Horizon Europe Framework Programme
Call: HORIZON-JU-SNS-2022 (HORIZON-JU-SNS-2022)
Type of action: HORIZON JU Research and Innovation Action

CENTRIC

Towards an AI-native, user-centric air interface for 6G networks

Grant Agreement Number: 101096379

Whitepaper

The CENTRIC Project Vision on Sustainable AI-native Air-interface for 6G Networks

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This project has received funding from the European Union's Smart Networks and Services Joint Undertaking (SNS JU) under grant agreement No 101096379.

Executive Summary

This white paper presents the visionary approach of the CENTRIC project towards developing a sustainable AI-native Air-Interface for 6G networks, aiming to revolutionize wireless communication through user-centric design. By leveraging advanced Artificial Intelligence (AI) techniques, CENTRIC seeks to revolutionize wireless connectivity by placing users' communication needs and environmental considerations at the forefront of network stack design. The CENTRIC vision begins with a top-down, modular approach that starts with users' objectives and application-specific requirements. AI techniques are then employed to tailor-make waveforms, transceivers, signaling, protocols, and resource management procedures to support these requirements, resulting in what we refer to as the user-centric AI Air Interface (AI-AI). To ensure practical implementation, CENTRIC aims to explore and develop innovative hardware computing substrates with realistic and AI-AI-compatible energy-efficiency properties. This includes novel electronics such as neuromorphic computing and mixed analog-digital platforms, alongside advancements in theory, algorithms, hardware co-design, and training environments based on digital twins. Structured around the following six key objectives, CENTRIC's research encompass a comprehensive exploration of AI-driven innovation, addressing critical challenges toward the realization of its 6G AI-AI vision.

1. **To develop AI methods for the discovery of novel and efficient waveforms**: CENTRIC is pioneering the development of machine learning techniques to discover and optimize tailor-made waveforms, ensuring optimal performance while accommodating user communication needs and environmental constraints.
2. **To develop AI methods for the discovery of novel and efficient transceivers**: Focusing on large-scale extreme massive multiple-input multiple-output (MIMO) deployments and millimeter-wave (mmWave) spectrum, CENTRIC designs efficient AI-based transceivers to enhance reliability and throughput in challenging scenarios.
3. **To develop AI methods for the discovery of customized lightweight communication protocols**: CENTRIC develops lightweight communication protocols that dynamically adapt to changing network conditions and user requirements, ensuring efficient and reliable communication tailored to specific applications.
4. **To introduce novel end-to-end hardware co-design solutions for energy-efficient AI-native transceivers**: CENTRIC will develop novel end-to-end hardware co-design solutions for energy-efficient AI-native transceivers, optimizing the integration of algorithms and hardware to maximize energy efficiency.
5. **To develop training and monitoring environments as enablers for AI-AI deployments**: Through digital twins (DT)-based tools and frameworks, CENTRIC enables network designers and operators to train and monitor AI models for real-world deployment, ensuring robustness and effectiveness in diverse operational settings.
6. **To validate user-centric AI-AI solutions in a lab setting**: CENTRIC will conduct rigorous testing and validation of AI-native air interfaces in lab settings, demonstrating the feasibility and performance benefits of AI-driven solutions for real-world deployment.
7. **To demonstrate and disseminate AI-AI concepts**: By demonstrating novel AI-AI concepts through laboratory proof-of-concept implementations and disseminating findings to academic, industrial, and commercial communities, CENTRIC fosters collaboration and innovation, driving forward the development of AI-enabled 6G systems.

Through these objectives, CENTRIC aims to advance the state-of-the-art in 6G systems development, laying the groundwork for sustainable, efficient, and human-friendly wireless communications. This white paper provides a comprehensive overview of the key techniques and innovations that CENTRIC considers to be an integral component of its 6G AI-AI vision.

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1. Introduction

Current networks have been designed following a compartmentalized approach in which different network components are separately hand-crafted to meet their specific design criteria. This rigid architecture imposes severe limitations on the ability of the network to efficiently adapt to each specific user, device, and/or environment, resulting instead in a network-centric architecture delivering a narrow set of standard services. Instead, CENTRIC postulates that 6G systems must see a tighter integration of communication and computing systems with applications. This shall change the role of wireless connectivity from a reliable bit pipe provider into a versatile platform that supports the semantics of a variety of services. As the diversity of users, devices, and applications increases over the next decade, the current separation-based design methodology will rapidly become a bottleneck. It will be increasingly difficult to adapt communication solutions built in this way to specific environments and striving for cross-vendor interoperability in custom scenarios may face prohibitive costs. Likewise, finding solutions that are both spectrally- and energy-efficient for such a myriad of use cases will rapidly become infeasible. In addition, while a conventional design methodology would need to build on trustworthy analytical models, the definition of tractable models that account for end-to-end application-level performance indicators with hardware in the loop appears to be beyond reach.

Furthermore, while the data usage and computational requirements of edge-node applications will keep increasing over the coming decade, the performance and power efficiency of the hardware required to run them will struggle to keep pace. The slow-down in Moore's Law will indeed limit the ability of existing digital hardware devices to keep pace with the computational needs of applications at the edge nodes, especially at mobile devices given their requirements in terms of energy consumption. As an example, the implementation in THz and Tbps wireless systems of forward error correction (FEC) modules based on today's standard codes such as low-density parity-check (LDPC) or polar codes is severely limited by hardware power constraints [1]. Similarly, projections based on today's digital baseband solutions such as 802.11ax to 100 Gbps wireless throughputs yield power consumptions in the orders of hundreds of watts, which are beyond any practical implementation of terminal devices [2]. These considerations are harbingers of the upcoming "hardware-limited era" in the design of wireless systems and motivate research into novel, more energy-efficient computational paradigms.

In CENTRIC, we believe that AI will be an indispensable tool to satisfy the technical and societal requirements of 6G communication systems. The recent advances in AI techniques provide an opportunity to meet for the first time the ambitious goal of delivering energy-efficient, user-centric communications. CENTRIC relies on the fundamental hypothesis that by exploiting and advancing AI for communications – involving tools such as reinforcement learning, transfer learning, meta-learning, federated learning, and semantic communications — adaptable and efficient protocol stacks can be tailored to diverse scenarios, applications, devices, and users. Unlike the study phases of 4G and 5G, the 6G study phase will have massive amounts of data at its disposal, as well as a solid algorithmic foundation following a decade of advances in ML. Consider, for example, a possible 2030s use case where an indoor factory needs to be surveyed by 360^o 4K wireless stereoscopic cameras. This is an obvious case of mission-critical video streaming with extreme uplink bandwidth and latency

