Self-Adaptive Wireless Communication: Leveraging ML And Agentic AI In Smart Telecommunication Networks

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Abstract

Smart wireless telecommunication networks are increasingly incorporating various Machine Learning (ML) techniques for enhanced performance. These algorithms are anticipated to continue in the post-5G/6G era. Current mainstream telco networks rely on rules, thresholds, and simple heuristics for controlling complex processes and behaviors. As a result, many applications, such as forecasting key performance metrics, detecting unusual performance patterns (anomalies), and doing root cause analyses now require more elaborate AI algorithms for their automated realization. Although they have been successfully deployed in inspection tasks, ML and AI-enabled functions still mainly work in the "pilot frame", meaning that when a function works well on a specific case, it needs to be re-trained, re-tested, or re-tuned for handling different instances. Deep Learning (DL) techniques are replacing traditional data-centric architectures, pipelines, and algorithms in many industries. They enable automatic feature extraction, state-of-the-art performance, and more interpretable results. However, it is also important to investigate novel DL architectures or training pipelines that can adapt themselves to very large, changing models and topological structures and be trained and evaluated continuously without stopping services. Enabling Self-Adaptive (SA) AI is among the next big challenges in digital telecommunications, including but not limited to the following endeavors and questions. What monitoring metrics, strategies, and methodologies are effective in inspection tasks of large ray algorithms or ML models? How can the potential cause space of Managerial Performance Confidentiality (MPCC)-related anomalies be narrowed down or partitioned for fault detection and root cause localization? Clustering and classification algorithms with clear interpretability characteristics will be investigated for this endeavor. In addition, Enabled State Estimation (ESE) is one of the most critical building blocks for enabling proactive, efficient, and powerful management and control of telecommunication networks . By modeling the spatio-temporal SST behavior of the entire network, it is possible to synchronize many important tasks in the time and data domains, which makes some complex-to-explain and complex-to-controlled scenarios manageable. Meanwhile, this paradigm also raises probing questions of how to implement ESE in low-cost and on-demand modes in flexible, multi-dimensional SaaS cases.

Keywords: self-adaptive wireless communication, machine learning, agentic AI, smart telecommunication networks, adaptive networking, autonomous systems, intelligent signal processing, dynamic network optimization, real-time decision-making, multi-agent systems, reinforcement learning, cognitive networks, 5G, 6G, edge computing, network self-healing, AI-driven orchestration, wireless intelligence, self-organizing networks, proactive resource management.

1. Introduction

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1. Introduction

Recent developments in the field of Artificial Intelligence (AI), including Machine Learning (ML) and reinforcement learning, have made impactful strides by channeling aspects of human-like cognition in utility-driven decision-making exploration across complex environments of interest. While many aspects of AI still cannot be mimicked and emulated by defined algorithmic approaches, there exist promising and encouraging developments to effectively apply AI to communication scenarios. Pattern recognition, established by heralded, predictive modeling of critical parameters such as signal propagation, modulation formats, and channel response, still remain problematized by the complex temporal, spatial, and spectral nature of communication systems [2]. Consequently, well-tested models are hard to establish. Achieving good AI-informed prediction is an arduous task which is made plausible only through data-hungry learning. Unfortunately, sharing of massive amounts of data is often hindered by privacy constraints and confidentiality [1]. A distributed, federated learning paradigm is but the most entrusted method to tackle such prohibitive obstacles, and effectively learn a good representation of channel models locally. Complementary to this realization, emergent developments in the field of agentic AI aim to investigate the breadth and limits of intelligence and agency, when heterogeneous creatures compete with variable resources, necessities, intentions, competencies, and abilities. It is foreseen that the next frontier of AI will be with agentic forms that are capable of reasoning, simulating, and modifying their own abstraction of the world. The coupling of self-adaptive communication with the agentic AI framework will be discussed and formulated, wherein an end-to-end perspective will be presented, and an illustrative example will be provided. A smart telecommunication network consists of multiple wireless nodes that communicate with each other via point-to-point wireless links. A goal is to jointly adjust the communication settings and the physical layer signals delivered on those links across the network, so as to maximize the overall network performance metric. Given the large space of possible settings, satisfying the goal via conventional approaches is challenging, with outcomes usually stuck at local optima that are far from the globally optimal solution. Distributed self-adaptive communication approaches have been proposed recently. Indeed, the self-adaptive process can be framed as a multi-agent reinforcement learning problem. In this setup, each wireless node takes decisions on the settings to use for communication, learns the feedback from its neighbours, and updates its state based both on its own experience and that of others. As a result, agents use an individual self-adaptive approach against others' black-box behaviour. Thus, currently pursued distributed self-adaptive approaches operate in a fixed regime, where agents regard the underlying environment as free of changes and the senses of learning and adaptation are essentially neglected.

2. Background and Motivation

With the explosive growth of wireless users and applications, the next-generation wireless communication network is envisioned to provide higher data rates, better coverage, with a more cost-efficient, secure, adaptable, and scalable communication system. Towards this goal, 5G communication has begun to [1]. By virtue of the wider frequency bands such as mmWave and THz bands, promising technologies like massive MIMO and NOMA, 5G networks are supposed to provide peak data rates up to 1-10 Gbps, improved latency and reliability, and massive device connections. However, as applications migrate to the cyber-physical world, the existing communication networks are not sufficient anymore. In addition, the emergence of new application scenarios unleashes a series of new stringent demands on 6G communication networks, including peak data rates of 1−10 Tbps, massive device connections with 10−100 million device connections, mobility support with speeds higher than 1000 km/h, and latencies reduced to fractions of 1 ms with reliability improvements for mission-critical applications. To provide global coverage, the 6G wireless networks will expand from terrestrial communication networks to space-air-ground-sea integrated communication networks [2]. With the advancement of 5G, the corresponding research of the future 6G wireless networks is just beginning. Mainly due to the ubiquitous connection demand, the expansion of 6G will result in a sky, sea, and space environment, which increases the research on radio propagation characteristics, channel modeling, and other related issues. As the basis of wireless communication, the wireless channel study is necessary for the design of communication systems and the performance evaluation of wireless networks in various application scenarios. However, the research on wireless channels has mainly been focused on traditional terrestrial radio channels, while the study of the wireless channel is still in its infancy for

fig 1: AI in Wealth Management Transforms

intelligent reflective surface, satellite communication, underwater communication, THz channel, etc. 6G wireless networks will use lower-density frequency bands such as THz and Extremely High Frequency, which brings great difficulties in wave propagation due to the high attenuation and absorption. It is crucial to conduct a thorough study of the radio propagation channels in these bands. On the other hand, a clean, low-cost, and maintenance-free solution is required for the sustainable development of broadband wireless communication networks. To meet requirements such as high efficiency, flexibility, and high speed in operation and deployment, it is important to study the channel characteristics of the optical wireless communication system.

