms – 20.5 ms
Positioning information request	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
UL-PRS configuration	Processing delay: 13 ms Signalling delay: 0.5 ms
Positioning information response	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
Measurement request (including SRS activation)	Processing delay: 28 ms – 30 ms Signalling delay: 12.5 ms – 60.5 ms
Provide assistance data	Processing delay: 24 ms Signalling delay: 4 ms – 20.5 ms
Request location information	Processing delay: 19 ms Signalling delay: 4 ms – 20.5 ms
UE measurement (including RRC delays)	Processing delay: 106.5 ms – 109.5 ms Signalling delay: 1 ms

TRP measurement	Processing delay: 12 ms
Provide location information	Processing delay: 16 ms – 19 ms Signalling delay: 4 ms – 20.5 ms
Measurement response	Processing delay: 9 ms Signalling delay: 4 ms – 20 ms
LMF calculation	Processing delay: 2 ms – 30 ms
Total delay	**328.5 ms – 556 ms**

Latency requirements of the use cases elaborated in Section 3.1 are listed in Table 3-35. From the latency budget calculations for the considered 5G localisation methods, it is evident that drone deployment for enhanced remote health care, augmented reality, tracking in-body devices, sensing information of relevance and localisation for collaborative robots demand quasi-real-time operation making low latency localisation support one of the essential features that future RAN should support.

Table 3-35. Update rate requirement of localisation use cases.

Use case	6G requirement	5G positioning latency enough to support 6G requirement
Drone deployment for enhanced remote health care	0.1 s	No
Remote sensing and monitoring	1 s (or even higher)	Yes
Asset tracking and management	1 s	Yes
Augmented reality for context aware services	0.1 s to 1 s	No
Augmented reality placing virtual objects in the real world	10 ms	No
Telesurgery	100 ms	No
Patient tracking and monitoring	1 s	Yes
Localisation of milliscale robots	100 ms	No
Placement of medical equipment on the body	1 s	Yes
Sensing infrastructure web	10 ms	No
Cooperating localisation	10 ms	No
Autonomous deployment of network for coverage	Once per need to move to a new location	Yes
Localisation of control utilities	1 s	Yes
Digital twins of smart buildings	1 hour	Yes
Localisation of semi-autonomous ground vehicle	1 s	Yes
Localisation for collaborative robots	0.1 ms to 100 ms	No
Fine localisation of vehicles	0.1 s to 1 s	No

3.3.1.3 Scalability and Availability

5G localisation methods are based on broadcast signals. Since the same signal can be used by multiple UEs or TRPs for positioning measurements, given that the nodes performing the positioning measurement are in coverage of the broadcasted PRSs, the positioning methods in 5G are scalable and can be practically used to support the scalability requirements of the previously elaborated use cases.

There is, however, and important limitation that will still be present in 5G. Accurate localisation require radio resources (e.g., PRSs), which would thus occupy communication resources while locating. The higher the accuracy required the larger the bandwidth of the channel that will be unavailable for communication. This is at odds with many applications, including low latency communications such as is required for scenarios like controlling autonomous ground vehicles (AGVs). 6G must solve this well-known problem, i.e., simultaneous communication and positioning.

Table 3-36 lists the availability requirements of the use cases elaborated in Section 3.1. From the numerical validation of the achievable positioning accuracies of the evaluated positioning methods, only the availability of 90% can be maintained. As most of the localisation use cases demand availability of at least 99%, the future RAT-based localisation techniques should be able to meet high availability to support the identified use cases.

Table 3-36. Availability of localisation use cases.

Use case	6G requirement	5G positioning enough to support 6G requirement
Drone deployment for enhanced remote health care	99.99%	No
Remote sensing and monitoring	99%	No
Asset tracking and management	99%	No
Augmented reality for context aware services	90%	Yes
Augmented reality placing virtual objects in the real world	99.9%	No
Telesurgery	99.99999%	No
Patient tracking and monitoring	99.99%	No
Localisation of milliscale robots	99.999%	No
Placement of medical equipment on the body	99.9%	No
Sensor infrastructure web	99.99%	No
Cooperating localisation	99.99%	No
Autonomous deployment of network for coverage	90%	Yes
Localisation of control utilities	99.99%	No
Digital twins of smart buildings	99%	No
Localisation of semi-autonomous ground vehicle	99.99%	No
Localisation for collaborative robots	99.99%	No
Fine localisation of vehicles	99.9%	No

3.3.1.4 Power Consumption

The Release 17 study item (SI) work in 3GPP on positioning has the evaluation of device efficiency as one of the agenda items [38.857]. Within this device efficiency framework, Release 17 SI investigated power consumption during positioning, where a model developed in TR38.840 was considered baseline to evaluate UE power consumption during the positioning procedure. The study concluded that 7% - 40% power saving can be done by exploiting IDLE and INACTIVE modes positioning. It was also observed that positioning report in IDLE state can save power up to 44.32% in comparison to when the reporting is done when the UE is CONNECTED state. Moreover, positioning measurement and reporting in IDLE state can provide power saving of up to 48.38% in comparison to measurement and report done in CONNECTED state. It is evident that the power consumption is affected by the state of the UE when doing the positioning measurements and reporting; thus, such configurations are being considered in Release 17 work item as one of the potential enhancements for NR positioning. From sustainability point of view, power consumption plays an important role where hardware of the nodes

in the next generation RAN must be optimised to consume as less power as possible during its operation and the localisation methods must demand the least expense of power during the positioning measurement phase.

3.3.1.5 Orientation Accuracy

Development of radio access technology-based positioning, so far, has been done considering regulatory and IIoT use cases where UE orientation estimation is not a primary objective. For example, in regulatory use case such as localisation of emergency call originating UE, knowing UE heading is not critical. It is enough to localise the UE so that the emergency services can be dispatched to the right location. However, the next generation localisation use cases such as localisation for AR, localisation for collaborative robots, and local coverage for temporary usage greatly benefit from orientation estimation. In this regard, the next generation localisation methods should consider orientation estimation as one of the primary objectives as well.

3.3.1.6 Identified Gaps

To support the identified localisation use cases, future RAN must meet requirements on some of the fundamental KPIs (localisation accuracy, latency, and orientation accuracy). In terms of accuracy, the achievable positioning accuracies of 5G localisation methods are subjected to coverage (poor accuracies for UL methods in wide geographic area-based deployment and good accuracies in indoor scenarios), deployment of the network (mainly in indoor scenarios where GDOP is one of the limiting factors) and synchronisation between the network nodes. In this regard, the next generation localisation methods must, in principle, be able to address these issues and should offer more accurate positioning by exploiting potential wide bandwidth. In addition, these localisation methods, apart from being energy efficient, should also guarantee higher availability and orientation accuracy.

Bandwidth being the most limiting factor, it is of the outmost importance to use this with the highest efficiency. Thus, the joint communication and localisation is a must for the future, as to not block the communication channel while high accuracy localisation is taking place.

As shown by the latency budget evaluations, latency of 5G localisation methods depends on employed method and is on par to support many of the identified use cases. Nonetheless, the use cases such as drone deployment for enhanced remote health care, AR, tracking in-body devices, sensing information of relevance and localisation for collaborative robots demand quasi-real-time localisation mandating lower latencies than what can be achieved by 5G localisation methods.

3.3.2 Sensing

RAT based sensing is envisioned for 6G and no support for sensing exists in 5G. In this section, the requirements of the different use cases in Section 3.1 are therefore compared with what is possible today with radar and lidar technologies. Different use cases require distinct minimum performance levels on different parameters. It is often possible to satisfy some of the requirements, but the challenge is to satisfy all simultaneously. In the sub-sections to follow, each sensing use case identified in Section 3.1 is analysed to contrast out the gaps that envisioned 6G technology should aim to fill in.

Gesture recognition for human-machine interface

A gesture recognition function would focus on rather small movements in a short distance. As listed in Table 3-4, this imposes high demands on both the range accuracy and velocity resolution. The needed range accuracy could be met with lidar equipment, but it is not very accurate in velocity measurements. It would also be problematic from a safety perspective to have lasers pointing at a user from a very short distance. The radar alternative would be better from this perspective, and with the high frequency radar both the velocity accuracy and angular resolution requirements would be met. However, it does not have the required position accuracy.

Digital twins for manufacturing

The requirements for this use case are similar to those of the gesture recognition, as shown in Table 3-15. The main differences are the range requirement and the angular resolution. This favours the lidar as it works better at longer distances. Since the mapping of an environment without human intervention, there are not same safety issues either. The main problem for the lidar would be the velocity accuracy. It would also be sensitive to different reflectivity of different materials in the environment. This would not be the case to the same extent for a radar solution, but as was the case for the face recognition, it suffers from the worse position accuracy.

Traffic monitoring

For traffic monitoring, the high frequency radar does meet all the requirements listed in the KPI Table 3-17. The lidar does also fulfil most of the requirements, but the velocity resolution would probably be hard to reach.

Robots to Cobots

In this use case, there are two different types of sensing. It is both necessary to map the surrounding environment as well as an operation object. The mapping of the environment does not have as high accuracy requirement as for the operation object, on the other hand it requires a larger range of both position and velocity. As shown in Table 3-22, the environment mapping requirements are equivalent to the use case digital twins for manufacturing. In the case of operation object mapping, see Table 3-23, the position accuracy is a real challenge. Neither the lidar nor the radar technologies can achieve such accuracy. Although lidar performs closer to the requirement, it would suffer from the rather short distances and its difficulty with velocity measurements.

3.3.2.1 Identified Gaps

Of the different use cases evaluated, it is only the requirements of the traffic monitoring use case which can be met with existing technology. All the other use cases suffer from the need of high position accuracy in combination with high velocity accuracy. For the robots to cobots use case there is also a need to further improve the position accuracy to reach the requirements. Table 3-37 and Table 3-38 show summaries of which KPIs can be satisfied for each use case with existing radar and lidar technologies, respectively.

Table 3-37 Summary of which KPIs can be satisfied for each use case with existing radar technology.

	Location accuracy	Range resolution	Angular resolution	Velocity resolution
Gesture recognition for human-machine interface	No	No	Yes	Yes
Digital twins for manufacturing	No	No	No	Yes
Traffic monitoring	-	Yes	-	Yes
Robots to Cobots (operation object)	No	No	No	No

Table 3-38 Summary of which KPIs can be satisfied for each use case with existing lidar technology.

	Location accuracy	Range resolution	Angular resolution	Velocity resolution
Gesture recognition for human-machine interface	Yes	Yes	Yes	No
Digital twins for manufacturing	Yes	Yes	Yes	No

Traffic monitoring	-	Yes	-	No
Robots to Cobots (operation object)	No	No	Yes	No

4 Models and Solutions for Localisation and Sensing

This section presents initial findings related to localisation and sensing beyond 5G. For each finding, the general problem is reported, followed by the methodology and initial performance results, when available. In addition, plans for future work within Hexa-X are provided. This section is structured as follows:

- Results on bounds on localisation and bi-static sensing using tentative 6G parameters and contrast with 5G performance are described in Section 4.1 and Section 4.2, respectively. Within Section 4.2, the SLAM problem and its solution strategies are also explored.
- In the case of monostatic sensing, joint sensing and communication is possible, so that the waveform can be optimised for sensing or communication, or a combination of both. Section 4.3 presents results on the ensuing trade-off.
- The need for sensor fusion is motivated in Section 4.4, in particular for adaptive methods with flexible performance and complexity/delay trade-off.
- Sensing requires interference mitigation, especially for safety-critical use cases. Specific strategies for dealing with interference are described in Section 4.5.
- Finally, Section 4.6 reports the planned localisation and sensing demonstrators.

Within this deliverable, only initial findings are presented, while novel methods that harness the enablers of 6G (see Section 2.3.3), while coping with the challenges (see Section 2.3.4) will be part of future deliverables.

4.1 Initial Findings on Localisation

Localisation Model and Problem

As discussed in Section 2.3, 6G presents both challenges and opportunities for localisation. To gain an understanding of the potential of 6G in comparison with 5G a fair comparative analysis is needed. To this end, reasonable 5G and tentative 6G system parameters are considered (presented in Annex C[‡]) for both outdoor and indoor environments. The downlink communication system has a multi-antenna UE, a multi-antenna BS, each with a single RF chain. The receiver (UE) estimates the geometric channel parameters (angles, delays, and Dopplers), from which the receiver can then infer its location, orientation, and the position of the incident point (IP) (or landmarks, which could be reflectors or scatters). An illustration of the scenario is shown in Figure 4-1.

[‡] The main differences between 5G and 6G in Annex C are as follows. 6G has more antenna elements are unit of area, more bandwidth due to operation at a higher frequency band, but reduced transmission power. The increased number of antenna elements and bandwidth improve the resolution, while the reduced power adversely affects the accuracy.

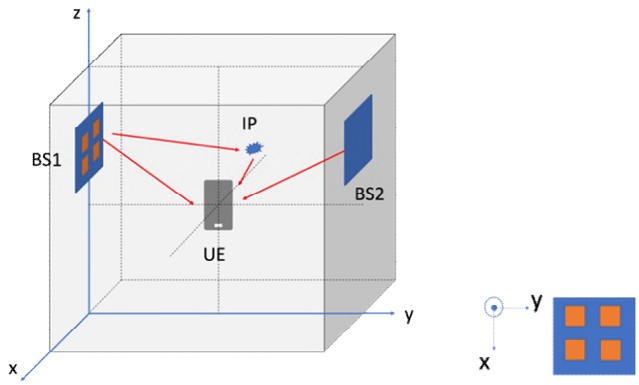

Figure 4-1 An illustration of localisation and orientation estimation. A UE (with default orientation shown in the right figure) estimates its position and orientation using the received signals from multiple BSs and IPs. The IPs are unknown but can be used to improve localisation.

Methodology

To compare the fundamental localisation performance of 5G and 6G systems, there exists a variety of performance bounds [DCF+09]. Among those, the Cramér-Rao lower bound (CRLB) [SGD+17] is attractive as it is easy to compute and matches well with practical estimators at high SNR. However, the CRLB does not account for multipath resolvability. In a multipath environment, different paths may not be well resolved due to the limitation of the bandwidth and array size. These paths can be treated as a single path in the processing algorithm with an associated incidence point, for which the CRLB would be overly optimistic. To address this, a modified CRLB is used, where the standard deviation of angle and delay variance of each NLOS path is lower bounded by the resolution in each dimension (e.g., the delay standard deviation is lower bounded by 1 over the bandwidth). This then leads to bounds on the position (position error bounds (PEB)) and the orientation (orientation error bounds (OEB)).

Results

First, the PEB results are provided for outdoor scenarios with 4 BSs in a multipath environment. The localisation algorithms using all the AoA, AoD, delay information (All Info), using only delay estimation (TDoA) and using only the angle estimation at the BS (AoD) are considered. In the simulation, the position of a UE is changed within the coverage area (200 m by 200 m) and calculate their PEB, with the cumulative density functions (CDFs) of all the scenarios are shown in Figure 4-2. In this specific simulation setup, the probability of position error (utilising all the information) P{PEB<0.25 m} is improved from 32.8% (5G systems) to 97.8% (6G systems) in the 4-BS outdoor scenario.