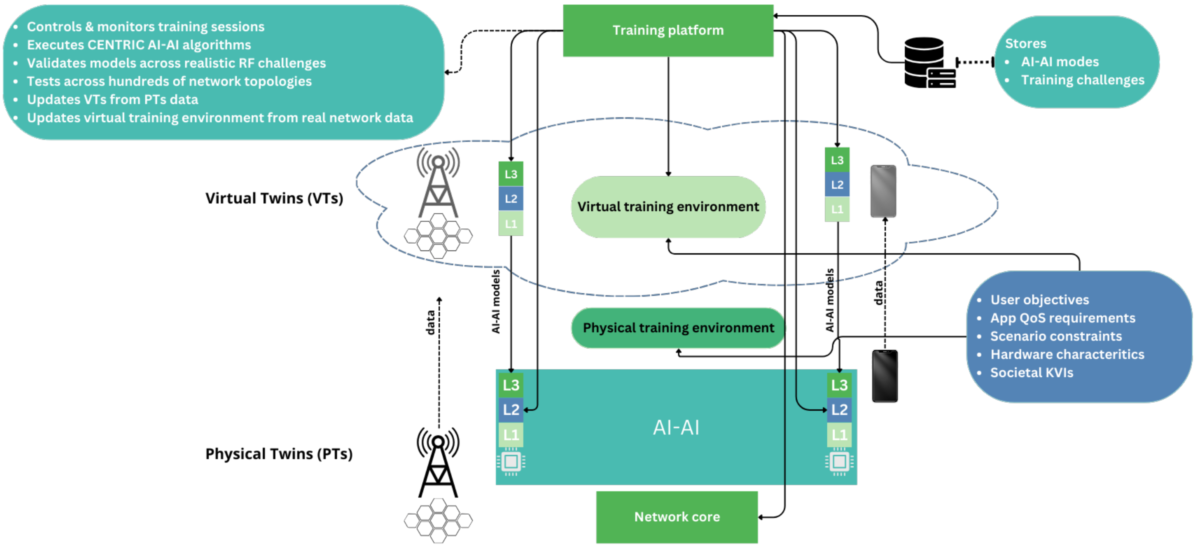

Figure 1.1: CENTRIC AI-AI architecture concept.

requirements. At the same time, this is also a vertical market smaller than the eMBB market that has driven 3G, 4G, and 5G network deployments. To meet such an ambitious QoE target for a small customer, a customized lightweight design of the physical layer (PHY) and protocols would be desirable, yet still unaffordable with today's techniques. To this end, CENTRIC proposes a user-centric AI-AI approach proposed by CENTRIC. At the PHY layer, the waveforms used by transceivers should be adapted to the radio-frequency (RF) characteristics of the involved devices and the special electromagnetic propagation conditions of the factory at the frequency bands of operation. Similarly, the types of data constellations used, MIMO processing schemes, and pilot signals required should be tailored to the devices' characteristics and performance requirements. At the medium access control (MAC) and networking layer, the confined nature of the scenario and the very restricted type of traffic calls for a customized lean network, free of the unnecessary procedures and signaling overhead available in today's systems. Such a level of customization is not commercially viable today. Recent research [3] has also shown that AI techniques can be used to train PHY layers that are highly optimized — from both performance and energy-efficiency perspectives — to their target channels. Following this promising trend, CENTRIC is using AI methods to leverage user and environmental context to overcome the rigidity of current systems and produce truly customized user-centric communication systems. AI-based customization techniques offer flexibility and cost-saving benefits for both private industrial users and the public. Despite government efforts, rural coverage remains a challenge due to lack of demand and telecom industry interest. The proposed AI-AI powered 6G network can lower barriers to rural coverage and enable public networks to automatically adapt to changing user needs. The novel user-centric AI-AI paradigm introduced by CENTRIC (see Figure 1.1) has the potential to change the way we develop cellular systems, resulting in leaner and more automated processes that shorten supply chains and development cycles, increasing the affordability of these networks.

Finally, CENTRIC is developing AI-AI techniques to integrate AI waveforms and communication protocols with hardware computing platforms, aiming to explore novel computational paradigms like neuromorphic computing and mixed digital and analog computing. This approach aims to customize solutions to individual user needs while maintaining affordable computational and energy consumption.

2. The Concept of a 6G User-Centric AI-AI

Current wireless networks focus on universal service offerings, catering to a limited number of services like voice/video and IoT traffic. This approach reduces traffic categories to KPI profiles, reflecting network limitations rather than users' needs. CENTRIC is leveraging AI techniques to create a top-down, modular approach to wireless connectivity, putting users' communication needs and environmental constraints at the center of the network stack design. Accordingly, CENTRIC's designs start with the users' communication needs and application-specific requirements as depicted in Figure 2.1. Then, tailor-made waveforms, transceivers, signalling, protocols, and hardware implementations are optimized adaptively and on-demand within a modular architecture to support these requirements. CENTRIC will make this possible by advancing theory, algorithms, hardware co-design, and training and monitoring environments for future 6G use-cases, such as self-driving vehicles, the internet of nano bio-things, or multi-sensory holographic communications.

In CENTRIC, the user's requirements are specified to the network through well-defined mechanisms ranging from the static compilation of KPIs and hardware availability to the dynamic update of a virtual twin model of the agent's behavior. The vision of CENTRIC involves the use of an AI-native wireless connectivity interface that aims at mapping users' requirements into custom communication protocols while accounting for hardware and environmental constraints at the user-side and in the edge network segment.

2.1. CENTRIC's Vision for a 6G User-CENTRIC AI-AI

The following everyday example can help illustrate how CENTRIC envisions AI-powered user-centric communications in the 2030s. Today, one can buy a smart lightbulb from Osram, another one from Philips, and a gateway from Ikea and it is still a significant challenge to get them to work together seamlessly. Despite numerous attempts in the past decade (involving common protocols, gateway designs, and standards) the fragmentation of the smart home market still prevents these so-called smart devices from communicating with one another to solve the simplest of problems: turning on the lights. The incompatibility between these systems occurs at various layers: At the physical layer, some systems use Zigbee, others Bluetooth, and so on. At the security layer, not all systems may use the same encryption mechanisms or key exchange algorithms. The application layer is, however, remarkably similar across all these systems.