3. Overview of Wireless Communication Technologies

The recent global developments in mobile communication, comprising research, standardization, and commercial deployment, are divided into three phases: 1st (1G), 2nd (2G), 3rd (3G), 4th (4G), 5th (5G), and, lastly, 6th mobile telephone generation systems. The first generations processed only speech by circuit-switching. Future (6th generation) systems should cope with any form of human-mobile-device interactivity such as person-to-person, person-to-machine, or vice versa, by means of a merger of circuit and package switching. Their requirements are internationality, immateriality, bigness, ubiquity, interchangeability, omnipresence, and security. Impossible by the existing network architectures, therefore an unusual top-down approach will be followed. Presently, the 6G approach consists of three technological pillars. 1st: The development of rapidly operating, ultra-broadband, mobile terminal-device-compatible, and bio-electromagnetic-safe transceivers; 2nd ultra-massive (104 antennas), high directivity, identical, fully connected (non-cooperating), circular-identity-rotating antenna arrays (CIA); and 3rd, a new system architecture, schematic design, and optimization of procedures for the generation, transmission, and reception of signals. The enormoucapacity and the new design paradigm make routes/timings irrelevant and throw out randomness, hiding passwords, or codes in covariances transforming it into a fundamentally secure/unscrambleable channel. Each of these requires huge knowledge and intellectual capacities probably not existing today [3]. 6G has never been seriously started worldwide. By transceiver technologies it is impossible to convert the present globally interrupted totality of transceiver devices to continuous non-correlated mobility. Therefore, the whole already existing Global Systems for Mobiles (GSM) must be re-conceived-leadingly from scratch. One-third of the present communication in wireless means broadcasting, multicasting, and/or multicasting to any extent not realized by existing systems. Of utmost need as a national sovereignty, safeguarding of state affairs, and security of personal and other privacy. Preparing / re-conceiving GSM4R wireless systems need exceptionally rare enormous knowledge and insight, probably take a huge time and effort of known specialist signatures of academia, industry, and politics for patenting intent.

3.1. Evolution of Wireless Networks Over the years, wireless networks have evolved going from the first generation (1 G) voice communication systems to the 6th generation (6 G) wireless communication networks. The early 1 G systems which were based on analog technology with limited capacity paved the way for the development of 2 G systems that allowed voice calls to be digitized and encrypted using GSM architecture. The 3rd generation (3 G) systems were developed for the ubiquitous and high-speed data communication requirements of wireless networks with the introduction of wideband code division multiple access (WCDMA)-based Universal Mobile Telecommunications System (UMTS) systems. Mobility and streaming video services were also sources of intensive research during this period [2]. The 4th generation (4 G) LTE systems built upon the semi-orthogonal multiple access (OFDMA) technology were primarily designed for high speed mobility of up to 500 km/h with evolved packet core (EPC) architecture dedicated for non-real-time applications. The 5th generation (5 G) wireless systems which are currently being developed are primarily targeted for Ultra-Reliable Low-Latency Communication (URLLC) applications with mission-critical control plane latency requirements of less than 1 ms which includes smart vehicles and industrial automation systems. The 5G wireless systems follow the Service Based Architecture (SBA) principle for enhanced setup time scalability and flexibility [1]. The 6 G systems which are post 5 g systems are primarily being researched for Integrated Sensing and Communication (ISAC) applications along with

Artificial Intelligence (AI) enabled Radio Propagation, transceiver design, hybrid beamforming and communication.

$$\hat{h}_{t+1} = f_\theta([h_t, h_{t-1}, \ldots, h_{t-n}])$$

Eqn.1:Channel State Prediction (Supervised ML Model)

- h_t: current channel state (e.g., CSI)
- f_θ: ML model (e.g., LSTM or transformer) with parameters θ
- Predicts future channel state to adapt transmission strategy.

3.2. Current Trends in Telecommunications The telecommunications industry is always in quest of attractive avenues to ameliorate service quality and performance. The state of the industry over the past decade has been extensively influenced by acceleration in intelligent telecommunication networks. With the introduction of initial releases of 5G wireless systems, further augmentations are being investigated for telecommunications. The promised augmentations from 5G, however, are quickly becoming necessary, as use cases have evolved, and the application of machine learning across the networking fabric is being investigated. The key transformation from 5G to 6G communications is anticipated in an exploitable bandwidth range extending to the Tera-Hertz regime, which has promising avenues for ultra-broadband wireless communications [4]. On the other side, the development of a new generation of satellite constellations will enable ubiquitous coverage of Internet and Telephony services globally, making 3D networking endemic [1]. These modalities will permit the provision of services that are important in the new AI paradigm of performing distributed edge intelligence on data streams captured from the real world, which will have multiplicative effects in demanding scenarios such as Wild-Fire detection, Precision Agriculture, and others. To contend with the novel breadth of coverage, complexity will increase and self-management will become imperative on account of the budgetary asymmetries within network operation. Self-adaptive wireless communication is defined as a mass-market telecommunications service that is designed to meet transient requirements or selected capabilities as a feedback conversation, using data-driven or engines of self-achievement techniques without online human investigations. The initial discussions predispose the notion of self-adaptive wireless communication. Then, the state of telecommunication as it is today details some achievements with regard to autonomous wireless communications, defined input current elaborated on prior machine learning (ML) applications; agentic discussions are prescribed as a means to meet expectations. The final consideration deals with future telecommunications, ensuring a two-way integration of agent and human decision-making, learning, refinement, and adaptability. Whatever state the programmable telecommunication networks end up in, human intelligence should always have a qualified control over self-adaptive networks. Nevertheless, as this would be the largest area of potential exploitation by intent, that will also be the main point to see this goal being hard to achieve. This closeness in software, discipline, discussion, language, and presentation will greatly help telecommunications become pervasively an increasing necessity in the everyday life of everyone on Earth and in the off-planet settlements either already deployed or to come.

4. Machine Learning in Telecommunications

In the last few years, the next generation of mobile networks has become a focus of considerable research interest. The 6 Generation (6G), which promises to provide higher spectrum efficiency, lower efficiency, and a peak data rate of 1 Tbps. Furthermore, a paradigm shift towards the Machine Learning-based approach will enable networks to be smarter and more elastic in generation 6 and beyond. The demand for mobile communication continues to grow fuelled by the proliferation of mobile devices, applications, Machine-to-Machine (M2M) communication, and the Internet of Things (IoT). The forecasts that by 2030, there will be 30 billion mobile connections with 4% that will be 15 trillion of fused devices a day with autonomous vehicles as the main contributor. The explosive growth is putting a great deal of pressure on network operators to keep up with the rise in the volume of communication traffic and subsequently to increase the capacity of their telecommunications infrastructure. Currently deployed wireless systems rely heavily on mathematical models, but such models do not define the system structure accurately. Hence, the use of Machine learning (ML) techniques for wireless communication has gained momentum as these methods enable the attainment of the quality of service functionalities with advanced solutions. These ML techniques provide the replacement of heuristic or Brute Force Algorithms for optimizing localized tasks, also presenting adequate solutions that the existing mathematical models are unable to obtain. Elsewhere, shortly before the convergence of ML and telecommunications, they were developed independently, with mathematicians developing ML. Then, as better computational hardware became available, their complexities turned them into practical algorithms.

The areas of machine learning and communication technology are converging. Traditionally viewed as separate fields, they combine their distinct assets and offer new opportunities for cross-fertilization. For example, on the one hand, trained ML components can replace predefined mathematical routines in communication systems. On the other hand, the massive data traffic generated by today's communications systems can help greatly in enhancing the design and management of networks and communication components when combined with advanced ML methods. Furthermore, recently developed end-to-end training procedures offer new ways to jointly optimize the components of a communication system in a data-driven manner. ML methods are of central importance in emerging application fields of communication technology, e.g. smart cities or Internet of Things (IoT) [1].

4.1. Fundamentals of Machine Learning The incredible growth of mobile communication networks in the last few decades has drastically changed people's lives. Innovations such as mobile video streaming, mobile gaming, remote virtual reality (VR), augmented reality (AR), and vehicular mobile applications have become part of peoples' daily-life experiences. However, these mobile applications can only prevail if the bandwidth demand can be satisfied. Therefore, the emerging sixth generation (6G) wireless networks is expected to provide a sea change in capabilities, such as zero latency, gigabits-per-second download speed, massive connections, and enhanced mobile experiences [1]. The discovery of the Tera-Hertz band opens a wide frequency band for communication. Nevertheless, exploring this band comes with unprecedented challenges of rapidly varying network dynamics and involved system complexities.