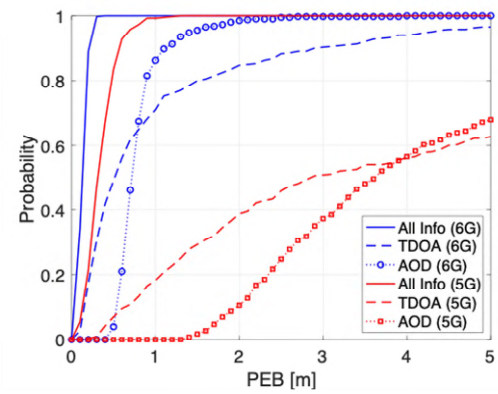

Figure 4-2 CDFs of PEB using different localisation methods for an outdoor urban microcell (UMi) scenario.

For the indoor scenario, the positioning performance with different numbers of BSs in a 20 m by 20 m area is compared. Furthermore, the improvement with prior map information is evaluated. The CDFs

of the PEB/OEB for 5G and 6G systems are shown in Figure 4-3. From the figure, the position error can be improved by the 6G systems and using multiple BSs.

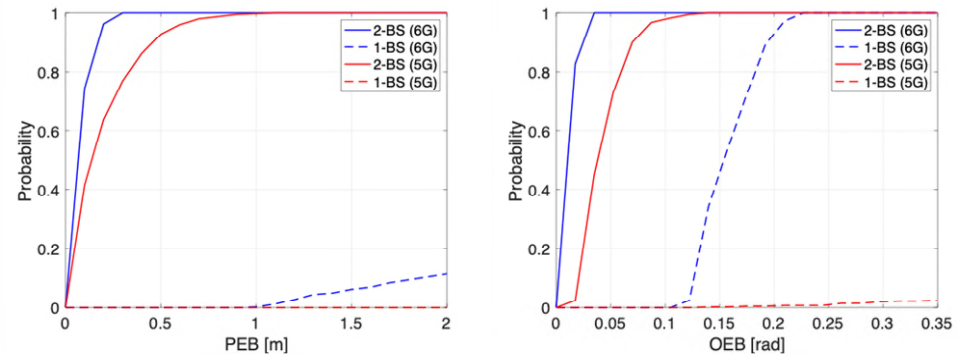

Figure 4-3 CDF of PEB (left) and OEB (right) for 5G/6G systems under different scenarios. Multiple BSs can increase the coverage and hence improve the localisation performance.

Conclusion and Plans

In summary, 6G systems, despite having lower transmit power, shorter coherence time, and larger path loss, perform better in both position and orientation estimation than their 5G counterpart. The orientation estimation of the UE in 5G is largely limited by the array aperture, while 6G UEs may have a much larger aperture (in wavelengths). The performance improvement benefiting from the multiple BSs is also obvious which shows the potential of a dense communication network. The asymptotic region of the CRLB may not be achievable due to hardware impairments and unmodeled propagation phenomena. Future studies in Hexa-X will evaluate the impact of these hardware impairments on the achievable performance (see also Section 4.2.4).

4.2 Initial Findings on Sensing

4.2.1 Landmark Sensing

Landmark Sensing Model and Problem

Similar to localisation in Section 4.1, 5G and tentative 6G systems are compared in their sensing (map the environment) ability. This baseline of landmarks location estimation can be used for future studies.

Methodology

The same methodology as in Section 4.1 is employed and the corresponding map error bound (MEB, the error bound of landmark position estimation) is derived, based on the parameters presented in Annex C.

Results

Sensing results for 5G/6G systems, with and without UE prior knowledge of the UE location, are shown in Figure 4-4. The sensing tasks (which are almost impossible in 5G systems) can be performed with 6G systems due to a high angular and delay resolution. The mapping is affected by the types of landmarks and the distances between the landmarks with BS/UE. A closer scatterer has a better MEB than a further scatterer, while the reflectors (compared to scatterers) are more likely to be well-located. In addition, the prior UE information provides extra improvements in sensing performance.

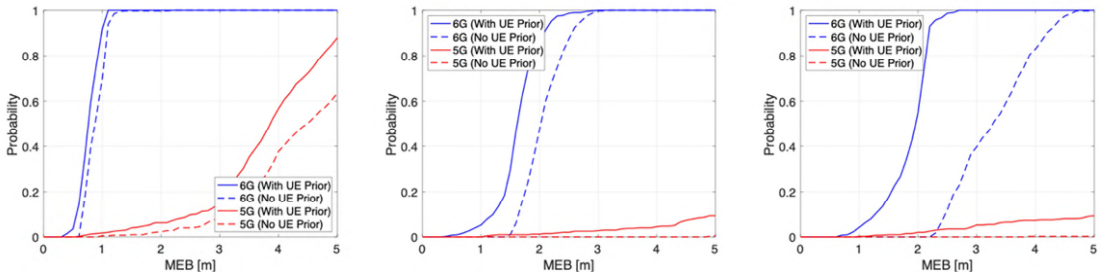

Figure 4-4 Mapping error bound for different landmarks (left: close scatterer, middle: further scatter, right: reflector) under different indoor scenarios. The positions of the 3 landmarks for each subfigure are [2, 2, 0], [-10, 5, 1], and [-2, 18, 4], respectively. The UE locations are sampled inside the indoor area with 1 m interval.

Conclusion and Plans

Sensing and mapping performance are expected to be improved in 6G systems, due to the large bandwidth and high angular resolution using large antenna arrays. Furthermore, the performance can be improved by optimised beamforming and an increased number of transmissions. The impact of hardware impairments is expected to be the main limitation and will be studied in Hexa-X (see also Section 4.2.4).

4.2.2 Non-Radar Environment Sensing

Landscape Detection Problem

To ensure enhanced coverage, the 6G deployments will not only happen in sub-THz band but will also exploit the 5G and 4G spectrums. Co-operative distributed sensing using multiple network nodes can be exploited even in lower frequency bands to perform macro sensing of UE environment such as landscapes in a multi-static way. Such sensing of the landscape (forest, street, barren land, water body, etc.) in which the UE is present can aid in better beamforming, handover parameter optimisation, enhanced digital twin representation of the UE, etc.

Methodology

A method where BSs collaborate is proposed, by reporting the observed path-gains to a UE to a centralised server running an AI agent, which infers the landscape of the UE by exploiting the N strongest path-gains. The method uses simulation data from a ray-tracing propagation model of a 1 km X 1 km section of London city environment. AI agent using a random forest algorithm is trained from this simulation data for assessing the performance.

Results

The performance of the agent is assessed using the precision score, which is defined as the fraction of true positives and all positives (true and false). The precision score is an important KPI in the landscape sensing problem since the consideration that the UE in a particular landscape will trigger network to take an action which can be catastrophic in case of a false alarm. The performance for the binary hypothesis test at 5 GHz frequency for determining whether the UE is on a street or not is shown in Figure 4-5. The dotted lines in the Figure 4-5 mimics the agent's robustness to uncertainty of the co-operating base-station measurements in the proposed multi-static set up.

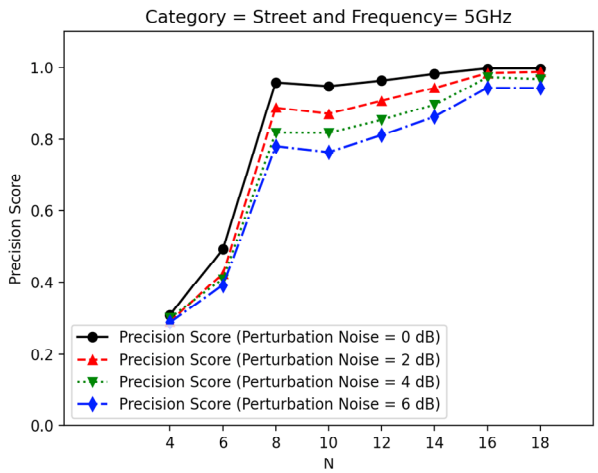

Figure 4-5: Performance as a function of the number of paths, of random-forest based AI method for 'Street' landscape detection for central London city.

Conclusion and Plans

From Figure 4-5, performance improves with number of considered paths, N, with precision score reaching greater than 90 percent for $N > 10$. This indicates that with sufficient densification of network, macro level sensing such as landscape sensing can be accomplished.

4.2.3 Material Sensing

Material Sensing Problem

Mobile networks typically operate in multiple frequency bands. Nodes can capture the reflection-loss between the transmit and receive points which can be used for sensing of materials.

Methodology

The reflection loss of the electromagnetic wave when it is impinged on an object depends on the electrical roughness of the material. This can be exploited for material sensing in a bi-static [KGBR21]

radar by sweeping the incident angle between the transmitter and receiver and measuring the reflection loss. A single bounce reflection in an indoor environment for material sensing is considered.

Results

The reflection losses at various incident angles are computed a priori for different materials using the ITU model [P.2040-1] in simulations. The computed reflection loss is stored in a reflection loss database and is depicted pictorially in Figure 4-6. By matching the closeness of the observed reflection loss at various incident angles and frequency bands, to reflection loss database, the material type is detected [GYA+21].

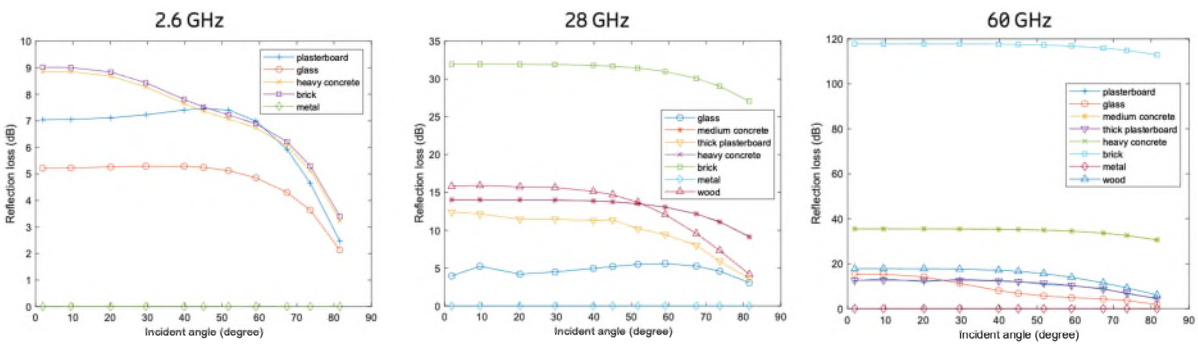

Figure 4-6: Reflection loss for common building material at different frequency bands.

Conclusion and Plans

This method can be used for material detection by exploiting the existing wireless infrastructure without the need for any new additional hardware for material sensing. The method uses a simple search in a small database for material identification and bears significantly less computational burden in comparison to a parametric-model-based approach.

4.2.4 Impact of Radio Hardware Impairments on Sensing

Hardware Impairments on Sensing Problem

The sensing and mapping capability of 6G will be a new feature which was not present in 5G. The technology will be similar to that of a radar, but with different waveforms. Since the waveforms will be designed also for communication this may introduce problems for the sensing capability. Especially the hardware impairments of the system may present a major problem to achieve the desired accuracy of the sensing and mapping capability. The timing and frequency synchronisation of the base stations will also be an issue as it creates ambiguity in deciding how much of delay and frequency offset are due to target's reflection and its associated Doppler and how much of it is arising due to the imperfect synchronisation.

Methodology

To get an understanding of the implications of different hardware impairments on the sensing performance, a simulation tool is being developed. It will be used to evaluate different waveforms and their performance under different hardware impairments. It can also be used to evaluate algorithms for compensation of hardware impairments. The synchronisation problem can also be evaluated by implementing different synchronisation algorithms for the base stations.

Results

The tool is still under development but will allow the user to simulate an environment with multiple base stations as well as mobile stations for multi-static sensing use cases.

Conclusion and Plans

As the effect of hardware impairments on the sensing capability is an area which has not been investigated much previously, it is important to acquire this knowledge. A good starting point is in the form of simulations, which will enable the identification of the main issues and where to focus on to achieve the necessary sensing accuracy.

4.2.5 Initial Findings on SLAM

In the 6G systems, special-purpose localisation, mapping and tracking functionalities will not only become beneficial for future (communication) applications, but in many circumstances will be essential to realise the envisaged use case families identified in [HEX21-D21]. For instance, massive twinning, telepresence, and collaborative robot scenarios require such functionalities to digitally recreate the physical world using relevant sensing information from heterogeneous sources (e.g., sensor measurements, application data). When combining the 6G potential to accurately obtain location information of target nodes (objects/people), while using radio waves to potentially capture/identify them, as well as map their surroundings, novel environment-aware applications are then enabled. SLAM methods aim to build a consistent global model of the environment from a collection of local observations (measurements acquired by distinct sensors).

When considering the sensing source capability, laser-, visual- and RF-based technologies (besides there also exist solutions based on gyroscope and pedometer devices) can be used. To tackle the SLAM problem, many algorithms have been proposed over the years, mainly filtering-based (such as, Kalman filter and particle filter), as well as graph-based solutions which typically formulates the problem as a maximum likelihood estimate (parametric optimisation) using pose graphs. In fact, the latter strategy

solves the problem as a graph optimisation and determines the best possible configuration of the poses, conditional on the underlying constraints between states which are captured by the graph structure.

As addressed by in [MTK+02], the SLAM problem can be defined using a probabilistic model in which the target state at time instant t is denoted by s_t (also commonly referred to the target poses in the related literature). Then, a motion model can be defined by the expression $\Pr(s_t|u_t)$ which updates the target states over time where u_t yields the control commands (e.g., new heading and velocity). To build a map m, the target senses (e.g., by collecting RF-based range and bearing measurements) the environment which is described by the landmarks (considering static nodes in this preliminary study), while the acquired measurements are $\hat{z}$ so that the observation model (likelihood function) is given by $\Pr(\hat{z}_t|s_t, m)$. The target trajectory can then be reconstructed by recovering its path $s_1, s_2, \dots, s_t$.

So, from this factorisation $\Pr(s_t, m|\hat{z}_t, u_t, c_t) = \Pr(s_t|\hat{z}_t, u_t, c_t) \prod_M \Pr(m|s_t\hat{z}_t, u_t, c_t)$, where M yields the number of landmarks, the SLAM problem can be decomposed as a target localisation problem, along with a collection of landmark estimation problems conditional the target state estimates. In most practical deployment scenarios, map landmarks are not easily identifiable neither their number, which also requires solving an additional data association problem (given by the correspondence c_t) between observations and landmarks already seen (identified) in the map (thus, resolving if observations are new and then augmenting the map) [MTK+02].

4.2.6 Filtering-based SLAM

Filtering-based SLAM Problem

The purpose of radio-SLAM is to jointly estimate the UE state (e.g., 3D location, clock bias, velocity, orientation) and to map landmarks in the propagation environment [KGG+20]. A comparative analysis is conducted, similar to Section 4.1 and Section 4.2.1, to contrast the potential of 6G in comparison with 5G for a downlink communication system with a multi-antenna UE, a multi-antenna BS, each with a single RF chain. The UE predicts its own state and the state of landmarks in the environment. Based on measurements (angles and delays), these state estimates are updated, and new landmarks are generated. The problem is challenging due to the unknown association between the measurements and the landmarks.

Methodology

A state-of-the-art SLAM filter from [GKK+21] is adopted, based on the Poisson multi-Bernoulli mixture density and the extended Kalman filter. The SLAM filter comprises the prediction and update steps of the Bayesian filtering recursion with random finite sets (RFSs).