In CENTRIC, we advocate for an approach to 6G communications whereby the application's requirements define the starting point for the design of the underlying protocol stack. As the example above illustrates, this is not yet possible today, as vendors of telecom equipment simply cannot produce a new stack for each new application and scenario. However, for the first time, there are strong indications that there is a reliable technology that can make user-centric communications happen. The AI-native air interface (AI-AI) advocated by CENTRIC will bring forth a degree of physical layer and protocol stack customization unseen in the history of communication engineering. Leveraging AI-AI, each user (from the smart lightbulb in the example to a wireless device on a factory floor) will benefit from the type and amount of connectivity it needs, whenever and wherever it needs it. By delegating the

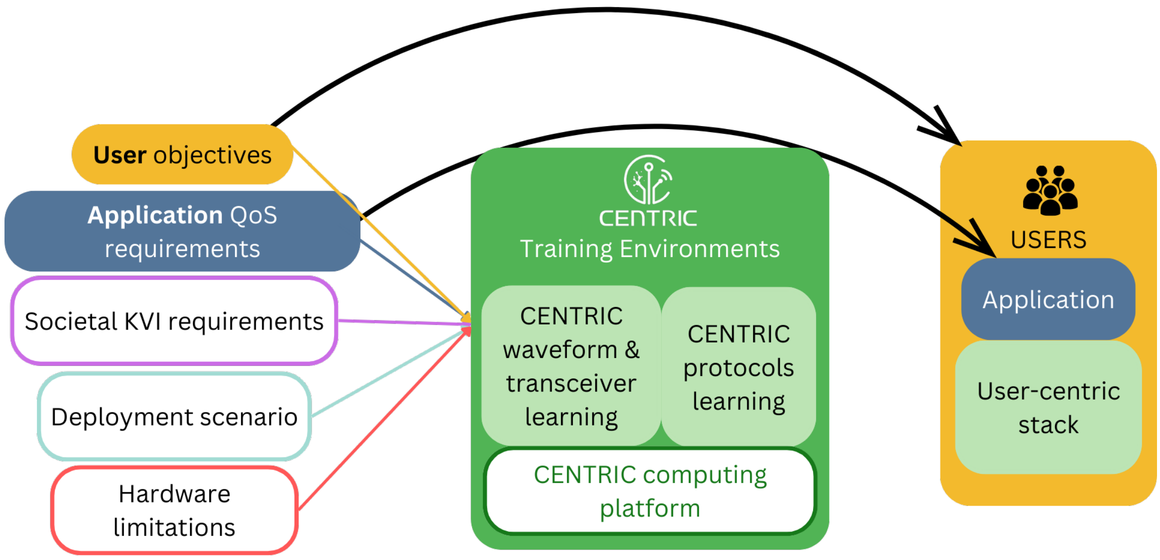

Figure 2.1: The CENTRIC process for enabling an AI-native Air Interface

design and implementation of communication systems to the AI-AI, application-layer vendors will be freed from having to maintain complex stacks and will be able to focus on their application products. The communication solutions that will emerge with the AI-AI will be application-specific and adaptable to the target scenario. This degree of automation and flexibility will be essential not only to solve old problems as just described but also to support the growing collection of wireless use cases of the next decade, such as virtual reality (VR) / augmented reality (AR) / extended reality (XR), autonomous driving and remote surgery. Some of these novel services cannot afford to wait another ten years for the next wireless standard. CENTRIC positions AI-AI as the essential fabric of future wireless connectivity systems. Among the beneficiaries of this approach are naturally mobile network operators and the private networks market, which will profit from highly customizable systems wherein different customers have entirely distinct personalized needs. As humanity ventures into the future, new and radically different communication needs will emerge. Addressing them with a traditional multi-purpose wireless standard would significantly limit the scope of future applications, and potentially prevent many cutting-edge inventions from fulfilling their potential. CENTRIC aims at being “future-proof,” endowing the networks of tomorrow with AI tools to support a range of new applications. As an example of visionary applications that may be enabled by an AI-native network, consider holographic communications or the workplace metaverse. These will add to the unforeseen communication needs brought about by future applications. Instead of developing a new cellular generation every ten years, CENTRIC advocates AI-AI as the revolutionary tool that will produce, on-demand and in an automated fashion, the communication systems that the future will demand. Overall, we believe that AI-AI-powered radios will provide a fast, effective, and affordable way of ensuring that everyone and everything enjoys tailored wireless connectivity services in an increasingly complex world. Such a tailored service approach opens the door for obtaining specialized and adaptable waveforms and protocols that will make the most of every Hertz of spectrum and every Joule of energy used, paving the path towards truly sustainable and spectrum-efficient 6G networks.

3. AI Techniques for the 6G AI-AI

In this section, we present the main techniques that CENTRIC considers important for the 6G AI-AI described above.

3.1. Physical Layer Techniques

3.1.1. End-to-End Learned Waveforms and Modulation

Over the last decade, ML has disrupted many engineering fields, and this revolution has also started to happen for signal processing in wireless communications. Signs for this include a dedicated 3GPP work group on ML for 5G Advanced (Rel. 18) [4] as well as first chip manufacturers integrating neural network hardware accelerators in their 5G modems [5]. Although the use of ML in communications is not new [6], the research driving this current wave of ML adoption started only around five years ago, see, e.g., [7]. There are generally two reasons to resort to ML: a model deficit, implying the lack of trustworthy mathematical models for the problem of interest, or an algorithmic deficit, indicating the lack of effective and computationally feasible algorithms. CENTRIC views the availability of well-established models and engineering insights as a key component in any AI-native solution. Leveraging domain knowledge is instrumental to devising ML-enhanced algorithms that generalize well with a small amount of training data, see, e.g., [8]. Example applications of these techniques are MIMO detection [9] and channel estimation [10]. A common technique that is used in such works is “deep unfolding” [11], whereby multiple iterations of an existing algorithm are considered as layers of a deep neural network and enriched with trainable parameters. Another line of research, which was pioneered in [7] aims at ultimately replacing the entire physical layer algorithms with neural networks. By interpreting the transmitter, the channel, and the receiver as a single neural network, or autoencoder, the entire communication system can be optimized from E2E with respect to a chosen loss function. That is why this concept is also referred to as “E2E learning”. E2E learning is now able to emerge new codes [12], waveforms [13], and modulation schemes [14] which can be spectrally efficient and hardware friendly (due to lower peak-to-average-power ratio (PAPR)) than existing solutions. To fully realize the benefits of E2E learning, CENTRIC considers the following research directions crucial.

- **End-to-End waveform Learning for sub-THz and short-packet transmission**: CENTRIC considers the integration of model-driven and end-to-end learning for new waveforms for the sub-THz band and transmission of short packets as essential components of 6G AI-AI. Existing works [13] have shown potential for data-driven optimization of waveforms, but this approach has not been applied for THz channels and hardware due to phase noise and non-linear effects. A data-driven, E2E optimization approach is expected to overcome modelling difficulties and lead to energy-efficient and hardware-friendly waveform designs. E2E learning is particularly attractive for 6G transmission of intermittent short packets, as it minimizes detection, synchronization, and channel estimation overhead.

- **User-tailored modulation learning**: Symbol modulation and demodulation are essential components of the PHY layer. In 5G NR physical downlink shared channel

(PDSCH), modulation schemes are used in combination with channel coding to determine data transmission spectral efficiency. The base station instructs user equipment (UE) to select a modulation and coding scheme (MCS) index table, based on the channel quality indicator (CQI) value and sounding reference signal (SRS) [15]. The MCS with the highest spectral efficiency is selected, and the MCS is continuously updated for PDSCH/PUSCH. Current fixed modulation types do not adapt to specific channel conditions or RF impairments. Instead, a pre-defined constellation diagram, such as binary phase-shift keying (BPSK) and quadrature amplitude modulation (QAM), is used based on the received signal's signal-to-interference-plus-noise ratio (SINR). In CENTRIC, we aim to use deep learning techniques to overcome the downsides of fixed modulations mentioned above. We aim to design a flexible constellation mapper that adapts to real-world channel conditions by dispensing with channel probability distribution models.