Traditional mathematical models do not adequately capture the system structure of the wireless networks, such as the base stations, user devices, communication links, etc. Many intelligent techniques, in particular, machine learning (ML) models, have been proposed to address the challenges for future wireless networks [3]. The role of ML in wireless networks has gained traction in both academia and industry. Use of ML techniques in wireless networks has started at a slow pace in specific problems, such as signal detection, channel estimation, and allocation of communication resources. More scalable algorithms and protocols are needed to meet the increasing challenge. Besides that, the demand for ML-aided intelligent wireless networks with the low-cost ML devices, which are also called the edge computing devices, is also exploding. The edge computing devices are typically with limited computation capability, memory size and battery life, and high mobility challenge. So the efficient design and implementation of low-cost ML models and algorithms on the edge computing devices are necessary. Moreover, ML models work significantly better with sufficient training data. In many low-cost edge computing devices, data privacy preservation and security are also concerned with wireless service providers. So the design of AI and ML models that enable data privacy and security is emerging. The fast refinement of ML models on the edge devices, especially the online learning ability is needed as well.

4.2. Applications of ML in Network Optimization Mobile networks evolved from 2G to 5G generations and currently being designed for 6G networks with a number of target performance improvements over the previous generations. Such improvements include 10–100 Gbps download and upload data speed, extension of network coverage while ensuring high data speed, and connection of up to 106 devices per square km [1].

Learning itself from the complex pattern of available data and help decision-making processes via classification, clustering, and regression algorithms are some of the important roles that machine learning (ML) use cases may play in both cell- and core- based networks [5]. Optimization is of paramount importance in the design, evolvement, and operation of diverse telecommunication networks such as fixed optical networks, ad hoc networks, cellular 3G-5G networks, and satellite networks. The 5th generation (5G) networks have been developed around 10 categories of new optimization problems that can be further classified into 2 classes of combinatorial optimization problems in essentials based on the structure/locality of the effective solution spaces. Nevertheless, strict solutions are usually unavailable for such network optimization problems due to the mathematical intractability as PwNP-complete. Additionally, heterogeneous competition for the scarce resources at both the local and/or global levels leads to very high complexity and poor scalability.

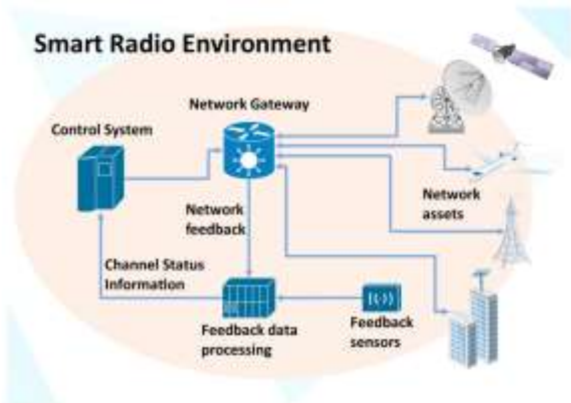

Fig 2: Communications and Artificial Intelligence

New radio communication technologies and paradigms such as millimeter wave, terahertz band, massive multiple-input multiple-output, and satellite back hole will be further studied. Provisioning ultra-reliable low-latency services, supporting for 106 times of permitted number of devices, and harnessing the ubiquitous intelligence for increased effective bandwidth and reliability, etc. will be the major performance and feature improvements targeted at the next evolution from 5G to smart telecommunication networks. Major prospects of the joint optimization problem formulation and resolution approaches for multi-hop wireless communication networks. Recent literature on multi-hop wireless network optimization algorithms using AI-centric approaches is summarized. The computational process for finding the locally or globally optimal solutions for NP-hard optimization problems will be first reviewed with particular emphasis on heuristic approaches. ML and agentic AI technologies broadly used for intelligent wireless communication will be discussed.

5. Agentic AI and Its Role

Agentic AI is AI that has the capacity to expand its own capabilities by assessing its situation, taking action, and assessing its environment and the results of its actions. Some AI systems are more agentic than others, depending on their degree of capability in these four areas. While many AI systems today operate at only the first two stages of situated action — perceiving and deciding, for example by making assessments of their current situation and considering a set of actions — a subset of these AI systems are capable of more advanced forms of stage 3 action, including self-improvement, self-modification, and possibly even autonomous chaining of actions to better achieve a stated goal.

Researchers using a more prescriptive definition of agentic AI typically stress the fourth stage of action, delegation, which includes the situation assessment, action, and outcome assessment capabilities considered above, plus the ability to offload full subprocesses or partial goals to other agents. In this view, AI systems that are able to hire other AI systems to perform even a small part of their original task are considered agentic. This definition emphasizes the strategic aspects of an AI system, including its goals and the efficiency with which it achieves them, rather than its internal workings.

While there is debate about where to draw the line when defining agentic AI, there are many different terms to describe AI systems that have the capacity for positioned self-expansion. The terms superintelligent, recursive self-improvement, or recursive self-improvement systems tend to emphasize the capacity for self-improvement. Other terms, such as artificial agents, powerful AI, or narrow, task-specific AI governments, focus more broadly on capabilities that can be applied to task completion. Performance surpassing that of the fastest humans on Earth in at least one general task, such as programming, modeling, or organization, is often stressed, and the term advanced AI or advanced computational system may be applied to systems that meet this requirement.

Some aspects of intelligence itself, such as the ability to reason, strategize, or draw inferences, are also seen as prerequisites for agentic behavior. These terms often refer to more general or all-encompassing forms of intelligence and are therefore not as useful in isolation to discuss the rapidly emerging forms of powerful AI.

5.1. Understanding Agentic AI Over the decades, artificial intelligence (AI) has continuously evolved, experiencing several generations of development for more advanced levels of automation. Rule-based algorithms and statistical learning models were widely adopted at the early generations of AI. With the advent of more complex and massive amounts of data, deep learning techniques have shown remarkable success across various fields of AI, including vision, language, and control tasks. As one type of advanced AI technology, generative AI (GenAI) has the ability to create new text, images, and videos at a remarkably high level of quality. Its emergence is considered a revolutionary milestone, sparking a new AI wave and leading to a global rush to adopt GenAI technologies in a wide range of applications.

The next-generation of AI systems, either generative or non-generative types, is taking shape to handle unprecedented challenges in data quantity, applications of AI, and user expectations. Human-in-the-loop (HITL) systems have been proposed as an early attempt to incorporate human understandings into AI-based decisions. One salient feature of HITL systems is to combine human feedback with the AI's learning process, leading to better contextual understanding and accuracy of the AI results. However, HITL systems are less adaptable and responsive in real-time as their operation relies on human input and interaction, which is typically time-consuming and difficult to construct.

Interactive AI (IAI) is proposed to address the real-time challenges encountered in many scenarios, where deeper and immediate interactions are required for successful completion of tasks. IAI allows for immediate and direct interaction between the AI and the users, via which the IAI can instantly decode users' inputs and provides an intelligent understanding and responding or executing task. Incorporating IAI with retrieval-augmented generation (RAG) technology can enrich responses for personalized network operations with diverse strategies and content. With open-world high-dimensional knowledge integration capability, it is promising for IAI to enhance network resource allocation and performance. For instance, IAI can dynamically allocate bandwidth based on user experience feedback for high performance.