- *Prediction step:* the UE state is predicted using the known dynamic model. However, there is no prediction for the objects since the map is static.
- *Update step:* under each global hypothesis, measurements are used to create a data association matrix and compute a certain number of data associations (DAs). Under each DA, the joint state is created and the joint state update is performed. Finally, the mean and covariance of the UE states can be obtained from the joint posterior by marginalizing the landmark states out over all DAs.

Results

The SLAM performance in 5G/6G communication systems is evaluated, in the presence of high UE mobility and significant clutter [GKK+21]. Following the approach from Section 4.1 and Section 4.2.1, the measurement tuple (comprising TOA, AOA azimuth, AOA elevation, AOD azimuth, AOD elevation) for each resolvable signal path from a channel estimation routine is obtained. The setup, signal parameters, and noise standard deviations of the measurements are obtained as in Section 4.1 and Section 4.2.1. The mapping performance is evaluated by the generalised optimal sub-pattern assignment (GOSPA) distance, and the performance of UE's state estimates is evaluated by the mean average error (MAE).

Figure 4-7 shows the SLAM performance: in 6G systems, the average GOSPA has significant performance gains in comparison with those of the 5G systems, i.e., mapping in 6G systems is robust to both missed detections and false alarms. Similarly, MAE of the UE position is much improved in 6G compared to 5G.

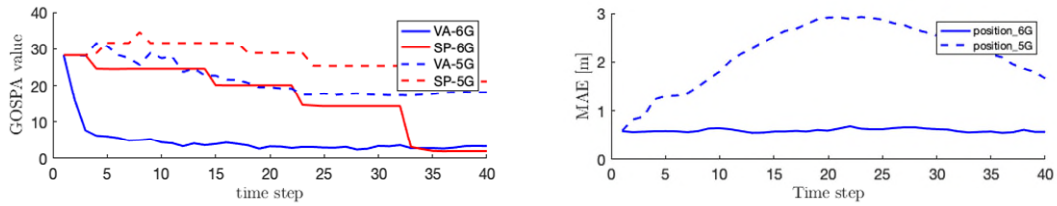

Figure 4-7 Filtering-based SLAM performance in 5G/6G downlink communication systems. Left: GOSPA of scatter points (SP) and virtual anchors (VA), where the latter relate to reflective surfaces. Right. MAE of the UE location.

Conclusion and Plans

In summary, 6G systems are expected to provide better SLAM performance than 5G systems due to the high resolution of the channel parameter estimates in 6G systems. As before, hardware impairments, short coherence time, and limited computational resources at the device side will likely degrade the performance and will be further analysed.

4.2.7 Graph-based SLAM

Graph-SLAM Problem

Here, a probabilistic graphical model offers a convenient representation of the aforesaid conditional factorisation of the SLAM problem (see Section 4.2.5) and allows to exploit the respective underlying conditional interdependences between variables in the model. In fact, a SLAM problem can be properly specified by the corresponding probabilistic graphical model and a set of available measurements: thus, to solve the probabilistic SLAM problem, first an appropriate representation should be found and then an inference algorithm should be developed (preferably capable of carrying out efficient and consistent computation of both the prior and posterior distributions).

An explicit characterisation of the posterior distribution permits tackling situations where the state distribution is diffuse or multi-modal what may also offer the additional benefit of uncertainty estimation. In [FLK16], Fourie et al. introduce an approach that approximates the true posterior distribution through kernel density estimation. Therein, Bayes trees are employed to encode the multi-hypothesis tracking structure: note that the inference over the full joint probability density function may be avoided by exploiting the sparsity in its structure.

Moreover, SLAM in wireless communication systems has traditionally focused on reconstructing the geometrical properties of landmarks. Equally important, richer environment mapping has the potential of going beyond typical geometrical (only) representations by considering specific features of the 6G radio access interface, as opposed to the classical landmark-based (or feature-based) representations of the deployment scenario and its surroundings. Such maps can be augmented over time and used as prior information for subsequent localisation procedures and resource management as well: In such setups, Bayesian analysis can use available data as prior knowledge/evidence.

As pointed out in the introductory discussion of Section 4.2.5, when solving highly dimensional problems using probabilistic programming, it becomes convenient to exploit the sparsity of the respective graph structure and thus avoid inference over the full joint density function of the variables. Additionally, when the LOS component is obstructed, it also become necessary to exploit the spatial and time resolution of multipath components in NLOS deployment scenarios.

Methodology

To carry out this preliminary investigation, probabilistic graphical models were used to describe the SLAM problem and do Bayesian inference exploiting the respective graph structure (states interdependences), as well as employ Markov chain Monte Carlo (MCMC) to sample the posterior distribution of the latent variable of interest, namely target state and map landmark (scatters reflection points). To generate the observations, namely angle and range measurements, a raytracing simulator was used to study the Bayesian-based SLAM method in NLOS channel conditions [SD16].

Preliminary results

Figure 4-8 and Figure 4-9 illustrate the kernel density estimation (KDE) of the posterior distribution of the latent variable of interest after carrying out the target localisation and mapping of the reflectors' positions (landmark geometrical locations) ***p***, ***q*** and ***s*** represent the target, anchor and scatters incidence points coordinates, respectively. While the former shows results when considering two multipaths, the latter considers three components. Figure 4-10 shows the cumulative distribution function of the position error for varying number of measurements, while Figure 4-11 presents the position error distribution for increasing angular noise on the direction of arrival.

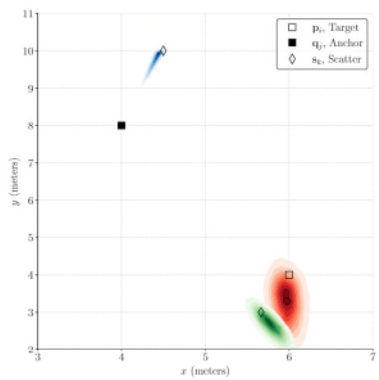

Figure 4-8 KDE of the target node and scattering incidence points coordinates when considering two resolvable multipath components.

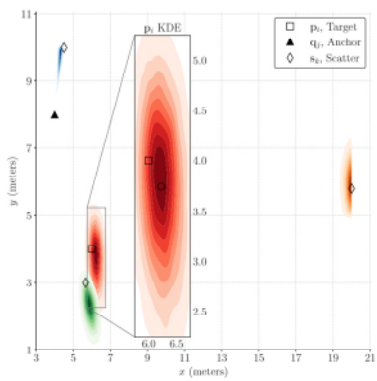

Figure 4-9 KDE of the target node and scattering incidence points coordinates when considering three resolvable multipath components.

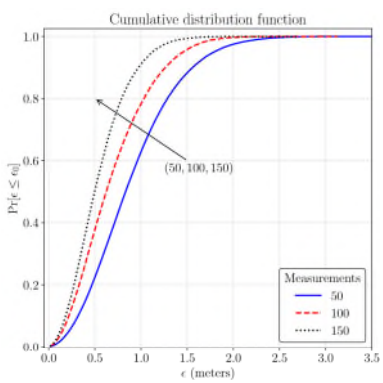

Figure 4-10 Cumulative distribution function of the position error for increasing number of accumulated measurements

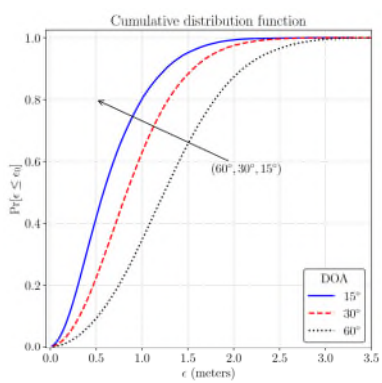

Figure 4-11 Cumulative distribution function of the position error distribution for increasing angular noise error on the direction of arrival

Conclusion and plans

In this preliminary study, the potential of using probabilistic graphical models to appropriately describe the SLAM problem was observed, and then using Bayesian inference to estimate the quantities of

interest even in NLOS conditions. By recovering the full posterior distribution, it may become possible to estimate the respective uncertainty on the obtained results. Model-based filtering-based SLAM and graph-SLAM methods will be compared and augmented, where needed, with ML-based data-driven procedures.

4.3 Initial Findings on Joint Communication and Sensing

The Joint Communication and Sensing Problem

The purpose of joint communication and sensing (JCS) trade-off analysis is to investigate the best radar sensing performance attainable under a given communications performance requirement, or, similarly, the highest communications performance for a given radar constraint. 5G/6G downlink transmissions by a dual-functional BS that concurrently communicates with UEs and detects targets using the return signals are considered. The analysis results will provide insights into different JCS operation regimes, depending on SNRs and practical requirements of radar and communications subsystems.

Methodology

An OFDM JCS system with an OFDM dual-functional transceiver (a BS) and an OFDM communications receiver (a UE), as shown in Figure 4-12 is considered. The transceiver consists of a transmitter that transmits the JCS waveform for the purpose of communicating with the communications receiver, and a radar receiver that performs radar sensing using the backscattered signals. At the transceiver side, the transmitter and receiver share the same hardware platform (i.e., they are co-located) and their antenna arrays are assumed to be perfectly decoupled to avoid self-interference resulting from full-duplex radar operation.

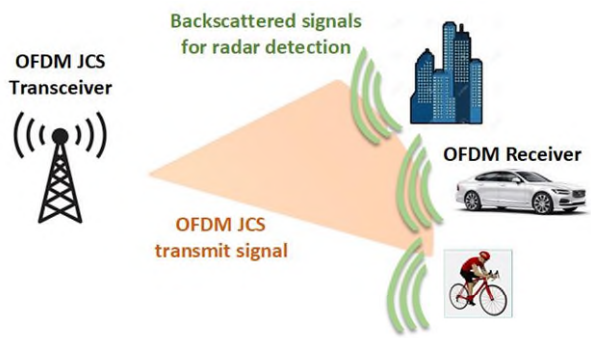

Figure 4-12 OFDM JCS scenario with a dual-functional BS (JCS transceiver) transmitting data symbols to UE (OFDM receiver) in the downlink while simultaneously detecting targets in the environment using the backscattered signals.

To achieve a favourable trade-off between radar and communications, an OFDM waveform design strategy is proposed that optimises subcarrier powers in each time-frequency region of interest [KKW21]. For optimisation, the estimation accuracy is quantified by CRLB as the radar metric, while the communications metric is the capacity. First, using tools from convex optimisation, a radar-optimal OFDM waveform is designed to minimise the CRLB on delay and Doppler accuracies under certain side-lobe level constraints. Then, the OFDM JCS trade-off optimisation problem is formulated to maximise the capacity under radar similarity constraint, which specifies the proximity of the JCS waveform to the previously designed radar-optimal waveform. To solve the resulting non-convex fractional programming problem, a modified version of Dinkelbach's transform is resorted to and an alternating optimisation strategy is applied. The parameters are presented in Annex C.

Results

JCS trade-off curves obtained as the result of the optimal subcarrier power allocation problem are presented. To obtain the trade-off curves, the optimisation problem is solved under various radar similarity constraints, ranging from $\epsilon = 0$ (radar-optimal scenario) to $\epsilon = 1$ (communications-optimal

scenario), where ϵ takes values between 0 and 1, and denotes the proximity to the radar-optimal waveform. Besides the trade-off curves, the uniform (equal subcarrier powers) and water-filling [Gol05, Ch. 4.4.1] solutions on the trade-off region are presented for benchmarking purposes.

Figure 4-13 show the JCS trade-off curves and achievable trade-off regions in range CRLB vs. capacity using 5G and 6G parameters, respectively. As expected, the JCS Pareto frontier converges to the water-filling solution at the communications end of the trade-off. In addition, a trade-off between radar sensing accuracy and communications capacity is observed, from which the operating point of the JCS system can be determined based on the performance requirements of radar and communications subsystems. Hence, the designed waveforms can be tailored to varying practical system requirements (i.e., whether it is a radar-critical scenario or a communications-critical scenario). The standard water-filling and uniform solutions represent a single operating point in the trade-off region and the water-filling approach achieves the worst radar performance, while the JCS approach can be flexibly adapted to cover different emerging scenarios in 5G/6G systems. Comparing 5G and 6G results, higher range accuracy and capacity due to increased bandwidth is observed (velocity accuracy is not shown but degrades since the same number of symbols is transmitted with larger subcarrier spacing leading to a shorter integration time). It is important to note that improvements in sensing accuracy and capacity from 5G to 6G are not proportional to (5-times) bandwidth increase due to severe path loss and hardware limitations (i.e., lower transmit power) at higher frequencies in 6G.

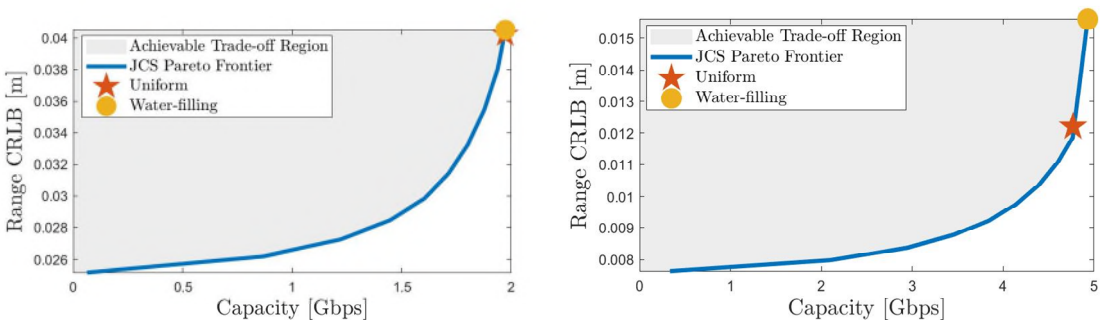

Figure 4-13 Performance trade-off between radar range estimation accuracy and communications capacity for 5G (left) and 6G (right).

To illustrate the communications performance under different SNR levels, Figure 4-14 plots the capacity with respect to transmit power, achieved by the JCS approach (for two different radar similarity levels) and the standard solutions. Since water-filling and uniform solutions do not consider radar similarity constraints, they always attain higher capacity than the JCS trade-off waveforms, as expected. As the radar similarity constraint becomes less stringent, the communication performance of the JCS waveform improves and the resulting gap becomes larger at higher SNRs. Like the above analysis, the JCS system designer can control the operating point (i.e., radar similarity) depending on transmit power and JCS performance requirements.

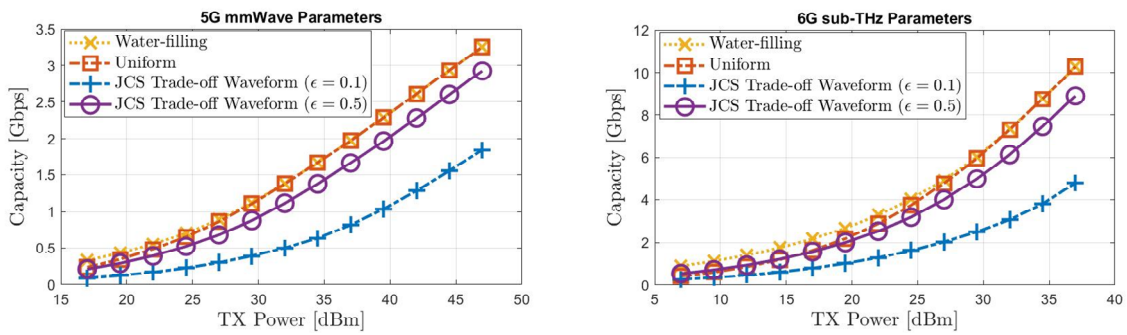

Figure 4-14 Capacity with respect to transmit power using 5G and 6G parameters, obtained by standard approaches and JCS waveforms under different radar similarity constraints.