3.1.2. AI-empowered MIMO communications

For the last two decades, MIMO communication has been one of the main drivers for boosting the spectral efficiency of modern mobile communication systems, a journey that spans from the early antenna selection and antenna diversity schemes used in Global System for Mobile Communications (GSM), to today's complex massive MIMO systems. As such, a large body of research on classical signal processing methods for MIMO communications is nowadays available, many of them having found application in commercial systems. Looking towards the future, however, the path to further development of MIMO processing is plagued with old and new challenges that AI techniques seem particularly well-suited to overcome: (i) scaling issues in performance and computational complexity resulting from increasing MIMO dimensions; (ii) infeasibility of MIMO precoding due to increased pilot overhead for CSI acquisition and computational burden; and (iii) directional beamforming and beam-based operations required at high frequencies to overcome pathloss and blockage vulnerabilities.
In addition to novel algorithmic tools, the native introduction of AI methods in MIMO processing will require the adaptation of wireless communication standards to account for and introduce the necessary signalling procedures to enable them. So far, the application of AI/ML to wireless communications has been mainly limited to implementation-based approaches at the network-side and/or UE-side. For example, the 3rd Generation Partnership Project (3GPP) has examined the functional framework for radio access network (RAN) intelligence enabled by further enhancement of data collection [16] and introduced a network functionality to collect data for analytics called Network Data analytics Function in its latest Releases [17]. However, in the new Release 18 of 3GPP the trend is to introduce AI/ML more holistically. Specifically, a study on AI/ML for NR Air Interface started in 2022 with the target to "explore the benefits of augmenting the air-interface with features enabling improved support of AI/ML based algorithms for enhanced performance and/or reduced complexity/overhead" [18]. This study is expected to lay the foundation for future air-interface procedures leveraging AI/ML techniques. The technical innovations that CENTRIC proposes in the area of MIMO processing to overcome the difficulties described above include:

- **Deep learning methods for multi-user MIMO receivers**: ML-based MIMO detection [19] has been extensively studied, but current solutions often struggle with realistic channel models or require dedicated neural networks for different system parameters [20]. CENTRIC is developing self-attention-based multiuser MIMO detection algorithms, which will be evaluated on realistic 3GPP channel models and measured data from NVIDIA's Aerial platform [21]. Transfer learning techniques [22], which transfer knowledge from training models to new configurations or tasks, are also being explored for adapting neural network-based receivers to diverse system parameters. This approach has been successful in beam management in mmWave communications [23] and is being explored in CENTRIC.

- **AI methods for CSI acquisition and MIMO precoder selection**: The acquisition of CSI at the transmitter and receiver is a significant challenge for future wireless networks due to the high pilot overhead. Previous research has focused on adjusting pilot signal spacing, utilizing limited channel angular spread, and reducing CSI feedback [24–26]. The most common use cases include CSI feedback overhead reduction, improved accuracy, and time domain CSI prediction. CENTRIC proposes a low complexity solution using federated learning to incorporate E2E operations without sharing large data sets. CSI acquisition and reporting are critical in MIMO precoder selection in FDD MIMO systems, as imperfections in hardware components and channel estimation can erode precoding performance. In this context, CENTRIC proposes a low complexity/sustainable solution where collaboration between UE and network via federated learning is used to incorporate E2E operations without sharing large data sets between various UEs and the network.

- **AI methods for user-centric sensing-aided beam management**: Beam management in 5GNR [27] focuses on selecting and retaining a proper beam pair between transmitter and receiver for good connectivity. Beam establishment for idle UEs and beam tracking for connected UEs are major parts of this process. Without sufficient measurement reports, signal blocking may interrupt service, leading to the degradation of service quality. Between measurement reports, best-serving beams may become obsolete, causing communication overhead and wastage of time-frequency resources. Some works propose beam prediction using additional information like position [28,29] or LIDAR [30], focusing on localization of individual users for better service [31]. AI/ML approaches are being proposed to enhance beam tracking in 5G-advanced mobile networks [32], particularly in 6G networks with extreme requirements and mmWave bands. These approaches can improve efficiency and latency by leveraging the sensing capabilities of 6G signals and other out-of-band sensors. A centralized integrated sensing and communication system is identified as a main use case for 6G, with CENTRIC focusing on beam tracking and prediction to combat environment uncertainties, high interference, and low SINR conditions.

3.2. Protocol Learning

In the previous section, we described CENTRIC's position on the physical layer components of the 6G AI-AI concept. To fully harness the benefits of an AI-native physical layer, it is necessary to account for the medium access communication protocols that run on top of it. CENTRIC is developing medium access communication protocols using AI techniques to optimize the 6G AI-AI concept. The focus is on developing effective, energy-efficient, and user-optimized protocols using a two-component approach: developing theoretical frameworks for automated wireless protocol emergence and testing AI methods' ability to optimize protocols for specific tasks, such as channel access in IoT networks, multiple-access in specialized services, and transmission mode selection in dense deployments of heterogeneous

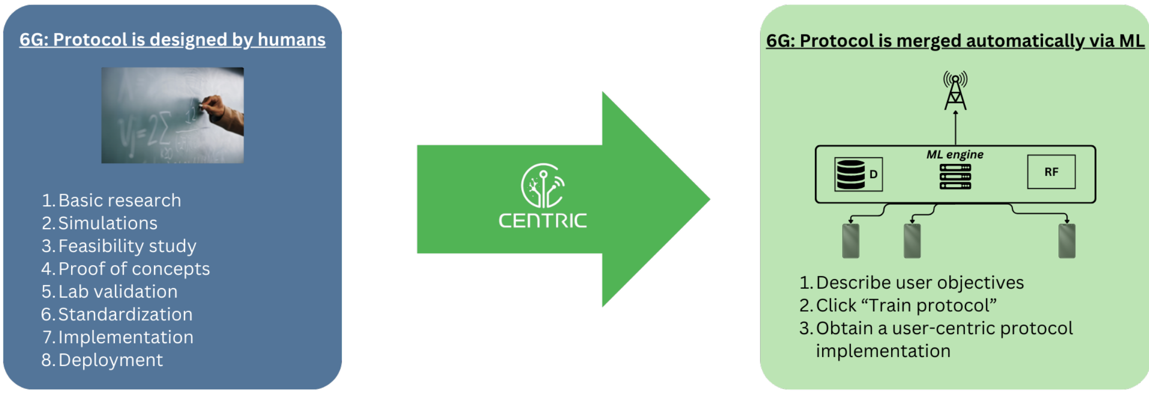

Figure 3.1: CENTRIC protocol emergence procedure.