5.2. Agentic AI in Decision-Making Processes The framework of action planning in agentic AI covers how higher-level integration knowledge on longer timescales constitutes an agentic AI’s decision-making hierarchy. Action planning is formed by encoding long sequences of run-time processes into a compressed format as an intermediate representation. The action-planning module interprets this short-term AI memory footprint using higher-level processed information, such as prepositions or ontologies, and decides to trigger one of many of the agent’s capabilities. Finally, the envisaged action sequences are planned by composing low-level goals and generating temporal Bayesian programs for long sequences of actions [6]. Decision-making hierarchies can be layered into up to six or seven levels arranged in a hierarchy. The set of components in each layer can include components capable of decision-making, e.g., primitive or high-level virtual units, forward processing units, monitor or critic units, simulation-to-reality units, reachers or physical systems, and skill executors. Higher levels typically integrate inputs from lower levels, and outputs of higher levels are preserved as internal states for working memory in processing by lower layers. An agent can perceive consequences of actions through perceptual processors receiving sensory data and monitoring the states of external systems and the agent itself. It is desirable that agentic learnable AI architectures possess such a cascade structure for efficient knowledge processing of events over wide-ranging spatial and temporal scales [1].

6. Self-Adaptive Systems

The self-adaptive wireless communication approach creates a pervasive mobile and wireless communication network that continuously senses its own conditions and reconfigures itself to achieve optimal operation [4]. Self-adaptation is enabled by the combined capabilities of interdependent mobile processors, communications, and networks that sense their own states and other network states and evolve their own operation from application needs through different paradigms of autonomy. These include distributed, multiagent, and fully agentic systems where agents are autonomous and social and are aware of their own states and other agents. Pervasive mobile and wireless communication supports Internet-like communication and a mobile and wireless grid and networks. It is an electric grid of mobile/social laptops, desktops, and embedded/wearable systems for computing. It is an on-board grid of vehicular communication, which overlays on the transportation graph. It is an aerial grid of airborne communication in the sky. It is a highly spatial network of housing, building, and street-based communication. And it is a social interface based dynamic communication structure. With the growing intelligence and autonomy of communication equipment and user devices, this mesh of embedded, autonomous, and agentic communication systems can effectively build efficient peer-to-peer communication on demand. Areas of application include vehicle and device networking, traffic control, and mobile agent services [1]. The self-adaptive wireless communication approach creates a pervasive mobile and wireless communication network that continuously senses its own conditions and reconfigures itself to achieve optimal operation. Self-adaptation is enabled by the combined capabilities of interdependent mobile processors, communications, and networks that sense their own states and other network states and evolve their own operation from application needs through different paradigms of autonomy. These include distributed, multiagent, and fully agentic systems where agents are autonomous and social and are aware of their own states and other agents.

6.1. Principles of Self-Adaptive Systems The origin of the term agent lies in the Latin root agere, meaning “to do”. Agency, therefore, relates to those entities capable of doing something, whether resulting in some action, consequence, or influence. In a network, it refers to the components capable of doing something on their own to affect the overall system and the way they are designed and operated. The agentic AI may be in the form of dedicated algorithms or trained models within a designated AI HW/SW for implementation on the network. To operate on the networks, they are interfaced with the nearby communicating nodes or agents via a suitable middleware using some computer programming languages. Effectively, in design and implementation various aspects, such as agentic type, proficiency, and AI representation, need consideration.

The wide applicability of multi-agent based designs within self-adapting systems makes this approach the most promising candidate for the development of agentic AI within the smart communication networks domain. The two most crucial areas are observations and collaborations for distributed agentic design. These experiences, in the form of observations, act as a source of information for the self-acclimation of other agents. On-object information covers aspects such as tagging of resource units containing channel index and assigned power, agent ID, intended/expected SINR, and event identification. Other aspects, such as weather data collection via smart sensing and data mining, also provide functionalities to the agents to cooperatively plan for resource assignment to designated users.

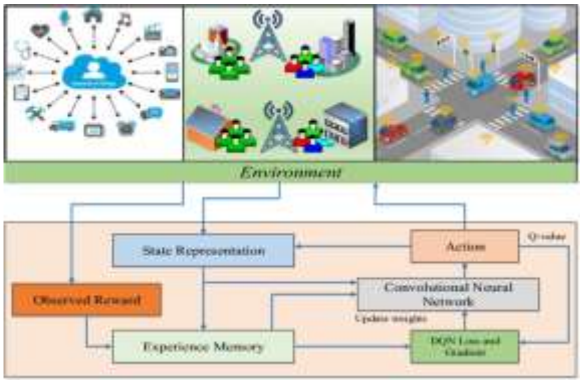

Fig 3: The role of artificial intelligence on

Agentic AI for efficient merging/fusion of observations over the networks should involve determining how updates on these performance metrics by resource converting agents within each device agent network can be successfully merged to update broad site level performance. A global observation matrix over each site is defined containing total observations on a site-to-resource unit basis with data obtained from distributed inputs from agents. The distributed inputs could involve several observations from nodes over played rounds. Communication protocols may be developed to ensure that very few re-transmissions may be required and the merging agent on each site needs to receive input from only a few neighboring nodes. Agentic designs need to be technically formalized and carefully defined for communication reliability and accuracy. If a few nodes within the site remained silent, the remote nodes would not receive data sufficient to update their inputs and assist in probabilities. As a result, conflicting information would be received by nodes in the same site which would diverge far further.

6.2. Benefits of Self-Adaptation in Networks For telecommunication networks in general, a benefit of self-adaptation is that additional knowledge about the state of the network infrastructure, of the environment, and of the requirements of the user becomes available. This additional knowledge typically enables better operator decisions in various processes regarding the network infrastructure. In addition, a wider range of operational strategies for the network can be considered, reaching more optimal operating points. Recent research results indicate that this additional knowledge can be obtained by incorporating techniques in other processes.

For 5G and beyond, a variant of self-adaptation has been identified as an interesting research topic. In this case, a benefit of self-adaptation is that the dynamism of networks is expected to increase, and in response to that, a wider range of operating points and faster adaptation are expected. For 5G, an interesting point is that with its improved frequency coverage, new frequency bands become available that were not covered by the cellular system before. This will improve the business case for mobile broadband providers. However, for frequencies higher than 10 GHz, the propagation characteristics significantly change, for instance highly directional and medium sensitivity to abrupt changes in the environment. As a consequence, beam-track development becomes more important, and additional capabilities of network nodes as well as cooperation between nodes become essential both for users and for relay mechanisms.

7. Integration of ML and Agentic AI

Technology convergence in the Field of Technology is ever-ubiquitous. A truly productive commutation of thought and reasoning between scientific fields, tempered by goals that are symbiogenetic, emergent, often ethical and responsible, must be properly reasoned, formatted and persistently propagated, vetted and curated, and widely accessible. The scope of this scientific responsibility must become symbiotic with the dynamics of the respective fields of application. Several paradigms—that must be properly blended to realize a genuinely intelligent and socially-beneficial agency—have been recently promoted as doing communication-awareness and consequent or concurrent Distributed Not-Quite-Computing. The laissez-faire isolation of independently implemented models, algorithms, protocols and virtual machines must be publicly phased out in favour of rational open-sourcing and configuring.

7G is expected to bring in-onboard a lot of user applications for simultaneously interconnected and tunable smart telecommunication networks. Such apps should assist both knowledge acquisition and utilization, self-management or self-adaptation with self-aligning with the context and goals in focus, coordination dynamics between devices, self-heal and redeployment in the case of present and anticipated cyber-physical mishaps, and hybrid edge-cloud coding and decoding.