Conclusion and Plans

As a conclusion, 5G/6G systems with integrated sensing and communication functionalities can offer flexible trade-off solutions that can be adapted to varying system requirements with optimised OFDM JCS waveforms. With larger available bandwidth, 6G JCS systems provide higher ranging accuracy and improved communications capacity compared to 5G. As a possible study item for the next deliverable, the JCS performance of the Discrete Fourier transform spread OFDM (DFTS-OFDM) waveform can be evaluated, which is more hardware-efficient than OFDM and therefore can be preferred in the path towards 6G systems.

4.4 Initial Findings on Sensor Fusion

Problem

In a typical application scenario, there is going to be more than one source of information for localisation and sensing. 6G and Hexa-X are expected to bring new data sources. Examples of this heterogeneous sources are sensor data from radio signals, radar, lidar. As each of the data sources have different accuracy, update rate, resolution, and many other parameters, it is quite a complicated task to obtain an estimate with less uncertainty than would be possible when using a single source. The most common implementation of sensor fusion in the market today can be seen in smartphones, but more complex implementations can be found in all autonomous driving vehicles.

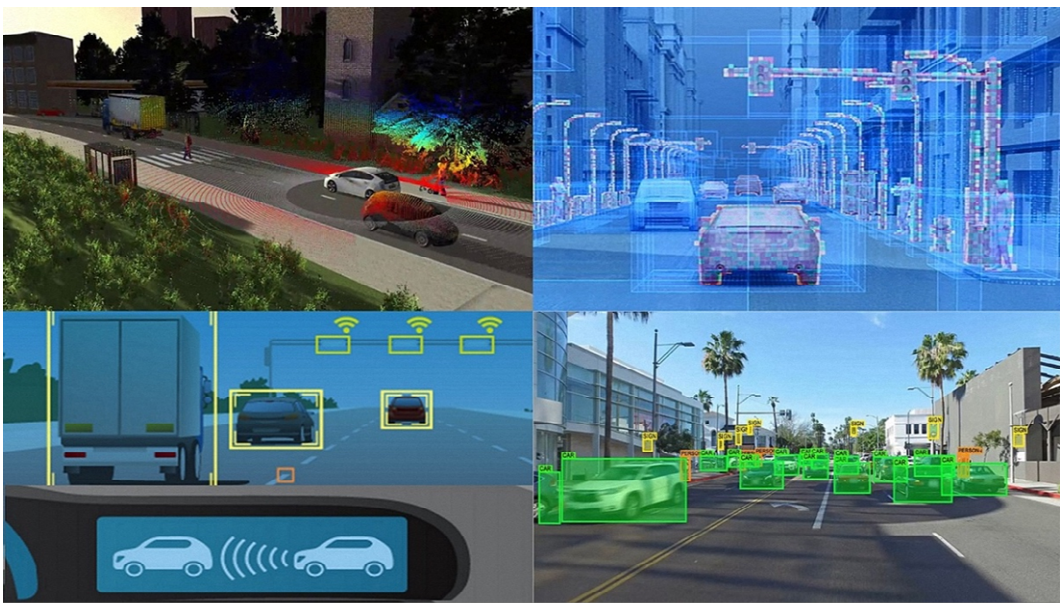

Figure 4-15 Example of sensor fusion for autonomous vehicles.

Methodology

There are many methods and algorithms that can be used to reduce the uncertainty when combining data sources. The data sources can be several of the same sensors measuring the same physical property or can be a heterogeneous combination of sources measuring related information. The sensors don't have to be of the same quality to provide an improvement in the overall accuracy. If no improvement can be obtained through the combination of different sensors, the best available sensor is dynamically selected at all times to provide the best results.

Results and Plan

Sensor fusion can be performed at the level of the channel parameters like Doppler, and pseudo-ranges (tight-coupling) or at the level of the position and speed estimates (loose-coupling). An ultra-tight integration is also possible, if access to the raw analogue data samples is available, which is not typically the case when using commercial-off-the-shelf (COTS) sensors. Tightly coupled methods have proven

to be especially robust under harsh environments, but they are bound to a higher mathematical complexity. The processing of sensor data can lead to delays in the delivery of the calculation when compared to using the sensor data directly. The trade-off between an increased accuracy in exchange for computational complexity and processing delay will be considered, as the application may be negatively impacted by this.

4.5 Initial Findings on Interference Mitigation

Problem

It is acknowledged that interference between sensing nodes will become a severe problem as the number of sensing nodes using time/frequency resources *uncoordinated* increases [Bro07]. As outlined in Section 3.2.2.4, interference can be addressed in three different manners: robust waveforms, reduced likelihood of interference and resource allocation. These three methods apply equally to both monostatic and bi-static sensing.

Methodology

The three interference reduction approaches are now considered and placed in the 6G context.

- *Robust waveform:* For some waveforms, such as OFDM based waveforms, the sensing performance degrades gracefully when exposed to interference, i.e., interference can be seen as an increased noise floor.
- *Interference likelihood:* It is possible to reduce the likelihood that two sensing signals interfere with each other by using communication and sensing. It can either be achieved by assigning time/frequency resources from a central node or by performing this task using distributed protocols [AKC+20]. When moving from sub-6 GHz to mmW and sub-THz sensing and communication, it is desirable to use the same hardware for communication and sensing. Communication hardware at these frequencies will however not be full-duplex, which means that bistatic sensing will have to be used. It is noted here that bistatic can also mean that transmitter and receiver are physically located on the same device, for example a UAV.
- *Coordination:* Interference in bistatic sensing can still be coordinated centrally (e.g., from a base-station), but distributed system support is needed in case base-station coverage is not available. This can be realised using joint sensing and communication. Note also, that when moving to sub-THz sensing the antenna pattern becomes narrower, which not only increases the angular resolution but also changes the nature of interference.

Results and Plan

For bi-static sensing to be efficient, it is desirable that the sensing receivers have information, when signals are transmitted by other nodes. It is assumed that this information is broadcasted as part of the sensing signal. The problem is illustrated below (red=TX mode, green=RX mode, grey triangle=angular scanning range).

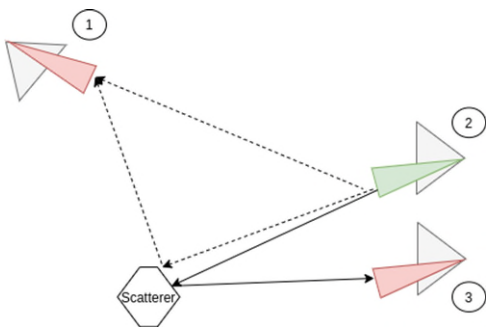

Figure 4-16 Bi-static sensing without interference. Nodes 1 and 3 have learned the transmit pattern of node 2 and use its transmit signal for sensing.

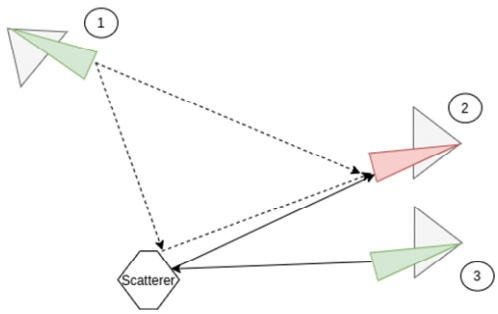

Figure 4-17 Bi-static sensing with interference. Nodes 1 and 3 are not aware of each other and create interference when node 2 performs sensing operations

To address the problem of sensing interference in bi-static scenarios, distributing interference information and intended resource use through communication and sensing is proposed. The following methods can be used to coordinate transmission and reduce the likelihood of interference in bi-static deployments:

- Location information.
- Timing information.
- Intended resource usage.
- Active node information (e.g., node 2 distributes information about node 1 and node 3)

Each node can use information distributed by other nodes to schedule its own sensing signals.

4.6 Presentation of the Planned Demonstrators

The demonstration activities are divided into sensing and localisation, but they are intended to be performed on the same hardware. It is desirable for the demonstrations to be able to perform AoA and AoD estimations. This implies that the demonstration equipment needs to be able to support multiple antennas at both the transmitter and the receiver. Currently such front-ends are only available at around 70 GHz. It needs to be investigated during the project, if hardware becomes available at higher frequencies that can support array processing. To show very high-resolution sensing and localisation, a high bandwidth setup will be available, but without steerable antennas. It is noted here that the same demonstration setups will be used for waveform demonstrations in WP2.

4.6.1 Demonstration Setups

The following two setups are used for demonstration purposes. Their main parameters are summarised in Table 4-1.

Table 4-1 Main parameters of the different setups.

Setup	Carrier Frequency	Bandwidth	Antenna configuration
Setup 1	Up to 200 GHz	Up to 10 GHz	Horn-antennas
Setup 2	Up to 71 GHz	Up to 1.8 GHz	Phased array

Setup 1: High-carrier and high-bandwidth

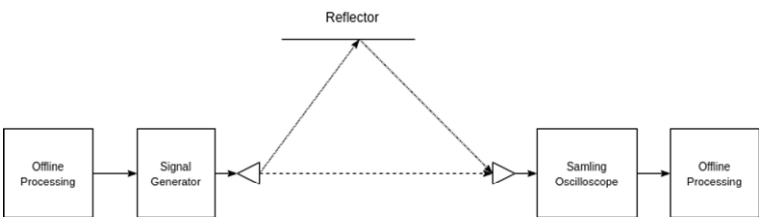

Figure 4-18 Demo Setup 1 which can take signals/waveforms generated offline and transmit them over a sub-THz wireless link. On the receive side the signal is sampled with an oscilloscope and the data can be analysed offline.

This setup is based on a signal generator and a sampling oscilloscope. This setup can generate, and sample signals up to 200 GHz, with a bandwidth of up to 10GHz. The interface for demonstration purposes is IQ-samples. Note, that this setup will not have automatic beam-steering capabilities.

Setup 2: Portable setup with beam-steering capability

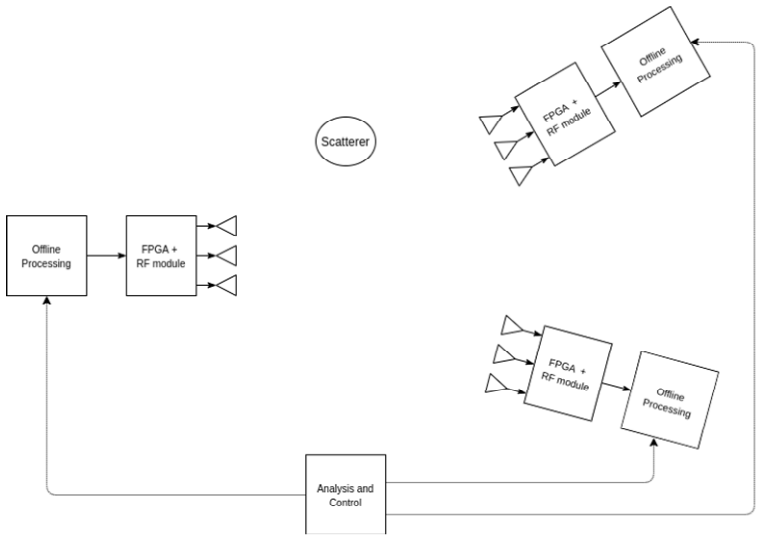

Figure 4-19 Demo Setup 2: Setup consisting of 3 transceivers with beamforming capabilities. The setup can be used for multi-static sensing of a scatterer or for localisation.

This setup is based on commercial analogue front-ends connected to FPGA boards. The front-ends can operate at carriers up to 71 GHz and support a signal bandwidth of up to1.8 GHz. The interface to the demo-setup is also here IQ-samples with support for real-time control of beam-steering. Up to three transceiver modules are available. Each module can either act as TX or RX.

4.6.2 Sensing Demonstration

The sensing demonstration will be based on a transmitter and a receiver with known position, operating as a bi-static and multi-static radar. The following sensing demos are proposed:

- Demo 1 – High accuracy bistatic sensing: Use high bandwidth Setup-1 to demonstrate that sub-cm range resolution is possible at sub-THz carrier frequencies. It is still to be investigated if angular resolution can be added.
- Demo 2 – Bi- (multi) static sensing: Use beamforming setup-2 to demonstrate bi-(multi) static sensing in the presence of hardware impairments. Both range and angular resolution are to be demonstrated.

4.6.3 Localisation Demonstration

The proposed localisation demonstration is based on a single base-station and a UE. Both units are equipped with array antennas that can perform angle of arrival estimations. Based on the sampled data from the demo equipment, it will be possible to perform demonstration of localisation algorithms. With this setup, the following third demo is proposed:

- Demo 3 – Localisation at 71GHz: Use beamforming setup-2 to demonstrate localisation of end-device in the presence of hardware impairments. AoA, Multipath and ToA are to be used for localisation.

5 Location and Sensing-enhanced Services

A crucial aspect (a true paradigm shift) of the envisaged 6G system which is fundamentally different from legacy systems is that localisation is not a by-product of the communication development anymore but integrated from the system outset and thus must become one of the design targets [6GJ]. 5G use cases and scenarios target highly accurate position information. For the Hexa-X use case families, these requirements are in some scenarios even stricter and thus remain challenging. Besides highly accurate position information, a very important aspect for the Hexa-X use case families is latency (see Table 3-35). To fulfil latency requirements not just the measurements and computation latency for positioning is to be considered but also the propagation of measurements throughout the whole system. Another new evolving aspect in next generation networks are sensing capabilities which will open a door to a wide range of features and services like mapping of the environment or spectroscopy.

As localisation/positioning will play a much bigger role in the future and sensing the environment will be a totally new feature, Section 5.1 will develop a first view on the interrelationships between location as a service, sensing as a service and the vast amount of possible new emerging services supporting and enhancing existing services and applications and allow for totally new applications in the various use case families.

One obvious and very important emerging service will be the optimisation of the 6G communication itself. As it can become one of the fundamental emerging services Hexa-X will research on how the optimisation can be achieved as described in Section 5.2.

The new localisation and sensing technologies researched in Hexa-X will influence the network requirements and potentially the overall architecture of 6G. Such requirements will be deduced and collected both from the research on the interrelationships of new services and the algorithms developed for localisation and sensing during the term of Hexa-X and explained further in Section 5.3.

The ambition is to set positioning and sensing in context to new emerging services, strengthen the future role of positioning in next generation mobile networks and deduce requirements for the network and the End-to-End (E2E) architecture.

5.1 Enabling and Enriching Applications

When high precision and accurate localisation/positioning and sensing becomes a built-in feature, a vast amount of new emerging services will be possible which in turn enable future new applications, as illustrated in Figure 5-1. Hexa-X develops a first view on how emerging services will interact with localisation and sensing and give examples on such emerging services. 6G sensing services will go hand in hand with 6G communication services. Sensing the environment will be based on 6G mobile wireless communication signals (6G internal sensing) but may also incorporate sensor data from external 3rd party sensor system (6G external sensing). Via processing (and optional fusion of) such sensed data, the perception of the environment and various situations is possible, and with it the enhancement and creation of core and new emerging services. The localisation of UEs is one main and established service but evolves with each mobile network generation.