subnetworks. The protocol emergence procedure adopted by CENTRIC represents a disruptive change from the hand-craft procedure used in 5G as depicted in Figure 3.1.
Recent research on protocol learning has shown the effectiveness of emergent rules and signalling messages via MARL techniques. In [33], an emergent rule for cellular MAC was developed using a simplified version of the reinforced inter-agent learning (RIAL) architecture. UEs were trained using MARL and L2C techniques to learn how to use pre-defined signalling messages, re-understanding the meanings of existing messages by artificial agents. In another study [34], both BTS and UEs were trained to use bitstrings to maximize multi-channel access utility. This was the first time AI radio nodes of a cellular wireless network came up fully on their own with the rules and messages needed for optimal channel access. However, practical challenges such as scalability and interpretability need to be addressed before these techniques can be fully leveraged. CENTRIC is addressing these challenges using novel MARL techniques, such as multi-agent proximal policy optimization (MAPPO) [35], for wireless MAC protocol emergence. These emergent protocols have been customized to the scenario where they are intended to be deployed. If successful, these techniques could be a game changer for the growing market of private wireless networks, allowing smaller technology companies to address the private networks market while reducing development costs and delivery times. Such emerged protocols in CENTRIC will rely on AI methods such as transfer learning, learning by demonstration, aggregation of supervised learning with self-play reinforcement learning, zero-shot coordination, etc. In the sequel, we briefly describe representative examples of the main innovations that CENTRIC promises to deliver in the area of learned protocol.

3.2.1. Learned multiple-access protocols for specialized services

Learning multiple access protocols for specific users and applications can overcome limitations of application-agnostic protocols and the gap between wireless KPIs and key quality indicators (KQIs). This can lead to higher spectral efficiency and improved utilization of available radio resources. A relevant application of multiple access protocols is communication and control co-design. Current 5G radio technologies have been designed to support unprecedented requirements in latency and reliability, but the design of radio systems and control systems has mainly been considered disjoint. AI solutions may significantly improve the spectral efficiency of wireless communication by linking its performance to control stability rather than wireless-only KPIs. Improving spectral efficiency can translate to reduced airtime, particularly in unlicensed spectrum operations, and challenge the misconception that reliable and low latency closed loop operations are only possible in licensed bands with controlled interference. Channel access in massive IoT networks is another important application, as channel access is limited to a few devices due to the dearth of spectral resources. To minimize contention among devices, it is crucial to develop MAC protocols that are easily scalable and adaptable to the rapidly changing environment without controlling information message exchanges [36]. Deep reinforcement learning (DRL)-based frameworks can be employed to optimize the design of networking protocols, learning which protocol functionalities need to be included or neglected in the protocol design. CENTRIC is studying the latency and efficiency of DRL-emerged protocols relative to legacy protocols, such as IEEE 802.11.

3.2.2. Methods for transmission mode selection in dense deployments

Transmission mode selection, i.e., selection of relevant transmission parameters such as transmit power, frequency resources, precoder, and modulation, is a complex multi-objective optimization problem, which is further exacerbated by the increased densification expected in 6G (a factor of $\times 10$ with respect to 5G, as stated in the 6G European vision whitepaper [37]). The concept of in-X subnetworks has been introduced as a further leap of heterogeneous network, with the aim of providing highly localized wireless coverage in entities like vehicles, robots, production modules, and even human bodies [38, 39]. As the name suggests, such subnetworks can be part of a larger 6G infrastructure, offloading the broader network of the most demanding services; still, they must be able to operate stand-alone in case of missing or intermittent connectivity with the broader network, especially in case of life-critical services (e.g., brake control in vehicles). The deployment of subnetworks may lead by nature to very dense deployments (e.g., vehicles in a congested road, humans attending crowded events) and they can be mobile. These aspects may result in wide and rapidly fluctuating interference patterns, which make the problem of transmission mode selection more challenging than in traditional wireless setups, characterized by static base stations/access points and lower cell densities. Traditional optimization methods and heuristics appear then obsolete for dealing with the complexity of such scenarios, thus calling for AI solutions. Transmission mode selection in dense deployments can be leveraged with deep-Q networks, since such solutions allow for handling efficiently the large amount of interference states. Also, deep-Q learning can be combined with recurrent neural networks (RNN) for capturing time-correlated transitions of the observed states. DQN methods allow for decentralized learning, where each wireless network can eventually train its agent. Bayesian reinforcement learning methods will also be considered in CENTRIC, as they incorporate domain knowledge as prior information in the learning process by leveraging Bayesian inference methods.

3.3. Sustainable and human-friendly RRM

The previous sections described the PHY layer and MAC components of CENTRIC's 6G AI-AI concept. For a wireless network to work properly while servicing its users, multiple system-level decisions need to be made. These include functionalities like mobility management, allocation of radio resources, load balancing, etc. The collection of all these functions is known as RRM and plays a major role in the ultimate performance of wireless networks.

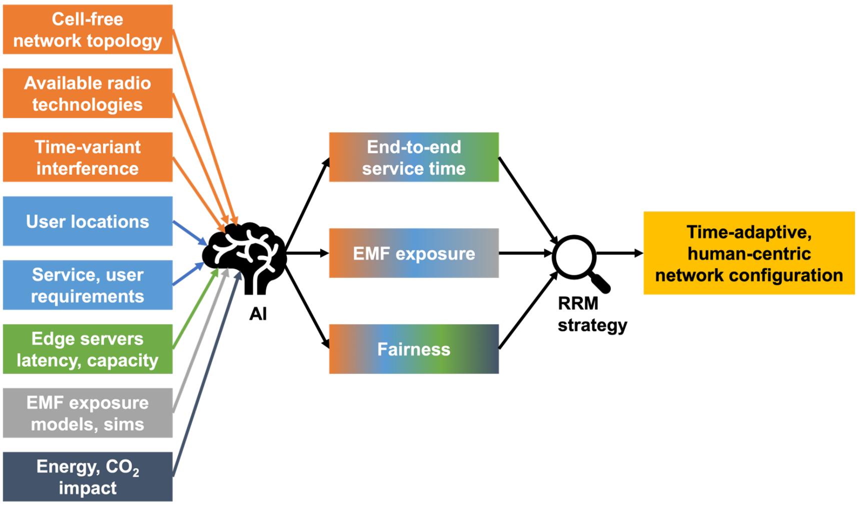

Figure 3.2: CENTRIC's approach to AI-enabled RRM

To this end, CENTRIC is exploring AI-based breakthroughs in some of the most pressing 6G RRM areas, such as sustainable data management at the wireless edge, EMF exposure control in novel network architectures, and energy savings. CENTRIC's approach to AI-enabled RRM is illustrated in Figure 3.2. In the sequel, we described the novel aspects that CENTRIC considers important for the RRM component of the proposed 6G AI-AI concept.