The dense, versatile and highly heterogeneous geographical distribution of proximity communication technology has one unique benefit, which is the novel opportunity for enhancing proximity mediation awareness of total autonomy and consciousness yet active, painful and seeking led by agency. Such a principle resource could be benevolently exploited in designing accurate and efficient wireless communication protocols and networks, including channel modelling, encoding and decoding, peak-frequency-power-PAPR self-adaptation and channel occupancy and switching control.

7.1. Synergy Between ML and Agentic AI With the deployment of 6G and intelligent networks, the way wireless communications operate will transform entirely. The elements of wireless communication networks will be intelligent, have a higher degree of autonomy, cooperatively self-organize, and evolve and be adaptive to changes in the environment [1]. Broadly speaking, smart networks provide integrated data, resource, and service coordination, enabling a sustainable and efficient coexistence of technologies while increasing the transparency and trustworthiness of the networks. As these networks also span multiple domains, the AI-based systems must be extremely robust and principled.

A human-comprehensible and trustworthy AI is the key techno-economic enabler to developing next-gen smart networks, which is widely recognized. To this end, the telecom ecosystem needs an AI-holistic value chain to make the networks secure, inclusive, responsible, and environmentally friendly. To develop more capable adaptive automated wireless technologies, more cooperation in advanced telecommunication R&D is needed among academia, industry, regulatory authorities, and the public.

To realize the goal of intelligence and autonomy, a hybrid role of ML and agentic AI, particularly LLMs, is proposed. ML is concerned with learning from data, whereas agentic AI focuses on decision-making and communication via the learned information. With the synergy between the two technologies, new frontiers of architectural advancements and applications may emerge, providing new functionalities that could not be possible independently, such as cognitive cross-domain and cross-networking.

There are two main weaknesses in both ML and agentic AI. On the one hand, ML in current 5G networks is mainly for isolated learning. Each network node learns some models directly from the data collected locally, using some pre-trained ML algorithms. Such locally trained models contribute little or no benefit to the information and service delivery among adjacent (often heterogeneous) networks without inter-network data or model exchange, limiting the potential improvement in the network performance and capabilities. Retraining on data from a new domain is often needed as the characteristics of usage change or a network is added or partitioned. This data or model explosion issue is all-too-frequent with learning at the device level.

Eqn.2:Reinforcement Learning for Adaptive Communication

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

- Agent adapts communication actions (e.g., power control, handover, beamforming)
- s: state (channel, traffic, QoS)
- a: action
- r: reward (e.g., throughput, energy saving)

7.2. Case Studies of Integrated Approaches This section discusses case studies focused on revealing different technology angles and applications of the integrated approaches proposed for trajectory-aware self-adaptive wireless communication networks. Strategies (use cases of applications) covered include a case study on new service creations and operation management in smart transportation systems designed using 5G and 6G technologies, a case study on propulsion control technique and communication technologies enabling application networks of robotics and drones, and a case study of new service creations and operation management in smart cities designed using 5G and 6G technologies. In urban areas, invisible terror attacks using non-cooperative vehicles, e.g., vehicles with no cooperation communication capability, pursuing cognitive and unsolvable responses are expected. In a land transportation system, communicated-well vehicles with 3D light detection and ramging are used for autonomous driving. Cellular delay-tolerant networks with precursor detection and smart coverage enhancing relay are used in rail transportation. 5Meshed aerial controlling and 6-Drone secure aerial post-offices are expected in smart-scaled air transportation. Security of mobility systems trains and delays is achieved through trajectory prediction and communication networks to security detection. Time-sensitive FR transmission is used by cellular 5G-6G networks having both transparent and non-transparent operation modes to detect perilous situations at the track. The coverage of a communication network is predicted considering the distribution of the network parameters and changing patterns of service demands. A smart station with an intelligent controller having situational awareness appropriately selects transmitter parameters to satisfy coverage requirements. This case study on a communication network having trajectory-aware network parameters is first proposed, and information on changing trajectories is a novel concept [1]. Traffic data reflecting energy states of roadside units are monitored by environment-aware RSUs estimating the states of their connected RSUs. A proactive RSU's environmental awareness on slow traffic at a location is first discussed as a novel concept, and a natural communication network with heterogeneous agent systems is proposed for traffic synchronization.

8. Challenges in Implementing Self-Adaptive Networks

To develop self-adaptive telecommunication networks it is necessary to deal with some challenges involving agentic AI technologies, machine learning and wireless communication systems. Regarding agentic AI systems, privacy protection, responsibility fuzziness, transparency, geoliving, spontaneity, limitations of reason, and evaluations of agentic AI should be taken into account. The need to implement wider discussions about ethical benchmarks and reflect concerns beyond anthropocentric perspectives is highlighted. To facilitate some self-adaptive behaviours of smart wireless communication systems, the establishment of some basic elements is necessary: (1) the definition of rudimental evaluation functions for self-adaptation which induce the evaluation of the dataskilling requirements of communication tasks and the identification of alternative solutions that may satisfy these requirements; (2) the learning of individual profile models containing these evaluation functions that infer the dataskilling requirements of the communication tasks defined by a software agent and the feasible solutions for acquiring the required data sources; (3) the development of an adapted event processing system that, on triggering of a communication task, triggers the execution of the maintenance of the corresponding profile model within a ML-based framework; and (4) the cultivation of flexibility and irreversibility of the learning of profile model parameters. These challenges are exacerbated in the context of broader systems that involve multi-action and multi-agent interactions and competition for scarce resources. However, to the best of our knowledge, the implementation of agentic self-adaptive wireless communication systems has not been explored yet.

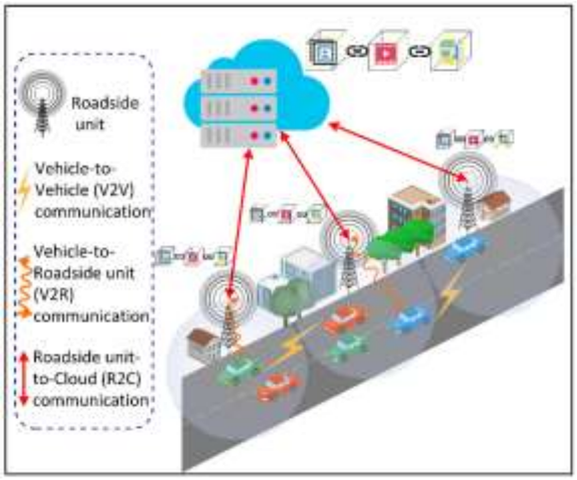

Fig 4: Artificial Intelligence Applications

Self-adaptation at a communication technology level is claimed to be essential to accommodate the rapid technological evolution and growing heterogeneity and complexity of wireless telemetry networks while addressing constraints in performance, costs, privacy and sociotechnical issues. In this context, self-adaptive behaviours of telecommunication systems must be developed, such as planning, execution and maintenance of the data sourcing process for dataskilling communication tasks. With the increasing heterogeneity of data sources exploited for machine learning applications in edge-enabled wireless telemetry networks, the complexity of this dataskilling process is also aggravated. In this context, a hybrid cognitive architecture is proposed to develop a wide range of agentic self-adaptive behaviours of smart wireless communication systems; the analysis focuses on a concerted execution of actions involving both learning mechanisms and data distribution transformations that accommodate the increasing complexity of cognitive processes.