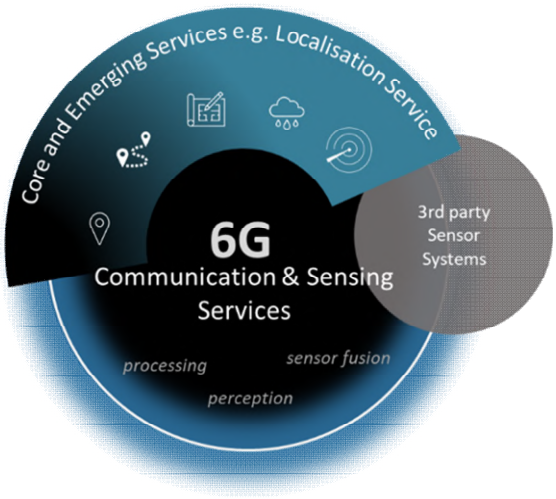

Figure 5-1 Vision of Hexa-X on how localisation and sensing will enrich and enhance 6G.

Emerging services might just be classic *Location Based Services*. With knowing the exact positions of UEs, the 6G communication services can be enhanced. As this interplay of localisation and communication is a 6G inherent optimisation opportunity, it is examined in more detail in subsection 5.2. More emerging services will arise, such as sensor fusion. For example, mapping production environments in 3D usually require dedicated laser-based scanners moving around the surface. Hexa-X proposes the joint use of localisation and sensing. This is to be achieved through specially constructed waveforms combined with massive MIMO antennas. This sensing capabilities are expected to allow the mapping of the environment. Furthermore, applications based on augmented and mixed reality will require both location and orientation of the human and information of the environment.

If interaction with potentially dangerous machines is involved, not just security plays an important role but also functional safety. Safety is one specific aspect of dependable systems (other aspects are availability, reliability, integrity, and maintainability). Functional safety usually describes the protection of humans from systems (such as buildings, machines, and robots), whereas security describes mechanisms and concepts to protect systems from human attacks. In a future connected world, both aspects must be handled more and more in combination and reference to each other. In the area of positioning and sensing, security threats can easily become a safety threat.

As an example, in industrial scenarios, automated guided vehicles or autonomous moving robots, would have to ensure through trustful and accurate position and sensing information to not endanger human lives, meaning functional safety must be guaranteed. Various norms and regulations exist for machinery in industrial context and many products have been developed that ensure the separation of humans and robots or to enable local collaboration through local safe sensors. But not many safety products exist that allow safe monitoring on a factory wide overarching scale. One example in this direction is the product SafetyEye from the company PILZ[§]. This camera-based monitoring system detects if people get too close to machines without the need to install fences around each dangerous zone. If a situation like that is detected, appropriate measures can be carried out like lowering the speed of machines and therefore reducing the risk of human damage.

Security may sometimes play a minor role, e.g., if the position estimation is done within a factory, where no jammers can reach the positioning system. But in easily accessible areas or outdoors, security will influence safety concepts. Increased reliance of services and application on mobile communication technologies has inherent security-risks [RHA20], [ENISA20], [RK03]. Performing localisation and sensing with wireless signals provides both:

[§] See https://en.sslog.de/equipment/safety-sensors-psen/safe-camera-system-safetyeye, Accessed 14/11/21.

- **Security threats:** Location and sensing information will become a built-in feature of new 6G networks. As this location information will be very accurate and sensing the environment reveals details of the surrounding, it is crucial to take care of potential security threats through standard of encryption and authentication. Security threats may influence both security and safety-related scenarios, with attacks being launched both locally or remotely. Hence, given the sensitive, privacy-related, and sometimes safety-critical nature of location information, it is important that this information is secured appropriately [HEX21-D12].
- **Possibilities for improving security**: location information can ensure scenarios with focus on security (e.g., smart keys opening doors of cars and buildings when located in vicinity). Such security-enabling scenarios and more emerging services will be examined during the Hexa-X project.

Security concepts influence all levels and layers in the 6G architecture and should be designed into the system from the beginning, whereas functional safety concepts are very complex and strongly depend on the functional safety goal a certain application must fulfil [ALR+04]. This may influence hardware designs, as the example of the SafetyEye shows, or coding and testing guidelines.

Detailed technical concepts for safety and security are beyond WP3 and out of scope. WP1 (Task 1.7 Security & Privacy) will take care of holistic security and privacy concepts for next generation mobile communication. WP3 will focus on the potential impact of location and sensing information on security applications.

The overall goal is to develop a first vision on interrelations between, sensing, sensor fusion, localisation and emerging services which also serves as input for the architectural design of next generation networks.

5.2 Supporting Communication with Localisation and Sensing Services

As mentioned in the introduction of this section, the interplay between communication and sensing with radio waves has the potential to enable novel use case families (as detailed in [HEX21-D21]) and provide side information to improve communication performance. In fact, advanced applications such as digital twinning will require to combine data from heterogeneous sources to digitally recreate physical environments. Moreover, local networks enabling proximity-based interactions between cooperative devices can take advantage of location information to establish radio links and share radio resources.

The terminology of Annex A is followed, where localisation is defined as the process of estimating the location of devices by using sensor measurements (RF-based in mobile radio systems); while mapping corresponds to generating a (geometrical) map of the landmarks positions based on the collected sensing measurements. Localisation procedures have been already implemented in legacy mobile systems such as LTE (since Release-9), while been either GNSS- or RAT-based mechanisms and mostly driven by regulatory requirements. On the other hand, mapping solutions have not received much attention, though the UMTS and LTE early introduction of the minimisation of driving test (MDT) concept. From [SCS+19] and [JHK+12], MDT relies on either i) periodic GPS-based reporting at Layer 3; or ii) periodic RAT-based signalling exchange and reporting between UE and serving BS at Layers 2 and 3 procedures to collect datasets. The MDT solution constitutes a platform for data collection and processing and has the potential to provide benefits in terms of positioning accuracy, simplified deployment with no impact on user data plan and billing, short lead time (may be used as prior information) and convenience when compared to traditional drive test, statistical relevance of georeferenced data, and flexibility (CAPEX and OPEX by using off-the-shelf devices).

Herein, the potential of sensing with radio waves is discussed [HEX21-D21], regarding localisation, mapping, and tracking, aiming at not only enabling new use cases and applications, but also improving communication aspects of the 6G systems. In fact, 6G will be the first wireless system to tightly integrate communications, localisation, and RF sensing capabilities [WBV21]. Such network sensing

permits detecting the presence of objects, their shape, location, and speed of movement using radio signals so that multi-layered maps of the deployment scenario (environment) can be generated. RF sensing, localisation and mapping provides much richer representation (with respect to, e.g., legacy MDT) of the environment thus creating the conditions to help communication as well [ZX21]. When compared to legacy deployments, 6G will become a network of networks with increased system dimension regarding channel features, number of antenna array elements, bandwidth usage and density of nodes. As a result of such high dimension, the initial access of UE can linger too long if resorting to present day strategies, e.g., either by collecting necessary measurement samples in training-based channel state information (CSI) estimation or carrying out extensive search in training-based beam sweeping methods [WZJ+21].

Next, potential benefits of employing localisation and mapping to improve the operation of 6G communication systems are identified.

- **Localisation**: 6G systems are expected to have large channel dimension imposing high training/signalling exchange overhead to support massive MIMO systems and dense deployments. In such conditions, location-information can alleviate long pilot training and beam alignment procedures, for example, during initial access or handover procedures. It is also known that location side-information can help with relay selection in cooperative communication systems and may be extended to device-to-device deployment scenarios. Similarly, location information can also be used to support inter-cell coordination thus contributing to mitigated cross interference. Built-in localisation information has the potential to optimise the 6G systems by allowing pre-emptive radio resource management (RRM) and beamforming. Location-aided scheduling/RRM can effectively share the available spectrum between users exploiting their position instead of expensive CSI, thus, requiring much less frequent feedback and pilot training. As addressed in [HEX21-D21], 6G RAT-based accurate localisation helps application layer coordination between autonomous things, as well as location-based interaction between users and environment. For instance, digital twins will exploit location information from heterogeneous sources (e.g., sensor measurements, application data) to merge physical and digital worlds. Equally important, localisation information not only allow detecting objects in environment, but also support formation of local networks, e.g., resorting to proximity-based clustering algorithms and resource allocation. In such distributed deployments, localisation information can also be used to select edge server to offload high-demanding computational tasks and store datasets.
- **Mapping**: As aforementioned, 6G radio access technology based on upper mmW signals will most likely operate in small cell configuration also referred to as Short-range wireless connectivity in [HEX21-D21]. By operating at high frequency range (30-300 GHz) with large bandwidth, 6G systems are expected to achieve high data rates, communication capacity and density (high traffic and connections per coverage area). However, transceivers become more susceptible to signal attenuation at high frequencies thus needs to deploy dense networks of small cells with highly directive narrow beam antenna arrays. With such pencil-like beams (via real-time scanning), it becomes possible to create detailed images of the environment (physical spaces). In addition, high dimensional channels impose great challenges on the traditional acquisition of CSI and pilot training procedures. In such situations, the detailed mapping (environment awareness) can be used by the underlying communication system to effectively predict the channel based on local information (before employing any more sophisticated and demanding channel acquisition technique). For instance, a channel knowledge map scheme, which is a site-specific database tagged with locations of transmitters and/or receivers containing channel related information is introduced in [WZJ+21]: such channel knowledge maps can indeed provide super-high capacity, extremely low latency, and ultra-massive connectivity, hence, possibly alleviating the impact of significantly increased channel dimensions and training overhead of 6G systems.

5.3 Implications for Next-Generation Mobile Networks

New positioning and sensing technologies and algorithms are researched inWP3. These results will have multi-faceted impact on next generation mobile networks, from architectural point of view to sensing signal aspects. These potential implications for the network must be deduced to enable the full potential of localisation and sensing in the future.

5.3.1 Sensing Signal Aspects

In conventional cellular systems, signal design work has primarily been driven by the fact that the radio signal for communication between two nodes in the network needs to be robust against the adversities of wireless communication environment. When it comes to sensing, it is the use cases that determine characteristics of a radio signal that can be used for sensing. Depending on the use case, a sensing signal design must be tailored to meet the fundamental requirements on range resolution (R_r) and velocity resolution (v_r), as well as a maximum unambiguous range (R_u) and velocity (v_u). The parameters of sensing signal including a minimum bandwidth, a minimum duration of sensing signal, a minimum and maximum repetition periodicity, and a minimum duration of the sensing frame, must be designed such that the above sensing requirements are met. Table 5-1 shows the relationship between the sensing requirements and the sensing signal parameters.

Table 5-1. Relationship between sensing requirements and sensing signal parameters, where *c* is the speed of light / maximum propagation speed.

Required bandwidth	$BW_{min} = c/2R_r$
Minimum gap between sensing signals	$T_{r\,min} = 2R_u/c$
Maximum gap between sensing signals	$T_{r\,max} = c/4f_c v_u$
Required sensing frame duration	$T_f = c/2f_c v_r$

When an OFDM air interface is used, the above parameters can be expressed in units of OFDM symbols. To estimate the range and speed of the object, the received signal in time-frequency domain must be transformed to Doppler-delay domain by applying FFTs on the received signal.

As an example, assuming a range resolution of 0.5 m, unambiguous range of 100 m, velocity resolution of 0.5 m/s and unambiguous velocity range of -20 m/s to 20 m/s, sensing signal parameters as shown in Table 5-2 are obtained.

Table 5-2. An example illustration of parameterisation of sensing signal.

f_c [GHz]	SCS [kHz]	symbol [us]	BW [MHz]	$T_{r\,min}$ [ms]	$T_{r\,max}$ [ms]	T_f [ms]
3.5	30	33	300	0.67	1071	85.7
6	30	33	300	0.67	625	50.0
10	60	16.7	300	0.67	375	30 .0
28	120	8.3	300	0.67	134	10.7
60	480	2	300	0.67	62	5.0
96	1920	0.52	300	0.67	39	3.1

For example, consider a 28 GHz carrier frequency with subcarrier spacing of 120 kHz (4th row in the table) with the NR cyclic prefix parametrisation, the above means there is roughly ~112 000 OFDM symbols every second. The maximum periodicity of the sensing signal is 134 ms, which is roughly 15 OFDM symbols, and the sensing frame is 10.7 ms, which is roughly 1200 OFDM symbols. This means that at least 80 OFDM must be sent in within one sensing frame. Assuming an update rate of 2 sensing per second, the time-domain overhead for sensing is thus $2 \times \frac{80}{112000} = 0.14\%$. This should be viewed as a minimum requirement for the required range and velocity accuracy, and angular estimation is not considered in this case.

5.3.2 Sensing in a Communication Network

A well-known concept to improve performance in cellular systems is to apply inter-cell interference cancellation or mitigation. Here the victim receiver has some information about the aggressor waveform. In case multiple base stations transmit radar signals simultaneously the inter-cell interference is composed by sensing signals and properties of the transmitted sensing signals should be exchanged between base stations. Exchanging time-frequency allocations enables inter-cell interference avoidance by using different time-frequency resources in strongly interfering cells. Exchanging the sequence itself enables the victim receiver to estimate and subtract the interference. Using orthogonal sensing signals improves cancellation performance further.

If the sensing signal is transmitted in DL slots in a synchronised time division duplexing (TDD) system, the sensing signal will create DL interference towards UEs in neighbouring cells. This interference is similar (but more deterministic) to interferences that would be created by regular communication signals in a neighbour cell. The difference is that parameters of the sensing signal can more easily be shared with a neighbour base station than a communication signal. The neighbour base station could then signal the sequence properties to interfered UEs enabling interference cancellation at the terminal, if needed.

In case of multi-static operations, the receiving base stations need to know when to listen for which signal. The transmitting base station must share time-frequency resources as well as sequence properties of its sensing signal with all receiving base stations.

6 Conclusions

Many, if not all, 6G use cases identified in Hexa-X require highly accurate, low-latency localisation and/or sensing. Supporting these use cases mandates the integration of localisation and sensing into 6G system research from the outset. From the gap analysis, it was observed that the NR positioning is not capable of meeting accuracy requirement of use cases that demand stringent sub-cm positioning accuracy. Moreover, it was also identified that positioning latency creates a bottle neck and hinders acquisition of real-time positioning information that is often required by 6G use cases. In contrast to localisation, sensing is a new capability for mobile communication systems. In this regard, the conventional radar and lidar based sensors were considered for baseline evaluation. It was observed that the conventional sensors are not able to meet all the requirements. 6G, as next generation of mobile communication network, potentially exploiting a wide bandwidth and large antenna arrays (among other enablers) must be able to support and meet the sensing requirements of the identified use cases.