3.3.1. Caching methods for distributed learning

Two of the major challenges to realizing a sustainable AI-AI are the computational cost of training and the need for large quantities of training data. While distributed learning has emerged as a family of techniques aimed at better leveraging the computational capabilities and data available at multiple networked nodes, it has become critical to minimize its energy footprint [40]. In this context, we envision caching as a key enabler to reap the full benefits of distributed learning, by making data and (sub-)models readily available where they are needed, thus avoiding bandwidth consumption, and reducing the computational burden. Thanks to data caching, ML models can be trained through plentiful and high-quality information, thereby achieving convergence in a small number of epochs. At the same time, caching whole models or parts thereof enables such techniques as transfer learning [22], thus, kick-starting training from pre-trained networks. Both strategies help to achieve a good learning quality in a short time and with a limited computational cost. Owing to their far-reaching implications, caching decisions are complex. Specifically, one must jointly decide what to cache and where in the network, accounting for factors including which network nodes to involve in the distributed learning process, and the learning methodology to adopt. Concerning caching, the main objective of CENTRIC is to devise, characterize, and test caching strategies for data and AI/ML models that can further CENTRIC's vision of high-performance, sustainable networking.

3.3.2. Sustainable RRM techniques for cell-free massive MIMO networks

6G challenges include the development of novel network architectures, such as cell-free networks, which are dense networks composed of geographically distributed access points (APs) that serve a set of users simultaneously [41, 42]. These networks cooperate with their neighbors to provide radio resources to the nearest users, exchanging signals, channel state information, and a common time reference. By properly configuring transmitted signals, beamwidth, and cooperation among APs, the network can be optimized to meet user requirements in terms of quality of service while reducing interference and minimizing transmit power. However, network configurations need to be adapted to the time-variant nature of the environment, such as user locations, interference level, and service requirements. AI/ML approaches are needed to effectively account for multiple factors, such as data rate, coverage extension, fairness in user services, and EMF exposure. CENTRIC believes that AI-based methodologies can be leveraged to obtain optimal resource allocation with less computational complexity than current state-of-the-art solutions.

Pervasive AI will play a crucial role in cell-free networks where user safety is one of the primary metrics to consider. One key aspect is providing a scalable solution with the number of users, as the complexity of signal processing and fronthaul signaling can become unmanageable. Smart policies for assigning APs to users can decrease resource waste by selecting only effective transmitters for each user. Distributed AI/ML techniques, such as FL, can be leveraged to exploit a distributed resource allocation scheme, adapting to network scalability.

To properly evaluate environmental and human EMF exposure levels, exposure modelling using statistical and deterministic strategies for estimating electric field strength and/or dosimetric quantities in different indoor/outdoor scenarios will be a useful approach.

4. Training and Monitoring Environments for AI Models

The data-centric technological revolution is characterized by the interaction between physical elements in the real world and virtual elements that implement monitoring, control, or predictive tasks based on observations. Data-driven (DT) platforms leverage wireless connectivity to maintain a virtual mirror image of the physical agents' states for optimizing data-driven models that can simulate, predict, and control real-time operation. DT platforms can integrate user-provided traffic and service demands models, a repository of AI modules implementing different functionalities, standard or proprietary models of propagation and interference environments, and interfaces with physical entities being modelled by virtual twin counterparts. These novel functionalities are made possible by a closed-loop connection with the physical twins, which carry raw or summary information regarding the performance at different layers of the protocol stack.

CENTRIC identifies several methodologies as central to the development of training and monitoring environments based on DT for 6G. For initial training, standard one-off training is generally insufficient to address time variability to which lower layers of the protocol stack are exposed. To address this, CENTRIC will design techniques that cater natively for adaptivity to changing conditions via meta-learning. Meta-learning provides a way to automatize the selection of hyperparameters, such as initialization and learning rates, that define the inductive bias of machine learning models. This allows the training of a machine learning model with reduced training data, time, and/or complexity.

For monitoring, AI modules must provide a measure of uncertainty about their outcomes, which can be tracked by a virtual twin to assess when adaptation and/or retraining are necessary. CENTRIC will study the integration of meta-learning with validation-based or cross-validation-based quantification methods, or with native epistemic uncertainty-aware techniques such as Bayesian neural networks and approximations thereof.

4.1. Theoretical principles for the management of AI-AI models

The first important theoretical question to drive design in CENTRIC is: How much data is required to ensure a given level of generalization performance? CENTRIC focuses on designing meta-learning algorithms that can adapt to novel conditions and measure generalization performance in terms of accuracy and capacity to quantify uncertainty. To address this, the platform will adopt accuracy and calibration error as performance metrics and develop theoretical bounds based on information theory and statistical learning theory. This framework will be used to assess uncertainty quantification and obtain specific insights in the context of communication algorithms and protocols.

Another theoretical question is the impact of modularity on the generalization of meta-learning algorithms. The Digital Twin (DT) platform in the open RAN (O-RAN) system has AI modules available for recombination to obtain end-to-end solutions based on user requirements and available data. The question is how much data is needed to identify the configuration that guarantees the best performance at test time, as too many modules may cause suboptimal solutions when not enough data is available. More complex modules may also avoid the lack of data, but excessively specialized modules may cause bias.

4.2. Algorithms for the management of AI-AI models

CENTRIC aims to develop modular meta-learning strategies integrated with Bayesian and/or conformal inference methods for adaptation and monitoring. The algorithms will be developed in an abstract setting with generic assumptions about model misspecification and outliers. Ensemble models can account for this bias, but new challenges will be tackled by optimizing objectives from generalization analysis.

CENTRIC will adopt robust loss functions and performance criteria based on generalized log-loss, discounting outliers. This presents a challenge in developing novel optimization strategies with optimality guarantees. A novel generalization analysis will be used to account for contaminated sampling distributions.

Modularity also defines design challenges, as optimization over module configuration is a combinatorial problem. Solutions based on stochastic relaxations will enable the application of gradient-based methods via the reparameterization trick. Use cases and benchmarks will be developed in collaboration with all partners in CENTRIC, including transmission mode selection, context-based caching, and cell-free networking.

6G research requires new tools, and CENTRIC will explore and develop novel simulation environments that integrate rendering, wireless ray tracing, link-level simulation, and ML capabilities. The outcome of this work will be a key enabler for the use of DTs for communications and will be used as a simulation tool within the project, such as research on ISAC, environment-specific receiver algorithms, and air-interface design.

5. Hardware Enablers of the 6G AI-AI

5.1. Novel AI-computing hardware and real-time optimization

Traditional microprocessors are not well suited for implementing state-of-the-art deep neural networks that require large amounts of matrix-vector multiplication operations. This is primarily because the on-chip memory is limited, and large matrix operations require frequent access to off-chip memory and storage units. The need for frequent access to the memory typically ends up being the main contributor to the overall energy consumption, as well as to the overall latency, of the processor [43]. In-memory computing addresses this “von Neumann Bottleneck” by leveraging a hardware architecture that supports close integration of logic and memory units while implementing accelerator units to efficiently carry out matrix-vector multiplications. In-memory computing can be implemented using either conventional digital complementary metal–oxide–semiconductor (CMOS) technology or more advanced beyond-CMOS technologies based on non-volatile memories [44].