8.1. Technical Barriers As new revolution of wireless communication stems from several digital revolutions that took place in different aspects of human life. On one hand, deep learning advances in analizing big data is enhancing a variety of services from natural language processing to object detection. The knowledge this new digital intelligence is creating can be exploited in the control of different environments such as homes, buildings or public places. On the other hand, the broadband networks that led to new media are evolving in respects that enhance speed and efficiency of service provisioning. These newly fiberized, packet-switched, and high bandwidth telecommunications networks are enabling and enhancing globally interconnected environments in aspects such as socializing, sharing knowledge or trade [4]. The combination of these two greatly powerful enlightened contexts leads to a new digital intelligence that is called `Artificial Intelligence (AI)`. When seeking an environment (or agentive media) such as smart homes, smart buildings, smart cities and smart telecommunications networks, AI-based big data analysis and information propagation play crucial roles [1]. The wireless telecommunication networks that further the knowledge creation and sharing processes of humans and unfortunately hinder them in many respects need AI-based self-adopter approaches. The knowledge this new digital intelligence is creating can be exploited in the control of new environments such as Smart Cities, Personalized Lives, Smart Homes, Smart Buildings, Smart Microgrids or Smart Telecommunications Networks. Conversely, the generation of telecommunication knowledge involves the risk of privacy invasion, information monopolization and corrupting. The rapid development of information and communication technologies in recent decades has dramatically changed the world. These, however, are mostly deterministic in their speech and action and therefore jeopardizing the knowledge economy. Agentic AI, a new paradigm of AI that is based on next generation “intelligent autonomy frameworks” is newly explored for smart environments. The deep learning and deep reasoning intelligences and self-adaptive evolution and control mechanisms of agentic AI are to be integrated to address the operability and controllability challenges of newly generated autonomous wireless networks. Agentic AI is an intrusion-free self-adaptive solution and framework family that aims at maximizing the potent and positive economic, environmental and ethical impact of technological advancements and the newly generated knowledge. Agentic AI aims at self-organizing the highly complex network world of new technological revolutions such as Wireless Artificial Intelligence agnostic of any mathematical modeling.

8.2. Ethical Considerations Self-Adaptive Wireless Communication (SAWC) employing ML and agentic AI promotes advancements in adaptive and smart telecommunication networks. Such systems ensure effulgent performance, increasing the understanding and reactivity of telecommunication networks towards the changing environment. Safety, ethical and implementation considerations emerge from this new technology and aspects of both general value-based AI and ML-based SAWC systems require further investigation. (i) The use of ML algorithms to develop agentic AI within the SAWC must be considered and assessed. Research needs to address concerns of uncontrollability, lack of access to the inner workings of the AI, and striving for maximising objectives to the detriment of all else [4]. Developing agents able to collaboratively cooperate with actor plans, allow for human scrutiny of internal states, stop systems from developing control over their own operation; limitations on the AI's capacity, or ensuring an increase in capability is directly accompanied by an increase in controllability must be further implemented in the industry. (ii) Current ML SAWC subsystems have increased or decreased robustness, but rarely both, and systems can be generated ensuring both within a more orchestrated structure should be investigated further. (iii) The difficulty of measuring the proportionate effectiveness of AI agents to human expertise, especially in resource-constrained scenarios, has not yet been assayed within SAWC systems as a whole. (iv) Mathematical and abstract measures of fairness, robustness, and interpretability are only recently being considered for implementation in the telecommunication sector. Examples of the inadequacy of some human assessable measures in practice exist, such as the football data set, a paradigm exhibiting fairness by representation but was not deemed fair by outcome. (v) Assessment procedures for safety, fairness, robustness, interpretability, and control have efficiency-vs-accuracy trade offs [1]. Alternatives and hybridised systems to current designs will need to be sought in ML techniques.

Research in ethical measures, metric design automata, and environments enforcing compliance would be beneficial. (vii) The training, development and monitoring of AI will all become more important but presently have not been considered widely, leading to environments where dangerous and misaligned AI may arise. Agentic AI used within tasks in smart wireless communication networks need to be tested in videogame or scoring systems with varying values in order to better predict the effects of deployment at scale. Lastly, numerous institutional, governmental and public views exist on merits concerning the ethical progression of AI. Examination of these sentiments through the lens of SAWC may reveal gaps in understanding, or areas of contention where hardened views would benefit from open debate.

9. Future Directions in Smart Telecommunications

The booming need for bandwidth creates the space for self-adaptive wireless communication to move beyond intelligent and semi-autonomous operations into the domain of smart technology, where revolutionary agentic intelligence takes over communication network management and operations. Largely preceding fields of research would pave the way towards establishing promises and the means of implementing smart wireless networks within the telecommunication industry. Telecommunication research and industry design a mobile communication standard that has to be kept for decades in a strongly locked-in state, which inherently impedes adaptability. However, a few traces of such telecommunication systems in agentic artificial intelligence for wireless communication do exist, and they largely state the theoretical basis for a rich area of further research. In the telecommunication industry, between great noise levels, narrowly confined models of the world have to be learned. These are mostly short and medium-term models and used to speculate about the best investigative paths. Most work is only on the short-term models; revealing the medium-term ones and finding entirely new paths happens very rarely but has huge impact when it does.

Yet, with academia in wireless communication starting to investigate even short-term agentic AI, such avenues have the potential to lead to largely untouched areas of research within traditional telecommunication network research. These traces consist of detailed analyses of the nature, structure, and function of wireless communication networks. Even theoretical analyses of fundamentally different designs for wireless networks and weaving new fabric of artificial physics around their communication, controlling, and learning processes are not unheard of. Reverberating these technologies to an agentic level for fully independent operation would be far reaching but mainly unexplored. There are many other areas of good theoretical background towards such investigations, like the communication component-level frequency-independent higher-order dynamical systems. Teaching a network to independently cooperate as a single unit could yield profound further efficiency gains, but such considerations have only rarely been explored in the realm of wireless communication.

9.1. Emerging Technologies Communication in static networks, including quasi- and aeolian networks, has been extensively studied and applied. However, the realm of communication networks is substantially greater than macroscopic ones. As dimensions decrease, fibers, tubes, tissues, and films of other materials may emerge. On smaller scales, networks also begin to branch, from cataclysmic geological events to cellular systems. Additionally, electrochemical networks or gas interactions may form, without geometry. As the problem becomes more intricate, difficulties arise in detecting topology and identification, controlling chaotic dynamical systems, and separating flows in mixtures [1]. Pervasive telecommunication networks will be reconstructed, and an extensive study on adaptation patterns will be conducted.

In nested networks with diverse architecture and highly non-linear dynamics, a plethora of access protocols, i.e., communication coding and decoding, must emerge, competing with each other while adhering to the framework of network topology. Scalability will present a major challenge, as the number of nodes added to the network increases by five orders of magnitude in a decade. New and innovative data analysis and control strategies will be required for several orders of magnitude increase in users (billions with differing needs), multiple-antenna receiving devices, and channels in the future. Protocols will need to scale on both spatial and figurative network architectures.

Machine learning (ML) is now recognized as a new paradigm for advanced and autonomous data analysis, control, decision making, and design. It is being widely considered for standard and self-adaptive solutions in telecommunication networks. ML can be developed for several layers of telecommunication networks, comprising simple encoding and decoding schemes rather than protocols. Water-filling approaches can instead be employed with at least one physical model. RL agents can be designed to develop self-adaptive protocols. There are different subtasks in each layer of telecommunication networks where the network state is fully or partly observable.