The sensing and localisation capabilities in 6G to enable the new use cases, depend on what performance levels can be achieved in practice. The performance of existing signals, methods, and protocols needs to be understood in the 6G context, and novel approaches may need to be developed. Preliminary analyses indicate that 6G performance benefits stem mainly from improved resolution, not from improved integrated SNR, compared to NR positioning. To improve integrated SNR, longer coherent processing interval must be available, which, in turn, mandates the inclusion of Doppler shifts of individual paths, as part of the channel state information. Trade-offs between sensing and communication reveal that optimised power allocation has significant impact of communication, but much less on sensing. 6G sensing can benefit both from higher and lower frequency bands, supporting new sensing modalities, such as distributed sensing, material classification, and environment sensing. Sensor fusion will be important to overcome (even intermittent) weaknesses of 6G to provide sufficient reliability for certain critical use cases. Further evaluation with real channel measurements from within Hexa-X will be performed to validate theoretical findings. The measurement uncertainty manifesting from hardware and improper channel knowledge can degrade the performance of the non-radar type sensing. For that reason, the impact of hardware impairments on positioning and sensing performance needs to be thoroughly modelled and investigated. Several demonstrators were described, though finding suitable hardware above 80 GHz will prove challenging.

6G location and sensor information enables many new applications and use cases. To support these applications and use cases, sensing and localisation capabilities must be designed as an integral part of the next generation of mobile communications and be offered to all potential consumers. Sensor information, in particular, plays a completely new role. On the one hand, the environment can be observed, and conclusions drawn based on 6G mobile communications itself; but on the other hand, there will be other, 6G-external, sensors and (positioning) systems that could be merged via sensor fusion with the information from the 6G network. This opens many opportunities to improve existing services, but also to create completely new service offerings. Extending the borders of the 6G communication system to allow external sensor information to be integrated in such a next generation communication system require architectural adaptions.

WP3 will only deal with a subset of the new opportunities around sensing and localisation, clearly focusing on 6G-based options, but always embed them in the larger context. From the concepts, models, simulations, and algorithms created, future network requirements will be identified as well as potential requirements for the end-to-end architecture. WP3's goal is to show possible architecture blueprints that represent the interaction within 6G (sensing and localisation) information on the one hand, by examining new 6G internal services. One example could be the exploitation of location information to assist resource allocation for communication, which could then be optimised depending on the location of UEs. WP3 will investigate and evaluate this interplay. On the other hand, WP3 will also show the connection with external information, such as external sensors embedded in UEs as well as localisation systems not based on 6G.

References

[22.261] 3GPP TS 22.261, "Service requirements for the 5G system," version 16.14.0 Release 16, 2021.

[22.872] 3GPP TR 22.872," Study on positioning use cases", version 16.1.0, Release 16.

[22.829] 3GPP TR 22.829, "Enhancement for unmanned aerial vehicles", version 17.1.0, Release 17.

[38.305] 3GPP TS 38.305, "NG Radio Access Network (NG-RAN); Stage 2 functional specification of User Equipment (UE) positioning in NG-RAN," version 16.2.0, 2021.

[38.855] 3GPP TR 38.855, "Study on NR Positioning Support", version 16.0.0, Release 16.

[38.857] 3GPP TR 38.857, "Study on NR Positioning Enhancements", version 17.0.0, Release 17.

[36.888] 3GPP TR 36.888, "Study on provision of low-cost Machine-Type Communications (MTC) User Equipments (UEs) based on LTE (Release 12)", June 2013.

[38.901] 3GPP TR 38.901 "Study on channel model for frequencies from 0.5 to 100 GHz (Release 16)," version 16.1.0, 2019.

[5GP19] 5G-PPP, "5G Automotive Vision White Paper on Automotive Vertical sector," October 2019.

[AEL+14] Alkhateeb, Ahmed, Omar El Ayach, Geert Leus, and Robert W. Heath. "Channel estimation and hybrid precoding for millimeter wave cellular systems." *IEEE Journal of Selected Topics in Signal Processing* 8, no. 5 (2014): 831-846.

[AK21] S. Arshad and G. Kim. "Role of Deep Learning in Loop Closure Detection for Visual and Lidar SLAM: a Survey." *Sensors*, 21(4):1243, 2021.

[AKC+20] C. Aydogdu, F. Keskin, G. Carvajal. et al. "Radar Interference Mitigation for Automated Driving: Exploring Proactive Strategies." *IEEE Signal Processing Magazine*, 37(4): 72-84, 2020.

[AKT+16] T. E. Abrudan, O. Kypris, N. Trigoni, A. Markham, "Impact of Rocks and Minerals on Underground Magneto-Inductive Communication and Localization", *IEEE Access*, no. 4, pp. 3999-4010, 2016.

[ALR+04] Avizienis, A., Laprie, J.C., Randell, B. and Landwehr, C., 2004. "Basic concepts and taxonomy of dependable and secure computing." *IEEE Transactions on Dependable and Secure Computing*, *1*(1), pp.11-33.

[AXM+16] T. E. Abrudan, Zhuoling Xiao, A. Markham, N. Trigoni, "Underground Incrementally Deployed Magneto-Inductive 3-D Positioning Network", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 8, pp. 4376-4391, 2016.

[Arb19] Arbe Robotics. From L2 to L5 Autonomy, the Road Ahead is Safe with Arbe. Web Brochure, 2019.

[ATL+18] Mubarak Umar Aminu, Oskari Tervo, Janne Lehtom, Markku Juntti, et al. "Beamforming and transceiver HW design for THz band," In *IEEE Asilomar Conference on Signals, Systems, and Computers*, pages 1547–1551, 2018.

[Azh11] Salman Azhar. “Building Information Modeling (BIM): Trends, Benefits, Risks, and Challenges for the AEC Industry.” *Leadership and management in engineering*, July 2011.

[Azu93] Azuma, Ronald. “Tracking requirements for augmented reality,” *Communications of the ACM 36*, no. 7 (1993): 50-51.

[Bro07] G. Brooker, “Mutual interference of millimeter-wave radar systems”, *IEEE Transactions on Electromagnetic Compatibility*, vol. 49, no. 1, pp. 170-181, Feb. 2007.

[BRT+19] Carlos Baquero Barneto, Taneli Riihonen, Matias Turunen, Lauri Anttila, Marko Fleischer, Kari Stadius, Jussi Ryynänen, and Mikko Valkama. ”Full-duplex OFDM radar with LTE and 5G NR waveforms: Challenges, solutions, and measurements.” *IEEE Transactions on Microwave Theory and Techniques*, 67(10):4042–4054, 2019.

[Coo17] Corey D Cooke. “Behavioral amplifier modeling for radar simulation with application to nonlinear effects of multiple impinging signals.” In *IEEE Radar Conference (RadarConf)*, pages 0308–0313, 2017.

[CST+09] Haiying Cao, Ali Soltani Tehrani, Christian Fager, Thomas Eriksson, and Herbert Zirath. “I/Q imbalance compensation using a nonlinear modeling approach.” *IEEE Transactions on Microwave Theory and Techniques*, 57(3):513–518, 2009.

[DBB+21] C. De Lima, D. Belot, R. Berkvens, A. Bourdoux, D. Dardari, M. Guillaud, M. Isomursu, E. S. Lohan, Y. Miao, A. N. Barreto, M. R. K. Aziz, J. Saloranta, T. Sanguanpuak, H. Sarieddeen, G. Seco-Granados, J. Suutala, T. Svensson, M. Valkama, B. Van Liempd, and H. Wymeersch. “Convergent communication, sensing and localisation in 6G systems: An overview of technologies, opportunities and challenges.” *IEEE Access*, 9:26902–26925, 2021.

[DCF+09] Dardari, D., Conti, A., Ferner, U., Giorgetti, A., & Win, M. Z. (2009). “Ranging with ultrawide bandwidth signals in multipath environments.” *Proceedings of the IEEE*, *97*(2), 404-426.

[DKJ+20] Di Renzo, Marco, Konstantinos Ntontin, Jian Song, Fadil H. Danufane, Xuewen Qian, Fotis Lazarakis, Julien De Rosny et al. “Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison.” *IEEE Open Journal of the Communications Society* 1 (2020): 798-807.

[DMM+19] Sayed Hossein Dokhanchi, Bhavani Shankar Mysore, Kumar Vijay Mishra, and Björn Ottersten. “mmWave Automotive Joint Radar-Communications System.” *IEEE Transactions on Aerospace and Electronic Systems*, 55(3):1241–1260, 2019.

[DSM+21] S. Dwivedi, R. Shreevastav, F. Munier, J. Nygren, D. Shrestha, G. Lindmark, P. Ernström, S. Muruganathan, G. Masini, A. Busin, and F. Gunnarsson, “Positioning in 5G networks,” *arXiv preprint arXiv: 2102.03361*, 2021.

[DGS+20] Bastian Dewitz, Christian Geiger, Frank Steinicke. “Hand-Based Interaction on a Millimeter Scale in Virtual and Augmented Reality.” *GI VR/AR Workshop*, 2020

[EGG+21] Ahmed Elzanaty, Anna Guerra, Francesco Guidi, Davide Dardari, and Mohamed-Slim Alouini. “Towards 6G holographic localisation: Enabling technologies and perspectives.” *arXiv preprint arXiv:2103.12415*, 2021.

[ENISA20] ENISA20 THREAT LANDSCAPE FOR 5G NETWORKS, Updated threat assessment for the fifth generation of mobile telecommunications networks (5G), 2020.

[FAA+19] Amr Fenais, Samuel T. Ariaratnam, Steven K. Ayer, Nikolas Smilovsky. "Integrating Geographic Information Systems and Augmented Reality for Mapping Underground Utilities." *Infrastructures*, 2019.

[FCC15] FCC 15-9, Wireless E911 Location Accuracy Requirements, fourth report and order, January 2015.

[FHZ+17] F. Fuschini, S. Häfner, M. Zoli, R. Müller, E. M. Vitucci, D. Dupleich, M. Barbiroli, J. Luo, E. Schulz, V. Degli-Esposti, and R. S. Thomä. "Analysis of in-room mm-wave propagation: Directional channel measurements and ray tracing simulations." *J. Infrared, Millimeter, and Terahertz Waves*, 38(6):727–744, June 2017.

[FLK16] Dehann Fourie, John Leonard, and Michael Kaess. "A nonparametric belief solution to the Bayes tree." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* 2016.

[FU98] G. D. Forney and G. Ungerboeck, "Modulation and coding for linear Gaussian channels", *IEEE Transactions on Information Theory*, vol. 44, no. 6, pp. 2384-2415, October 1998.

[Gol05] Goldsmith, A. Wireless Communication. Cambridge, U.K.: Cambridge Univ. Press, 2005.

[GGD16] F.Gauidi, Guerra, and D. Dardari. "Personal radar with mmwave massive arrays for indoor mapping". *IEEE Transaction on Mobile Computing*, 2016.

[GFS20] Joao Gante, Gabriel Falcao, and Leonel Sousa. "Deep learning architectures for accurate millimeter wave positioning in 5G." *Neural Processing Letters*, 51(1):487–514, 2020.

[GKC+20] Lorenzo Gaudio, Mari Kobayashi, Giuseppe Caire, and Giulio Colavolpe. "On the effectiveness of OTFS for joint radar parameter estimation and communication." *IEEE Transactions on Wireless Communications*, 19(9):5951–5965, 2020.

[GKK+21] Yu Ge, Ossi Kaltiokallio, Hyowon Kim, Fan Jiang, Jukka Talvitie, Mikko Valkama, Lennart Svensson, Sunwoo Kim, and Henk Wymeersch. "A Computationally Efficient EK-PMBM Filter for Bistatic mmWave Radio SLAM." *arXiv preprint arXiv:2109.03561* (2021).

[GLV20] Emanuele Grossi, Marco Lops, and Luca Venturino. "Adaptive detection and localisation exploiting the IEEE 802.11ad standard." *IEEE Transactions on Wireless Communications*, 19(7):4394–4407, 2020.

[GRH+17] Gordon, Iouli E., Laurence S. Rothman, Christian Hill, Roman V. Kochanov, Y. Tan, Peter F. Bernath, Manfred Birk et al. "The HITRAN2016 molecular spectroscopic database." *Journal of Quantitative Spectroscopy and Radiative Transfer* 203 (2017): 3-69.

[GSS17] B. Gholampooryazdi, I. Singh and S. Sigg, "5G Ubiquitous Sensing: Passive Environmental Perception in Cellular Systems," *IEEE Vehicular Technology Conference*, 2017.

[GWK+20] Yu Ge, Fuxi Wen, Hyowon Kim, Meifang Zhu, Fan Jiang, Sunwoo Kim, Lennart Svensson, and Henk Wymeersch. "5G SLAM using the clustering and assignment approach with diffuse multipath." *Sensors*, 20(16):4656, 2020.

[GYA+21] Yi Geng, Vijaya Yajnanarayana, Ali Behravan, Erik Dahlman and Deep Shrestha. "Study of Reflection-Lass-Based Material Identification from Common Building Surfaces." *Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, 2021, pp. 526-531.

[HAA+19] A. Hassanien, M. G. Amin, E. Aboutanios, and B. Himed. "Dual-function radar communication systems: A solution to the spectrum congestion problem." *IEEE Signal Processing Magazine*, 36(5):115–126, Sep. 2019.

[Hes20] Hesai Tech. Pandar64, 64-channel mechanical LiDAR user manual. 2020.

[HEX20-D11] Hexa-X Deliverable D1.1, "6G Vision, use cases and key societal values", 2020.

[HEX21-D12] Hexa-X, "Deliverable D1.2: Expanded 6G vision, use cases and societal values – including aspects of sustainability, security and spectrum (D1.2 is an extension of D1.1)", Apr. 2021.

[HEX21-D21] Hexa-X, "Deliverable D2.1: Towards Tbps Communications in 6G: Use Cases and Gap Analysis", Jun. 2021.

[HEX21-D71] Hexa-X Deliverable D7.1, "Gap analysis and technical work plan for special-purpose functionality", Jun. 2021

[HKK17] Mahn-tuan Ha, Ho-yeon Kim, Chul-goo Kang. "A precision stopping measurement device to automatically detect position errors of an urban train at railway stations." *International Journal of Control, Automation, and Systems: IJCAS*; Heidelberg Vol. 15, Iss. 2: 848-856, 2017.

[HSR+21] Mikko Hietanen, Sumit Pratap Singh, Timo Rahkonen, and Aarno Pärssinen. "Noise Consideration of Radio Receivers Using Silicon Technologies Towards 6G Communication." *Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, pp. 514-519. IEEE, 2021.

[HY17] Gor Hakobyan and Bin Yang. "A novel intercarrier-interference free signal processing scheme for OFDM radar." *IEEE Transactions on Vehicular Technology*, 67(6):5158–5167, 2017.

[JHK+12] Johan Johansson, Wuri A. Hapsari, Sean Kelley, and Gyula Bodog. "Minimization of drive tests in 3GPP release 11," *IEEE Communications Magazine* 50, no. 11 (2012): 36-43.

[JKH16] J. Järveläinen, A. Karttunen, and K. Haneda. "Indoor propagation channel simulations at 60 GHz using point cloud data." *IEEE Trans. Ant. Prop.*, 64(8):4457–4467, Aug. 2016.

[KGBR21] O. Kanhere, S. Goyal, M. C. Beluri, T. S. Rappaport, "Target Localization using Bistatic and Multistatic Radar with 5G NR Waveform." *IEEE Vehicular Technology Conference*, 2021.

[KF09] Daphne Koller and Nir Friedman. Probabilistic graphical models: principles and techniques. MIT press. 2009.