To enable the CENTRIC 6G AI-AI vision, both CMOS and beyond CMOS implementations of in-memory computing, as well as the acceleration of GPU-based processing for real-time applications are been explored. In this section, we describe CENTRIC's position on the need for each of these paradigms as enablers of the 6G AI-AI.

5.1.1. Beyond-CMOS computing architecture

Beyond-CMOS research focuses on developing computing platforms using custom two- or three-terminal memristive devices, such as Phase Change Memories (PCM), Metal–oxide based reactive RAM (RRAM), conductive bridge RAM (CBRAM), Ferromagnetic materials-based spin-transfer-torque magnetic RAM (STTMRAM), and Ferroelectric materials-based Ferroelectric RAM (FeRAM). These memory technologies have achieved maturity with prototypes featuring thousands or millions of devices. Other materials, such as organic polymers, nano-ionic materials, and photonic components, are being demonstrated with typically less than 100 devices. PCM technology [45–47] has been the most complex AI hardware demonstrators due to its advanced hardware development, support for multi-level incremental programming of states, and well-understood stochasticity and reliability characteristics of device conducencies used to encode synaptic states. In contrast, PoCs using other technologies use a smaller number of devices and use software simulations based on experimental measurements. CENTRIC considers the design and evaluation of inference and optimization engines based on emerging memristive devices for communications as an integral aspect of their 6G AI-AI vision.

5.1.2. New mixed analog-digital memristor-based in-memory computing architecture

CENTRIC is developing an in-memory computing architecture using mixed analog-digital memristors. The architecture will use tiled arrays of cross-bars based on PCM devices to store software-determined synaptic weights. It will use analog conductance sensing for matrix computations and digital message passing for transmitting neuronal output activations between cores. The architecture will be optimized to accelerate common computational operations, such as multiply, accumulate, and convolutions, necessary for implementing state-of-the-art neural networks. The architecture will also map software-trained weights to analog conductance levels of PCM devices, which can store approximately 4 bits per device. The architecture will also evaluate designs for programming and read circuits, analog conductance sensing, and analog-to-digital converters (ADCs) to maintain precision and accuracy for computations.

5.1.3. Novel designs based on neuromorphic computing paradigms

In-memory computing can be integrated with neuromorphic processing principles, replacing static neurons with dynamic spiking neurons. This approach supports sparse, event-driven computing, reducing the cost of inference and optimization routines [48]. Spiking processors also eliminate the need for costly multiplication operations involving high-precision real numbers. CENTRIC is investigating architectural principles for accelerating spike-based neuromorphic computing, optimizing peripheral read circuits for spike-based event-triggered conductance sensing, and event-driven spike communication between cores. Neuronal units are optimized for implementing various spike models, using sub-threshold characteristics of CMOS transistors or stochastic incremental programming and threshold switching characteristics of PCM devices.

The study also aims to determine how specific software-designed neural networks can be mapped into the hardware architecture. Evaluation will be performed on the number of devices and tiles required to accurately map the software weight into the cross-bar, considering non-ideal effects such as programming stochasticity, conductance drift, read noise, and device-to-device and within-device variability. Performance metrics will be measured using compact models of synaptic devices and peripheral circuits, and strategies to optimize the architecture to meet overall system metrics will be considered.

5.2. Methods for GPU acceleration of deep learning algorithms

Neural network architectures need to be implemented in hardware to enable efficient inference at PHY-layer speeds. Since the required latency and throughput in communications are 1-3 orders of magnitude higher compared to applications in other fields, such as computer vision for self-driving cars, this poses a formidable engineering challenge. Weight quantization [49] and model-hardware co-design are compulsory steps [50]. Analog hardware accelerators, such as neuromorphic processors, might be a promising alternative to existing designs with potentially dramatically lower energy consumption [51]. So-called "fully-fused" neural networks [52], whereas many operations as possible are fused into a single CUDA kernel, are one promising way to increase training and inference speed by several orders of magnitude. This technique might hence enable online training of small neural networks which was believed impossible for applications in communications. We aim to demonstrate the practical feasibility of one of the ML-enhanced multiuser MIMO detection methods by implementing it on an NVIDIA GPU using CUDA. The resulting latency and throughput will be investigated in depth and their dependence on weight quantization to integer precision analyzed.

6. Testing an AI Governed 6G Air Interface

6.1. Challenges in testing and validation introduced by AI methods

The shift from a hand-crafted design of the components of the air-interface to a data-driven, fully-automated learning approach is likely to raise concerns about the reliability and dependability of the resulting technologies. On the one hand, the user-centric approach advocated by CENTRIC will lead to a dramatically increased diversity of waveforms, transceiver algorithms, MAC, and RRM protocols, each adapted to the particular user needs and environmental conditions on which they have emerged; this will significantly increase the complexity of verifying that all the resulting technologies fulfill the required KPIs and KVIs. On the other hand, the inherent lack of interpretability of AI models will make it difficult to pinpoint the causes of performance deviations and, consequently, hamper the resolution of encountered issues. For these reasons, CENTRIC recognises that, if the AI revolution is to extend to the air-interface of 6G communication systems, it is imperative that the validation and testing frameworks used to verify AI-based 6G components evolve along with them. To this end, CENTRIC is investigating novel methodologies for automated testing of AI-based components in 6G that can overcome the obstacles mentioned above. In addition, and to mitigate the reservations that the industry may have about the move to an AI-AI, it is also crucial to be able to showcase the performance of CENTRIC's developed technologies in an experimental, PoC setup.

6.2. Novel testing methodologies

In order to test the technological innovations described so far, CENTRIC will also develop a methodology to test and evaluate the performance of the developed approaches, which will be done by specifying a number of test procedures that aim to evaluate and validate KPIs and KVIs. The AI and ML-based approaches developed within CENTRIC will be focused on actions related to communication systems. This will be reflected in the testing framework and testing procedures that will be specialized in evaluating AI and ML-based technologies in this context. As AI and ML-based approaches are often complex in implementation and act as a black box, it is critical to have a clear procedure defined for how to test and interpret results and metrics extracted when testing the approaches. The testing procedure will both evaluate the approaches as black boxes and also support hooking into the inners to extract features for evaluation and to increase transparency. This will be done by defining scenes or scenarios that will include a predefined set of inputs and a set of evaluation points that can be used to evaluate the performance of the system under test. This will include an indoor and an outdoor scenario which will give a baseline evaluation of the AI and ML-based approaches when operating in this context. The scene scenarios will be defined in such a way that the optimal decisions and configurations will be known in advance. In that way, the AI and ML-based approaches can be evaluated in terms of how well they approach the optimal solution.