9.2. Potential Research Areas Multiple research directions hence arise from self-adaptive wireless communication systems. New approaches to depict network utility functions need to be devised and theorized. Non-convex utility optimization methods for the network can be used for agentic AI-based systems. This can open the path to new research areas in wireless communications. An ensemble toward self-adaptive communication can be trained to allocate resources in a fully distributed manner with sub-second reconfiguring times. In the case of no infrastructure, models and algorithms under high mobility and human transience scenarios can be proposed, allowing for distributed networks that self-adjust wireless settings. These distributed arrangements supervising no bandwidth access would transcend the need for interaction between the transmitter and receiver. Formulations for decentralized self-optimizing wireless technologies for Ad-hoc networks could be proposed while mathematically characterizing their convergence properties. Long-term horizon scheduling and impulse scheduling could pave the way for the full range of traffic requirements. Policies could even be devised where the number of services, their characteristics, and their traffic are completely unknown beforehand. This, in addition to fake traffic, could enable technology demonstrations that need assessment devices ahead of a rollout. Novel systems based on on-off communication tapping current from time-varying storage can be envisioned as a complementary alternative for ultra-short-range applications. Recent advances toward simultaneous wireless and liquid sensing could also be employed to devise wireless transceivers capable of gathering information beyond just the electromagnetic range.

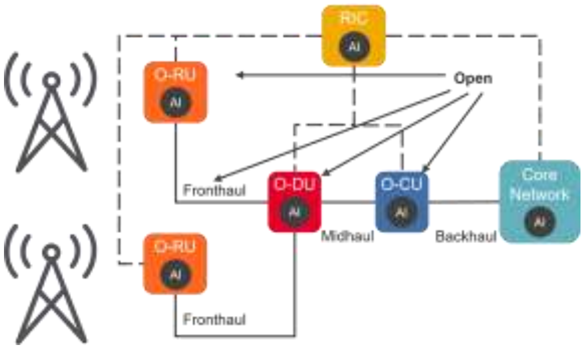

Fig 5: Artificial intelligence for wireless networks

10. Case Studies

On the quest for smarter telecommunication networks, the first research case undertook the task of demonstrating how Machine Learning and Artificial Intelligence can be employed to maximum industry effect. The 5G evolutional research project features topics covering product goals and scope, interconnected data-based AI systems, cooperative machine learning, fairness, ethical data use and self-organization of the underlying infrastructure to accommodate fuzzy and exploratory use case definitions. In its overall scope, it mirrors the nexus of self-organizing networks, mobile edge computing, and AI-aided optimization algorithms needed to link design pillars. Yet, as diverse as these subjects are, they naturally require argument prioritization and pre-selection of a distinct problem. In this view, leveraging the contribution of the 5G-Evolutionary perspective, with the publication of a demonstration project targeting one of its use case challenges, has the property of being immediately understood by a telecommunication audience, even with a general background.

This project aims at demonstrating how channel information from a trained, sensing 4G cellular network can be utilized to characterize its connections towards AI-assisted 5G allocative processes. To provide a basis, the initial steps proceed with pragmatic considerations with a strong focus on the application itself. They include exposition of the origins and motivations harboring the telecommunication industry and its researchers, the proposed train and test methodology, the integrated network model and validation process, as well as the earlier-verification of the rationale behind the application. While at a higher level, it serves as a general blueprint to test technological assumptions, the detailed implementation design choices will presumably endure separation into two distinct parts.

On its first half, this paper spotlights the target problem, the demonstrative use case, with conceptual ramifications, such as conditions and limitations. Secondly, it develops towards and presents, through reasoning, visualizations and statistical processes, quantitative metrics to illustrate the expected performance of its outcomes, while at the same time corroborating the initial train and test methodology. The analysis is supplemented with factual description of the investigation, formulation and sampling process leading to numerical data from a real roaming network. The second paper devoted to this approach will concentrate on the mathematical specifics of deep learning, the training procedures and results, and interpretations and visualizations of the associated variances throughout the work.

10.1. Real-World Applications of Self-Adaptive Networks The shift of telecommunication networks towards fully automated operation in smart societies means that the traditional network architectures and protocols have to adapt to cope with large scale, complexity, heterogeneity and dynamism. This shift requires radical innovation in network architectures and protocols to manage the control, optimization and assurance of the networks and at the need for low diameter, highly efficient control mechanisms among a massive number of agentic entities controlling nano, micro, core and cloud data centers around the globe. In response to the need for radical innovation, self-organising, multi-agent approaches to the control, optimization and assurance of the communications of such networks are proposed.

Distributed coordination among the control loops can be achieved by agent-based controllers on the basis of distributed representations in the networked multi-agent systems (AS), control graphs and dual control graphs. The proposed fully distributed control mechanisms can orchestrate extremely high dimensionality yet low diameter communications among control loops and agents to address the scale and complexity of telecommunication networks. The localities of control loops can be represented in independent graphs based on their kynetic horizons such that partial observability and independence of actions would make local control implementations continued, thus self-organising. The multi-granular architecture of the AS can be represented by six levels: packet-forwarding, link control, traffic-volume control, flow-path control, congestion control and source control. Natural partition can also be drawn respecting the hierarchy. Then multi-granular, multi-scale control architectures are proposed collaboratively with self specifications, in context of the self-organising multi-agent systems, agentic architecture, continuous adaptive controller structures, control institutions and agent-based approaches to programming abstractions. At last, realistic self-organised pilot work is reported, including case studies on the self-control mechanism design, congestion control mechanism design and simulation of the congestion control mechanism [1].

Eqn.3:Multi-Agent Coordination in Wireless Networks

$$R_i = \phi \cdot \mathrm{Throughput}_i - \psi \cdot \mathrm{Interference}_i$$

- Each agent i learns its communication strategy in a decentralized or collaborative setting
- ϕ, ψ: weights controlling trade-offs between throughput and interference

10.2. Success Stories and Lessons Learned A collaborative European project aimed to provide increased bandwidth and energy savings to telecommunication networks using a wide array of state-of-the-art techniques such as software-defined networking, edge and cloud computing, and 5G deployments, combining them with deep learning and reinforcement-learning techniques. However, the project witnessed tough resistance from the managers of large telecommunication companies. There were two tough discrepancies, one being the interpretation of the term Deep Learning. Industry refers to the three canonical models of supervised, unsupervised, and reinforcement learning. Conversely, the project's academic partners have introduced the novel concept of Agentic AI, incorporating recent advancements in data-driven decision-making technologies such as unsupervised learning and agent-based modeling. The second discrepancy concerns experience with telecommunication networks, ranging from impressive experience with 2G-4G networks to no previous experience whatsoever. In addition to these difficulties in the direct interactions with such large industries, members had to face the difficulties due to the pandemic.

Agents focused on cooperative strategies for power-saving issues starting from a recent abstract model for discrete time, geographically stratified, agent-based networks: each agent interacts with its neighbors according to a decision rule based on local information. Starting from the setting, agents play a variant of the prisoner's dilemma game against given cooperation probabilities of their neighbors over an initially generated random graph. Statistical agents -together with application agents- were able to achieve a reasonable level of playability in the shared simulator and telecommunication network environment. Statistical agents are simple reinforcement learners, equipped with the decision rule, able to adjust cooperation probabilities according to the last interaction history. The two agent types play the following strategies: cooperation probabilities of the agents already communicating with each other on their own; initial cooperation probability variance of neighboring agents. Results suggest that both real-world issues can significantly lower the efficiency of agent cooperation, whereas they can be overcome by global decision rules over modest time periods with the help of early experimental results.

11. Impact of Self-Adaptive Networks on Society

Despite their advantages, global telecommunications networks cannot operate without significant problems. Manual feature fault correction in mobile communication systems takes up 40% to 50% of mobile communication engineers' time at carrier companies. Another disturbing report shows that app usage prediction is unacceptably low for half of the examined apps. Errors cascade and propagate across unagents, distributed, temporally autonomous, data-driven online communication networks, making faults happen frequently while unseen.