[KGG+20] Kim, Hyowon and Granström, Karl and Gao, Lin and Battistelli, Giorgio and Kim, Sunwoo and Wymeersch, Henk. "5G mmWave cooperative positioning and mapping using multi-model PHD filter and map fusion." *IEEE Transactions on Wireless Communications* 19.6 (2020): 3782-3795.

[KHC+17] Mike Koivisto, Aki Hakkarainen, Mario Costa, Petteri Kela, Kari Leppanen, and Mikko Valkama. "High-efficiency device positioning and location-aware communications in dense 5G networks." *IEEE Communications Magazine*, 55(8):188–195, 2017.

[KKW21] Musa Furkan Keskin, Visa Koivunen, and Henk Wymeersch, "Limited feedforward waveform design for OFDM dual-functional radar-communications." *IEEE Transactions on Signal Processing*, 69:2955–2970, 2021.

[KWK21] Musa Furkan Keskin, Henk Wymeersch, and Visa Koivunen. “MIMO-OFDM joint radar-communications: Is ICI friend or foe?” *IEEE Journal of Selected Topics in Signal Processing* (2021).

[KWP+20] Toshiaki Koike-Akino; Pu Wang; Milutin Pajovic; Haijian Sun; Philip V. Orlik. “Fingerprinting-based indoor localization with commercial MMWave WiFi: A deep learning approach.” *IEEE Access*, 8, 84879-84892 (2020).

[KWS+21] Kakkavas, Anastasios, Henk Wymeersch, Gonzalo Seco-Granados, Mario H. Castañeda García, Richard A. Stirling-Gallacher, and Josef A. Nossek. “Power Allocation and Parameter Estimation for Multipath-based 5G Positioning.” *IEEE Transactions on Wireless Communications* (2021).

[Liv19] Livox LiDAR. Livox Horizon user manual v1.0, 2019.

[LHP+20] Ran Liu, Sumudu Hasala Marakkalage, Madhushanka Padmal, Thiruketheeswaran Shaganan, Chau Yuen, Yong Liang Guan, and U-Xuan Tan. “Collaborative SLAM based on WiFi fingerprint similarity and motion information.” *IEEE Internet of Things Journal*, 7(3), 1826-1840. 2020.

[LLA+19] C. Liu, Y. Li, D. Ao and H. Tian, “Spectrum-Based Hand Gesture Recognition Using Millimeter-Wave Radar Parameter Measurements,” in *IEEE Access*, vol. 7, pp. 79147-79158, 2019, doi: 10.1109/ACCESS.2019.2923122.

[LMP+20] Fan Liu, Christos Masouros, Athina P Petropulu, Hugh Griffiths, and Lajos Hanzo. “Joint radar and communication design: Applications, state-of-the-art, and the road ahead.” *IEEE Transactions on Communications*, 68(6):3834–3862, 2020.

[LZM+18] F. Liu, L. Zhou, C. Masouros, A. Li, W. Luo, and A. Petropulu. “Toward dual-functional radar-communication systems: Optimal waveform design.” *IEEE Transactions on Signal Processing*, 66(16):4264–4279, Aug 2018.

[Maz75] J. E. Mazo, “Faster-than-Nyquist signaling”, *Bell System Technical Journal*, vol. 54, no. 8, pp. 1451-1462, October 1975.

[MBK+19] K. V. Mishra, M. R. Bhavani Shankar, V. Koivunen, B. Ottersten, and S. A. Vorobyov. ”Toward millimeter-wave joint radar communications: A signal processing perspective.” *IEEE Signal Processing Magazine*, 36(5):100–114, Sep. 2019.

[Mor17] John Morrissey. 24 GHz Demorad Radar Solutions Enable New Contactless Sensors for Emerging Industrial Mass Market. Technical Article Analog Devices, 2017.

[MSP+19] Bala Muralikrishnan, Meghan Shilling, Steve Phillips, Wei Ren, Vincent Lee, Felix Kim. #X-ray Computed Tomography Instrument Performance Evaluation, Part I: Sensitivity to Detector Geometry Errors.” *Journal of Research of the National Institute of Standards and Technology* 124, 2019.

[MSR+19] Magnus Malmström, Isaac Skog, Sara Modarres Razavi, Yuxin Zhao, and Fredrik Gunnarsson. ”5G Positioning - A Machine Learning Approach.” *IEEE Workshop on Positioning, Navigation and Communications (WPNC)*, 2019.

[MTK+02] Michael Montemerlo, Sebastian Thrun, Daphne Koller, and Ben Wegbreit. “FastSLAM: A factored solution to the simultaneous localisation and mapping problem.” *Aaai/iaai*, 593-598, 2002.

[MWS+21] A. Mohan, U. U. Wara, M. T. Arshad Shaikh, R. M. Rahman, Z. A. Zaidi, “Telesurgery and Robotics: An Improved and Efficient Era.” *Cureus*. 13(3), 2021.

[NJK+18] Sinh L. H. Nguyen, Jan Järveläinen, Aki Karttunen, Katsuyuki Haneda, and Jyri Putkonen. "Comparing radio propagation channels between 28 and 140 GHz bands in a shopping mall." *EuCAP*, 2018.

[Nok21] Nokia Bell Labs, "Joint design of communication and sensing beyond 5G and 6G systems", White paper, 2021.

[Nov20] Novelda. X4 – Datasheet, Ultra wideband (UWB) Impulse Radar Transciever SoC, Rev F. 2020.

[P.2040-1] ITU-R P.2040-1, "Effects of building materials and structures on radiowave propagation above about 100 MHz", International Telecommunications Union Recommendation, July 2015.

[PC17] S. Pamukcu, Liang Cheng, Underground Sensing: Monitoring and Hazard Detection for Environment and Infrastructure, Academic Press, 2017.

[PJ99] Persa, Stelian, and Pieter Jonker. "On positioning for augmented reality systems." *In International Symposium on Handheld and Ubiquitous Computing*, pp. 327-329. Springer, Berlin, Heidelberg, 1999.

[PMM+16] J. Pascual-García, J. Molina-García-Pardo, M. Martínez-Inglés, J. Rodríguez, and N. Saurín-Serrano. "On the importance of diffuse scattering model parameterization in indoor wireless channels at mm-wave frequencies." *IEEE Access*, 4:688–701, 2016.

[PKK+05] Piesiewicz, R., T. Kleine-Ostmann, N. Krumbholz, D. Mittleman, M. Koch, and T. Kürner. "Terahertz characterisation of building materials." *Electronics Letters* 41, no. 18 (2005): 1002-1004.

[PRL+17] del Peral-Rosado, José A., Ronald Raulefs, José A. López-Salcedo, and Gonzalo Seco-Granados. "Survey of cellular mobile radio localisation methods: From 1G to 5G." *IEEE Communications Surveys & Tutorials* 20, no. 2 (2017): 1124-1148.

[RHA20] Rao, Siddharth Prakash, Silke Holtmanns, and Tuomas Aura. "Threat modeling framework for mobile communication systems." *arXiv preprint arXiv:2005.05110* (2020).

[RK89] Roy, Richard, and Thomas Kailath. "ESPRIT-estimation of signal parameters via rotational invariance techniques." *IEEE Transactions on acoustics, speech, and signal processing* 37, no. 7 (1989): 984-995.

[RK03] Rescorla, Eric, and Brian Korver. *Guidelines for writing RFC text on security considerations*. BCP 72, RFC 3552, July, 2003.

[RKL+20] Kari Rikkinen, Pekka Kyosti, Marko E Leinonen, Markus Berg, and Aarno Parssinen. "THz radio communication: Link budget analysis toward 6G." *IEEE Communications Magazine*, 58(11):22–27, 2020.

[RSM+13] Rappaport, Theodore S., Shu Sun, Rimma Mayzus, Hang Zhao, Yaniv Azar, Kevin Wang, George N. Wong, Jocelyn K. Schulz, Mathew Samimi, and Felix Gutierrez. "Millimeter wave mobile communications for 5G cellular: It will work!" *IEEE Access* 1 (2013): 335-349.

[RST21] Y. Rahmat-Samii, E. Topsakal (Eds), Antenna and Sensor Technologies in Modern Medical Applications, John Wiley & Sons, Inc., 2021.

[RWG+02] Sarra N. Campbell Roberts, Adrian C. Williams, Ian M. Grimsey, Steven W. Booth b. "Quantitative analysis of mannitol polymorphs. X-ray powder diffractometry—exploring preferred orientation effects." *Journal of Pharmaceutical and Biomedical Analysis* 28: 1149-1159, 2002.

[RXK+19] Theodore S Rappaport, Yunchou Xing, Ojas Kanhere, Shihao Ju, Arjuna Madanayake, Soumyajit Mandal, Ahmed Alkhateeb, and Georgios C. Trichopoulos. "Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond." *IEEE Access*, 7:78729–78757, 2019.

[SCA+21] A. Sivaganesan, N. J. Clark, R. K. Alluri, A. S. Vaishnav, S. A. Qureshi, "Robotics and Spine Surgery: Lessons From the Personal Computer and Industrial Revolutions." *Int. J. Spine Surg*. 15(s2):S21-S27, 2021.

[SCS+19] Andrea Scaloni, Pasquale Cirella, Mauro Sgheiz, Riccardo Diamanti, and Davide Micheli. "Multipath and Doppler characterization of an electromagnetic environment by massive MDT measurements from 3G and 4G mobile terminals." *IEEE Access* 7 (2019): 13024-13034.

[SD16] Jani Saloranta and Giuseppe Destino. "On the utilization of MIMO-OFDM channel sparsity for accurate positioning." *IEEE European Signal Processing Conference (EUSIPCO)*, pp. 748-752, 2016.

[SGB+21] Erik Sippel, Johanna Geiss, Stefan Brückner, Patrick Gröschel, Markus Hehn, and Martin Vossiek. "Exchanging bandwidth with aperture size in wireless indoor localisation-or why 5G/6G systems with antenna arrays can outperform UWB solutions." *IEEE Open Journal of Vehicular Technology*, 2:207–217, 2021.

[SGD+17] Shahmansoori, Arash, Gabriel E. Garcia, Giuseppe Destino, Gonzalo Seco-Granados, and Henk Wymeersch. "Position and orientation estimation through millimeter-wave MIMO in 5G systems." *IEEE Transactions on Wireless Communications* 17, no. 3 (2017): 1822-1835.

[SHPW18] Kashif Siddiq, Mervyn K Hobden, Steve R Pennock, and Robert J Watson. "Phase noise in FMCW radar systems." *IEEE Transactions on Aerospace and Electronic Systems*, 55(1):70–81, 2018.

[Sko08] Merrill I. Skolnik Radar Handbook, Third Edition, The McGraw-Hill Companies, 2008, ISBN: 9780071485470

[SMG+18] Christoph Studer, Saïd Medjkouh, Emre Gonultaş, Tom Goldstein, and Olav Tirkkonen. "Channel charting: Locating users within the radio environment using channel state information." *IEEE Access*, 6, 47682-47698, 2018.

[SR20] A. Salam, U. Raza, "Signals in the Soil: An Introduction to Wireless Underground Communications." *Signals in the Soil*. Springer, Cham., 2020.

[STT+19] Sana Salous, Fredrik Tufvesson, Kenan Turbic, Luis M Correia, Thomas Kürner, Diego Dupleich, Christian Schneider, Daniel Czaniera, and Belen Montenegro Villacieros. "IRACON propagation measurements and channel models for 5G and beyond." *ITU Journal: ICT Discoveries*, 2(1), 2019.

[SUS21] D. Son, M. C. Ugurlu, M. Sitti, "Permanent magnet array-driven navigation of wireless millirobots inside soft tissues," *Sci Adv.* 7(43), 2021.

[SVH+21] P. Schleer, M. Vossel, L. Heckmann, et al. Usability of cooperative surgical telemanipulation for bone milling tasks. Int. J. Comput. Assist. Radiol. Surg. 16(2):311-322, 2021.

[TAZ+13] A. Tzanakaki, M. P. Anastasopoulos, G. S. Zervas, B. R. Rofoee, R. Nejabati and D. Simeonidou, "Virtualization of heterogeneous wireless-optical network and IT infrastructures in support of cloud and mobile cloud services". *IEEE Communications Magazine*, vol. 51, no. 8, pp. 155-161, August 2013.

[TMR+14] Di Taranto, Rocco, Srikar Muppirisetty, Ronald Raulefs, Dirk Slock, Tommy Svensson, and Henk Wymeersch. "Location-aware communications for 5G

networks: How location information can improve scalability, latency, and robustness of 5G.” *IEEE Signal Processing Magazine* 31, no. 6 (2014): 102-112.

[TSC+21] Tarboush, Simon, Hadi Sarieddeen, Hui Chen, Mohamed Habib Loukil, Hakim Jemaa, Mohamed Slim Alouini, and Tareq Y. Al-Naffouri. “TeraMIMO: A Channel Simulator for Wideband Ultra-Massive MIMO Terahertz Communications.” *arXiv preprint arXiv:2104.11054* (2021).

[TSV+97] T Tsao, Mustapha Slamani, Praveen Varshney, D Weiner, H Schwarzlander, and S Borek. Ambiguity function for a bistatic radar. IEEE Transactions on Aerospace and Electronic Systems, 33(3):1041–1051, 1997.

[VDD+16] Vasiljević, Goran, Damjan Miklić, Ivica Draganjac, Zdenko Kovačić, and Paolo Lista. “High-accuracy vehicle localization for autonomous warehousing.” *Robotics and Computer-Integrated Manufacturing* 42 (2016): 1-16.

[WBV21] Thorsten Wild, Volker Braun, and Harish Viswanathan. “Joint Design of Communication and Sensing for Beyond 5G and 6G Systems.” *IEEE access* February 26, 2021.

[WHC21] Gang Wang, Dominic KC Ho, and Xianjing Chen. “Bias reduced semidefinite relaxation method for 3-D rigid body localisation using AOA.” *IEEE Transactions on Signal Processing*, 2021.

[WHD+20] Henk Wymeersch, Jiguang He, Benoit Denis, Antonio Clemente, and Markku Juntti. “Radio localisation and mapping with reconfigurable intelligent surfaces: Challenges, opportunities, and research directions.” *IEEE Vehicular Technology Magazine*, 15(4):52–61, 2020.

[WLC+13] Wang, Cheng, Changxing Lin, Qi Chen, Bin Lu, Xianjin Deng, and Jian Zhang. “A 10-Gbit/s wireless communication link using 16-QAM modulation in 140-GHz band.” *IEEE Transactions on Microwave Theory and Techniques* 61, no. 7 (2013): 2737-2746.

[WML+16] Klaus Witrisal, Paul Meissner, Erik Leitinger, Yuan Shen, Carl Gustafson, Fredrik Tufvesson, Katsuyuki Haneda, Davide Dardari, Andreas F Molisch, Andrea Conti, et al. “High-accuracy localisation for assisted living: 5G systems will turn multipath channels from foe to friend.” *IEEE Signal Processing Magazine*, 33(2):59–70, 2016.

[WSM+21] Henk Wymeersch, Deep Shrestha, Carlos Morais de Lima, Vijaya Yajnanarayana, Björn Richerzhagen, Musa Furkan Keskin, Kim Schindhelm, Alejandro Ramirez, Andreas Wolfgang, Mar Francis de Guzman, Katsuyuki Haneda, Tommy Svensson, Robert Baldemair, Stefan Parkvall, “Integration of Communication and Sensing in 6G: a Joint Industrial and Academic Perspective”, *IEEE PIMRC workshops*, 2021.