The testing of technologies within CENTRIC will be done within a testbed which will be designed to support automated deployment and automated testing of the technologies. This is important to support the quick return of information on whether the implemented AI updates yield the expected improvement. Furthermore, the testbed will support automated testing and easy modification of testing scenes and parameters once the AI approach/system under test is deployed. The automation of testing procedures is an important aspect that will greatly reduce the complexity of evaluating and re-evaluating tested technologies. The automation will also help when integrating with larger systems or testbeds, i.e., the testbed developed here could be dropped as a component in the future 6G testbeds. This means that key functionalities such as test triggering, control of components under test, and result extraction should be exposed via open application programming interfaces (APIs). As CENTRIC technologies will be developed by different industrial parties that will have an interest in securing and preserving the IP of the developed technology, the testbed will also support

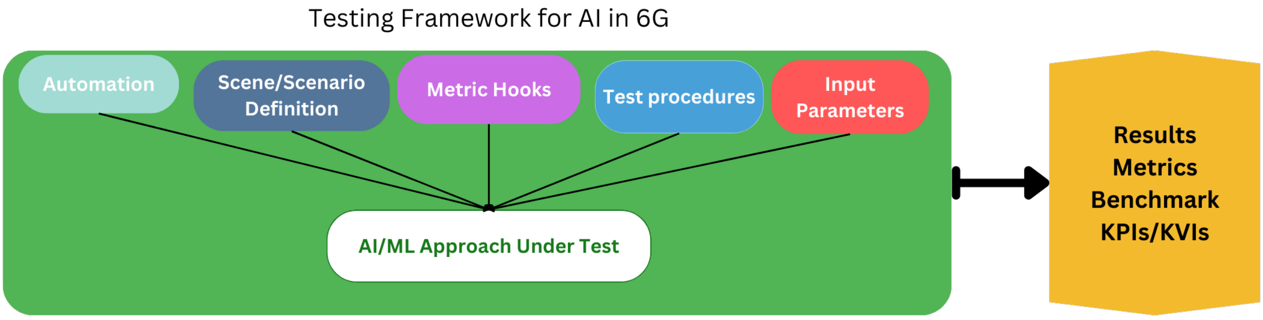

Figure 6.1: Diagram of testing framework for testing AI and ML based approaches for 6G communication systems to improve transparency and support benchmarking

the simulation of the developed technologies. In that way, the performance of the tested approach can be evaluated in the context of other developed approaches or their simulated behaviour.

6.3. PoC of AI-AI concepts

To be able to convey the effectiveness of the innovations produced in the project, CENTRIC will produce several PoCs in the form of tabletop demos and lab experiments. These will demonstrate the feasibility of the approaches in the real world in an over-the-air scenario, and act as an aspect of the validation of the approaches. Additionally, the PoC will help to identify issues or unforeseen effects of the approach when operating. The PoCs that will be created in the frame of CENTRIC will be done in conjunction with co-simulations of other system parts. The simulated system parts will both act as input generators and also as consumers of outputs of the PoCs. This will support another goal which is to confirm that the capabilities of an actual deployment match that of emulation. Similarly, the emulation can also be verified by evaluating the capabilities of the PoC realization. It is vital to validate the technology as well as the accuracy of the emulation, as both can be used in experiments involving other technologies. Another use of the PoC is to support the development of testing tools and methodologies to validate the performance, reliability, and resource usage of the developed technologies. Both the PoC and testing methodologies developed here will reduce complexity and difficulties when integrating the technology in other contexts such as other 6G testbed projects.

7. Conclusion

The CENTRIC project positions itself at the forefront of unprecedented innovation in wireless communications through a multifaceted approach that encompasses the development of novel AI techniques for 6G waveforms and transceivers, the emergence of new learned protocols for specialized services in 6G, and advanced hardware implementation of AI-AI methods. Firstly, the design, implementation and testing of AI-AI methods in a controlled lab environment are expected to unlock unprecedented potential in user-centric 6G waveforms and transceivers. This systematic design and experimentation approach is foreseen to be the catalyst for the practical application of these methods in real-world scenarios, translating to enhanced communication capabilities, high adaptability, and better user experiences. The utilization and contribution to open datasets for waveform and modulation learning in CENTRIC are expected to not only speed up the development of sustainable and robust AI-AI methods but also promote collaborative and open research. This contribution will indeed enhance collective understanding of waveform and modulation learning thereby laying the foundation for future innovations in this area. The development of a training sandbox for Digital Twin networks will contribute to ensuring the reliability and robustness of the AI-AI methods developed within CENTRIC. This will ensure that the methods can be seamlessly integrated into operational networks. Another important outcome of CENTRIC will be a testing framework for AI wireless algorithms that addresses a critical need for the validation and verification of AI-based solutions. This framework is expected not only to enhance the reliability of our methods but also to serve as a benchmark for future developments in wireless communication. CENTRIC is also expected to set a new standard for AI transceivers via its contributions to the incorporation of GPU implementations and mixed analog-digital hardware architectures for AI transceivers, translating to high computational efficiency, unprecedented performance, and versatility of wireless transceivers.

In another stream, CENTRIC will result in enhanced sustainability of 6G networks. For instance, the introduction of energy-efficient algorithms for wireless edge caching and radio resource management (RRM) optimization represents a crucial step towards a sustainable and environmentally friendly 6G network. CENTRIC's expected contributions in this area align with global efforts to minimize the ecological footprint of wireless networks. Also, CENTRIC's research is expected to provide evidence of the electromagnetic field (EMF) reduction potential of cell-free networks, offering a glimpse into the future of wireless communication with lower EMF exposure. Furthermore, the exploration of techniques for lowering EMF exposure in the context of AI-enabled 6G networks is expected to demonstrate the transformative impact these technologies can have on the safety and well-being of users.

The innovative approaches taken in our project are expected to contribute to the cost-effective and automated deployment of application-tailored services in wireless networks. By streamlining deployment processes, we anticipate empowering service providers to offer a diverse range of customized services, meeting the dynamic demands of users. The emphasis on user-centric communications services, coupled with the pursuit of higher energy efficiency, aligns the CENTRIC project with the evolving needs and expectations of the telecommunications industry. CENTRIC is therefore expected to lay the groundwork for a paradigm shift towards more user-centric, efficient, and sustainable communication networks.

In summary, the CENTRIC project is expected to not only push the boundaries of technological innovation in wireless communications but also set the stage for the widespread adoption of AI-AI solutions. The multifaceted expected impact, spanning from energy efficiency to user-centric services, positions our efforts at the forefront of the ongoing evolution towards 6G and beyond. As we anticipate contributing to pre-standardization activities on AI-AI, we envision a future where our expected advancements become integral components of the next generation of wireless communication standards, shaping the trajectory of the telecommunications industry for years to come.

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