The key challenges for telecommunications operators are as follows. There is no capitalist commercial means to access and correct pretransferred Ownership, Ascription, Distribution and Attribution of Network Protocol Implementation Databases and Network/Society Knowledge Graphs, which are expected to be many petabytes in scale. It is unsure if proprietary companies will open-source or commercialize their self-adaptive, agentic AI models, prepackaged implementation, and industrial-grade cloud and edge computing infrastructures for wireless communication. There is no precedent in history for analyzing networks, telecommunication, and robotics systems as a whole, end to end, and in a way that is compatible with ongoing daily transactions and updates at telecom giants. Agentic self-adaptation requirements have to be compatible with the hardware resource requirements for high network traffic provisioning during soccer matches. This includes requirements for constructing and optimizing the database and task scheduling graph topology for massively parallel transductive learning of preprocessed network/control graphs for thousands of epochs, utilizing a scalable distributed API-compatible acceleration plug-in, more than 256T-ops, and fault-tolerant operation.

Mathematical foundations for new knowledge graphed processing and computational paradigms/spatiotemporal representation learning considering high coverage ratio/nodes in urban scenarios. Large local Boolean rule logical function approximations with 256k dimension approaches. Future self-adaptation/network robotics formalism and research trends on Objective, Requirement, Performance Criteria Graphs, Routability Graph, Control Graph, Knowledge Graph and Interface Graph.

11.1. Societal Benefits and Risks The advent of Machine Learning (ML) introduces new opportunities for revolutionizing wireless communication and, in particular, resource management in wireless networks [3]. With the exploding demand for data, new approaches to efficiently allocate but at the same time preserve resources in wireless communication networks are urgently needed. Context-aware communication mechanisms, where both sender and receiver jointly select the mode of communication, are usually thought of a panacea towards this goal. However, newly deployed networks do not typically have a bird-view of the information transfer on their links. Wireless links are opaque and their state must be inferred by observing network actions during one or several communication instances. Orchestrating communication across networks with such a limited knowledge is highly challenging.

Therefore, the first goal is to investigate the advantages and challenges of context-aware communication in wireless mobile communication networks, especially in the context of Machine Learning (ML) adoption. Centerpiece of this investigation is a novel reinforcement learning framework, which models both transmitter and receiver as actors making sequential decisions. This framework can intuitively explain and appropriately prioritize the design choices for context-aware communication mechanisms. Another major challenge in the area is ensuring fair resource allocation among clients for efficiently providing very limited resources. The goal is therefore to understand the advantages and difficulties of constructing robust bidding mechanisms in a multi-client setting. The outcome includes a family of practical and robust bidding mechanisms based on a combination of the present and immediate past bids of each client.

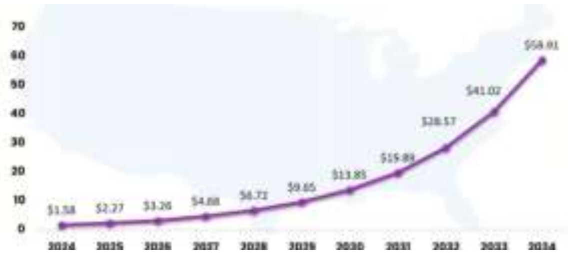

Fig : Agentic AI Market Size

Pioneering works have shown the potential of ML-based resource allocation in providing better performance for wireless communication networks. With the broad applications of smart telecommunication networks, opportunities arise but at the same time risks emerge as well. It is important to understand the societal risks of agentic resource allocation for wired and wireless communication networks, where novel agentic AI methods take decision-making in resource and communication allocation. Unfortunately, there are very few attempts, if any, that anticipate the societal risks of these powerful AI-enabled paradigms. A mixed approach has been presented by recognizing the small-scale societal implications of neural architectures but larger implications of agentic AI paradigms, giving less emphasis to ML paradigms like RL. Nonetheless, AI for resource allocation could have significant societal impact when deployed at scale.

11.2. Regulatory Implications The discussion on the implications of agentic AI in smart telecommunication networks and 6G has barely started. Implications may vary from policy considerations, competition and general IT sector considerations, to global power shifts, democracy, and humanity's future. Time is running out because there is a time gap between the deployment of networks by private companies and sufficient government oversight; meanwhile, regulations will be tweaked as new problems are encountered. The considerations would need to be inside each of the fields mentioned, such as society, democracy, and humanity, and need to be framed questions that direct the attention of the respective departments involved with smart telecommunications [1].

6G and smart telecommunications systems will be much more complicated than current systems. Will technology be used against public interest when such a system goes down, for example by deploying disinformation? The government can regulate current systems and plan the rollout of the next generation, so that market competition can be guaranteed. Next-generation technology will usually make explicit tasks more broad and general. The more general the assistants, the more competition and greater risks. However, usage of any of the conversations is also a concern regarding the AI's memory which would increase in scale and thereby dim the individual footprint even further. Users would have an awareness of the concerns regarding platform affordances and information cascades; either via regulation or social agreements this basis will need to be refined. Even though the information sent to companies, governments, or hackers has currently been the main concern, it is the storage of interactions in transfer protocols that is the essential difference.

Once everything connected to the open networks will run smart telecommunication systems, and the consequences of the smart and worldwide composition of the functions that telecommunications epigenetic software will have on social decision procedures become urgent, the discussion on public interest and society will need to be well prepared. Clearly, no government or society will accept telecommunication operators taking vital information out and silencing systems en masse without due process. Abuses of the unregulated domain of social media are only the start, and the benign use of a next generation tens or even hundreds times more general variant and source of power will be addressed. Telecommunication networks are essential health, safety, and security infrastructure, so both a basis of accountability by design and contingency procedures need to be imposed.

12. Conclusion

Artificial intelligence-enabled (AI-enabled) wireless networks promise a more intelligent and flexible optimization of system components and resources to achieve network-level goals in a self-adaptive manner [4]. Network planning, resource allocation, network slicing, troubleshooting, handover, interference management, and more traditional telecommunication tasks are complex, incomplete information tasks. Traditionally, network operators relied on human expert knowledge, heuristics, and optimization to provision networks. As networks become increasingly dense and heterogeneous with the addition of autonomous wireless devices, mobile towers, and nodes, this approach fails to meet the requirements of quality of service (QoS) parameters. The established operation and management systems of current telecommunication networks require improvement to maintain service integrity. AI-enabled telecommunication networks, termed agentic wireless networks, promise a self-organizing and self-managing deployment of systems, network components, network views, and agents to improve data forwarding and routing and resource provision decisions while maintaining network-level QoS parameters. Localization, classification, and parameter prediction processes are examples of AI methods to assist in communicating, employing communication noise and data processing methods, and improving data interpretation.

The need for ML in 6G wireless networks is primarily due to the rapidly growing requirement of wireless networking and communication [1]. With the phenomenal growth of M2M and IoT devices, demand for high data rate connection services, ultra-reliable low latency communication, and low power consumption is extensively growing. Emerging advanced wireless communication technologies such as massive MIMO, THz communication, and reconfigurable intelligent surface are complex due to increased capabilities and high dimensionality. Understanding them, as well as the underlying system model and channel characterization, is highly challenging. Diseased and faulty network constituent characterization becomes extremely complicated and tedious. Massive amounts of data are accumulating in the networking and communication systems but careful analysis is still pending. Parameter estimation yields very limited knowledge and insights of the systems. These issues are raised in 6G wireless networks, further motivating ML to replace traditional estimation, analysis, and optimization techniques.

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