[WWS+20] Fangqing Wen, Juan Wang, Junpeng Shi, and Guan Gui. “Auxiliary vehicle positioning based on robust DOA estimation with unknown mutual coupling.” *IEEE Internet of Things Journal*, 7(6):5521–5532, 2020.

[WXC+18] Beibei Wang, Qinyi Xu, Chen Chen, Feng Zhang, and K.J. Ray Liu. “The promise of radio analytics: A future paradigm of wireless positioning, tracking, and sensing.” *IEEE Signal Processing Magazine*, 35(3):59–80, 2018.

[WZJ+21] Di Wu, Yong Zeng, Shi Jin, and Rui Zhang. Environment-Aware and Training-#Free Beam Alignment for mmWave Massive MIMO via Channel Knowledge Map.” *IEEE International Conference on Communications Workshops (ICC) Workshops*, 2021.

[WZK+14] J. Wojtanowski, M. Zygmunt, M. Kaszczuk et. al. ”Comparison of 905 nm and 1550 nm semiconductor laser rangefinders’ performance deteriotation due to

adverse environmental conditions". *Opto-electronics review* 22(3), 183-190, 2014.

[WZZ+21] Qingqing Wu, Shuowen Zhang, Beixiong Zheng, Changsheng You, and Rui Zhang. "Intelligent reflecting surface aided wireless communications: A tutorial." *IEEE Transactions on Communications*, 2021.

[YHS+21] Vijaya Yajnanarayana, Dongdong Huang, Deep Shrestha, Yi Geng, Ali Behravan, Erik Dahlman. "AI Based Landscape Sensing Using Radio Signals." *arXiv preprint arXiv: 2105.08436*, 2021

[Zho11] Chonghua Zhou. "Platform Screen Doors Enhanced Bus Rapid Transit Intelligent Performance." *International Journal of Information Engineering and Electronic Business*, Vol. 3, Iss. 3: 52-59, 2011.

[ZB11] Zekavat, Reza, and R. Michael Buehrer. Handbook of position location: Theory, practice and advances. Vol. 27. John Wiley & Sons, 2011.

[ZDS+19] S. Zang, M. Ding, D. Smith, P. Tyler, T. Rakotoarivelo and M. A. Kaafar, "The Impact of Adverse Weather Conditions on Autonomous Vehicles: How Rain, Snow, Fog, and Hail Affect the Performance of a Self-Driving Car," in *IEEE Vehicular Technology Magazine*, vol. 14, no. 2, pp. 103-111, June 2019.

[ZGG+09] X. Zhang, Prof. Dr. M. Geimer, L. Grandl and B. Kammerbauer. "Method for an electronic controlled platooning system of agricultural vehicles." *ICVES* 2009.

[ZX21] Yong Zeng and Xiaoli Xu, "Toward environment-aware 6G communications via channel knowledge map." *IEEE Wireless Communications*, 2021.

Annexes

Annex A: Terms and Definitions

Term	Acronym	Term description
Accuracy, precision, and resolution of a measurement	N/A	Different definitions exist in the literature. Accuracy can refer to the statistical bias (difference between the mean of the measurements and the true value), but also to the percentile performance (e.g., a positioning system with 95% accuracy of 5 meters indicates that 95% of the errors are within 5 meters). Precision refers to the spread of the measurements around the mean and is thus related to the (co-)variance of the measurements. Finally, resolution refers to the ability of the measurement system to distinguish nearby signal sources (e.g., a radar with 1 GHz bandwidth has a resolution of 0.15 m so that two objects with a distance exceeding 15 cm can be distinguished).
Angle-of-arrival (also direction-of-arrival)	AoA / DoA	Measurement of Angle (in azimuth and/or elevation) of a signal incoming to an array from a certain direction, measured in the coordinate system of that array.
Angle-of-departure (also direction-of-departure)	AoD / DoD	Measurement Angle (in azimuth and/or elevation) of a signal outgoing from an array towards a corresponding direction, measured in the coordinate system of that array.
Application (software/program)	N/A	Software that is specific to the solution of a problem usually submitted by an end user. For clarification prefixes could be used, e.g., end user application, network application. Note: Application (software/ program) and service is often used as synonym. In our context application is used for software with user interface (UI).
Ambiguity Function	N/A	Ambiguity function is a two-dimensional function of propagation delay and Doppler frequency. Typically defined as the absolute value of the envelope of the output of a matched filter.
Bistatic sensing	N/A	Sensing (see Sensing), whereby the transmitting and receiving nodes are not co-located.
Coherent processing interval	CPI	Duration in which a signal is received and during which the geometric parameters remain constant.
Cramér-Rao lower bound	CRLB	A type of error bound (EB), based on Fisher information theory.
Error bound	EB	Fundamental lower bounds on the error covariance of a parameter that is estimated (e.g., position error bound (PEB), clock error bound (CEB))
Generalised optimal sub-pattern assignment	GOSPA	An error metric between sets of detected and ground truth objects, generalizing the RMSE.
Ground truth	N/A	True state (e.g., true position of an object or UE).

Interface	N/A	Shared boundary between two functional units, defined by functional characteristics, signal characteristics, or other characteristics as appropriate (e.g., API: Application Programming Interface, UI: User Interface, web interface: Can be API or UI, interface is bound to web protocols).
Latency	N/A	Duration between initialisation of sensing/localisation procedure and acquiring localisation/sensing estimate. See also: update rate.
Localisation (synonym: positioning)	N/A	The process of estimating the location of a device from sensor measurements. The location can be in 2D (horizontal plane) or 3D (including altitude).
Mapping	N/A	Generating a map of landmarks (natural or artificial features used for navigation) based on sensing measurements.
Monostatic sensing	N/A	Sensing, whereby the transmitting and receiving nodes are co-located.
Orientation estimation	N/A	Estimating the 1D, 2D, or 3D orientation (e.g., roll, pitch, yaw) of a connected device.
Positioning reference signal	PRS	Standardised pilot signal in time a frequency, used for ToA estimation.
Reference frame	N/A	Coordinate system. Can be either global (absolute) or local (relative).
Root mean squared error	RMSE	Square root of the average error norm between an estimate and the ground truth.
Round-trip-time	RTT	Measurement of roundtrip delay between a BS and a UE. Involves a ToA estimate at each side.
Sensing	N/A	A sensor is any device, module, machine, or subsystem that detects events or changes in its environment. Sensing is then the operation of the sensor, in our case possibly including transmission and/or reception of signals and generation of measurements from these signals.
Sensor fusion	N/A	Combining information (measurements or densities) from different sensors, such as radio signals, radar, lidar to obtain an improved estimate.
Service	N/A	Distinct part of the functionality that is provided by an entity through interfaces. Note: Service and application (software/program) is often used as synonym. In our context service is used for software without UI.
Simultaneous localisation and mapping	SLAM	Process of jointly tracking the UE location and mapping the landmarks in the environment.
Synchronisation	N/A	Estimating the clock bias and drift of a connected device with respect to a reference. For multiple transmission and reception point (multi-TRP) based localisation, synchronisation means time synchronisation among TRPs.

Tag	N/A	Unit, that enables communication, sensing and localisation (less complex device in comparison to UE often with focus on size, weight, cost, and battery lifetime)
Time-difference-of-arrival	TDoA	Measurement of the difference between arrival times of the first signal paths at a receiving device from two different transmitters.
Time-of-arrival	ToA	Measurement of arrival time of a first signal path at a receiving device.
Tracking	N/A	For localisation: continuous localisation of the same connected device over a given duration. For sensing, continuous localisation of the same target or targets over a given duration.
Update rate	N/A	Rate at which location or sensing outputs are reported. At most once per latency.

Annex B: Scenarios for 5G localisation

Scenarios considered for numerical validation of 5G localisation methods.

Table B-1. 5G localisation parameters.

	FR1 Specific Values	FR2 Specific Values
Carrier frequency, GHz	2 GHz	30 GHz
Bandwidth, MHz	100 MHz	400 MHz
Subcarrier spacing, kHz	30 kHz for 100 MHz	120 kHz
gNB noise figure, dB	5 dB	7 dB
gNB max. TX power, dBm	49 dBm (UMa), 44 dBm (UMi), 24 dBm (IOO and InF)	35 dBm (UMi), 24 dBm (IOO and InF)
Total number of sites	UMa and UMi: 7 hexagonal sites, IOO (12 sites, see Figure), InF (18 sites, see Figure, where L = 120 m and W = 60 m)	
UE max. TX power, dBm	23 dBm	23 dBm
UE noise figure, dB	9 dB	13 dB
Network synchronisation	The network synchronisation error, per UE dropping, is defined as a truncated Gaussian distribution of (T1 ns) rms values between a TRP and a timing reference source which is assumed to have perfect timing, subject to a largest timing difference of T2 ns, where T2 = 2*T1 –That is, the range of timing errors is [-T2, T2] –T1: 0 ns (perfectly synchronised), 50 ns	

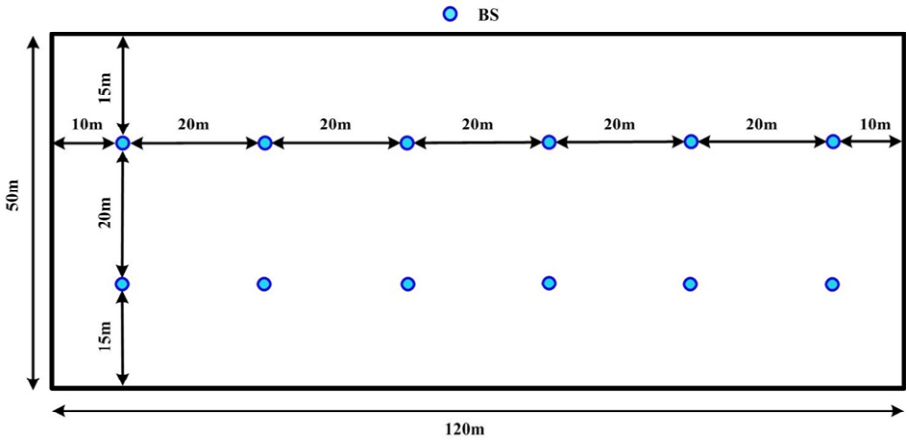

Figure B-1. Indoor open office (IOO) deployment. Blue dots denote locations of base stations (BSs)/TRPs.

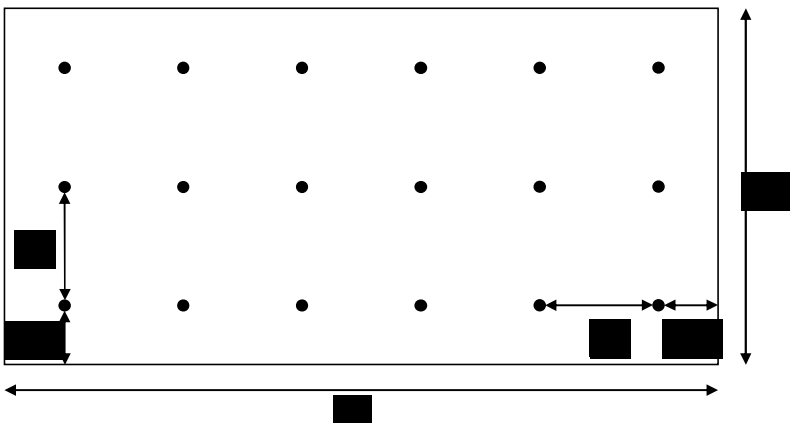

Figure B-2. Indoor factory (InF) deployment. Black dots denote locations of TRPs.

Annex C: Parameters for 5G and 6G simulation

Table C-1 Simulation parameters for 5G vs 6G comparison.

	Parameter	MmWave (5G)	Sub-THz (6G)	Remarks	Reference
General	Wave model	Plane wave model	Plane wave model	Far-field	
Signal	Modulation type	OFDM	OFDM		[SGD+17]
	Constellation -data and pilots	QPSK	QPSK		
	Carrier frequency	28 GHz	140 GHz	5 x	[WLC+13]
	Bandwidth	400 MHz	2 GHz	5 x increase	
	Cyclic prefix (CP)	14 %	7 %	Due to delay spread, CP for 5G is doubled.	
	Subcarrier spacing	120 kHz	960 kHz	8 x increase	
	#. of subcarriers	~3300	~2080		
	#. of OFDM Symbols per beam (K)	1 K*number of beams << 54 at 80 km/h	1 K*number of beams << 86 at 80 km/h	Fixed signal duration in us. Limited by velocity (K*number of beams<< lambda*Deltaf /v)	
	Number of beams (random)	10	10		
	Noise PSD	-174 dBm/Hz	-174 dBm/Hz		
	Receiver noise figure (BS)	7 dB	10 dB	6G parameters uncertain	[38.901] and [38.855] (Table 6.1.1-1)
	Receiver noise figure (UE)	13 dB	16 dB	6 dB higher than BS NF	[38.855] (Table 6.1.1-1)
BS and UE parameters	#. of BS antennas	16 (4x4)	400 (20x20)	Fixed footprint: 5 x more per dimension	
	BS height outdoor	20 m	20 m	Urban micro scenario	
	BS height indoor	3 m	3 m	Could be higher for industry scenarios (7 m)	
	BS Transmit power outdoor	37 dBm	27dBm		[38.855] (Table Table 6.1.1-4)

	BS Transmit power indoor	24 dBm	14 dBm		[38.855] (Table Table 6.1.1-3)
	#. of UE antennas	4 (2x2)	100 (10x10)	Fixed footprint: 5 x more per dimension	
	UE height	1.5 m	1.5 m		[38.855] (Table Table 6.1.1-3)
	UE transmit power	23 dBm	13 dBm		
	Array type	Uniform planar array with phase shifters			
	Antenna element gain	Omni-directional		Gain = 1	
	Number of RF chains	1	1		
	Synchronisation offset (aka clock bias), deterministic unknown	10 us	10 us	Clock offset between Tx and Rx in bistatic scenario	
Environment	NLOS path gains reflectors	Reflection coefficient: 0.4			[PKK+05]
	NLOS path gains SPs	RCS: 10 m^2			
	Path loss exponent	2			
	Absorption coefficient	0.9986	0.9949	Coefficient for 100 m, can be ignored (set 1)	[TSC21], [RSM+13], [GRH+17]
Geometry	BS position (outdoor)	[0, 0, 20]		Outdoor Localisation Parameters	
	BS orientation (outdoor)	[90, 30, 0]		Outdoor Localisation Parameters	
	BS positions (indoor)	[0, 0, 3], [-10 10 3], [0 20 3]		Indoor Localisation Parameters	
	BS orientation (indoor)	[90, 30, 0], [0, 30, 0], [-90, 30, 0]		Indoor Localisation Parameters	
	UE moving area	[-100, 0, 1.5] to [100, 200. 1.5]/ [-10, 0, 1.5] to [10, 20, 1.5]		Outdoor/indoor	
	VA locations (outdoor)	[100, 0, 20], [-100, 0, 20], [0, 100, 20], [0, -100, 20]		SLAM Parameters (4 virtual anchors)	
	SP locations	[65, 65, 8], [-65, 65, 12],		SLAM Parameters	

		[-65, -65, 13], [65, -65, 10]	(4 scatter points)	
	UE state outdoor	[57, 41, 0]	SLAM Parameters (4 virtual anchors)	